Predictability, Non-normality, Volatility and Stability in Emerging Asian Markets

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Abstract: In this research we investigated monthly excess returns in six emerging Asian stock markets i.e. India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand over the relevant risk-free rates for possible existence of predictable components in these countries' stock markets over the relevant risk free rates. We modeled excess returns in these markets using non Gaussian state space or unobserved component models that encompass non normality to account for fat tails and conditional heteroskedasticity to account for time varying volatility that may be present in the excess return series. Our results show that statistically significant persistent predictable components exist in India, Malaysia, and Pakistan with excess returns at 5 per cent and in Thailand at 10 per cent level of significance. Likewise, our results also show an evidence of statistically significant non-normality and time varying volatility in excess return series for all the countries studied except India where market appears to have normal behaviour. Moreover, leverage effect being insignificant in all the stock markets, stability does not appear to be an issue except for Pakistan where stock price volatility does not appear to show a regular trend pattern over time. The efficiently estimated excess returns ranges between 0.6 per cent per month for Malaysia to 1.6 per cent per month for Indonesia.

Keywords: Fat tails, stable distributions, state space, stock return predictability
JEL classification: C22, C53, G14

1. Introduction

Stock return predictability is a central issue in empirical finance. In fact, our empirical knowledge on predictability of stock returns has been subject to constant updating over time, driven by the development of a number of new econometric methods that enable us to assess the evidence of stock return predictability more accurately. The growing interest in predictability of stock returns has been ever increasing not only because of the development of new econometric techniques but also because it could lead to ample economic gains with suitable trading strategies (Xu 2004). Fama (1991) provides an exhaustive literature survey on predictability of stock returns, and researchers including Bekaret (1995), Harvey (1995a), Haque *et al.* (2001, 2004), Claesson *et al.*(1995), and Buckberg (1995) show the existence of stock returns predictability and Bekaert and Hodrick (1992) and Fama and French (1992) show existence of a predictable variation in returns in the developed countries.

Emerging financial markets (EFM) have gained enormous attention from investors, researchers, and policymakers in the past few decades because of several factors that include strong performance of EFM over time and stock returns in some of these markets far exceeded than those of the industrial countries' financial markets, or mature financial markets (MFM). Cohen (2001) shows that the characteristic return-risk trade-off in the ESM

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undermined the prospects of MSM as quality markets. Moreover, Mobius (1994) demonstrated that due to their high rate of economic growth, the growth in most developing countries is expected to far exceed the rate of growth in the developed countries resulting in an increase in the long-run stock returns in ESM, over and above those offered by the MSM.

The strong performance of EFM over time has been accompanied with high volatility in stock returns involving significant risks for both the international investors as well as the real economic development of the countries concerned. In this context Cohen (2001) demonstrate that stock returns volatility in ESM is much higher than those in the MSM. However, while high volatility of emerging markets is marked by frequent sudden changes in variance, the periods of high volatility are found to be associated with important events in each country rather than global events. However, low correlation between EMS and MSM provides diversification opportunities to the investors in the developed countries to enhance expected return on their portfolio of investment while reducing the risk on their portfolio. This paradigm has been empirically validated by Divecha *et al*.(1992), Haque *et al.* (2001), Harvey (1995), and Wilcox (1992) using data from the segments of emerging markets they studied.

Historically, financial economics has been dominated by the linear paradigm and linear models have been widely employed in time series analysis pertaining to financial data. However, a wide body of empirical research[2] emerged in the past few decades suggesting use of non-linear models at least for time series data pertaining to stock returns. According to Antoniou *et al.* (1997) and Sarantis (2001), these non-linearities may be attributable to difficulties in executing arbitrage transactions, market imperfections, irrational investors' behaviour, diversity in agents' beliefs, and heterogeneity in investors' objectives. Likewise, Summers (1986), Fama and French (1988), Lo and MacKinlay (1998), Poterba and Summers (1985) and Bailey *et al.* (1990) show evidence against random walk hypothesis in emerging markets.

A number of recent studies that include Panos *et al.* (1997) and Sarantis (1999) and Taylor and Peel (2000) show that predictable components in stock returns are stochastically non linear and are better explained by the asymmetric dynamic process. Likewise, Akgiray and Booth (1988), Jensen and de Vries (1991), Buckel (1995), Mantegna and Stanley (1995), and McCulloch (1997) showed an existence of non-normality in stock returns. Likewise, Nelson (1991) Danielsson (1994), Pagan and Schwert (1990), Diebold and Lopez (1995), and Goose and Kroner (1995) concluded for existence of volatility persistence in stock returns.

Meanwhile, Watson (1986), Conard and Kaul (1988), and Harvey (1989) employed state space or unobserved component models on stock returns with the assumptions that underlying errors are i.i.d. normal and that stock returns evolve from first order autoregressive process. Some time later, McCulloch (1996a) demonstrated that stock returns are typically non Gaussian and have fat tails. Bidarkota and McCulloch (2004) using US monthly stock

[2] The proposition of non-linearities in stock returns was demonstrated by Hinich and Patterson (1985), Scheinkman and LeBaron (1989), and Hsieh (1991) for US stock markets, Abhyankar *et al.* (1995) and Opong *et al.* (1999) for UK stock markets, Kosfeld and Robé (2001) for Germany, Antoniou *et al.* (1997) for Turkey, Barkoulas and Travlos (1998) for Greece, Sarantis (2001) for G7 markets, Lim and Liew (2004) for selected Southeast Asian markets, and De Gooijer (1989) and Ammermann and Patterson (2003) for random sample of world stock markets.

price data on New York Stock Exchange, AMEX and NASDAQ proved these stylised facts that the stock returns are typically non Gaussian and have fat tails. Inefficient estimation would result if the features petaining to non normality and time varying volatility are not included in the models that are employed to forecast possible existence of predictable components in return series. That is why, in the present research, we employed non-Gausian state space or unobserved component models, which is basically a signal extraction approach. Our unobserved component models encompass non-normality to account for fat tails, conditional heteroskedasticity to account for time varying volatility in the stock excess returns data, that is widely recommended in the literature. In addition, our unobserved component models include leverage term in their GARCH formulation taking into account the impact of negative shocks on generation of future volatility when compared to a positive shock of equal magnitude which allows us to study stock market stability in a given stock market over time. The contribution of the present study is to employ non-Gaussian state space models, that is, a signal extraction approach in conjunction with features that account for fat tails, time variying volatility, and leverage effects for possible existence of predictable components in stock excess return series pertaining to selected emerging Asian stock markets.

We modeled excess return series[3] for India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand stock markets using non-Gaussian space state or unobserved component models that account for non normality and volatility persistence in the series. Because of the non Gaussian nature of shocks, we relaxed the normality assumption in favour of stable distributions[4] as in Bidarkota and McCulloch (1998). We employed recursive algorithm due to Sorensen and Alspach (1971), extended by Kitagawa (1987) to include a smoother formula for possible existence of predictable components in return series assuming that these series are non-Gaussian with fat tails, because the powerful Kalman filter is efficient only with a normal distribution. However, when the errors are non-normal as is in our case, the Kalma filter no longer works efficiently.

The rest of the study is organised as follows. Section 2 outlines the most general state space model employed in the study. In Section 3, we present empirical results, hypotheses tests, and results on hypotheses tests. The discussion on results is found in Section 4. Finally Section 5 encompasses the conclusions.

2. Model for Stock Returns Predictability

We employed a non-Gaussian state space model that includes non-normal errors and GARCH-like effects to find possible existence of predictable components (if any) in all the excess return series. Following Bidarkota and McCulloch (2004), model 1 is the most general form of the state space model employed in this study which incorporates non-normality,

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[3] We started our analysis on a number of other Asian emerging markets including Bangladesh, China, South Korea, Sri Lanka and Taiwan but these countries were excluded from our empirical analysis because of data limitation which hampered our empirical exercise; the study was therefore limited only to India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand stock price indexes.

[4] Although stable distributions were proposed by Mendalbrot (1965), state space models with stable distribution were employed by Mantangna and Stanley (1995), Buckel (1995), McCulloch (1997), and Bidarkota and McCulloch (2004) to model non-Gaussian return series.

GARCH-like effects as well as a term in the GARCH specification of this model to account for leverage effect. The most general model is shown in the following equations:

$$r_t = x_t + \varepsilon_t \quad \varepsilon_t \sim c_t z_{1t}, \qquad z_{1t} \sim iid\ s_\alpha\,(0,1) \tag{1}$$

$$(x - \mu) = \phi\,(x_{t-1} - \mu) + \eta_t \quad \eta_t \sim c_\eta c_t z_{2t}$$
$$z_{2t} \sim iid \quad S_\alpha\,(0, 1) \tag{2}$$

$$c_t^\alpha = \omega + \beta c_{t-1}^\alpha + \delta\,|\,r_{t-1} - E\,(r_{t-1}\,|\,r_1,....,r_{t-2})|^\alpha$$
$$+ \gamma d_{t-1}\,|\,r_{t-1} - E\,(r_{t-1}\,|\,r_1,....,r_{t-2})\,|^\alpha \tag{3}$$

where

$$d_{t-1} = \begin{cases} 1 & if\ r_{t-1} - E\,(\mathrm{r}_{t-1}\,|\,\mathrm{r}_1, \mathrm{r}_2, ..., \mathrm{r}_{t-2}) < 0 \\ 0 & otherwise \end{cases}$$

where r_t is the observed one-period excess return series, x_t is unobserved persistence components in the series, and Z_1, and Z_2 are independent white noise processes. In the most general model (Model (1)) shown above, we restricted non-normality ($\alpha = 2$) for obtaining Model (2), which is shown in Equations (4) - (6).

$$r_t = x_t + \varepsilon_t,\ \varepsilon_t \sim \sqrt{2}c_t z_{1t},\ z_{1t} \sim iid\,N\,(0, 1) \tag{4}$$

$$(x_t - \mu_t) = \phi\,(\mathrm{x}_{t-1} - \mu) + \eta_t,\ \eta_t \sim \sqrt{2}c_\eta c_t z_{2t},\ z_{2t} \sim iid\,N\,(0, 1) \tag{5}$$

$$c_t^2 = \omega + \beta \mathrm{c}_{t-1}^2 + \delta\,|\,\mathrm{r}_{\,t-1} - E\,(\,r_{\,t-1}\,|\,r_1, r_2,......, r_{t-2})\,|^2$$
$$+\ \gamma d_{\,t-1} - E\,(r_{t-1}\ \,|\,r_1, r_2\,,..., r_{t-2})\,|^2 \tag{6}$$

Abstracting from time varying volatility ($\beta = \delta = \gamma = 0$) in our most general model i.e. Model (1), we obtained Model (3), which is shown in Equations (7) and (8):

$$r_1, = x_t + \varepsilon_t, \quad \varepsilon_t \sim S_\alpha\,(0, c) \tag{7}$$

$$(x_t = \mu) = \phi\,(x_{t-1} - \mu) + \eta_t, \quad \eta_t \sim S_\alpha\,(0, c_\eta, c) \tag{8}$$

When we restricted predictable component ($\phi = 0$) in our most general model i.e. model (1) which is shown in Equations (1) - (3), the shocks (ε_t and η_t) were not separately identified, therefore the scale ratio (c_η) was also not identified. Thus, the resulting model after restricting $\phi = 0$ in Model (1), is Model (4) which is shown in Equations (9) - (10).

$$r_t = \mu + \varepsilon_1, \quad \varepsilon_t \sim c_t z_t \quad z_t \sim\ iid\,S_\alpha\,(0, 1) \tag{9}$$

$$c_t^\alpha = \omega + \beta c_{t-1}^\alpha + \delta\,|\,r_{t-1} - \mu|^\alpha + \gamma d_{t-1}\,|\,r_{t-1} - \mu|^\alpha \tag{10}$$

where

$$d_{t-1} = \begin{cases} 1 & 1\ if\ r_{t-1} - \mu < 0 \\ 0 & 0\ otherwise \end{cases}$$

Model (5) was obrained restricting non-normality ($\alpha = 2$) in Model (4). Model (5) is shown in Equations (11) - (12).

$$r_1 = \mu + \varepsilon_t, \quad \varepsilon_t \sim \sqrt{2}c_t z_t, \quad z_t \sim iid\, N(0, 1) \tag{11}$$

$$c_t^2 = \omega + \beta c_{t-1}^2 + \delta \,|\, r_{t-1} - \mu|^2 + \gamma d_{t-1}\, |r_{t-1} - \mu|^2 \tag{12}$$

Finally, we restricted time varying volatility ($\beta = \delta = \gamma = 0$) in Model (4) to obtain Model (6) which is presented in Equation (13):

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim S_\alpha(0,c) \tag{13}$$

A random variable x will have stable distribution $S_\alpha(\delta, c)$ when its log characteristic function can be represented as $ln\, E\,[\exp(ixt)] = i\delta t - |\, c_t|^\alpha$. The parameter $c > 0$ measures scale whereas the parameter $\delta\,(-\infty,\infty)$ measures location. The characteristic exponent (a∈ $(o, 2]$) governs the tail behaviour. A small value of α represents thicker tail, but when characteristic exponent $\alpha = 2$, this distribution is symmetric stable whose variance is $2c^2$. In Equation (3) above the term d_{t-y} captures the leverage effects due to Nelson (1991), and Hamilton and Susmel (1994). However, when the errors are normal, the model of volatility persistence reduces to GARCH normal process.

The persistent component x_t is assumed to follow a simple AR (1) process which implies possible predictable variations in excess returns. Significance of predictable component in Equations 1-3 warrants useful forecast of returns from $E\,(r_1|r_1,.....,r_{t-1})$. However, when c_η and ϕ or any of these are negligible, the returns become purely random which might display spurious predictions.

Stable distributions have thick tails so large shocks are associated with these distributions. Contrary to the Gaussian case, this setup encompasses big market crashes and booms. When individual stock is stably distributed, returns are also stably distributed; however, this paradigm is not true for other fat tail distributions like student-*t*.

For detecting possible existence of time varying volatility in India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand stock price excess returns, we employed simple GARCH (1,1)-like model for conditional scales in Equation 3. However, those who employed[5] GARCH (1,2) models failed to reveal strong evidence of the second moving average term. Therefore, we employed simple GARCH (1,1) model augmented with dummy variable d_{t-1} to account for the leverage effects which makes our model capable of taking into account any asymmetric response to stock volatility due to positive or negative return shocks.

A stable subordinated process with conditional scaling (SSCS) exhibits GARCH-like conditional heteroskedasticity and stable distributions. Under certain restrictions, stable and GARCH-like processes are equivalent when considering unconditional distributions (De Vries 1991). In this study, we adopted usual GARCH formulation for conditional heteroskedasticity with slight modifications to account for stable errors and leverage effects.

The most general state space model (shown in Equations 1-3) is capable of detecting both short and medium run memory in stock returns. However, it can not capture possible existence of long memory in return series that may be present due to the autocovariance function with hyperbolic asymptotic rate of decay.

The non Gaussian state space model shown in Equations (1) - (3) creates complications in estimation even when conditional heteroskedasticity is excluded from the model. Moreover, the powerful Kalman filter is efficient only when the errors are normal. We, therefore,

[5] See Pagan and Schwert (1990), French, Schwert and Stambough (1987).

employed general recursive filtering algorithm of Sorenson and Alspach (1971) that was extended by Kitawaga (1987) to include a smoother formula which provides a formula for computing log likelihood function and optimal filtering and predictive densities under any type of error distribution. The recursive equations were employed to compute filtering and predicting densities, given in the form of integrals whose close form analytical expressions are generally intractable, except in very special cases. Therefore, in this study, we numerically evaluated these integrals as in Bidarkota and McCuloch (2004).

Although Zolotarev's (1986) proper integral representation can be used to evaluate stable distribution and density, stable distribution can also be evaluated using inverse Fourier transformation of characteristic function. However, McCulloch (1996b) developed fast numerical approximations to stable distributions and density with expected relative density of the precision 10^{-6} for $\alpha \in [0.84, 2]$. Since in the present research, we employed numerical approximations due to McCulloch (1996b) to evaluate stable distribution and density, it explains why we restricted the charactristric exponent (α) in this range.

3. Empirical Results

3.1. Data Sources

We employed monthly excess returns on Asian emerging stock markets[6] i.e. India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand over the relevant risk free rates. The stock prices for all the countries were obtained from DataStream. The risk free rates for Malaysia, Philippines, and Thailand were obtained from October 2004 version of *International Financial Statistics* (IFS) CD-ROM and the risk free rates for the remaining countries were obtained from DataStream. Excess returns are expressed as per cent per month throughout the study. Table 1 shows additional information about the data series employed in this study and Figures 1 to 6 plot excess return series respectively for India, Indonesia, Malysia, Pakistan, Philippines, and Thailad stock price indexes.

Table 1: Data description for emerging Asian markets

Country	Stock price index	Data stream code	Risk-free rate	Data span
India	S&P CNX 500	ICRI500	Call Money	2/1/1991- 2/1/2004
Indonesia	Jakarta SE Composite	JAKCOMP	Call Money	1/1/1986- 2/1/2004
Malaysia	Kuala Lumpur Comp. DS-CALC.	KLPCOMZ	T bill rates	2/1/1986- 2/1/2004
Pakistan	Karachi SE 100	PKSE100	T bill rates	1/1/1989-2/1/2004
Philippines	Philippine-DS Market	TOTMKPH	T bill rates	10/1/1987-2/1/2004
Thailand	Bangkok S.E.T.	BNGKSET	MM rates	1/1/1977-2/1/2004

[6] S&P CNX 500 for India, Jakarta SE Composite for Indonesia, Kuala Lumpur Composite for Malaysia, Karachi SE 100 for Pakistan, Philippine-DS Market for Philippines, and PSI General, and Bangkok S.E.T. for Thailand over the relevant risk free rates respectively for India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand.

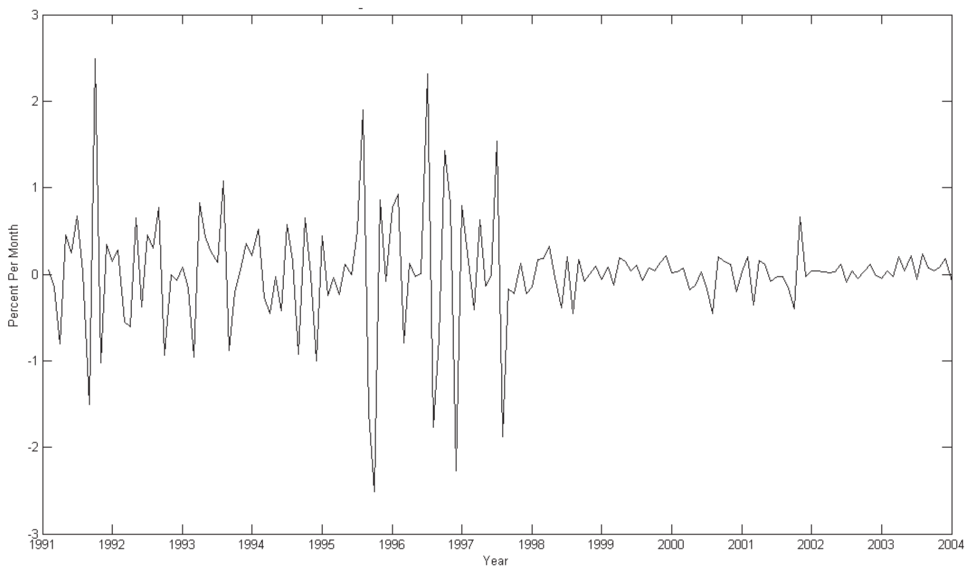

Figure 1: *India S&P SNX 500 excess stock returns*

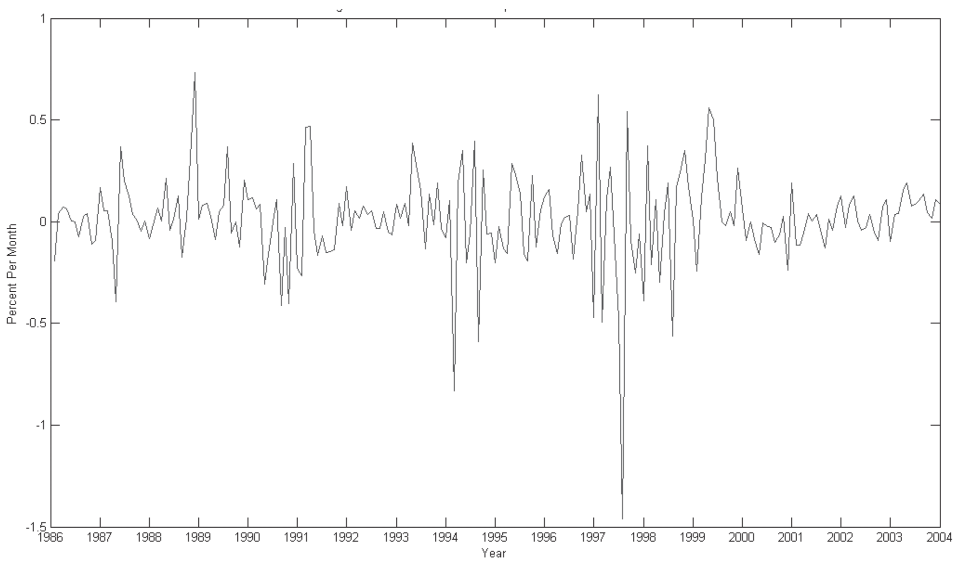

Figure 2: *Indonesia Jakarta Composite excess stock returns*

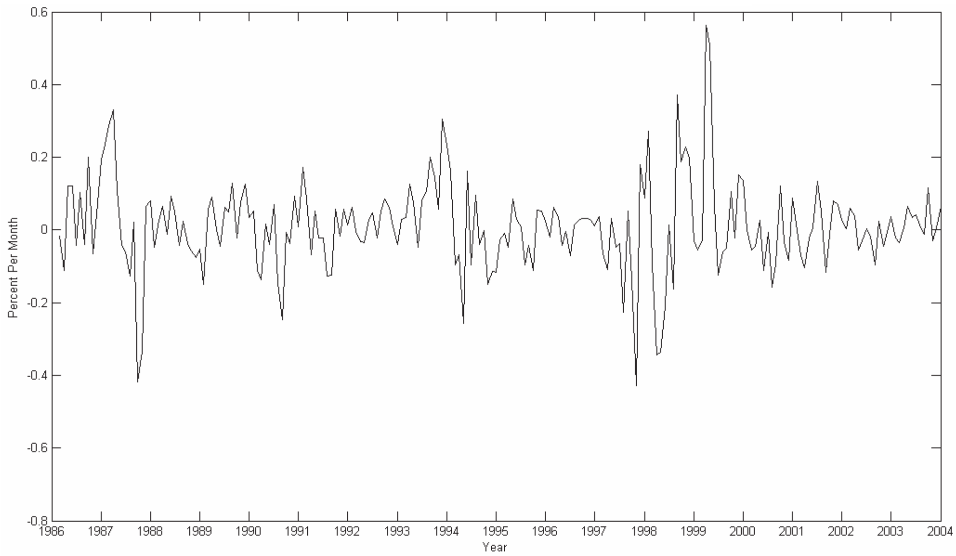

Figure 3: *Malaysia Kuala Lumpur Composite excess stock returns*

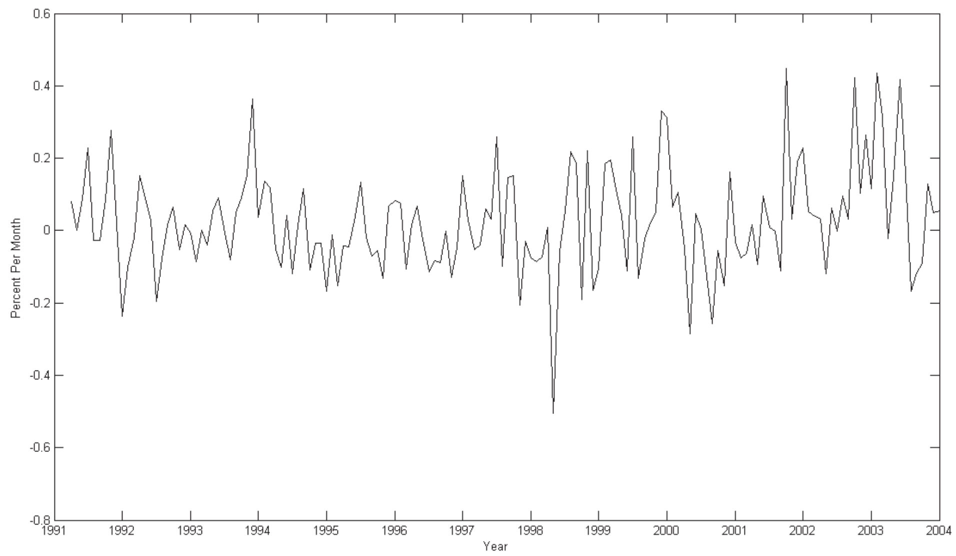

Figure 4: *Pakistan KSE 100 excess stock returns*

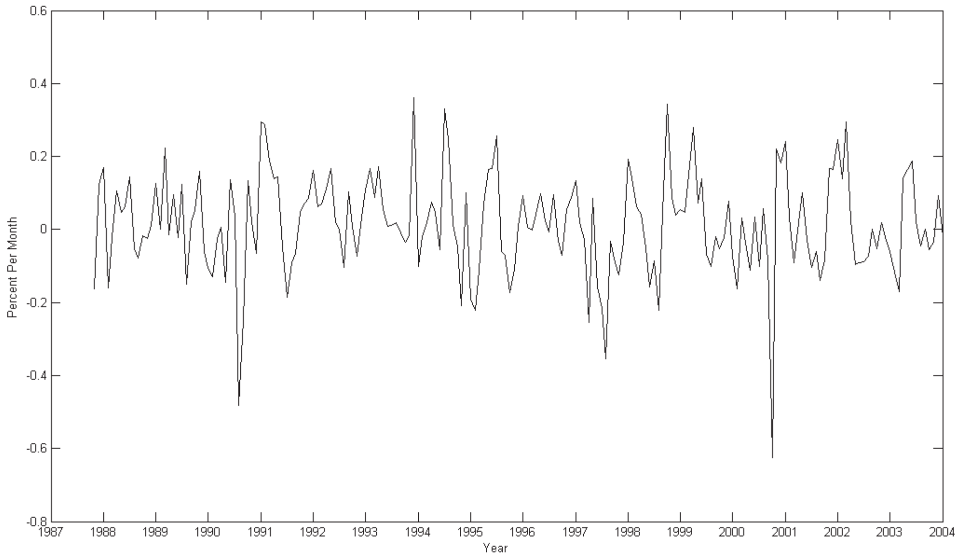

Figure 5: *Philippines-DS Market excess stock returns*

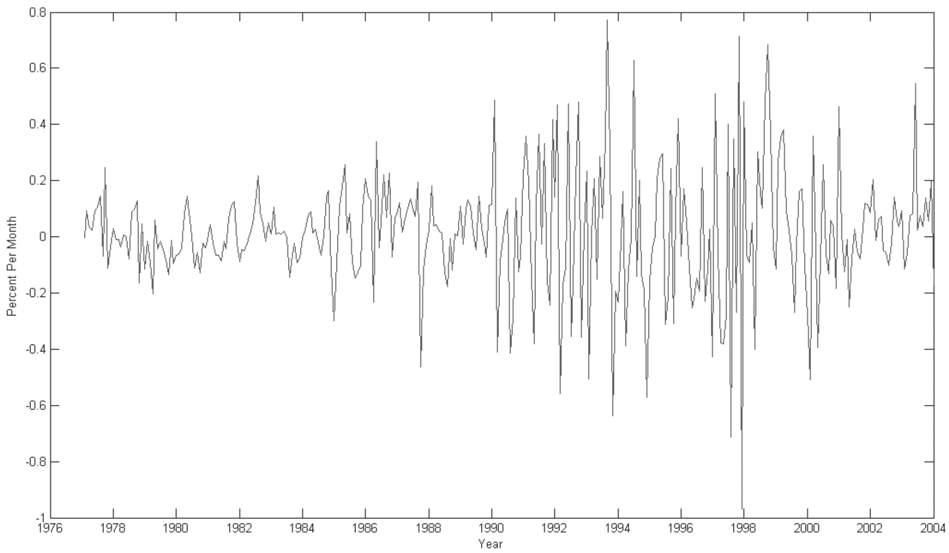

Figure 6: *Thailand Bangkok S.E.T. excess stock returns*

3.2. Estimation Results

Table 2 show estimation results for the India stock price index for the most general model (model 1) and its five restricted versions estimated for the present study. The results presented in this Table show parameter estimates for characteristic exponent α, volatility persistence parameter β, ARCH parameter δ, leverage parameter γ, signal to noise ratio c_η, and AR coefficient for persistent component of returns ϕ. The results for the remaining countries i.e. Indonesia, Malaysia, Pakistan, Philippines, and Thailand are presented in Tables 3-7 in a similar manner.

The stock price indexes pertaining to Indonesia, Malaysia, Pakistan, Philippines, and Thailand that can be characterised by a low value of characteristic exponent α show non normal behaviour in these markets, and volatility persistence parameter β reveals persistence in stock return volatility in all the markets. However, the value of the characteristic exponent α for India is close to 2 which shows normal behaviour in this market.

Figures 7-12 show mean of the filter density $E(x_t|r_1, r_2, r_3,.......,r_t)$ for India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand respectively. These plots show that predictable components appear to be constant and variations in parameter estimates of predictable components might not be components in forecasting excess returns.

3.3. Hypothesis Tests

The main hypothesis of this study is possible existence of predictable components in India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand stock prices over the relevant risk free rates. We tested the null hypothesis of no predictable component against the alternative hypothesis of predictable components in all the excess returns series. Moreover, we also investigated the impact of exclusion of predicable components on statistical significance of non normality and time varying volatility on the forecasting models employed in this study.

We employed three hypothesis tests to test for no persistence in predictable components, normality test and test for no volatility persistence. All the tests were based on likelihood ratio test statistics calculated from models (1) - (3) and their restricted versions. Model (1) is the most general state space model [shown in Equations (1) –(3)], Models (2) and (3) are the restricted versions of Model (1) that restrict non normality and time varying volatility respectively to obtain Model (2) and Model (3). These tests are elaborated in the following paragraphs.

According to the null hypothesis of no persistence in mean returns, return series are random. For testinig the null hypothesis for this test, we restricted predictable component ($\phi = 0$) in Model (1). While doing so, the shocks ε_t and η_t were not separately identified, therefore, the scale ratio c_η was also not identified. Moreover, the standardised likelihood ratio test statistics due to Hansen (1992) may result in under-rejection of the null or subsequent power loss as noticed by Hansen himself. These test statistics were computationally intensive in our case because of the type of the type of models we used; therefore the inferences for this test are based on critical values from χ_1^2, and χ_2^2 distributions.

The null hypothesis of no persistence of predictable component ($\phi = c_\eta = 0$) was rejected for Malaysia, Pakistan, and Philippines at 5 per cent level of significance using critical values from x_1^2 distribution only, showing persistence in predictable components in these countries. When switching significance level from 5 to 10 per cent level, the null

Table 2: Model estimates for India excess returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.999 (9.52e-5)	2 (restricted)	1.826 (0.148)	1.999 (0.000)	2 (restricted)	1.904 (0.133)
μ	0.010 (0.009)	0.009 (0.009)	0.012 (0.008)	0.010 (0.001)	0.010 (0.008)	0.068 (0.005)
ω	0.000 (0.000)	0.000 (0.000)		0.000 (0.001)	0.001 (0.008)	
β	0.843 (0.105)	0.846 (0.102)		0.766 (0.165)	0.766 (0.001)	
δ	0.081 (0.054)	0.081 (0.055)		0.060 (0.033)	0.060 (0.165)	
γ		0.935 (0.625)	0.965 (0.631)		0.000 (0.000)	4.47e-10 (0.033)
c_η	0.000 (0.000)	3.19e-7 (0.000)	0.004 (0.002)			
c			18.334 (10.143)			0.012 (0.008)
ϕ	0.318 (0.227)	0.310 (0.220)	0.105 (0.085)			
Log L	142.485	142.419	137.806	140.269	140.269	135.906
LR(α = 2)	0.132			0.000		
LR(β=δ=γ=0)	9.358			4.363		
LR(ϕ =c_η=0)	4.432	4.300				

Notes:

1. The following unobserved component or state space model was employed to estimate the results:

$$r_t = x_t + \varepsilon_t \qquad \varepsilon_t \sim c_t z_{1t}, \qquad z_{1t} \sim i\,i\,d s_\alpha(0,1) \tag{1}$$

$$(x-\mu) = \phi(x_{t-1}-\mu)+\eta_t \qquad \eta_t \sim c_\eta c_t z_{2t}$$
$$z_{2t} \sim i\,i\,d \qquad S_\alpha\ (0,1) \tag{2}$$

$$c_t^\alpha = \omega + \beta c_{t-1}^\alpha + \delta\,|\,r_{t-1} - E(r_{t-1}\,|\,r_1,\ldots,r_{t-2})\,|^\alpha$$
$$+\gamma d_{t-1}\,|\,r_{t-1} - E(r_{t-1}\,|\,r_1,\ldots,r_{t-2})\,|^\alpha \tag{3}$$

2. All estimates are rounded off to the third decimal place.
3. LR (α = 2) gives the value of the likelihood ratio test statistic for the null hypothesis of normality.
4. The small-sample critical value at the 0.01 significance level for a sample size of 300 is reported to be 4.764 from simulations in McCulloch (1997).
5. LR (β = δ = γ = 0) is the test for no volatility persistence.
6. LR (ϕ = c_η = 0) was evaluated atχ_1^2 and χ_2^2 p-values.
7. Model (2) restricts non-normality, Model (3) time varying volatility and Model (4) predictable component in the most general model shown in Equations (1-3). Models (5) and (6) were obtained by restricting non-normality and time varying volatility respectively in Model (4).

hypothesis was rejected in Thailand which now emerged as a candidate to show persistence in predictable components in excess returns. However, we have not been able to reject the null of no predictable components in India and Indonesia that revealed persistence in predictable components in these countries at a conventional level of significance.

Normality test is employed to find possible existence of non-normality in all the series. The Likelihood Ratio (LR) test statistics for this test were calculated from log likelihood functions estimated from Models (1) and (2). Model (2) was obtained by restricting non-normality (α=2) in Model 1. The LR test statistics for this test had non standard distribution because the null hypothesis lay on the boundary of the admissible values for α, therefore, the standard regularity conditions were not satisfied. Therefore, our inferences for normality test are based on the critical values due to McCulloch (1997).

According to the LR test statistics for normality test that is presented in column 1, rows 11 in Tables 2-7 respectively, for India, Idonesia, Malysia, Phillippine, Pakistan, and Thailand, the null hypothesis of normality is rejected for Indonesia, Malaysia, Pakistan, Philippines and Thailand using critical values from McCulloch (1997). These results also show that even after accounting for GARCH-like behaviour, the excess returns are significantly non-normal. However, the results on normality test for India are in sharp contrast.

The test for homoskedasticity or no volatility persistence was constructed restricting time varying volatility ($\beta=\delta=\gamma=0$) in Model (1). We calculated likelihood ratio (LR) test statistics from log likelihood functions estimated from unrestricted and restricted versions of Model (1). The LR test statistics for each country are presented in column 1, rows 12 in Tables 2-7 respectively, for India, Indonesia, Malaysia, Phillippines, Pakistan, and Thailand. Statistical inferences for this test are based on χ_3^2 distributions. The results based on these LR test statistics show existence of volatility persistence in all the series at 5 per cent level of significance using critical values from χ_3^2 distribution. Inferences do not change when we switch significance level from 5 per cent to 10 per cent level.

As mentioned in the preceding sections, non-normality and time varying volatility do exist in excess return series, which is well documented in the literature. Exclusions of such features from time series models that are employed to forecast predictable components in stock returns can produce inefficient results. To test this paradigm empirically, we excluded non-normality from our models that caused our estimation results to show existence of statistically significant predictable components in India and Philippines at 5 per cent level of significance using critical values from distributions. These results reveal that only 2 out of 6 countries show persistence in excess returns when compared to our earlier results (that are based on the most general model and its relevant restricted versions) reported in the preceding paragraph that show persistence of predictable components in 4 out of 6 countries. Therefore, our results confirm enhanced inefficiency in prediction due to exclusion of non normality from our unobserved component models.

For additional tests on non-normality, in addition to using critical values from x_1^2 distribution, we also employed critical values from x_2^2 distributions because of the reasons explained in the preceding paragraphs. This caused inferences to change substantially and now Malaysia, Pakistan, and Philippines also began to show persistence in excess returns at 5 as well as 10 per cent levels of significance. The remaining series do not show persistence in excess returns when using critical values from x_2^2 distributions.

Table 3: Model Estimates for Indonesia Excess Returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.525	2 (restricted)	1.400	1.623	2 (restricted)	1.453
	(0.165)		(0.000)	(0.093)		(0.133)
μ	0.012	-0.007	0.014	0.016	-0.005	0.102
	(0.013)	(0.001)	(0.012)	(0.009)	(0.011)	(0.008)
ω	0.002	0.009		0.002	0.008	
	(0.002)	(0.001)		(0.001)	(0.002)	
β	0.625	0.014		0.719	0.119	
	(0.114)	(0.127)		(0.094)	(0.103)	
δ	0.141	0.393		0.419	0.345	
	(0.072)	(0.228)		(0.040)	(0.133)	
γ	0.007	0.175		0.109	0.077	
	(0.006)	(0.232)		(0.059)	(0.184)	
c_η	0.067	0.095	0.087			
	(0.082)	(0.256)	(0.012)			
c			0.248			0.017
			(0.184)			(0.011)
ϕ	0.426	0.710	0.540			
	(0.009)	(0.241)	(0.169)			
Log L	68.727	47.722	46.880	67.965	47.415	45.808
LR ($\alpha = 2$)	42.010			41.100		
LR ($\beta=\delta=\gamma=0$)	43.694			44.314		
LR ($\phi=c_\eta=0$)	1.524	0.614				

Table 4: Model estimates for Malaysia excess returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.806	2 (restricted)	1.631	1.820	2 (restricted)	1.541
	(0.068)		(0.110)	(0.162)		(0.111)
μ	0.005	0.007	0.004	0.006	0.006	0.062
	(0.008)	(0.009)	(0.010)	(0.000)	(0.006)	(0.005)
ω	0.000	0.000		0.001	0.000	
	(0.001)	(7.75e-5)		(0.000)	(0.006)	
β	0.687	0.748		0.679	0.728	
	(0.089)	(0.044)		(0.081)	(0.042)	
δ	0.166	0.181		0.129	0.137	
	(0.079)	(0.054)		(0.038)	(0.033)	
γ	1.180	0.597		1.33e-8	3.19e-8	
	(0.477)	(0.288)		(0.000)	(0.000)	
c_η	0.124	2.16e-21	0.037			
	(0.172)	(0.000)	(0.009)			
c			1.102			0.007
			(0.504)			(0.006)
ϕ	0.445	0.631	0.505			
	(0.099)	(0.189)	(0.090)			
Log L	193.439	187.055	174.973	185.637	181.504	163.172
LR ($\alpha = 2$)	12.768			8.266		
LR (β=δ=γ=0)	36.932			44.93		
				(0.000)		
LR (ϕ=c_η=0)	15.604	2.836				

Table 5: Model estimates for Pakistan excess returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.610	2 (restricted)	1.749	1.748	2 (restricted)	1.748
	(0.110)		(0.131)	(0.130)		(0.177)
μ	0.013	0.024	0.012	0.015	0.023	0.088
	(0.013)	(0.016)	(0.002)	(0.011)	(0.011)	(0.008)
ω	0.000	0.007		0.014	0.010	
	(0.000)	(0.007)		(0.006)	(0.009)	
β	0.000	0.014		0.031	0.004	
	(0.000)	(1.079)		(0.468)	(0.946)	
δ	0.002	6.45e-13		2.85e-13	8.58e-13	
	(0.005)	(8.46e-10)		(1.06e-10)	(2.36e-9)	
γ	18.170	0.541		1.66e-9	3.038e-10	
	(0.442)	(6.34e-7)		(3.20e-7)	(5.916)	
c_η	6.25e-9	1.25e-10	0.086			
	(6.77e-7)	(1.65e-7)	(0.007)			
c			0.001			0.016
			(0.003)			(0.012)
ϕ	0.191	0.613	0.156			
	(0.070)	(0.313)	(0.001)			
Log L	88.494	83.738	85.411	82.529	79.792	82.528
LR ($\alpha = 2$)	9.512			5.474		
LR ($\beta=\delta=\gamma=0$)	6.166			0.002		
LR ($\phi=c_\eta=0$)	11.930	2.418				

Table 6: Model estimates for Philippines excess returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.705	2 (restricted)	1.644	1.831	2 (restricted)	1.854
	(0.000)		(0.117)	(0.100)		(0.089)
μ	0.008	0.011	0.013	0.014	0.013	0.086
	(0.011)	(0.014)	(0.013)	(0.008)	(0.009)	(0.005)
ω	6.42e-6	5.29e-9		0.002	0.002	
	(6.74e-6)	(0.000)		(0.002)	(0.001)	
β	0.802	0.348		0.712	0.702	
	(0.026)	(0.000)		(0.216)	(0.179)	
δ	0.001	9.26e-14		0.019	1.64e-9	
	(0.000)	(0.000)		(0.041)	(2.38e-6)	
γ	19.636	932.514		0.056	0.059	
	(2.430)	(0.000)		(0.046)	(0.048)	
c_η	2.746	101195.44	0.003			
	(0.000)	(0.000)	(0.001)			
c			21.321			0.016
	(4.280)					(0.009)
ϕ	0.303	0.341	0.344			
	(0.063)	(0.065)	(0.072)			
Log L	136.243	124.259	131.795	122.245	114.426	118.593
LR ($\alpha = 2$)	23.968			15.638		
LR (β=δ=γ=0)	8.896			7.304		
	(0.031)					
LR (ϕ=c_η=0)	27.996	4.028				

Table 7: Model estimates for Thailand excess returns

Parameters	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
α	1.854	2 (restricted)	1.400	1.872	2 (restricted)	1.477
	(0.000)		(0.000)	(0.071)		(0.092)
μ	0.007	0.001	0.010	0.008	0.004	0.109
	(0.008)	(0.009)	(0.010)	(0.007)	(0.008)	(0.008)
ω	0.000	0.000		0.000	0.000	
	(0.000)	(0.000)		(0.001)	(0.000)	
β	0.806	0.694		0.829	0.793	
	(0.054)	(0.107)		(0.045)	(0.097)	
δ	0.109	0.196		0.080	0.095	
	(0.042)	(0.109)		(0.024)	(0.053)	
γ	0.109	0.453		1.07e-7	4.07e-10	
	(0.231)	(0.239)	(4.90e-6)	(0.000)		
c_η	8.56e-9	8.56e-9	0.009			
	(5.54e-7)	(0.000)	(0.002)			
c			10.917			0.009
			(2.700)			(0.009)
ϕ	0.488	0.474	0.145			
	(0.205)	(0.179)	(0.060)			
Log L	111.209	100.111	64.660	109.848	98.819	54.612
LR ($\alpha = 2$)	22.196			22.058		
LR (β=δ=γ=0)	93.098			110.472		
	(0.000)			(0.000)		
LR (ϕ=c_η=0)	2.722	2.584				

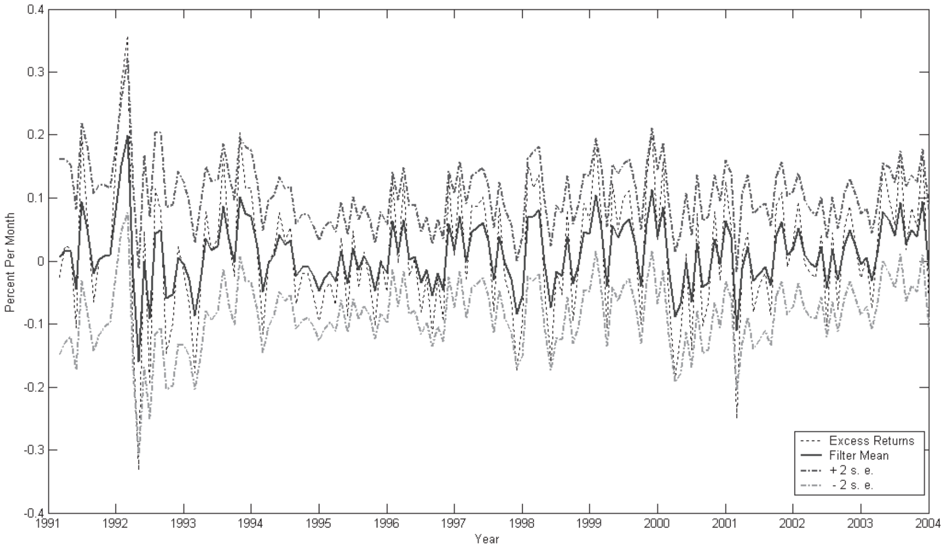

Figure 7: *India S&P CNX 500 excess returns and filter estimates*

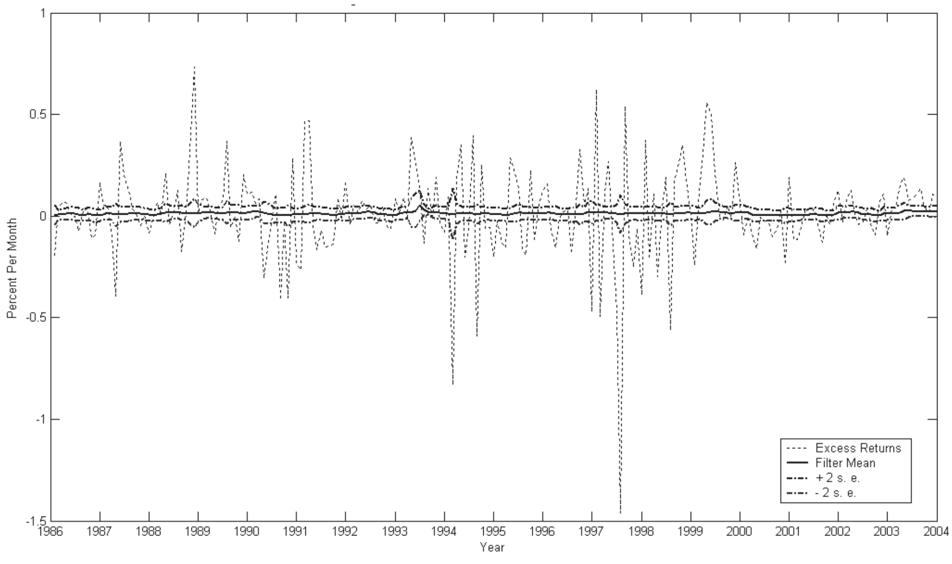

Figure 8: *Indonesia Jakarta Composite excess returns and filter estimates*

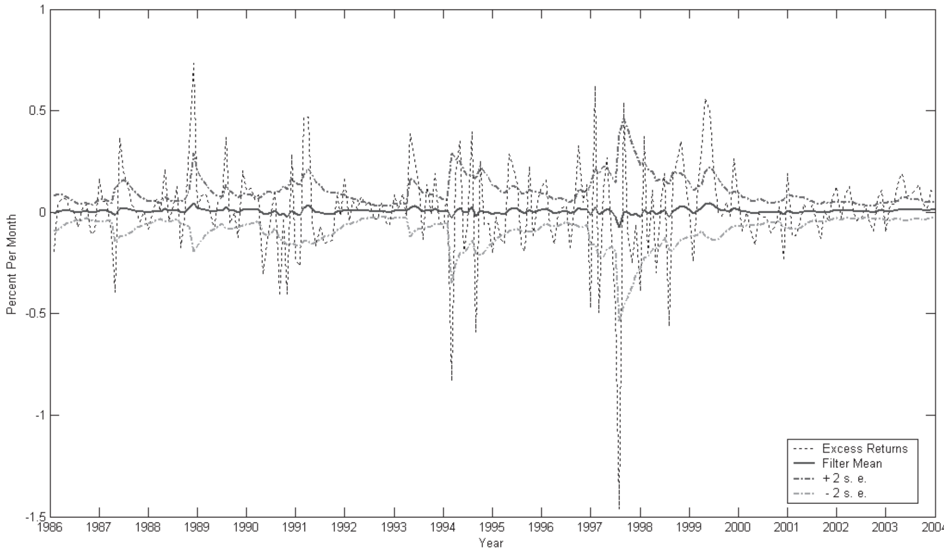

Figure 9: *Malaysia Kuala Lumpur Composite excess returns and filter estimates*

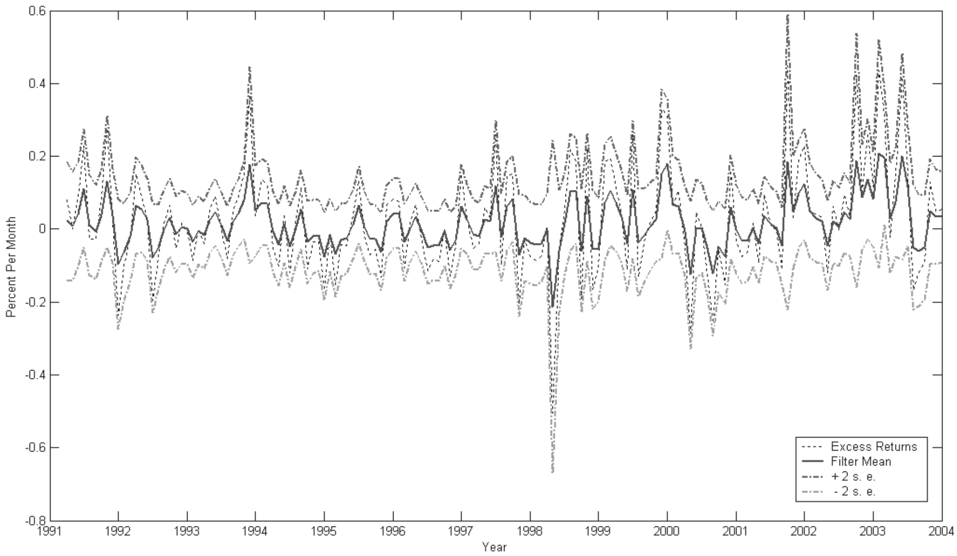

Figure 10: *Pakistan KSE 100 excess returns and filter estimates*

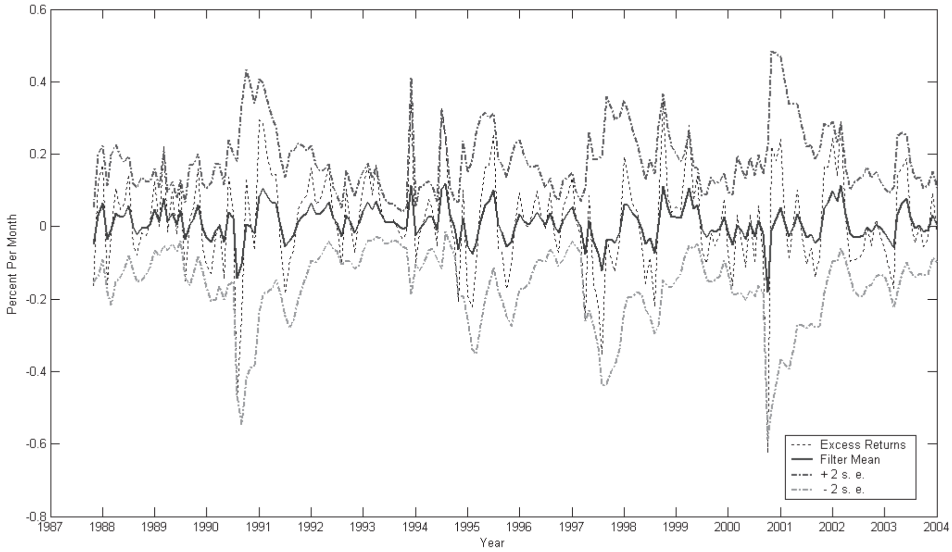

Figure 11: *Philippines-DS Market excess returns and filter estimates*

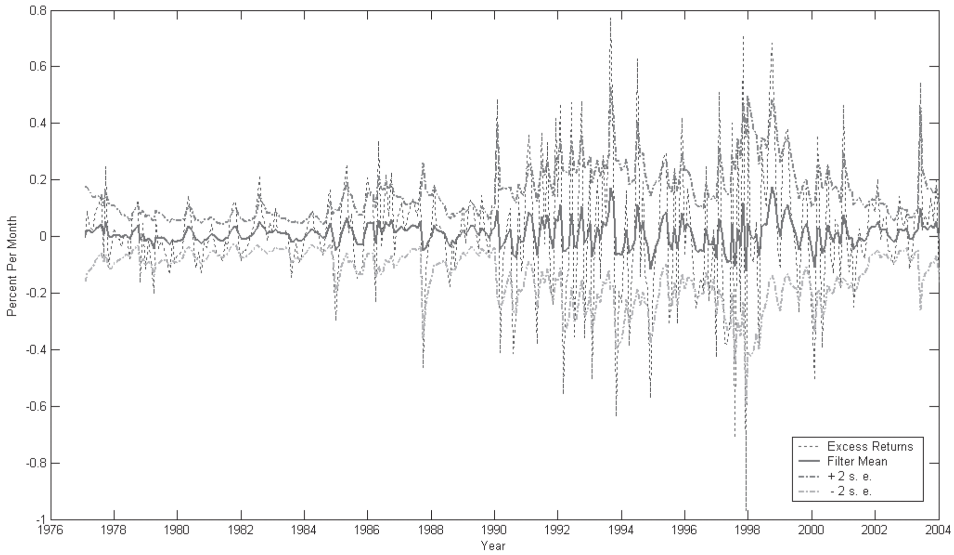

Figure 12: *Bangkok S.E.T excess returns and filter estimates*

3.5. Stability Tests

For testing persistence of predictable component, time varying volatility, and non-normality in excess returns series, we estimated the versions of the most general state space or unobserved component model (Model (1) that is shown in Equations (1) - (3)) that encompasses leveraged term d_{t-1}. Additionally, we also estimated versions of the most general models using Equation (3) (GARCH-stable volatility) that restricts leverage term in the GARCH specification of our most general model, which allows us to calculate LR test statistics to test the null hypothesis of no leverage effects. Using log likelihood estimates from leverage and no leverage models we calculated LR test statistics for the most general state space model and its restricted versions to test the null hypothesis of 'no leverage effect' which was tested setting $\gamma = 0$ against the alternative hypothesis of leverage effects ($\gamma > 0$).

Our results on leverage effects (not reported for brevity) strongly reject the null hypothesis of no leverage effect in favour of the alternative hypothesis of the existence of leverage effects ($\gamma > 0$) for India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand excess returns at a conventional level of significance. Inferences do not change when we switch the level of significance from 5 per cent to 10 per cent level. These results show that stability is not an issue in any of the markets studied.

4 Discussion

Our study results show that significant non-normality does exist in monthly excess returns for Indonesia, Malaysia, Pakistan, Philippines, and Thailand excess returns even after accounting for conditional heteroskedasticity. Similarly, volatility persistence is also statistically significant in India, Indonesia, Malaysia, Philippines, and Thailand stock excess returns.

Leverage effects in volatility is insignificant; however, there is evidence of statistically significant predictable components in four out of six markets studied. Moreover, statistically significant evidence of volatility persistence and non-normality does exist in most countries studied.

Our Model 4 which is obtained by restricting predictable components (ϕ) in our most general state space or unobserved component model (Model 1) and is shown in Equations 9-10 encompasses non normality and a GARCH-like process. In our Model 1, we assume that predictable components in returns series follow an autoregressive (AR) process, therefore, abstracting from conditional heteroskedasticity, our state space model for observed stock returns becomes a simple AR process plus noise. Then, this model becomes synonymous to Summers (1986) mean reverting unobserved component or state space model which takes the following form:

$$p_t = q_t + z_t \tag{14}$$
$$q_t = u + q_{t-1} + u_t \tag{15}$$
$$z_t = \phi + z_{t-1} + v_t \tag{16}$$

where p_t is the log of the stock prices index and q_t is an unobserved random walk component, and z_t is an unobserved stationary component where, $1 \leq \phi < 0$ and u_t and v_t are serially and mutually independent white noise processes.

Compared to the Gaussian state space model due to Summers (1986) which is shown in Equations (15) - (16) above, our Model (4) is capable of capturing stable GARCH volatility since we obtained it by restricting predictable components in our most general form, hence it is capable of capturing stable GARCH volatility clusters in all the excess returns series. The volatiliy clusters generated using Model 4, for India, Indonesia, Malaysia, Pakistan, Philippines, and Thailand stock markets respectively are presented in Figures 13 to 18.

Looking at stock returns volatility, for example, for India that is shown in Figure 13, it transpires that returns volatility appears to be enhanced in the neighbourhood of 1992-93 showing that the Indian economy was affected because of the Gulf war in the early 1990s. The stock returns volatility diminished to a very low level in 1996 and then increased though much less than that of early 1990s in the period 1998 to early 2002. A plausible explanation for this increased stock return volatility can be attributable to sanctions on India and Pakistan due to nuclear experiments and the Asian financial crises and thereafter due to global slowdown in the economic activity around year 2001. For the remaining countries included in the study, we can have a similar explanation for enhanced volatility in the years from 1997 and 2001. However, stock return volatility for Pakistan that is presented in Figure 16 appears to be much different compared to the other markets studied in the sense that its graph does not show any trend or volatility pattern over time. It rather shows spikes in 1992, 1998, and close to 2000-2001 which may have been caused respectively by the Gulf war, international sanctions on India and Pakistan for nuclear tests and the Asian financial crises, and also perhaps due to the worldwide slowdown in economic activity. The results on stock returns volatility for the remaining countries that are shown in Figures 14, 15, 17 and 18 can be investigated in a similar manner in the light of the extraordinary events that occurred in these economies during the sample period.

Our results show that our mean reverting unobserved component model that encompasses non-normality and GARCH-like process is capable of extracting signals of predictable components from excess returns in all the series at a conventional level of significance except for Thailand where predictable components are significant at 10 per cent level of significance. Moreover, stock return volatility is characterised by GARCH-like behaviour in Indonesia, Malaysia, Pakistan, Philippines, and Thailand except for India which shows normal behaviour in their stock market.

5. Conclusions

In this study, we employed non Gaussian state space models to find possible existence of persistent predictable components in India, Indonesia, Pakistan, Philippines, and Thailand stock prices over the relevant risk-free rates. Our state space models fully account for non normality and volatility persistence that might be present in the return series.

The estimated value of the characteristic exponent α for India excess returns demonstrate normal behaviour, and encompasses ample evidence of stock return volatility characterised by GARCH-like behaviour. Indonesia, Malaysia, Pakistan, Philippines, and Thailand excess stock returns demonstrate significant leptokurtosis and the estimated value of characteristic exponent α is well away from the value pertaining to normal behaviour in these countries. Excess stock returns exhibit ample persistence in stock return volatility in most of these series which can be characterised by a GARCH-like process. There is insignificant leverage effect in stock return volatility in all the markets studied which shows that a negative shock

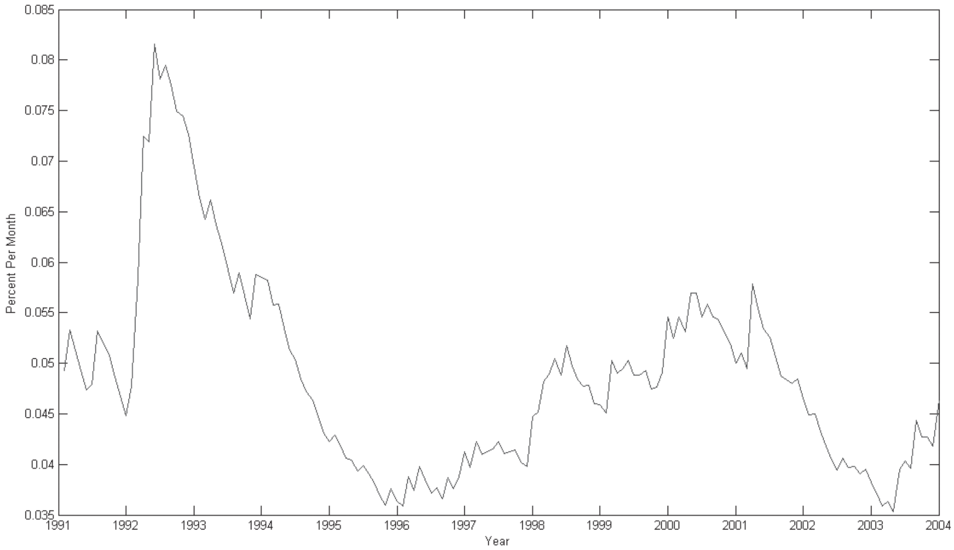

Figure 13: *India S&P CNX 500 stock returns volatility: Stable-GARCH (1,1) Model 4*

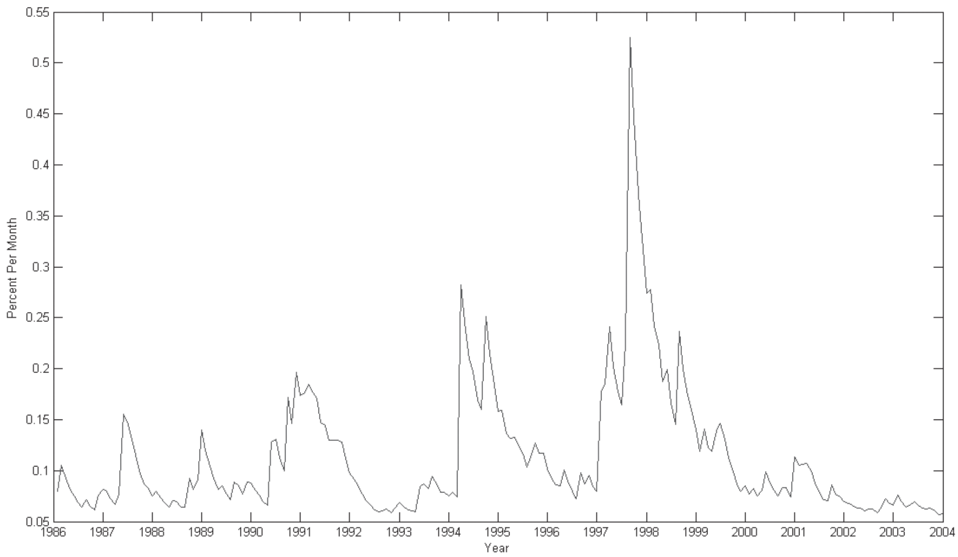

Figure 14: *Indonesia Jakarta Composite stock returns volatility: Stable-GARCH (1,1) Model 4*

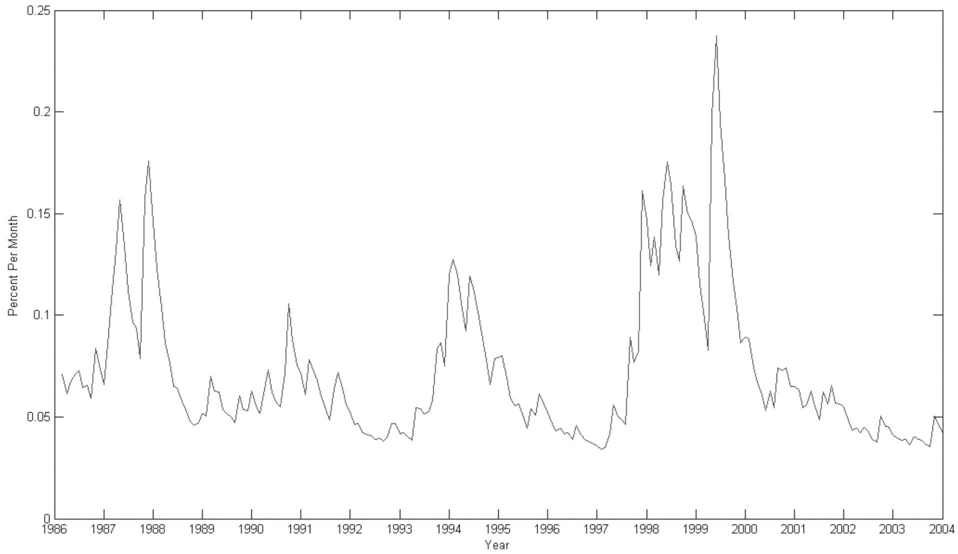

Figure 15: *Malaysia Kuala Lumpur Composite stock returns volatility: Stable-GARCH (1,1) Model 4*

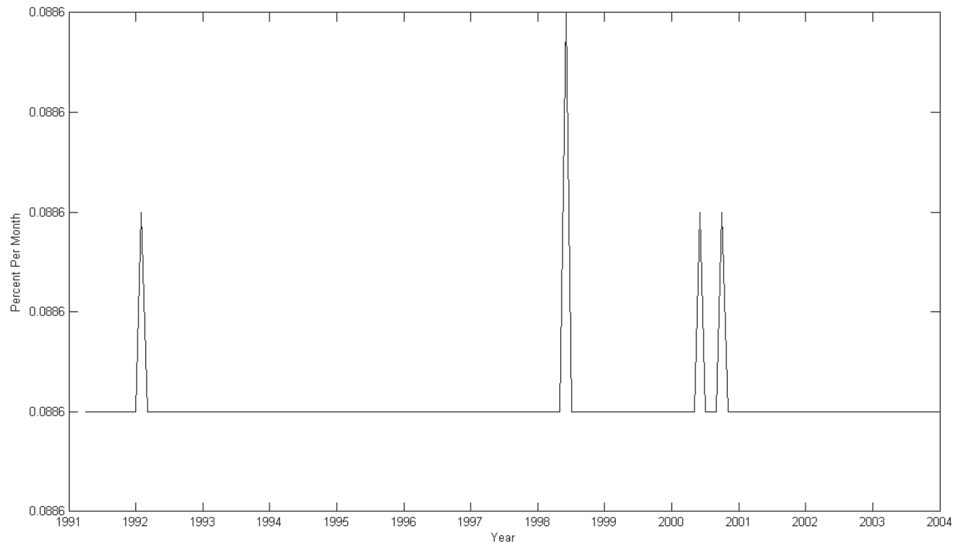

Figure 16: *Pakistan KSE 100 stock returns volatility: Stable-GARCH (1,1) Model 4*

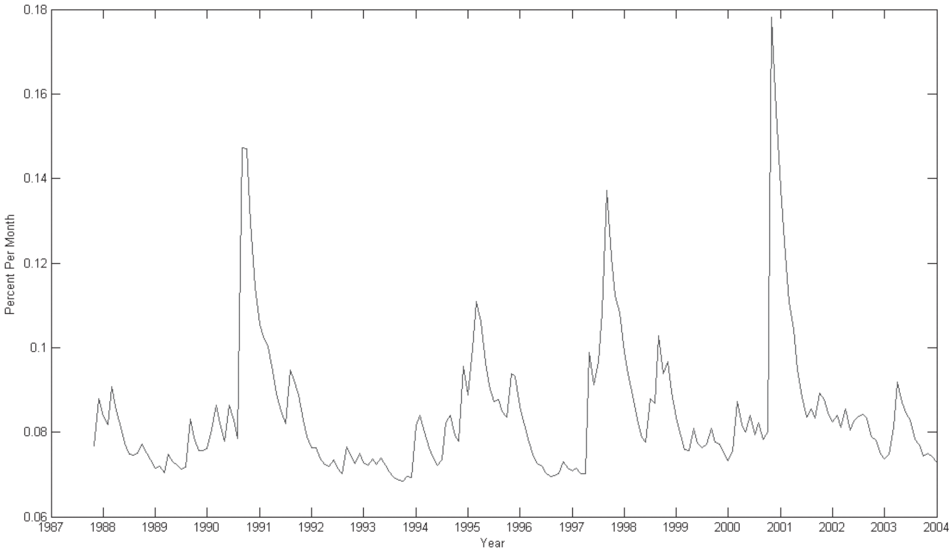

Figure 17: *Philippines-DS Market stock returns volatility: Stable-GARCH (1,1) Model 4*

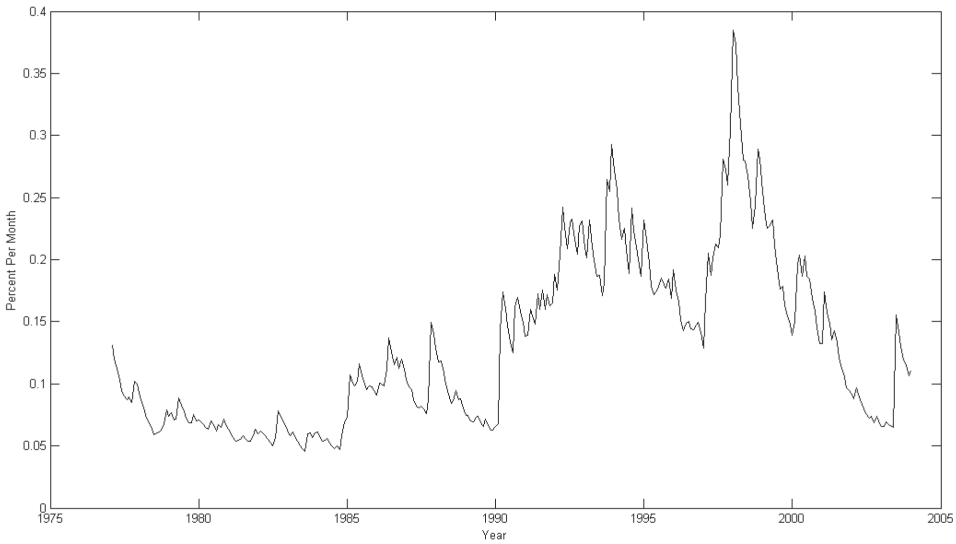

Figure 18: *Thailand Bangkok S.E.T stock returns volatility: Stable-GARCH (1,1) Model 4*

does not necessarily generate higher future stock returns volatility compared to a positive shock of an equal magnitude which means that statility in these markets is not an issue.

Our results on predictability of monthly stock returns are statistically significant in India, Malaysia, Pakistan, and Philippines excess returns at 10 per cent level and in Thailand at per cent level of significance using critical values from χ^2_1 distributions. The efficiently estimated excess returns vary from a range between 0.6 per cent per month for Malaysia to 1.6 per cent for Indonesia. Finally exclusion of predictable components from our state space models alters inferences on non normality and volatility persistence and omitting non normality from our models increases estimation inefficiency of the models.

References

Abhyankar, A.H., L.S. Copeland and W. Wong. 1995. Nonlinear dynamics in real-time equity market indices: evidence from the United Kingdom. *Economic Journal* **105**: 864-880.

Akgiray V. and G. Booth. 1988. The stable law model of stock returns. *Journal of Business Economics Statistics* **6**: 51-57.

Antoniou, A., N. Ergul and P. Holmes. 1997. Market efficiency, thin trading and non-linear behaviour: evidence from an emerging market. *European Financial Management* **3(2)**:175-190.

Ammermann, P.A. and D.M. Patterson. 2003. The cross-sectional and cross-temporal universality of nonlinear serial dependencies: evidence from world stock indices and the Taiwan Stock Exchange. *Pacific-Basin Finance Journal* **11**: 175-195.

Barkoulas, J. and N. Travlos. 1998. Chaos in an emerging capital market? The case of the Athens Stock Exchange. *Applied Financial Economics* **8**: 231-243.

Bekaert, G. 1995. Market integration and investment barriers in emerging equity markets. *The World Bank Economic Review* **9**: 75-107.

Bekaert, G. and R. Hodrick. 1992. Characterising predictable components in excess returns in equity and foreign exchange markets. *Journal of Finance* **47**: 467-509.

Bidarkota, P. and H. McCulloch. 2004. Testing for persistence in stock returns with GARCH-stable shocks. *Quantitative Finance* **4**: 256-265.

Bidarkota, P. and H. McCulloch. 1998. Optimal univariate inflation forecasting with symmetric stable shocks. *Journal of Applied Econometrics* 3: 659-670.

Buckberg, E. 1995. Emerging stock markets and international asset pricing. *The World Bank Economic Review* **9**: 51-74.

Buckle, D. 1995. Beyesian inferences for stable distribution. *Journal of American Statistical Association* **90**: 605-13.

Claessens, S., S. Dasgupta and J. Glen. 1995. Returns behaviour in emerging stock markets. *The World Bank Economic Review* **9**: 131-151.

Cohen, S. I. 2001. Stock performance of emerging markets. *The Developing Economies* **XXXIX(2)**: 168–88.

Conrad, J. and G. Kaul. 1988. Time-variation in expected returns. *Journal of Business* **61**: 409-425.

Danielsson, J. 1994. Stochastic volatility in asset prices estimation with simulated maximum likelihood. *Journal of Econometrics* **64**: 315-400.

De Gooijer, J.G. 1989. Testing non-linearities in world stock market prices. *Economics Letters* **31**: 31-35.

De Vries, C. 1991. On the relation between GARCH and stable process. *Journal of Econometrics* **48**: 313-24.

Diebold, F. and J. Lopez. 1995. Modeling volatility dynamics in macroeconomics: developments. In *Tensions and Projects,* ed. K. Hoover. Boston, MA: Kulwer-Academics.

Divecha, A., J. Drach and D. Stefek. 1992. Emerging markets: a quantitative perspective. *Journal of Portfolio Management* **19**: 41-50.

Engle, R. and T. Bollerslev. 1986. Modeling the persistence of conditional variances. *Econometric Reviews* **5**: 1-50.

Fama E. 1991. Efficient capital markets: II. *The Journal of Finance* **XLVI**: 1575-617.

Fama, E. and K. French. 1992. The cross-section of expected returns. *The Journal of Finance* **47**: 427-465.

Fama, E. and K. French. 1998. Permanent and temporary components of stock prices. *The Journal of Political Economy* **96**: 246-273.

French, K., G. Schwert and R. Stambaugh. 1987. Expected stock returns and volatility. *Journal of Financial Economics* **19**: 3-29.

Goose, D. and K. Kroner. 1995 The relationship between GARCH and symmetric stable processes, finding the source of tails in financial data. *Journal of Empirical Finance* **2**: 225-51.

Hamilton, J. and R. Susmel. 1994. Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics* **64**: 307-33.

Hansen, B. 1992. The likelihood ratio test under nonstandard conditions: testing the Markov switching model of GNP. *Journal of Applied Econometrics* **7** (supplement): S61-S82.

Haque, M., M. Hassan and C. Neal. 2004. An empirical examination of stability, predictability, and volatility of Middle Eastern and African emerging stock markets. *The Review of Middle East Economics and Finance* **2**: 19-42.

Haque, M. M. Hassan and O. Varela. 2001. Stability, risk premia and predictability in Latin American emerging stock markets. *Quarterly Journal of Business and Economics* **40**: 23-44.

Harvey, A. 1989. *Forecasting, Structural Time Series Models and the Kalman Filter.* Cambridge: Cambridge University Press.

Harvey, A. 1995a. The risk exposure of the emerging equity markets. *The World Bank Economic Review* **9**: 19-50.

Harvey, A. 1995b. Predictable risk and returns in emerging markets. *The Review of Financial Studies* **8**: 773-816.

Hinich, M.J. and D.M. Patterson. 1985. Evidence of nonlinearity in daily stock returns. *Journal of Business and Economic Statistics* **3**: 69-77.

Hsieh, D.A. 1989. Testing for non-linearity in daily foreign exchange rate changes. *Journal of Business* **62:** 339-368.

Jensen, D. and C. de Vries. 1991. On the frequency of large stock returns: putting booms and busts into perspective. *Review of Economics and Statistics* **73**: 18-24.

Kitagawa, G. 1987. Non-Gaussian state space modeling of non stationary time series. *Journal of the American Statistical Association* **400**: 1032-63.

Kokoszka, P. and M.Taqqu. 1995. Fractional ARIMA with stable innovations. *Stochastic Process and their Applications* **60**: 19-47.

Kosfeld, R. and S. Robé. 2001. Testing for nonlinearities in German bank stock returns. *Empirical Economics* **26**: 581-597.

Lim, K.P. and V.K.S. Liew. 2004. Non-linearity in financial markets: evidence from ASEAN-5 exchange rates and stock markets. *Journal of Applied Finance* **10(5)**: 5-18.

Lo, W. and A. MacKinlay. 1998. Stock market prices do not follow random walk: evidence from a simple specification test. *The Review of Financial Studies* **1**: 41-66.

Lumsdaine, R. 1996. Consistency and asymptotic normality of the quasi-maximum likelihood estimator in IGARCH (1,1). *Econometrica* **64**: 575-96.

Mandelbrot, B. 1963. The variation of certain speculative prices. *Journal of Business* **36**: 394-419.

McCulloch, H. 1997. Measuring tail thickness in order to estimate the stable index: a critique. *Journal of Business and Economic Statistics* **15**: 74-81.

McCulloch, H. 1996a. Financial applications of stable distributions. In *Handbook of Statistics*, ed. G. Maddala G and C. Rao. Vol. 14. Amsterdam: Elsevier:

McCulloch, H. 1996b. Numerical approximation of the symmetric stable distribution and density. In *A Practical Guide to Heavy Tails: Statistical Techniques for Analysing Heavy Tailed Distributions,* ed. R.Adler, R. Feldman, and M.Taqqu. Boston: Birkhauser.

Mantegna, R. and H. Stanley. 1995. Scaling behavior in the dynamics of an economic index. *Nature* 376: 46-9.

Mobius, M. 1994. *The Investor's Guide to Emerging Markets*. McGraw-Hill.

Nelson, D. 1991. Conditional heteroskedasticity in asset returns: a new approach. *Econometrica* **59**: 347-70.

Opong, K.K., G.Mulholland, A.F. Fox and K. Farahmand. 1999. The behaviour of some UK equity indices: an application of Hurst and BDS tests. *Journal of Empirical Finance* **6:** 267-282.

Pagan, A. and G. Schwert. 1990. Alternative models for conditional stock volatility. *Journal of Econometrics* **45**: 267-90.

Panos, M., N. Robert and P. David. 1997. Transactions costs and nonlinear adjustment in real exchange rates: an empirical investigation. *Journal of Political Economy* **105 (4)**: 862 - 879.

Poterba, J. and L. Summers. 1988. Mean reversion in stock prices: evidence and implications. *Journal of Financial Economics* **22**: 27-59.

Sarantis, N. 2001. Non linearities, cyclical behaviour and predictability in stock markets: international evidence. *International Journal of Forecasting* **17**: 459-482.

Sarantis, N. 1999. Modeling non linearities in real effective exchange rates. *Journal of International Money and Finance* **18**: 27 - 45.

Sorenson, H. and D. Alspach. 1971. Recursive Bayesian estimation using Gaussian sums. *Automatica* **7**: 465-79.

Summers, L. 1986. Does the stock market rationally reflect fundamental values? *Journal of Finance* **41**: 591-601.

Taylor, M. and D. Peel. 2000. Nonlinear adjustment, long-run equilibrium and exchange rate fundamentals. *Journal of International Money and Finance* **19**: 33-53.

Watson, M. 1986. Univariate detrending methods with stochastic trends. *Journal of Monetary Economics* **18**: 49-75.

Wilcox, J. 1992. Taming frontier markets. *Journal of Portfolio Management* **19**: 51-56.

Xu, Y. 2004. Small levels of predictability and large economic gains. *Journal of Empirical Finance* **11**: 247-275.

Zolotarev, V. 1986. *One Dimensional Stable Laws.* (Providence RI: American Mathematical Society) (English Translation).