Institute of Business Administration Karachi
Leadership and Ideas for Tomorrow

Business Review

Article 4

Volume 2 Issue 1
January - June 2007

1-1-2007

On predictability in South Asian stock markets

Khurshid M. Kiani
The University of West Indies, Kingston, Jamaica, West Indies

ARTICLE

On Predictability in South Asian Stock Markets

Khurshid M. Kiani
The University of West Indies, Kingston, Jamaica, West Indies

ABSTRACT

In this research I investigate persistence in monthly excess stock returns over risk free rates in two South Asian stock markets i.e. S&P CNX 500 and KSE 100 stock price indexes using non-Gaussian state space or unobservable component model with stable distributions and volatility persistence.

Results from non-Gaussian state space models show that both markets encompass volatility persistence. KSE 100 has a stable characteristic exponent of α 1.748, but for S&P CNX 500 index the value for the characteristic exponent α is 1.999 which shows normal behavior in this market. Both markets encompass persistent signal in returns at 10% level of significance. The efficiently estimated excess returns for S&P CNX 500 are 0.01% per month (0.12% per annum), and 0.015% per month (0.18% per annum) for KSE 100 index.

Key phrases: *stock return predictability; unobserved components; fat tails; stable distributions*

JEL Codes: *C22, C53, G14*

Word Count Main Text: *2434*

1. INTRODUCTION

Fama (1991) shows that predictability in stock returns have been explored extensively in the literature. The motive behind exploring stock returns predictability is economic gains that could be attained due to suitable trading strategies (Xu 2004). However, researchers have focused on two aspects of empirical distribution of stock returns which they think are important for accurate predictability. For example, Akgiray and Booth (1986), Jensen (1991), de Vries (1991), Buckel (1995), Mantegna and Stanley (1995), and McCulloch (1997) found evidence of non-normality in stock returns. On the other hand Nelson (1991) Danielsson (1994), Pagan and Schwert (1990), Diebold and Lopez (1995), and Goose and Kroner (1995) found evidence of volatility persistence in stock returns.

Conard and Kaul (1988) employed state space or unobservable component model to predict stock returns considering that shocks in both the observation and state Equations are normal. Similarly, state space models have also been used by Harvey (1985) and Watson (1986) with the assumptions that the underlying errors are normal. However, McCulloch (1996a) and Bidarkota and McCulloch (2004) modeled stock returns to be non-Gaussian with fat tails.

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

In this study, I investigate possible existence of persistent predictable signal in monthly S&P CNX 500 and KSE 100 indexes excess returns over the respective risk free rates. In order to account for non-Gaussian data, I model returns within the framework of Parisian stable distributions that were also employed by Mantangna and Stanley (1995), Buckel (1995), and McCulloch (1997). Therefore, as in Oh (1994) and Bidarkota and McCulloch (1998), I relax normality assumption in favor of stable distributions because Kalman filter is not operable efficiently with stable distributions. Similarly, to explicitly account for volatility persistence in the return series I employ GARCH-like model. The motive behind this study is to find stock market predictability in KSE 100 index (Pakistani stock market) and compare it with neighboring south Asian stock market (S&P CNX 500: Indian Stock Market). The findings from this study are intended to help policymakers as well as business community in Pakistan.

The remaining paper is organized as follows. Section 2 outlines the most general model used in this paper, and some estimation issues. In section 3, I present data sources, empirical results, and hypotheses tests, and finally section 4 includes conclusions of the study.

2. STATE SPACE MODEL FOR STOCK RETURNS

In this research six versions state space or unobserved time series econometrics models are used. Model 1 is the most general model that encompasses unobservable component in stock returns including non-normal errors and GARCH-like effects which is shown in following thee Equation:

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

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

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

Where,

$$d_{t-1} = \begin{cases} 1 & \text{if } r_{t-1} - E(r_{t-1}|r_1, r_2, \ldots\ldots\ldots, r_{t-2}) < 0 \\ 0 & \text{otherwise} \end{cases}$$

Here r_t is the observed one-period excess return, x_t is an unobserved persistence components in the series, and Z_1 and Z_2 are independent white noise processes.

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Model 2 is obtained restricting α = 2 in model 1 which can be written as:

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

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

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

Setting $\beta = \delta = \gamma = 0$ in model 1 gives model 3, which is shown in Equation 3:

$$r_1 = x_t + \varepsilon_t,\qquad \varepsilon_t \sim S_\alpha(0, c) \tag{3a}$$

$$(x_t - \mu) = \phi(x_{t-1} - \mu) + \eta_t,\qquad \eta_t \sim S_\alpha(0, c_\eta, c) \tag{3b}$$

When restricting ϕ = 0 in model 1, the shocks ε_t and η_t are not separately identified so c_η is also not identified. The resulting model is model 4 which is shown in Equations 4 :

$$r_t = \mu + \varepsilon_t,\qquad \varepsilon_t \sim c_t z_t,\qquad z_t \sim iid\ S_\alpha(0,1) \tag{4a}$$

$$c_t^\alpha = \omega + \beta c_{t-1}^\alpha + \delta\,|\,r_{t-1} - \mu\,|^\alpha + \gamma d_{t-1}\,|\,r_{t-1} - \mu\,|^\alpha \tag{4b}$$

Where,

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

Model 5 shown in Equation 5 is obtained setting α = 2 in model 4 .

$$r_1 = \mu + \varepsilon_t,\qquad \varepsilon_t \sim \sqrt{2}c_t z_t,\qquad z_t \sim iid\ N(0,1) \tag{5a}$$

$$c_t^2 = \omega + \beta c_{t-1}^2 + \delta\,|\,r_{t-1} - \mu\,|^2 + \gamma d_{t-1}\,|\,r_{t-1} - \mu\,|^2 \tag{5b}$$

Restricting $\beta = \delta = \gamma = 0$ in model 4 results in model 6 which is presented in Equation 6:

$$r_t = \mu + \varepsilon_t,\qquad \varepsilon_t \sim S_\alpha(0, c) \tag{6}$$

A random variable x will have stable distribution $S_\alpha(0, c)$ when its log characteristic function can be represented as:

$$\ln E\exp(ixt) = i\delta t - |\,c_t\,|^\alpha \tag{7}$$

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

The parameter $c > 0$ measures scale whereas the parameter $\delta(-\infty,\infty)$ measures location and $\alpha \in (o,2]$ is the characteristic exponent that governs the tail behavior. A small value of α indicates thicker tail and normal distribution pertaining to symmetric stable family encompassing α = 2 whose variance is equal to $2c^2$.

In the process contained in Equation (1c) we restrict $\omega > 0, \beta \geq 0, \delta \geq 0,$ and $\gamma \geq 0.$ The theoretical term involving dummy variable d_{t-1} captures leverage effects that are transmitted from negative shock to increase in future volatility more than a positive shock of equal magnitude (Nelson 1991, and Hamilton Susmel 1994). Abstracting from the threshold term, when the errors are normal, the model of volatility persistence reduces to GARCH-normal process.

Any predictable variation in excess return is because of persistent component x_t ,which are assumed to follow a simple AR (1) process. When predictable component in Equation 1 becomes significant, than) $E(r_1 \mid r_1,....., r_{t-1})$ provides a useful forecast of returns. However, when c_η and ϕ or one of these is negligible, the returns are purely random, so these may display spurious predictions.

2.1. Estimation Issues

Non-Gaussianity of the state space model in Equation 1 creates complication in estimation even without the presence of conditional heteroskedasticity. This happens because the Kalman filter is no longer optimal due to the non-Gaussian nature of shocks.

The general recursive-filtering algorithm due to Sorenson and Alspach (1971) provides optimal filtering and predictive densities under any distribution for the errors and the formula for computing the log likelihood function. These formulae are presented in Appendix-A.

The recursive equation that is employed to compute filtering and predicting densities are given in the form of integrals whose close form analytical expressions are generally intractable, especially in very special cases. In this study, I numerically evaluate these integrals.

Stable distribution and density may be evaluated using Zolotrav's (1986) proper integral representation or by taking inverse Fourier transformation of the characteristic function. However, McCulloch (1996b) has developed a fast numerical approximation to stable distribution and density that has an expected relative density of the precision of 10^{-6} for $\alpha \in$ [0.84, 2]. I, therefore, restrict α in this range for computational convenience.

Lumsdaine (1996) shows that the effect of initial values in GARCH volatility process on the properties of the parameter estimates in GARCH (1, 1) is asymptotically negligible. Diebold and Lopez (1995) suggests to set the initial conditional variance ($2c_0^2$,where it exists) equal to sample variance at the first iteration and the subsequent

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

iterations to sample variance from simulated realizations with estimated parameters (from the previous iterations). Engle and Bollerslev (1986) suggests initializing the GARCH process using estimates of c_0 unconditional value obtained from the volatility process in Equation 1c.

3. EMPIRICAL RESULTS

3.1 Data Sources

Monthly excess returns in two South Asian stock markets over relevant risk free rates are employed from March 1991 through February 2004. Monthly stock prices for Pakistani stock market index KSE 100 and Indian stock market index S&P CNX 500 were obtained from Datastream. Pakistan Treasury bill rates and Indian central bank discount rates are the two risk free rates that were obtained from September 2004 version of International Financial Statistic (IFS) CD-ROM. Excess returns are expressed as percent per month throughout the study. Figure 1 plots excess return series for S&P CNX 500 index and Figure 2 plots excess return series for KSE 100 index. The plots shown in these Figures encouraged me to employ models for detecting possible persistence of mean returns using state space or unobserved component model of stock returns.

3.2 Estimation Results

Tables 1 and 2 show the estimation results for S&P CNX 500 and KSE 100 stock price index for different models estimated for this study. These Tables 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 of persistent component of returns ϕ. There is ample difference in two markets that can be characterized by low values of characteristic exponent α, the volatility persistence parameter β, and high values of leverage parameter γ in KSE 100 index compared to S&P CNX 500. The predictable component in KSE 100 stock price index is statistically significant whereas there is less evidence of statistically significant predictable component in S&P CNX 500.

Figures 3 and 4 show filter mean $E(x_t \mid r_1, r_2, r_3, \ldots\ldots., r_t)$ for Indian and Pakistani stock markets respectively. These plots show that predictable component appear to be constant which indicates that variation in its parameter estimates might not be component in forecasting access returns.

3.3 Hypotheses Test

In the following sub-sections the tests for normality, volatility persistence, and persistence in mean returns are elaborated. All tests are based on likelihood ratio test statistics.

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

3.3.1 Test for Normality

This test is based on the null of α = 2 in model 1. The LR test statistics for this test has non-standard distribution because the null hypothesis lies on the boundary of the admissible values for α ; therefore, standard regularity conditions are not satisfied. Inferences are therefore derived from test statistics based on the critical values due to McCulloch (1997).

Based on LR test statistics, the null hypothesis for KSE 100 index can easily be rejected at a significance level of better than 0.005 using critical values from McCulloch (1997). However, using LR test statistics, the null hypotheses of normality, and no volatility persistence for S&P CNX 500 index is not rejected. The study results indicate that even after accounting for GARCH-like behavior, the excess returns are significantly non-normal.

3.3.2 Test for Volatility Persistence

The test for no volatility persistence (homoskedasticity) can be formulated by restricting $\beta = \delta = \gamma = 0$ in model 1. The statistical inferences for this test are based on χ_3^2 distributions.

The LR for the null of no GARCH which is to test $\beta = \delta = \gamma = 0$ reported in Tables 1 and 2 respectively for S&P CNX 500 and KSE 100 indexes. Homoskedasticity in both the markets is strongly rejected with χ_3^2 critical values.

3.3.3 Test for Persistence in Mean Returns

The null hypothesis for this test is obtained from setting ϕ = 2 in model 1 which assumes that return series are random. In this case the standard likelihood ratio test statistics for this test are not applicable because the two shocks ε_t and η_t are not separately identified so the scale ratio c_η is also not identified. Similarly, the bound for the asymptotic distribution of a standardized likelihood ratio test statistics due to Hansen (1992) which is applicable in such cases may result in under-rejection of the null or a subsequent power loss as noticed by Hansen himself. In addition, the test statistics is computationally very intense especially for this study, so I refrain from using it. Therefore, the inferences reported are based on the critical values obtained from χ_1^2 and χ_2^2 distributions.

Based on the LR test statistics for S&P CNX 500 index, the null hypothesis of no persistence in mean returns $(\phi = c_\eta = 0)$ is rejected at 10 percent level of significance using critical values from χ_1^2 distribution. However, the null can not be rejected using critical values from χ_2^2 distribution at 10% level of significance. For KSE 100 stock price index, the null is rejected at 10% level of significance using critical values from χ_2^2 or even χ_1^2 distribution. Therefore, after accounting for normality and volatility persistence there exist statistically significant persistent signals in both the markets.

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

3.3.4 Additional Tests on Normality and Volatility Persistence

The tests for non-normality and volatility persistence are repeated considering model 4 as an alternative model. In this case model 5 is null model for non-normality and model 6 for homoskedasticity. The intuition behind these additional tests is to find the impact of excluding predictable component (from state space model) on the inferences from our model.

LR test statistics for normality and volatility persistence are reported in last two rows of column 5 in Tables 1 and 2 respectively for S&P CNX 500 index and KSE 100 index. Based on these results we failed to reject hypotheses of normality and no volatility persistence for S&P CNX 500 index. However, we reject both normality and no volatility persistence component in KSE 100 index. Figures 5 and 6 plot scales from model 4 for S&P CNX 500, and KSE 100 index respectively which show the evidence of highly non-constant scales in these markets, however, scales for KSE 100 index shows spikes in different time periods exhibiting a tendency towards stock market crashes.

3.3.5 Test for Leverage Effect

Absence of leverage effect imply that negative shock do not necessarily lead to negative increase in future volatility than positive shocks of the same magnitude. This hypothesis can be tested setting $\gamma = 0$, with $\gamma > 0$ as alternate hypothesis that the leverage effect exists. The results (not reported for brevity) strongly reject the null hypothesis in favor of leverage effects both for S&P CNX 500 and KSE 100 index.

3.4 Discussions on Results

The study results on hypothesis tests reveal that monthly KSE100 index excess returns from March 1991 through February 2004 do posses significant non-normality that is predictable even after accounting for conditional heteroskedasticity. Similarly, volatility persistence is also statistically significant. Leverage effects in volatility is insignificant, however, there is an evidence of statistically significant predictability at 10% level using critical values from χ^2_2 as well as χ^2_1 distribution. Statistically significant evidence of volatility 14 persistence exists in S&P CNX 500 index but there is no evidence of non-normality in this market. The state space models do not show statistically significant persistent signal in return series after taking into account volatility persistence at 10% level of significance using critical values χ^2_2 from distribution, but we are not able to reject the null of no persistent signal in returns using critical values from χ^2_1 distribution for this market at 5% level of significance.

As shown in Figure 6 KSE 100 index show highly non-constant scales and when compared to S&P CNX 500 index (Figure 5), the Figure shows random spikes in the years 1992, 1998, and 2000-2001. The plausible cause of these spikes are the external events during these years e.g. Gulf War, Asian Financial Crises, and crises after

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

September 11, 2001 respectively that sensitized stock market agents that caused in instability in the stock prices and hence the market. Policymakers might be interested to address underlying policy issues enhance investor's confidence that would strengthen the stock markets in the country and help stabilize the economy.

4. CONCLUSION

In this study non-Gaussian state space or unobserved component models are employed to find possible predictability in two South Asian stock markets (S&P CNX 500 and KSE 100). The state space models fully account for non-normality and volatility persistence that might be present in return series. S&P CNX 500 index demonstrate estimated value of characteristic exponent α which is close to normal behavior, however, the excess return encompass ample evidence of stock return volatility characterized by GARCH-like behavior. KSE 100 excess stock returns demonstrate significant leptokurtosis. The estimated value of characteristic exponent is well away from the value pertaining to normal behavior in this market, and excess stock returns exhibit ample persistence in stock return volatility that can be characterized by a GARCH-like process. There is insignificant leverage effect in the stock return volatility in both the markets (S&P CNX 500, and KSE 100) indicating that the negative shocks do not necessarily lead to greater increases in future volatility than the positive shocks of the equal magnitude. Unlike S&P CNX 500, KSE 100 index exhibits scale spike that shows a tendency towards stock market crashes. Policymakers might be interested to address underlying policy issues that might help improving the major stock market of the country.

The study results on predictability of monthly stock returns are statistically significant in KSE100 index but such results are less significant for S&P CNX 500 index. The efficiently estimated excess returns for S&P CNX 500 are 0.01% per month (0.12% per annum), and 0.015% per month (0.18% per annum) for KSE 100 stock price index.

Appendix A: Sorenson-Alspach Filtering Equations

Let y_t, t = 1,..., T, be an observed time series and x_t an unobserved state variable, stochastically determining y_t. Denote $Y_t = \{y_1, ..., y_t\}$ The recursive formulae for obtaining one-step ahead prediction and filtering densities, due to Sorenson and Alspach (1971), are as follows:

$$p(x_t|Y_{t-1}) = \int_{-\infty}^{\infty} p(x_t|x_{t-1})p(x_{t-1}|Y_{t-1})dx_{t-1}\,, \qquad \text{(A1)}$$

$$p(x_t|Y_t) = p(y_t|x_t)p(x_t|Y_{t-1}) \,/\, p(y_t|Y_{t-1})\,, \qquad \text{(A2)}$$

$$p(y_t|Y_{t-1}) = \int_{-\infty}^{\infty} p(y_t|x_t)p(x_t|Y_{t-1})dx_t\,. \qquad \text{(A3)}$$

Finally, the log-likelihood function is given by:

$$\log p(y_1,\dots,y_T) = \sum_{t=1}^{T} \log p(y_t|Y_{t-1}). \tag{A4}$$

REFERENCES

Andrews, D.W.K., 2001. "Testing when a parameter is on the boundary of the maintained hypothesis", Econometrica, Vol. 69, No. 3, 683-734.

Akgiray, V. and G. Booth, 1988. "The stable law model of stock returns", J. Business Econ. Statistics, 6, 51-7.

Barberis, N., 2000. "Investing for the long run when returns are predictable", Journal of Finance 54, 225-264.

Bidarkota, P.V. and J.H. McCulloch, 2004. "Testing for persistence in stock returns with GARCH-stable shocks", Quantitative Finance, Vol. 4, No. 3, 256- 265.

Bidarkota, P.V. and J.H. McCulloch, 1998. "Optimal univariate inflation forecasting with symmetric stable shocks", Journal of Applied Econometrics, Vol. 13, No. 6, 659-670.

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

Cecchetti, S.G., P-s. Lam, and N.C. Mark, 1990. "Mean reversion in equilibrium asset prices", American Economic Review, Vol. 80, No. 3, 398- 418.

Cochran. S.J. and R.H. Defina, 1995. "Duration dependence in the US stock market cycle: a parametric approach", Applied Financial Economics, 5, 309-18.

Conrad, J. and G. Kaul, 1988. "Time-variation in expected returns", Journal of Business, Vol. 61, No. 4, 409-425.

Crato, N., 1999. "Some International evidence regarding the stochastic memory of stock returns", Applied Financial Economics, 4, 33-9.

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

De Vries, C.G., 1991. "On the relation between GARCH and stable process", Journal of Econometrics.

Diebold, F.X. and J.A. Lopez, 1995. "Modeling volatility dynamics Macroeconomics: Developments", Tensions and Projects Ed K Hoover (Boston, MA: Kulwer-Academics) pp. 427072.

Durbin, J. and S.J. Koopman, 2000. “Time series analysis of non-Gaussian observations based on state space models from both classical and Bayesian perspectives”, Journal of The Royal Statistical Society, Series B, 62, Part 1, 3-56.

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

Fama, E.F., 1991. “Efficient capital markets: II”, The Journal of Finance Vol. XLVI, No. 5, 1575-617.

French, K.R., G.W. Schwert and R.F. Stambaugh, 1987. “Expected stock returns and volatility”, Journal of Financial Economics 19, 3-29.

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

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

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

Harvey, A.C., 1989. “Forecasting, structural time series models and the Kalman filter”, Cambridge University Press.

Jensen, D.W., and C.G. de V ries, 1991. “On the frequency of large stock returns: putting booms and busts into perspective”, Review of Economics and Statistics, 73, 18-24.

Liu, S.M. and B.W. Brorsen, 1995. “Maximum likelihood estimation of a GARCH-stable model”, Journal of Applied Econometrics, Vol. 10, 273-85.

Lo, A., 1991. “Long-term memory in stock market prices”, Econometrica, 59, 1279-313.

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

Lumsdainee, 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, J.H., 1997. “Measuring tail thickness in order to estimate the stable index α : A critique”, Journal of Business and Economic Statistics, Vol. 15, No. 1, 74-81.

Ibid, 1996a. "Financial applications of stable distributions", in: G.S. Maddala and C.R. Rao (eds.), Handbook of Statistics, Vol. 14 (Elsevier, Amsterdam), 393-425.

Ibid, 1996b. "Numerical approximation of the symmetric stable distribution and density", in R. Adler, R. Feldman, and M.S. Taqqu (eds.), A Practical Guide to Heavy Tails: Statistical Techniques for Analyzing Heavy Tailed Distributions, Boston: Birkhauser.

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

Nelson, D.B., 1991. "Conditional heteroskedasticity in asset returns: A new approach", Econometrica, Vol. 59, No. 2, 347-70.

Oh, C.S., 1994. "Estimation of time-varying term premia of U.S. Treasury securities: using a STARCH model with stable distributions", Unpublished Ph.D. dissertation, The Ohio State University.

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

Sorenson, H.W., and D.L. Alspach, 1971. "Recursive Bayesian estimation using Gaussian sums", Automatica, 7, 465-79.

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

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

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

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

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Table 1: Model Estimates (for S&P CNX500 Excess Returns) with Leverage Effects

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 ($\alpha = 2$)	0.132			0.000		
LR ($\beta = \delta = \gamma = 0$)	9.358			4.363		
LR ($\phi = c_\eta = 0$)	4.432	4.300				

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Notes on Table 1

1. The following unobserved component or state space model with non-normality (stable model) is employed to estimate the results shown in the table.

$$r_t = x_t + \varepsilon_t, \quad \varepsilon_t \sim c z_{1t}, \quad z_{1t} \sim \text{iid } S_\alpha(0,1) \tag{1a}$$

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

2. All estimates are rounded off to the third decimal place.

3. Hessian-based standard errors for the parameter estimates are reported in parentheses. LR ($\phi = c_\eta = 0$) gives the value of the likelihood ratio test statistic. It is a test for no predictable components in excess returns. Under this null, the distribution of the LR test statistic is non-standard (see section 3.2 in the text for an elaboration).

4. P-values generated by estimating Gaussian versions of Models 1 and 2 with data simulated from the estimated Gaussian Model 2 are reported in parentheses.

5. LR (α = 2) gives the value of the likelihood ratio test statistic for the null hypothesis of normality.

6. 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).

7. LR ($\beta = \delta = \gamma = 0$) is the test for no volatility persistence. This test is evaluated at χ^2_3 p-values.

Published by iRepository, February 2021

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Table 2: Model Estimates (for KSE100 Excess Returns) with Leverage Effects

Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
α	1.610 (0.110)	2 (restricted)	1.749 (0.131)	1.748 (0.130)	2 (restricted)	1.748 (0.177)
μ	0.013 (0.013)	0.024 (0.016)	0.012 (0.002)	0.015 (0.011)	0.023 (0.011)	0.088 (0.008)
ω	0.000 (0.000)	0.007 (0.007)		0.014 (0.006)	0.010 (0.009)	
β	0.000 (0.000)	0.014 (1.079)		0.031 (0.468)	0.004 (0.946)	
δ	0.002 (0.005)	6.45e-13 (8.46e-10)		2.85e-13 (1.06e-10)	8.58e-13 (2.36e-9)	
γ	18.170 (5.916)	0.541 (0.442)		1.66e-9 (6.34e-7)	3.038e-10 (3.20e-7)	
c_η	6.25e-9 (6.77e-7)	1.25e-10 (1.65e-7)	0.086 (0.007)			
c			0.001 (0.003)			0.016 (0.012)
ϕ	0.191 (0.070)	0.613 (0.313)	0.156 (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	7.892				

Notes on Table 2.
1. See notes in Table 1.

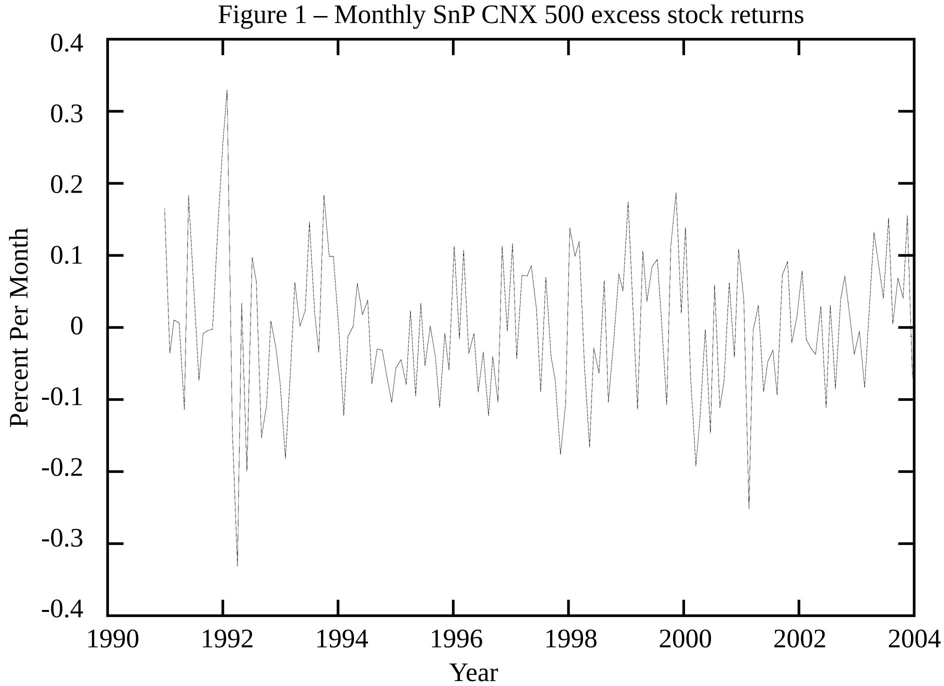


Figure 1 – Monthly SnP CNX 500 excess stock returns
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
Percent Per Month
1990
1992
1994
1996
1998
2000
2002
2004
Year

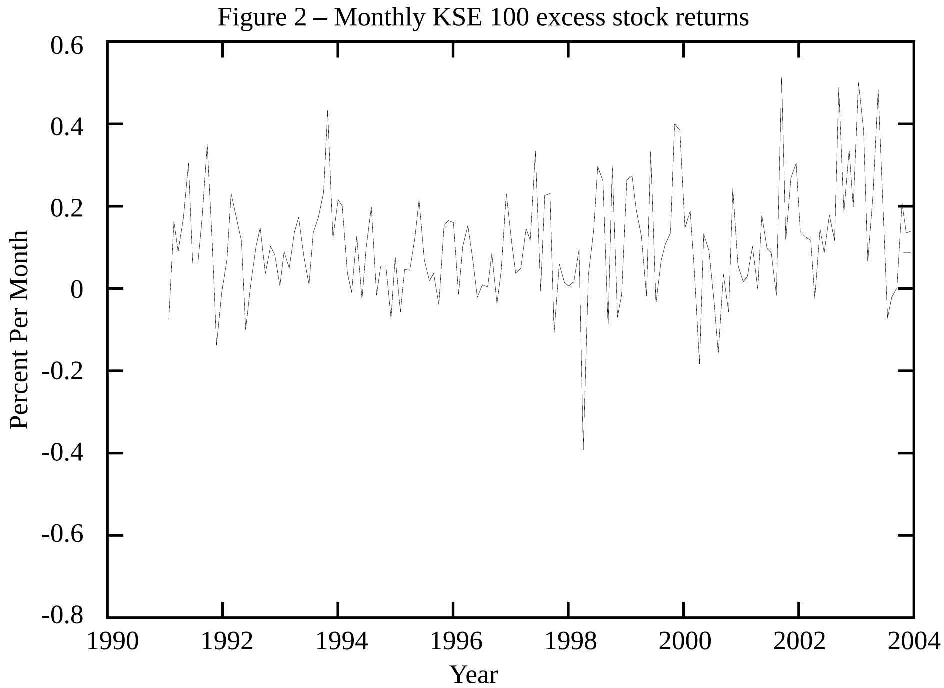


Figure 2 – Monthly KSE 100 excess stock returns
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
Percent Per Month
1990
1992
1994
1996
1998
2000
2002
2004
Year

https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Figure 3 – SnP CNX 500 excess returns and filter estimates

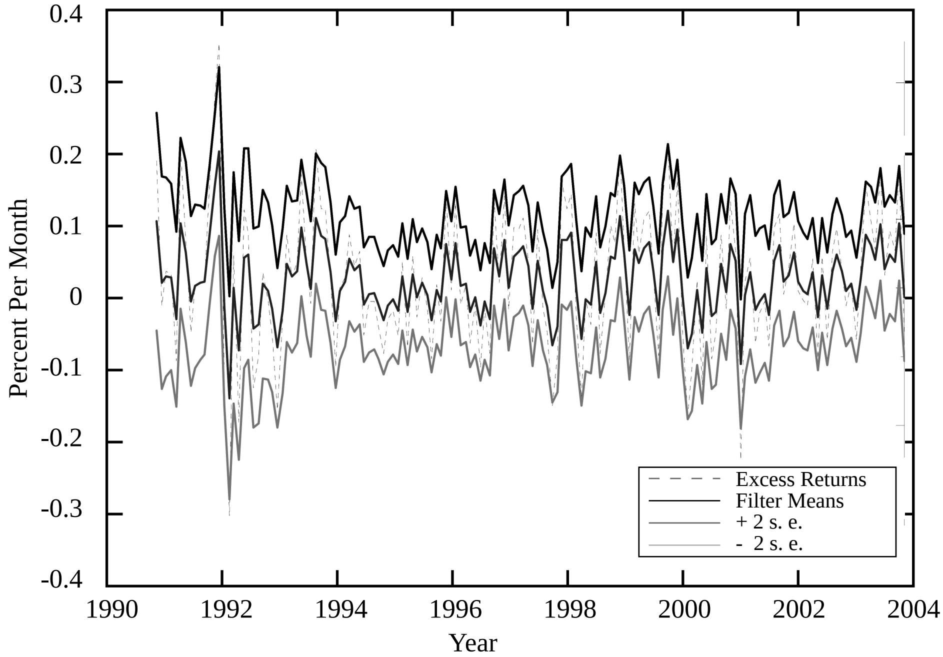
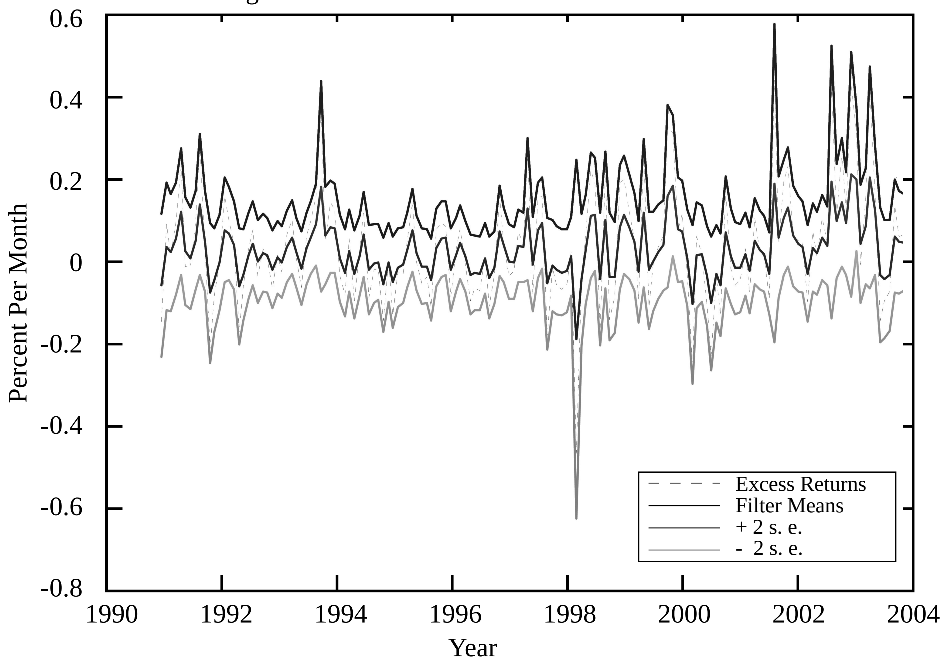


Figure 4 – KSE100 excess returns and filter estimates



https://ir.iba.edu.pk/businessreview/vol2/iss1/4
DOI: https://doi.org/10.54784/1990-6587.1111

Figure 5 – Stock returns volatility-stable GARCH (1,1) Model 4

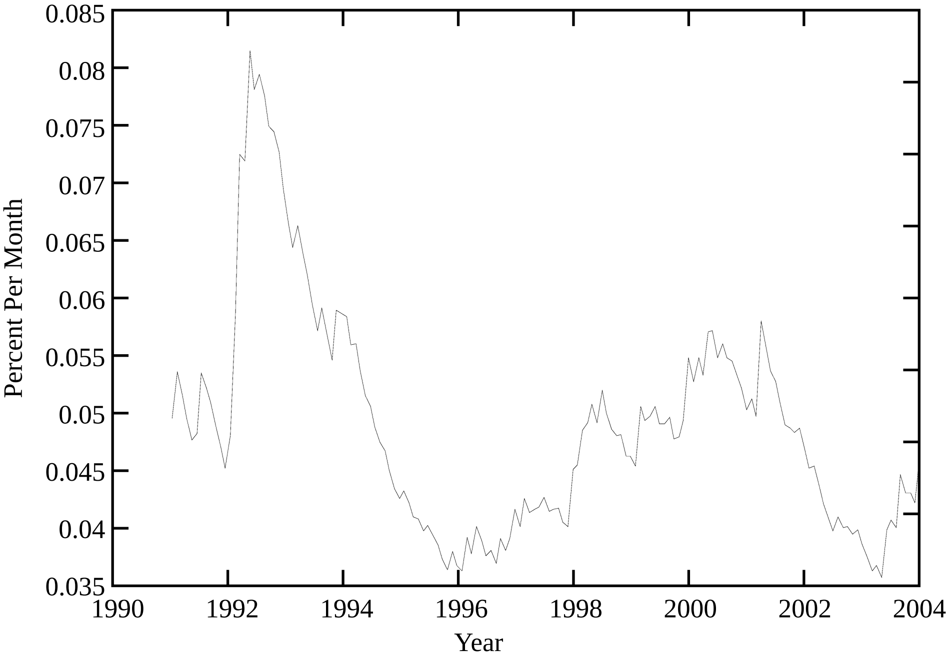
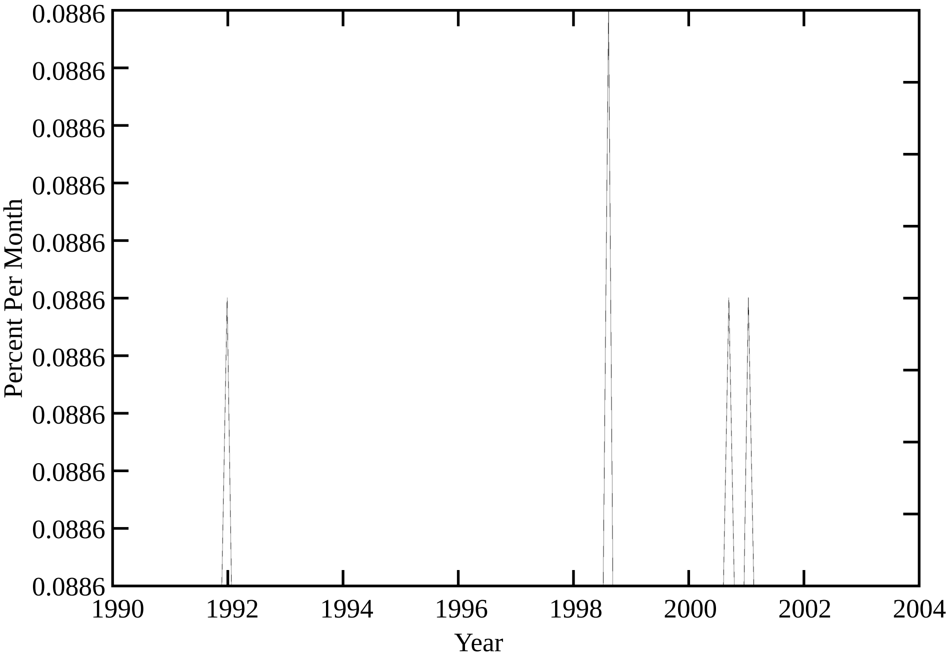


Figure 6 – Stock returns volatility-stable GARCH (1,1) Model 4



Published by iRepository, February 2021