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Analysis of forecastability of Portfolio Returns Volatility: Evidence from Pakistani Stock Market

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ABSTRACT

The present study attempts to evaluate and analyze the in-sample fit and out-sample fit forecasting performance of the high/low beta portfolio returns based on the specific to general approach of the EGARCH model respectively. The researcher has attempted to construct daily 10 equally weighted beta (β) portfolios (10 stocks each) to test forecastability of portfolio returns volatilities for the time period of July 2000 to June 2016 respectively. Based on the specific-to-general approach employed in the ARMA (1, 0)-EGARCH (1, 1) model, the estimation results of the model considers the general approach superior over the specific approach. The findings of the in-sample fit and the out-sample fit forecasting performances of the high/low beta portfolio returns volatilities have shown that the root mean square error and the mean absolute error and its bias proportions are the efficient forecasting error measures to model and evaluate the in-sample fit and the out-sample fit forecasting performances of the low-beta portfolio returns respectively. The present study tends to be beneficial for the investors for investment decisions and also for the macro-economic policy makers for construction of portfolios, valuation of securities and risk management respectively.

Keywords: High/Low Beta Portfolios, Volatility, EGARCH Model, Forecasting Error Statistics,

INTRODUCTION

Since the last two decades, the stock market volatility is contributing in the key investment decisions and stock portfolio development for the investors as well as the portfolio managers. According to Loudon, Watt and Yadav (2000), contrary to Efficient Market Hypotheses Fama (1970), the systematic variation of time in a stock returns' volatility which is captured by the variance can be split into the non-predictable and predictable component where the latter is termed as the conditional variance which is a function of the past information set i.e. at time t-1. This information set could be the firm related factor such as price-to-earnings ratio, book-to-market value and the economic factors such as the foreign exchange rate and the stock market return respectively.

Since, finance practitioners and the economic policy makers usually rely on the market estimates of volatility of securities as a yardstick for the exposure to financial markets and consider volatility as a key input in various investment decisions and portfolio creations therefore the predictable component; the conditional variance of the stock returns becomes important to be modeled and forecasted. That is why; various irrational pricing theories have come into existence such as the speculative bubbles theory, noise theory and the over- reaction theory that emphasizes on the deviation between the asset's fundamental value and the market price; the former being the rational component and the latter being the irrational component respectively. The Autoregressive Conditional Heteroskedasticity (ARCH) by Engle 1982 and the more generalized GARCH model by Bollerslev 1986's were proposed to explain the conditional variance. These methods and their variants were used to explain volatility of some mature and emerging stock markets (Akgiray 1989; Kearney and Daly 1998; Tay and Zhu 2000; Khil and Lee 2002).

The motivation to investigate forecastability of the stock return volatility comes from the fact that it is not only the central issue of the developed capital markets but has also gained prominence in the emerging capital markets. These markets always endeavor to remain efficient because of an intense global competition among the financial markets. The emerging markets are the developing economies that are into continuous effort for economic growth and capital markets stabilization due to better demographics and more room for economic growth avenues. Though, the emerging markets within itself engrave some unique risks of less transparency of potential investment opportunities, high volatility and increased illiquidity still these markets have become the integral part of the global investment avenues for the developed capital markets because of the stable and modern capital reforms and macro-economic development measures being taken by the emerging capital markets and Pakistani stock market is one amongst these.

Keeping in view this basic objective of the investors, it is one of the second contributions of this study in the Pakistani literature that has again attempted to evaluate and analyze the in-sample fit and out-sample fit forecasting performance of the high and low beta portfolio returns based on the specific to general approach of the EGARCH model respectively. Previously, the researcher has attempted to evaluate and model the forecastability of the stock returns at stock market level by employing the symmetric and the asymmetric GARCH family of models respectively. This very study has attempted to find out the predictability behavior of each of the high beta portfolios returns and each of the low beta portfolios returns that either their predictability behavior is same or vary from one another.

The present study attempts to construct daily 10 equally weighted beta (β) portfolios (10 stocks each) to test forecastability of portfolio returns volatilities for the time period of July 2000 to June 2016 respectively. To analyze and model the forecastability of the portfolio returns volatility, the study has employed the specific to general approach of each of the high/low beta portfolio returns in the EGARCH model respectively.

The plan of the study comprises of four sections. Section two comprises of literature review, section three explains the data and methodology, section four comprises of interpretation of empirical results and section five gives the summary and conclusion.

LITERATURE REVIEW

The Autoregressive Conditional Heteroskedasticity (ARCH) volatility model that best captures the stylized facts of the forecastability of the stock return volatility has been originally introduced by Engle (1982). The model tends to capture the volatility clustering property of the stock prices that suggests that the stock returns are not constant over time possessing the long memory behavior respectively. Extensive literature is available to test the forecastability of the stock returns either at firm level or market level. In a recent study, Mubarik and Javed (2016) found the asymmetric GARCH models to be superior to the symmetric GARCH model to test the forecastability of the Pakistani market index volatility respectively. The impact of structural shifts in conditional volatility on variance persistency of asymmetric GARCH models is studied by Muhammad and Shuguang (2015). The dataset comprises of daily stock returns of four European markets and three Asian emerging markets. The authors have applied EGARCH and TGARCH models for the study. The results reveal that if the models are implied in the absence of structural shifts then there is an overestimation of persistency in conditional variance of stock returns and by considering the structural shifts in volatility with GARCH type models reduces the persistency in conditional variance of stock returns. In another study, Gokbulut and Pekkaya, (2014) found the TGARCH and the CGARCH models to be the superior forecasting volatility models for the Turkish stock market on the daily basis. Among some topical studies related to structural shifts (Aggarwal, 1999) applied ICSS algorithm to examine sudden changes in volatilityof eleven emerging markets from 1985 to 1995, the stock market crash of 1987 was major factor that was sufficiently detected by ICSS algorithm in their sample.

Garcia and Vaidyanathan (2014) tried to explain the forecastability of stock returns volatility by incorporating uncertain structural breaks in predictive variable, dividend price ratio, rather than following the stationary processes with constant long-run means. The estimation method incorporates the uncertainty about magnitude, timing and location of structural breaks. the findings reveal that by adjusting the structural changes with dividend price ratios considerably increases the predictive power of dividend price ratio for in sample and out of sample stock. Another effort is put on by Zheng and Miao (2012) to predict the stock returns of shanghai stock exchange. The dataset contains the daily closing price of Shanghai Composite Index. . The authors have used Box-Jenkins ARMA model and ARMA-GARCH model respectively. The two models are used to evaluate the out-of sample forecasting performance and the results reveal that ARMA-GARCH model is better than ARMA model in forecasting the future movements of market. In another study, Aono and Iwasaiko (2010) examined the Japanese stock market returns in two ways. The study used two sets of variables to examine their predictability. First set of variables contains market price earnings ratios and second set of variables comprises of lagged stock return and interest rates. The authors find that interest rate and lagged stock returns have more predictive power as compared to market price earnings ratios. Husain and Uppal (1999) examined stock market volatility in Pakistan using daily stock prices on 36 companies, eighty sectors indices and a market index using ARCH and GARCH models from January 1, 1989 to December 30, 1993. Their consequence point out that GARCH (1,1) is an applicable representation of conditional variance. They also find Evidence of persistence in variance in returns.

The random level shift and short memory component model to capture the forecastability of stock returns has been proposed by Lu and Perron (2009) in their respective study. The authors have applied the model to log-absolute returns of S&P 500, AMEX, Dow Jones, and NASDAQ indices. The level shift component model is found to be an important feature to provide improved forecasting volatility when using squared returns as proxy. A stochastic volatility model including short memory and level shift model is studied by Qu and Perron (2008) respectively. The authors have proposed the Bayesian inference procedure for the study. The model is applied to the data of S & P 500 and NASDAQ daily returns. The authors find the model proves to be a good fit to the data and forecasts as well. Similarly, Hammoudeh and Li (2008) noted the major decline in volatility persistency by including the sudden structural shifts in variance while forecasting the volatility of stock markets of Gulf countries.

RESEARCH METHODOLOGY

The present study employs the data of the stock prices, the turnover of shares, the economic variables, the deterministic events and the stochastic change points as the study is based on the specific to general approach to model and analyze the forecastability of portfolio returns respectively. The specific approach is the autoregressiveness of order one of each of the portfolio returns and the general approach is achieved after adding the trading volume (turnover of shares), the economic returns, the deterministic events (dummies) and the stochastic change points (discrete points) step by step to the autoregressiveness of order one of each of the portfolio returns respectively.

Daily stock prices and the daily turnover of shares comprises of 100 listed stocks (firms) including both of the financial and non-financial firms selected out of 750 stocks as on June 30, 2016 for the time period of July 2000 to June 2016 respectively. The stocks are selected on the basis of active trading of the stock, representative of the sector and the existence of the stock for the entire period of analysis. Daily stock returns and the economic variables returns are calculated by the following logarithmic formula;

$R_f = \ln(p_t) - \ln(p_{t-1})$

Where R_f indicates the return of the variable, ln indicates logarithm, p_t indicates current day price and p_{t-1} indicates the previous day price of a firm.

For any capital changes, the term p_t of the stock price is further adjusted for any capital changes expressed as;

$$p_t^{\cdot} = \frac{S_t}{S_{t-1}}\left[P_t\left(1 - \frac{RI_t SP_t}{S_{t-1} PR_t SP_t}\right) + D_t\right] \quad (1)$$

Where $S_t = S_{t-1} + RI_t + SS_t$

P_t indicates the actual closing price at time t, S_t denotes the share outstanding at time t, RI_t are rights issues, SS_t labels the stock dividends, SP_t labels the subscription price for the rights, PR_t is ex-date of right issues and D_t denotes the cash dividend. The high frequency (daily) high/low portfolios sorted on beta are constructed by following Fama & Macbeth (1973) by using the formula given below;

$$\widehat{\beta_i} = \frac{\widehat{cov}(\widetilde{R_m}, \widetilde{R_a})}{\widehat{\sigma}^2 m(\widetilde{R_m})} \quad (2)$$

Where $\widehat{cov}(\widetilde{R_m}, \widetilde{R_a})$ is the covariance between the market return and the asset return. In the above equation, βi's of portfolios behave as the accurate estimates of β's than the βi's of the individual stocks. Next, the trading volume is computed by taking log of turnover of shares where the term turnover indicates the number of shares traded of a particular stock as expressed below; $V_t = ln(o_t)$ Further, the trading volume portfolios are estimated by adding up the (log) turnover of shares of the stock of each portfolio sorted on beta (10 stocks each) as expressed below;

$$Vp = \sum_{i=1}^{n} \ln(ot)pi \quad (3)$$

Where $\ln(ot)pi$ denotes the (log) turnover of shares to compute the trading volume portfolios of each of the 10 portfolios (10 stocks each) respectively.

To move further towards the general approach of the study, the deterministic (observed) events are taken into account that occur in the economy and can be easily identified in the time series data. In total, eleven deterministic events are taken into account by introducing the intercept dummies into the estimation models to avoid the overestimation of each of the 10 portfolios returns volatilities. Hence, each dummy takes value of 1 after event and zero before the event. To complete the general approach of the model, the study finally has included the change points that occur in the unconditional variance of the stock returns named as the stochastic change points also called as the discrete shifts (Tiao and Inclan, 1994). To identify the discrete shifts, the present study has employed the Iterated cumulative sums of squares (ICSS) algorithm in the unconditional variance equation of each of the 10 stock return portfolios respectively.

According to Box and Jenkins (1970), the ARMA models are an important class of time series models that takes into account the data generating process of the stock returns. These models suggest that the current values of returns along with other factors depend on the previous values of the returns and the white noise disturbance terms. In general an ARMA (m, n) GARCH (p, q) model can be expressed as:

$$R_{pt} = \alpha_0 + \sum_{j=1}^{m} \alpha_1 R_{pt-j} + \sum_{k=1}^{n} \alpha_{2k} \varepsilon_{t-k} + \varepsilon_t \quad (4)$$

$\varepsilon t \approx N(0, h_t)$

$$h_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} h_{t-j} + \sum_{i=1}^{q} \beta_{2i} \varepsilon_{t-i}^2 \quad (5)$$

Where, R_{pt} is portfolio returns, α_{1j} and α_{2k} estimates the autoregressive and moving average term h_t is conditional variance, β_{1j} and β_{2i} estimates the GARCH and ARCH coefficients respectively and ε_t is error term that depends on previous information.

Conditional mean equation (4) is extended to general form as follows

$$R_{pt} = \alpha_0 + \sum_{j=1}^{m} \alpha_1 R_{pt-j} + \sum_{k=1}^{n} \alpha_{2k} \varepsilon_{t-k} + \alpha_4 V_p + \alpha_5 E_t + \sum_{n=1}^{N} \alpha_{6n} D_n + \sum_{l=1}^{L} \alpha_{7l} D_L + \varphi h_t + \varepsilon_{it} \quad (6)$$

Condition variance equation for EGARCH-M

$$\log h_t^2 = \omega + \sum_{i=1}^{q} \beta_{1i}\left(\left|\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right| - E\left[\left|\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right|\right]\right) + \sum_{j=1}^{p} \beta_{2j} \log h_{t-j}^2 + \sum_{k=1}^{r} \beta_{3k} \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \beta_4 V_p + \beta_5 E_t + \sum_{n=1}^{t} \beta_{6n} D_n + \sum_{l=1}^{L} \beta_{7l} D_l \quad (7)$$

Vp stands for volume portfolio of each of the 10 portfolios, E stands for the economic variables, D_n= 1 for each of the 11 deterministic events and 0 otherwise, D_l =1 for the period starting from the data of (variance) change point identified from the ICSS algorithm onwards to the last observation and 0 otherwise.

The EGARCH model attempts to examine the forecastability of portfolios stock return volatilities within two sets of the sample i.e. the in-sample fit forecasting performance of the portfolios stock return volatilities falling within the time period of July 2000 to June 2014 and the out-sample fit forecasting performance of the portfolios stock return volatilities falling within the time period of July 2014 to June 2016. These in-sample fit and out-sample forecasting performances are evaluated by using four standard symmetric measures identified as root mean square error (RMSE*)*, the mean absolute error (MAE) and the Theil inequality coefficient (TIC)and the mean squared error (MSE). These statistical measures are expressed as;

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2} \quad (8)$$

Where $\hat{\sigma}_t^2$ indicates forecasting of volatility, σ_t^2 shows volatility at actual.

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{\sigma}_t^2 - \sigma_t^2\right| \quad (9)$$

$$TIC = \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2 - \sigma_t^2)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t^2)^2}\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\sigma_t^2)^2}} \quad (10)$$

The Theil inequality coefficient tends to range between zero and one and zero shows a perfect fit. Mean Squared Error (MSE) comprises of three proportion components termed as the bias proportion, variance proportion and the covariance proportion expressed as;

$$Bp = \frac{(\overline{\hat{r}_t} - \overline{r_t})^2}{\frac{1}{t^\circ}\sum_{t=1}^{t^\circ}(\hat{r}_t - r_t)^2} \quad (11)$$

$$Vp = \frac{(s\hat{r}_t - Sr_t)^2}{\frac{1}{t^\circ}\sum_{t=1}^{t^\circ}(\hat{r}_t - r_t)^2} \quad (12)$$

$$Cp = \frac{2(1-p)s\hat{r}_t - Sr_t}{\frac{1}{t^\circ}\sum_{t=1}^{t^\circ}(\hat{r}_t - r_t)^2} \quad (13)$$

Where the total sum of these three proportions equal to 1 where $B_P=V_P=0$ and $C_P=1$ and are computed in terms of the total forecasted error.

To initiate with the estimation techniques, the sample comprising of the random-walk and the time dependent properties of the stocks and the economic variables are turned stationary as strongly suggested by Engle (1982). For this very purpose, the Augmented Dickey Fuller stationarity test is employed as shown below;

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p}\beta_i \Delta y_{t-1+} e_t \quad (14)$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=1}^{p}\beta_i \Delta y_{t-1+} e_t \quad (15)$$

$$\Delta y_t = \cap_0 + \gamma y_{t-1} + \cap_0 t + \sum_{i=1}^{p}\beta_i \Delta y_{t-1+} e_t \quad (16)$$

Where Δy_{t-1} denotes the stationary process and ε_t is a white noise process. Further to test for the ARCH effects and serial correlation with ten lags, the Lagrange Multiplier test is employed as shown below;

$$\mathrm{Var}(\mu_t) = \sigma^2{}_t = \gamma_0 + \gamma_1 \mu^2{}_t \quad (17)$$

The $\mathrm{Var}(\mu_t)$ indicates no autocorrelation when γ_1 is 0 and $\sigma^2{}_t = \gamma_0$

RESULTS AND DISCUSSIONS

To initiate the estimation of forecastability of the high/low beta portfolio returns, the Augmented Dickey Fuller stationarity test (ADF) is employed at trend and trend and intercept on the stock prices, and the economic variables respectively. The results have shown the presence of unit root at trend level and at trend and intercept at 1st difference, however, the results indicate the rejection of unit root and confirm of stationarity respectively.

The descriptive statistics of the portfolio returns, the trading volume and the economic variables returns are reported in table 1. The results reveal the negative and positive skewness of the portfolio returns with the values greater than 0 thereby providing evidence of asymmetry. Likewise, the kurtosis values lower or higher than the value 3 indicate the leptokurtic distribution with the extreme values and thicker tails of each of the entire portfolio returns respectively. Another test of normality, the Jarque-bera (JB) test is employed to test the normality of the data of the variables undertaken in the research study. The results of p value of JB test supports the non-normality of the stock returns respectively thereby confirming for the leptokurtic distribution of the stock returns respectively. Similar results are observed for the economic variable returns respectively.

Table 1

Descriptive Statistics of Portfolio Returns, Trading Volume Portfolio and Economic Variables Returns

Portfolios Returns	Mean[a]	S.D[b]	Skewness	Kurtosis	JB-test	P-value[c]
RP1	0.82	13.4	-0.23	25.01	79255.3	0.00
RP2	0.90	16.9	0.76	13.75	14310.8	0.00
RP3	0.79	16.9	0.02	37.60	24392.7	0.00
RP4	0.53	18.4	-0.74	14.37	61145	0.00
RP5	0.64	22.1	0.32	21.24	39620.7	0.00
RP6	0.58	21.1	0.34	15.49	3004.12	0.00
RP7	0.54	17.9	-0.540	15.23	12258.1	0.00
RP8	0.65	18.5	0.17	17.14	5032.62	0.00
RP9	0.50	24.0	-1.63	43.97	155430.	0.00
RP10	0.40	23.6	-0.53	43.97	14560.8	0.00
VP1	0.50	0.27	-5.47	67.84	528193.	0.00
VP2	0.50	0.27	-5.581	60.87	463723.	0.00
VP3	0.49	0.28	-5.91	59.18	299037.	0.00
VP4	0.49	0.26	-2.54	14.72	32254.0	0.00
VP5	0.60	0.30	-0.23	5.71	770.820	0.00
VP6	0.77	0.21	-4.35	78.84	805077.	0.00
VP7	0.80	0.52	-9.21	78.84	137549	0.00
VP8	0.77	0.61	-0.78	4.98	569.616	0.00
VP9	0.60	0.58	-2.54	21.34	98764.4	0.00
VP10	0.69	0.50	-8.64	114.83	181656	0.00
OIL	0.87	0.67	-0.25	2.19	8.46E+	0.00
EX	0.58	0.55	0.77	4.55	9.84E+	0.00
FXR	0.52	0.39	-0.78	2.63	619.638	0.00
RM	0.68	0.36	0.60	978.75	1.11E+	0.00
GOLD	0.83	0.86	0.57	1.78	511.488	0.00

To model and evaluate the in-sample fit and the out-sample fit forecasting performances of the high/low beta portfolio returns volatilities, the sample data in the present study has been split into two parts i.e. the in-sample fit and the out-sample fit of the ten high/low beta portfolio returns volatilities. For the in-sample fit forecasting performance, 10 years sample period is selected i.e. from July 2000 to June 2014 and the 2 years out-sample fit forecasting performance of the sample period July 2014 to June 2016 is taken. The evaluation of the in-sample fit and the out-sample fit forecasting performances is done through the forecasting measures of the root mean square error statistics, the mean absolute error statistics and its bias proportions , the mean absolute percentage error and the Theil inequality error statistics respectively. The empirical results are reported from table 2 to table 6 respectively.

Results of the in-sample fit and out-sample fit forecasting performances of the high/low beta portfolios. The findings of the low-beta portfolio returns indicate the significant in-sample and out-sample forecasting performances of the general approach of the EGARCH-M model and indicate the long-run predictive power than that of the high beta portfolio returns volatilities respectively. In contrary, the high-beta portfolios returns volatilities tend not to indicate the significant in-sample fit and the out sample fit forecasting performances respectively. Hence, it could be suggested that the high-beta portfolio returns volatilities tend to be more volatile and entail the tendency to create inertia and quickly respond to any surprises/shocks that may encounter them and may not pose the accurate forecast ability of the portfolio returns volatilities which is also empirically evident from the work of Fama and French (1988a) respectively.

The findings of the in-sample fit and the out-sample fit forecasting performances of the high/low beta portfolio returns volatilities have shown that the root mean square error and the mean absolute error and its bias proportions are the efficient forecasting error measures to model and evaluate the in-sample fit and the out-sample fit forecasting performances of the low-beta portfolio returns respectively. The findings of the in-sample fit and the out sample fit forecasting performances of high-beta portfolio returns have shown the mixed results. The Theil inequality error statistic of the in-sample fit and the out-sample fit forecasting performances of both of the high-beta portfolio returns volatilities as well as the low-beta portfolio returns volatilities have shown the poor fit forecasting performances respectively.

Table 2

Empirical Results of In-sample and Out-sample Fit Forecasting Performance of Portfolio Returns1and Portfolio Returns 2 by using EGARCH-M Model (Specific to General Approach)

Portfolio Returns 1

	RMSE	MAE	MAPE	TIC	BP	VP	CP
			IN-SAMPLE FORECASTING				
S	22.52	14.91	119.2	0.96	0.000	0.94	0.05
Vp	20.51	14.06	107.4	0.96	0.000	0.94	0.05
E	20.46	13.99	118.7	0.92	0.000	0.85	0.14
D	20.43	13.98	115.9	0.91	0.000	0.85	0.14
G	26.99	14.32	209.9	0.70	0.000	0.01	0.98
			OUT-SAMPLE FORECASTING				
S	28.38	17.82	169.5	0.96	0.001	0.95	0.04
Vp	28.89	18.46	157.9	0.95	0.000	0.93	0.06
E	28.93	18.43	149.8	0.86	0.000	0.73	0.26
D	33.33	19.02	166.8	0.79	0.001	0.23	0.76
G	30.08	18.63	164.2	0.86	0.000	0.59	0.40
			Portfolio Returns 2				
			IN-SAMPLE FORECASTING				
S	21.03	13.24	148.1	0.96	0.000	0.94	0.05
Vp	19.09	13.02	324.1	0.95	0.001	0.91	0.079
E	19.05	12.97	734.1	0.91	0.000	0.85	0.14
D	19.04	12.93	450.1	0.89	0.000	0.82	0.17
G	27.37	13.19	211.1	0.70	0.000	0.00	0.99
			OUT-SAMPLE FORECASTING				
S	27.01	13.97	116.8	0.96	0.004	0.93	0.06
Vp	26.99	13.95	114.4	0.95	0.004	0.92	0.06
E	26.89	13.92	163.0	0.93	0.000	0.90	0.09
D	26.80	13.88	154.1	0.92	0.000	0.88	0.11
G	26.85	13.82	137.4	0.91	0.000	0.84	0.15

Note: S stands for specific approach, Vp stands for volume portfolio, E stands for economic variables, D stands for deterministic events, G stands for General approach, RMSE stands for root mean squared error, MAE stands for mean absolute error, MAPE stands for mean absolute percentage error, TIC stands for Theil Inequality Coefficient, BP stands for bias proportion, VP stands for variance proportion and CP stands for covariance proportion.

Table 3

Empirical Results of In-sample and Out-sample Fit Forecasting Performance of Portfolio Returns3 and Portfolio Returns 4 by using EGARCH-M Model (Specific to General Approach)

Portfolio Returns 3

	RMSE	MAE	MAPE	TIC	BP	VP	CP
			IN-SAMPLE FORECASTING				
S	19.42	13.7	164.1	0.92	0.000	0.8	0.12
Vp	19.28	13.5	131.6	0.91	0.000	0.8	0.13
E	19.25	13.5	192.8	0.89		0.8	0.16
D	19.27	13.5	220.7	0.87	0.000	0.7	0.22
G	19.23	13.4	219.7	0.86	0.000	0.7	0.25
			OUT-SAMPLE FORECASTING				
S	19.91	14.2	209.5	0.92	0.005	0.8	0.13
Vp	19.86	14.1	134.8	0.92	0.003	0.8	0.13
E	19.80	14.1	183.8	0.90	0.000	0.8	0.16
D	19.63	13.9	156.2	0.84	0.000	0.7	0.29
G	19.65	14.0	130.4	0.87	0.000	0.7	0.22
Portfolio Returns 4							
			IN-SAMPLE FORECASTING				
S	18.98	13.6	122.0	0.93	0.000	0.9	0.099
Vp	19.80	13.7	126.9	0.93	0.000	0.9	0.098
E	19.76	13.6	164.2	0.92	0.000	0.8	0.11
D	19.75	13.6	185.1	0.90	0.000	0.8	0.15
G	19.72	13.6	194.0	0.89	0.000	0.8	0.18
			OUT-SAMPLE FORECASTING				
S	15.61	10.6	108.8	0.93	0.002	0.8	0.10
Vp	15.60	10.6	108.3	0.94	0.002	0.9	0.09
E	15.56	10.7	116.3	0.93	0.000	0.8	0.128
D	15.49	10.6	116.3	0.92	0.000	0.8	0.12
G	15.39	10.5	117.0	0.86	0.000	0.7	0.23

Note: S stands for specific approach, Vp stands for volume portfolio, E stands for economic variables, D stands for deterministic events, G stands for General approach, RMSE stands for root mean squared error, MAE stands for mean absolute error, MAPE stands for mean absolute percentage error, TIC stands for Theil Inequality Coefficient, BP stands for bias proportion, VP stands for variance proportion and CP stands for covariance proportion.

Table 4

Empirical Results of In-sample and Out-sample Fit Forecasting Performance of Portfolio Returns5 and Portfolio returns 6 by using EGARCH-M Model (Specific to General Approach)

Portfolio Returns 5

	RMSE	MAE	MAPE	TIC	BP	VP	CP
			IN-SAMPLE FORECASTING				
S	13.37	9.50	149.9	0.8	0.00015	0.8	0.1
Vp	13.77	9.82	185.8	0.8	0.00090	0.7	0.2
E	13.69	9.75	225.2	0.8	0.00020	0.7	0.2
D	13.69	9.74	198.6	0.8	0.00024	0.7	0.2
G	13.69	9.72	226.5	0.8	0.00026	0.6	0.3
			OUT-SAMPLE FORECASTING				
S	11.81	8.31	120.5	0.8	0.00413	0.8	0.1
Vp	11.77	8.26	116.5	0.8	0.00353	0.8	0.1
E	11.72	8.19	112.2	0.8	0.00025	0.7	0.2
D	11.65	8.18	117.1	0.8	0.00024	0.7	0.2
G	11.58	8.13	119.4	0.8	0.00073	0.7	0.2
Portfolio Returns 6							
			IN-SAMPLE FORECASTING				
S	20.00	13.5	134.1	0.9	0.00020	0.9	0.0
Vp	19.01	13.2	195.2	0.9	0.00027	0.8	0.1
E	18.98	13.1	242.4	0.9	0.00049	0.8	0.1
D	18.96	13.1	234.0	0.9	0.0007	0.8	0.1
G	18.92	13.0	250.1	0.8	0.00036	0.7	0.2
			OUT- SAMPLE FORECASTING				
S	23.26	14.6	112.40	0.93	0.000968	0.91	0.08
Vp	23.12	14.6	122.62	0.90	0.000101	0.88	0.11
E	22.86	14.6	123.45	0.87	0.000231	0.84	0.15
D	22.70	14.5	122.28	0.85	0.000534	0.82	0.17
G	22.61	14.4	130.81	0.84	0.000296	0.79	0.20

Note: S stands for specific approach, Vp stands for volume portfolio, E stands for economic variables, D stands for deterministic events, G stands for General approach, RMSE stands for root mean squared error, MAE stands for mean absolute error, MAPE stands for mean absolute percentage error, TIC stands for Theil Inequality Coefficient, BP stands for bias proportion, VP stands for variance proportion and CP stands for covariance proportion.

Table 5

Empirical Results of In-sample and Out-sample Fit Forecasting Performance of Portfolio Returns7and Portfolio Returns 8 by using EGARCH-M Model (Specific to General Approach)

Portfolio Returns 7

	RMSE	MAE	MAPE	TIC	BP	VP	CP
			IN-SAMPLE FORECASTING				
S	20.00	13.5	134.1	0.9	0.00020	0.9	0.0
Vp	19.01	13.2	195.2	0.9	0.00027	0.8	0.1
E	18.98	13.1	242.4	0.9	0.00049	0.8	0.1
D	18.96	13.1	234.0	0.9	0.0007	0.8	0.1
G	18.92	13.0	250.1	0.8	0.00036	0.7	0.2
			OUT- SAMPLE FORE CASTING				
S	23.26	14.6	112.4	0.9	0.00096	0.9	0.0
Vp	23.12	14.6	122.6	0.9	0.00010	0.8	0.1
E	22.86	14.6	123.4	0.8	0.00023	0.8	0.1
D	22.70	14.5	122.2	0.8	0.00053	0.8	0.1
G	22.61	14.4	130.8	0.8	0.00029	0.7	0.2
Portfolio Returns 8							
			IN-SAMPLE FORECASTING				
S	19.38	12.5	131.2	0.9	0.00025	0.9	0.0
Vp	18.01	12.1	129.7	0.9	0.00007	0.9	0.0
E	17.97	12.0	151.8	0.9	0.00045	0.8	0.1
D	17.97	12.0	148.2	0.9	0.00028	0.8	0.1
G	17.94	12.0	158.6	0.8	0.00056	0.8	0.1
			OUT-SAMPLE FORECASTING				
S	23.77	14.1	139.8	0.9	0.00128	0.9	0.0
Vp	23.77	14.1	141.6	0.9	0.00139	0.9	0.0
E	23.72	14.0	113.2	0.9	0.00003	0.9	0.0
D	23.66	14.03	110.85	0.91	0.000379	0.84	0.1
G	23.50	13.98	135.73	0.88	0.000119	0.79	0.2

Note: S stands for specific approach, Vp stands for volume portfolio, E stands for economic variables, D stands for deterministic events, G stands for General approach, RMSE stands for root mean squared error, MAE stands for mean absolute error, MAPE stands for mean absolute percentage error, TIC stands for Theil Inequality Coefficient, BP stands for bias proportion, VP stands for variance proportion and CP stands for covariance proportion.

Table 6

Empirical Results of In-sample and Out-sample Fit Forecasting Performance of Portfolio Returns9and Portfolio Returns 10 by using EGARCH-M Model (Specific to General Approach)

Portfolio Returns 9

IN-SAMPLE FORECASTING

	RMSE	MAE	MAPE	TIC	BP	VP	CP
S	18.45	13.0	196.10	0.8	0.00014	0.7	0.2
Vp	17.79	12.4	207.23	0.8	0.00023	0.7	0.2
E	17.77	12.4	192.09	0.8	0.00007	0.7	0.2
D	17.82	12.4	221.35	0.8	0.00056	0.6	0.3
G	17.71	12.3	250.41	0.8	0.00031	0.6	0.3
OUT-SAMPLE FORECASTING							
S	20.71	15.1	150.21	0.8	0	0.7	0.2
Vp	20.71	15.1	149.54	0.8	0	0.7	0.2
E	20.68	15.0	166.41	0.8	0.00048	0.7	0.2
D	20.42	14.8	159.54	0.8	0.00031	0.6	0.3
G	20.37	14.8	154.23	0.8	0.00030	0.6	0.3
Portfolio Returns10							
IN-SAMPLE FORECASTING							
S	21.10	13.9	7514.22	0.9	0.00001	0.9	0.0
Vp	20.37	13.1	120.485	0.9	0.00002	0.9	0.0
E	20.29	13.0	134.62	0.9	0.00002	0.8	0.1
D	20.28	13.0	140.16	0.9	0	0.8	0.1
G	20.28	13.0	142.69	0.9	0.00003	0.8	0.1
OUT-SAMPLE FORECASTING							
S	23.58	16.7	34312.7	0.9	0.00107	0.9	0.0
Vp	23.57	16.6	24359.4	0.9	0.00124	0.9	0.0
E	23.54	16.6	22277.7	0.9	0.00053	0.9	0.0
D	23.54	16.6	25355	0.9	0.00195	0.8	0.1
G	23.54	16.6	24403.	0.9	0.002371	0.86	0.13

Note: S stands for specific approach, Vp stands for volume portfolio, E stands for economic variables, D stands for deterministic events, G stands for General approach, RMSE stands for root mean squared error, MAE stands for mean absolute error, MAPE stands for mean absolute percentage error, TIC stands for Theil Inequality Coefficient, BP stands for bias proportion, VP stands for variance proportion and CP stands for covariance proportion.

CONCLUSIONS

The present study attempts to evaluate and analyze the in-sample fit and out-sample fit forecasting performance of the high/low beta portfolio returns based on the specific to general approach of the EGARCH model respectively. The researcher has attempted to construct daily 10 equally weighted beta (β) portfolios (10 stocks each) to test forecastability of portfolio returns volatilities for the time period of July 2000 to June 2016 respectively. Contrary to the efficient market hypothesis (EMH), the forecasting performance of each of the high/low beta portfolio returns volatilities have shown significant results when estimated by the EGARCH-M model respectively. According to Andersen et al. (2003) the general practice is to use the daily stock returns to model daily forecasts in contrary to higher frequency intraday stock returns and that the forecasting behavior of the stock returns increases with the return interval Poterba and summers (1988). The forecasting performance of the portfolio returns is split into two parts i.e. the in-sample fit and the out-sample fit of the ten portfolio returns volatilities. For the in-sample fit performance, ten years sample period is selected i.e. from July 2000 to June 2014 and for the out-sample fit forecasting performance, two years of the sample period comprises of July 2014 to June 2016 to estimate and analyze the empirical results based on the MAPE, MAE, Theil In equality and MSE forecasting measures.

Based on the specific-to-general approach employed in the ARMA (1, 0)-EGARCH (1, 1) model, the estimation results of the model have considered the general approach superior over the specific approach. The findings indicate that all of the low beta portfolio returns volatilities show the significant in-sample forecasting measures with the lower values except for the mean absolute percentage error (MAPE) and the total value of all the proportional measures of MAE being equal to 1. Likewise, the out-sample fit forecasting performances of all the low beta portfolio returns volatilities are also significant thereby emphasizing on the long-run predictability of the variances of the low beta portfolio returns respectively. The in-sample fit forecasting measures and the out sample fit forecasting measures of high-beta portfolio returns indicate that the high-beta portfolio returns are more volatile and sensitive to the news or the surprises respectively. The results of the present study is in line with the previous work of the researchers (Mubarik and Javed, 2016) in the Pakistani market respectively.

Policy Implications

The present study implicates the superior behavior of the EGARCH model based on the specific to general approach to evaluate analyze the forecasting performance of the high/low beta portfolios returns. The model emphasizes on the significant role of the asymmetric behavior of the forecast ability of the portfolio returns thereby emphasizing on the fact that the negative news tend to create short-run inertia in the stock market and tend to be beneficial for the investors to shape their investment decisions. The study tends to be significant also for the macro-economic policy makers for construction of portfolios, valuation of securities and risk management respectively.

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