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The Relationship Between Idiosyncratic, Stock Market Volatility and Excess Stock Returns

SUMMARY: This research explained the relationship between idiosyncratic, stock market volatility and excess stock returns. It used the dependent variable of excess returns (ER) and independent variables of idiosyncratic volatility (IV), stock market volatility (MV), detrended volatility (DV), and risk free (RF). This study used the companies' data of the Karachi Meezan, 30 index, which is an Islamic free float index. The time span of data was ranging from 2012 to 2016. The results show the value weighted idiosyncratic stock return volatilities has a predictive power for excess stock market returns. Further by introducing risk free rate of return in the model, it shows a positive and strong inclination of predicting the excess stock market. Out-of-sample estimates of the model is also good and fit on many estimators in forecast evaluation.

KEYWORDS: Capital asset pricing model (CAPM), Out of sample forecast, in sample forecast, idiosyncratic volatility, stock market risk return relation, stock return predictability.
JEL CODES: D81, G12, J11, R53

Usually Stock markets are key indicators of any country's economic system, and the monetary policies are made to stable the economy of a nation. These monetary policies are prepared based on economic indexes such as stock indices, fund returns, inflation, interest and exchange rates. These financial indicators have time evolution. Volatility forecasting affects the financial decisions such as hazard management and portfolio choice. By modeling the financial time series in a best way it is necessary to model and forecast volatility of the concern financial time series especially the financial returns with suitable volatility model.

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VOLATILITY

It is virtually impossible to forecast volatility, because at one end it's reasons are not predictable but at the other side the returns itself have not adequate information about volatility to determine its future existence. It is commonly recognized that high volatility can occur because of heavy variation caused by domestic and international incidents.

Stock returns volatility is an important subject in finance and theories such as MPT, EMH, CPAM, APT, 3 Factor and 5 Factor models, BSM, ARCH family models all are related to volatility and its association with assets returns or prices discovery. Due to a positive relationship between volatility and returns, asymmetrical effect occurs, this phenomenon is accepted in many financial and behavioral finance theories such as modern portfolio theory and capital asset pricing model. Volatilities are measured through current and historical data, the current price volatility is called implied while in historical prices both conditional and unconditional volatilities are measured. The conditional volatility concept assumes that prices carry market historical memories and data was affected by the past micro and macro events. While the unconditional volatility are assumed free from historical memories of stock performance and other economic data effect. The historical or conditional volatility is further divided into weighted and unweighted volatilities, however, the prediction of volatility itself is a vast and complex undertaking. It is difficult to forecast a trendy volatility by considering the variables of economic circumstance, political instability, strikes, terrorism and inflation rates. This survey seeks to document the idiosyncratic volatility and show its association with excess returns and market volatility.

Literature identified that idiosyncratic volatility is the function of firm's operational policies, management decisions and firm investment decisions, nevertheless, it is diversifiable through effective portfolio management. Interestingly, few authors identified, such as Jagannathan et al., 1989; Turner et al., 1989, that idiosyncratic volatility has an inverse relation with excess returns, but after an amazing findings came out from different sources and researches that actual idiosyncratic volatility has a postive relationship with excess returns.

KSE Meezan Index (KMI–30)

KMI 30 was preceded by the combine struggle of KSE and Al Meezan bank. Like KSE 100, KMI index have top 30 companies based on their operation. KMI–30 is calculated from the cognitive operation of free float market capitalization. Index in KMI–30 is an Islamic index and it was screened for this six sharia criteria.

❶ *Business of the Investee Company:* This means the core business should not be HARAM or forbidden in Shariah such as acquiring interest in its services or involved in selling liquor, pork, operating night clubs, gambling or selling pornographic content or prostitutions. Etc.

❷ *Interest Bearing Debt to Total Assets:* To minimize interest association, the company should maintain a ratio of 37% of interest bearing debt to total assets.

❸ *Noncompliant Investments to Total Assets:* Investment in interest bearing securities such as money market instruments, TFCs, DSCs, Bonds, etc. should be minimized and will be held under 33% total investment.

❹ *Non-complaint Income to Total Revenue:* A non complaint income, i.e. income from interest bearing securities and income from non complaint business such as gambling, etc. shall not be larger than 5%.

❺ *Illiquid Assets to Total Assets:* To avoid any chance of interest, Islamic finance preferred illiquid assets i.e. other than cash and cash equivalent and The ratio of Illiquid Assets to Total Assets should be at least 25%..

❻ *Net Liquid Assets / Share vs. Market Price / Share:* The proportion of net liquid assets by share should be equal or less than the ratio of Market Price per share of an Islamic business. Net liquid assets per share is calculated by utilizing this rule: Net Liquid Assets per Share = (Total Assets – Illiquid Assets – Long Term Liabilities – Current Liabilities) / Number of Shares Outstanding

Objective & Contribution of the Study

Most of the studies related to the nexus of idiosyncratic volatility, stock market volatility and excess returns have been made at international level and there is no research available on this topic in Pakistan. The purpose of this work is to determine the relationship of idiosyncratic volatility with excess stock returns and market volatility. Further, the relationship of excess market returns will also be checked with detrended idiosyncratic volatility, market unpredictability and risk free rate of return for both in-sample and out-sample prediction with forecast evaluations.

This research will attempt to document the idiosyncratic volatility of Islamic index (Karachi Meezan, 30 index) companies, which is a free float index and under supervision of Sharia compliance code of business. It is likewise assumed that Islamic index companies will be free of excessive volatility as it is forbidden in the Islamic way of finance. The pursuit will be the specific contributions of this inquiry;

❶ For first time idiosyncratic volatility will be measured for Pakistani stock market.

❷ Islamic time series (indices) will be held back for excessive volatility, with the objective to reconfirm that Islamic indices are free from excessive volatility according to the objective of Islamic finance.

LITERATURE REVIEW

The exact investigation of this subject has endeavored to depict the method for the straight association between the prohibitive mean and the restrictive vacillation of the unusual profit for stocks. According to *Whitelaw* (1994) considered the Co integration between the conditional means and volatility of common origins. He explained the importance of "commercial paper-Treasury yield spread in predicting time variation in volatility". The conditional mean and volatility has shown an asymmetric connection, which comes out differently in relation to the contemporaneous connection inspected already. The unpredictability drives the normal returns, and this time changing connection is set up by using relationships, contemporaneous connections, and a vector auto regression. These effects bring into request the estimation of showing expected returns as a regular component of restrictive unpredictability.

Dhingra et al., (2016) analyze the quality of the confirmation on Indian stock returns, and raise the question whether such consistency could have been really abused by examiners to secure the advantages of the buy and hold technique in business records.

James and Edmister (1983) inspected the connection between regular stock returns, exchanging action and firm size. They found that exchanging movement and house size are really much connected. *Lettau and Ludvigson* (2001) investigated the role of fluctuations in the total utilization of the ratio between wealth and expenditure by utilizing the quarterly data set of US financial market. *Christos,* (2011) worked on stock price and trading volume behavior of listed banks before and during the financial crisis of 2008–2009. Banks under investigation were separated into two classes, i.e. large banks and small banks, which behaved differently under the crisis. He found that place was a low frequency correlation phenomenon based on stock price dynamics and stronger deviations from the Efficient Market Hypothesis during the crisis and for the group of firms with high institutional participation.

Yang, and Zhang, (2000) examined the causes of volatility in individual common stocks. They examined the period of 24 years comprise of 1976 to 2000 during which, quarterly accounting data set was incorporated at firm level. Evidences suggested there is an adverse downfall in the corporate returns while the unpredictability is increased within this span of time. *Bali and Cakici* (2008) went on the cross sectional relation between idiosyncratic volatility and expected stock returns. Their answers show that the data frequency used to estimate idiosyncratic volatility, the weighting scheme applied to compute average portfolio returns, the breakpoints utilized to classify stocks into quantile portfolios. The portfolio level analysis based on two measures of idiosyncratic volatility (estimated using daily and monthly data), three weighting schemes (value weighted, equal weighted, inverse volatility weighted), three breakpoints (CRSP, NYSE, equal market share) and two samples (NYSE/AMEX/NASDAQ and NYSE) indicate that no strong significant relation exists between idiosyncratic volatility and expected yields.

The grade to which stock returns were obvious seemed altogether low in the midst of most markets in the 1960s, yet unfolded to a level where, net of exchange costs, it could have been misused by many related financial specialists and inspectors in the unstable markets of the 1970s. *Andersen and co-writer*, (1996) took a shot at joint conveyance for return instability and exchanging volume at the day by day story. Their finding recommends that the model might be valuable for investigation of the monetary elements behind the watched unpredictability bunching in returns.

Darrat, Shafiqur and Zhong, (2003) used five minute Intraday data and measure return volatility by the exponential generalized autoregressive conditional heteroscedasticity method. Their finding was that the DJIA stocks show no contemporaneous correlation between volume and volatility.

Zhang and Wei (2006) examined the causes of volatility in individual common stocks. They examined the period of 24 years comprise of 1976 to 2000 during which, quarterly accounting data set was incorporated at firm level. Evidences suggested there is an adverse downfall in the corporate returns while the unpredictability is increased within this span of time. They found that volatility related to the returns of common stock returns is highly based upon the volatility of returns on equity in cross sections while holding a negative relation to ROE.

Until of late, the importance of idiosyncratic Volatility in asset valuation has gotten less attention in literature. Idiosyncratic volatility should assume no role in asset valuing, because under the presumptions of CAPM Idiosyncratic volatility is practically zero. However, investors rarely hold well broadened portfolios and *Merton* (1987) recommends that speculators are adjusted for the possessions of under diversified portfolios. Then idiosyncratic volatility has pulled in scientist's considerations. A few fields have discovered noteworthy connections amongst returns and idiosyncratic volatility with making some enthusiasm, and additionally some controversy.

Malkiel and Xu (2000) exploration claimed that idiosyncratic volatility is most useful in naming and explaining the cross sectional returns, returns obtained by building up a portfolio as equity mutual funds have direct relation with idiosyncratic volatility elements. *Campbell,* Malkiel and XU (2001) looked into the idiosyncratic firm level volatility of share market for the period of 1962 to 1997. Nevertheless, the survey has found that market condition has a significant impact over the volatilities. Malkiel and Xu (2002) evaluated the part idiosyncratic risk played in resource evaluating, both in theory and practice. Malkiel and Xu (2000) analyzed the behavior of idiosyncratic volatility for the period of Post world -war II. Their study utilized idiosyncratic volatility data used as aggregate developed by *Fama and Schwert* (1977), model. They reasoned that the volatility of general common stock followed upward trends over the time span. They further indicated that the idiosyncratic volatility of general common stocks has a relationship with the level of ownership possessed by the financial institutions. They too concluded that idiosyncratic volatility has a strong positive relationship with the projected future profits and growth. They have utilized the GARCH model for their estimations, even so, the OLS regression was employed among the variables for the recognition of relationships. They studied NYSE, NESDEQ and AMEX stock indices for their analytic thinking.

Bali and Cakici (2008) went on the cross sectional relation between idiosyncratic volatility and expected stock returns. Their answers show that the data frequency used to estimate idiosyncratic volatility, the weighting scheme applied to compute average portfolio returns, the breakpoints utilized to classify stocks into quantile portfolios. Using a screen for size, monetary value and liquidity play critical parts in regulating the existence and import of a relation between idiosyncratic risk and the cross section of expected returns.

This survey will look into this relationship within the land of Pakistan. For that function, the study will apply the same number of variables and methodologies existing in the old literature.

THE METHODOLOGY AND MODEL

Daily data for the period of 2012–2016 was taken from the sources of KMI, KSE and state bank of Pakistan. *William Sharpe's* well-known model Capital Asset Pricing model (CAPM) explains required rate of return as a function of market risk also called systematic risk or beta. Further, beta is benchmarked at 1 for market equal risk, less than 1 as less risky and higher than 1 as riskier asset. The Harry Markwitch modern portfolio theory and William Sharpe's CAPM suggested the direct relationship between risk & return through his well known postulate of "the higher the risk the higher will be the return and vice versa."

$$Re = Rf + \beta \times (Rm - Rf) \qquad (1)$$

Re = Expected return, *Rf* = risk free rate, β = Beta of the security, *Rm* = Expected market return

Modeling historical data through an OLS method is called in-sample regression, which might show the relationship between variables in beta of interest. Yet, when the same model is utilized to forecast values, the model is called out of sample regression.

Following are the techniques used in out of sample analysis:

Mean Absolute Error *(MAE)*

It is used to measure how close predictions are in the final results.

$$MAE = \sum_{t=t0+h}^{T} |e_t| / (M-h-1) \qquad (2)$$

Mean Squared Error *(MSE)*

It measures the average of the squares of the error.

$$MSE = \sum_{t=t0+h}^{T} e^2 / (M-h-1) \qquad (3)$$

Theil Inequality Coefficient

It was initially utilized for economic inequality, however, after it is employed in a statistical analysis help identify measures of redundancy, diversity, isolation, segregation, inequality and non-randomness.

$$T = \sum_{p=1}^{n} \left\{ \left(\frac{1}{n}\right) \times \left(\frac{y_p}{\mu_y}\right) \times \ln\left(\frac{y_p}{\mu_y}\right) \right\} \qquad (4)$$

Mean absolute percentage Error *(MAPE)*

Also known as an absolute percentage deviation. It is a standard of predictive accuracy of a forecasting method in statistics.

$$MAPE = \frac{1}{h+1} \sum_{t=s}^{s+h} \left| \frac{\hat{X}_{t-1}(1) - X_t}{X_t} \right| \qquad (5)$$

Root mean squared error *(RMSE)*

It is used to measure the differences between values predicted by a model and the values actually observed. These individual differences are also called residuals and the RMSE aggregates them into a single measure of predictive ability.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \qquad (6)$$

Bias proportion
Bias Proportion shows that how far the mean is from the actual one.
Variance proportion
It tells that variance is how much farther than the actual variance.
Covariance proportion
It measures the remaining unsystematic forecasting error.

Excess Return

Excess return is calculated by subtracting the additional return from actual i.e. if risk less is 1.7% and return is 6% so excess return is 4.3%. This excess return may be positive or minus. It is created by the skill of the investor or portfolio manager and is one of the most widely used criterion of risk adjusted performance.

Risk Free

Risk free rate is the return which shows no risk, like Treasury bills. The three months Treasury bill is a useful proxy because the markets believe there to be almost no prospect of the Government default on its debt instruments. Hence we have also taken rates for 3 months treasury bills from State bank of Pakistan.

THE FINDINGS

The capital asset pricing model is used to calculate the idiosyncratic volatility of stocks. *Campbell, et al.,* (2001) find an aggregate trend in individual firm level volatility, unlike market level volatility. We use idiosyncratic volatility to check the increasing trend in firm level. The *Table 1* gives correlation coefficients among Excess Return (ER) and Idiosyncratic Volatility (IV), Detrended Volatiltiy (DV), Market Volatility (MV) and Risk Free rate (RF). The analysis indicates a minor degree of relationship between all variables. Specifically, the relationship is at a medium level, but positive in the steering. The interest remains with excess returns and its association with IV, DV, MV and RF. With IV the association is medium and positive and hence led to our assumption that IV is a significant contributor in explaining the excess proceeds. Further, the detrended idiosyncratic volatility and risk free rate of return also show a good relationship with ER, similar in direction but lesser in magnitude as compare with IV. The MV show low positive relationship with ER.

The *Table 2* gives us regression analysis. The excess returns (ER) were first regressed against the idiosyncratic volatility (IV) as a one on one model. The F value suggested model fitness, the t test and its p-value describe significant relationship between ER and IV. The R-Square value is 48% and idiosyncratic volatility is handy by describing the excess returns.

In 2nd model with IV the detrended idiosyncratic volatility is employed as independent variables. However, the results show that the model is fit, the R-Square is increased , however, the IV explained the ER but the DV remain insignificant.

In the 3rd model, with the IV and DV another explanatory variable market volatility is also appended. The model is fitted, R-square also increased, however, the significance of IV remains unchanged, but the DV and MV show no significant relationship with ER. In our fourth model with IV, DV and MV the RF is also admitted as a indepdent variable.

Table 1

CORRELATION MATRIX

	ER	IV	DV	MV	RF
ER	1.000				
IV	0.484	1.000			
DV	0.423	0.820	1.000		
MV	0.087	0.149	–0.013	1.000	
RF	0.481	0.503	0.411	0.002	1.000

Source: own editing

Table 2

FORECASTING IN-SAMPLE EXCESS RETURNS (FULL SAMPLE)

	IV	DV	MV	RF	*R*-Square	*F*-test
Model–1	0.140				0.48	45.33
	(6.733)					(0.000)
	(0.000)					
Model–2	0.120	0.001			0.486	22.78
	(3.321)	(0.643)				(0.000)
	(0.001)	(0.521)				
Model–3	0.117	0.001	0.007		0.487	15.43
	(3.080)	(0.709)	(0.363)			(0.000)
	(0.002)	(0.479)	(0.717)			
Model–4	0.066	0.001	0.013	0.593		16.65
	(1.73)	(0.837)	(0.737)	(4.048)	0.561	(0.000)
	(0.085)	(0.404)	(0.462)	(0.000)		

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The F test value remains unchanged and show valid model, however, the value of R-square drastically increase from mere 48% to a significant 56.1%. Further, the beta coefficients of all independent variables remain insignificant except RF. Hence, it is concluded from all models, that the excess returns are mostly explained by idiosyncratic volatility unless the risk free rate of returns is introduced as an explanatory variable.

Case 1: Autoregressive Excess Return with Panel Regression method

To create Equation for Excess Returns (ER), to carry out this task, we first must specify and estimate a model. Let's model the ER level as a linear function of a time trend and seasonal components. We assume, there is no seasonal effect, hence discards the seasonal factors and no dummies for monthly sessions are created.

In table no 1, the results indicated no trend effect and the predictive power is also low. Hence, it is reasoned that the auto regressive factor did not predict the in-sample forecast of ER and not fit for data. Since, the in-sample indicates almost fitted line for both actual and residuals ER *(see Figure 1)*, then it's imperative to attend the out-sample models to check the prediction of ER.

The out of sample forecast validated the model appropriateness and contextually lead us to the decision of the potential utility of the model under analysis. The basic decision of appropriating lies with the minimum average errors produce from the estimation of loss function. The loss function is the difference between standard Box-Jenkins function and transform function developed on indicator variables.

Mean Absolute Error (MAE) and Mean Squared Error (MSE)

Mean Absolute Error (MAE) and Mean Squared Error (MSE) are used to check the validity of out sample forecasting. The mathematical representation of MAE and MSE are as follow;

$$MAE = \sum_{t=t0+h}^{T} |e_t| / (M-h-1) \quad (7)$$

$$MSE = \sum_{t=t0+h}^{T} e^2 / (M-h-1) \quad (8)$$

The forecasting evaluation decision is normally based on lower MAE or MSE value for out of sample forecasting. Nevertheless, sometime we get complex results in which MAE results, lower value for one method and MSE results lower value for another method. In such state of affairs, the researcher should base their forecasting evaluation on only one average loss function such as MSE.

Theil Inequality Coefficient, MAPE and Other Methods

The Thiel inequality coefficient was initially used for economic inequality, however, later its uses in statistical analysis help identify measures of redundancy, diversity, isolation, segregation, inequality, non-randomness and comparability. The formula of Theil Index is broken under;

$$T = \sum_{p=1}^{n} \left\{ \left(\frac{1}{n}\right) \times \left(\frac{y_p}{\mu_y}\right) \times \ln \left(\frac{y_p}{\mu_y}\right) \right\} \quad (9)$$

The absolute percentage error (MAPE) measure of forecast evaluation is criticized for the problem of asymmetry and instability, specifically in case when the out and in sample values are low. Normally these problems arise from MAPE estimation of small values;

- The larger value of MAPE resulted from equal errors of the actual values.
- The larger value of MAPE also results from smaller value of the original serial publication.
- Outlier may distort comparisons
- Cannot be compared with other models.

$$MAPE = \frac{1}{h+1} \sum_{t=s}^{s+h} \left| \frac{\hat{X}_{t-1}(1) - X_t}{X_t} \right| \quad (10)$$

Case–1 Out of Sample Forecast Evaluation

The *Figure no 2* shows us the result of the data set from 2012–2016 with no proxy for future estimation. The results show all out of sample forecast evaluation techniques, the values of MSE and MAE are low and therefore indicated a panel regression is a best fit. Nevertheless, the Thiel inequality model suggested a different level and the existing model of panel auto regression with trend element is not a true fit of the usable information. The MAPE value is large and thus indicated the similarity in the errors of actual and forecasted series. Bias Proportion shows that how far the mean is from the actual one, which is almost zero in-

Figure 1

TIME LINE OF ACTUAL AND RESIDUALS

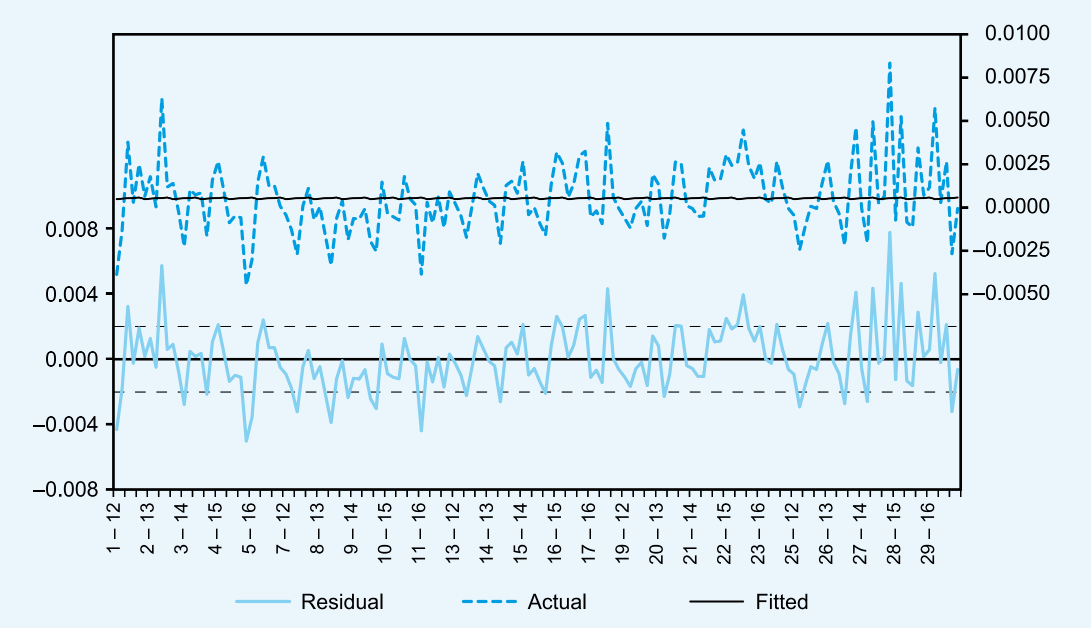

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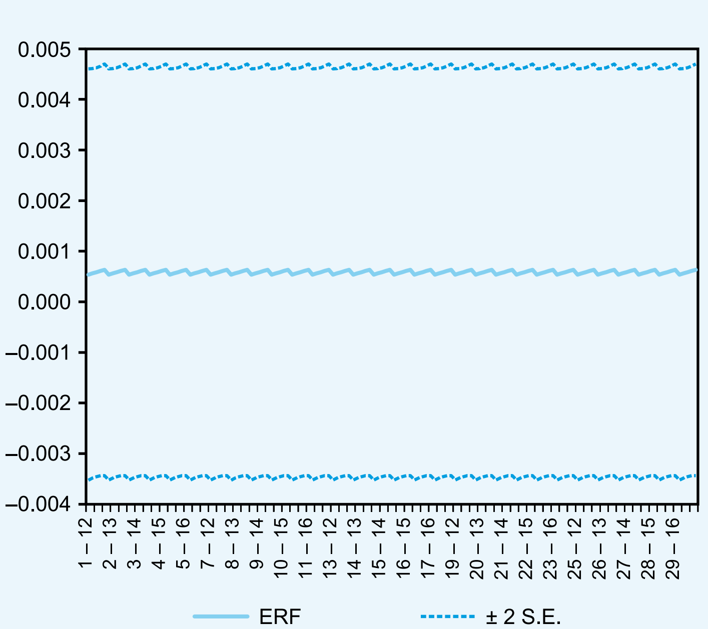
Figure 2

OUT SAMPLE FORECAST EVALUATION



Forecast: ERF
Actual: ER
Forecast sample: 2012–2016
Included observations: 150

Root Mean Squared Error	0.002004
Mean Absolute Error	0.001515
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.749811
Bias Proportion	0.000000
Variance Proportion	0.967344
Covariance Proportion	0.032656
Theil U2 Coefficient	NA
Symmetric MAPE	138.0983

Source: own editing

dicated for similar or identical mean with no deviation in actual and forecasted time series. Variance Proportion tells that variance is how much farther than the actual disagreement. From Figure no 2 the value of VP is large and close to 1, which indicated almost 97 % difference in actual and forecasted time series. Covariance Proportion calculates the remaining estimating errors. Since, the value is too small as observed in table no 2 (0.0326), so we cannot say, the out-sample forecast is very good for the observed data.

Case–2 Out of Sample Forecast Evaluation (with Proxy of Year 2016)

Since in case–1, the forecast evaluation has not shown a significance difference between actual and forecasted return values of the observed 30 companies returns over the time horizon of 2012–2016. In case 2 we assume 2016 as proxy year for which the forecasted value will be influenced by the values of 2012–2015. *(See Table 3 and Figure 3)*

Table 4 shows the trended auto regression for 2012–2015, however, the previous values have demonstrated no significant relationship with each other. In *Figure no. 4,* the forecast evaluation shows almost similar effects to that of case–1. The lower RMSE & MAE values indicated almost similar values or rather low values for actual and forecasted series. The Theil Inequality coefficient and variance proportion values are high and indicate the difference in forecasted and actual time series. Still, the bias proportion and covariance proportion tests show similar results to MSE and MAE.

Case–3 Out of Sample Forecast Evaluation (with Exogenous Variables)

Since, both auto-regression equations have shown no substantial deviation in actual and forecasted time series. Right away in 3rd case, four exogenous variables are introduced as a function of excess returns. Theoretically excess returns are always a function of market volatility, idiosyncratic volatility, de-trended idiosyncratic volatility and risk free rate of replication. *Table no 5* given below, shows the

Table 3

TIME MODEL OF ER WITH TREND (WITH NO SEASONAL DUMMIES)

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
C	0.000537	0.000285	1.882224	0.061800
@TREND	2.35E–05	0.000116	0.201966	0.840200
R-squared	0.000276	Mean dependent var		0.000584
Adjusted R-squared	–0.006479	S.D. dependent var		0.002011
S. E. of regression	0.002018	Akaike info criterion		–9.560520
Sum squared resid	0.000602	Schwarz criterion		–9.520378
Log likelihood	719.0390	Hannan-Quinn criter.		–9.544212
F-statistic	0.040790	Durbin-Watson stat		1.685732
Prob (F-statistic)	0.840220			

Source: own editing

Figure 3

COMBINED FORECAST

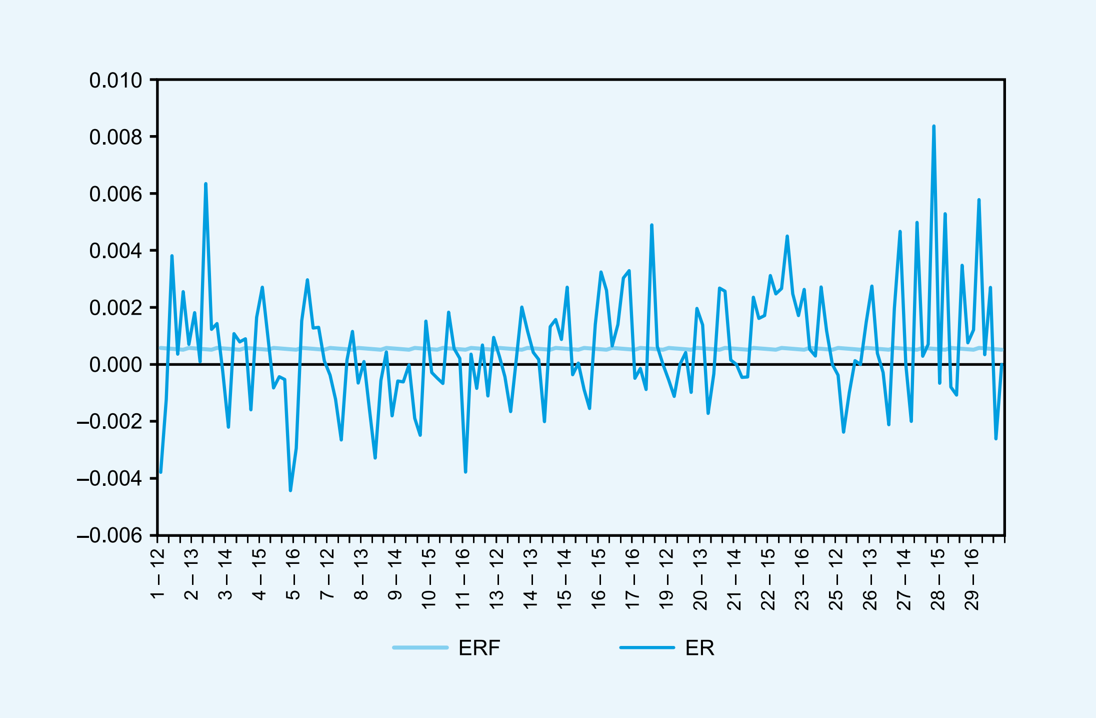


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Table 4

OUT OF SAMPLE FORECAST FOR 2012–2015

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
C	0.000537	0.000285	1.882224	0.061800
@TREND	2.35E–05	0.000116	0.201966	0.840200
R-squared	0.000276	Mean dependent var		0.000584
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Prob (F-statistic)	0.840220			

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Figure 4

FORECAST EVALUATION

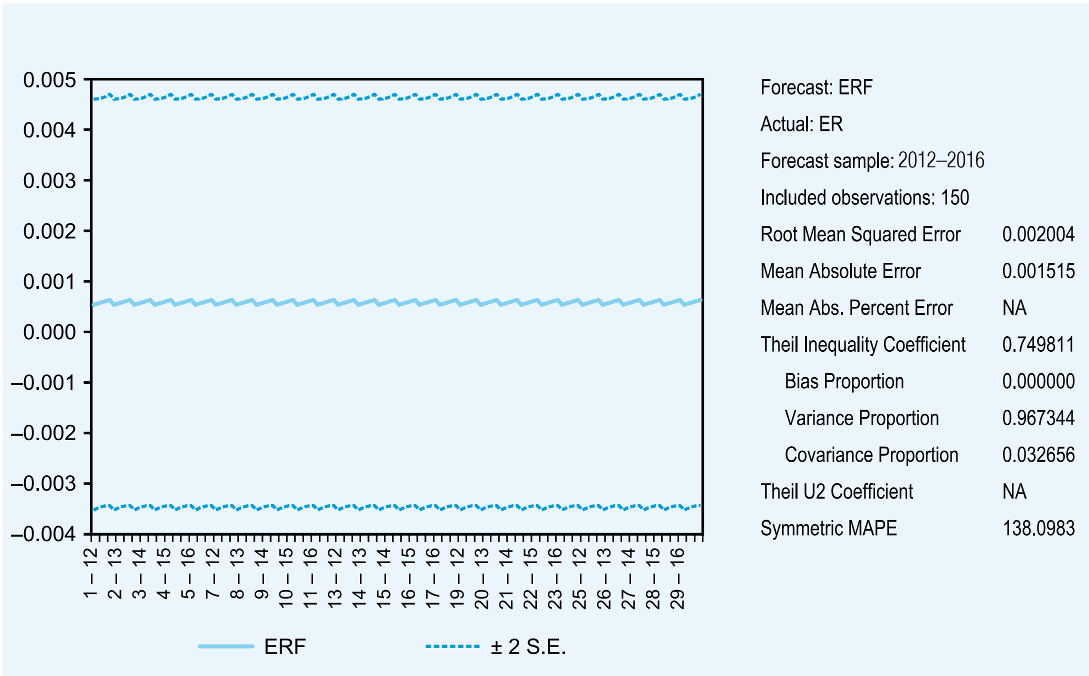

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Table 5

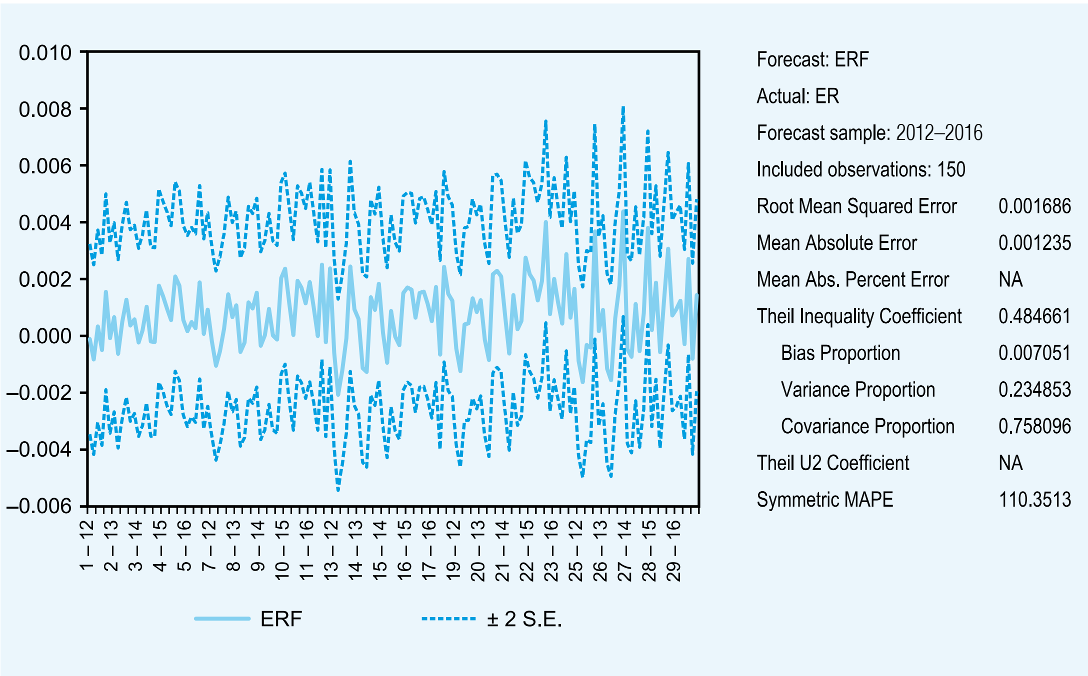
PANEL REGRESSION (WITH EXOGENOUS VARIABLES)

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.
C	–0.000872	0.000960	–0.908423	0.365600
MV	0.017867	0.018937	0.943478	0.347400
IV	0.045469	0.046366	0.980665	0.328800
DV	0.001931	0.001175	1.643670	0.103000
RF	0.489831	0.158751	3.085526	0.002600
@TREND	4.71E–05	0.000135	0.349755	0.727200
R-squared	0.368621	Mean dependent var		0.000553
Adjusted R-squared	0.340929	S.D. dependent var		0.002026
S. E. of regression	0.001645	Akaike info criterion		–9.934042
Sum squared resid	0.000308	Schwarz criterion		–9.794668
Log likelihood	602.0425	Hannan-Quinn criter.		–9.877442
F-statistic	13.31143	Durbin-Watson stat		1.497036
Prob (F-statistic)	0.000000			

Source: own editing

Figure 5

FORECAST EVALUATION WITH EXOGENOUS VARIABLES



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panel least square method. The risk free rate of return shows significant results while coefficient has a positive relation with excess return. This clearly indicated that idiosyncratic volatility has a positive relationship with excess returns, but the coefficient is not significant. The R-Square is 36.8%, which is justifiable. The forecast evaluation tests suggested similarity between actual and forecasted time series and all the evaluation methods (MSE, MAPE, MAE, Theil Coefficient, variance proportion, bias proportion & covariance proportion) are in concurrence.

SUMMARY AND CONCLUSIONS

This study comprehensively investigates the intended relationship and concludes that the value weighted idiosyncratic stock return volatilities exhibit predictive power for excess stock market returns. Our results shed light on the in sample forecasting in which the effects of correlation analysis show that idiosyncratic volatility explained the excess returns. Further, the detrended idiosyncratic volatility and risk free rate of return also show a good relationship with ER, similar in direction but lesser in magnitude as compare with IV. The MV show low positive relationship with ER. Following the regression analysis it is resolved from all four models, that the excess returns are generally explained by idiosyncratic volatility unless the risk free rate of returns are inserted as an explanatory variable.

This research first shows autoregressive excess returns with panel regression method. Out of sample forecast validated the model appropriateness contextually and lead us to the decision of the potential utility of the model under analysis. The basic decision of appropriating lies with the minimum average errors produce from the estimation of loss function. The loss function is the difference between standard Box-Jenkin function and transform function developed on indicator variables. The study develop and excute three cases for out of sample forecast evaluation. For Case 1 data was taken from 2012 to 2016. The results come from the sample evaluation techniques, which are the value of MSE, MAE, MAPE, Bias proportion, variance proportion and co-variance proportion. As evidence, the values of these are minor, so we cannot suppose that the values of out-sample forecast is really beneficial for the observed data. Because the forecast evaluation has not shown a significance difference between actual and forecasted return value of the observed 30 company's returns over the time horizon of 2012–2016.

Case 2 shows out of sample forecast evaluation with proxy of year 2016. In which table 3 shows the trended auto regression for 2012–2015, however, the previous values have shown no significant relationship with each other. While in table 4 the forecast evaluation shows almost similar effects to that of case 1. Thus both the auto regression equations have shown no substantial deviation in actual and forecasted time series. In the third case four exogenous variables are introduced as a function of excess returns. The coefficient has positive relations with excessive returns and RF shows significant effect. This clearly indicated that idiosyncratic volatility has a positive relationship with excess returns, but the coefficient is not significant. The R-Square is 36.8%, which is justifiable. The forecast evaluation tests suggested similarity between actual and forecasted time series and all the evaluation methods (MSE, MAPE, MAE, Theil Coefficient, variance proportion, bias proportion and covariance proportion) are in concurrence.

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