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Do local and global macroeconomic variables help forecast volatility of Pakistani stock market?

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ABSTRACT

Emerging markets are characterized by higher volatility and higher associated returns as compared to developed markets. The excessive volatility in emerging markets is often considered a result of inherent instability and unpredictability of country's political, institutional and macroeconomic environment. Increasing globalization and integration of financial markets imply that volatility of emerging markets may also be affected by global macroeconomic and business conditions. We investigate this issue for an emerging market namely Pakistan. An important objective of this research is to provide empirical evidence on whether local and global macroeconomic variables help forecast volatility of this market over and above the GARCH models which predict volatility on the basis of past shocks and past accumulated variance. Using monthly data over the post liberalization period from early 1990 to 2010 we show that global variables have higher explanatory power to affect Pakistani stock market volatility compared to the global information variables.

1. INTRODUCTION

Stock price volatility plays a central role in economic and financial decision making. In risk management value-at-risk (VaR) estimates require conditional standard deviation of asset returns. For example assuming normality of returns the 99% VaR is simply the -2.33 times the standard deviation of returns. Since for active risk management VaR is needed on a daily basis one period ahead conditional volatility forecast can be employed to calculate VaR. In asset pricing conditional standard deviation is required in estimating conditional beta of assets and for gauging time varying risk return tradeoff. Increase in stock market volatility has resulted in the emergence of derivative markets as provider of a risk management instruments. Volatility is an important ingredient in option pricing models. In performance measurement and asset allocation applications conditional standard deviation is employed to compute Sharpe ratio and estimating the optimal portfolio weights. Active risk management, portfolio allocation and other financial decision need to be continuously updated in response to new information. These applications in financial decision making point towards the importance of volatility forecast.

The linkages of macroeconomy and financial markets have always been an active area of research in economics. Policy makers and market regulators also need to monitor stock market volatility closely. High market volatility results in reallocation of funds in fixed income securities e.g. bills, bonds and other interest bearing instruments which generate lower but more stable income stream than the stock market. But a greater supply of funds in fixed income securities will adversely affect the rate of returns in these instruments which at times may be smaller than the inflation rate causing loss to investors in real term. High volatility will also discourage new IPOs since issuing new equity capital is difficult during volatile period. This decrease in supply of long term capital would deteriorate growth potential of the economy.

Although downside volatility is more relevant for measuring investment risk, variance of stock returns is generally treated as risk measure. For example Markowitz (1952) framework of the development of optimal portfolio is based on mean and variance of portfolios and Engle's (1982) pioneering work on volatility models use conditional stock return variance where future variance is modeled based on current and past information. The ARCH model is basically a statistically construct which measures variance from past price shocks. Subsequently the extensions of the basic ARCH model allowed the asymmetric response of volatility to downside and upside market movements e.g. the EGARCH model of Nelson (1991).

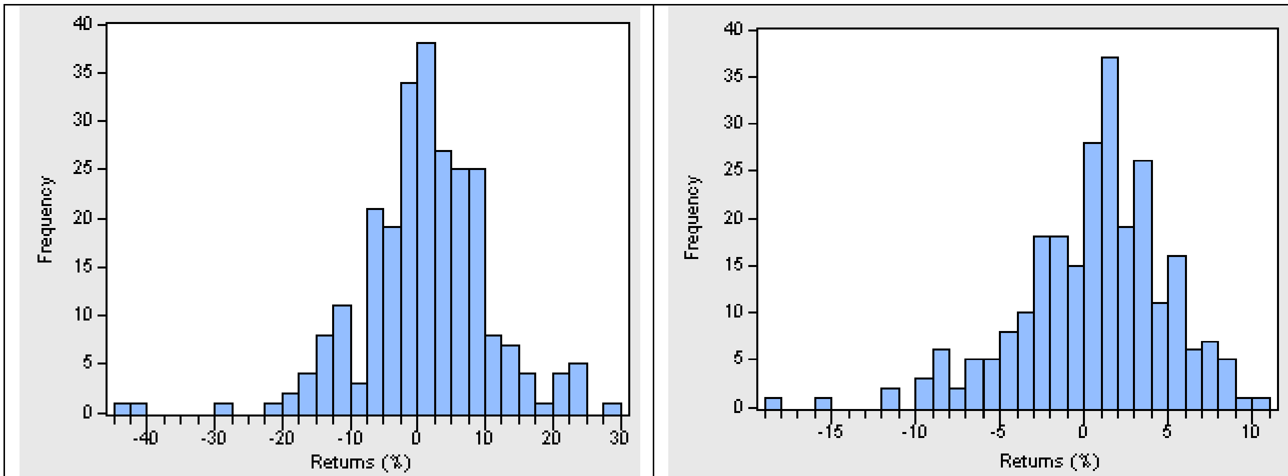
Pakistan's stock market possesses the typical features of an emerging market. For this market Iqbal et al. (2010) show that the US information variables improve the explanatory power of expected returns relative to local factors and local information variables in a conditional asset pricing framework. On the basis of this evidence they suggest to consider global information and global risk factors when assessing the cost of capital at the local economies. It is therefore worthwhile to investigation whether stock market volatility in Pakistan is linked to local and global macroeconomic and business cycle variables. Accordingly this paper aims at investigating the role of local and global macroeconomic variables in forecasting volatility of Pakistani market. Specifically do these variables help forecast the conditional stock market volatility over and above the past shocks and past accumulated volatility as captured by GARCH models. The GARCH model captures the stylized features of financial market e.g. volatility clustering, thicker tail distribution and predictability of volatility from past patterns. It is interesting to know whether local and global macroeconomic and market related variables contribute significantly in explaining and forecasting volatility of this stock market.

We estimate and forecast the volatility of the market represented by the Karachi Stock Exchage-100 Index which is a value weighted index of one hundred most active firms keeping in view sectoral representation. Some descriptive statistics on the aggregate stock market index stock are reported in Table 1. The same statistics are also provided as a reference. The table clearly shows that typical features of merging market having higher average returns and dispersion, thicker tails as indicated by excess kurtosis and more extreme movement of index returns on both high and low end compared to the developed US market. The same features are also evident from Figure 1 which presents the return distribution of the two markets.

Table 1: Descriptive Statistics of KSE-100 Index vis-a-vis S&P-500 Index returns (%) (Jan1990-Dec 2010)

	Mean	Median	Maximum	Minimum	St-Dev.	Skewness	Kurtosis
KSE-100	1.194	1.271	29.688	-44.880	9.678	-0.586	6.173

S&P-500	0.534	1.043	10.579	-18.564	4.413	-0.820	4.603



Panel a: KSE-100 Index Returns

Panel b: S&P-500 Index Returns

Normality of returns is easily rejected using any statistical test e.g. Jarque-Bera test for both the markets. Iqbal (2008) provides further detail of the Pakistani stock market and its standing in an international perspective.

2. MODELING VOLATILITY

2.1 The models for volatility forecasting

We consider the GARCH and one of the most useful extensions of this model to capture asymmetry i.e. the EGARCH model of Nelson (1991). Quality and reliability of volatility forecast also depends crucially on the correct specification of mean equation. Infrequent and non-synchronous trading of emerging markets is quite well known; see for example Iqbal and Brooks (2007) for evidence from Pakistan. Therefore for correct specification of the mean equation of the GARCH model these data issues have to be taken into account. Harris and Sollis (2003, p-48) point out that infrequent and non-synchronous trading of stocks included in the market index and temporal aggregation give rise to moving average terms. In addition owing to a lesser degree of efficiency of emerging markets and consequent evidence of returns predictability the autoregressive terms will also be useful. We therefore specify the volatility models as having the GARCH (p,q) structure for conditional variance 'h_t' with conditional mean equation for returns 'r_t' as being generated by the ARMA(m,n) process.

$$r_t = \mu + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{i=0}^{n} \theta_i u_{t-i},$$
$$\theta_0 = 1,\ u_t = z_t \sqrt{h_t},\ z_t \sim N(0,1)\ or\ z_t \sim t(\nu) \tag{1}$$
$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i h_{t-i} + \sum_{j=}^{q} \beta_j u_{t-j}^2 + \sum_{k=1}^{s} \lambda_k X_{k,t-1}$$

Where r_t represents KSE-100 index returns. Following the literature we use $p = q = 1$ in conditional variance equation. Because of conditional nature of volatility equation the exogenous macroeconomic variables X appear with lag 1. More lags may results in multicollinearity issue. The distribution of the random error z_t is specified as either standard normal or student *t* distribution with ν degrees of freedom. The degree of freedom is not necessarily an integer. The parameters can be estimated using the method of maximum likelihood which is routinely available in commercial softwares. For standard normal errors the contribution to the likelihood of time *t* observation is:

$$l_t = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log h_t - \frac{1}{2h_t}(r_t - W_t^{'}\varphi)^2 \tag{2}$$

Where W_t contains the ARMA terms and φ is the set of associated parameters of the mean equation. In case of student *t* errors with ν degrees of freedom the contribution to the likelihood of time *t* observation is:

$$l_t = -\frac{1}{2}\log\left(\frac{\pi(\nu-2)\Gamma(\frac{\nu}{2})^2}{\Gamma(\frac{\nu+1}{2})^2} \right) - \frac{1}{2}\log h_t - \frac{\nu+1}{2}\log\left(1 + \frac{(r_t - W_t^{'}\varphi)^2}{h_t(\nu-2)} \right) \tag{3}$$

Where 'Γ' represents the gamma function. The MLE maximizes the sum of l_t across the sample of T observations. For stationarity of conditional variance in addition to the condition $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$ we also require exogenous variables to be stationary. This variance specification may be problematic because of violation of non-negativity constraint especially due to large negative values of the exogenous variables. The alternative the EGARCH model is specified as:

$$r_t = \mu + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{i=0}^{n} \theta_i u_{t-i},$$
$$\theta_0 = 1,\ \ u_t = z_t \sqrt{h_t},\ \ z_t \sim N(0,1)\ or\ z_t \sim t(\nu) \tag{4}$$
$$\log(h_t) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \log(h_{t-i}) + \sum_{j=1}^{q} \beta_j \left| \frac{u_{t-j}}{h_{t-j}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{h_{t-k}} + \sum_{l=1}^{s} \lambda_l X_{l,t-1}$$

This specification ensures positive conditional variance and also allows asymmetric reaction of time *t* variance to shock in previous periods. As in GARCH model we employ $p = q = r = 1$. We employ exogenous variables one at a time as well as in groups of local variable, global variables and all variables together.

2.2 The macroeconomic variables to be employed:

A look at the literature linking macroeconomic variables and stock market volatility reveals that a common set of macroeconomic variables are used in the empirical work. Engle et al. (1993) employed GDP, inflation based on consumer prices index, exchange rate, and short term interest rates. Officer (1973) explained volatility during the 1930s based on leverage and the volatility of industrial production. Schwert (1989) sought linkages between financial volatility and macro volatility based on short term interest rate, long term bond rates, producer price inflation rate, industrial production growth rate, and monetary base growth rate. Morelli (2002) explained stock market volatility on the basis of estimated volatilities of exchange rate, industrial production, inflation, real estate sales, and money stock. To explain volatility of technology stock Sadorsky (2003) used, industrial production, oil futures prices, interest rate, consumer price index and exchange rate. Kearney (1998) employed business cycle variables including the interest rate on call money, exchange rate, rate of inflation and the level of industrial production to explain Irish stock market volatility. Guided by the literature and keeping in view data availability at monthly frequency we collected the local and global variables to measure macroeconomic and business condition. As is common in empirical studies we use mostly the US data to represent global variables. The following local Pakistani variables (in local currency) are employed in percentage changes form. *I.* manufacturing production index, *II.* consumer price index, *III.* short term interest rate measured by call money rate, *IV*. monetary aggregate (M2), *V*. nominal exchange rate of Pak Rupee with US dollar. The global variables considered in this study are as follows: *I*. US industrial production index, *II*. US consumer price index, *III*. US short term interest rate, *IV*. S&P 500 index, *V*. NYSE trading volume *VI*. World oil price, *VII*. World gold price. These macroeconomic variables measure either the investors expectations of returns, summarize business cycle or measure returns to alternative investment opportunities.

2.3. Evaluation of Volatility Forecast

Since volatility is unobservable, evaluating its forecast has been a challenging task. Many researchers employ observed squared return to represent the observed volatility and compare it with forecast obtained from volatility models i.e. h_t . This one period observed return provides a very poor proxy of actual volatility. The model based volatility behaves quite smoothly but the observed return show a large amount of noise indicated by a high degree of ups and down. According to Poon and Granger (2003) as the sampling frequency increases the sum of squared returns in a unit time approaches the true integrated volatility. Our unit of time is a month. We therefore approximate the true volatility of month *t* by sum of square of daily continuously compounded returns in a calendar month i.e.

$$\sigma_t^2 = \sum_{t=1}^{N_t} r_t^2 \tag{5}$$

where N_t is the number of daily returns r_t in the calendar month *t*. We use daily returns since finding intraday price data is difficult for emerging markets. Many empirical studies on volatility forecasting employ this proxy of realized variance e.g. Brailsford and Faff (1996).

We use a rolling window forecast to evaluate volatility forecasts. Using monthly data for the first six year i.e. a sample of 72 monthly observations we estimate volatilitilty model and obtain one month ahead forecast $\hat{h}_{t+1}$ to be compared with realized variance for month 73. We then leave out the first monthly observation and include observation for month 73 for estimating the volatility model and obtaining one month ahead forecast which is to be compared with realized variance for moth 74. We repeat this process for the entire available data sample. This process yields a series of one period ahead forecast. We use the rolling window approach evaluating volatility forecast so that our forecast evaluation is not affected by peculiarities of particular time period for forecast evaluation. This approach also enables the parameters of volatility model to vary over time allowing them to be updated with changing trading behavior and business cycle variation. Swanson and White (1997) also found that rolling window specifications performed better than the fixed window specification for forecasting economic variables.

To evaluate volatility forecast out of sample, several measures are employed in the literature. Mean square error (MAE) is quite popular but may be affected by outliers. Alternatively the Mean Absolute Percentage Error (MAPE) is also used. However, the distribution of percent errors may be severely skewed since the maximizing likelihood function involves optimizing a nonlinear function which may yield excessively large values of volatility forecast especially in a rolling window approach used in this study. (evidence..)We therefore chosen to use a more outlier robust measure based on the median of percentage absolute forecast error i.e. MdAPE given by

$$MdAPE = Median\ \ of\ \left| \frac{\sigma_t^2 - \hat{h}_t}{\sigma_t^2} \right| \qquad (6)$$

Where σ_t^2 month t is realized variance obtained as the sum of squared daily returns as in (5) and $\hat{h}_t$ is the forecast variance for month t obtained from the volatility model. This forecast evaluation measure is advocated by authors e.g. Vokurka, Flores and Pearce (1996).

3. THE DATA

The daily and monthly data on stock market indices of KSE-100 and S&P-500 are obtained from the *Yahoo Finance*. The data sample comprises January 1990 to December 2010 except for Pakistani macro data on exchange rate, call money rate, money stock (M2) and consumer prices for which most recent available data correspond to July 2010. Pakistani macroeconomic data are obtained from the International Financial Statistics. Most US macro data and the oil prices (West Texas Intermediate spot price) are obtained from the website of economic research division of the *Federal Reserve Bank of St. Louis*.

The data on gold prices, NYSE trading volume and dividend yield of the US market are obtained from the site www.wrenresearch.com.au.

4. RESULTS AND DISCUSSION

Estimation strategy: model selection criteria suggest that an ARMA(3,3) model is suitable for the mean equation. In addition the EGARCH model appears to outperform the GARCH counterpart especially with student t error as the error distribution. Therefore for variance equation we specify and EGARCH(1,1) specification. If residual diagnostic tests indicate series correlation we increase the lags of AR and MA components for the mean equation. Similarly if the squared residual indicate serial correlation we increase the order of EGARCH components. In the following table w report the coefficient of the mean and variance equation.

We exclude the observations for apr 1990, sep 2008 to nov 2008 during which market remained inactive trading suspension trading was suspended following market crises.

Table 1 report the EGARCH model parameter estimates when local (Pakistani variables are employed) in the volatility equation. A test of serial correlation on residuals (Ljung Box test reported in the table indicates that except for the money stock equation the mean equation is correctly specified since there is no additional serial correlation. Lagged consumer price inflation and exchange rate have significantly positive impact on the market volatility. The best model appear to be the model when lagged exchange rate is employed in the volatility equation as evident from the information criteria AIC and BIC. Table 2 present the results for global variables. It appears that the trading activity measured by New York Stock Exchange (NYSE) trading volume and oil prices have significant reduce the Pakistani stock market volatility. This results point towards the fact that the investors in Pakistani market reduce their risk exposure when oil prices increase and the foreign market activity is high. At these period trading activity remain limited thus stock market are less volatile. Statistical fit of these model is however no better than models with either interest rate is used (as evident from AIC) or simple EGARCH without any macro variables (as seen from BIC). No other global variables have significant impact on the Pak stock market volatility.

Table 3 present some statistics and when set of all local, global and both local and global variables are considered simultaneously in the volatility equation. Both AIC and BIC criteria and indicate that the best model to explain Pak stock market volatility is obtained when local macro variables are employed. This our results are consistent with studies which show that emerging market are driven primarily by local information.

Tables 1: Local (Pakistani) variables

$$r_t = \mu + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{i=0}^{n} \theta_i u_{t-i},$$

$$\theta_0 = 1, \; u_t = z_t \sqrt{h_t}, \; z_t \sim N(0,1) \; or \; z_t \sim t(\nu)$$

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \log(h_{t-i}) + \sum_{j=1}^{q} \beta_j \left| \frac{u_{t-j}}{h_{t-j}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{h_{t-k}} + \sum_{l=1}^{s} \lambda_l X_{l,t-1}$$

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	No Macro variable	Manufacturing Production	Consumer Prices	Money Stock	Exchange Rate
	Conditional Mean Equation				
μ	1.306 (0.0179)	1.595 (0.005)	1.290 (0.026)	1.429 (0.001)	1.583 (0.006)
ϕ_1	-0.897 (0.000)	1.030 (0.003)	0.277 (0.833)	0.030 (0.965)	1.034 (0.028)
ϕ_2	-0.658 (0.002)	-0.917 (0.000)	-0.804 (0.059)	-0.059 (0.919)	-0.922 (0.000)
ϕ_3	-0.742 (0.000)	0.664 (0.005)	-0.052 (0.959)	-0.056 (0.919)	0.656 (0.034)
θ_1	1.018 (0.000)	-0.919 (0.006)	-0.167 (0.898)	0.039 (0.954)	-0.929 (0.046)
θ_2	0.758 (0.001)	0.786 (0.000)	0.730 (0.030)	0.040 (0.943)	0.803 (0.001)
θ_3	0.723 (0.000)	-0.639 (0.006)	0.105 (0.911)	-0.022 (0.966)	-0.624 (0.045)
λ_1		-0.0061 (0.473)	0.916 (0.008)	0.0008 (0.7472)	0.103 (0.008)
α_0	0.520	0.545	0.855	4.330	0.510

	(0.089)	(0.077)	(0.196)	(0.039)	(0.093)
α_1	0.861 (0.000)	0.859 (0.000)	0.782 (0.000)	-0.039 (0.933)	0.849 (0.000)
β_1	0.188 (0.122)	0.163 (0.158)	0.239 (0.1311)	0.320 (0.068)	0.163 (0.163)
γ_1	-0.0004 (0.994)	0.006 (0.926)	0.016 (0.857)	0.023 (0.841)	0.063 (0.425)
LB(12) residual	7.858 (0.249)	7.889 (0.246)	9.519 (0.146)	13.472 (0.036)	5.824 (0.443)
LB(24) residual	21.678 (0.247)	21.267 (0.266)	23.522 (0.171)	29.710 (0.040)	20.845 (0.287)
LB(12) sq. residual	9.532 (0.146)	9.164 (0.166)	9.573 (0.144)	8.911 (0.179)	9.082 (0.169)
LB(24) sq. residual	15.096 (0.655)	15.531 (0.625)	15.723 (0.612)	15.174 (0.650)	18.335 (0.434)
AIC	7.856	7.302	7.330	7.403	7.293
BIC	7.458	7.489	7.519	7.591	7.482

P-values of the coefficients and diagnostic tests appear in parenthesis

Tables 2: Global (US) variables

$$r_t = \mu + \sum_{i=1}^{m} \phi_i r_{t-i} + \sum_{i=0}^{n} \theta_i u_{t-i},$$

$$\theta_0 = 1, \; u_t = z_t \sqrt{h_t}, \; z_t \sim N(0,1) \; or \; z_t \sim t(\nu)$$

$$\log(h_t) = \alpha_0 + \sum_{i=1}^{p} \alpha_i \log(h_{t-i}) + \sum_{j=1}^{q} \beta_j \left| \frac{u_{t-j}}{h_{t-j}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{h_{t-k}} + \sum_{l=1}^{s} \lambda_l X_{l,t-1}$$

	No Macro variable	Industrial Production	Consumer Prices	Interest Rate	NYSE Trading Volume	S&P 500 Index	Oil Prices	Gold Prices
	Conditional Mean Equation							
μ	1.306 (0.0179)	1.450 (0.008)	1.151 (0.006)	1.465 (0.018)	1.506 (0.005)	1.287 (0.020)	1.501 (0.000)	1.481 (0.006)
ϕ_1	-0.897 (0.000)	0.371 (0.755)	1.022 (0.000)	0.711 (0.278)	-0.822 (0.000)	-0.774 (0.023)	0.041 (0.964)	0.056 (0.948)
ϕ_2	-0.658 (0.002)	-0.840 (0.038)	-0.900 (0.000)	-1.076 (0.000)	-0.608 (0.002)	-0.748 (0.000)	-0.120 (0.851)	-0.145 (0.798)
ϕ_3	-0.742 (0.000)	0.017 (0.985)	0.656 (0.007)	0.479 (0.449)	-0.773 (0.000)	-0.592 (0.048)	-0.084 (0.885)	-0.110 (0.848)

θ_1	1.018 (0.000)	-0.252 (0.831)	-0.919 (0.001)	-0.609 (0.372)	0.933 (0.000)	0.888 (0.009)	0.031 (0.972)	0.027 (0.974)
θ_2	0.758 (0.001)	0.755 (0.018)	0.777 (0.002)	1.026 (0.000)	0.691 (0.003)	0.837 (0.000)	0.095 (0.876)	0.122 (0.817)
θ_3	0.723 (0.000)	0.044 (0.959)	-0.636 (0.001)	-0.404 (0.534)	0.740 (0.000)	0.597 (0.040)	0.017 (0.975)	0.036 (0.946)
	Conditional Volatility Equation							
λ_1		0.096 (0.428)	-0.228 (0.401)	0.003 (0.477)	-0.016 (0.044)	-0.009 (0.608)	-0.027 (0.081)	-0.041 (0.132)
α_0	0.520 (0.089)	0.808 (0.147)	0.762 (0.109)	0.685 (0.114)	3.390 (0.021)	0.537 (0.096)	4.344 (0.008)	4.251 (0.016)
α_1	0.861 (0.000)	0.780 (0.000)	0.814 (0.000)	0.811 (0.477)	0.185 (0.571)	0.860 (0.000)	-0.044 (0.903)	-0.027 (0.945)
β_1	0.188 (0.122)	0.285 (0.095)	0.214 (0.098)	0.261 (0.088)	0.397 (0.057)	0.180 (0.135)	0.313 (0.075)	0.330 (0.067)
γ_1	-0.0004 (0.994)	0.008 (0.933)	0.008 (0.9113)	-0.004 (0.957)	-0.023 (0.855)	0.008 (0.903)	0.027 (0.081)	0.020 (0.858)
LB(12) residual	7.858 (0.249)	9.626 (0.141)	9.512 (0.147)	7.306 (0.293)	8.537 (0.201)	7.523 (0.275)	12.756 (0.047)	13.073 (0.042)
LB(24) residual	21.678 (0.247)	22.210 (0.223)	22.847 (0.197)	20.426 (0.309)	21.548 (0.253)	21.999 (0.232)	27.840 (0.065)	30.058 (0.037)
LB(12) sq. residual	9.532 (0.146)	9.319 (0.156)	10.327 (0.112)	9.540 (0.145)	17.788 (0.022)	9.1004 (0.168)	10.222 (0.116)	10.487 (0.106)
LB(24) sq. residual	15.096 (0.655)	14.531 (0.694)	16.137 (0.583)	19.317 (0.373)	21.023 (0.278)	17.953 (0.665)	14.602 (0.689)	16.688 (0.545)
AIC	7.856	7.309	7.302	7.309	7.304	7.303	7.366	7.374
BIC	7.458	7.495	7.488	7.495	7.491	7.490	7.552	7.561

$$Q^* = T(T+2)\sum_{k=1}^{m}\frac{\tau_k^2}{T-k} \quad \sim \chi^2(m)$$

LR = 2(ULLF-RLLF) $\sim \chi^2(\textit{number restrictions})$

Tables 3: Incremental Contribution/ Information contents of local, global and all macro variables

	All local variables	All global variables	Both local and global variables
AIC	7.324	7.256	7.300
BIC	7.571	7.256	7.634
LB (12) residuals	4.927 (0.553)	7.200 (0.303)	6.815 (0.338)
LB (24) residuals	19.601 (0.356)	18.110 (0.448)	18.744 (0.408)

LB (12) sq residual	8.315 (0.216)	29.506 (0.000)	7.444 (0.282)
LB(24) sq residuals	15.181 (0.650)	35.793 (0.003)	15.394 (0.635)

5. CONCLUSION

This paper investigates whether local or global macro variables are more relevant in affecting Pakistani stock market volatility. We found that the statistical of the model is the best when the local macro variables are employed. Among the most important local variables are exchange rate and inflation both of which increase stock market volatility. Also when global oil prices increase Pakistani investors tend to avoid their risk exposure by participating less in the trading activity since market becomes quieter when oil prices increase in the previous month. Similar results hold when the global stock markets become more volatile.

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