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Time Varying Stock Market Volatility: The Case of an Emerging Market

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Abstract

One of the key determinants for investment in financial markets is the tradeoff between risk and expected returns. While returns are relatively easy to quantify, the risk measurement has always posed challenges for investors. Engle's (1982) proposition of time varying volatility has seriously challenged the use of standard deviation as a static estimate of risk. This phenomenon is more severe in emerging markets where stock prices are far from Gaussian world. In this paper, we examine the volatility patterns in Karachi Stock Exchange using GARCH framework between 2004 and 2012. We report that a period which witnessed significant growth vis-à-vis market capitalization and trading volumes, volatility clustering was obvious. This implies that all estimates of risk in this period based on standard deviations must be flawed and would have understated the actual risk. This has serious implications because risk assessment plays a vital role in estimating cost of capital, firm valuations and capital budgeting. Based on our finding, we propose that higher order moments of returns should be considered for prudent risk assessment.

Keywords: Volatility clustering, autoregressive heteroscedasticity, emerging markets, Karachi stock exchange.

Introduction

Asset pricing has been a dominant theme in financial literature for the last fifty years. The financial market theory revolves around a rational investor who wants to maximize returns by assuming some acceptable level of risk. This warrants for existence of an optimal relation between risk and return, thus, making risk an important determinant of asset pricing. The theory of asset pricing leads back to Bachelier's "*Theory of Speculation*" in which he recognized that past, present and even discounted future events are reflected in market prices of financial assets[1]. He ascertained that fluctuations in financial markets cannot be predicted; however, their likelihood can somewhat be evaluated mathematically. Inspired by this early notion of market efficiency, some fifty years later, Markowitz[2] presented a meaningful measure of market risk – variance of returns – that revolutionized the financial theory in the later half of twentieth century. "*Portfolio Selection*" divided investment into efficient and inefficient set where investors are expected to hold the feasible set of portfolios. Building on Markowitz's work Tobin[3] presented his separation theorem. Tobin's Separation Theorem separates the portfolio selection problem into first finding that optimal combination of risky securities and then deciding whether to lend or borrow, depending on investor's preference towards risk. He concluded that if there was only one risky portfolio plus borrowing and lending, the optimal portfolio would be the market portfolio. The full potential of Bachelier's theory was only realized some 50 years later by Mandelbrot[4] and Fama[5]. Their findings, that the variance of returns is not constant over time (heteroscedasiticity) and that the distribution of price changes were not Gaussian but leptokurtic, are among the foundations of modern financial theory. Fama concluded that the empirical distributions of share prices followed not a *Gaussian* but a Stable *Paretian* distribution with characteristic exponent less than 2, that is, with finite mean but infinite variance.

The portfolio theory of Markowitz and Tobin brought us the first generation models of asset pricing by Sharpe[6], Mossin[7], and Litner[8]. Their work resulted in the capital asset pricing model (CAPM), which specifies the relationship between financial security return and relevant risk. CAPM has been widely discussed in the empirical and theoretical literature of financial economics with some early appreciation. However, the development in estimation and analysis techniques raised questions on simplistic assumptions of CAPM and researchers have proposed various extensions of the basic model along with more complex estimation techniques. Engle's[9] proposition of autoregressive conditional heteroskedasiticity (ARCH) has changed the view of financial economists about risk. In general, volatility is associated with uncertainty and unpredictability. It measures the variability about central tendency. Since the term is synonym with risk, it becomes crucial for the financial markets and its estimate serve as a barometer for the vulnerability of stock markets. The existence of excessive volatility or "noise" affects the usefulness of stock prices as "*signal*" about the intrinsic value of the firm – questioning the core concept of market efficiency.

Significant research has been done on modeling time varying conditional heteroscedastic returns since if returns and volatility can be forecasted, dynamic asset allocation models can be constructed that use time dependent mean variance optimization over each period. Barra and Higgins[10] suggested that a major contribution of ARCH literature is the prediction possibility of changes in time series volatility that result from non linear dependence and not from exogenous changes in variables. Non constant variance represents the likelihood of more than expected outliers from normal distribution, thus, a heteroscedastic process will follow heavy tailed distribution.

Since Engle's proposition of the Autoregressive Conditional Heteroscedastic (ARCH) model, there has been a large body of literature on volatility forecast. The empirical evidence is rather mixed as to which volatility forecast model performs best. Akgiray[11] researched US stock markets and found that a GARCH (1, 1) model outperformed more traditional technical analysis. Brailsford and Faff[12] employed Australian data to compare the predictive performance of several statistical methods with GARCH and TGARCH models. The results suggested that the ARCH class of models and a simple regression model provide superior forecasts of volatility. However, the various model rankings were shown to be sensitive to the error statistic used to assess the accuracy of the forecasts. Malkiel and Xu[13] used a disaggregate approach to study the behavior of stock market volatility. While the volatility for the stock market as a whole has been remarkably stable over time, the volatility of individual stocks appears to have increased. There are some possible reasons to believe that volatility in the stock market as a whole should have increased over recent decades. Improvements in the speed and availability of information, the growth in the proportion of trading done by institutional investors and new trading techniques all may have increased the responsiveness of markets to changes in the sentiment and to the arrival of new information. The facts, however, at least with respect to the market as a whole, do not suggest that the volatility has increased. They have not looked at the market portfolio but rather at individual stocks and industry average. By looking at the disaggregated volatility of stock prices, they reached a different conclusion that volatility in the stock market has increased considerably during the past quarter century.

Yu[14] evaluated the performance of nine alternative models for predicting stock price volatility. The data set he used is the New Zealand Stock Market Exchange (NZSE40) capital index, which covers 40 largest and most liquid stocks listed and quoted on the New Zealand Stock Market Exchange, weighted by the market capitalization without dividends reinvested. The sample consists of 4741 daily returns over the period from 1 January 1980 to 31 December 1998. The competing models contained both simple models such as the random walk and smoothing models and complex models such as ARCH type models and a stochastic volatility model. Four different measures were used to evaluate the forecasting accuracy. The main results demonstrated that the stochastic model provided the best performance among the competing models.

Batra[15] examined the time variation in volatility in the Indian stock market during 1979-2003. He has used the asymmetric GARCH methodology augmented by structural changes. The paper identifies sudden shifts in the stock price volatility and nature of events that cause these shifts in volatility. He undertook an analysis of the stock market cycles in India to see if bull and bear phases of the market have exhibited greater volatility in recent times. The empirical analysis in the paper reveals that the period around the BOP crisis and subsequent initiation of the economic reforms in India is the most volatile period in the stock market.

Emerging markets are subject to higher stock volatility with the inherent economic risks. These markets are marked with many estimation problems including non-synchronous trading. Most of the non-synchronous trading phenomenon happens in emerging stock markets because in those markets the trade is low (thin). In presence of thin trading, the traditional ordinary least square (OLS) estimates of risk are seriously biased. In the OLS model, returns on a given security i are regressed against the concurrent returns of the market. Basically, such estimation has a disadvantage because it gives unstable and biased Beta[16]. Biased Beta usually happens in thin-trading markets. Thin-trading phenomenon that makes biased Beta is identical with non-synchronous trading that is caused by infrequent trading. In this sense, there might be some sleeping stocks. Non-synchronous trading problems arise in securities due to the time lag between the setting of market clearing prices for securities and the market index computed at the end of a discrete time interval, known as the intervalling effect. Thus OLS is a weak method of producing better Beta estimators[17].

Pakistan is an emerging financial market with three stock exchanges. These include Karachi Stock Exchange (KSE), Lahore Stock Exchange (LSE) and Islamabad Stock Exchange (ISE). Like most of the emerging economies, Investors place lower importance on stock fundamentals and they trade taking index returns as barometer. The likely scene in a Pakistani bearish market could follow the following sequence of events. If index is trading on a lower side, panic sale might come in which would cause the index to decline further. Thus, a circle will follow unless the circuit breakers are triggered. It is a common perception that Pakistani stock markets are highly volatile and this is due to insider trading by brokers. The practice of wash trades is common which sometimes create panic within investors. Thus, volatility plays a much vital role and investors rely less on fundamentals. The manipulation by the informed traders increases volatility which further increases the participation cost for the common investors and thus, tendency of ordinary investor's participation decreases. These kinds of costs are sometimes pointed out as the reason for underdevelopment of markets since they affect the depth of the market and adversely affect its intermediary role.

LSE and ISE are comparatively smaller markets. As KSE is the main traded market, the two smaller markets have a strong tendency to imitate KSE 100 index performance. The correlation matrix of index returns of three stock markets for a period of eight years (April 2004 – September 2012) is given below.

Table-1
Correlation Matrix of Index Returns
(April 2004 – September 2012)

	KSE 100	LSE 25	ISE 10
KSE 100	1	0.76	0.74
LSE 25	0.76	1	0.56
ISE 10	0.74	0.56	1

From table 1, the imitation theory is evident with LSE 25 and ISE 10 returns being highly correlated with KSE 100 returns (76% and 74% respectively). Although, a high correlation between returns of ISE 10 and LSE 25 exists at 56%, yet it is significantly lower than their correlations with KSE 100 returns. Since their inception, all the three markets have come a long way. The development in KSE can be gauged by the indicators in table 2. These indicators include market capitalization, listed capital, average daily turnover and Index value. All these indicators present an upward trend. The most significant of these is the KSE 100 index and it represents an increase of 21% from 2005 to 2007. However, the daily fluctuations do not present a very rosy picture and as mentioned earlier the market returns are highly volatile. Since it is obvious that KSE represents the major chunk of financial activities in Pakistan, we will just consider KSE for our analysis.

The reforms in Pakistan's Stock Exchanges took place in 90s and areas like risk management, governance, transparency and investors protection were improved. The outcome of these reforms should be a reduction in volatility but actually in the post reform era, despite an increase in market depth, the volatility has increased. The successive bear traps resulted in the exit of many small investors. Securities and Exchange Commission of Pakistan (SECP) came into the scene but the watch dog faced serious resistance from the market players, thereby increasing the uncertainty of the situation. The major step of SECP to counter excessive volatility was the introduction of circuit breakers in 2001. The circuit breakers are responsible to control excessive volatility by halting trade. The inclusion of circuit breakers is expected to neutralize trade by providing cooling off period during highly uncertain markets thus preventing investors from panic. However, in Pakistan's case these circuit breakers worsened the situation. During the March 2005 crisis, investors were unable to square their positions since major stocks opened at the lower limit leaving no room for trade. There were negligible trades for a whole week and investors using margin financing were forced to hold their inventories thus paying higher margin costs. Thus, the circuit breakers might cause liquidity problems restricting the sellers from executing sale orders since no buyer will be willing to buy on the lower limit in an anticipation of further price decline.

Since volatility plays an important role, it is important to identify the volatility pattern of market returns in Pakistan. The primary objective of this paper is to model the time varying volatility in Pakistan's Stock Markets.

Table-2
Karachi Stock Exchange at a Glance

	2006	2007	2008	2009	2010
Equities					
Listed Companies	651	654	653	651	644
Listed Capital (Rs in million)	515,029.54	671,269.47	750,477.55	814,478.74	919,161.26
Market Capitalization (million)	2,766,583.84	4,329,909.79	1,858,698.90	2,705,879.83	3,268,948.59
New Companies Listed	9	14	10	4	6
Listed Capital (in million)	14,789.76	57,239.93	15,312.12	8,755.74	33,438.45
KSE – 100 INDEX					
High	12273.77	14814.85	15676.34	9845.74	12031.46
Low	8766.98	10066.32	5865.01	4815.34	9229.6
Year End	10040.5	14075.83	5865.01	9386.92	12022.46
Turnover of Shares					
Total Shares (in million)	63,046.52	65,956.89	36,527.96	44,446.88	33,529.72
Average Daily Turnover (in mlns)	260.69	268.23	146.55	179.88	132.64

Source: *Karachi Stock Exchange,* 1 USD = PKR 94 approximately

Methodology

To model the volatility of KSE on aggregate level, we will use the return on KSE 100 index. The sample period is between April 2004 and September 2012. The daily returns for this period will be estimated using the following logarithmic expression.

$$R_i = Ln\left[\frac{P_t}{P_{t-1}}\right]$$

The index number will be used as price proxy to model returns and volatility. A simple measure of volatility is the standard deviation over the sample period. However, in such case the problem lies in the choice of sample period. If the period is long, the estimated standard deviation might not be relevant at present. On the contrary, a smaller period tends to include noise in the results. Moreover, the investor is concerned with the holding period volatility or the conditional variance rather than long run variance forecast. The descriptive statistics of KSE 100 returns for the sample period are reported in table 3.

Table-3
Descriptive Statistics KSE 100 Returns

Mean	0.0010
Median	0.0022
Maximum	0.0580
Minimum	-0.0606
Std. Dev.	0.0160
Skewness	-0.4669
Kurtosis	4.3926
Jarque-Bera	85.1567
Probability	0.0000

From table 3, it is evident that KSE 100 has volatile daily returns with a maximum of 5% and a minimum of -6.0%. The mean return is around 1% with a standard deviation of almost 1.6%. The observed Kurtosis is 4.39 with skewness of -0.46. Kurtosis is a measure of whether data are peaked or flat relative to normal distribution. The negative skewness indicates that returns are negatively skewed and together with kurtosis implies that underlying distribution of returns is not normal. The significant Jarque Bera value further validates the existence of a non normal distribution. The non normal returns call for estimation using GARCH model which generalizes the ARCH model by using ARMA process. This GARCH can be represented for returns (y_t) and volatility (σ^2) as follows.

$$y_t = \mu + \sum_{j\in J} \rho_j y_{t-j} + \varepsilon_t$$

$$\varepsilon_t \sim \mathrm{N}(0,\sigma_t^2)$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{i=q} \gamma_i \varepsilon_{t-i}^2 + \sum_{i=1}^{i=p} \beta_i \sigma_{t-i}^2$$

In the above setup, (y_t) is referred to as the mean equation and the (σ^2) represents the variance equation. The mean equation is specified as an autoregressive moving average process, ARMA (p,q), which assumes that a time series is a linear combination of its past values and as well as current and past values of random errors. The first step in modeling the GARCH process involves specifying a model for the return series. An ARMA(1,1) model is identified for the return series based on Box and Jenkins methodology. An ARCH- LM test will be carried out to ensure that the underlying process is in consort with the postulated GARCH process. Testing for ARCH error involves two steps. In the first step returns are estimated as an ARMA (1,1) process. In the second step, squared residuals from the above regression are regressed on a constant and lags. Once the ARCH effects are established, we will use GARCH (1,1) to model the volatility in returns.

Results and Discussion

There were two steps involved in the GARCH modeling of volatility. The first phase comprises of detection of ARCH effects in the data. An ARMA (1,1) model was estimated. The correlogram of squared residuals from ARMA(1,1) is reported in table 4.

Table-4
Correlogram of Squared Residuals ARMA (1,1)

	AC*	PAC**	Q Stat	Prob
1	0.4710	0.4710	161.38	-
2	0.3710	0.1930	262.01	-
3	0.3210	0.1190	337.38	0.0000
4	0.2850	0.0800	396.69	0.0000
5	0.3380	0.1690	480.30	0.0000

*Autocorrelation, **Partial Autocorrelation

The correlogram was estimated using 10 lags. It shows autocorrelation in squared residuals which could be due to volatility clustering. Thus to check for the presence of ARCH effect, we perform ARCH-LM test (5 lags) on KSE 100 return and report salient statistics in table 5.

Table-5
ARCH LM Test (5 Lags Included)

ARCH Test			
F-statistic	57.48564	Probability	0.000000
Obs*R- squared	206.7337	Probability	0.000000

The reported F and LM statistics indicate presence of ARCH effects in KSE 100 daily returns identifying non normality of index. Once the presence of ARCH effect has been established we move to the second phase which is the use of GARCH (p, q) type model to analyze the volatility in returns. We will use GARCH (1, 1) process which is the most commonly used measure to model the volatility of returns. The results from GARCH (1, 1) model are reported in table 6.

Table-6
GARCH (1,1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002286	0.000448	5.105744	0.0000
AR(1)	0.056610	0.040306	1.404496	0.1602
Variance Equation				
C	1.14E-05	3.79E-06	3.002746	0.0027
RESID(-1)^2	0.257178	0.060214	4.271084	0.0000
GARCH(-1)	0.713392	0.050207	14.20900	0.0000
T-DIST. DOF	9.600549	3.727804	2.575390	0.0100
R-squared	0.001296	Mean dependent var		0.001034
Adjusted R-squared	-0.005639	S.D. dependent var		0.016003
S.E. of regression	0.016048	Akaike info criterion		-5.791139
Sum squared resid	0.185435	Schwarz criterion		-5.753225
Log likelihood	2108.183	F-statistic		0.186908
Durbin-Watson stat	1.926579	Prob(F-statistic)		0.967570

Table 6 provides mix results for the GARCH (1, 1) process. It is clear that the estimates of mean equation are not significant. While on the contrary, the variance estimates are strongly significant. If we use t statistics in GARCH model with certain degrees of freedom, this will allow for excess kurtosis in the conditional distribution. The degree of freedom will determine the kurtosis of the conditional distribution. For the degrees of freedom greater than 4, we will always have a conditional kurtosis of more than 3. Thus, in both unconditional and conditional distributions, the GARCH with t estimates exhibits fat tails as compared to normal distribution. Apart from this, the higher order moments are not time dependent. The Durbin Watson stats identify absence of serial correlation. There could be many reasons for weak mean results. The used data is for a period that obviously contained noise with extreme maximum and minimum returns. There were periods when very low trade took place since either the stocks opened on the lower limits or the upper limits. However, the model captured the volatility and significant variance coefficients support the time varying volatility hypothesis i.e. conditional volatility changes over time due to clustering volatility.

Although the absence of serial correlation should be sufficient to demonstrate the fit, we further consider ARCH – LM test on residuals of GARCH (1, 1) model. The reported statistics from table 7 indicate that GARCH (1, 1) model has captured the persistence in volatility and no ARCH effect is left in the residuals.

Table-7
ARCH LM Test on GARCH (1,1)

ARCH Test:			
F-statistic	1.403153	Probability	0.220924
Obs*R-squared	7.005896	Probability	0.220202

An important aspect must be noted here. Information plays a vital role in financial markets and hypothesis on ARCH effects assume that these effects are due to the variations in rate of information flow. Nelson suggests that ARCH effects and their persistence will vary according to the sample frequencies and a high frequency data (an hourly return vis-à-vis) is likely to be a better fit than a daily or weekly return data. Moreover leverage effect is expected to be captured in a better way in an hourly data as compared to weekly or even daily data. We checked the leverage effects using EGARCH. The resulting statistics show significant (at 1%) volatility persistence (0.901) and a significant positive leverage effect (0.046). The positive leverage effect implies that positive returns are associated with higher volatility than negative returns of same magnitude. The asymmetric function was also significant and it reveals that past residuals have an impact on current volatility. Since flow of information varies during the trading day, an hourly data will model the volatility more significantly as compared to low frequency data. Unfortunately for Pakistani market, high frequency data was not available, otherwise; more significant ARCH effects and volatility clustering could have been examined. We expect more significant results for our model in case of high frequency data.

Conclusion

Emerging markets are faced with estimation problems vis-à-vis asset pricing models. Since volatility plays an important role in asset valuation and investment decisions, it is important to model with precision. Moreover, the recent studies have shown that volatility varies over time and constant variance assumption is flawed. Since investors are concerned about conditional variance, long term variance is, at times, meaningless. Pakistan is a classic case of emerging market which is subject to high volatility. The high volatility becomes more complex when the market is manipulated by the informed players and market makers. We have considered a sample period which is assumed to be the most volatile in the history of Pakistan's stock market. The empirical evidence indicates presence of time varying volatility. Therefore, valuations in such markets should be dealt carefully by taking into account conditional variance. These findings have strong implications for fund managers and investment analysts who rely on a Gaussian style standard deviation as measure of risk for their exposures.

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