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Risk Modelling Pakistan Stock Market within the Context of Shanghai Stock Exchange

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ABSTRACT
This study presents a comparative predictive performance of different VaR models used by Securities and Exchange Commission of Pakistan (SECP) and literature recommended simple VaR models for Chinese Stock market for Chinese Securities Regulatory Commission (CSRC). In this study, we have used Historical Simulation as Non-Parametric Method, GARCH, Variance-Covariance and EWMA as Parametric and Filtered Historical Simulation as Semi-Parametric Method to calculate VaR. Another aspect focused in this thesis is China Pakistan Economic Corridor (CPEC). This study has tried to check wither CPEC create impact on risk modelling in KSE and SSE. So, we have examined the more accurate predictive model of Value at Risk for Pakistan and China before the time of CPEC and after starting these mega projects. For this purpose, we have used the data of Karachi stock Exchange 100 Index of Pakistan and Shanghai Composite Index of China from 1st Jan 2001 to 31st Dec 2016. Furthermore, this data is divided by using a breakpoint of CPEC 20 April 2015. The VaR is calculated by different approaches before and after CPEC for both stock markets.The major findings of the study showed that VaR models of GARCH family like ARMA-GARCH, FHS-GARCH and EWMA provides more accurate results for both stock markets. Finding shows that VaR models used for KSE 100 index and SSE composite index have been changed before and after starting of CPEC. Despite all of this the risk modelling of both countries have not been changed completely. So it does not mean that CPEC "Game Changer" have no impact on the financial markets of Pakistan and China. Because the main limitation of my study is non-availability of complete data of both stock markets after CPEC, due to the in-progress projects. When all of these projects of infrastructure, energy and communication will be complete then this change will be more prominent. At that time, this study will be a foundation for the researchers. Furthermore, models like EVT, Capula, Monte-Carlo should be applied to have more sophisticated models.

KEYWORDS: RiskModelling, Pakistan Stock Market, Shanghai Stock Market, VaR models

INTRODUCTION

Financial market plays vital role to boost economic growth of a country. A growing stock market is an indicator of economic growth. All businesses assume some sort of risks and market risk is one of them (Demirguc Kunt, & Levine, 1996). If risk is not efficiently addressed it causes stock crash that leads towards default of investors and the ultimate cause of institutional failure. So, the efficient management of market risk have become crucial in current uncertain financial markets. The extensive movements in market prices of financial assets as well as increased use of derivatives call for risk measures are creating more than ever growing financial risks. Nowadays, not just supervisory authorities but also management of institution requires a quantitative measure of market risk, for investment decisions and fulfilling external regulations (Rockinger, & Jondeau, 2001).

Nowadays VaR has become the standard measure to evaluate financial risk (Jorion, 2007). VaR suggest the worst-case scenario over a targeted horizon that will not be exceeded from a given level of confidence. It is believed that VaR helps to realise institutions about their financial limits of loses (Jorion, 2001).

As Pakistan is an emerging economy with heavy tail behaviours due to fluctuational political and economic environment. Equity market of Pakistan has high volatility and incidence of extreme returns. Pakistani stock market has faced crises in 2000, 2002, 2005, 2006, and then in 2008. In 2008, the stock prices plunged by fifty-five percent (5600 points) in just 4 months. Due to this, many local and foreign investors have taken away their investments. (Qayum & Sharif, 2008), and Pakistan was removed from the MSCI Emerging Market Index in Dec 2008. Afterword's according to Bloomberg Karachi Stock Exchange is the third best performer in the world since 2009 to 2015. In 11th Jan 2016 KSE is converted to Pakistan Stock Exchange (PSX). As per current ranking of best performing Asian stock market in 2016 Pakistan is on the top (Teso, & Karunungan, 2017) and globally on 5th rank after Brazil, Kazakhstan, Peru and Russian stock markets (Bloomberg. 2016).

Securities and Exchange Commission of Pakistan (SECP) is a financial regulatory authority of Pakistan. In SECP the VaR based margin traded system was introduced by the virtue of Securities Rule 2011.The existing system was using Variance Covariance, Historical / Filtered Historical Simulation and the exponential weighted moving average VaR models to calculate Value at Risk (SECP, 2013, p.10).

China and Pakistan are geographical neighbours and having good friendly relations. Both countries have successfully managed a strong bilateral trade and economic ties over the years. China has gradually emerged as a partner of imports and exports with Pakistan. This relation was first started in Jan 1963 when both countries signed the first long term Bilateral trade agreement. In 2006, a Free Trade Agreement (FTA) was signed that was implemented in 2007. Which have increased the trade volume between China and Pakistan (Irshad, 2015).

The China-Pakistan Economic Corridor (CPEC) is the combination of several projects in Pakistan (Ahmed, & Mustafa, 2016). President of China Mr, Li Keqiang emphasized the construction of the CPEC during his visit to Pakistan in May 2013 (Tiezzi, 2014). The current Pakistani Government has also taken this project very seriously. This corridor will connect Kashgar in north-western China to Gwadar Port in Baluchistan (Pakistan). This corridor will make Gwadar a significant port, not only for Pakistan but also for China. By the completion of this corridor it will be a Gateway from China to Middle East and Africa. This corridor will also cut the 12000 kilometres' route from Middle East countries to Chinese ports for oil supplies (Malik, 2012).

The concepts of CPEC "The Game Changer" and the extensive need of risk management have motivated for the search of more appropriate methodologies able to capture the Pakistani market behaviour more applicable and have more predictive power to forecast even rare events that have heavy consequences. Since so far, too little attention has been given to risk modelling of stock market of Pakistan specially in the context of some special event and the context of Shanghai stock Exchange of China. This study tried to fill this gap and present a detailed risk analysis of Pakistan Stock Market by using Value at Risk aggregate, before and after of CPEC. These VaR methods are classified in three main categories.

Parametric Non-Parametric Semi Parametric

Parametric methods include GARCH, Variance-covariance and Exponential Weighted Moving Averages. In semi-parametric method, includes Filtered Historical Simulations and non-parametric includes Historical simulation. To evaluate these methods back testing technique proposed by Christoffersen is used. The data being used is the daily returns of the KSE 100 index and SSE Composite Index from Data Stream of Jan 2000 to Oct 2016.

First objective is to test that whether existing risk framework of SECP (SECP, 2013, p.10) and literature suggested VaR models for Chinese Stock market (Chen, 2017); (Cheng & Zhang, 2014); (Fan et al, 2008) have valid predictive power to avoid the probability of stock crash or not, and predict which one is the best model having more accuracy. Second objective is to find the impact of "The Game Changer" CPEC on risk modelling in KSE & SSE. It means in this study we have examined the more accurate predictive model of Value at Risk for Pakistan and China before the time of CPEC and after starting these mega projects.

This study is especially beneficial for investors, financial managers, policy makers, decision makers of China and Pakistan specifically. Every investor wants to invest in a secure economic market to gain maximum returns with minimum risks. Therefore, in financial Risk Management measurement of risk is much important. If risk is identified, measured properly, it can be managed properly. VaR is method to calculate the value of stock at risk of loss in future.

METHODOLOGY

For applying Value at Risk, we have use the data of the daily returns of the KSE100 index (Karachi Stock Exchange) of Pakistan & SSE Composite Index (Shanghai Stock Exchange) of China, taken from Data Stream Thomsonone for the period of January 04, 2001 to Dec 31, 2016. Furthermore, we have divided the data of both markets using a breakpoint of 20 April 2015 (the signing date of CPEC). Value at Risk is calculated for the complete data of (2000-2016), data of "Before breakpoint CPEC" (Jan 2000-19 Apr 2015) and data of "After breakpoint of CPEC" (20 Apr 2015-31 Dec 2016) for both countries. The calculation of VaR methods are classified into three main categories.

- Parametric
- Nonparametric and
- Semi Parametric.

THE HISTORICAL SIMULATION APPROACH

The historical simulation is the simplest non-parametric method of VaR. In this method, there is no need to make assumptions regarding distributions. For this approach, first we have to take a big sample of historical data. Then we make a subsample of same length called window. The length of a window is called window size.

Let Suppose T, = sample size

n = window size

R_t^p = percentile of each window

W_0 = worth of portfolio

So the portfolio VaR can be written as:

$$\widehat{VaR_{t+1/t}} = -W_0 R_t^p$$

For next day's VaR at time *t*, the portfolios' return at time t and n-1 preceding return will be taken into calculation. Thus, Historical Simulation is all about taking desired sample percentile of rolling windows. Interpolation is used when the desired percentile is in between the two adjacent loses (Butler & Schachter, 1998).

This same procedure continues for the next days. In HS same weights are assigned to all of the observations in a window. Historical simulation does not give high weights to the recent observations (Hendricks, 1998). Window size selection is also an important issue. Normally the window size is 250 or 500 observations and confidence interval is 95% and 99% (Chappell & Dowd, 1999). If small window size is selected then recent returns are included but if large window size is selected then recent and previous both returns are included (Dowd, 2000).

FILTERED HISTORICAL SIMULATION

As we explained above, the main deficiency of HS as a non-parametric method is its disability in modelling the volatility dynamics of the returns. Also in the parametric method, the choice of right distribution is difficult, so Hull and White (1988) combined the two previous methods Historical Simulation and GARCH Method to receive one called FHS. It has been observed that the probability distribution of a market variable divided by its volatility estimate will become roughly stationary. So, Hull and White suggested that historical simulation can be improved by incorporating volatility updating scheme through GARCH into it. Because this method is the combination of a parametric and non-parametric method, it can be called a semi-parametric technique.

For Filtered Historical Simulation we don't use any theoretical distribution we use the Historical distribution of the returns. Any time series model which generates residuals from our returns is suitable for us, so we introduce ARMA-GARCH which removes the serial correlations by MA and volatility clusters by GARCH.

Let's suppose that the historical change in a variable *v* for the time *t* in days with in the sample period for $t < N$ can be represented by h_{tv}. Also, the historical GARCH estimates of daily variance of the percentage change in variable j made for day *t* is $\sigma_{tv}{}^2$ and let $\sigma_{Nv}{}^2$ is the most recent GARCH estimates of the daily variance. As the $\frac{h_{tv}}{\sigma_{tv}}$ will be stationary. Then the VaR estimates for day *N* can be determined as follows:

$$h_{tv}{}^* = \sigma_{Nj} \frac{h_{tv}}{\sigma_{tv}}$$

Where the t^{th} sample percentage change for variable *v* is set to $h_{tv}{}^*$ instead of h_{tv}.

GARCH MODEL:

Volatility is a statistical measure of the dispersion of returns for a given asset, portfolio or index. It measures the size of errors occurred in different variables of financial market such as returns. Normally, volatility is not constant but it is varying with time. The value of VaR will increase as volatility increase. So, the investors will try to change the assets, from their portfolios whose volatility has been predicted to increase.

Volatility clustering is a well-known phenomenon for financial time series. It means "large changes tend to be followed by large changes and small changes tend to be followed by small changes" The ARCH (Autoregressive Conditional Heteroscedasticity) proposed by Engle, (1982) captures the effects of volatility clustering.

In most of the scenarios GARCH (1,1) is the most useful structure in the case of financial time series. But in our analysis, GARCH (2,1) and GARCH (2,2) are also been used. Normal distribution is used. In case of ARMA (1,1)-GARCH (1,1) model, the mean equation and variance were as follows:

$$r_t = \mu + \delta\epsilon_{t-1} + \emptyset r_{t-1} + \epsilon_t$$
$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \eta_t$$

In case of ARMA (2,1)-GARCH (2,1) model, the mean equation and variance were as follows:

$$r_t = \mu + \delta\epsilon_{t-1} + \delta\epsilon_{t-2} + \emptyset r_{t-1} + \epsilon_t$$
$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \alpha\epsilon_{t-2}^2 + \beta\sigma_{t-1}^2 + \eta_t$$

In case of ARMA (2,2)-GARCH (2,2) model, the mean equation and variance were as follows:

$$r_t = \mu + \delta\epsilon_{t-1} + \delta\epsilon_{t-2} + \emptyset r_{t-1} + \emptyset r_{t-2} + \epsilon_t$$
$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \alpha\epsilon_{t-2}^2 + \beta\sigma_{t-1}^2 + \beta\sigma_{t-2}^2 + \eta_t$$

The coefficients of the mean equation are normally highly significant. The coefficient of AR term shows that the returns today heavily depend on its value on yesterday. The coefficient of MA term is negatively correlated with today return. This shows that if yesterday residual is increased then the today's return will decrease and vice versa. The constant term is near to zero. This is consistent with the mean reversion property of the financial returns.

Conditional variance is denoted by σ^2_t as it depends on the past information. It is a function of three terms. First, constant is denoted by ω, which is a weighted average of a long-term average. ε^2_{t-1} which is known as ARCH term. ARCH term is a lag of the squared residual from mean equation. It is considered as the news about volatility from last period. GARCH term is denoted by σ^2_{t-1}. It is the forecast of variance from last period. Normally the sum of the coefficients of ARCH and GARCH is equals to 1. This tells that the shock to the conditional variance will be highly persistent.

RISK METRICS OR EWMA MODEL:

The difference between the Risk Metrics and the GARCH is the calculation of standard deviation. In the risk metrics method, standard deviation is calculated by Exponential Moving Averages (EWMA). So, we can say that it is a non-stationary version of GARCH model. In the Risk Metrics, the sum of the persistence parameters should be one.

$$\alpha_1 + \beta_1 = 1$$

The conditional variance forecast at time *t* in EWMA can be written as:

$$\widehat{h_{t+1}} = \omega + \alpha_1 \varepsilon_t^2 + \beta_1 h_t$$

By extending above equation

$$\widehat{h_{t+2}} = \omega + \alpha_1 \varepsilon_{t+1}^2 + \beta_1 h_{t+1}$$
$$= \omega + \omega\beta + \alpha\varepsilon_{t+1}^2 + \alpha\beta\varepsilon_t^2 + \beta^2 h_t,$$
$$h_{t+\tau} = \omega \sum_{i=1}^{\tau} \beta^{i-1} + \beta \sum_{i=1}^{\tau} \beta^{i-1} \varepsilon_{t+\tau}^2 + +\beta^{\tau} h_t$$

For $\tau \to \infty$ and $\beta < 1$, we have

$$h_t = \frac{\omega}{1-\beta} + \alpha \sum_{i=1}^{\infty} \beta^{i-1} \varepsilon_{t-i}^2$$

For EWMA model, the standard deviations will be as:

$$\widehat{\sigma_t^2} = \left(\frac{1}{1+\lambda+\lambda^2+\cdots+\lambda^n}\right)(\sigma_{t-1}^2 + \lambda\sigma_{t-1}^2 + \cdots + \lambda^n \sigma_{t-n}^2)$$

For $n \to \infty$ and $\lambda<1$,

$$\widehat{\sigma_t^2} = (1-\lambda) \sum_{i=1}^{\infty} \lambda^{i-1} \sigma_{t-i}^2$$

Let us assume that ε_t^2 is a proxy for σ_t^2 then above two equations will be AR series with long distributed lags. Therefore, we use the following equation for simplicity:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda) r_{t-1}^2$$

λ is estimated by root mean squared error (RMSE) criterion (Morgan, 1996). The RMSE can be written as

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(r_{t+1}^2 - \hat{\sigma^2}_{t+1|t}\right)}$$

EWMA has only one unknown parameter which is λ, known as decay parameter. The beauty of this model is, only a very small number of returns have to be stored for VaR calculation. When once standard deviation σ_t^2 is calculate, the past returns are no more required

Decay parameter λ is usually set to 0.94 or 0.97 but typically in the case of Pakistan for KSE 100 index, λ is set to 0.91. VaR for Risk Metrics is calculated for 99% and 95%.

VARIANCE-COVARIANCE

The Variance-Covariance methods is a parametric method either conditional or unconditional based on the way of estimating risk changes. Jorion (2001) explains the assumption of the Variance-Covariance approach is that the random outcomes are normally distributed. For assets portfolios, normally distributed returns of each security or asset will produce a portfolio with normally distributed returns, this assumption simplifies the model significantly. Linsmeier and Pearson (2000) state that value at risk can be found easily when the parameters of the returns distribution have been estimated for the entire portfolio. This method depends on the estimation of the variance and co-variance matrix (Stambaugh, 1996). The VCV method initiates a probability distribution of the hidden risk values through relative simple computations. For example, for calculating the VaR for a single asset, where the hidden risks values are normally distributed having mean of Rs100 billion and a monthly standard deviation is Rs10 billion with the confidence level of 95%, the value of VaR will not below than Rs60 billion (Jordan,1996).

Following are the four steps of this method to address the risk. First of all, it requires to take each asset from portfolio and translate them into standardized instruments. Secondly each asset has given the position in standardised instruments. In third step after standardizing the asset the user has to calculate the variance co-variance by searching historical data. Finally, the user has to calculate VaR by using weights of second step and variance co-variance from third step (Zhao, 2013). Following are the two basic assumptions of this method: First is linear assumption. Which means the relationship between value changes of an asset and its returns shows the liner change for a given period of time. Second is the normal distribution assumptions. Which means the returns of risk factors are in line with using the normal distribution (Lal,2012; Cabedo,2003).

STATISTICAL ANALYSIS:

In this portion Value at Risk is calculated by three common Parametric methods. This includes Variance-Covariance (VCV) method, Exponential Weighted Moving Average (EWMA) or Risk Metrics and General Autoregressive Conditional Heteroscedasticity (GARCH). In the nonparametric models, Historical Simulation and in semi- parametric models Filtered Historical Simulation model is discussed. Historical Simulation will be taken for 250 and 500 days at 95% and 99% level. The data of KSE and SSE is used. Furthermore, we have divided the data into three main categories, total selected time frame, after and before the break point of CPEC.

The predictive performance of these VaR models were tested by Unconditional Coverage $\mathbf{LR_{uc}}$, Independence ($\mathbf{LR_{ind}}$)& Conditional Coverage test ($\mathbf{LR_{cc}}$). These tests are proposed by P. F. Christoffersen (1998), P. Christoffersen and Pelletier (2004). Another simple measure is used for simplicity which is called failure rate which tells how many times the VaR exceeds the forecasted VaR. Failure rate is percentage of ratio between number of exceedance and total number of observation. Following tables shows the Failure rate of different VaR approaches at a left tail probability of 1% 5% for an Average Estimated VaR value.

Market	Model	1%		5%	
		Average VaR Estimate	Failure Rate	Average VaR Estimate	Failure Rate
KSE	EWMA λ= 0.91	2.85%	2.34%	2.02%	5.58%
KSE Before CPEC	EWMA λ= 0.91	2.94%	2.36%	2.08%	5.63%
KSE After CPEC	EWMA λ= 0.91	1.84%	1.80%	1.30%	5.18%
SSE	EWMA λ= 0.91	3.34%	2.78%	2.36%	6.20%
SSE Before CPEC	EWMA λ= 0.91	3.25%	2.63%	2.30%	6.19%
SSE After CPEC	EWMA λ= 0.91	4.07%	4.27%	2.87%	6.31%
KSE	GARCH (1,1)	4.54%	1.67%	3.21%	4.54%
KSE Before CPEC	GARCH (1,1)	4.92%	1.79%	3.48%	4.71%
KSE After CPEC	GARCH (1,1)	1.87%	2.20%	1.32%	4.81%
SSE	GARCH (1,1)	3.46%	2.03%	2.45%	5.50%
SSE Before CPEC	GARCH (2,2)	3.37%	1.77%	2.38%	5.38%
SSE After CPEC	GARCH (2,1)	3.59%	3.61%	2.54%	5.22%
KSE	HS 250 days	3.52%	1.23%	2.26%	5.27%
KSE Before CPEC	HS 250 days	3.59%	1.29%	2.35%	5.40%
KSE After CPEC	HS 250 days	2.56%	0.67%	1.27%	3.38%
SSE	HS 250 days	4.07%	1.23%	2.26%	5.27%
SSE Before CPEC	HS 250 days	3.72%	1.26%	2.39%	5.31%
SSE After CPEC	HS 250 days	7.00%	1.58%	3.81%	5.84%
KSE	HS500 days	3.80%	1.00%	2.37%	4.71%
KSE Before CPEC	HS500 days	3.90%	1.01%	2.47%	4.76%
KSE After CPEC	HS500 days	2.69%	0.90%	1.29%	3.60%
SSE	HS500 days	4.16%	1.39%	2.51%	5.32%
SSE Before CPEC	HS500 days	3.87%	1.15%	2.45%	5.06%
SSE After CPEC	HS500 days	6.56%	3.38%	2.99%	7.43%
KSE	FHS-GARCH	5.51%	1.15%	3.32%	4.83%
KSE Before CPEC	FHS-GARCH	5.97%	1.20%	3.67%	5.14%

KSE After CPEC	FHS-GARCH	2.62%	0.80%	1.34%	3.81%
SSE	FHS-GARCH	4.21%	1.34%	2.54%	5.36%
SSE Before CPEC	FHS-GARCH	4.06%	1.10%	2.49%	5.19%
SSE After CPEC	FHS-GARCH	7.37%	3.33%	3.77%	6.25%
KSE & SSE	VCV	6.26%	2.15%	4.44%	7.00%
KSE & SSE Before CPEC	VCV	7.01%	1.75%	4.97%	4.66%
KSE & SSE After CPEC	VCV	2.46%	6.84%	1.73%	8.12%

VaR explains that the exceedance will not be greater than p*100% of the time. When original loss is greater than VaR values it's called exceedances. Unconditional Coverage **LR_{uc}** shows the exceedances. So, Correct Unconditional Coverage does not give a proper answer for all the scenarios. For example, if the exceedances or violations are equals or less than 1% in long period of time, it can be managed, but if these violations are in very short period of time then there are a lot of chances for the bankruptcy. That's why another test is required to check the independency of the violations, and help to reject clustered violations. "Independence test" is the test of independence. The statistics for this test is a likelihood ratio statistic of the null hypothesis for serial independence against the alternative of 1st order Markov dependence.

The presence of the time dependent heteroskedasticity in financial time series demands a test of conditional coverage accuracy. So, we need to check the independence of VaR violation along with average number of violation's correctness simultaneously. Volatility clustering can be captured by this test called conditional coverage (LR_{cc}). This test formulated by uniting the two tests (LR_{uc} & LR_{ind}). Conditional Coverage (LR_{cc}) is simply computed as the sum of the two individual LR_{uc}, LR_{ind} tests and the test statistics will be given as:

$$LR_{cc} = LR_{uc} + LR_{ind} \sim X_2^2 \ .$$

Table of LR_{cc} for different VaR approaches

Var Methods								
			LRcc					
Type	**Approaches**	**C.L**	**For KSE Pakistan**	**KSE Pakistan Before CPEC**	**KSE Pakistan After CPEC**	**For SSE China**	**SSE China Before CPEC**	**SSE China After CPEC**
Non-Parametric	HS-250	0.99	15.3742	16.2088	7.11285	3.44121	3.03136	4.13942
		0.95	66.5803	60.4083	9.37117	10.3126	3.5275	18.1399
	HS-500	0.99	12.0815	12.6663	5.28494	9.36904	1.24001	18.4868
		0.95	77.0328	70.7775	7.87841	17.4678	6.73787	18.2922
Parametric	VCV	0.99	64.4026	21.3959	64.0033	64.4026	21.3959	64.0033
		0.95	622.34	19.738	11.003	622.34	19.738	11.003
	GARCH	0.99	16.4647	19.24742	10.9832	35.0649	18.0675	24.789
		0.95	8.98732	5.605008	5.04772	**2.60663**	1.24349	**0.46659**
	EWMA	0.99	52.6198	48.7573	4.68704	89.9372	68.9389	26.5891
		0.95	16.6004	15.5114	**0.54717**	11.9277	10.3796	2.31201

Semi-Parametric	FHS-GARCH	0.99	**1.18605**	**1.79594**	5.68301	4.46777	**0.8578**	9.51954
		0.95	9.61046	6.28593	6.20626	2.46215	1.16033	4.24492

Following table shows that Methods of GARCH family provides more accurate results than other methods. FHS- GARCH of 1% was appropriate model for KSE and GARCH 5% for SSE as a whole. When we have separated the data of both markets FHS-GARCH at the significance level of 1% is suitable for KSE of Pakistan before CPEC but after CPEC, EWMA at 5% level is showing more appropriate results. For SSE of China FHS-GARCH method at 1% was more appropriate model before CPEC but GARCH model of 5% is more suitable after CPEC. But we cannot mention a single method fit for the stock of both markets (Vee et al. 2012), moreover the GARCH adopted VaR methods are more appropriate.

Table of Selected Models of VaR with Significance Level

Markets	Models	Significance level
KSE Of Pakistan	FHS-GARCH	1%
KSE of Pakistan Before CPEC	FHS-GARCH	1%
KSE Pakistan After CPEC	EWMA	5%
SSE of China	GARCH	5%
SSE of China Before CPEC	FHS-GARCH	1%
SSE of China After CPEC	GARCH	5%

CONCLUSION

The main purpose of this study was to test either the existing risk frame work of SECP and literature recommended simple VaR models for Chinese Stock market (Chen, 2017); (Cheng & Zhang, 2014); (Fan et al, 2008) have valid predictive powers to avoid the stock crash or not. For this purpose, technique proposed by Christoffersen (1998), Christoffersen and Pelletier (2004) is used to verify the accuracy of VaR models. Secondly, the purpose is to test that methods of VaR used before CPEC are same after starting of CPEC or not.

The major findings of the study showed that the results of VaR models of GARCH family like ARMA-GARCH, FHS-GARCH and EWMA looks more accurate for both stock markets than their existing adopted and preferred VaR models. It means the existing VaR models used by SECP and literature recommended VaR models to CSRC do not have valid predictive power.

In the results of this study the VaR methods have changed for KSE and SSE before and after CPEC but results showed that CPEC is not changing the risk modelling completely. So, it does not mean that CPEC "Game Changer" has no effect of the financial markets of Pakistan and China. Because the main limitation of this study is non-availability of complete data after CPEC, due to the under-progress projects. When all of these projects of infrastructure, energy, transportation and communication will complete then this change will be more prominent in financial as well as industrial sector. At that time, this study will be a foundation for the researchers. Furthermore, the complex models like EVT, Capula, Monte-Carlo should be applied to have more sophisticated models. In this study only stock markets are taken but no consideration has been given to banks and insurance sectors of Pakistan and China. So that can be another gap for research purpose.

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