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Diversification of Risk: Investing in KSE-ALL and NYSE-Composite in Chorus

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Abstract: This paper is aimed at exploring whether stock market investors can meaningfully diversify their investment risk by investing in Pakistani and international stocks simultaneously. To serve the purpose, Johansen's cointegration test was administered to check for any long-run association between KSE All Share Index --- an index representing shares of Pakistani companies --- and the NYSE Composite --- an index representing international firms primarily the North American common stocks. Daily data was taken for the two indices for 10 years from January 01, 2011 to December 31, 2020, which led to 2479 observations for the KSE All Share Index and 2517 observations for the NYSE Composite. Both the trace test and the maximum eigenvalue test indicated at least one cointegrating equation at five percent level. The vector error correction model revealed the existence of a significant long-run association between the two indices at level. However, the beta coefficient of the cointegrating equation was very slightly positive and highly insignificant leading to the rejection of the possibility of any long-run association between the two indices. Moreover, the Granger Causality test run with a view to detect any short-run relationship between the two stock indices also gave insignificant and inconclusive results. It can, therefore, be inferred that changes in one of the two stock indices cannot be predicted or explained by changes in the other, and, thus, attempting to diversify one's portfolio by instantaneously investing in both the indices may lead to a reduced exposure to the overall portfolio risk as the two indices are uncorrelated both in the short- and in the long-run.

Keywords: Stationarity, Cointegration, Granger Causality test, VECM, KSE All Share Index, NYSE Composite.

Introduction

Diversification naturally appeals to the risk-averse creature inside every investor (Singh, 2020). Being primarily risk averse, stock investors always prefer to diversify their risk. In a local context, however, achieving meaningful diversification is sometimes a lofty contest because the natural states of the economy is affecting virtually all the stocks in a region in a systematic manner. It is probably because of this reason that many risk averse individuals prefer to invest globally in an attempt to make themselves more diversified. Off course, countries are not all entirely synchronized with respect to their economic cycles, and hence, if the economy of one country is undergoing contraction or trough, this could be offset by the economy of the other country that is experiencing expansion or peak (Horne &Wachowicz, 2005).

This paper is intended to explore whether investing simultaneously in stocks listed on Pakistan Stock Exchange and in those listed on the New York Stock Exchange will leave an investor any more diversified than if the same amount of investment is being made in only one of these two countries. Put it the other way, effort is made to know whether, or not, it is reasonable to expect to achieve what is known as the *global diversification* by investing in the two stock indices just mentioned.

The New York Stock Exchange (abbreviated as NYSE) is a North American stock exchange. In terms of market capitalization, it is by far the largest in the world at around $27 trillion US dollars as of December 2020. The NYSE Composite is a stock market index that includes the common shares of all companies listed on the New York Stock Exchange including foreign listings. There are over 2000 stocks listed in the index, of which more than 1600 are US companies and over 360 are foreign firms. It is, however, pertinent to note that the foreign firms are among the largest listed on the exchange. Of the 100 largest companies listed in NYSE Composite in terms of market capitalization, more than half, i.e., 55 firms, are foreign based companies. It should also be noted that the top 100 companies have the largest impact on the index. Thus, having many of the biggest and most familiar foreign listings that account for one-third of the total market capitalization of the index, the NYSE Composite represents much of the *entire* world's stocks and is itself globally diversified.

The PakistanStock Exchange (abbreviated as PSX), on the other hand, is a stock exchange in Pakistan with trading floors in three cities of the country, i.e., Karachi, Lahore and Islamabad. The KSE All Share Index (abbreviated as KSE-ALL) is an index that includes all of the common stock listed on PSX. There are 443 companies listed in the index with an overall market capitalization of PKR 8trillion (USD $50 billion) as of December 2020. This market capitalization is hardly a quarter of the daily trading volume of the NYSE Composite which has averaged over 200 billion dollars as of 2020.

The primary objective of this paper is to attempt to examine how much are the common stocks of Pakistani companies integrated in the long-run with those of international, primarily North American, companies, or, how much is the KSE-ALL integrated with the NYSE Composite. A more positive correlation between them would entail lesser diversification advantages. On the other hand, a negative association between these two would mean better diversification opportunities leading to a reduced risk of the overall portfolio.

In many cases, there is a *zero* or *no* correlation between two investments. Investing in such uncorrelated securities, or markets, also leads to meaningful diversification as not all of the components of such a portfolio are likely to fall at the same time; rather, when some parts fall in value, the other (uncorrelated) parts will more probably stay the same in value. Hence, diversification reduces risk even when securities are uncorrelated (Kevin, 2000).

It is expected that the current study may offer useful insights to potential investors regarding the prospects associated with diversifying their investments across the two stock markets under consideration.

Review of Literature

Despite that many empirical studies have pointed towards the interdependence of international markets, the existing literature is still vague regarding this interdependence among developed and developing markets and has given mixed results in this respect. Results of empirical studies show that stock markets around the world have time varying cointegrating relationships (Awokuse, Chopra and Bessler, 2009). There have been varied results in the past regarding international stock diversification opportunities which could be due in part to the different methodologies being employed, sample periods or sampling frequencies (Huyghebaert and Wang, 2010), or the time-varying property of the relationship between stock markets (Bekaert and Harvey, 1995; Yang *et al.*, 2003; Brada*et al.*, 2005; De Jong and De Roon, 2005). Many research studies have attempted to theoretically or empirically find the co-movement among stock markets of different parts of the world. A number of studies, however, have focused on the correlations among stock returns and their volatility around the world.

Cointegration analysis has long been used by researchers to explore long-run associations in financial economics. Engle and Granger (1987) stated that whenever any two given time series variables are found to have a unit root and their linear combination is figured out to be stationary, the said time series are cointegrated. Cointegration differs from the statistical measure of *correlation* which is a rather short-term measure. Thus, a high correlation in returns of two stock markets will not necessarily indicate a high level of cointegration between them (Alexander, Giblin, &Weddington, 2002).

The following lines describe some of the seminal works carried out to explore long- or short-run relationships in stock markets around the globe. Chan, Gup and Pan (1997) analyzed 18 large stock market indices of the world and checked for their interdependency but found that none of the indices was cointegrated with others. Similarly, Pascual (2003) checked for the degree of long-term association between German, French and British stock markets for the years 1960 to 1999 using quarterly data. They also found no cointegration between those markets. Narayan and Smith (2005) explored the relationship between stock indices of Oceania and G7 countries using monthly data from 1967 to 2003. Their results were mixed depending on the type of the test used for cointegration.

Some authors note that during crises periods, the stock markets of many countries get cointegrated since the crises affect virtually all stocks in a systematic manner (Granger and Morgenstern, 1970; Arshanapalli*et al.*, 1995; Malliaris and Urrutia, 1992; Hon, Strauss and Yong, 2006; Khalid and Rajaguru, 2007; Huyghebaert and Wang, 2010). For instance, in a study, Yang, Kolari and Min (2003) established that the markets of Japan, US and 10 Asian countries were found to be more cointegrated during financial crises than the time before crises. The reason behind this could be that crises in financial markets may change investment behavior which, in turn, changes the interdependence of stock indices before and after any such crises or shock (Edwards, 2000).

Some earlier studies also attempted to find comovements among international stocks. Jeon and Chiang (1991), for instance, found that the stock prices of Frankfurt, New York, London and Tokyo were cointegrated in the long-run. Similarly, Malkamaki*et al.* (1993) explored the long-run relationship between Danish, Swedish, Norwegian and Finnish stock markets and concluded that the Swedish market was primarily followed in the long-run by the other markets. Hassan and Naka (1996) attempted to find the relationship among the UK, US, Japanese and German stock markets and found that both short-term and long-term association was there among them. Bemerew(1999) checked for the long-run relationship between the Czech and Slovak markets but found that there was no such link between the two. Kumar

(2002) also tried to find any linkage between the US and the Indian stock markets. He found that the Indian market closely follows the US stock market specifically in the long-run. Click and Plummer (2005) analyzed the association among the ASIAN countries' stock markets. They found that the markets of those countries were very integrated but thecointegration was probably there because of the post financial crises period being chosen for the study. Ahmad *et al.* (2005) investigated the association among the Japanese, US, and Indian stock markets. They found no relationship at all, be it in the short-run or in the long-run, among those markets. Aggarwal and Kyaw (2005) studied the integration among the Canadian, Mexican and the US markets. They found that stock markets of the three countries became more integrated after the North American Free Trade Agreement. Bose and Mukherjee (2006) did a research by investigating the integration of the Indian stock market with that of the developed and the developing economies of the world. They concluded that the Indian stock market was more connected with the developing countries and less integrated with the developed economies. Arouri and Jawadi (2008) found American and French stock markets to be closely integrated although the integration so found was time varying. Siddiqui (2010) found that the stock markets of China and India were not cointegrated in the shorter or longer run. Sharma and Bodla (2011) examined the interrelationship between Pakistani, Indian and Sri Lankan stock markets and found a slight cointegration among those markets. MohanasundaramandKarthikeyan (2015) attempted to find the existence of any long-run association among the markets of US, South Africa and India but concluded that no such relationship was there. Deo and Prakash (2017), on the other hand, found that the Indian market was very closely associated with major stock indices of the world. Golab*et al.* (2018)also conducted a study by examining the relationship between Europeanmarkets and its major trading partners including USA, China, Australia and Japan. They concluded that these largest economies were all very closely integrated.

To conclude, a plethora of empirical evidences is available regarding the cointegration of international stock markets. Some studies have found the relationship to be significant while others have failed to find any. In the context of Pakistan, however, limited research has been carried out to check for the international diversification of the country's stock market. This study, therefore, endeavors to conduct a detailed analysis of the cointegration of Pakistan Stock Exchange with that of the New York Stock Exchange with a view to finding whether the two stock markets have any long- or short-run association.

Methodology

In order to explore whether the two stock market indices, i.e., the KSE-ALL and the NYSE Composite, are integrated with each other in the long-run, the Johansen Cointegration test has been employed. The Granger Causality test, however, has been used to check for the short-term predictive causality between the two time series.

Since for cointegration analysis, the variables should both be stationary at the same level, therefore, the augmented dickey fuller test is applied to check for the unit root of each index separately. After ensuring that both the indices are stationary at the same level, the optimal lag length has been identified using the Akaike information criterion and the Schwarz Criterion among other information criterion values. The cointegration between the two indices is then explored using the lag length as specified by most of the information criteria values. The Vector Error Correction Model (VECM) is then employed to predict the long-run relationship and the Granger Causality / Block Exogeneity Wald test is run to see whether the variables are able to forecast each other. The inverse roots of AR Characteristic Polynomial is also used to check for the stability of the model.

The study is based on daily adjusted closing index points of both the indices, i.e., theKSE-ALL and the NYSE-Composite,for ten years starting from January 2011 until December 2020, which led to 2479 observations for KSE-ALL and 2517 observations for NYSE-Composite. To give just a sketchy feel for both the indices, KSE-ALL closed on 8,235 points on January 03, 2011 (the first working day of the year 2011) and finally closed on 30,780 points on December 31, 2020. Whereas, on the other hand, NYSE-Composite started its journey from 8,044 pointswith the onset of 2011and reached 14,525 points as the year 2020 winded up. It should be remarked that the NYSE-Compositehas a value of 5000 points while the KSE-ALL has a base value of 1000 points.

Analysis and Findings

Since for the determination of the long-run relationship between our variables, i.e., the KSE-ALL and the NYSE-Composite, we need cointegration analysis and since the analysis requires that the variables be both integrated at the same order, we, therefore, run a unit root test separately for the variables to check for the number of differences at which they become stationary.

Unit Root Test

Starting with the KSE-ALL, we run the unit root test to check for its stationarity. Results in table 1 show that KSE-ALL is non-stationary when taken at level. The t-statistic reads -1.264 with a *p*-value of .648 and hence the null hypothesis of a unit root cannot be rejected. We,therefore, also check for the unit root in KSE-ALL at the first difference.

Table 1: *Unit root test for KSE-ALL at level and at 1stdifference*

Null Hypothesis: KSE-ALL has a unit root		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic (at level)	-1.264	.648
Augmented Dickey-Fuller test statistic (at 1st difference)	-42.615	.000

Taking the first difference makes our time series stationary (see table 1). Hence, KSE-ALL is stationary at the first difference. The ADF now has a highly significant t-statistic of -42.615 which is significant at 0.01 level.

We will now be checking for the unit root in our second variable, i.e., the NYSE-Composite. Table 2 presents the unit root test of NYSE-Composite taken both at level and at first difference.

Table 2: *Unit root test for NYSE-Composite at level and at first difference*

Null Hypothesis: NYSE-Composite has a unit root		
	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic(at level)	-1.183	.684
Augmented Dickey-Fuller test statistic (at 1st difference)	-15.907	.000

As was the case with KSE-ALL, NYSE-Composite is also non-stationary at level. This is suggested by the ADF's t-statistic value of -1.183 in table 2 which is smaller than the minimum required value of 1.96 in absolute terms. Hence, the t-statistic is insignificant.

Table 2also provides the unit root test of NYSE-Composite taken at the first difference. The results show that NYSE-Composite too becomes stationary at first difference (t-statistic = 15.907, *p*-value <.0001). Hence, it can be inferred that cointegration analysis may be carried out for assessing the long-run relationship, if any, between the two time series variables since both become stationary at the first difference.

Optimal Lag Selection

We now proceed with selecting the optimal lag length for our variables. Although it may sound reasonable to take 1 to 4 lags for annual and quarterly data and 12 to 36 lags for monthly data, in our case with daily data, however, all the information criteria values including the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SC), the Hannan-Quin Information Criterion (HQ), and all the other statistics including the sequential modified LR test statistic, and the Final Prediction Error (FPE) referred to at *three* being the most suitable number of lags. It is pertinent to note that the when the optimal lag length was traced with higher numbers of lags being entered in the lag selection analysis, the results were confusing as all the information criteria suggested *dissimilar* number of lags for inclusion in the analysis.

Table 3: *Optimal lag length --- Four lags included*

VAR Lag Order Selection Criteria
Endogenous variables: KSE-ALL NYSE-Composite
Sample: 1 2517
Included observations: 2477

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-46125.10	NA	5.13e+13	37.244	37.249	37.246
1	-32053.93	28108.27	5.99e+08	25.886	25.900	25.891
2	-32008.59	90.482	5.79e+08	25.853	25.876	25.861
3	-31989.69	37.704*	5.72e+08*	25.841*	25.874*	25.853*
4	-31987.44	4.473	5.73e+08	25.842	25.884	25.857

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The optimal lag selection has been portrayed in table 3 and, as can be noticed, all the test statistics in the table suggest *three* lags for our study. Therefore, only three lags were included in the analysis of cointegration.

Checking for Cointegration

After determining the appropriate number of lags for incorporation in our analysis, we proceed by checking for the evidence of cointegration between our two time series variables. Table 4 provides results of the two unrestricted cointegration rank tests --- the Trace test and the Maximum Eigenvalue test. The trace test statistic has a value of 17.028 which is significant at .05 level indicating that there is at least one Cointegrating equation at 5% level. Down the table, likewise, we see that the maximum eigenvalue test statistic has a value of 15.283 which is significant at 0.5 level also entailing the existence of at least one Cointegrating equation at the five percent level. Hence, we may establish that KSE-ALL and NYSE-Composite are associated in the long-run.

Table 4: *Checking for Cointegration at a Lag Length of Three*

Included observations: 2477 after adjustments
Series: KSE-ALL NYSE-Composite
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	.006	17.028	15.495	.029
At most 1 *	.0007	1.744	3.841	.186

Trace test indicates 1 cointegrating equation at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	.006	15.283	14.265	.034
At most 1 *	.0007	1.744	3.841	.187

Max-eigenvalue test indicates 1 cointegrating equation at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level

Vector Error Correction Model (VECM)

The unrestricted cointegration rank tests have shown that KSE-ALL and NYSE-Composite do have a long-run relationship. To what extent are they related is not determined yet. In order to measure the degree of the long-run association, we run the Vector Error Correction estimates.

The first part of the VECM model presented in table 5 confirms the existence of a strong long-run association between NYSE-Composite and KSE-ALL. As per the unstandardized beta coefficient, a 1-unit increase in NYSE-Composite translates into a 4.9 units of increase in KSE-ALL. Put it the other way, it can be implied that the previous period's error will be corrected in the following period at an adjustment rate of 492 percent approximately.

It should be noted that although the model depicts a *negative* relationship between these two variables, the relationship, in effect, is *positive* owing to the fact that since the error becomes equal to zero in equilibrium, the actual value of the dependent variable is equal to its estimated value leading to the change in signs of all beta coefficients.

In the second part of the error correction, we have the cointegrating equation between NYSE-Composite and KSE-ALL which is very weakly positive (β = .0006) and highly insignificant (*p*-value = .631). This equation should, for the purpose of determining the cointegration between the two variables, have a negative and significant beta coefficient. An insignificant association here suggests that although there is in the long-run run a relationship between the two variables as per the cointegration test, this relationship is not that strong as per the coefficient of error correction. This connotes if NYSE-Composite increases in the short-run, we may not easily infer that KSE-ALL will also increase simultaneously. It is, however, gratuitous to mention that KSE-ALL is positively and significantly dependent upon its one-period lagged value (β = .157, *t*-stat = 7.772).

Table 5: *Vector Error Correction Model*

Vector Error Correction Estimates
Sample (adjusted): 5 2481
Included observations: 2477 after adjustments
Standard errors in ( ) & t-statistics in [ ]

CointegratingEq:	CointEq1	
KSE-ALL(-1)	1.000	
NYSE-Composite(-1)	-4.915	
	(.620)	
	[-7.926]	
C	30345.86	
Error Correction:	**D(KSE-ALL)**	**D(NYSE-Composite)**
CointEq1	.0006	.002
	(.0009)	(.0005)
	[.631]	[3.863]
D(KSE-ALL(-1))	.157	.018
	(.020)	(.010)
	[7.772]	[1.669]
D(KSE-ALL(-2))	-.012	.002
	(.020)	(.011)
	[-.565]	[.150]

D(KSE-ALL(-3))	.016	-.0006
	(.020)	(.011)
	[.786]	[-.060]
D(NYSE-Composite(-1))	-.019	-.098
	(.038)	(.020)
	[-.495]	[-4.859]
D(NYSE-Composite(-2))	.062	.119
	(.038)	(.020)
	[1.628]	[5.940]
D(NYSE-Composite(-3))	-.067	.019
	(.038)	(.020)
	[-1.750]	[.952]
C	7.742	2.011
	(4.288)	(2.257)
	[1.805]	[.891]

Model Stability

After checking for cointegration, we examine what is called the model stability using the inverse roots of AR characteristic polynomial. Theoretically, the estimated VAR is stable, and hence, stationary, if all roots have a modulus less than one and lie inside the circle. A stable model requires that there are no dots or roots over or outside the circle. In our case, there is only one dot lying over the circle and the rest are all inside it. Therefore, we may infer that our model is stable.

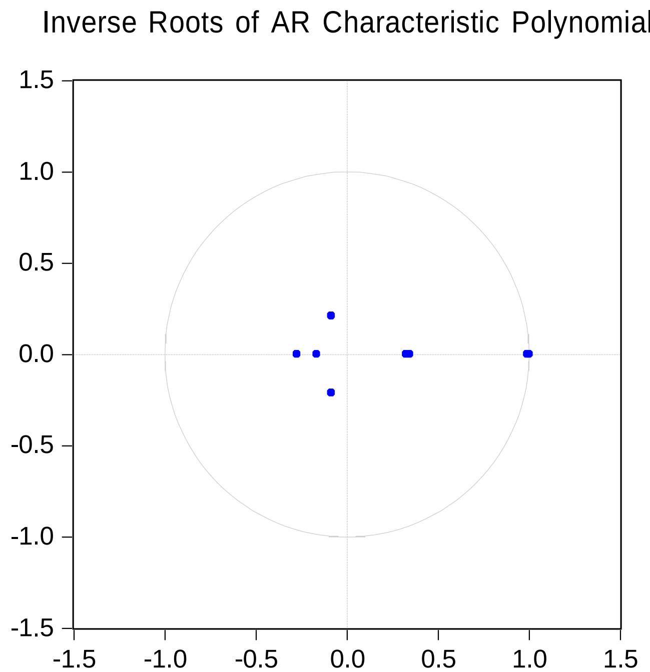

Figure 1: Model Stability

Granger Causality / Block Exogeneity Wald Test

We have so far checked for, and established, the long-run association between our two time series variables. Whether these two indices are related to each other in the short run or not will be checked using the Granger Causality test. The following table depicts results of the said test.

Table 6: *Granger Causality / Block Exogeneity Wald Test*

VEC Granger Causality/Block Exogeneity Wald Tests			
Sample: 1 2517			
Included observations: 2476			
Dependent variable: D(KSE-ALL)			
Excluded	Chi-sq	Df	Prob.
D(NYSE-COMPOSITE)	7.273	4	.122
All	7.273	4	.122
Dependent variable: D(NYSE-Composite)			
Excluded	Chi-sq	Df	Prob.
D(KSE-ALL)	7.634	4	.106
All	7.634	4	.106

The Granger Causality test detects no short-run relationship between the two stock indices. The result is not very unusual as the Cointegrating equation between NYSE-Composite and KSE-ALL given in the vector error correction model (see table 5) was also highly insignificant (and positive as well). Hence, there is no short-term or temporal relatedness between our variables of interest. We cannot forecast changes in one stock index in response to a change in the other index in the short run.

Impulse Responses

In this concluding section of the analysis, impulse response function is displayed to gauge the time contour of the effect of a shock, or an impulse, in NYSE-Composite on the projected future values of KSE-ALL. It shows what will happen to KSE-ALL if there is a one percent shock provided to the model via NYSE-Composite. By examining the graph below, one can potentially comprehend the dynamic linkage between NYSE-Composite and KSE-ALL.

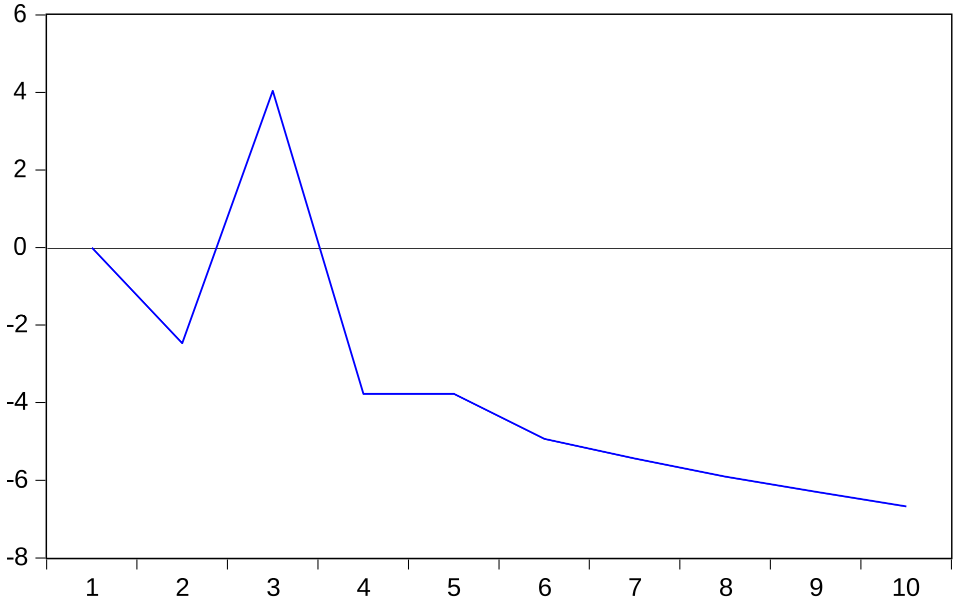

Figure 2: Impulse Response of KSE-ALL to Cholesky One S.D NYSE-Composite Innovation

Conclusion

The aim to this study was to explore whether creating a portfolio consisted of Pakistani and international (primarily US based) stocks would fetch a given investor any diversification benefits. To serve the purpose, an attempt was made to investigate the existence of any relationship --- be it in the long-run or in the short-run, positive or negative --- between our two time series variables, i.e., the NYSE-Composite and the KSE-ALL. The unrestricted cointegration rank tests (both the *trace* and the *maximum eigenvalue*) hinted at the existence of at least one cointegrating equation between these stock indices. The vector error correction model also exhibited a reasonably strong positive association between the two at level. However, at the first difference, the coefficient of the cointegration equation between NYSE-Composite and KSE-ALL was close to zero and highly insignificant. Since for the cointegration to exist, the cointegration equation should be negative and significant at five percent level, therefore a long-run relationship between our two series cannot be established with reasonable accuracy. Finally, the Granger Causality test which was run to determine the existence of any short-run association between the two indices also rendered insignificant results leading us to conclude that no *temporal relatedness* was found between the two. To sum up, it can be held, therefore, that the benefits of international diversification (that can be gained by simultaneously investing in two negatively-correlated or zero-correlated stock markets) can very readily be achieved as no evidences of any significant relationship have been obtained between NYSE-Composite and KSE-ALL, both in the short-run and the long-run, for the period from 2011 until 2020. Although a negative correlation makes diversification even more effective, a zero correlation between the two investments also makes a portfolio robust enough to withstand most economic downfalls. Hence, an investor owning a portfolio of stocks from NYSE-Composite and KSE-ALL can be thought off to be reasonably diversified and one should not expect his or her entire portfolio to get ruined by just one stray bullet.

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