Global Journal of Management and Business Research: A Administration and Management
Volume 21 Issue 12 Version 1.0 Year 2021
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals
Online ISSN: 2249-4588 & Print ISSN: 0975-5853

Design of Portfolio using Multivariate Analysis

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Abstract- Stock markets are considered a barometer of the respective country's economy around the world. Modern portfolio theory advocates diversification for risk management, which helps maintain returns as long as indices around the world are not perfectly correlated. The relationship exists across markets; as a result, co-movement has drawn the attention of individual investors and portfolio managers for the construction of their portfolios to maximize returns for a given level of risk. The study of co-movements provides inputs for portfolio construction and facilitates the identification of markets where indices may move in the same direction or the opposite direction and the country's stock markets that are not correlated. A review of the literature revealed that statistical tools like Correlation, Factor analysis, and Granger causality test, etc., are some of the tools that can be used to understand co-movements of markets. Alan harper et al. (2012) study used principle component analysis and inferred that Indian stock returns are aligned with its trading partners and concluded that maximizing the investors' returns by reducing the risk. Tak Kee Hui concluded that factor analysis provides inputs for selecting foreign markets for risk diversification. This study examines the potential for diversification using 22 world stock market indices using multivariate analysis.

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GJMBR-A Classification: *JEL Code: M19*

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Design of Portfolio using Multivariate Analysis

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Abstract- Stock markets are considered a barometer of the respective country's economy around the world. Modern portfolio theory advocates diversification for risk management, which helps maintain returns as long as indices around the world are not perfectly correlated. The relationship exists across markets; as a result, co-movement has drawn the attention of individual investors and portfolio managers for the construction of their portfolios to maximize returns for a given level of risk. The study of co-movements provides inputs for portfolio construction and facilitates the identification of markets where indices may move in the same direction or the opposite direction and the country's stock markets that are not correlated. A review of the literature revealed that statistical tools like Correlation, Factor analysis, and Granger causality test, etc., are some of the tools that can be used to understand co-movements of markets. Alan harper et al. (2012) study used principle component analysis and inferred that Indian stock returns are aligned with its trading partners and concluded that maximizing the investors' returns by reducing the risk. Tak Kee Hui concluded that factor analysis provides inputs for selecting foreign markets for risk diversification. This study examines the potential for diversification using 22 world stock market indices using multivariate analysis. Few indices have a strong co-movement among the sample indices, and Sensex has a weak correlation with a few indices like Tadawul (Saudi Arabia, Amman SE General (Jordan), BLOM (Lebanon), and MSM (Oman). China, Jordan, Lebanon, Qatar, and Saudi Arabia are weakly correlated with other countries except with the countries geographically associated similarly France, Germany, Belgium, US, Canada, and Mexico are highly correlated, and the rest having moderately correlated. PCA analysis results are consistent with correlation results.

Keywords: diversification. co-movements, factor analysis, portfolio.

I. Introduction

Stock markets worldwide are the most researched topic by different people like portfolio managers, investors, researchers, policymakers and academicians, etc. One of the barometers for measuring the economy is the stock market index. Among the many techniques for risk management, diversification is the one. It can be done by mixing the variety of assets, including stocks and indices which are non –perfectly correlated into a portfolio. Harry Markowitz, a Nobel prize winner, has laid the foundation for Modern Portfolio Theory in 1952. There on investment community started focusing on portfolio risks, expected returns, and diversification and its advantages. Many researchers attempted to understand the stock markets' co-movement of various markets across the globe and selected markets over time. Presently, the topic has become the most popular topic in finance for research. In a globalized economy, the integration of financial markets provides an opportunity to investors, i.e., institutional as well as individual, to generate returns and at the same time manage risk. It gives a platform to strike a balance between risk and return. The integration of various world economies and their liberal policies has provided an opportunity for investors if they wish to diversify. The intention behind the international diversification across countries that are not perfectly correlated is to minimize the variability in the returns on portfolios. Optional risk-reward is also one of the objectives of international diversification as it offers many benefits to all investors around the world. (Mansourfar, et.al, 2010). Stock markets worldwide do not move in the same direction as the country's economic indicators, viz., industrial growth, monetary and fiscal conditions, political scenario, and taxation are unique and specific to the respective country, and returns offered by the markets also vary.

Co-movements of the market's information guide the investors on investment alternatives. A high level of co-movement of stock markets does not benefit from diversification across markets and countries, whereas Low levels of co-movement of stock prices offer investors the benefit of diversifying their holdings across the markets. Diversification strategies can be designed based on acumens of various market co-movements, which affect the risk-return relationship or the expected return from investing in a portfolio of markets. Economists and Capitalists are interested in understanding co-movements of needs. The former is interested in capital movements among countries, and the latter is keen on the effects of co-movements on equity segmentation. (Panton, Lessig, and Joy 1976). For an international investor co-movement of the world, markets are critical for developing a diversification strategy. Many countries have encouraged inflows of capital by having liberal economic policies that result in capital account surplus. Capital market reforms create suitable conditions for investors to take care of risk-return profiles. The present work emphasizes examining an opportunity to investors, both retail and institutional, for diversification by considering 22 world stock indices using multivariate analysis. Alan Harper and Zhenhu Jin

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(2012) concluded that investors could diversify their portfolios to increase their returns while managing the risk, which has been adopted for the present study.

II. Review of Literature

The inter-relationship between national stock markets has been the subject of several papers in the general area of investment management and international finance research. Apart from exploring and presenting the relationship between national stock markets, these papers have helped develop essential tools necessary for the statistical analysis of correlation structure. Numerous studies have been conducted to explore the linkages among various financial markets around the world. Integration of world markets has provided many opportunities to the investors to look for different investments options across world markets to manage risk and returns. Diversification is a strategy to manage the risk that investors can use by understanding other stock markets globally. As risk diversification is the primary concern for most investors, they tend to look into the possibility of widening their investment choices across the countries or creating a region-based investment strategy. This requires the understanding of regional and global linkages of stock markets.

Abbas Valadkhani et al. (2008) investigated the relationship among the selected 13 stock markets returns. To understand the co-movements, the authors deployed principle components analysis and maximum likelihood methods on the monthly data from 1987 to 2007. The authors found that stock markets in the Asian countries are correlated highly, and factor analysis proved a well-defined common factor, and both the methods like ML and PC have provided similar results. Alan Harper and Zhenhu Jin (2012) study was conducted to find the linkage between Indian stock market returns with its eleven major trading partners. Monthly stock data for 11 years, i.e., 2000 to 2010, was used for analysis and found that investors can enhance their returns by managing the risks in India's trading partners' country's stock markets. Principle component analysis has been used and inferred that Indian stock returns are aligned with its trading partners. Hence, investors can diversify their investments by choosing the country's stock indices to improve their returns and minimize risk.

Maran Marimuthu (2010) has examined the co-movements of the Asian markets with developed markets by considering Malaysian, Indian, Chinese, the US, and the UK equity markets using Statistical models like Johansen multivariate cointegration, Vector Error Correction Model, and Granger causality test. The author found that there is a long-run relationship among the regional markets. Malaysia and India Granger cause each other. There is no role of China in the regional market. In addition, shocks in one country seem to affect other countries briefly in the Asian context. Maran has concluded that the US market is still the main influential factor in the Asian markets. Wen-Chung Guoa and Hsiu-Ting Shihb (2008) investigated the co-movement of stock prices and its association with herd behavior during a period of high-tech mania using daily equity returns for each stock. The analysis consists of return dispersion, volatility dispersion, and the directional co-movement of stock prices for a sample of 443 stocks from January 1996 to December 2000, covering industries like electronics, the Internet, communication, etc., semiconductors. The authors found that both return dispersion and volatility dispersion correlate with extreme market movements for high-tech stocks. It was found that herding, measured by directional co-movement, is more prevalent in high-tech industries than traditional economic industries. It also found an asymmetric result that herding has tremendous significance during extreme up markets.

Tak-Kee Hui (2005) studied the possibility of Singaporean investors diversifying into US and Asia Pacific markets. Factor analysis was performed on weekly data for the ten stock market indices, covering the period January 1990 to June 2001 to investigate the systematic covariation of the stock market returns to select markets for a Singaporean investor to invest in. Tak suggested that Singaporean investors or portfolio managers select relatively large and well-developed markets for risk diversification and invest in the USA, Australia, and Japan markets. In addition to that, there would not be any significant risk reduction by investing in the Hong Kong, Philippines, South Korea, Thailand, and Singapore markets simultaneously. Therefore, a Singaporean investor can invest in the USA, Australia, Japan, and Taiwan. Kivilcim Metin and Gulnur Muradoglu (2001) focus is forecasting stock returns in emerging markets using their interrelations to significant world stock exchanges and regional counterparts by using international co-movements for weekly stock prices by employing the Engle–Granger (1987) two-step cointegration technique. Kivilcim et al. found that unconditional variances were much higher for emerging markets than their mature counterparts. All national markets are cointegrated with the world leaders and other emerging markets according to their geographical proximity.

Jorg Bley (2007) focused on determining the contemporary interactions of the stock markets of Bahrain, Egypt, Israel, Jordan, Kuwait, Lebanon, Morocco, Oman, Palestine, Qatar, Saudi Arabia, Tunisia, Turkey, and the United Arab Emirates by using daily historical prices for a period ranging from 1/2000 to 12/2004. The data series is divided into two sub-periods, the first period includes 130 weekly observations, and the second period covers the subsequent 128 weeks. The author found that changing stock market dynamics

within the Middle East and North African (MENA) countries region still yield substantial intraregional diversification benefits and suggest the inclusion of regional equity in a global portfolio. In addition, Jorg opinioned that Gulf Cooperation Council (GCC) stock markets are likely to achieve the highest level of homogeneity within the MENA region, as its economies are increasingly synchronized in preparation for an economic union and may lead to a greater level of self-sufficiency of the regional economies which could translate into the manifestation of the currently low external stock market dependency.

Kedarnath Mukharjee and RK Mishra (2007) studied how Indian equity markets responded to the world markets movements and tried to examine the interdependencies of markets worldwide by considering daily closing prices of all the major equity indices for a period of 16 years starting from 1990 to 2005. Twenty-three countries are taken for the study to find co-movements of prices among the markets using Geweke measures of feedback. The annual feedback measures indicated that a significant same day relationship among the stock markets in India with that of almost all other foreign countries considered in the study and also found that there is a degree of integration among the markets over some time, resulting in a higher co-movement of prices among markets and therefore higher market efficiency at the international market scenario.

Shaista Wasiuzzaman and Lim Ai Li (2009) examined whether co-movements between stock markets exist for four stock markets included in this study: Malaysia, Singapore, the US, and Japan. The indices used are Kuala Lumpur Composite Index (KLCI), Straits Times Index (STI), Standard and Poor's 500 (S&P 500), and Nikkei 225 for Malaysia, Singapore, the US, and Japan, respectively. The sample has been considered based on the liquidity criterion measured by a stock's average daily traded value. The period of investigation spans January 2000-December 2006. The observations consist of the daily returns of each stock market. Daily returns are used instead of weekly or monthly returns because daily returns are more capable of capturing all possible interactions. The study used three methods to examine the linkages or co-movements, namely, correlation analysis, cointegration analysis, and Granger causality test. The results of the correlation analysis suggest that financial market linkages are weak among the four countries undertaken in this study. Cointegration tests reveal that there is a long-run relationship as there is at most a single cointegrating vector. Finally, the Granger causality test shows that most stock markets influence the other stock markets. Overall, the four stock markets seem to have financial market linkages or co-movements.

Preeti Sharma (2011) studied the issue of co-movement between Asian emerging stock markets and developed economies using cointegration and correlations in the index returns using Six years' weekly data of 8 Asian Stock Markets and United States of America for the period of six years, spans from January 2002 to December 2007. The author found that among the selected Asian markets, the highest positive correlation is found between Singapore and the Philippines, followed by Singapore and Malaysia and the Philippines and Malaysia. This signifies that Singapore, the Philippines, and Malaysia are the economies whose stock markets usually move in tandem. Japan and China, followed by the United States of America and China, have the most minor correlation among the sample. But as the economies are undergoing different reforms and fundamentals keep on changing, the author cautioned that due care should be taken while making investment decisions.

Searat Ali et al. (2011) study investigated the co-movement of Pakistan's Equity Market with the markets of India, China, Indonesia, Singapore, Taiwan, Malaysia, Japan, USA, and the UK by using a cointegration test on monthly stock prices from the period of July 1998 to June 2008. The results disclosed that there is no co-movement of Pakistan's equity market with the UK, USA, Taiwan, Malaysia, and Singapore markets. In contrast, the stock prices of the Pakistan equity market move together with the stock prices of India, China, Japan, and Indonesia; hence there is no scope of risk minimization for investors through diversification of international markets in these countries. Furthermore, the authors found that the role of the stock exchange structure is not found in the co-movement of the Pakistan stock market with the selected stock markets.

Razan Salem et al. (2011) focused on examining significant portfolio benefits diversification internationally, especially for middle east investors. The authors considered developed markets like USA, Germany, and Japan and a few developing markets, including Oman, for the study by taking daily data from 2008 to 2010. By using statistical tools like correlation and partial correlation, it was found that investors in the middle east can enjoy the benefits of international portfolio diversification despite regional political uncertainties and uncertainties at the global level, including financial. The authors recommended that middle-east investors consider including Brazil, Jordan, Japan, and Oman markets as part of constructing an international portfolio.

Rajesh Chakrabarti examined the nature of regional inter-dependence among selected Asian stock markets and that among selected European markets before and during the Asian crisis while looking at both the "spillover" angle of stock market interrelationship as well as the evolution of the correlation structure over time. The data consists of daily close-to-close returns for eight East Asian developing countries and eight West European developed countries. The East Asian

countries are Hong Kong, Indonesia, South Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand. In contrast, the European countries are France, Germany, Italy, the Netherlands, Portugal, Spain, Switzerland, and the United Kingdom. This gives us two groups of equal size for comparison purposes. Because we use groups of neighboring countries and the time zone difference within either group does not exceed 2, issues of lead-lag structure for studying volatility spillovers and covariance are not critical for us, and current data can be used for this study. The data covers five years from 12/31/93 to 12/31/98. Thus, we have 1305 data points in our sample. We consider 7/2/97 to be the beginning of the Asian crisis. In our study, we look at the correlation structure of the eight Asian countries and compare it with the correlation structure among the European countries.

Salim M Darbar and Partha Deb (1997) investigated the co-movements of equity returns for indices of four major equity markets, namely Toronto 300 share index, Topix, the financial times stock exchange 100 shares, and S&P 500 index for a period of 1 Jan 1989 to 31 Dec 1992 by using Multivariate GARCH framework. The authors found that the US and Japan have transitory correlations, but there is no evidence of permanent correlation, and conditional correlations can change considerably in reaction to the news. Portfolios can be adjusted based on the variations shown in correlations. Michel Beine and Bertrand Candelon (2007) examined the impact of trade and financial liberalization on the degree of stock market co-movement among emerging economies using a sample of 25 developing countries observed over 15 years. The authors estimate the impact of reforms that aim at opening these countries to trade and financial channels to the rest of the world. Estimating time-varying cross-country correlations allows the econometric investigation to be performed using a panel data framework, raising the quality of the statistical inference. Our results offer strong support in favour of a positive impact of trade and financial liberalization reforms on the degree of cross-country stock market linkages.

Ritesh Patel (2017) found that various investors like Foreign institutional investors, High net worth individuals, institutional investors, retail investors derive an advantage in diversifying the fourteen stock markets that the author considered in the study. The author used the Johnsen cointegration test to find the relationship among the selected stock markets and found a long-term relationship among the selected stock markets. The Granger causality test proved that BSE returns are affected by BVSP, FTSE-100, and MXX. The author suggested that investors take their portfolio investment decision by observing the long- and short-term markets integration Indian market.

III. Rationale for the Study

The literature review revealed that many studies had been carried out to understand the co-movements and integration of the various stock markets. The studies focused more on American, European, Asia, and Asia Specific markets, but limited work has been done covering Asia Pacific, Europe, American, and Middle East markets. Hence, the present study included middle east markets apart from the other world markets. The study's findings can be used by the retail and institutional investors, especially the Indian investors, for designing their portfolio and those who are seeking other than their markets for risk minimization. This study has been carried out to investigate the potential for diversification into various stock indices by using the concept of cointegration and co-movement among world stock markets. One of the well-known multivariate analysis techniques, like factor analysis, has been used in the study to understand the relationship among the latent variables. It obtains a reduced set of uncorrelated latent variables using a set of linear combinations of the original variables to maximize the variance of these components, and few studies have been conducted using the Principle Component analysis and Maximum Likely hood methods (Abbas Valadkhani et al. 2008). Factor analysis is used to determine the co-movements among the 22 selected world markets covering major continents like Asia, Asia Pacific, Europe, North America, America, Belgium, etc. Alan Harper and Zhenhu Jin's (2012) approach has been adopted for the present study.

IV. Methodology of the Study

Monthly indices data for the period from1 Jan 2000 to 31 Dec 2018 are used in the present study. Twenty-two stock markets indices were considered for the study. They are ASX 200 (Australia), Nikkei 225 (Japan), KOSPI (South Korea), Hang Seng (Hong Kong), Jakarta Composite Index (Indonesia), SSE Composite Index (China), Taiwan Capitalization Weighted Stock Index, Sensex (India), Amman SE General (Jordan), BLOM(Lebanon), QE General (Qatar), MSM 30(Oman), Tadawul (Saudi Arabia), Tel Aviv (Israel), CAC 40 (France), DAX 30 (Germany), BEL 20 (Belgium), Euronext 100, DJIA (United States), TSE (Canada), BOVESPA (Brazil) and BMV (Mexico). The monthly returns have been calculated and tested their stationary by using ADF and PP tests. Factor analysis conceptually helps identify the variables that have similar patterns associated with the latent factor or variable. Factor analysis traditionally assumes that there is no unit root in time series data. This model is well known multivariate analysis model (Hair et al., 1998; Tabachnick and Fidell, 2001; Tsay, 2002). Similarly, the same concept can be used to identify the markets which are associated and not associated. This information is

vital for the design portfolio. The linear combination of stock market returns accounts for the variance in the data as a whole Alan Harper and Zhenhu Jin (2012).

V. Empirical Results

In this section, quantitative results obtained from the statistical analysis have been presented in the below tables. Various tests conducted are: correlations test, KMO test, component matrix test, communalities test, and rotated component matrix test.

Table 1: Results of Correlations among 22 stock markets

	ASX 200(Australia)	Nikkei 225(Japan)	KOSPI(South Korea)	Hang Seng (Hong Kong)	Jakarta Composite Index(Indonesia)	SSE Composite Index(China)	Taiwan Capitalization Weighted Stock Index	Sensex(India)	Amman SE General(Jordan)	BLOM(Lebanon)	QE General(Qatar)	MSM 30(Oman)	Tadawul(Saudi Arabia)	Tel Aviv(Israel)	CAC 40(France)	DAX 30(Germany)	BEL 20(Belgium)	Euronext 100	DJIA(United States)	TSE(Canada)	IBOVSPA(Brazil)	BMV(Mexico)
ASX	1	.627**	.557**	.633**	.436**	.198**	.477**	.507**	.120**	.006	-.050	.163**	.170**	.420**	.663**	.613**	.627**	.681**	.613**	.662**	.500**	.555**
Nikkei	.627**	1	.590**	.605**	.390**	.211**	.481**	.490**	.126**	-.028	-.053*	.127**	.202**	.344**	.604**	.592**	.529**	.613**	.542**	.534**	.422**	.445**
KOSP	.557**	.590**	1	.650**	.438**	.203**	.647**	.534**	.109**	-.014	.018	.044	.111**	.399**	.517**	.542**	.443**	.522**	.470**	.509**	.486**	.525**
Hang	.633**	.605**	.650**	1	.456**	.340**	.574**	.595**	.125**	-.030	-.009	.118**	.132**	.416**	.594**	.590**	.538**	.609**	.522**	.563**	.512**	.544**
Jakart	.436**	.390**	.438**	.456**	1	.198**	.390**	.430**	.162**	.076**	.037	.189**	.146**	.313**	.341**	.343**	.370**	.366**	.289**	.368**	.366**	.348**
SSE	.198**	.211**	.203**	.340**	.198**	1	.223**	.153**	.031	.012	.043	.095**	.112**	.162**	.150**	.158**	.151**	.157**	.137**	.133**	.162**	.112**
Taiwa	.477**	.481**	.647**	.574**	.390**	.223**	1	.447**	.091**	.021	.014	.081**	.114**	.313**	.450**	.451**	.379**	.458**	.398**	.449**	.424**	.404**
Sens	.507**	.490**	.534**	.595**	.430**	.153**	.447**	1	.122**	.028	.018	.088**	.128**	.356**	.493**	.504**	.474**	.506**	.429**	.477**	.429**	.457**
Amm	.120**	.126**	.109**	.125**	.162**	.031	.091**	.122**	1	.065*	.011	.259**	.231**	.126**	.087**	.110**	.114**	.099**	.074**	.073*	.081**	.065*
BLOM	.006	-.028	-.014	-.030	.076**	.012	.021	.028	.065*	1	.037	.078**	.045	.023	.013	-.003	.021	.017	-.017	.029	-.036	-.002
QE	-.050	-.053*	.018	-.009	.037	.043	.014	.018	.011	.037	1	.016	.028	.054*	-.081**	-.079**	-.041	-.075**	-.071*	-.075**	-.056*	-.030
MSM	.163**	.127**	.044	.118**	.189**	.095**	.081**	.088**	.259**	.078**	.016	1	.349**	.190**	.137**	.105**	.153**	.144**	.092**	.135**	.075**	.029
Tada	.170**	.202**	.111**	.132**	.146**	.112**	.114**	.128**	.231**	.045	.028	.349**	1	.169**	.180**	.166**	.161**	.182**	.124**	.129**	.109**	.048
Tel	.420**	.344**	.399**	.416**	.313**	.162**	.313**	.356**	.126**	.023	.054*	.190**	.169**	1	.392**	.399**	.353**	.400**	.333**	.365**	.305**	.323**
CAC	.663**	.604**	.517**	.594**	.341**	.150**	.450**	.493**	.087**	.013	-.081**	.137**	.180**	.392**	1	.918**	.844**	.985**	.767**	.725**	.573**	.635**
DAX	.613**	.592**	.542**	.590**	.343**	.158**	.451**	.504**	.110**	-.003	-.079**	.105**	.166**	.399**	.918**	1	.802**	.918**	.765**	.680**	.576**	.640**
BEL	.627**	.529**	.443**	.538**	.370**	.151**	.379**	.474**	.114**	.021	-.041	.153**	.161**	.353**	.844**	.802**	1	.876**	.711**	.622**	.483**	.543**
Euron	.681**	.613**	.522**	.609**	.366**	.157**	.458**	.506**	.099**	.017	-.075**	.144**	.182**	.400**	.985**	.918**	.876**	1	.789**	.730**	.565**	.644**
DJIA	.613**	.542**	.470**	.522**	.289**	.137**	.398**	.429**	.074**	-.017	-.071*	.092**	.124**	.333**	.767**	.765**	.711**	.789**	1	.698**	.547**	.655**
TSE	.662**	.534**	.509**	.563**	.368**	.133**	.449**	.477**	.073*	.029	-.075**	.135**	.129**	.365**	.725**	.680**	.622**	.730**	.698**	1	.614**	.623**
IBOVS	.500**	.422**	.486**	.512**	.366**	.162**	.424**	.429**	.081**	-.036	-.056*	.075**	.109**	.305**	.573**	.576**	.483**	.565**	.547**	.614**	1	.612**
BMV	.555**	.445**	.525**	.544**	.348**	.112**	.404**	.457**	.065*	-.002	-.030	.029	.048	.323**	.635**	.640**	.543**	.644**	.655**	.623**	.612**	1
**. Correlation is significant at the 0.01 level (1-tailed).																						
*. Correlation is significant at the 0.05 level (1-tailed).																						

Source: Authors calculations

Table 1 depicts stock market returns correlation with all the sample countries in the study. Sensex is correlated among the sample ranging from weak to highly correlated. Further, it can be inferred that Sensex has a weak correlation with few indices like Tadawul (Saudi Arabia, Amman SE General (Jordan), BLOM (Lebanon), and MSM (Oman). A geographical and economic association is one of the critical drivers for having such a relation. From the results depicted in Table 1, China, Jordan, Lebanon, Qatar, and Saudi Arabia are weakly correlated with other countries except with the countries geographically associated similarly France, Germany, Belgium, US, Canada, and Mexico are highly the rest having moderately correlated.

Table 2: Results of KMO Measure and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.940
Bartlett's Test of Sphericity	Approx. Chi-Square	15311.880
	Df	231
	Sig.	.000

Source: Authors calculations

For measuring the sample adequacy, the Kaiser-Meyer-Olkin (KMO) statistical method can be used, which measures the proportion of variance in the data variables that underlying factors might cause.

Values close to 1 generally indicate that the factor analysis is helpful for the present study data. As the KMO measure of sampling, adequacy was as high as the measure of .940, which is excellent as per the review of the literature, and it is an indication that the study can proceed with Principle Component Analysis and the Bartlett test of sphericity

Table 3: Results of Total Variance explained

Total Variance Explained									
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.285	42.206	42.206	9.285	42.206	42.206	6.999	31.812	31.812
2	1.673	7.605	49.811	1.673	7.605	49.811	3.616	16.436	48.248
3	1.401	6.370	56.181	1.401	6.370	56.181	1.697	7.714	55.962
4	1.021	4.641	60.822	1.021	4.641	60.822	1.069	4.860	60.822
5	.959	4.357	65.179						
6	.921	4.188	69.368						
7	.769	3.498	72.865						
8	.731	3.322	76.188						
9	.711	3.232	79.419						
10	.661	3.004	82.423						
11	.611	2.778	85.201						
12	.531	2.415	87.616						
13	.504	2.290	89.906						
14	.393	1.786	91.692						
15	.386	1.754	93.446						
16	.329	1.494	94.941						
17	.294	1.336	96.276						
18	.287	1.305	97.582						
19	.251	1.139	98.721						
20	.181	.821	99.542						
21	.089	.405	99.947						
22	.012	.053	100.000						
Extraction Method: Principal Component Analysis.									

Source: Authors calculations

The co-movements of stock market returns can be examined using the Principle Component analysis, a multivariate technique that helps in reducing the number of variables. Precisely it reduces the number of factors through observed correlations among the variables or factors. The above table 3 shows variance explained in each of the factor(s). It can be observed from the above-stated results that four factors have an Eigenvalue greater than one. The cumulative percentage of the summation of percentage variance for factor 1 is 42.206, for factor 2 is 49.811, for factor 3 is 56.181, and for factor 4 is 60.822. This analysis helped to find out an optimal number of factors, i.e., four.

Table 4: Results of Component Matrix

Component Matrix[a]				
	Component			
	1	2	3	4
ASX 200(Australia)	.801			
Nikkei 225(Japan)	.737			
KOSPI (South Korea)	.723		-.390	
Hang Seng (Hong Kong)	.782			
Jakarta Composite Index (Indonesia)	.535	.352		
SSE Composite Index (China)		.307		
Taiwan Capitalization Weighted Stock Index	.632		-.385	
Sensex (India)	.666			
Amman SE General (Jordan)		.514		
BLOM (Lebanon)				.780
QE General (Qatar)				.518
MSM 30 (Oman)		.590	.446	
Tadawul (Saudi Arabia)		.541	.404	
Tel Aviv (Israel)	.520			
CAC 40 (France)	.893			
DAX 30 (Germany)	.876			
BEL 20 (Belgium)	.816			
Euronext 100	.906			
DJIA (United States)	.806			
TSE (Canada)	.807			
IBOVSPA (Brazil)	.697			
BMV (Mexico)	.743			
Extraction Method: Principal Component Analysis.				
a. 4 components extracted.				

Source: Authors calculations

The component matrix results in table 4 above; many of the stock markets results are highly correlated with factor 1 followed by factor 2, factor 3, and factor 4. In factor 1, Indian stock market returns are correlated with many world stock market returns covering South Asia and European countries.

Table 5: Results of Communalities

Communalities		
	Initial	Extraction
ASX 200(Australia)	1.000	.645
Nikkei 225(Japan)	1.000	.579
KOSPI (South Korea)	1.000	.690
Hang Seng (Hong Kong)	1.000	.723
Jakarta Composite Index (Indonesia)	1.000	.469
SSE Composite Index (China)	1.000	.280
Taiwan Capitalization Weighted Stock Index	1.000	.577
Sensex (India)	1.000	.518

Amman SE General (Jordan)	1.000	.381
BLOM(Lebanon)	1.000	.677
QE General (Qatar)	1.000	.382
MSM 30(Oman)	1.000	.592
Tadawul (Saudi Arabia)	1.000	.539
Tel Aviv (Israel)	1.000	.345
CAC 40(France)	1.000	.907
DAX 30(Germany)	1.000	.852
BEL 20(Belgium)	1.000	.767
Euronext 100	1.000	.925
DJIA (United States)	1.000	.749
TSE(Canada)	1.000	.680
IBOVSPA(Brazil)	1.000	.503
BMV(Mexico)	1.000	.604
Extraction Method: Principal Component Analysis.		

Source: Authors calculations

Table 5 shows communalities which can be between 0 to 1, and the values reported in the above table indicate that all initial communalities have a value of 1; hence it can be inferred that the common factors explain all of the variances in the stock market returns among the sample markets Alan Harper and Zhenhu Jin (2012).

Table 6: Results of Rotated Component Matrix

Rotated Component Matrix[a]				
	Component			
	1	2	3	4
ASX 200 (Australia)	.645			
Nikkei 225 (Japan)	.531	.516		
KOSPI (South Korea)		.716		
Hang Seng (Hong Kong)		.693		
Jakarta Composite Index (Indonesia)		.583		
SSE Composite Index (China)		.508		
Taiwan Capitalization Weighted Stock Index		.685		
Sensex (India)		.566		
Amman SE General (Jordan)			.604	
BLOM (Lebanon)				.802
QE General (Qatar)				.576
MSM 30 (Oman)			.764	
Tadawul (Saudi Arabia)			.722	
Tel Aviv (Israel)				
CAC 40 (France)	.926			
DAX 30 (Germany)	.891			
BEL 20 (Belgium)	.849			
Euronext 100	.933			
DJIA (United States)	.845			
TSE (Canada)	.768			
IBOVSPA (Brazil)	.596			
BMV (Mexico)	.701			
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 5 iterations.				

Source: Author calculations

The rotated component matrix results are depicted in Table 6 above, and the findings show that the first factor has large weights for France, Germany, Belgium, Euronext, US, Canada, Mexico, which can be concluded that these stock market returns are highly correlated and designing a portfolio using these markets indices will not help to derive the diversification benefits. The second factor extracted countries like India, Taiwan, China, Japan, South Korea, Hong Kong, and Indonesia are correlated. The third factor extracted countries like

Saudi Arabia, Oman, and Jordan, and the last factor has only two countries like Lebanon and Qatar. Hence, it can be inferred that constructing a portfolio using countries under each of the factors will not benefit the portfolio. Hence, while designing the portfolio, investors and institutions should include a country stock index from all four factors to diversify. For example, a portfolio could have indices like DJIA, SSE Composite Index, MSM 30, and BLOM. The factors also have geographical diversification, which helps in deriving the advantage.

VI. Conclusion

The correlation values in the study find that Sensex has a weak relationship with few indices and strong relationships with other stock market indices. Sensex has a weak correlation with few indices like Tadawul (Saudi Arabia), Amman SE General (Jordan), BLOM(Lebanon), and MSM (Oman). Rotated component matrix results concur with it because these markets indices have fallen in a different factor. Hence investors, including institutions in India, can use this grouping of the indices while constructing their portfolios. For instance, an investor designed a portfolio using indices like ASX 200 (Australia), Nikkei 225 (Japan), CAC 40 (France), DAX 30 (Germany), BEL 20 (Belgium), Euronext 100, DJIA (United States), etc., the benefits of diversification are minimal. Though the number of indices is included, their correlations are high and fall in the same factor. Hence, investors need to design portfolios by considering factor 1, factor 2, factor 3, and factor 4 to have wide diversity. As these countries are geographically and economically spread out, the investor can enjoy the risk and return portfolio benefits.

References Références Referencias

1. Abbas Valadkhani et al (2008), A factor analysis of international portfolio diversification, Studies in Economics and Finance, Vol. 25 No. 3, pp. 165-174, DOI 10.1108/108673708108946
2. Alan Harper and Zhenhu Jin (2012), Comovements and Stock Market Integration between India and its top trading partners: A Multivariate analysis of International Portfolio Diversification, International Journal of Business and Social Science, Vol.3. No.3, Feb 2012.
3. Jorg Bley (2007), How Homogeneous are the Stock Markets of the Middle East and North Africa? Quarterly Journal of Business & Economics, Vol. 46, No. 3, pp. 3-26.
4. Kedarnath Mukharjee and RK Mishra (2007), International stock market integration and its economic determinants: A study of Indian and World equity markets, Vikalpa, Volume 32, No 4, October – December 2007, pp. 29-44.
5. Kivilcim metin and Gulnur muradoglu (2001), Forecasting Integrated Stock Markets Using International Co-Movements Russian and East European Finance and Trade, vol. 37, no. 5, September–October 2001, pp. 45–63.
6. Komlavi Elubueni Assidenou (2011), "Cointegration of Major Stock Market Indices during the 2008 Global Financial Distress, International Journal of Economics and Finance, Vol. 3, No. 2; May 201, pp 212-222.
7. Mansourfar, G., Mohamad, A., and Hassan, T. (2010). "A review on international portfolio diversification in Middle East and North African region". African Journal of Business Management. vol. 4. No. 19. pp 4167-4173. www.academic journals.org/AJBM.
8. Maran Marimuthu (2010), The Co-Movements of the Regional Stock Markets and Some Implications on Risk Diversification, The IUP Journal of Applied Economics, Vol. IX, No. 2.
9. Michel Beine and Bertrand Candelon (2007), Liberalization and Stock Market Co-Movement Between Emerging Markets, CESIFO Working Paper No. 2131category 6: Monetary Policy and International Finance October 2007.
10. Panton DB, Lessig P, and Joy OM (1976), Co-movement of international equity markets: A taxonomic approach, Journal of Financial and Quantitative Analysis, 11(3), 415-433.
11. Preeti Sharma (2011), "Asian emerging economies and united states of America: Do they offer a diversification benefit?", Australian Journal of Business and Management Research, Vol.1 No.4, pp. 85-92.
12. Rajesh Chakrabarti, Co-movements among National Stock Markets in a Region: A Comparison of Asia and Europe, Retrieved from https://pdfs. semanticscholar.org/3821/156e445ff13c2089d4d1c 6b7971b451839e4.pdf.
13. Razan Salem, Thair Al Shaher and Ohoud Khasawneh (2011), "International Portfolio Diversification Benefits for Middle Eastern Investors", Journal of Money, Investment and Banking ISSN 1450-288X Issue 22. http://www. eurojournals.com/JMIB.htm
14. Ritesh Patel (2017), Co-Movement and Integration Among Stock Markets: A Study of 14 Countries, Indian Journal of Finance, Volume 11, Issue 9, September 2017, DOI: 10.17010/ijf/2017/v11i9/11 8089.
15. Salim M Darbar and Partha Deb, Co-Movements in International Equity Markets, The Journal of Financial Research, Vol XX, No.3, Fall 1997, pp. 305-322.
16. Searat Ali, Babar Zaheer Butt and Kashif ur Rehman (2011), Comovement Between Emerging and Developed Stock Markets: An Investigation Through Cointegration Analysis, World Applied Sciences Journal 12 (4), pp. 395-403.

17. Shaista Wasiuzzaman and Lim Ai Li (2009), Linkages Between the Malaysian Stock Market and Some Selected Markets, The ICFAI University Journal of Financial Economics, Vol. VII, No. 1, 2009, pp. 22-35.
18. Tak-Kee Hui (2005), Portfolio diversification: a factor analysis approach, Applied Financial Economics, 15, 821–834.
19. Wen-Chung Guoa and Hsiu-Ting Shihb (2008), The co-movement of stock prices, herd behaviour and high-tech mania, Applied Financial Economics, 18, 1343–1350.