COMOVEMENTS AND STOCK MARKET INTEGRATION BETWEEN INDIA AND ITS TOP TRADING PARTNERS: A MULTIVARIATE ANALYSIS OF INTERNATIONAL PORTFOLIO DIVERSIFICATION

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Abstract

It has been documented that strong (weak) comovements between stock markets provide less (more) diversification opportunities for investors. This study seeks to determine empirically if investors of Indian stock market can further diversify their portfolios by investing in the stock markets of India's top trading partners.. This study uses data from India and its major trading partners to conduct principle component analysis. We find that India investors can further diversify their portfolios by investing in the stock markets of a few of its major trading partners.

Key Words: Stock Markets, Factor Analysis, India, Portfolio Investments

1. INTRODUCTION

The mean–variance relationship that exists in the international equity markets as a result of comovements has drawn the attention of investors seeking diversification. Investors constantly seek diversification opportunities to maximize the expected rate of return. That is the basis of modern portfolio theory. As the economies around the world become more integrated and the developing countries open their emerging markets, more diversification opportunities become available to both individual and institutional investors. At the heart of this phenomenon are the comovements in assets prices and stock market integration, which have been studied extensively in international finance (Bai& Green, 2010; Bekeart& Harvey, 1995; Bekeart, Hodrick,& Zhang, 2009; Errunza, Hogan, & Hung, 1999; Jin, 2005; G. Meric, Ratner, &Meric, 2007; Puthuanthong& Roll, 2009). *Comovements* are defined "as the movement of assets that is shared by all assets at time *t*" (Baur, 2003, p. 2).

The study of comovements in asset prices provides significant insight into possible diversification strategies that impact the risk–return relationship or the expected return from investing in a portfolio of stocks. Asset pricing theory provides the theoretical framework for analyzing comovements and stock market integration. Ifcomovementsamong markets become stronger, opportunities for diversification and the benefits will be reduced (Ilano&Bruneau, 2009). Understanding market comovements are important for other reasons. Economists are interested in comovements because comovements may affect the flow of capital between countries. Capital market theorists are interested in this because it affects equity market segmentation (Panton, Lessig, & Joy, 1976).Also, integration in stock markets is important as well. According to Onour (2010), "Integration in stock markets may provide some advantage in terms of gains in market efficiency but also entails potential pitfalls. Greater integration among stock markets implies stronger comovements between markets, thereby reducing the opportunities for diversification" (p. 30). This has implications for assembling efficient portfolios.

Although the study of comovements and stock market integration has been well documented in the literature with respect to developed markets, emerging markets such as India has received less attention (Modi, Patel, & Patel, 2010; Wong, Agarwal, & Du, 2004).The purpose of this study is to investigate the relationships in stock market returns between India and its major trading partners (China, Germany, Hong Kong, Israel, Malaysia, Netherlands, Singapore, Switzerland, U.K., and U.S.).

We use monthly return data from January 2000 to December 2010. The indexes used in this study are SSE Composite, DAX, HengSeng, SENSEX, TA 100, KLSE, AEX, Strait Times, SSMI, FTSE 100, and S&P 500 from January 2000 to December 2010. Monthly returns of each index are calculated and are used to perform a principle component analysis. The paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 describes the data. Section 4 discusses the methodology. Section 5 discusses the empirical results followed the conclusion.

2. LITERATURE REVIEW

The Indian stock market provides a unique perspective for analyzing comovements and stock market integration because of its burgeoning economy and its subsequent linkages to other economies. For instance, Modi et al. (2010) examined the stock market indices of India, Hong Kong, China, Mexico, Brazil, the UK, and the United States from July 1, 1997, to June 30, 2008. Using a multivariate analysis consisting of cointegration and principal component analysis, they found that low correlations exist between Indian stock markets and Mexico, the UK, and the United States.Modi et al. also found that the lowest correlations exist between the India (SENSEX) and U.S. (NASDAQ) stock exchanges. The implications are that investors can diversify their portfolios by investing in stocks listed on the SENSEX and NASDAQ simultaneously.

Wong et al. (2004) observed this relationship by evaluating the long run and short run relationship and linkages between the Indian Stock Exchange (BSE 200) and the United States (S&P 500), Japan (Nikkei 225), and UK (FTSE 100) from January 1, 1991, to December 31, 2003. Wong et al. found that the Indian stock market is integrated with developed markets and sensitive to dynamics in these markets in the long run. The researchers also found that short-run stock returns in the United States and Japan Granger cause Indian stock markets but not the opposite. Granger causality is a technique that examines the relationship between two or more time series by examining whether times series are cointegrated over both the short and long run. Valadkhani,Chancharat, and Harvie (2008) studied the relationships between the stock market returns of 13 countries using principle component analysis. Monthly data from 1987 to 2007 was examined for correlations using Morgan Stanley Capital International Database. Valadkhaniet al. found that high correlations exist between countries located in the same geographic region primarily Asia. Additionally, correlations were found to be high in developing countries as well.

These findings suggest that geographic and economic development do matter with respect to comovements of stock returns and has implications for financial portfolio diversification and reducing systemic risk. In other words, high correlations depict less diversification opportunities. The implications are that investors should seek diversification opportunities where correlations are low. Likewise, Jin (2005) observed this relationship between Shanghai, Hong Kong, and Taiwan markets. Daily, weekly, and monthly data were retrieved from three indices in host countries from July 1997 to December 2001.The findings revealed that the Hong Kong and Taiwan stock markets are highly correlated while the correlations among Hong Kong, Taiwan, and Shanghai were not, even though economic integration was shown by examining trade. The researcher further suggests that the Chinese government avoid interfering with the market and allow the market to perform accordingly. He also found that the lack of correlation among Shanghai, Hong Kong, and Taiwan depicts that investors are able to diversify their portfolios by investing in Shanghai and Hong Kong or Shanghai and Taiwan stock markets simultaneously. Economic integration allows investors to diversify their portfolios. However, economic integration is not the only factor that affects comovements. Global events and financial crises also affect comovements.

For instance, I. Meric, Ratner, Nygren, and Gulser (2007) compared the comovements of seven Latin American counties with the U.S. and Canadian equity markets 5 years before September 11, 2001, and 5 years after September 11, 2001, using maximum likelihood, principal component analysis (PCA), and Granger causality. They found that equity markets changed significantly pre-September 11 and post-September 11. The PCA indicated that all nine equity markets changed after September 11. I. Meric et al. also found Granger causality depicted that the lead/lag relationship changed significantly after September 11. I. Meric et al. found that diversification benefits diminished after September 2001in these stock markets and reduced the advantages of global portfolio diversification.

3. DATA

The data are monthly stock market total return indexes obtained from Yahoo! Finance. The total return is expressed in U.S. dollars.

The emphasis of the analysis will be placed on Indian stock returns from the U.S. investor perspective in order to make the comparison for diversification benefits in emerging markets. Data is collected from January 2000 to December 2010. All indexes are converted to logarithms. Table 1 illustrates the level of stock market returns between India and its top trading partners. The Indian stock market is highly correlated with Hong Kong at .700 and Singapore at .693. Also, the Indian stock market shares high correlations with Israel at .556, Germany at .552, the Netherlands at .585, the United Kingdom at .574, the United States at .585, Switzerland at .508, and Malaysia at .522. However, the Indian stock market shares a weak correlation with China at .353. The other interesting finding is the existence of high correlations between similar countries in terms of geographical association or economic development. For instance, the correlations between Hong King and Singapore is .748, the Netherlands and Germany is .886, the United Kingdom and the United States is .873, the United Kingdom and Germany is .834, the USA and Germany is .825, and the Netherlands and Switzerland is .812.

Table 1: Correlations between India and Its Top Trading Partners

	China	Sing	India	HK	Israel	Germ	Neth	UK	U.S.	Swit	Mal
China	1.000	.338	.353	.492	.294	.288	.321	.282	.342	.297	.335
Sing	.338	1.000	.693	.748	.544	.662	.710	.667	.711	.588	.583
India	.353	.693	1.000	.700	.556	.552	.585	.574	.585	.508	.522
HK	.492	.748	.700	1.000	.582	.661	.665	.679	.718	.581	.553
Israel	.294	.544	.556	.582	1.000	.538	.561	.554	.583	.511	.412
Germ	.288	.662	.552	.661	.538	1.000	.886	.834	.825	.802	.479
Nether	.321	.710	.585	.665	.561	.886	1.000	.862	.801	.812	.488
UK	.282	.667	.574	.679	.554	.834	.862	1.000	.873	.799	.442
U.S.	.342	.711	.585	.718	.583	.825	.801	.873	1.000	.773	.446
Swit	.297	.588	.508	.581	.511	.802	.812	.799	.773	1.000	.358
Mal	.335	.583	.522	.553	.412	.479	.488	.442	.446	.358	1.000

4. METHODOLOGY

The methodology used in this study replicates prior studies conducted byValadkhani,Chancharat, and Harvie (2008) and Meric, Prober, Eichhorn, and Meric (2009). Both studies relied on principle component analysis to examine comovements. However, this study differs due to different indexes and different sampling frames. The indexes used in this study are SSE Composite, DAX, HengSeng, SENSEX, TA 100, KLSE, AEX, Strait Times, SSMI, FTSE 100, and S&P 500 from January 2000 to December 2010. The stock market indexes are drawn from Yahoo! Finance. Monthly returns of each index are calculated and are used to perform a principle component analysis. The dependent variables will be measured by taking the monthly logarithmic changes $\ln(P_t - P_{t-1})$ in stock market index returns of India and its top trading partners denominated in U.S. dollars, while the independent variables (common factors) are linear estimates of the combinations of the original variables. WhereP_t is the price of a country's stock market index at time$t$, andP_{t-1} is the price of a country's stock market index at time t– 1. The stock market index returns will be combined into a linear combination which is referred to as the first principal component of the ρ variables. The linear combinations of variables, called factors, account for the variance in the data as a whole."Factor analysis is a statistical technique used to identify a relatively small number of factors that explain observed correlations among variables" (Norusis, 2008, p. 389).

5. EMPIRICAL RESULTS

The first step in conducting a Principle Component Analysis is to perform the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy.

Table 2: KMO Measure and Bartlett's Test

Test		Result
KMOmeasure of sampling adequacy		.927
Bartlett's test of sphericity	Approx. chi-square	1243.790
	Df	55
	Sig.	.000

The results from the KMO depict a measure of .927. A measure close to one confirms that all partial correlation coefficients are small, compared to ordinary correlation coefficients.

According to Kaiser (as cited in Norusis, 2008), measures in the 0.90s are marvelous, in the 0.80s meritorious, in the 0.70s middling, in the 0.60s mediocre, in the 0.50s miserable, and below 0.50 unacceptable. Based on the KMO measure it is reasonable to go ahead with principle component analysis.

In order to investigate the comovement of returns, a principle component analysis is performed. The principle component analysis is a multivariate technique used to reduce a large number of variables that explains the observed correlations among the variables. In order to determine how many factors to keep, an examination of the percentage of variance is performed. Table 3 illustrates the total variance explained by each factor. The total column represents the total variance explained by each factor. The percentage of variance column explains the percentage of each factor. The cumulative percent is the summation of the percentage of variance.For instance, factor 1 has a variance of 6.97, which is 63.38% of the total variance of the 11 components. From the cumulative percent column, one can see that over 50% of the variance is explained by first two factors, 63.38 and 73.28, respectively. The findings from the eigenvalue-greater-than-1 depict that the first two factors were greater than unity. Figure 1 is a depiction of the scree plot as a criterion to determine the number of common factors. The scree plot is a plot that illustrates the total variance associated with each factor. The scree plot confirms that two factors account for a large proportion of the variance. There is a steep drop-off after the second factor, which supports the findings earlier presented by the eigenvalues, that only two common factors explain a large percentage of the variance in stock market returns between India and its top trading partners.

Table 3: 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	6.972	63.381	63.381	6.972	63.381	63.381	5.017	45.608	45.608
2	1.089	9.897	73.277	1.089	9.897	73.277	3.044	27.669	73.277
3	.728	6.617	79.894						
4	.577	5.246	85.140						
5	.461	4.188	89.328						
6	.312	2.834	92.162						
7	.245	2.229	94.391						
8	.200	1.815	96.206						
9	.197	1.789	97.995						
10	.140	1.276	99.271						
11	.080	.729	100.000						

After determining the optimal number of factors, an examination of the component matrix is evaluated. Table 4, the component matrix, depicts that the Indian stock market has a large correlation of .758 with factor 1 and smaller correlation with factor 2. Additionally, the first factor is highly correlated with the stock market returns of the Netherlands at .903, the United States at .898, the United Kingdom at .892, Germany at .886, Hong Kong at .846, Singapore at .838, Switzerland at .827, India at .758, Israel at .701, and Malaysia at .628. Chinese stock market returns had the lowest correlation at .457 for factor 1. The second factor is most highly correlated stock market returns in China at .580, Malaysia at .426, and Hong Kong at.263. The second factor shows a weak correlation associated with the stock returns of Switzerland at –.343, the United Kingdom at –.288, the Netherlands at –.242, and the United States at –.200.

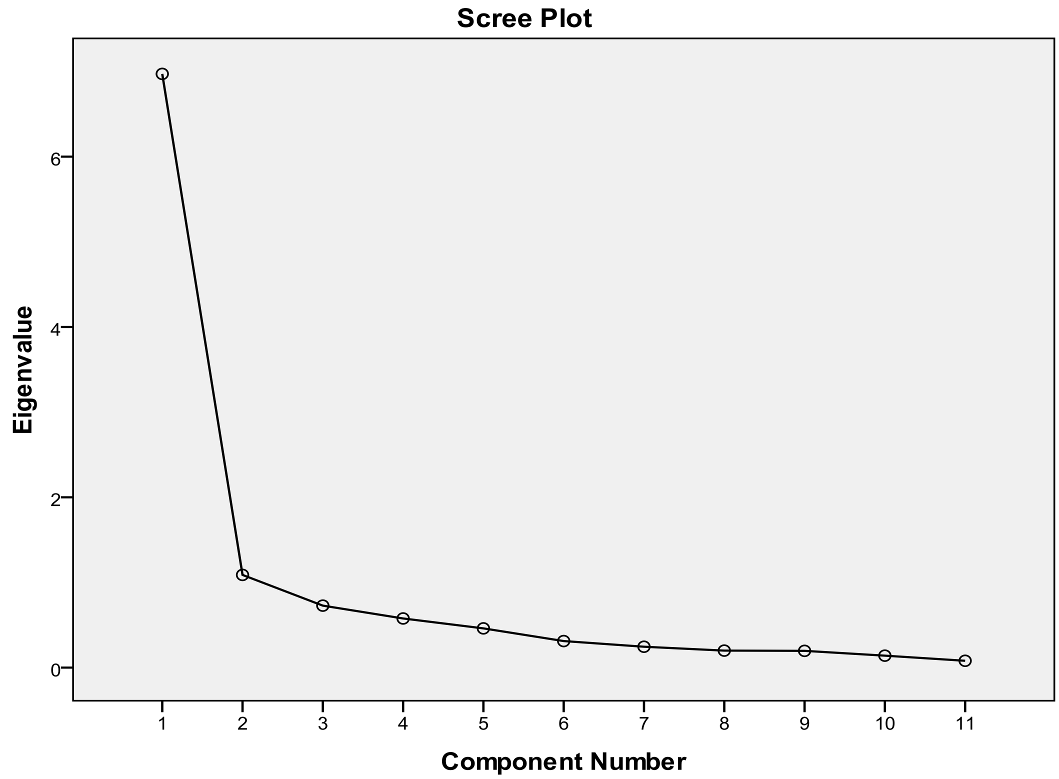

Figure 1

Table 5 illustrates the communalities between India and its top trading partners. For example, consider the component matrix from Table 4. Factor 1 explains .758 of Indian stock returns, while factor 2 explains .296.The value associated with the communality of Indian stock returns is .662 (see Table 5). This is computed by squaring both factors 1 and 2 and adding the outcomes together. For instance, $.758^2 + .296^2 = .662$. According to Norusis (2008),"the proportion of variance explained by the common factors is called the communality of variables.

Table 4: Component Matrix

	Component	
Country	1	2
Netherlands	.903	–.242
U.S.	.898	–.200
UK	.892	–.288
Germany	.886	–.280
HK	.846	.263
Singapore	.838	.153
Switzerland	.827	–.343
India	.758	.296
Israel	.701	.111
Malaysia	.628	.426
China[a]	.457	.580

Note. Extraction method: Principal component analysis.
[a]Two components extracted.

Communalities can range from 0 to 1, with 0 indicating the common factors don't explain any variance and 1 indicating the opposite" (p. 406).Viewing the results in Table 5 all initial communalities have a value of 1, indicating that the common factors explain all of the variance in stock market returns between India and its top trading partners.

Table 5: Communalities

Country	Initial	Extraction
China	1.000	.546
Singapore	1.000	.726
India	1.000	.662
HK	1.000	.785
Israel	1.000	.503
Germany	1.000	.863
Netherlands	1.000	.873
UK	1.000	.878
U.S.	1.000	.846
Switzerland	1.000	.801
Malaysia	1.000	.576

Note. Extraction method: Principal component analysis.

Next, therotated component matrix is computed. Table 6 presents the results from the rotated component matrix. The findings revealed that the first factor has relatively large weights for the United Kingdom, Germany, the Netherlands, Switzerland and the United States (.895, .885, .877, and .849, respectively). This indicates that these stock markets are highly correlated and including them in the same portfolio would not provide good diversification benefit. The second factor has relatively high weights for China, Malaysia, Hong Kong, India, and Singapore (.738, .710, .703, .679, and .609, respectively). This indicates that these stock markets are highly correlated and including them in the same portfolio would not provide good diversification benefit.To maximize portfolio diversification benefit, investors in stock markets with high factor loadings in principle component 1 can diversify into stock markets with high factor loadings in principle component 2.

Table 6: Rotated Component Matrix

	Component	
Country	1	2
UK[a]	.895	.278
Germany[a]	.885	.282
Netherlands	.877	.322
Switzerland	.873	.197
U.S.	.849	.355
Israel	.509	.494
China	.039	.738
Malaysia	.267	.710
HK	.540	.703
India	.448	.679
Singapore	.597	.609

Note. Extraction method: Principal component analysis. Rotation method: Varimax with Kaiser normalization.
[a]Rotation converged in three iterations.

The first factor has low relatively low weights for Israel, China, Malaysia, Hong Kong, India, and Switzerland (.509, .039, .267, .540, .448, and .597, respectively) and the second factor has relatively low weights for the United Kingdom, Germany, the Netherlands, Switzerland, and the United States (.278, .282, .322, .197, and .355, respectively). Investors can achieve substantial portfolio diversification benefits by investing in different principle components with low weights. The implications are that investors seeking to maximize the benefits associated with portfolio diversification can do so by investing in the Indian stock market and the stock markets in Germany, the Netherlands, the United Kingdom, Switzerland, and the United States, respectively.

6. CONCLUSION

The key findings from this study are that investors can maximize their returns and reduce their risks by investing in India and a few of its top trading partners.

A principle component analysis was used to compute monthly index returns of 11 countries from January 2000 to December 2010. The KMO and Bartlett's sphericity test confirms that a principle component analysis can be performed. The rotated component matrix illustrated that investors can achieve cross-country diversification by investing in India's stock market and the stock markets of India's top trading partners. The rotated component matrix also illustratedthat Indian stock returns do share a geographical association with its top trading partners. The results show those Indian stock markets are integrated among its top trading partners. By incorporating the results from this study, investors, as a practical recommendation will be able to diversify their portfolios to increase expected returns and reduce systemic risk.

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