Asset Correlation and the Optimal Portfolio Size Determination – Case of Nifty 50 and NASDAQ 100 Indices

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Abstract

Portfolio diversification benefits and optimum portfolio size depend on the internal correlation structure of the market. Investors require a small number of assets to get the maximum diversification benefit in a highly correlated market, however, such a market offers relatively lesser diversification opportunities. In the present study, the correlation for stock returns in India and the US was calculated to determine the optimal size of portfolios in the respective markets. Returns for all stocks indexed in NIFTY 50 and NASDAQ 100 were considered for calculating average correlations for Indian and U.S. markets between 2017 and 2019. The results showed higher correlations for the NASDAQ 100 in comparison to Nifty 50, indicating relatively better diversification opportunities provided by the Indian market as compared to the U.S. However, lower correlations for Nifty 50 required a larger number of assets to be included in the portfolio to diversify the unsystematic risk. Correlations between Nifty-50 and Nasdaq-100 indices for the past three years 2017–19 were also calculated. The results showed a relatively low correlation between the two indices, which is good for international diversification opportunities. In addition, the present study established a relationship of correlation structure between the two indices and foreign capital inflows in India for the respective years. This study also captured the cross-country returns and risks for the Indian and the U.S market.

Keywords : **portfolio diversification, correlation structure, optimal portfolio size, foreign portfolio investors**

JEL Classification Codes : G11, G15, F34

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The modern portfolio theory emphasizes on the merits of international diversification. According to the theory, it pays to diversify internationally as long as the stock returns in different markets are less than perfectly correlated. An internationally diversified portfolio allows a reduction in overall portfolio risk by offsetting individual country risk factors and reduces portfolio systematic risk to the 'world' risk factors alone. The practicality of international diversification depends on the correlation coefficients across markets, as well as the risks and returns of each constituent of the international portfolio. To determine the degree to which systematic risk can be reduced, investors seeking effective portfolio diversification wish to identify the countries whose stock prices move together, those that move in opposite directions, and stock price movements that are unrelated to one another. On the contrary, for a single market portfolio, diversification benefits and optimum portfolio size depend on the internal correlation structure of the market. A higher correlation amongst the stocks in a market requires a lesser number of securities for constructing a diversified portfolio but results in reduced diversification benefits.

For the current research paper, in the first step, correlations for stocks in the Indian and U.S. markets are calculated to know the optimal portfolio size in these countries. Returns on NIFTY 50 (representing the Indian

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equity market) and NASDAQ 100 (representing the U.S. equity market) are considered for calculating average correlations between Indian and US stock indices for the last three years. The paper, further, investigates the relationship between the correlation structure of two indices and foreign capital inflows in India for the respective years. In the process, the study also captures the cross-country returns and risk for the Indian and U.S markets.

Literature Review

The theoretical models of portfolio selection developed by Markowitz (1952), Sharpe (1964), and Grubel (1968) provided a positive explanation and normative rules for the diversification of risky assets. However, the history of the research on international diversification is merely about 40 years old. Most of the research on international diversification analyzes the benefits from developed markets' perspective. In the early years of research about international diversification, only the benefits are certified to have existed. Levy and Sarnat (1970) recommended that the U.S. investors should never restrict their portfolios to developed countries. The authors provided evidence that European markets namely, Belgium, France, Germany, and Italy demonstrate a very high correlation with the U.S. market, so the U.S. investors should not take the asset of these countries into their portfolios. Conversely, they should invest in the countries which have low or even negative correlation with theU.S. market such as Austria, Denmark, Japan, and Mexico. Sharpe (1974) presented the estimation methods to impute the expected returns of an investment firm using its holdings of securities. He argued that such organizations could alternatively utilize these estimates themselves in an iterative manner to improve their portfolio. Green (1986) evaluated the robustness of the security market line relationship for mean-variance inefficient market proxy. Green's analysis focused on the behavior of the benchmark errors.

The gains of international diversification are dependent on the correlation between the investors' home market and the target country's market (Chan et al., 1999). A portfolio with combined securities from two markets, with lower correlation, is said to provide an improvement in terms of reduced portfolio variance.

Solnik (1974) demonstrated the degree of risk reduction when diversifying internationally. The author compared the portfolio diversification in foreign securities with the domestic portfolio from the U.S. perspective. It was shown that the risk of a portfolio in terms of variability of returns will be less than the risk of its separate parts.

The study of co-movements and stock market integration has been well documented in the literature for the developed markets (Elton et al., 1978; Fama & French, 1997). Litterman and Winkelmann (1998) demonstrated the covariance matrix estimation methods used at Goldman Sachs for large-scale risk management and asset allocation problems. They presented the application of the method for multi-currency portfolio risk management, optimal asset allocation, and derivative pricing. More recently, Mo et al., (2022) proposed a dynamic spatial GARCH-Copula (s GC) model to evaluate the portfolio risk of international stock indices. Results of the study suggested that the risk prediction model with spatial dependence outperforms a model neglecting spatial effects, and risk prediction during the economically stable periods was also more accurate than during the crisis period. On the contrary, emerging markets such as India have received less academic attention (Wong et al., 2005). In the context offrontier markets, Joshi (2017) examined the case of Vietnam and reported that frontier markets demonstrate a high correlation with the World market. This coupled with low indigenous mean returns and higher variance results in lower asset allocation by the global investors in such markets. Interestingly, the Indian stock market provides a unique perspective for analyzing co-movements and stock market integration because of its burgeoning economy and its subsequent linkages to other economies.

Agrawal et al. (2020) presented a comprehensive literature review on the stock market integration with special reference to India. They found that low correlations exist between Indian stock markets and Mexico, the UK, and the United States. Meric et al. (2011) studied the co-movement of the Indian stock market with thirteen other stock markets before, during, and after the 2008 financial crisis. They reported significant time-varying volatility in the correlation of the Indian stock market with other stock markets. Wong et al. (2005) 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 the UK (FTSE 100) from January 1, 1991 to December 31, 2003. The authors found that the Indian stock market is integrated with developed markets and is sensitive to dynamics in these markets in the long run. They also found that short-run stock returns in the United States and Japan Granger cause Indian stock markets but not the opposite, signifying that the Indian stock market is integrated with other world markets in the long run and this is important when attempting to diversify portfolios.

For the domestic assets in India, Perumandla and Kurisetti (2018) examined the conditional correlation and volatility linkages between equity and commodity market assets using the DCC GARCH framework. They found that a mixed portfolio of equity-commodity demonstrates a relatively lower correlation compared to standalone equity or commodity portfolios. Srinivasa and George (2016) examined the impact of market sentiments upon return volatility in the Indian equity market. Authors found that an initial shock in the sentiment component creates a varying magnitude of responses in volatility. More recently, Lakshmanasamy (2021) examined the dynamic causality between crude oil, exchange rate, and BSE SENSEX and their volatilities. The results of the study confirm that one market's volatility and volatility spillover triggered volatility and spillovers in other markets.

As observed, the documentation of co-movements in the literature revolved mainly around the developed markets. Also, the correlation structures between the international markets and amongst the securities of the local market are time-varying. Thus, this study fills the gap by calculating the correlations using returns on NIFTY 50 and NASDAQ 100 for the Indian and US stock indices respectively for the years 2017–2019. This study also captures the post-global financial crisis behavior of cross-country returns for the Indian and U.S markets.

Data and Methodology

For calculating correlations between the returns on securities in the Indian market and U.S. market, daily weighted share indices were collected from Thomson Reuters' Eikon database and were analyzed from January 2017 to December 2019. Returns for the period later than December 2019 have not been considered on account of the ongoing COVID-19 pandemic and its economic consequences. Dungey et al. (2007) reported that the correlation between various asset returns increases manifold during periods of economic crises. Therefore, the period of the ongoing COVID-19 pandemic has not been considered appropriate for the correlation study. Returns of NASDAQ 100 were denominated in dollars and NIFTY 50 was denominated in rupees. The daily returns were calculated on basis of this data. For calculating the variance of the portfolio, the general formula used was:

$$\sigma p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} wi\ wj\ Cov\,(ri, rj) \qquad (1)$$

To establish the relationship between systematic risk and security correlations, the naïve diversification strategy was considered, in which an equally weighted portfolio is constructed, meaning that $wi = 1/n$ for each security. In this case, equation (1) can be rewritten as follows:

$$\sigma p^2 = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{n}\ \sigma i^2 + \sum_{\substack{j=1 \\ j\neq 1}}^{n} \sum_{i=1}^{n} \frac{1}{n^2}\, Cov\,(ri,rj) \qquad (2)$$

There are n variance terms and $n\ (n–1)$ covariance terms in equation (2) if the average variance and average covariance of the securities in the market as defined as:

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^{n} \sigma i^2$$

$$Cov = \frac{1}{n\,(n-1)} \sum_{\substack{j=1 \\ j\neq 1}}^{n} \sum_{i=1}^{n} Cov\,(ri, rj)$$

Then portfolio variance can be expressed as :

$$\sigma p^2 = \frac{1}{n}\,\sigma^2 + \frac{n-1}{n}\,Cov \qquad (3)$$

Equation (3) establishes a very important link between the portfolio variance and the number of securities considered in the portfolio *n*. When there is no diversification, i.e., where all the investment goes into only one security, the variance of the portfolio will be equal to the average variance of the security, and as *n* increases the dependence of portfolio variance on an average variance of securities decreases and it is explained more by the average covariance among securities.

Further, to see the fundamental relationship between systematic risk and security correlations, it is assumed that all securities have a common standard deviation, σ, and all securities pairs have a common correlation coefficient, ρ. Then the covariance between all pairs of securities is $\rho\sigma^{2,}$ and equation (3) can be rewritten as:

$$\sigma p^2 = \frac{1}{n}\,\sigma^2 + \frac{n-1}{n}\,p\sigma^2 \qquad (4)$$

Equation (4) explains the effect of correlation on portfolio variance explicitly. When $\rho = 0$, the insurance principle is obtained, where portfolio variance approaches zero as n becomes greater. For $\rho > 0$, however, portfolio variance remains positive. In fact, for $\rho = 1$, portfolio variance equals σ^2, regardless of *n*, demonstrating that diversification is of no benefit; in the case of perfect correlation, all risk is systematic. More generally, as *n* becomes greater, equation (4) shows that systematic risk becomes $\rho\sigma^2$. In the current paper, the average correlation for stocks in the Indian and U.S. markets was calculated to know the optimal size of portfolios in these countries.

Results and Discussion

Table 1 shows the average correlation of stock returns for the Indian and U.S. markets using all the stocks in Nifty- 50 for India and Nasdaq -100 for the U.S. for the past three years 2017 – 2019. This period is a very important phase of the markets for the study because it represents the period immediately before the ongoing COVID-19 pandemic. The average correlation for the Indian market was found to be relatively low in comparison

Table 1. ***Average Correlation of Returns for Nifty-50 and NASDAQ-100 Stocks***

		2017	2018	2019
NIFTY 50	Annualized Returns	25.68%	4.81%	11.83%
	Annualized Standard Deviation	8.94%	12.65%	13.57%
	Average Correlation	0.254	0.312	0.194
NASDAQ 100	Annualized Returns	26.95%	–0.27%	33.05%
	Annualized Standard Deviation	10.20%	22.56%	16.30%
	Average Correlation	0.403	0.482	0.296

to the U.S. market for all the years under study. A less correlated market signifies more scope for diversification in comparison to a highly correlated market.

Both the market showed a very similar pattern in terms of correlation structure over the past three years. Correlations increased from 0.254 to 0.312 for India and from 0.403 to 0.482 for the U.S. for the year 2017 to 2018, and then decreased for the years 2018 to 2019 for India from 0.312 to 0.194 and for the U.S. from 0.482 to 0.296. Increasing correlation among the securities shows that the market is influenced more by some common factors (systematic risk) and decreasing correlation signifies the dominance of unsystematic risk. Unsystematic risk is diversifiable, so it is beneficial for portfolio investors.

For calculating the optimal size of the portfolio, given the average correlation among the stocks in the Nifty 50 index, equation 4 was used as follows :

First, we need to determine the minimum portfolio variance given the average correlation among the stocks in the Nifty 50 index :

Thus, Equation (4) is further simplified :

$$\sigma p^2 = \frac{1}{n}\sigma^2 + \frac{n-1}{n}\rho\sigma^2$$

$$\sigma p^2 = \frac{\sigma^2}{n}[1 + (n-1) * \rho]$$

$$\sigma p^2 = \frac{\sigma^2}{n}[1 + n*\rho - \rho]$$

$$\sigma p^2 = \frac{\sigma^2}{n}[(1-\rho) + n*\rho]$$

$$\sigma p^2 = \sigma^2[\frac{1-p}{n} + \rho] \quad (5)$$

It can be observed that diversification benefit will be maximized when the number of securities held in the portfolio becomes very large therefore, when $n => \infty$, $\sigma p^2 = \rho\sigma^2$

Then, we need to assume the level of portfolio variance as a percentage of minimum possible variance. Suppose that an investor requires his portfolio's variance to be 110% of the minimum possible variance. Putting the value of $\rho = 0.254$ for Nifty 50 for the year 2017, equation 5 can be rewritten as follows :

$$1.1 *(0.254)\sigma^2 = \sigma^2 [\frac{1-0.254}{n} + 0.254]$$

$$1.1 *(0.254) = [\frac{1-0.254}{n} + 0.254]$$

Solving the above equation for *n*, we obtain *n* = 29.37 or approximately 29 stocks. However, if the investor prefers to have portfolio variance to be just 105% of the minimum possible variance, then the number of stocks required to reach that level of diversification will be higher, and the number can be obtained as follows :

$$1.05 *(0.254) = [\frac{1-0.254}{n} + 0.254]$$

Solving the above equation for n, we obtain *n* = 58.74 or approximately 59 stocks. Finally, if a high risk-averse investor prefers to have portfolio variance to be just 101% of the minimum possible variance, then the number of stocks required to reach that level of diversification will be even higher, and the number can be obtained as follows :

$$1.01 *(0.254) = [\frac{1-0.254}{n} + 0.254]$$

Table 2. ***Average Correlation and Number of Stocks Required to Achieve Different Levels of Diversifications as a Percentage of Minimum Possible Variance***

Year	Average Correlation	Minimum Possible Portfolio Variance	110% of Minimum Variance	105% of Minimum Variance	101% of Minimum Variance
			NIFTY 50		
2017	0.254	0.203%	29	59	294
2018	0.312	0.499%	22	44	221
2019	0.194	0.357%	42	83	415
			NASDAQ 100		
2017	0.403	0.419%	15	30	148
2018	0.482	2.453%	11	21	107
2019	0.296	0.786%	24	48	238

Solving the above equation for n, we obtain $n = 298.4$ or approximately 299 stocks. From the above calculations, it is clear that in addition to the average correlation among the stocks in the market, the number of stocks required in the portfolio depends on the levels of diversification targets as a percentage of minimum possible variance. Using the same process as above, table 2 presents the number of stocks required for Indian and U.S. markets for the years 2017, 2018, and 2019.

It is evident from Table 2 that the minimum possible portfolio variance for a diversified portfolio was lower for the Indian market than the U.S market for all the years under study. However, in India, the portfolio manager had to hold more stocks to diversify away from the unsystematic risk completely. A lower correlation for stock return for the Indian market in comparison to the U.S. indicates that the average portfolio size in India is supposed to be larger than the U.S. Besides the average correlation among the stocks, another factor that mattered for the size of the portfolio was the preferred level of diversification benefit expressed in terms of the percentage of the minimum possible variance. For a completely undiversified portfolio where $n = 1$, the portfolio variance is the variance of the single stock. However, as n becomes larger the portfolio variance is explained more by the correlation among the stocks than the standalone variance of the stocks. As the portfolio variance is unbounded for the number of stocks, portfolio variance will be minimized when $n = >\infty$. Therefore, it was essential to assume a target level of diversification in terms of the percentage of the minimum possible variance to obtain the ideal size of the portfolio given the average correlation among the stocks in the market.

As presented in Table 2, at the 110% level of minimum possible variance position, in India 29, 22, and 42 stocks were required for the years 2017, 2018, and 2019, respectively. For the target level of 105% of minimum possible variance position, 59, 44, and 83 stocks were required for the three consecutive years, and for the level of 101% of minimum possible variance position, a much larger portfolio was required comprising of 294, 221, and 415 stocks respectively for the years 2017, 2018, and 2019. Since the average correlation among the stocks was lower in the U.S., optimal portfolio size required a lesser number of stocks – for 110% of minimum variance position, 15, 11, and 24 stocks for the three consecutive years, for 105% of minimum variance position, 30, 21, and 48 stocks, and for 101% of the minimum variance position, 148, 107, and 238 stocks were required for the year 2017, 2018, and 2019, respectively.

Table 3 shows the correlation between Nifty-50 and Nasdaq-100, internal correlations for Nifty-50 stocks, and net foreign capital flows in Indian equity for the past three years 2017 – 2019.

The average correlation between Nifty 50 and Nasdaq100 was recorded at the highest level in the year 2017, and in the same year, there was a maximum net foreign portfolio investment of ₹ 25635 Cr. In the next year 2018, the correlation got reduced to 0.4764, however, the net foreign portfolio investment turned negative to – ₹ 88 Cr.

Table 3. ***Comparison of Foreign Capital Inflows in Equity with Average Correlation in the Nifty 50 Stocks and Correlation Between Nifty 50 and Nasdaq 100***

Financial Year	Net Foreign Portfolio Investments in Equity(₹ crores)	Correlation Among Nifty 50 Securities	Correlation Between Nifty 50 and Nasdaq 100
2017	25635	0.2549	0.5184
2018	–88	0.3121	0.4764
2019	6153	0.1937	0.1303

In the year 2019, the correlation between Nifty 50 and Nasdaq 100 had the lowest value of 0.1937 with net foreign portfolio investment in equity of ₹ 6153 Cr. Therefore, no definite pattern could be established between the correlation of the two indices and the net foreign capital inflow in equity. Similarly, there was no definite pattern found between the average correlation among the stocks of Nifty 50 and net foreign capital inflows in equity.

Conclusion and Policy Implications

The average correlation for stock returns for the Indian market recorded was relatively low in comparison to the U.S. market for all the years under study. A less correlated market signifies more scope for diversification in comparison to a highly correlated market. However, it requires a larger portfolio size for diversification of the unsystematic risk. Both the market showed a very similar pattern in terms of correlation structure over the past three years. Correlations increased from the year 2017 to 2018, and then decreased for the years 2018 to 2019 for both India and the U.S. Increasing correlation among the securities shows that the market is influenced more by some common factors (systematic risk) and decreasing correlation signifies the dominance of unsystematic risk. There was no definite pattern found between the correlation of the two indices and the net foreign capital inflow in equity. Similarly, there was no definite pattern found between the average correlation among the stocks of Nifty 50 and net foreign capital inflows in Indian stocks.

Since the Indian stocks are relatively less correlated in comparison to the U.S. market stocks, investors and professional asset managers in the U.S. can reduce the variance of their international portfolio by investing in stocks from the Indian market. However, they need to hedge their portfolio against the currency risk, as the dollar returns on their Indian investment will vary with the exchange rate between the Indian rupee and the U.S. dollar. Moreover, U.S. asset managers need to increase the size of their international portfolio while considering an investment in Indian stocks. An optimal Indian portfolio requires 72 percent to 109 percent more stocks than the equivalent U.S. market portfolio. On the other hand, Indian investors and asset managers can achieve diversification benefits by holding a relatively lower number of U.S. stocks. They are likely to benefit in terms of enhanced rupee returns on their U.S. dollar investment on account of the appreciation of the U.S. dollar against the Indian rupee.

Limitations of the Study and Scope for Further Research

This study focuses on only two markets, namely the U.S. and India for the examination of optimal portfolio size. Future researchers can widen the scope of the study by investigating other emerging market economies as well as some frontier markets. For determining the optimal portfolio size in India and U.S., the study computes correlations for 50 stocks of Nifty-50 and 100 stocks of Nasdaq-100. Although Nifty-50 represents a substantial portion of the market capitalization of the Indian stock market, the study ignores the existence of many mid-cap and small-cap stocks. Similarly, Nasdaq-100 largely represents the technology stocks of the U.S. market, thus, ignoring the other sectors of the U.S. economy. There is considerable scope for the inclusion of the other segments of the respective markets for the examination of optimal portfolio size.

Author's Contribution

Dr. Himanshu Joshi conceived the idea, synthesized the relevant literature, collected the data, conducted the empirical testing, and finally wrote the paper.

Conflict of Interest

The author certifies that he has no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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