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International Portfolio Diversification using Co-Integration Approach: Evidence from BRICS Countries

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ABSTRACT

The dynamics of the world economy are changing continuously and the economic development across the globe have made the emerging economies a major center of investment. The possibility of international portfolio diversification among the BRICS countries may help investors maximize their utilities by earning a higher return with a given level of risk. Thus, the main purpose of this study is to investigate the international portfolio diversification benefits and to assess the short- and long-term integration of the BRICS stock markets based on the variance covariance and innovation covariance matrix. Furthermore, the study has also applied MAD tracking error and SD tracking error in order to track the constructed portfolio whether it is mimicking its benchmark or not. The study used the weekly prices data set of the stock markets over the period of January 2009 to December 2019. The empirical results showed that BRICS portfolio risk based on innovation covariance matrix is lower than that of calculated via variance covariance matrix. Besides, BRICS indices have low integration in the long run as compared to the short run. Furthermore, the results indicate that BRICS portfolio risk and return are no different from its benchmark both in long and short run thus, it is mimicking its benchmark. The findings of this study is useful for the portfolio managers.

1. Introduction

BRICS is a bloc of emerging economies of the world, which stands for Brazil, Russia, India, China and South Africa. Initially, in 2009 Brazil, Russia, India and China came across to form BRIC bloc but later in 2010 South Africa also joined changing it to BRICS. BRICS countries collectively accounts for approximately 25 percent of the earth's region with more than 40 percent of the world's population and includes 46 percent of the world's labor force (Al-Mohamad, Rashid, Bakry, Jreisat, & Vo, 2020). Besides, BRICS region contributes almost 30 percent to the world's Gross Domestic product as well as 50 percent to the global economic growth (Rasoulinezhad & Jabalameli, 2018). Moreover, it has been projected that in 2050 the combined GDP of BRICS countries will exceed 128 USD trillion whereas, G7 countries will achieve the target of 66 USD trillion (Hammoudeh, Sari, Uzunkaya, & Liu, 2013). BRICS bloc has now become one of the main players in the global economy due to significant production of goods and services as well as includes largest potential consumer market with meaningful improvement in their share of world trade over the last couple of decades from 3.6 percent to 15 percent. Apart from this, there has been immense increase in the exports and imports of BRICS countries collectively with exports increased from 494 USD billion in 2001 to 2902 USD billion in 2016 and imports increasing from 417 USD billion in 2001 to 2339 USD billion in 2016

(Rasoulinezhad & Jabalameli, 2018). BRICS countries due to increase in their economic growth and higher return on investments has turned out be one of the attractive economic markets for foreign investors e.g. Foreign direct investment (FDI) inflows to BRICS nations have increased from 81 billion USD in 2000 to 221 billion USD in 2012. Keeping in view all these economic and financial transactions with respect to BRICS bloc clearly witnesses it as an attractive emerging financial markets for international investors (Adu, Alagidede, & Karimu, 2015). Economic conditions vary from country to country, their fiscal and monetary policy differ from each other and as well as their return generation mechanisms. In today's financial markets it is quite difficult to find a market that perfectly correlates with another market that is the reason going for the international portfolio diversification. Thus, investor can gain from holding a portfolio that is diversified across the number of regions or countries. Modern transportation, free trade agreements, communication technologies, and free flow of capital are the main causes of the increase in investment in foreign markets (Milanovic, 2003). Hence, giving opportunities to the domestic investors to add international securities in their portfolios. The benefits of investing in international securities is it enhances the overall performance of the portfolio the reason being there exists low correlation among the international financial securities as compared to the domestic ones (Solnik, 1974; Watson, 1978). Moreover, the low correlation among the international assets results in substantial returns from diversification (Eun, Huang, & Lai, 2008). Thus, lower the association among the markets greater will be the benefits of the diversification. Previous studies have applied numerous approaches to figure out the magnitude and direction of the co-movement among the financial markets along with international portfolio diversification benefits associated with it. Naccarato, Pierini, and Ferraro (2019) employed the VECM model to check co-integration between the 3 pairs of actual co-integrated stock from the European stock market. Besides, Joyo and Lefen (2019) employed DCC-GARCH to check the co-integration between Pak. and its trade partners for a period of 2005-2018. They concluded that after financial crises stock market integration decreased between developed and emerging markets. Kaur and Sarin (2019) applied the ARDL test to check the co-integration between the savings and investments. Khan, Teng, and Khan (2019) employed the ARDL model to check co-integration between the explained and explanatory variables. Lamia and Naziha (2019) employed EG causality test and VECM methodology in their research, Causality test for direction and Johansen & VECM for integration between developed markets and MENA countries, they found short term integration between developed and MENA financial markets and bi-directional causality. Manzoor, Ahmad, Iqbal, and Amin (2019) applied the ARDL approach for co-integration between G[2], M2[3], oil prices and dollar prices. Thus, after reviewing most of the previous literature this study is the first one to construct a portfolio on the basis of innovation covariance matrix which is further used to determine the tracking error for the constructed portfolio.

The present study contributes to the existing body of literature in number of ways. Firstly, it uses both variance covariance matrix and innovation covariance matrix to construct portfolio based on the stock indices of BRICS economies and to find out the benefits of IPD benefits. Secondly, it examines the short and long run co-integration among the BRICS stock indices. Thirdly, this study tracks the performance of the BRICS portfolio in comparison with its benchmark that is assessed via calculating the tracking error of the selected BRICS portfolio. Furthermore, the paper layout is divided in to different sections. Section 2 presents the literature studies. Section 3 refers to the data and methodology. Section 4 includes the results. At last, conclusion is presented in section 5.

2. Literature Review

Studies in the past have clearly addressed the benefits of international portfolio diversification with respect to the markets of developed and emerging economies (Bailey & Stulz, 1990; Michaud, Bergstrom, Frashure, & Wolahan, 1996; Wheatley, 1988). Gilmore and McManus (2002) in their study examined the short- and long-term correlation between the US stock market and three Central European stock markets (Poland, Hungary, Czech Republic) their findings suggest that US local investor can gain portfolio diversification benefits from the Czech, Hungarian and Polish stock markets. Besides, Guidi and Ugur (2014) investigated the degree to which the South Eastern European (SEE) stock markets are integrated with their counterparts in developed markets of Germany, UK, USA and whether international portfolio diversification benefits exists over the entire period of 2000-2013, the results reveal that SEE stock markets are weakly co-integrated with the stock markets of Germany and UK thus, indicating the presence of arbitrage opportunities and international portfolio

[2] Govt. Expenditure
[3] Money supply

diversification whereas, no static co-integration between the SEE and USA stock markets. Additionally, Heshmat (2019) in his study reported that Egyptian local investors can gain portfolio diversification benefits from investing in the stock markets of middle east, north Africa, European, Asian and united states. Apart from this, Dasgupta (2016) in his study, to find out the advantages of international portfolio diversification investigated the dynamic linkages and co-integration of emerging economies all over the world with special emphasis on the US and India, their empirical results reveal that over the entire period of 2003-12 there is no benefit of international portfolio diversification for US and other investors in the long run however, in the shorter run the stock markets of Brazil and China can be an attractive opportunity for the US investors to gain the portfolio diversification benefits. Moreover, Bhar and Nikolova (2009) investigated the level of integration and time varying relationship between the BRICS nations and their emerging regional economies and the world and their study found that among the set of BRIC countries India has the strongest integration with regional and global economy linkage followed by Brazil, Russia and China. Grobys (2010) in his study provided the evidence from SWEDISH STOCK market that co-integration based optimal index tracking portfolios performs 7.63% p.a. better than the correlation-based index tracking portfolios with volatility being 1.19 base points lower than Correlation based portfolios. Besides, Sheu and Liao (2011) in their study proved the presence of long run dynamic co-integration relationships and short run Granger-causality relationships between the US and each of the BRIC countries with alteration in their relationships during the Global Financial crisis period. Major advantage of BRICS emerging economic bloc for investors is the ability of each country in the BRICS group tends to have limited power and strengthening cooperation is a prerequisite to grow with each other in the world after crisis (Xu & Hamori, 2012). Whereas, Al-Mohamad et al. (2020) investigated the short term causalities and long term integration among BRICS stock markets both pre and post-BRICS formation, employing Johansen and Julies co-integration test the results suggest that the financial integration between the stock markets of BRICS countries increased after the formation of BRICS bloc which has caused the increase in responsiveness to the shock in the stock markets of BRICS region as compared to the pre formation of BRICS trading block. Thus, after reviewing most of the financial literature this study by nature is the first one to incorporate the innovation covariance matrix in constructing the BRICS portfolio which is further utilized to the track the performance of the BRICS portfolio with its index as well as the results of innovation covariance portfolio-based portfolio is compared with covariance matrix based portfolio.

3. Data and Methodology

The study has used the weekly data of BRICS countries stock indices prices over the period of 1st January 2009 to 31st December 2019 downloaded from www.DATASTREAM.com (Thomson Reuters) database. The reason for using weekly data rather than daily data is because the stock market holidays across the countries are different therefore the study have used the weekly data set. Furthermore, Table 1 illustrates the currencies and ticker codes for the BRICS countries along with the selected stock indices of each country.

Table 1. Country name, ticker name, equity index, currency.

S.No.	Country	Ticker Name	Equity Index	Currency
1	Brazil	Sao Paulo Stock Exchange	BRAZIL BOVESPA	Brazilian Real
2	South Africa	FTSE	FTSE/JSE ALL SHARE	South African Rand
3	Russia	Moscow Exchange	MOEX RUSSIA INDEX	Russian Federation Ruble
4	India	National Stock Exchange of India Ltd.	NIFTY 500	Indian Rupee
5	China	Shanghai Stock Exchange	SHANGHAI SE A SHARE	Chinese Yuan Renminbi

All the empirical analysis is performed on the returns of the stock indices, calculated through the formula of continuous compounding as illustrated in equation 1.

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \times 100 \qquad (1)$$

Where R_t represents the returns at time t, P_t shows the current price, P_{t-1} shows the previous period price and ln is the log natural function.

3.1 Portfolio Construction

Initially, the study has constructed a portfolio based on correlation (covariance matrix) and co-integration matrix (ICM) and have compared the results of these two techniques for BRICS portfolio. Portfolio constructed through covariance matrix shows short term portfolio performance. Whereas, portfolio constructed through ICM shows long term performance of portfolio. In section 3.2 to 3.4, risk and return are discussed and section 3.5 and 3.6 discuss the portfolio construction measures. And to check How selected indices portfolios is performing? Researchers have applied different tracking error measures to check the performance of selected indices of BRICS portfolio to its benchmark index. For this purpose, Emerging markets index is selected as benchmark for BRICS because all BRICS countries are emerging markets. The lower the tracking error for the BRICS portfolio the more it is mimicking its benchmark index.

3.2 Portfolio Returns

Equation 2 shows the formula for calculating the portfolio mean or returns, which is the sum of the weighted average returns of selected indices.

$$E(R_p) = \sum_{i=1}^{n} w_i R_i \qquad (2)$$

Where, $\sum w_i$ = 1

$E(R_p)$ = mean return of a portfolio

w_i = weight of equity index in portfolio

R_i = mean return of i^{th} asset

n = no. of observation

3.3 Portfolio Risk

The calculation of portfolio risk is based on Modern Portfolio Theory (Markowitz, 1952). According to Markowitz (1952) MPT theory, portfolio variance consists of stock returns variance as well as correlation between the stock returns. Hence, to measure portfolio risk both variance and standard deviation are used. Note that standard deviation is the square root of variance. Equation 3 shows the formula for the portfolio risk.

$$\sigma_p = \sqrt{\sum_{i=1}^{n} w_{i.}^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{\substack{j=1 \\ i \neq j}}^{n} w_i w_j \sigma_{ij}} \qquad (3)$$

Where, σ_p= portfolio S.D. (risk)

w_i= proportion of equity index

σ_i^2= variance of i^{th} asset

σ_{ij}= covariance of i^{th} and j^{th} asset

3.4 Returns in Matrix Form

Portfolio mean given in the form of matrix. Portfolio mean equals to the product (matrix of weights of assets and average return matrix of assets).

$$E(R_p) = WR' \tag{4}$$

W= matrix of weights of stocks in the portfolio,

R'= transpose of matrix of Average return of individual assets.

$$E(R_p) = [w_1 \quad w_2 \quad \cdots \quad w_n]\begin{bmatrix}\bar{R}_1 \\ \bar{R}_2 \\ \vdots \\ \bar{R}_n\end{bmatrix}$$

3.5 Risk in Matrix Form

The mathematical representation of the portfolio risk in the form of matrix is shown in equation 5. Which can be described as the product of weight matrix, variance-covariance matrix, and transpose of weight matrix.

$$\sigma_p^2 = W\sum W' \tag{5}$$

W= matrix of weights of stocks in the portfolio.

∑= variance-covariance matrix.

W'= transpose of matrix of weights of stocks in the portfolio.

3.6 Co-Integration Based Risk

Co-integration is a long-term co-movement technique. There are different models of Co-integration such as ARDL, VAR, VECM, Johansen co-integration and EG methodology used in previous studies. Below are few recent research studies quoted of co-integration and different models are used to check co-integration. ARDL used by (Das, McFarlane, & Jung, 2019). Naccarato et al. (2019) employed the VECM model to check co-integration. Joyo and Lefen (2019) employed DCC-GARCH to check the co-integration. Khan et al. (2019) employed the ARDL model to check co-integration between the explained and explanatory variables. Lamia and Naziha (2019) employed EG causality test and VECM methodology in their research. Manzoor et al. (2019) applied the ARDL approach for co-integration.

Co-integration techniques are used to examine the long-term relationship between variables, even the variables have unit root. In case of spurious regression economist used co-integration technique (Rao, 1997). All the studies quoted above are used to check co-integration, whether co-integration exists or not. No previous studies have used ICM co-integration for calculation of portfolio risk.

$$\sigma_p^2 = W'ÇW \tag{6}$$

W= matrix of weights of stocks in the portfolio,

Ç= Innovation covariance matrix (ICM).

3.7 Innovation Covariance Matrix (ICM)

ICM is a measure of Co-integration. Co-integration based on ICM is given appendix A.

Innovation co-variance matrix (ICM) 2x2

$$Ç = \begin{bmatrix}\sigma_\mu^2 & \sigma_{\mu v} \\ \sigma_{\mu v} & \sigma_V^2\end{bmatrix}$$

Where, Ç = ICM,

σ_μ^2= variance of μ_t, ($X_t = \gamma X_{t-1} + \mu_t$)

σ_V^2 = variance of V_t, ($Y_t = \gamma Y_{t-1} + V_t$)

$\sigma_{\mu v}$ = covariance of μ_t,V_t

3.8 Portfolio Optimization

This study will use excel to optimize both types of portfolios. The below criteria of optimizing and constraints will use for covariance portfolio as well as ICM portfolio.

Minimize the above portfolio risk.

Min. $\sigma_p^2 = W'\sum W$

Subject to the following constraints.

$\sum$w = 1, portfolio fully invested

W ≥ 0 = short selling not allowed

3.9 Tracking Error

Tracking error (T.E) is the volatility of portfolio return minus benchmark (index) return. According to Clarke, Krase, and Statman (1994) T.E is the "difference between the managed portfolio return & index (Benchmark) return. The method used below is proposed by (Chu, 2011).

3.91 Absolute Deviation

This measure of tracking error is the mean absolute deviation of difference between portfolio return and Benchmark index (Chu, 2011).

$$T.E_{AD,j} = \frac{\sum_{j=1}^{n} |e_{j,t}|}{\text{n}} \tag{7}$$

Where,

$T.E_{AD,j}$= Tracking error absolute deviation

$e_{i,t} = R_{p,t} - R_{b,t}$ (Difference between Portfolio return and benchmark index)

n = Number of observations

3.9.2 Standard Deviation

Tracking error is the standard deviation of difference between portfolio return and benchmark return (Chu, 2011).

$$T.E_{SD,j} = \sqrt{\frac{\sum_{t=1}^{n}(e_{j,t} - \overline{e_j})^2}{n-1}} \tag{8}$$

Where,

$T.E_{SD,j}$ = Standard deviation of T.E

$e_{i,t} = R_{p,t} - R_{b,t}$ (Difference between Portfolio return and benchmark index)

$\overline{e_j}$ = average of $e_{i,t}$

n = Number of observations

4. Empirical Results

Summary statistics of BRICS countries indices are given in table 2 over the period from January 2009 to December 2019 based on weekly data. In table 2, among all the countries in BRICS economic block Russian stock index has the highest average returns along with the highest volatility. On the other hand, stock index of China has the lowest average returns whereas, South African stock market among the BRICS countries stock indices and the lowest volatility. Furthermore, the results of Jarque-Bera test for normality rejects the hypothesis of normal distribution, which means that stock index returns for all the BRICS countries follow the pattern of asymmetric distribution. Besides, the value of kurtosis for all the BRICS stock indices returns is above 3, thus Brazilian, Russian, Indian, Chinese and South African stock market returns exhibit fat tail phenomena.

Table 2. Summary statistics.

Country Returns	Mean	Median	Max.	Min.	S.D.	Skew.	Kurt.	J-Bera	Prob	Obs.
Brazil	0.1973	0.3642	16.5617	-10.5207	2.9853	0.0991	4.4691	52.5545	0.0000	574
China	0.0869	0.1531	9.1444	-14.3069	2.9929	-0.5486	5.5132	179.8517	0.0000	574
India	0.2499	0.3938	16.8901	-9.4935	2.4334	0.3776	7.2771	451.1621	0.0000	574
Russia	0.2777	0.2619	12.1113	-14.7716	3.0859	-0.3054	6.3864	283.1995	0.0000	574
S. Africa	0.1711	0.2351	6.5358	-7.6943	2.0413	-0.1421	3.7181	14.2642	0.0008	574

Max. = Maximum, Min. = Minimum, S.D = Standard Deviation, Skew. = Skewness, Kurt. = Kurtosis, Obs.= observations J-Bera = Jarque-bera, Prob. = Probability

4.1 BRICS Prices and Returns

Fig 1-5 and fig 6-10 shows the pricing and return graphs for each of the BRICS countries indices. Overall, the graphs represent that the BRICS region indices points are increasing for the selected period except china index has downfall in 2015. This also reflects in summary stats illustrated in table 2 because china is offering lowest return for selected period. Overall returns graphs are mean reverting and also follow the phenomena of volatility clustering for all the BRICS stock indices.

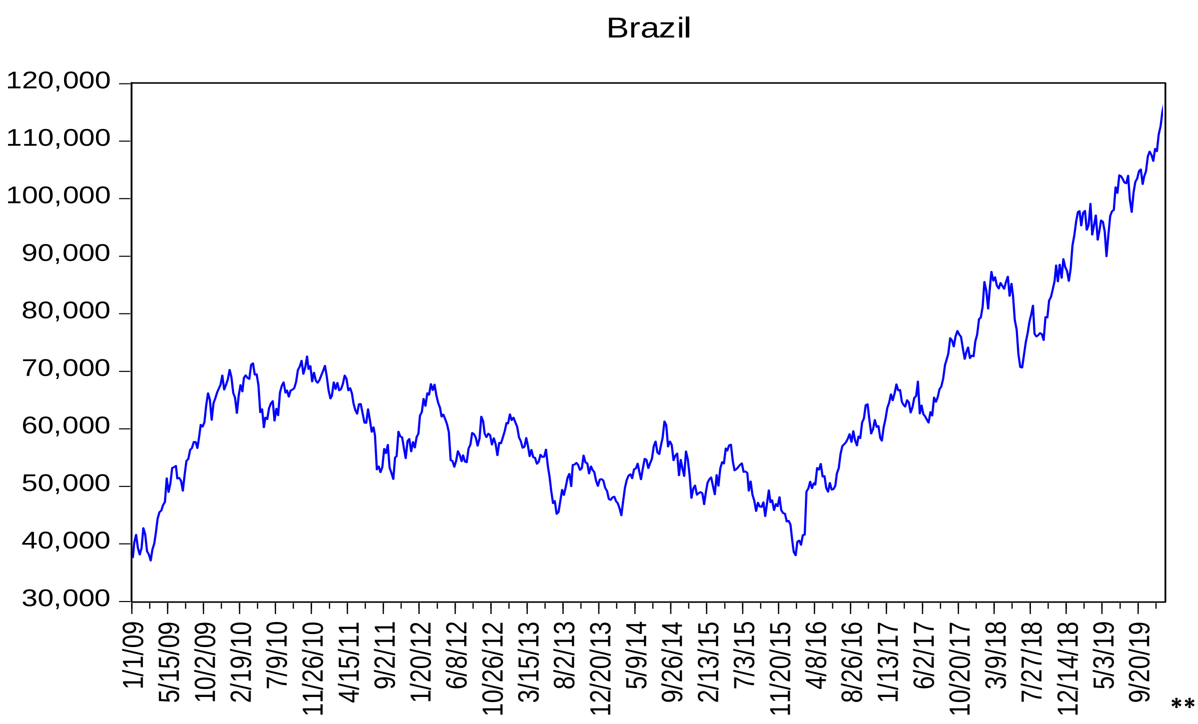

Figure 1: Represents the Brazilian stock index pricing over the selected period of time.

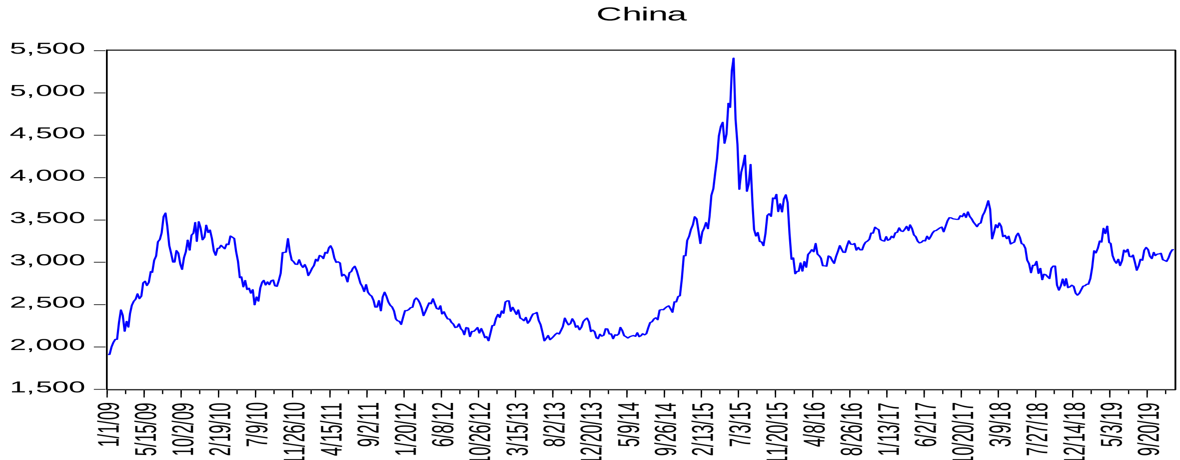

Figure 2: Represents the pricing of the Chinese stock index over the selected period of time.

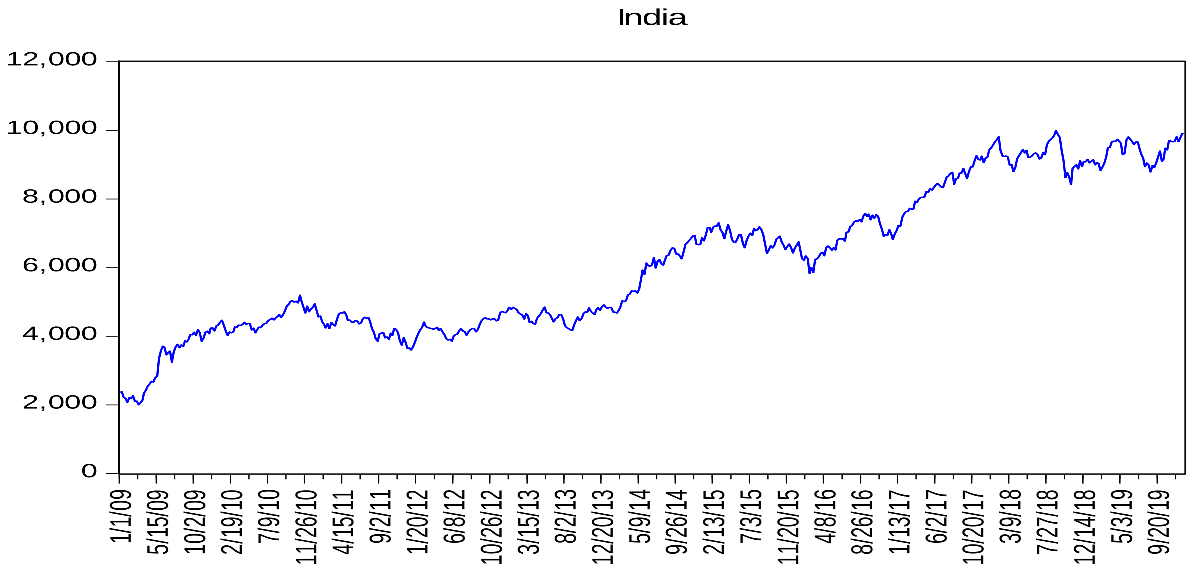

Figure 3: Represents the Indian stock index pricing over the selected period of time.

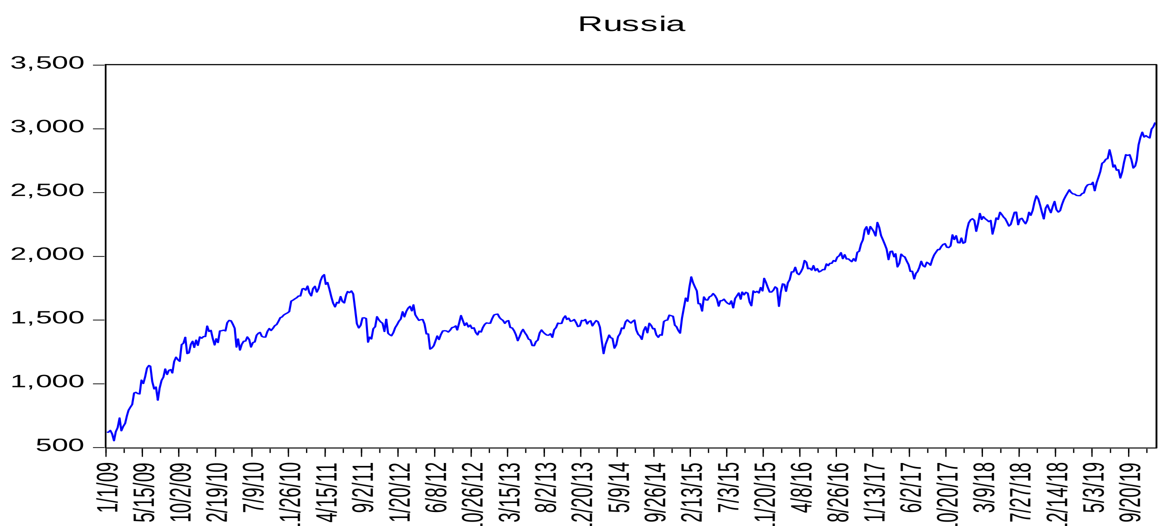

Figure 4: Shows the pricing of Russian stock index over the selected period of time.

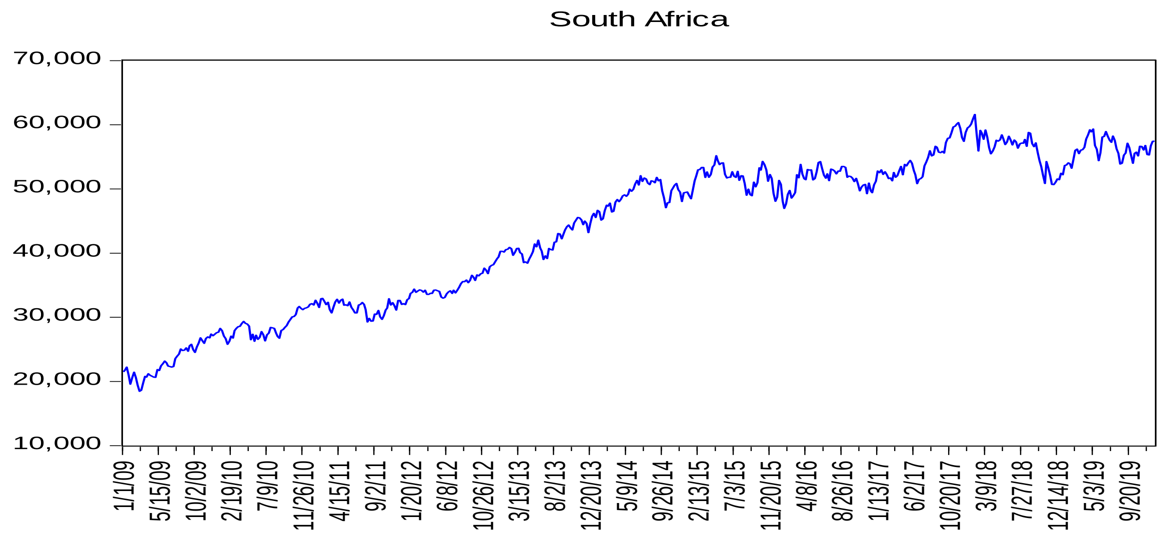

Figure 5: Shows the South African stock index pricing over the selected period of time.

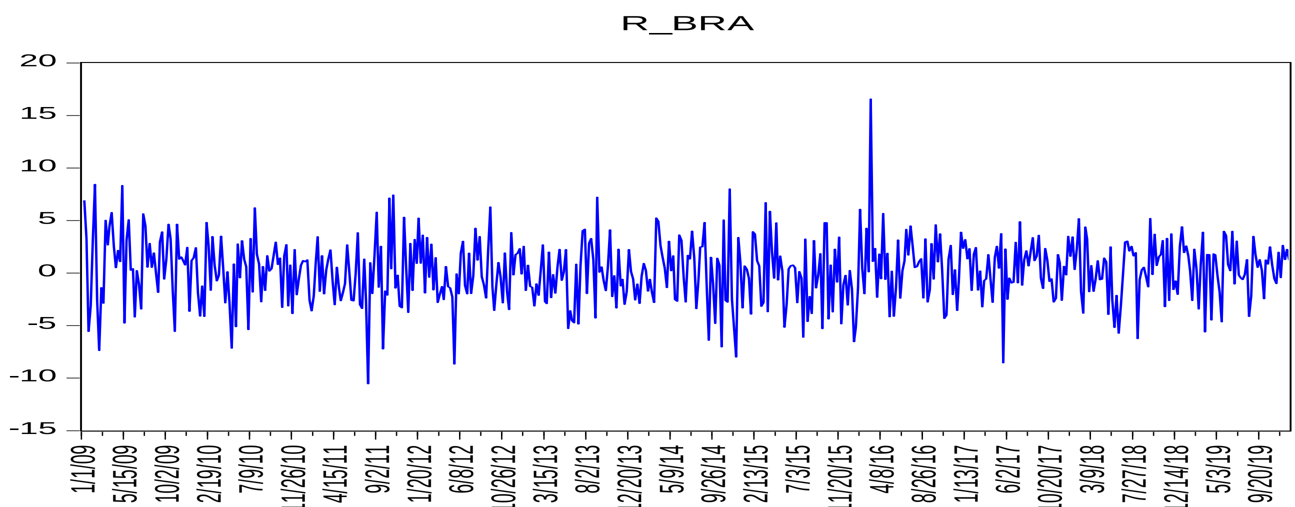

Figure 6: Depicts the Brazilian stock index returns over the selected period of time.

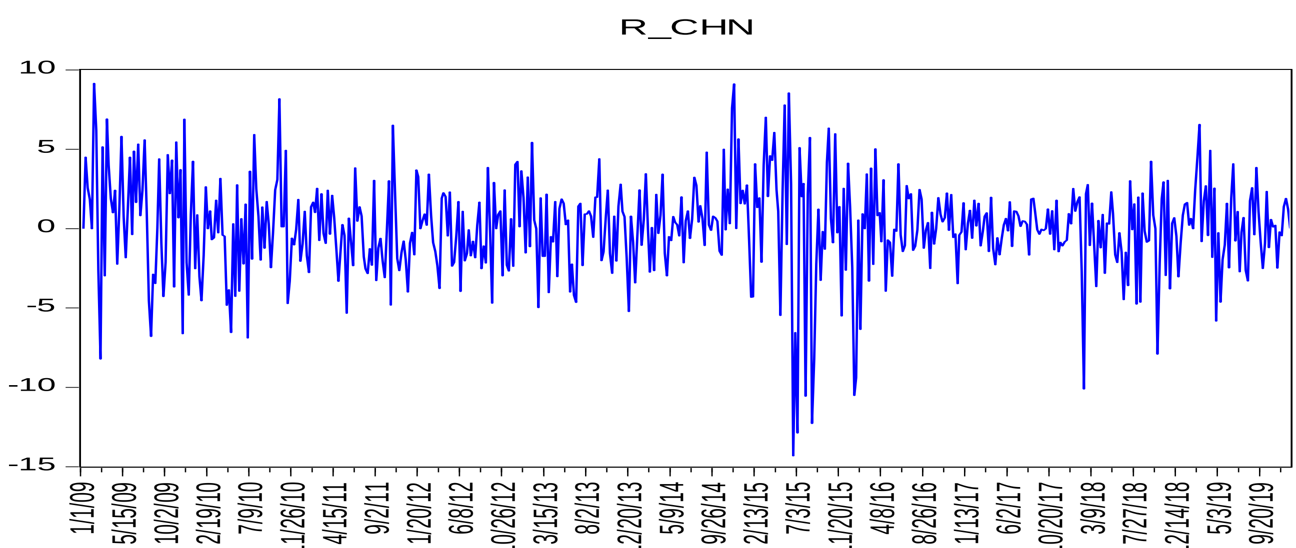

Figure 7: Depicts the Returns of Chinese stock index over the selected period of time.

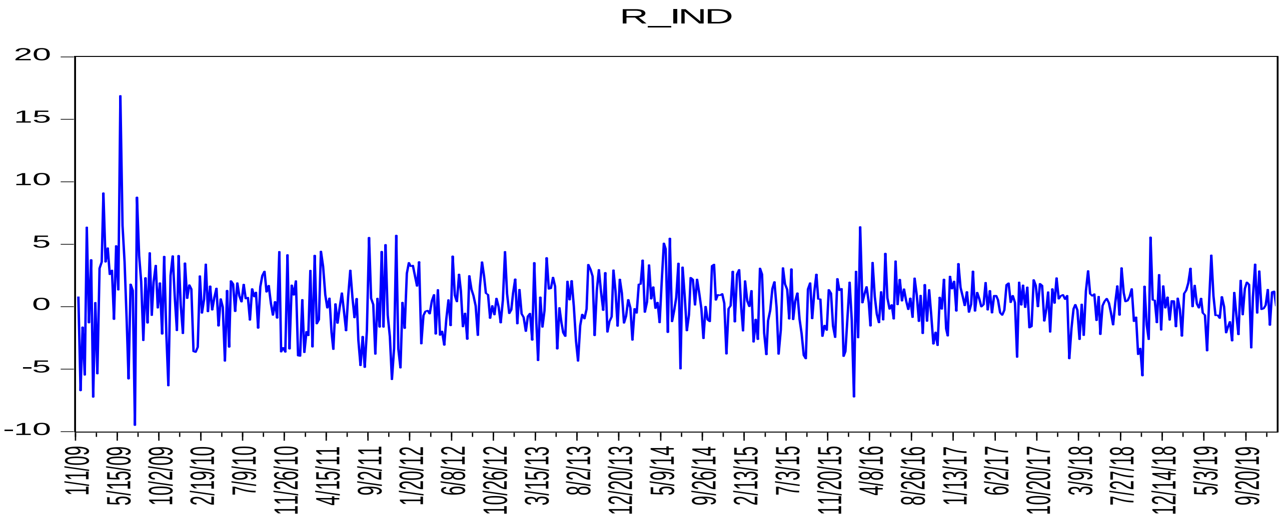

Figure 8: Represents the Indian stock index returns over the selected period of time.

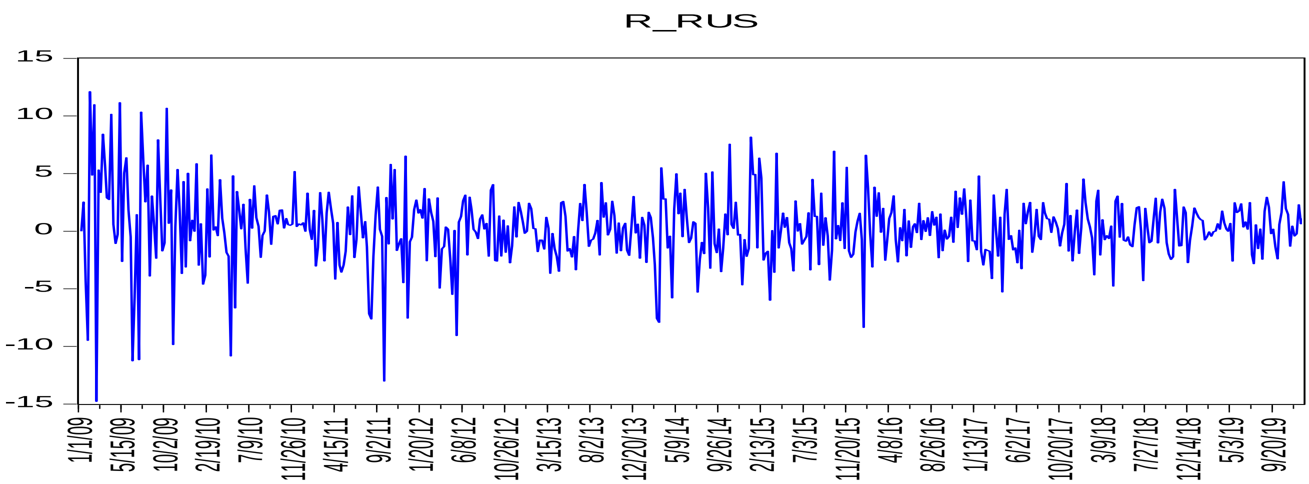

Figure 9: Represents the Russian stock index returns over the selected period of time.

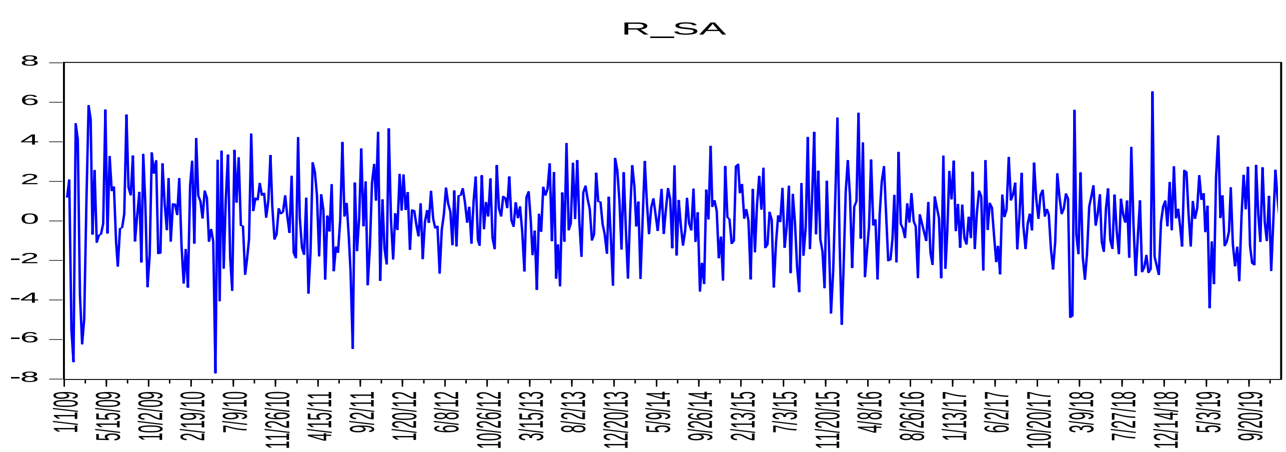

Figure 10: Shows the South African stock index returns over the selected period of time.

4.2 Portfolio Based on Covariance

Covariance based portfolios means portfolio risk calculation through covariance matrix. In table 3, BRICS portfolio risk are calculated through covariance matrix. BRICS portfolio has shown volatility in its portfolio. Furthermore, table 3 represents the risk and returns along with the coefficient of variation for the BRICS portfolio.

Table 3. Covariance based portfolio results.

Minimum Variance Portfolio (Covariance Matrix)				
Portfolio name	**Mean**	**Variance**	**SD**	**C.V**
BRICS	0.176815381	3.106464	1.762516	9.968117

SD = Standard deviation, C.V = Coefficient of variation

4.3 Portfolio Based on Innovation Covariance Matrix

Correlation calculated from Innovation covariance matrix (ICM) is used to identify the co-integration between two series such as indices. This study used ICM for the calculation of portfolio risk. The purpose of using ICM is to check whether portfolio risk is same for long term or it change in long term.

Table 4 shows the results of portfolio based on ICM. Portfolio mean is same as in table 3 because the portfolio mean calculation method is same in both the cases. Risk calculated through ICM is different from table 3 values. Standard deviation of BRICS portfolio is lower than the table 3 values. This reveals that BRICS indices has low co-integration in long run as compared to short run.

Table 4. Innovation covariance-based portfolio results.

Minimum Variance Portfolio (Innovation Covariance Matrix)				
Portfolio name	**Mean**	**Variance**	**SD**	**C.V**
BRICS	0.176829702	3.099187794	1.760451	9.95563

SD = Standard deviation, C.V = Coefficient of variation.

The results of section 4.2 and 4.3 reveals that BRICS indices are highly correlated in short run and has low co-movement.

4.4 Portfolio Tracking Error

Tracking error is used to measure the portfolios performance with respect to its benchmark index. High tracking error value means that portfolio is deviating from its benchmark. For selected portfolios different benchmark are selected. For BRICS benchmark is “MSCI emerging market index”.

Table 5. Tracking Error results.

Portfolio	**Portfolio (Covariance Matrix)**		**Portfolio (ICM)**	
	$\boldsymbol{T.E_{SD,j}}$	$\boldsymbol{T.E_{AD,j}}$	$\boldsymbol{T.E_{SD,j}}$	$\boldsymbol{T.E_{AD,j}}$
BRICS	1.477657	1.12974	1.48108259	1.130794752

Tracking error results given in table 5 shows that both in short and long run the T.E for BRICS portfolio is not very high, which means that BRICS portfolio risk and return is not very different from its benchmark. Overall, the value of T.E error comprehends that BRICS portfolio based on the inputs from covariance matrix and innovation covariance matrix mimics its benchmark up to certain meaningful level.

4.5 Efficient Frontier

Efficient frontier is the portfolio risk and return graphical representation showing efficient points. Any point below EF is inefficient, any point above EF is non-attainable. Figure 11 shows the comparison of two efficient frontiers of BRICS portfolio, where one is formed on the basis of covariance matrix while the other is formed based on the innovation covariance matrix. Furthermore, the results show that for a given level of risk BRICS return in long run is higher than short run (covariance) or for a given level of risk the BRICS portfolio return based on innovation covariance matrix is higher than the portfolio returns arising from the covariance matrix. Overall, it can be concluded that BRICS portfolio constructed via ICM approach is more efficient than constructed through covariance matrix.

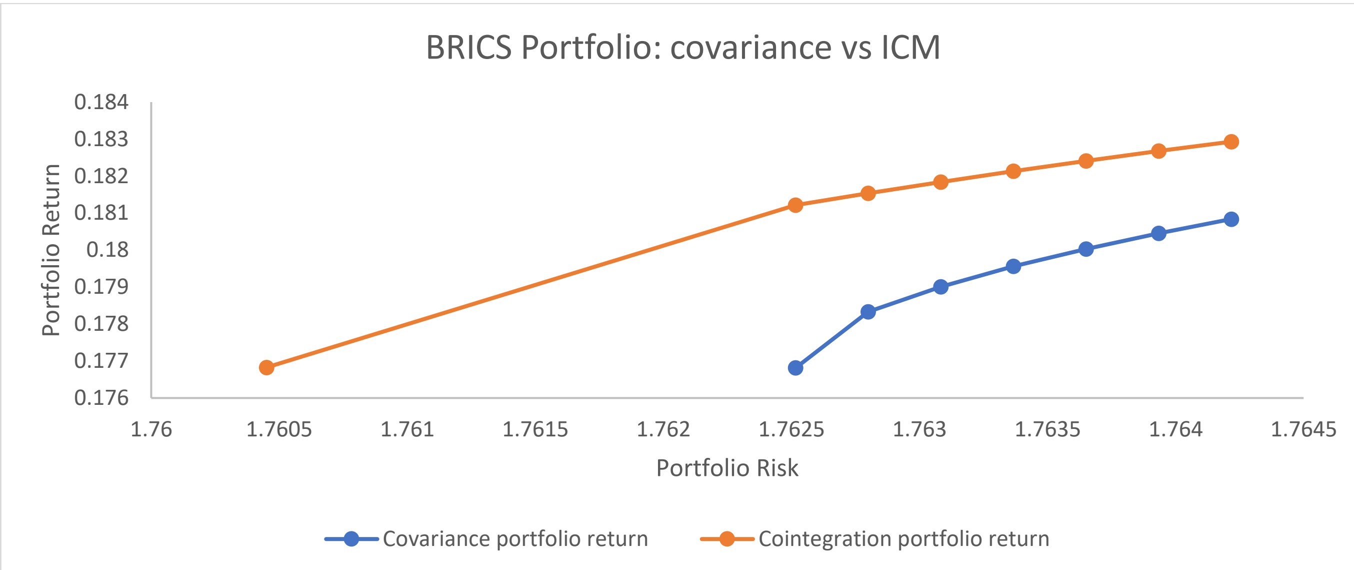

Figure 11. BRICS efficient frontiers comparison.

5. Conclusion

In this study, we have studied the IPD benefits with respect to the BRICS portfolio. The main aim of this study was to investigate the long-term and short-term integration in the BRICS portfolio indices. Additionally, BRICS indices portfolio is constructed which is further used to investigate the tracking error between the BRICS portfolio and its benchmark. Besides, we have used the covariance matrix and innovation covariance matrix (ICM) for the calculation of portfolio risk. We have also applied MAD tracking error and SD tracking error of Chu (2011), to investigate whether BRICS portfolio is tracking its benchmark or not. The study used the weekly prices data over the period of January 2009 to December 2019 for the entire BRICS countries and all the empirical analysis was performed continuous compounding returns. From the statistical and empirical results, we found that BRICS portfolio risk calculated through ICM is lower than that of calculated through Covariance matrix. Besides, the results implied that BRICS indices have low integration in long run as compared to short run. Furthermore, based on tracking error results we conclude that in long run, BRICS portfolio's return and risk is not different from its benchmark. Whereas, in short run BRICS risk and return deviates from its benchmark risk and return.

5.1 Implications & Future directions

Portfolio managers can use this research methodology for portfolio risk calculation. This methodology will help in determining portfolio risk for long term investment. This is also new approach in portfolio theory, both theorist and manager can benefit from this study. This study also adds new dimension for portfolio risk calculation in the current literature. Investors can diversify their investment based on the Innovation Covariance matrix (ICM) instead of using Correlation matrix. ICM is new approach in portfolio diversification. It will help those investors who want to diversify in the longer run. Correlation is not good for measure for long term investment as reported by (Lhabitant, 2017). So, ICM is appropriate measure for long term investment which is more practical measure than Correlation (variance-covariance matrix). Additionally, this study in future can be extended to other economic blocks such as PACIFIC, BALTIC, G7 and G20 countries with taking different frequency data set. Besides, the same procedure can be applied to other financial securities such as bonds and cryptocurrencies.

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