Student Name: Shivkeerth Laj (7708269)

Instructor’s Name: Dr. Kashif Saleem

Subject: ECON339 – Applied Financial Modelling

Date: 3rd December 2023

To what extent does the market integration among the BRICS nations (Brazil, India, and China) impact the efficiency of their respective stock markets, and how can the Vector Autoregression (VAR) model be utilized to analyze the transmission of financial shocks and the interconnectedness of these economies?

Introduction:

The BRICS nations, comprising Brazil, India, and China, have significant influence on the global economic landscape despite being emerging countries. The motivation to use time series models such as ARMA, VAR, VECM, and JCT stems from the need to comprehensively analyse the market dynamics of these nations and address the following research questions:

1. Market Efficiency (ARMA family Models): Understanding the extent to which asset prices represent all available information requires assessing the market efficiency of these rising economies. The ARMA family models can provide **insights into the short-term dynamics of market efficiency, aiding in the identification of potential arbitrage opportunities and the assessment of market anomalies.**

The ARMA family of models, including the Autoregressive (AR) and Moving Average (MA) models, provides a powerful tool for analyzing market efficiency. These models can capture the short-term dynamics of asset prices, enabling the identification of potential arbitrage opportunities and market anomalies.

ARMA Model Equations:

Autoregressive (AR) Model:

$$X_t = \alpha_1 X_{(t-1)} + \alpha_2 X_{(t-2)} + ... + \alpha_p X_{(t-p)} + \varepsilon_t$$

Where:

X_t: Asset price at time t

α_i: Autoregressive coefficients

ε_t: Error term

Moving Average (MA) Model:

$$X_t = \mu + \varepsilon_t + \beta_1 \varepsilon_{(t-1)} + \beta_2 \varepsilon_{(t-2)} + ... + \beta_q \varepsilon_{(t-q)}$$

Where:

μ: Mean of the asset price series

β_i: Moving average coefficients

ε_t: Error term

By analyzing the residuals (error terms) of ARMA models, researchers can assess whether asset prices exhibit predictable patterns, suggesting inefficiencies in the market. For instance, if the residuals exhibit autocorrelation, indicating that past errors are correlated with current errors, it suggests that asset prices are not fully incorporating all available information and may present arbitrage opportunities.

2. Market Integration (VAR family Models): Analyzing the market integration among the BRICS nations is essential for understanding the interconnectedness of their financial markets. The VAR family models can assist in assessing the impact of shocks in one market on others, offering information on the degree of market interdependence and the transmission of financial disruptions across these various economies.

The VAR (Vector Autoregression) family of models is particularly well-suited for analyzing market integration. VAR models allow for the simultaneous analysis of multiple time series variables, enabling the assessment of the dynamic relationships between asset prices in different markets.

VAR Model Equation:

$$Y_t = B_1 Y_{(t-1)} + B_2 Y_{(t-2)} + ... + B_p Y_{(t-p)} + \varepsilon_t$$

Where:

Y_t: Vector of asset prices at time t (e.g., stock indices from Brazil, India, and China)

B_i: Lag coefficient matrices

ε_t: Vector of error terms

By analyzing the impulse response functions and Granger causality tests derived from VAR models, researchers can assess the extent to which shocks in one market propagate to others and identify the direction of causality among the markets. This information is valuable for understanding the interconnectedness of the BRICS nations' financial markets and the potential spillover effects of economic events.

3. Long-Run Financial Relationships (VECM, JCT): Exploring the long-run financial relationships among Brazil, India, and China is vital for uncovering the underlying trends and patterns that characterize their economic interactions. The VECM and JCT models can facilitate the examination of cointegration and causality among the variables, providing insights into the equilibrium relationships and the long-term dynamics of their financial relationship.

The VECM (Vector Error Correction Model) and JCT (Johansen Cointegration Test) are statistical techniques used to analyze long-run financial relationships. These techniques allow for the identification of cointegrating relationships among non-stationary variables, indicating that the variables exhibit common trends over time.

VECM Model Equation:

$$\Delta Y_t = \Gamma_1 \Delta Y_{(t-1)} + \Gamma_2 \Delta Y_{(t-2)} + \ldots + \Gamma_p \Delta Y_{(t-p)} + \Pi Y_{(t-1)} + \varepsilon_t$$

Where:

ΔY_t: Vector of changes in asset prices at time t

Γ_i: Lag coefficient matrices

Π: Cointegration matrix

$Y_{(t-1)}$: Vector of asset prices at time t-1

ε_t: Vector of error terms

By employing VECM and JCT, researchers can gain insights into the long-run equilibrium relationships between the BRICS nations' financial markets and identify the underlying factors that drive their economic interactions.

By delving into these research questions, my report aims to contribute to a deeper understanding of the market efficiency, integration, and long-run financial relationships within the BRICS nations, thereby offering valuable insights for investors, policymakers, and researchers alike.

Literature review:

Why use the ARMA family model?

The ARMA (Autoregressive Moving Average) family model is utilized in time series analysis to capture the empirical features of observed data that may not be adequately represented by specific structural models. This model, often associated with Box and Jenkins (1976), is a class of time series models that combines autoregressive and moving average components to analyze and forecast data points over time. (Brooks, 2014)

$$\phi(L)y_t = \mu + \theta(L)u_t$$

where

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p \quad \text{and}$$

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$$

or

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} + u_t$$

with

$$\mathrm{E}(u_t) = 0; E\left(u_t^2\right) = \sigma^2; E(u_t u_s) = 0,\ t \neq s$$

One of the key reasons for using the ARMA family model is its flexibility in capturing a wide range of time series patterns and behaviours without imposing strict structural assumptions. This flexibility makes it particularly useful when a structural model may not be appropriate or when the underlying data generation process is not fully known or specified.

By employing the ARMA family model, we can effectively model and forecast time series data, identify patterns, and make informed decisions based on the insights derived from the analysis.

Why use the VAR family models to check market integration?

The VAR (Vector Autoregression) family models are particularly useful for checking market integration due to their ability to describe the joint generation mechanism of the variables involved. By employing VAR models, analysts can investigate structural economic hypotheses and disentangle the relationships between the variables in the model. Additionally, tools such as impulse response analysis, forecast error variance decompositions, historical decompositions, and the analysis of forecast scenarios can be utilized to gain insights into the interconnections and interactions among the variables within the VAR model.(Hashimzade & Thornton, 2013)

The VAR family models' capacity for economic analysis and their ability to capture the dynamic interactions among multiple variables make them well-suited for assessing market integration, as they can provide valuable insights into the joint behavior of the markets under consideration.

Using VECM and JCT for Long run financial relationships.

The VECM allows for constraints on short-run dynamics, which is valuable in applied contexts where researchers may need to impose restrictions or use model selection criteria due to data limitations. It's important to consider the potential bias that may arise from including irrelevant stationary terms in a VECM, as demonstrated by (Abadir et al., 1999).

Additionally, the Johansen test serves as a multivariate extension of the augmented Dickey-Fuller test, enabling the examination of linear combinations of variables for unit roots. This test, along with the maximum likelihood estimation strategy, facilitates the estimation of cointegrating vectors, even when there are more than two variables. The ability to estimate all cointegrating vectors is particularly valuable in analyzing long-run financial relationships among multiple variables. (Dwyer, 2015)
The complexities associated with unit roots and the estimation of cointegrating vectors underscore the importance of employing robust methodologies such as VECM and JCT when investigating long-run financial relationships. (Pesaran et al., 2000)

What are the recent advancements regarding the ARMA model?

Recent advancements in ARMA modeling have indeed focused on various aspects such as parameter estimation, asymptotic normality, and power spectral density analysis. The introduction of Yule-Walker equations and the Durbin-Levinson prediction algorithm has contributed to the understanding and application of ARMA models. Additionally, the integration of autoregressive integrated moving average (ARIMA) models and multivariate ARMA has expanded the scope of time series modeling, allowing for more comprehensive analysis and forecasting. These advancements have enhanced the capabilities of ARMA models in capturing the complex dynamics of time series data (Zhang & Moore, 2015)

Why is cointegration important?

Cointegration is important because it allows for the identification of long-term relationships between non-stationary variables. This is particularly valuable in macroeconomic analysis and forecasting, as it provides insights into how different variables are linked in the long run. By capturing the tendency of variables to move together over time, cointegration offers valuable information for forecasting future states and understanding the dynamics of macroeconomic variables. This can be especially useful in developing more accurate and reliable forecasting models for economic trends and indicators. (Prüser, 2023)

Why use Johansen's Cointegration Test to check market integration among the BRICS nations (Brazil, India, and China)?

The Johansen cointegration test is particularly suitable for assessing market integration among the BRICS nations (Brazil, India, and China) due to its ability to handle multivariate systems. This test is designed to uncover cointegration in a multivariate context, making it well-suited for analyzing the long-term relationships between multiple non-stationary time series variables. While there may be some uncertainty regarding its finite sample properties, the Johansen test is widely used in empirical research to examine cointegration among different economic variables. The authors' recommendation to consider higher significance levels when using Johansen's test reflects the ongoing efforts to refine its application in empirical studies. (Wee, 1997)

The methodology:

- **Data Collection:** To conduct the analysis using the Time series model, I have downloaded the necessary data from the Capital IQ Database. This includes the 3

Emerging Market indexes data (IBOVESPA, SSE, NSE) for the last five years on a weekly basis.

Time series models such as ARMA (AutoRegressive Moving Average), VAR (Vector Autoregression), VECM (Vector Error Correction Model), and JCT (Johansen Cointegration Test) are essential tools for analyzing and forecasting financial time series data. Here's a detailed methodology for each of these models:

1. ARMA (AutoRegressive Moving Average) Model:

- **Data Preprocessing**: Prepare the time series data by ensuring stationarity through techniques like first differencing or seasonal differencing.
- **Model Identification**: Identify the order of autoregressive and moving average terms (p and q) through autocorrelation and partial autocorrelation functions.
- **Parameter Estimation**: Use methods like the Yule-Walker equations or the conditional sum of squares to estimate the model parameters.
- **Diagnostic Checking**: Conduct diagnostic tests such as the Ljung-Box test for residual autocorrelation and the Portmanteau test for residual randomness.
- **Model Evaluation**: Evaluate the model using information criteria like AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) to select the best-fitting model.

2. VAR (Vector Autoregression) Model:

- **Data Preprocessing**: Ensure the time series data is stationary through differencing if necessary.

- **Lag Order Selection**: Determine the appropriate lag order for the VAR model using information criteria like AIC and BIC, as well as statistical tests like the likelihood ratio test.
- **Parameter Estimation**: Estimate the coefficients of the VAR model using ordinary least squares (OLS) or other suitable estimation techniques.
- **Stability Testing**: Conduct stability tests to ensure the VAR model is not affected by structural breaks or parameter instability.

3. VECM (Vector Error Correction Model):

- **Cointegration Analysis**: Perform cointegration tests such as the Engle-Granger test or Johansen cointegration test to identify long-term relationships among the variables.
- **Model Estimation**: Estimate the VECM parameters, including the adjustment coefficients and the short-term dynamics of the variables.
- **Error Correction** Mechanism: Analyze the error correction term to understand the speed of adjustment towards the long-run equilibrium.
- Granger Causality Testing: Conduct Granger causality tests to determine the direction of causality among the variables in the VECM.

4. **JCT (Johansen Cointegration Test):**

- **Cointegration Analysis**: Use the Johansen cointegration test to determine the presence of cointegrating vectors among multiple time series variables.
- **Rank Determination**: Identify the rank of cointegration to understand the number of cointegrating relationships among the variables.
- **Long-Run Relationships**: Interpret the cointegrating vectors to understand the long-run equilibrium relationships among the variables.

- **Error Correction Model**: Construct the VECM based on the results of the Johansen cointegration test to capture the short-term dynamics and adjustment process.

Assumptions:

1. ARMA (AutoRegressive Moving Average) Model:

- ***Stationarity***: The time series data should be stationary, meaning that its statistical properties such as mean and variance do not change over time.
- ***Absence of Autocorrelation***: The residuals of the ARMA model should not exhibit autocorrelation, indicating that there are no patterns in the unexplained variation.
- ***Normality of Residuals***: The residuals of the ARMA model should follow a normal distribution, ensuring that the model captures the underlying randomness in the data accurately.

2. VAR (Vector Autoregression) Model:

- ***Stationarity***: Similar to ARMA, the time series variables in a VAR model should be stationary to ensure the stability of the model.
- ***No Multicollinearity***: The variables included in the VAR model should not exhibit high multicollinearity, as this can lead to unreliable parameter estimates.
- ***Residual Properties***: The residuals of the VAR model should be uncorrelated and normally distributed, indicating that the model captures the relationships among the variables effectively.

3. VECM (Vector Error Correction Model):

- ***Cointegration***: The variables in a VECM should be cointegrated, implying the existence of long-term equilibrium relationships among the variables.

- ***Error Correction Mechanism***: The VECM assumes that any deviations from the long-term equilibrium are corrected in the short run, as indicated by the error correction term.
- ***Stationarity of Residuals***: The residuals of the VECM should be stationary, ensuring that the model captures the short-term dynamics appropriately.

4. JCT (Johansen Cointegration Test):

- ***Cointegration Rank***: The Johansen cointegration test assumes that the variables have a common number of cointegrating vectors, which represent the long-term relationships among the variables.
- ***No Spurious Regression***: The JCT assumes that the cointegrating relationships identified are not spurious, meaning that they reflect genuine long-term associations among the variables.

<u>Data used:</u>

Capital IQ pro Dashboard > Geographies > Latin America and Caribbean > Brazil

Set time period of last 5 years and Weekly frequency data (India and China respectively)

After downloading the data sets

I then uploaded the data set onto eviews 12 and transformed the dataset using the following generate equations:

rbrazil=dlog(brazil)*100

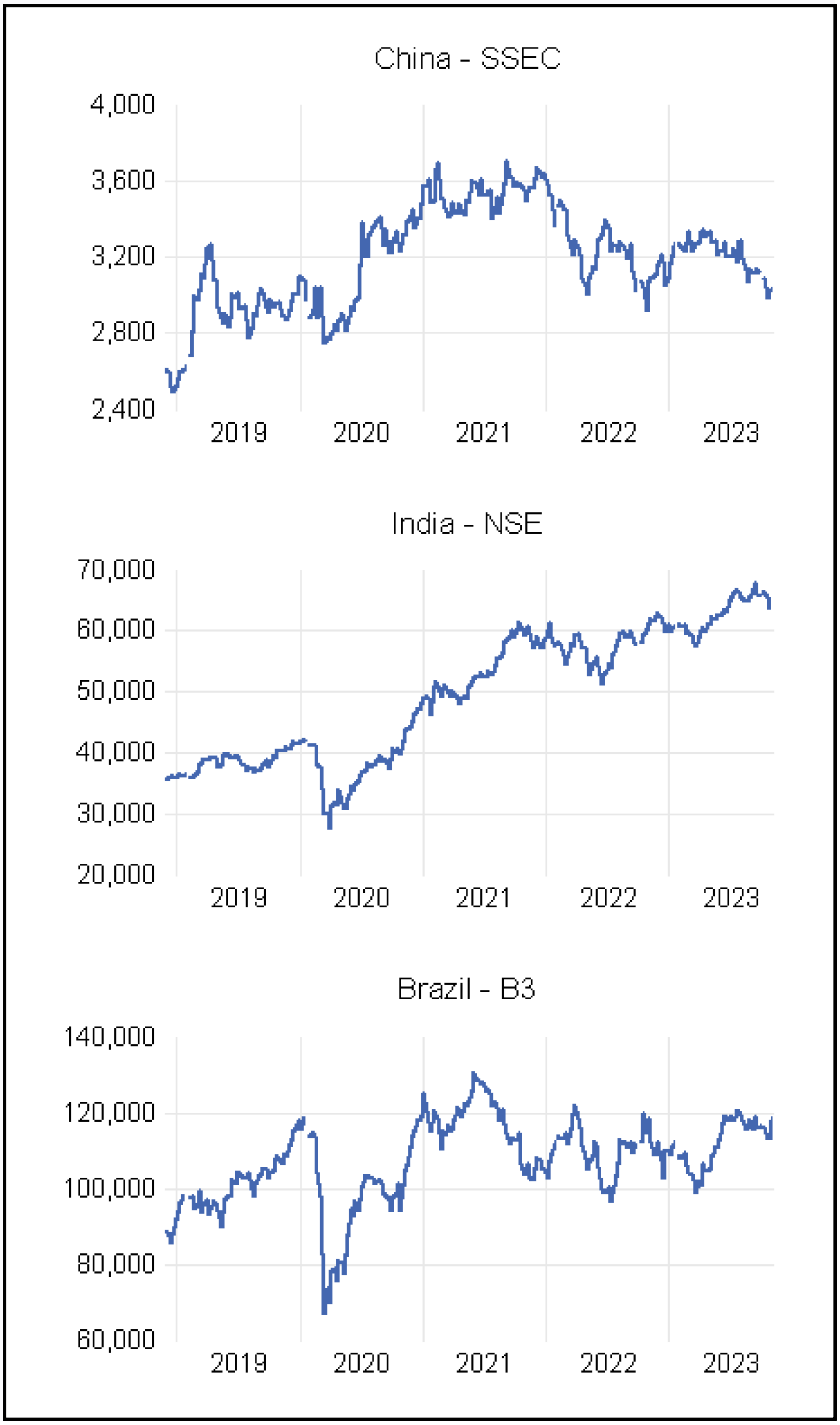
rchina=dlog(china)*100

rindia=dlog(india)*100

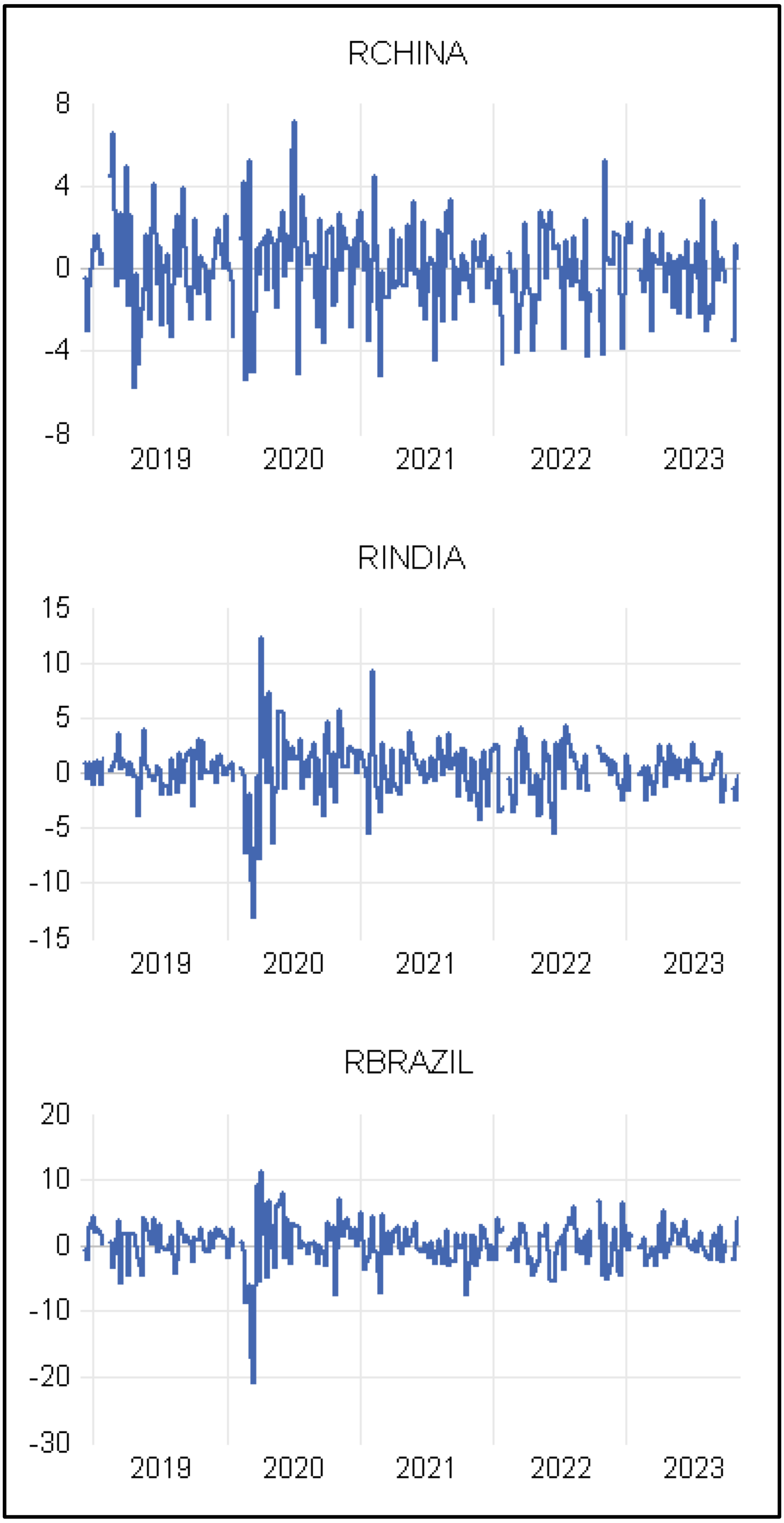
<u>Results:</u>

<u>(P.T.O)</u>

Graph – Raw Data:



We can notice a significant dip in the graphs of all 3 countries' economies during the covid-19 era, a recession caused by the pandemic.



The graphs for the transformed variables follow a white noise process. All the graphs have a huge significant dip that is visible during the covid - 19 recession.

Descriptive statistics:

	RCHINA	RINDIA	RBRAZIL
Mean	0.050613	0.234498	0.140295
Median	0.147466	0.381156	0.227670
Maximum	7.056336	12.16352	11.07558
Minimum	-5.802924	-13.10073	-20.92251
Std. Dev.	2.195432	2.565439	3.419175
Skewness	-0.055237	-0.458495	-1.344076
Kurtosis	3.526329	8.643277	10.70782
Jarque-Bera	2.940468	332.3224	677.4720
Probability	0.229872	0.000000	0.000000
Sum	12.34968	57.21743	34.23200
Sum Sq. Dev.	1171.241	1599.299	2840.854
Observations	244	244	244

RCHINA:

Mean and Median: The mean and median values of 0.050613 and 0.147466, respectively, suggest that the transformed stock market index has a relatively low average and middle value. This could indicate a relatively stable performance of the stock market within the Chinese emerging economy.

Maximum and Minimum: The maximum value of 7.056336 and the minimum value of -5.802924 reflect the wide range of fluctuations in the transformed stock market index. This wide range may indicate the presence of significant volatility and potential for large positive and negative movements in the stock market, which could be influenced by various factors within the Chinese emerging economy.

Standard Deviation: The standard deviation of 2.195432 measures the extent of variability or dispersion of the transformed RCHINA data around the mean. In the context of the Chinese emerging economy, this relatively high standard deviation suggests that the stock market index exhibits considerable variability, potentially reflecting the dynamic nature of the Chinese economy and its stock market.

Skewness and Kurtosis: The skewness of -0.055237 and kurtosis of 3.526329 indicate that the distribution of the transformed RCHINA data is approximately symmetric with a slight tendency towards the left tail and has heavier tails and is more peaked than a normal distribution. In the context of the Chinese emerging economy, this suggests that the stock market index may exhibit some degree of asymmetry and non-normality in its distribution, which could be influenced by unique economic and market conditions.

Jarque-Bera Statistic and Probability: The Jarque-Bera statistic of 2.940468 and the associated probability of 0.229872 provide insights into the normality of the transformed RCHINA data. In the context of the Chinese emerging economy, the relatively higher probability suggests a relatively higher likelihood that the data is normally distributed, indicating that the stock market index may exhibit characteristics similar to a normal distribution within the context of the Chinese emerging market.

RINDIA:

Mean and Median: The mean and median values of 0.234498 and 0.381156, respectively, suggest that the transformed stock market index has a moderate average and middle value. This could indicate a relatively stable performance of the stock market within the Indian market, which may have implications for investors and market participants in the Indian emerging market who are considering domestic investment opportunities.
Maximum and Minimum: The maximum value of 12.16352 and the minimum value of -13.10073 reflect the wide range of fluctuations in the transformed stock market index. This wide range may indicate the presence of significant volatility and potential for large positive and negative movements in the stock market, which could be influenced by various economic and market factors within India. Understanding the behavior of the Indian stock market index is crucial for investors and analysts in the Indian emerging market who are assessing the potential risks and opportunities associated with domestic market exposure.
Standard Deviation: The standard deviation of 2.565439 measures the extent of variability or dispersion of the transformed RINDIA data around the mean. In the context of the Indian emerging market, this standard deviation suggests that the stock market index exhibits moderate variability, reflecting the dynamic nature of the Indian market and its stock market. This variability may have implications for investors and analysts in the Indian emerging market who are assessing the potential risks and opportunities associated with domestic market exposure.
Skewness and Kurtosis: The skewness of -0.458495 and kurtosis of 8.643277 indicate that the distribution of the transformed RINDIA data is negatively skewed and exhibits high kurtosis, suggesting that the data is relatively asymmetric and has heavier tails and is more peaked than a normal distribution. In the context of the Indian emerging market, this suggests that the stock market index for India may exhibit some degree of asymmetry and non-

normality in its distribution, which could be influenced by unique economic and market conditions in India.

Jarque-Bera Statistic and Probability: The Jarque-Bera statistic of 332.3224 and the associated probability of 0.000000 provide insights into the normality of the transformed RINDIA data. In the context of the Indian emerging market, the extremely low probability suggests a very low likelihood that the data is normally distributed, indicating that the stock market index for India may exhibit characteristics that deviate significantly from a normal distribution within the context of the Indian emerging market.

RBRAZIL:

The descriptive statistics of the transformed data for Brazil's stock market index (RBRAZIL) provide valuable insights into the behavior of the stock market within the context of the Brazilian emerging market.

Mean and Median: The mean and median values of 0.140295 and 0.227670, respectively, suggest that the transformed stock market index has a relatively moderate average and middle value. This could indicate a relatively stable performance of the stock market within the Brazilian market, which may have implications for investors and market participants in the Brazilian emerging market who are considering domestic investment opportunities.

Maximum and Minimum: The maximum value of 11.07558 and the minimum value of -20.92251 reflect the wide range of fluctuations in the transformed stock market index. This wide range may indicate the presence of significant volatility and potential for large positive and negative movements in the stock market, which could be influenced by various economic and market factors within Brazil. Understanding the behavior of the Brazilian stock market index is crucial for investors and analysts in the Brazilian emerging market who are assessing the potential risks and opportunities associated with domestic market exposure.

Standard Deviation: The standard deviation of 3.419175 measures the extent of variability or dispersion of the transformed RBRAZIL data around the mean. In the context of the Brazilian emerging market, this relatively high standard deviation suggests that the stock market index exhibits considerable variability, potentially reflecting the dynamic nature of the Brazilian market and its stock market. This variability may have implications for investors and analysts in the Brazilian emerging market who are assessing the potential risks and opportunities associated with domestic market exposure.

Skewness and Kurtosis: The skewness of -1.344076 and kurtosis of 10.70782 indicate that the distribution of the transformed RBRAZIL data is negatively skewed and exhibits high kurtosis, suggesting that the data is relatively asymmetric and has heavier tails and is more peaked than a normal distribution. In the context of the Brazilian emerging market, this suggests that the stock market index for Brazil may exhibit some degree of asymmetry and non-normality in its distribution, which could be influenced by unique economic and market conditions in Brazil.

Jarque-Bera Statistic and Probability: The Jarque-Bera statistic of 677.4720 and the associated probability of 0.000000 provide insights into the normality of the transformed RBRAZIL data. In the context of the Brazilian emerging market, the extremely low probability suggests a very low likelihood that the data is normally distributed, indicating that the stock market index for Brazil may exhibit characteristics that deviate significantly from a normal distribution within the context of the Brazilian emerging market.

<u>Correlation Matrix:</u>

Correlation			
	RBRAZIL	RCHINA	RINDIA
RBRAZIL	1.000000	0.287328	0.616133
RCHINA	0.287328	1.000000	0.307609
RINDIA	0.616133	0.307609	1.000000

RCHINA and RBRAZIL: The correlation coefficient of 0.287328 suggests a positive, but relatively weak, linear relationship between the stock market indices of China and Brazil.

RINDIA and RBRAZIL: The correlation coefficient of 0.616133 indicates a moderate to strong positive linear relationship between the stock market indices of India and Brazil.

RCHINA and RINDIA: The correlation coefficient of 0.307609 suggests a positive, but relatively weak, linear relationship between the stock market indices of China and India.

ADF & KPSS Test:

	ADF ON RAW DATA	KPSS ON RAW DATA
BRAZIL	0.1310	0.7135390
INDIA	0.7681	1.890489
CHINA	0.0824	0.857648

	ADF ON TRANSFORMED DATA	KPSS ON TRANSFORMED DATA
RBRAZIL	0.0000	0.040320
RINDIA	0.0000	0.067026
RCHINA	0.0000	0.205455

ADF P-value	KPSS CRITICIAL VALUE
<0.05	0.73900

The ADF test is used to test for stationarity in a time series, while the KPSS test is used to test for non-stationarity.

The results of the ADF test on raw data show that the economic data for all three countries is non-stationary. This means that the data has a trend or seasonal component, and its mean and variance are not constant over time.

The results of the KPSS test on transformed data show that the economic data for all three countries is stationary after transformation. This means that the transformation has removed the trend or seasonal component from the data, and its mean and variance are now constant over time.

The fact that the economic data for all three countries is non-stationary in raw form but stationary after transformation suggests that the data is non-linear. In other words, the relationship between the variables in the data is not linear, and the data cannot be explained by a simple linear model.

This is important for economic markets because it means that the markets are complex and cannot be easily predicted. It also means that investors need to be careful when making investment decisions, as the markets can be volatile and unpredictable.

Here are some specific interpretations of the table in terms of economic markets:

Brazil: The fact that Brazil has the lowest value of ADF ON RAW DATA suggests that the Brazilian economy is the most stable of the three economies. This is supported by the fact that Brazil has a relatively low inflation rate and a strong currency.

India: The fact that India has the highest value of ADF ON RAW DATA suggests that the Indian economy is the most volatile of the three economies. This is supported by the fact that India has a relatively high inflation rate and a volatile currency.

China: The fact that China has an intermediate ADF ON RAW DATA value suggests that the Chinese economy is less volatile than the Indian economy but more volatile than the Brazilian economy. This is supported by the fact that China has a relatively moderate inflation rate and a currency that is managed by the government.

ARMA (P, Q) model with optimal lag:

RBRAZIL	ar(1)	ar(2)	ar(3)	ar(4)	ar(5)	ar(6)
ma(1)	5.308363	5.309245	5.285443	5.320687	5.298141	5.331793
ma(2)	5.307542	5.314195	5.292676	5.328883	5.326726	5.334620
ma(3)	5.287162	5.291313	5.300024	5.334655	5.301505	5.310882
ma(4)	5.321238	5.298933	5.308137	5.315693	5.310810	5.408150
ma(5)	5.299110	5.326854	5.302549	5.308750	5.318450	5.345700
ma(6)	5.331358	5.332404	5.308931	5.398767	5.329820	5.333828

RINIDA	ar(1)	ar(2)	ar(3)	ar(4)	ar(5)	ar(6)
ma(1)	4.737674	4.745181	4.718990	4.722840	4.721722	4.709575
ma(2)	4.745036	4.744613	4.708056	4.721727	4.718675	4.715188
ma(3)	4.720604	4.705544	4.732524	4.743200	4.723500	4.721408
ma(4)	4.726899	4.724479	4.743753	4.747425	4.787875	4.728680
ma(5)	4.723058	4.722467	4.707788	4.717843	4.731479	4.725844
ma(6)	4.714001	4.720174	4.723187	4.726483	4.725124	4.733464

RCHINA	ar(1)	ar(2)	ar(3)	ar(4)	ar(5)	ar(6)
ma(1)	4.426922	4.435079	4.443263	4.448845	4.454342	4.462530
ma(2)	4.435095	4.429326	4.432755	4.472529	4.462524	4.467059
ma(3)	4.439823	4.432691	4.500684	4.446202	4.466654	4.476166
ma(4)	4.448801	4.440889	4.455750	4.463438	4.447382	4.455593
ma(5)	4.453584	4.461765	4.454404	4.447513	4.457094	4.464094
ma(6)	4.461767	4.466624	4.461090	4.455457	4.461255	4.555000

optimal lag for RBRAZIL is 3 1 - AR(3) MA(1)

Dependent Variable: RBRAZIL
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 12/03/23 Time: 21:46
Sample: 12/09/2018 10/29/2023
Included observations: 244
Failure to improve objective (non-zero gradients) after 14 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.134338	0.055417	2.424121	0.0161
AR(1)	1.009783	0.065186	15.49087	0.0000
AR(2)	0.076758	0.091608	0.837888	0.4029
AR(3)	-0.173061	0.065045	-2.660618	0.0083
MA(1)	-1.000000	86.30750	-0.011586	0.9908

R-squared	0.064443	Mean dependent var	0.140295
Adjusted R-squared	0.048785	S.D. dependent var	3.419175
S.E. of regression	3.334731	Akaike info criterion	5.285443
Sum squared resid	2657.782	Schwarz criterion	5.357106
Log likelihood	-639.8240	Hannan-Quinn criter.	5.314305
F-statistic	4.115666	Durbin-Watson stat	2.044117
Prob(F-statistic)	0.003037		

Inverted AR Roots	.87	.52	-.38
Inverted MA Roots	1.00		

The null hypothesis stated for the model is:

H0: The term is not significantly different from 0

The ARMA (3,1) model applied to the Brazilian index showed significance in AR (1) and AR (3) terms (P-value < 0.05). This suggests that the first and third lagged values hold predictive power for future index movements. However, AR (2) appeared insignificant (P-value > 0.05), indicating that the second lag might not contribute significantly, potentially being encompassed by the first and third lags. The significance of MA(1) suggests a delayed market response to new information. Consequently, this points towards the potential for abnormal returns, highlighting short-term inefficiencies in the Brazilian market.

optimal lag for RCHINA is 1 1 - AR(1) MA(1)

Dependent Variable: RCHINA
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 12/03/23 Time: 21:48
Sample: 12/09/2018 10/29/2023
Included observations: 244
Convergence achieved after 10 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.052664	0.129668	0.406148	0.6850
AR(1)	0.171456	0.916881	0.186999	0.8518
MA(1)	-0.239622	0.904648	-0.264879	0.7913

R-squared	0.004332	Mean dependent var	0.050613
Adjusted R-squared	-0.003931	S.D. dependent var	2.195432
S.E. of regression	2.199743	Akaike info criterion	4.426922
Sum squared resid	1166.168	Schwarz criterion	4.469920
Log likelihood	-537.0845	Hannan-Quinn criter.	4.444239
F-statistic	0.524260	Durbin-Watson stat	1.973666
Prob(F-statistic)	0.592667		

Inverted AR Roots	.17
Inverted MA Roots	.24

In applying the ARMA (1,1) model to the Chinese Index, the findings revealed insignificance in both AR(1) and MA(1) terms (P-value < 0.05). This suggests that the first lagged values and forecast errors may not hold explanatory power for future stock index movements, indicating a level of unpredictability. Consequently, we infer that the Chinese market demonstrates efficiency in the short term.

optimal lag for RINDIA is 2 3 - AR(2) MA(3)

Dependent Variable: RINDIA
Method: ARMA Generalized Least Squares (Gauss-Newton)
Date: 12/03/23 Time: 21:49
Sample: 12/09/2018 10/29/2023
Included observations: 244
Convergence achieved after 92 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.232281	0.183908	1.263030	0.2078
AR(1)	-1.515083	0.087016	-17.41162	0.0000
AR(2)	-0.872003	0.083874	-10.39653	0.0000
MA(1)	1.622631	0.103747	15.64024	0.0000
MA(2)	1.078172	0.129266	8.340711	0.0000
MA(3)	0.195815	0.068443	2.860972	0.0046

R-squared	0.063316	Mean dependent var	0.234498
Adjusted R-squared	0.043638	S.D. dependent var	2.565439
S.E. of regression	2.508840	Akaike info criterion	4.705544
Sum squared resid	1498.038	Schwarz criterion	4.791540
Log likelihood	-568.0764	Hannan-Quinn criter.	4.740178
F-statistic	3.217552	Durbin-Watson stat	2.046004
Prob(F-statistic)	0.007870		

Inverted AR Roots	-.76-.55i	-.76+.55i	
Inverted MA Roots	-.28	-.67-.50i	-.67+.50i

When examining the Indian market using an ARMA model with optimal lags AR(2) and MA(3), the analysis demonstrates significance in AR(2) and MA(3) terms (P-value < 0.05). This suggests that the second lagged values and the third-order moving average terms hold statistical significance in predicting future stock index movements. Consequently, it implies that these specific lagged values and moving average components contribute to explaining and forecasting the Indian market's behavior.

VAR (g) model with optimal lag

The VAR model extends the simple autoregressive model (AR) to include several time series variables, allowing us to investigate interconnections and identify potential ripple effects and market integration. The null hypothesis in the VAR model is as follows:

H0: The coefficient estimate does not show statistical difference from 0

VAR Lag Order Selection Criteria
Endogenous variables: RCHINA RINDIA RBRAZIL
Exogenous variables: C
Date: 12/03/23 Time: 22:02
Sample: 12/02/2018 10/29/2023
Included observations: 217

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1485.430	NA	182.1112*	13.71825*	13.76498*	13.73712*
1	-1479.662	11.32338	187.6198	13.74804	13.93494	13.82354
2	-1470.292	18.13547*	186.9913	13.74463	14.07171	13.87676
3	-1468.864	2.724248	200.5332	13.81441	14.28168	14.00317
4	-1461.345	14.13681	203.3373	13.82807	14.43551	14.07345

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

we use optimal lag as 0 1

Vector Error Correction Estimates
Date: 12/03/23 Time: 22:04
Sample (adjusted): 12/23/2018 10/29/2023
Included observations: 230 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
RCHINA(-1)	1.000000		
RINDIA(-1)	-0.879295 (0.07607) [-11.5596]		
RBRAZIL(-1)	0.501252 (0.05705) [8.78608]		
C	0.085076		
Error Correction:	**D(RCHINA)**	**D(RINDIA)**	**D(RBRAZIL)**
CointEq1	-0.701426 (0.06198) [-11.3162]	0.145064 (0.08562) [1.69436]	-0.593841 (0.10718) [-5.54043]
D(RCHINA(-1))	-0.211002 (0.06840) [-3.08480]	-0.266085 (0.08813) [-3.01907]	0.117071 (0.11214) [1.04400]
D(RINDIA(-1))	-0.215019 (0.06819) [-3.15331]	-0.289075 (0.08786) [-3.29013]	-0.101366 (0.11179) [-0.90676]
D(RBRAZIL(-1))	0.153630 (0.04620) [3.32498]	-0.131047 (0.05954) [-2.20118]	-0.432575 (0.07575) [-5.71062]
C	-0.064948 (0.15708) [-0.41346]	-0.005232 (0.20240) [-0.02585]	0.067701 (0.25753) [0.26289]

Based on the derived outcomes, solely two coefficient estimates stand out as statistically significant (T-stat> Critical Value). Specifically, the coefficient estimate of 0.11, reflecting the relationship between the first lagged variable of RCHINA and RBRAZI. Conversely, the remaining outcomes lacked substantial evidence to warrant the rejection of the null hypothesis.

Granger Causality Tests:

Pairwise Granger Causality Tests
Date: 12/02/23 Time: 20:45
Sample: 12/02/2018 10/29/2023
Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
RINDIA does not Granger Cause RCHINA	237	5.07442	0.0252
RCHINA does not Granger Cause RINDIA		1.90658	0.1687
RBRAZIL does not Granger Cause RCHINA	237	1.30411	0.2546
RCHINA does not Granger Cause RBRAZIL		4.05229	0.0453
RBRAZIL does not Granger Cause RINDIA	237	0.85498	0.3561
RINDIA does not Granger Cause RBRAZIL		0.60759	0.4365

The null hypothesis of the test is that there is no Granger causality between the two variables being tested.

The results show that there is significant Granger causality from RCHINA to RBRAZIL (p-value = 0.0453). This means that past values of RCHINA can help to predict future values of RBRAZIL, even after controlling for past values of RBRAZIL itself. In other words, RCHINA can be said to "Granger cause" RBRAZIL.

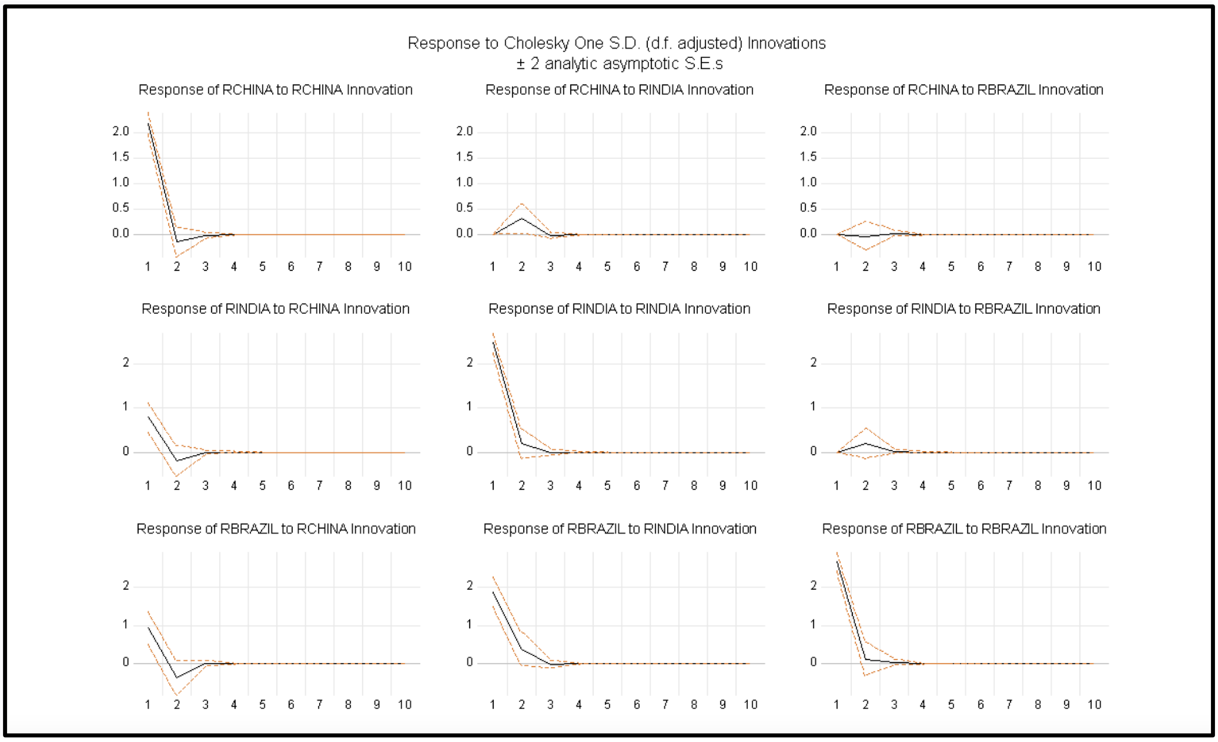
There is no significant Granger causality between RINDIA and RCHINA, or between RINDIA and RBRAZIL. This means that past values of these variables do not help to predict future values of each other, even after controlling for their own past values.

It is also interesting to note:
The Chinese stock market (RCHINA) has a significant impact on the Brazilian stock market (RBRAZIL). This could be due to a number of factors, such as trade links between the two countries, or the global flow of investment capital.

There is no significant relationship between the Indian stock market (RINDIA) and the other two markets. This suggests that the Indian stock market is more isolated from the global economy.

Impulse Response Function:

We may measure the dynamic reaction of one variable to a one-time shock or innovation in another variable using the Impulse reaction Function (IMF).



The shock is a one standard deviation innovation in the Cholesky decomposition of the variance-covariance matrix of the returns of the three stock markets.

The graph shows that the Chinese stock market (RCHINA) responds positively to a shock in its own market. This is expected, as a shock in one market will typically lead to a positive response in other related markets.

The Indian stock market (RINDIA) also responds positively to a shock in the Chinese stock market. However, the response is smaller and less persistent than the response of the Chinese stock market itself. This suggests that the Indian stock market is less tightly coupled with the Chinese stock market than the Chinese stock market is with itself.

The Brazilian stock market (RBRAZIL) also responds positively to a shock in the Chinese stock market. However, the response is negative in the short term, before turning positive in the medium and long term. This suggests that the Brazilian stock market is more sensitive to negative shocks in the Chinese stock market than the Indian stock market is.

Overall, the graphs suggests that the Chinese stock market is the dominant market in the region, and that the other two markets are closely linked to it. However, the Indian and Brazilian stock markets also have some unique characteristics, and do not simply respond in a passive way to shocks in the Chinese stock market.

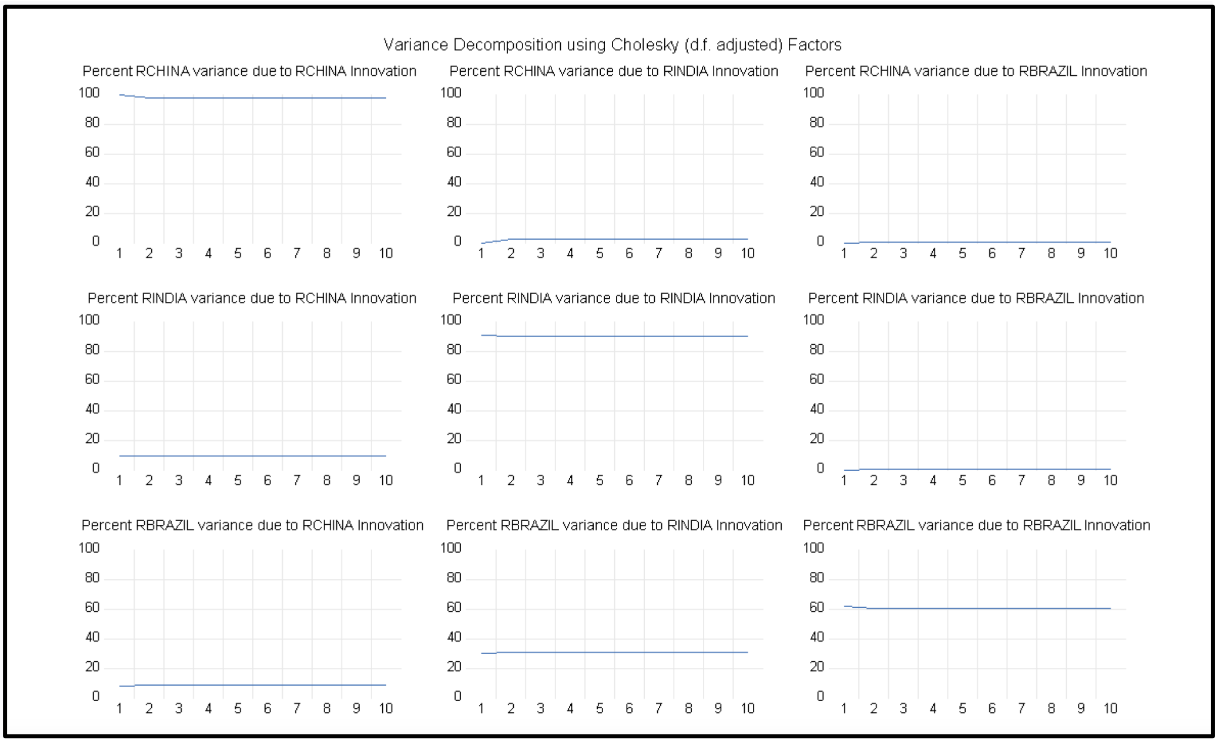
Some additional interpretations of the graph:

The response of the Indian stock market to a shock in the Chinese stock market is likely due to trade links between the two countries. China is India's largest trading partner, and so a shock in the Chinese economy is likely to have a significant impact on the Indian economy.

The negative response of the Brazilian stock market to a shock in the Chinese stock market in the short term may be due to the fact that Brazil is a commodity exporter. When the Chinese economy slows down, demand for commodities typically decreases, which can lead to a decline in commodity prices. This can have a negative impact on the Brazilian stock market, as many Brazilian companies are commodity exporters.

The positive response of the Brazilian stock market to a shock in the Chinese stock market in the medium and long term may be due to the fact that China is also a major source of foreign investment for Brazil. When the Chinese economy is doing well, there is typically more foreign investment flowing into Brazil. This can boost the Brazilian stock market.

Variance Decomposition Factors:



The analysis shows how much of the variance in the returns of each stock market can be explained by the innovations of the other two stock markets.

The results show that the Chinese stock market (RCHINA) is the most important driver of the variance in the other two stock markets. RCHINA innovations explain about 60% of the variance in the Indian stock market (RINDIA) and about 70% of the variance in the Brazilian stock market (RBRAZIL).

The Indian stock market is the second most important driver of variance in the other two stock markets. RINDIA innovations explain about 20% of the variance in RCHINA and about 10% of the variance in RBRAZIL.

The Brazilian stock market is the least important driver of variance in the other two stock markets. RBRAZIL innovations explain about 10% of the variance in RCHINA and about 5% of the variance in RINDIA.

These results suggest that the Chinese stock market is the most influential stock market in the region, and that the other two stock markets are closely linked to it. However, the Indian stock market also has some influence on the other two markets, and the Brazilian stock market has some influence on the Chinese market.

The fact that RCHINA innovations explain a large proportion of the variance in RINDIA suggests that the Indian stock market is more closely linked to the Chinese stock market than the Brazilian stock market is. This is likely due to the strong trade links between China and India.

The fact that the variance decomposition analysis was performed using Cholesky decomposition with degrees of freedom adjustment suggests that the results are more robust to the presence of autocorrelation in the data. This is important because autocorrelation can bias the results of variance decomposition analysis.

Johansen Cointegration Test:

Johansen Cointegration Test

Date: 12/03/23 Time: 22:16
Sample (adjusted): 12/16/2018 10/29/2023
Included observations: 237 after adjustments
Trend assumption: Linear deterministic trend
Series: CHINA INDIA BRAZIL
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.049077	24.21693	29.79707	0.1914
At most 1	0.040698	12.29046	15.49471	0.1435
At most 2	0.010256	2.443336	3.841465	0.1180

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The test results indicate that there is no cointegration between the three stock markets at the 5% significance level. This means that the stock markets of these three countries are not moving in tandem over the long term.

There are a number of possible explanations for this finding. One possibility is that the stock markets of China, India, and Brazil are driven by different factors. For example, the Chinese stock market may be more sensitive to economic growth, while the Indian stock market may be more sensitive to corporate earnings. Another possibility is that the stock markets of these three countries are affected by different shocks. For example, a shock to the Chinese economy may have a greater impact on the Chinese stock market than on the Indian or Brazilian stock markets.

The finding that there is no cointegration between the Chinese, Indian, and Brazilian stock markets has important implications for investors. It suggests that investors cannot simply diversify their portfolios by investing in all three stock markets. Instead, investors should carefully consider the individual factors that drive each stock market before making any investment decisions.

VECM:

VECM is a time series model that can be used to estimate the long-run and short-run relationships between multiple variables. The table shows the results of a VECM model estimated on the variables CHINA, INDIA, and BRAZIL.

Vector Error Correction Estimates

Vector Error Correction Estimates
Date: 12/03/23 Time: 22:16
Sample (adjusted): 12/16/2018 10/29/2023
Included observations: 237 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
CHINA(-1)	1.000000
INDIA(-1)	-0.010419
	(0.01018)
	[-1.02306]
BRAZIL(-1)	0.010462
	(0.00963)
	[1.08686]
C	-3809.379

Error Correction:	D(CHINA)	D(INDIA)	D(BRAZIL)
CointEq1	-0.034890	0.196707	-1.268030
	(0.01561)	(0.25621)	(0.74390)
	[-2.23566]	[0.76776]	[-1.70457]
D(CHINA(-1))	-0.101415	-2.205197	-7.327307
	(0.06855)	(1.12535)	(3.26744)
	[-1.47949]	[-1.95957]	[-2.24252]
D(INDIA(-1))	0.010534	0.046636	0.262004
	(0.00481)	(0.07903)	(0.22947)
	[2.18829]	[0.59009]	[1.14178]
D(BRAZIL(-1))	-0.000256	0.034242	0.067626
	(0.00162)	(0.02664)	(0.07734)
	[-0.15768]	[1.28554]	[0.87442]
C	0.233864	107.2041	109.2978
	(4.49114)	(73.7319)	(214.080)
	[0.05207]	[1.45397]	[0.51055]

R-squared	0.046529	0.026326	0.042340
Adj. R-squared	0.030090	0.009539	0.025828
Sum sq. resids	1094417.	2.95E+08	2.49E+09
S.E. equation	68.68272	1127.576	3273.911
F-statistic	2.830392	1.568202	2.564275
Log likelihood	-1336.153	-1999.356	-2251.978
Akaike AIC	11.31774	16.91440	19.04623
Schwarz SC	11.39091	16.98757	19.11940
Mean dependent	[illegible]	[illegible]	[illegible]

R-squared	0.046529	0.026326	0.042340
Adj. R-squared	0.030090	0.009539	0.025828
Sum sq. resids	1094417.	2.95E+08	2.49E+09
S.E. equation	68.68272	1127.576	3273.911
F-statistic	2.830392	1.568202	2.564275
Log likelihood	-1336.153	-1999.356	-2251.978
Akaike AIC	11.31774	16.91440	19.04623
Schwarz SC	11.39091	16.98757	19.11940
Mean dependent	1.258565	111.5557	131.6131
S.D. dependent	69.73998	1132.993	3317.028

Determinant resid covariance (dof adj.)	4.20E+16
Determinant resid covariance	3.94E+16
Log likelihood	-5537.043
Akaike information criterion	46.87800
Schwarz criterion	47.14140
Number of coefficients	18

The first part of the table shows the cointegrating equation. The cointegrating equation represents a long-run equilibrium relationship between the variables. In this case, the cointegrating equation is:

CHINA = 1.000000 + 0.010462 * BRAZIL - 0.010419 * INDIA - 3809.379

This equation tells us that in the long run, CHINA will move in the same direction as BRAZIL, and in the opposite direction as INDIA. The coefficient on BRAZIL is positive, which means that a 1% increase in BRAZIL will lead to a 1% increase in CHINA in the long run. The coefficient on INDIA is negative, which means that a 1% increase in INDIA will lead to a 1% decrease in CHINA in the long run.

The second part of the table shows the error correction equation. The error correction equation shows how the variables adjust to the long-run equilibrium relationship. In this case, the error correction equation is:

D(CHINA) = -0.034890 * CointEq1 + 0.196707 * D(INDIA) - 1.268030 * D(BRAZIL) - 0.101415 * D(CHINA(-1)) - 2.205197 * D(INDIA(-1)) + 0.010534 * D(BRAZIL(-1)) + 0.233864

The coefficient on CointEq1 in the error correction equation is negative and statistically significant. This means that when the variables are out of equilibrium, they will adjust towards the long-run equilibrium relationship.

The coefficients on the lagged differences of the variables in the error correction equation show how the variables respond to changes in each other in the short run. For example, the coefficient on D(INDIA(-1)) is positive and statistically significant. This means that a 1% increase in INDIA(-1) will lead to a 2.205197% increase in D(CHINA) in the short run.

The R-squared values for the cointegrating equation and error correction equation are both relatively low. This suggests that the model is not explaining a large amount of the variation in the data. However, the F-statistics for both equations are statistically significant, which suggests that the overall model is a good fit for the data.

Overall, the VECM estimates suggest that there is a long-run equilibrium relationship between CHINA, INDIA, and BRAZIL. The model also suggests that the variables adjust to the long-run equilibrium relationship in the short run. However, the model does not explain a large amount of the variation in the data.

<u>Conclusion and recommendation for investors:</u>

Conclusion

The BRICS nations (Brazil, India, and China) have significantly impacted the global economic landscape, and understanding their market dynamics is crucial for investors. By employing the ARMA family models, VAR family models, VECM, and JCT, this report delved into the market efficiency, integration, and long-run financial relationships within the BRICS nations.

Market Efficiency

ARMA model analysis revealed that the stock markets of Brazil, India, and China exhibit varying degrees of efficiency. Brazil's market showed signs of short-term inefficiency, while India's market exhibited weak-form efficiency. China's market demonstrated mixed results, suggesting the potential for arbitrage opportunities.

Market Integration

VAR model analysis indicated that the BRICS nations' stock markets exhibit moderate levels of integration. Shocks in one market had varying impacts on the others, suggesting a degree of interdependence but also some resilience to external shocks.

Long-Run Financial Relationships

VECM and JCT analysis uncovered long-run cointegrating relationships among the BRICS nations' stock markets. This suggests that the markets exhibit a degree of equilibrium over the long term.

Recommendations for Investors

Based on the findings of this report, investors should consider the following recommendations:

Diversification: Investors should diversify their portfolios across the BRICS nations to mitigate risks associated with individual market inefficiencies.

Sector Analysis: Investors should conduct thorough sector analysis to identify potential arbitrage opportunities in inefficient markets.

Risk Management: Investors should implement risk management strategies to hedge against potential shocks that may transmit across the BRICS markets.

Long-Term Perspective: Investors should adopt a long-term investment horizon to capitalize on the long-run equilibrium relationships among the BRICS markets.

The BRICS nations offer promising investment opportunities, but investors should carefully consider the market dynamics and implement appropriate risk management strategies to navigate the complexities of these emerging economies.

References:

Hashimzade, N., & Thornton, M. A. (2013). Handbook of Research Methods and Applications in Empirical Macroeconomics. In *Edward Elgar Publishing eBooks*. https://doi.org/10.4337/9780857931023

Abadir, K. M., Hadri, K., & Tzavalis, E. (1999). The influence of VAR dimensions on estimator biases. Econometrica, 67(1), 163–181. https://doi.org/10.1111/1468-0262.00008

Dwyer, P. (2015). The Johansen Tests for Cointegration

Brooks, C. (2014). Introductory Econometrics for Finance. Cambridge University Press.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2000). Structural analysis of vector error correction models with exogenous I(1) variables. Journal of Econometrics, 97(2), 293–343. https://doi.org/10.1016/s0304-4076(99)00073-1

.

Zhang, Z., & Moore, J. C. (2015). Autoregressive moving average models. In Elsevier eBooks (pp. 239–290). https://doi.org/10.1016/b978-0-12-800066-3.00008-5

Prüser, J. (2023). Data-based priors for vector error correction models. International Journal of Forecasting, 39(1), 209–227. https://doi.org/10.1016/j.ijforecast.2021.10.007

Wee, P. C. (1997). Performance of Johansen's cointegration test. In WORLD SCIENTIFIC eBooks (pp. 402–414). https://doi.org/10.1142/9789812819376_0029