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The influence of macroeconomic variables on the dynamic conditional correlations of stock market returns.

An empirical evidence of BRIC economies

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Foreword

This thesis was written for our Master's Degree in Business Engineering with specialization in International Business at the Louvain School of Management. This was a challenging but exciting research topic as it is a blend of financial and economical fields.

This thesis would not have been possible without the support of various relatives and people who have helped us through the entire process. We would like to particularly thank Leonardo Iania, Associate Professor of Finance at the Louvain School of Management, for his advice, guidance and patience. We would also like to thank Mustafa Khalfouni for his time, Mathieu Demarets for his help as well as our family for their endless support. This thesis would not have been possible without their continuous support.

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1. Introduction

Every rational investor aims to maximize returns while minimizing risk. International portfolio diversity is a strategy for effectively allocating resources and lowering the risk of investments. This type of portfolio can actually be more efficient than domestic portfolios (Bahlous & Yusof, 2014). The variability of the investor's returns can indeed be lowered by spreading the assets across different nations (Arif, Iqbal, Ali & Sohail, 2017). However, when markets are integrated with each other, the benefits of diversity may be reduced (Syriopoulos, 2011). The term “integrated markets” refers to assets from different markets but with similar risk and return (Tilfani, Ferreira, Dionisio, & El Boukfaoui, 2020). In theory, the overall risk of a financial portfolio is lower when the correlation between stocks is low, and vice versa. Therefore, an investor willing to build an international portfolio would pay attention to the fluctuations of correlations between markets in order to assess the risk of his financial portfolio and to understand what determines these correlations (Dong, An, Liu, Li & Yuan, 2020). The extensive research on market integration generally reveals that financial integration is beneficial to markets in good economic times. However, integration also contains bad aspects such as the faster transmission of financial shocks which makes domestic financial markets more unstable and less efficient (Devereux & Yu, 2020; Ferson, 2018; Gan, Gamal, Rambeli, Lim, Habibullah & Zainal, 2020). Nevertheless, in the long run, the costs are quickly offset by the benefits of integration (Babecký, Komarek & Komárková, 2017).

Over time, market integration has expanded as a result of capital market liberalization laws, technological improvements, and the growth of multinational companies. Many researchers have demonstrated the links that financial markets around the world have with each other. Francis and Leachman (1998) show that the United States has a significant influence on other markets. However, there is very little research on the interconnectedness of emerging countries with each other. It is regrettable because many investors would benefit from this. Investors' focus has, indeed, progressively shifted in recent years from developed to emerging countries. Four major new economic powers in particular stand out from the other developing countries; the BRIC (Brazil, Russia, India and China). The BRIC countries have swiftly evolved and become more integrated into the developed world, namely with a notable progression

of their stock markets regarding the size and volume of investments (Mensi, Hammoudeh, Reboredo & Nguyen, 2017). Moreover, diverse financial reforms have been implemented in the BRIC countries, playing a positive role also in the establishment of a favourable economic outlook (Rehman, 2021).

The term “BRIC” refers to the acronym created in 2001 by a Goldman Sachs economist named Jim O’Neill to describe the economic bloc of four developing countries: Brazil, Russia, India and China. O’Neill (2001) claims in his thesis that the BRIC countries would become the fastest growing market economies. A few years later, another report from Goldmans Sachs named *"Dreaming with BRIC: The Path to 2050”* declared that by 2050, the growth of BRIC countries may be larger than the one of the G7 in USD measures (Wilson & Purushothaman, 2006). The four BRIC nations collectively account for more than 23,6% of the world's GDP, from 12% in 2009 (Zhang, Sha & Xu, 2021). Large populations, abundant natural resources, and tremendous growth potential all characterize the BRIC countries (Sakovich, 2021). Their impact on the global economic and political level is significant (Tripathi & Kumar, 2015). By 2030, 41% of global market capitalization would be represented by the BRIC while China is expected to become the world's largest equity market, with its market capitalization surpassing that of the US (Mensi et al., 2014). Furthermore, the economies of the BRIC are undergoing significant social and political development, which describe many traits of an emerging market. As a result, it has a very high development potential and draws foreign investors (Sakovich, 2021).

Over the last couple of years, the stock market has become a key indicator of the performance of developing economies. Stock markets are also a matter of great importance in the BRIC and other emerging economies for several reasons. First, they allow for the optimal allocation of scarce financial resources to their most productive uses. Then, they enable the capitalization of companies and also serve as an investment avenue for investors. In addition, it helps support economic growth and facilitates price discovery of financial assets. Finally, stock markets improve liquidity, provide risk management tools such as derivatives and reduce transaction costs (Tripathi & Kumar, 2015). Various studies show that stock market is an explanatory variable for economic growth (Beck & Levine, 2004; Levine & Zervos, 1998; Rehman, 2021).

In order for an investor to properly diversify his portfolio within the BRIC, it is essential for him to be aware of the correlations between their stock markets, but also to understand what drives these correlations. For this purpose, macroeconomic variables may be used since they are among the main drivers of stock market development (Garcia & Liu, 1999). Many individuals in the economic and financial sphere are interested in the relationship between macroeconomics factors and the stock market. It is indisputable that when an investor completely understands the relationship between a macroeconomic variable and the stock market, they may make better decisions. Consequently, this lowers their risk exposure as well (Barakat, Elgazzar & Hanafy, 2006). In addition, macroeconomic variables have the advantage of being easily accessible.

This thesis examines whether the macroeconomic variables can help investors understanding with greater accuracy the dynamic conditional pairwise correlation of BRIC in order to assess the risk level of their portfolio.

This thesis contributes to the finance and econometric disclosure literature in two ways. First it defines the time-varying correlation between the BRIC countries, i.e. Brazil, Russia, India and China from 2005 and 2021 based on an econometric technique; the DCC-GARCH model. Indeed, this model has been and still is frequently used to analyse correlations over time, but very few studies have analysed the variation in the integration of these four countries with each other (Nikkinen et al., 2013; Dong et al., 2020; Malik, Sharma & Kaur, 2021). The analysis of BRIC financial markets is still an area that has been little researched. Second, many studies (Bekaert, 1995; Bekaert and Harvey, 1995; Bekaert et al., 2013; Bracker et al., 1999; Büttner and Hayo, 2011; Didier et al., 2012) have been realised in regard to the relationship between macroeconomic variables and stock market integration for developed markets, while few articles can be found in the literature on this relationship for emerging markets and especially for BRIC stock markets (Hammoudeh, Sari, Uzunkaya & Liu, 2012; Narayan, Srianantha kumar & Islam, 2014). Our thesis will use five macroeconomic variables such as the inflation rate, the exchange rate, the interest rate, the money supply of each BRIC countries and the international oil price to assess the correlation between BRIC stock markets returns.

Looking at the previous researches on the correlation between BRIC stock markets (Dong et al, 2020; Tripathy, 2015; Prakash et al, 2017; Ouattara, 2017; Maiti, 2021; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013; Heliodoro, Dias, Alexandre & Vasco, 2020; Mishra, 2022; Ngwakwe's, 2020), it is expected to find a volatile but growing integration. Moreover, it can be expected that the correlations increase during the periods of financial crisis and that the Chinese stock market does not strongly influence the other stock markets. In fact, we observed volatile correlations and an increase of the integration during the periods of global financial crisis and the 2016 Chinese financial crash. A stronger correlation between Brazil, Russia and India is likely as these are more economically open countries (Naik & Padhi, 2015; Parkash et al., 2017). According to our findings, the correlation between Brazilian and Indian stock market returns is the highest, followed by the correlation of Brazilian and Russian one. From the results of previous works (Tavares, 2009; Didier et al., 2012; Narayan et al., 2014; Volosovych, 2011; Pretorius, 2002; Nardo et al., 2022; Bracker et al., 1999; Sutherland, 2022), a negative impact of the exchange rate and a positive influence of the money supply and the inflation on the financial integration within the BRIC are expected. It can also be expected to observe positive but also negative relationship between the interest rate and oil price and, the dynamic conditional correlations (Fratzscher, 2002; Lee and Kim, 2020; Bracker et al, 1999; Narayan et al., 2014; Wu et al, 2020; Hammoudeh et al.2012). A stronger influence of the interest rate is expected as this macroeconomic variable is heavily used by the BRIC nations to control their economies especially in times of crisis (Banerjee & Vashisth, 2010). From our findings, a generalization on the impact of the macroeconomic variables on the correlations cannot be drawn. Regarding the regressions, each variable has its own impact. However, it was observed that the exchange rate and the interest rate seemed to have a stronger influence on the dynamic conditional correlations than the other variables.

This thesis is structured as follows. First, a review of the literature on the topic will be done. Then, the methodology to answer the central research question is developed followed by the analysis and discussion of the results obtained. Finally, the conclusion will be drawn.

2. Literature Review

2.1. Characteristics of BRIC Economies

Brazil, Russia, China and India (BRIC countries) are considered to be the four major emerging markets in the world and are likely to be the dominant economies in the global market by the year 2050 (Krusling, n.d.). It is therefore important at this stage to assess their own economic contribution and level of efficiency. As stock market shocks become more frequent and complex, a thorough analysis and understanding of these emerging markets is required.

In terms of nominal GDP, Brazil is the thirteenth largest economy (World Population Review, 2021). Since 1990, several reforms have been implemented in Brazil, reducing the state intervention in the economy, liberalizing the flow of capital and trade, and privatizing state-owned businesses (Gallagher & Chudnovsky, 2009). The reforms have changed significantly the Brazilian stock market in terms of market capitalization, the total value of stocks traded, and the turnover ratio. The year 2007 recorded a significant peak of market capitalization in the history of Brazil's stock market at that time. Another positive output from the reforms is the improvement of the Brazilian stock market thanks to the expansion of available financial instruments, strengthening of market infrastructure and the foundation of a diversified investor base (Nyasha & Odhiambo, 2013). The literature also adds that the historically high interest rates is another factor that help Brazil attracts international investment (Newman, Rickert & Schaap, 2011). Between 2014 and 2016, the Brazilian economy experienced a severe recession, which then caused the value of financial assets to decline significantly. The adoption of unsustainable fiscal and monetary policies that encouraged an increase in inflation and public debt, as well as the decline in commodity prices on the global market, are reasons used to understand the recession (Vartanian, dos Santos, da Silva & Fronzaglia, 2022). After that, from the start of 2016 until March 2020, the Brazilian stock markets experienced a period of tremendous enthusiasm. Between its lowest point in January 2016 and its highest point in January 2020, the Ibovespa index's market value tripled (Laurini & Chaim, 2021).

Russia is the eleventh largest economy in the world in terms of nominal GDP (Statista, 2022). Since the collapse of the Soviet Union, Russia has gone through several changes that have

included becoming more integrated into the global economy. Russia was the country most affected by the 2008 global financial crisis. The fall in oil prices had a big impact on Russian banks and companies. However, from 2011, the economy started to grow modestly. Market liberalization initiatives in the 2010's and the country's huge crude oil reserves have attracted many investors. Nevertheless, there are several features of Russia that could concern international investors. One major concern is the lack of transparency, which is a significant barrier to drawing in foreign investment (Tripathy & Garg, 2013). Moreover, Russia is significantly exposed to its trading partners' activities, both in terms of imports and exports and in terms of limits on financial flow (Costola & Lorusso, 2022). Then, the Crimean war that began in 2014, leading to annexation, had a negative impact on the Russian stock market. Indeed, this war has resulted in various sanctions and brought Russian returns down sharply (Hoffmann & Neuenkirch, 2015). Study's results of Gurvich and Prilepskiy (2015) confirmed that that Russian state-controlled banks, oil and gas industries were directly impacted by Western financial sanctions between 2014 and 2017. Furthermore, Costola and Lorusso (2022) supported this finding by stating that that the third wave of sanctions against Russia in 2017, following the annexation of Crimea, had a negative impact on the Russian economy.

India is ranked sixth in the world in terms of nominal GDP (World Population Review, n.d.). India is rapidly developing as an open economy and its rate of integration with the world economy is increasing. However, India faces many long-term challenges. Indeed on the one hand, the country's growth is slower than other BRIC countries as India faces persistent inflation, high international oil prices and declining investment (Tripathy & Garg, 2013). On the other hand, India ranks third in the index of disclosure requirements (La Porta, Lopez-de-Silance, and Shleifer, 2006). Owners of establishments who have complete control are India's strongest institutional elements. The regulations regulating listing, trading, and settlements were explicitly laid forth by the Indian financial markets (Tripathy & Garg, 2013). The study of Yadav (2017) shows that Indian stock cycles have longer bullish phases, higher amplitude and higher volatility.

China is one of the largest economies in the world with the second largest position in nominal Gross Domestic Product (GDP) and purchasing power (Statista, n.d.). In general, it is often argued that China is the dominant country of the BRIC and considered to be the most

economically developed nation of this group (Goncharov, 2021). There are three dominant sectors in China. Firstly, the state-owned sectors are still mainly under government control. Secondly, the listed sectors are traded on the stock exchange. Both of these sectors are subject to weak legal protections and standard financing channels, which slow down their development. Finally, the private sector is not completely private, it is a mixture of private and government control, but the local government shows a favourable attitude towards this sector, which favours its growth in addition to its governance efficiency. Over the last 15 years, China faced numerous economic challenges. The major changes in the economic structure of China were done after the financial crisis of 2008. In 2010-2011, the country has experienced a high inflation rate due to this credit stimulus programme (Tripathy & Garg, 2013). In 2015-2016, China faced a stock market crash coming from the bubble in Chinese stock market. Indeed, between 2014 and early 2015, the SSE (China Stock Index) rose by 150 percent. However, this spectacular rise made little sense. Indeed, the country's economy was experiencing a significant slowdown in growth. The economic basis for this increase was neither justified nor consistent, and it was clear that the Chinese market was entering bubble territory. The financial bubble finally burst at the end of 2015 to have a strong negative effect on the stock markets in early 2016 (Global, n.d.).

One of the similarities among those four emerging nations is that the 2008 financial crisis hindered their pace of growth (Molano, 2009). One aspect that these countries also have in common is that their production is not yet at their maximum. BRIC countries have not yet exploited their full potential. Indeed, their productivity levels are below their own potential and below that of the developed countries (Nikolaou, 2021). It could even seem surprising that China and India are also dealing with this issue, given their extreme economic growth over the past fifteen years (Todaro & Smith, 2021). Similarities exist between China and India, including their vast geographic region, supportive governmental policies, and massive labour forces. Additionally, the middle class is growing in both countries, which is essential to maintaining long-term economic progress (Lao & Singh, 2011). In terms of exports as a percentage of GDP, Russia leads the ranking among the BRIC. Russia is a country that seems to want to increase its wealth thanks to its export levels, in order to have a favourable balance of trade (Krugman et al., 2015). Over the last ten years, Brazil seems to be the only country to have increased its export levels significantly, while China and India have decreased them. Also

noteworthy is the fact that the BRIC's exports levels have not been negatively impacted by the 2020 COVID-19 crisis. Their export levels are in fact almost unchanged in 2020 compared to 2019 (Nikolaou, 2021). In 2020, apart from Russia which is well above, India, China and Brazil have roughly the same percentage of exports (Nikolaou, 2021). Subsequently, Russia also has the highest level of imports as percentage of GDP, 20.6%, which is made possible by its greater level of exports.

The BRIC have been important global energy consumers (Su, Huang, Qin & Umar, 2021). It has been shown that the BRIC economies strongly rely on crude oil and that they have a large share of supply and demand of crude oil. In 2020, the four countries accounted for approximately 28 percent of the total global oil demand (Sönnichsen, n.d.). On the one hand, China and India are, after the United States, the two biggest importers of oil with a total of 21.4 percent of the global oil consumption in 2021 (Statista, 2021) and on the other hand, Russia and Brazil are ranked among the biggest producers and exporters in the world with a total of 15.5 percent of the global oil production in 2021 (Sönnichsen, n.d.).

On the political side, these four emerging nations have experienced different changes in the last twenty years. On the one hand, authoritarianism has grown in China and Russia, while on the other, populists have quickly gained power in Brazil and India (Chatterjee & Naka, 2022).

2.2. Relationship between BRIC Stock Markets

The first studies of interconnectivity links between undeveloped markets were mainly carried out in Asian markets in the early 2000s. Daly (2003) found, for example, that developed markets (Australian, German and US) were not very interconnected with South East Asian markets, but also that the South East Asian markets were poorly interconnected. Divecha, Drach and Stefek (1992) also made the same finding about Asian markets integration. Barus (1997) therefore concluded that societal, economic and political similarities had no influence on the correlation of stock markets in developing Asian countries. Palac-McMiken (1997), after performing two studies on the subject for ten Asian countries; one in 2000 and one in 2002, found that the integration of Asian stock markets was increasing.

In view of the studies done on other developing markets, it would be relevant to say that the BRIC are following the same path and that, little by little, the link of interconnectivity is growing between them. Tripathy (2015) demonstrates the presence of a two-way causal link between the Russian and Indian markets as well as between the Russian and Brazilian markets. It shows that both market are depending in each other and impacting each other. She found that there is a unidirectional causality between Indian and Brazilian stock market meaning that every change in the Indian stock market return affect the Brazilian stock market return in the short-term rather than the opposite. The study performed by Dong et al (2020) shows that there is indeed a long-term correlation between the BRIC but that this link has not always maintained a positive direction. Their overall results also show that there is a distinct co-movement among the BRIC countries but the correlation differs at different time and frequency. Prakash, Nauriyal and Kaur (2017) reported that there is indeed a long-term financial cointegration but the long-term link is weak. This also proves that the evolution of correlations within the BRIC countries contains complex and dynamic features. Moreover, their degree of openness is not similar, which also affects the evolution of integration between countries. Indeed, the stock markets of Brazil, India and Russia are highly open, but China's economy, because of its high regulatory processes, seems to lag behind in this aspect. Ouattara (2017) found that of the four BRIC countries, China was the least integrated. Tripathy (2015) confirms Ouattara's finding through his study on BRIC stock market integration. It shows that there is no short-term relationship between the Chinese stock market and the other BRIC members' stock market. Hence, a short-term change in the Chinese stock markets should not cause a change in the Indian, Brazilian and Russian stock markets. China therefore operates independently and does not transmit information directly, this may be linked to restrictions on the international movement of capital in the country. The highest level of regional and global integration is demonstrated by India, which is followed by Brazil, Russia, and then China (Naik & Padhi, 2015).

Globalization and the opening up of financial markets have strongly influenced the co-integration of countries around the world, which has also increased the risks within diversified portfolios (Maiti, 2021). For the BRIC countries, a higher level of financial market integration between them has been observed after a period of global crisis such as the sub-prime crisis in 2008 or the COVID-19 crisis in 2020 (Maiti, Vukovic, Vyklyuk & Grubisic, 2022).

2.2.1. 2008 Financial Crisis

Before the financial crisis of 2007-2008, the BRIC financial markets attracted very few investors. Although it was estimated that, between 2000-2008, BRIC countries contributed to 30% of global GDP growth (Banerjee & Vashisth, 2010), these emerging markets were very uncertain and volatile. Investors preferred to allocate their funds to more stable markets. However, the global crisis has changed many investment prospects in emerging markets and more particularly in the BRIC (Patel, 2019).

A study performed by Ahmad, Sehgal, & Bhanumurthy (2013) showed that all the BRIC markets were substantially affected by the Global Financial crisis but not at the same time and at the same level as the developed markets. The study of Dimitriou, Kenourgios and Simos (2013) demonstrated that the effects of the shock in the BRIC financial market was not perceived in the early stage of the crisis. Mensi, Hammoudeh and Kang (2017a) find that the financial crisis has had a decoupling effect for the Russian market compared to other BRIC countries. Nikkinen, Saleem and Martikaine (2013) examine the extent of contagion, i.e. the intensification of cross- market integration after a shock in a country or group of countries (Dornbusch, Park & Claessens, 2000), by using a bivariate GARCH-BEKK model applying daily total return indices and estimate four pairwise models. Results showed that contagion is observed in the BRIC but with a higher level of severity in the Russian financial sector. A study also reported that, after the US financial crisis, stock markets of BRIC have become more integrated within themselves and with the US market from early 2009 onward (Bekiros, 2014).

After the financial crisis of 2008, it was shown that China and India were the two major emerging market countries that were not in recession in 2009 (Lemoine, 2009). Due to their high level of integration with the developed markets, Brazil and Russia suffered the most while China and India were only impacted by a small decrease in their GDP growth (Banerjee & Vashisth, 2010). Indeed, the two countries together contributed three quarters of global growth over the 2008-2010 period. The recession that the other countries witnessed allowed India and China to increase their weight in the world economy. Zouhair, Lanouar & Ajmi (2014) support the argument by showing that China and India had very low correlation with the US at that time compared to Brazil which shows high correlation coefficients. These

results are confirmed by the study of Aloui, Aïssa & Nguyen (2011). Morales and Gassie-Falzone (2011) performed a bivariate EGARCH structure on index returns and the results showed that China was the most isolated country of the BRIC.

In his study (2013), Stuenkel examined *"How and why institutionalized cooperation between the BRIC countries began"*. One of the two arguments of this research is that the financial crisis of 2008, which deeply affected the financial markets of developed countries, has allowed emerging powers, mainly the BRIC, to develop unprecedented cooperation. The financial crisis has led to a crisis of legitimacy in the international financial system, which has opened a window of opportunity for the BRIC to gather around a fundamental issue; the importance to reform the international financial order.

One of the many reasons for the faster restructuring of the BRIC markets after the crisis was the announcement by the BRIC economies of the implementation of new financial stimulus measures. The monetary response of the BRIC economies was, for all of them, to cut interest rates. The fiscal response differed from country to country. While Brazil and Russia opted for tax cuts to support private demand, India and China went for direct public expenditure on infrastructure expansion (Banerjee & Vashisth, 2010).

2.2.2. COVID-19 Crisis

At the end of 2019, the virus named COVID-19 appears in Wuhan, China. Very quickly, the virus spreads throughout the world and in January 2020, the World Health Organization (WHO) officially declares the global pandemic. The virus quickly became a global threat to human lives but also to the financial markets. Regarding the COVID-19 infection cases, BRIC countries were the worst affected nations, 18.76 million of cases for India, followed by 14.45 million for Brazil, 4.81 millions for Russian and 0.1 million for China (Mishra, 2022), the effects on their financials are expected to be highly negative and significant. However, the long-term consequences of this pandemic on the financial market remain uncertain and unknown (Xu & Len, 2021).

Heliodoro, Dias, Alexandre & Vasco (2020) demonstrate, via the Gregory-Hansen test, that integration within the BRIC stock markets has increased significantly over the COVID period. Malik, Sharma & Kaur (2021) performed an analysis on the evolution of BRIC dynamic correlations during the COVID-19 period. They observed that the correlation between China and India did not show an increasing sign over the period. This finding is surprising because in 2016, when a negative shock hit China, this correlation of the stock markets increased sharply. For China and Russia, the correlation proved to be more volatile and with large variations over the period. They also show that Russia and Brazil are proving to be great strategic, economic and technological allies in times of crisis. Indeed, they have greatly increased their trade and military cooperation which leads them to have a strong global position and therefore to be able to respond quickly in times of crisis.

The financial impact is not uniform. Indeed, COVID-19's influence on G-7, i.e. the seven world's advanced economies (Canada, France, Germany, Italy, Japan, the United Kingdom, the United States and the European Union) and BRIC nations was studied by Ledwani et al. (2021), who found that stock behaviour differed between the two groupings of economies. For example, all BRIC nations saw a rise in average index prices during the pandemic period compared to the pre-pandemic period (Rajput & Sufiya, 2022). Mishra (2022) found out that the level of connectedness between BRIC countries was weakened during the COVID-19. Ngwakwe's (2020) study shows that, during the COVID-19 period, the performance of China's and India's stock markets is predictive of and insightful into the behaviour of the Brazilian stock market. In the same vein, the performance of Russian stock markets also allows investors to better understand the movements of Indian stocks.

Chavali, Samman, & Jamil (2021) conducted a study on the reaction of BRIC stock markets to the announcement of the global pandemic. They mainly based their analysis on two distinct periods within the four countries; firstly a period of 30-60 days after the announcement of the first case in the territory and secondly the period after these 30-60 days and the financial responses of each country. It was shown that for each of the four countries, the impact on their stock market returns was negative in the first period. From this negative effect, local governments quickly took economic support measures such as travel bans, lockdowns, and stimulus packages which allowed the negative effect of COVID-19 to disappear in three of the

countries: Russia, India and China. For Brazil, the effect was indeed reduced but not totally eliminated.

Rajput & Sufiya (2022) reported that, except between February 2020 and March 2020, the returns of all BRIC countries, except for China, were steady indicating constant return. It may be claimed that during a pandemic, a high degree of uncertainty imposes a high degree of risk, resulting in higher returns for indexes with a high degree of variability. The degree of variation varies from nation to country, depending on the intensity of the epidemic in that country. Malik, Sharma and Kaur (2021) concluded their study that once the COVID-19 pandemic is finally over, the system of international relations will be revisited in a new light and to the advantage of the BRIC.

2.3. Portfolio Diversification in BRIC

Diversification is a risk management strategy that mixes a variety of investments within a portfolio. In an effort to reduce exposure to any one asset or risk, a diversified portfolio combines a variety of different asset classes and investment vehicles. This strategy is justified by the idea that a portfolio made up of many asset classes would, on average, produce superior long-term returns and reduce the risk of any one holding or security (Segal, 2021).

International diversification is a crucial tool for improving the performance of investors' portfolios. The benefits of international portfolio investments are numerous. The benefits for an investor of developing an international financial portfolio are mainly based on the higher proportion of wealth, participation in the growth of other markets, the possibility of hedging, and higher yields (Bartram & Dufey, 2001). Studies also show that international diversification can decrease the risk of correlation between assets due to the distance between markets and also to industrial diversification. Industrial diversification is the fact that industry markets vary across countries (Roll, 1992). Benefits of foreign portfolio diversification can be obtained when the markets are not interconnected (Arif, Iqbal, Ali & Sohail, 2017).

Many studies have been conducted on the link between financial integration and international diversification. However, the results and discussions are ambiguous. On the one

hand, financial market integration makes international diversification more efficient and effective through the elimination and/or reduction of barriers to capital movements and segmentation factors. But, on the other hand, this integration would have increased correlations between financial markets, which would reduce the benefits of international diversification strategies. Thus, the interdependence and integration of financial markets may undermine the benefits of international portfolio diversification (Zayati, Chaabene & Bellalah, 2016). Modern portfolio theory shows that gains in international diversification are inversely related to the level of integration of financial markets, which has progressed significantly as a result of trade liberalization, the dismantling of barriers to international investment and capital movements between markets. King, Sentana and Wadhwani (1994) found that the similarity of market reactions to events is explained by the increase in market integration, which leads to sub-optimal portfolio allocation and reduces the performance of international diversification.

Most studies on the integrity of the BRIC among themselves show that most BRIC financial markets offer a broad portfolio diversification opportunity for international financial investors, especially in non-crisis periods. Investors wishing to invest in the BRIC should first of all have a clear view of the rate of integrity of the countries among themselves (Khaki, Jreisat & Bakry, 2020). Ouattara (2017) adds, via his findings, that a long-term investor would see increased returns if he invested in the BRIC over the long term because they are not highly integrated on the long-term. Although there is a long-term correlation, it remains weak, not perfect and is not likely to have a strong impact on the long-term investor's portfolio.

For an investor who wants to invest in the BRIC and diversify his or her portfolio, Dong et al (2020) suggest, based on their results, several possibilities depending on the investor's risk level. First, a high-risk investor would prefer to invest their portfolio stocks in Brazil. A moderately risk-averse investor should combine a portfolio of Brazilian, Indian and Russian assets. Finally, they would advise a highly risk-averse investor to select portfolios from the Chinese stock market with a combination of one of the Brazilian, Indian or Russian stock markets. Maiti et al. (2022) indicate that investors will not benefit if they invest exclusively in Russia and China. Joshi (2016) reports that an optimized financial portfolio within the BRIC should contain the following weights; the highest is allocated to China (39.89%), closely

followed by India (35.00%) and Russia (16.61%). Finally, the lowest weight is assigned to Brazil (8.5%). Ashfaq, Ayub, Mujtaba, Raza & Gulza (2021) consider China and India as truly representative economies within the BRIC and as strongly favourable to equity investment.

Khaki, Jreisat & Bakry (2020) show that the linkages between the BRIC financial markets are growing, which reduces the positive effects of the international financial portfolio. Although the increasing integration of the BRIC stock markets affects the performance of an international portfolio, an international investor should still be attracted to these economies because they show significant growth to compensate for the decline in developed economies. They also add that there are many factors that influence integration but also help to better understand it and thus build an effective international financial portfolio. They refer in particular to the evolution and understanding of macroeconomic variables in countries. Bekaert (1995) finds that the macroeconomic variables were in a way barriers to integration.

2.4. Macroeconomics Variables and BRIC Stock Markets

"*The stock market is but a mirror, which provides an image of the underlying or fundamental economic situation*" (Galbraith, 1955). Therefore, the effects of macroeconomic variables on stock returns have been widely discussed in the literature. Tripathi & Kumar (2015c) state that stock returns are influenced by macroeconomic factors through their effect on future cash flows and the discount rate. Chen et al (1986) also claim that the variations in macroeconomic state variables affect the return rate, the dividend pay-out ratio and future cash flows given the influence on investors preference over time. Macroeconomic factors such as inflation, interest rate, exchange rate, money supply and oil prices have long been assumed to have a considerable impact on stock market performance in general. Tripathi & Kumar (2016) confirmed the statement by saying that the correlation between stock returns and macroeconomic factors has significantly increased in the post 2008 crisis which indicates the deepening of the contemporary relationship.

Many players in the financial world are interested in the relationship between exchange rates and stock market index prices, given the important impact they have on the economy (Mroua & Trabelsi, 2020). However, there is no consensus on the effect that exchange rates have on

stock indexes. The literature is indeed divided on the existence of a positive or negative relationship with stock market returns (Tripathi & Kumar, 2015a). Gay (2008) investigated the effects of international macroeconomic variables on stock market returns for the BRIC countries. More precisely, the study's purpose is to analyse, by using the Box-Jenkins ARIMA methodology, the time-series relationship between stock market index prices and exchange rate. The findings indicate that the relationship is not significant. It can be attributed to the fact that other macroeconomic variables also play their part in the process of determining stock price expectations. However Gay (2008) found that the exchange rates and stock prices are positively correlated for China, India, Brazil but not for Russia. Mohapatra and Rath (2015) studied the links between stock prices and key macroeconomic factors for the period 2000-2012 in three BRIC countries: India, Brazil and China and their results exhibit that there is a long-run unidirectional causality between the exchange rate and stock prices. More recently, a study reveals that changes in the exchange rate have significant impacts on stock market returns. Furthermore, the exchange rate coefficient's negative sign implies that the value of the BRIC stock indexes rises when the local currency's value rises versus the USD, and inversely (Mroua & Trabelsi, 2020). In order to study the impact of the exchange rate, interest rate, inflation and oil on stock market performance in BRIC nations, Lone et al (2021) measured short and long-run relationships via the PMG/ARDL model. These models confirmed the short and long-run relationships of for all these countries. Agrawal and Srivastava (2011) used a GARCH model to analyse the relationships between stock market returns and exchange rates volatility in India. The results illustrate that there exists a bidirectional causality between the two. Tripathi and Kumar (2015) also observed significant impact from exchange rate on stock returns in the BRIC countries, with the influence being negative. In another study, Tripathi and Kumar (2016) added that exchange rate is a significant determinant of the stock return behaviour in the pre- and post-global recession periods for the BRIC nations.

Mukherjee & Naka (1995) stated that in general inflation and high interest rates affect stock market returns negatively, in part because of the company's increased cost of capital. Indeed, inflation's increase comes with lower expected earnings growth and higher required real returns while the increase of interest rate is accompanied by a rise of the discount rate (Tripathi and Kumar, 2015). Tripathi and Kumar (2015), in their study about the influence of

macroeconomic factors on stock returns in BRIC markets, found that inflation only has a significant impact in Brazil. They also discovered interest rate has been found to impact negatively and significantly stock returns, which has been confirmed by Mohapatra and Rath (2015). In a later study about the BRIC, Tripathi & Kumar (2016) observed that stock returns are negatively correlated to inflation rate. Contrary to above, various studies have shown that the stock market and inflation have a positive association (Sohail & Hussain, 2011 ; Venkatraja, 2014; Tripathi & Kumar, 2014; Adam & Tweneboah, 2008; Shahbaz, Hooi Lean & Kalim, 2013). Furthermore, according to Hosseini, Ahmad and Lai's (2011)'s research, there are both long- and short-term relationships between China and India's stock market indices and inflation rate. Mohapatra and Rath (2015) confirmed this causality. In their research into the interactions between macroeconomic factors and stock prices in China, Soenen and Johnson (2001) discovered that inflation influenced the Chinese stock markets. The NIFTY index, one of the main Indian stock market index, was analysed by Patel (2012) and the results show that inflation and interest rates are both influencing the index.

Through most of the studies, oil price is taken into account when assessing the impact of macroeconomic variables on stock market returns. Crude oil's major contribution to the global energy industry is an explanation among others of this increased interest in it (Batia & Mitra, 2020). The price of crude oil undoubtedly affects stock markets as well as actual economies. As a consequence of its crucial role in the economic growth of all nations that import or export oil, the crude oil price has received attention from both investors and policy makers (Wu, Zhu, Xu, Yang, 2020). In their study of the influence of oil price fluctuations on stock market returns in 21 emerging economies, Basher and Sadorsky (2006) discovered great evidence of the effect of oil prices being positive and statistically significant to stock market returns for most of the countries analysed. More recently, study's results of Ji, Liu, Zhao, and Fan (2020) confirmed a mostly positive and time-varying dependence between stock returns and oil price shocks. Nevertheless, since crude oil is crucial to the manufacturing of many goods and services, an increase in crude oil prices might have a negative impact on businesses' production costs. A rise in production costs might lead to lower profitability and a decline in the value of these companies' stocks (Batia & Mitra, 2020). Then, changes in the price of crude oil would also impact on business earnings and cash flows from the demand side as well. An illustration of this is that a rise in oil prices would make people feel more fearful about the

possibility of losing their jobs in the future, which would motivate them to save more money. Stock prices would suffer as a result of this (Xu, 2015). Tripathi & Kumar (2015) authors observed negative and significant impacts in the short and long run from oil prices on the BRIC stock returns. However, according to a study conducted by Robert Gay (2008), the stock market in BRIC countries is not significantly affected by the oil price. Finally, it has been argued that fluctuations in oil prices affect countries depending on their status (Cologni & Manera, 2008; Park & Ratti, 2008; Kilian & Park, 2009; Ono, 2011). For instance, on the one hand, an oil importing nation would negatively be impacted by an oil price increase since it would lead to a cost of capital and inflation's rise (Tripathi & Kumar, 2015). On the other hand, an oil exporting nation will benefit from rising oil prices since it will increase predicted future cash flows.

There is also room for discussion on the net impact of the money supply on stock market returns. Indeed, if we take the case where the money supply is increased, a positive impact on stock market returns occurs via the increase in liquidity that allows more investments and lowers the interest rate (Mukherjee & Naka, 1995; Chaudhuri & Smiles, 2004 quoted by Tripathi & Kumar, 2015). Tripathi and Kumar (2015b) found that money supply has a significant and positive impact on stock returns in the BRIC countries. Later, Tripathi and Kumar (2016) discovered an important positive relationship of BRIC stock returns with money supply changes. The positive relationship between the money supply and stock market indices was also proven by Patel's 2012 study in the Indian stock exchange (SENSEX). BRIC countries have a low level of monetization and have not reached a critical level. Therefore, the increase of money supply in BRIC countries is important to stimulate economic growth (Nizhegorodtsev & Goridko, 2015). However, a negative impact could occur due to the substantial inflationary pressure created by the increase of money supply. When the central bank increases the money supply in the economy faster than the economic growth, inflation occurs. Indeed, the increase of the money in circulation is therefore higher than the increase of the goods produced in the territory, the demand of goods increases but the offer cannot follow (Gorton, 2021). Finally, according to Chakraborty and Gupta (2017), the Indian stock market is not significantly influenced by the money supply.

2.5. Macroeconomics Variables as Drivers of Market Integration

The influence of macroeconomic variables on the integration of international stock markets has already been the subject of numerous studies. Researches generally focus on analysing how the stock markets of different countries are correlated (Bracker, Docking & Koch, 1999). In theory, it has been repeatedly demonstrated that financial market integration is fundamentally linked to economic growth and the reduction of macroeconomic volatility between countries (Baele, Ferrando, Hordahl, Krylova & Monnet, 2004). The study of Campbell and Hamao (1992) similarly highlight the potential macroeconomic sources of covariance between markets of different countries. Many studies on time-varying correlation and integration of stock markets find that macroeconomic variables have a strong influence on bilateral lead-lag linkages between stock markets of different countries (Guvenen, 2009).

Researchers found that the exchange rate is expected to have a negative influence on the pairwise correlation and that a greater divergence in interest rates, inflation rates is usually associated with lower market integration (Didier et al., 2012). Lee and Kim (2020) have analysed the roles of monetary performance convergence between the (pairwise) countries of European Union. The results of their study suggest that the exchange rate stability due to the Euro's introduction and the inflation performance similarity had a positive influence on the integration of the countries. Kim, Moshirian and Wu (2005) also undermine the results by arguing that exchange rate stability has led to better financial market integration for some, mostly countries with historical different economic structures, but not all EU countries. Tavares (2009) examines how cross-country stock return co-movements in developed and emerging markets are impacted by economic integration. His study was concentrated on 40 economies, developed and developing. He found that real exchange rate volatility decreases the correlation of stock returns. Narayan, Srianantha kumar and Islam (2014) used the GARCH and linear regression tool to examine the patterns and cause of the stock market integrations of emerging Asian economies, i.e. China, India, Korea, Singapore, Malaysia and Thailand. For some pairwise, they found that an increase in the exchange rate leads to an increase in the correlation. However, this result was not the case for India, the exchange rate does not seem to be a significant determinant of its correlation with the other countries analysed.

Lee and Kim (2020) indicate that the interest rate had nearly no impact on the integration of the countries. This finding goes against the study of Fratzscher (2002) who found that the short-term interest rates played a significant role on the integration of EU stock markets. According to Bracker et al. (1999), the interest rate has a negative correlation with the degree of global interdependence. Nevertheless, Narayan, Srianantha kumar and Islam (2014) exhibit that the there is a positive relationship between short term interest rates and correlation between India and China.

Volosovych (2011), in his analysis of markets in 15 advanced economies, argues that the policy variable (inflation) plays a role in the evolution of the financial integration process. Nardo, Ossala and Papanagiotou (2022) support his argument by stating that inflation is an important determinant of the correlation between financial markets of different countries as it is a variable closely related to competition, growth and financial development of countries. According to Pretorius (2002), countries with similar levels of inflation will have similar valuations, which will cause stock prices to converge and lead to significant stock market co-movement. Narayan et al. (2014) found that an increase in inflation weaken the integration of Chinese and Indian stock markets. However, this result can only be the case for India and China because the study of Bracker et al (1999) who sought to identify the extent of co-movement in different financial markets, indicates an increase in inflation induces a greater fluctuation of capital and trade from a country i to a country j, implying a stronger tendency of the market in country i to follow market j. Comparing these results with those of Sutherland (2002) who found that an increase in the domestic money supply caused an expansion of domestic and foreign consumption and consequently an increase in capital flight out of the country, it may be inferred that the macroeconomic variable money supply also has a positive relationship with the integration of countries' stock markets.

Siliverstovs, L'Hégaret, Neumann and Von Hirschhausen (2005) looked at the integration of the US, European and Japanese oil and gas markets. The analysis shows that these markets do not seem to be cointegrated despite their economic similarity and the correlation between their stock markets. Hammoudeh, Sari, Uzunkaya and Liu (2013) confirm that the oil price shows very little sensitivity to BRIC stock market correlations despite the fact that Russia is a producing country. They added that this surprising finding may be related to the long-term

commitment of oil price contracts between the BRIC countries. According to Yang, Cai and Hamori (2017), crude oil is a key factor in the co-movements between the Russian and oil-importing country stock markets. The results from Lui, Tseng, Wu and Ding (2020) show that the price of crude oil has had a significant impact on the co-movement between oil-importing and oil-exporting nations, but only a little impact on the co-movement within oil-importing countries and a slight impact on the co-movement within oil-exporting countries. They emphasized that Russia supplies around 10% of the world's oil exports but differs from other oil exporting nations in that it is less dependent on oil-related activities because of its robust industrial infrastructure. The majority of the other oil-exporting nations lack sophisticated industrial infrastructures, thus they import most of their commodities from industrialized and developing nations like China. They are oil-dependent countries. The co-movements of the Russian and oil-importing countries' stock markets are therefore less affected by the crude oil price than the co-movements of the stock markets of other oil-exporting and oil-importing countries.

3. Methodology

3.1. Research Design

Our sample includes several dependent and independent variables which are expressed in monthly data for a 17-year time period. The monthly time-series data start in January 2005 and end in December 2021.

The stock market indexes of the four countries are used to obtain the time-varying correlations between the different stock returns. These variables consist of BOVESPA, MOEX NIFTY and SHCOMP. These data are retrieved from two different sources: Yahoo Finance and Bloomberg. A detailed view of the data and the precise sources can be found in **Table *1*** below. Using the BRIC stock market returns, a multivariate Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model is performed to obtain the time-varying correlations. This model is explained later in the section 3.3.1. The Multivariate DCC-GARCH Model.

Then, a multiple linear regression is performed to determine whether some macroeconomic variables can explain what drives the time-varying stock returns correlations of the BRIC stock markets obtained thanks to the DCC-GARCH model. The dynamic conditional correlations represent the dependent variables of the multiple linear regression. As for the independent variables, they include the following five macroeconomic variables: interest rate, exchange rate, inflation, money supply and oil price. These variables were chosen according to their availability and the literature. Their succinct definition and source are shown in **Table *2***. In order to have stationary variables, the macroeconomic variables are transformed using logarithmic returns.

3.2. Data and Variables

3.2.1. Data Source

The study developed below aims to take as complete a sample as possible over the 15-year period in order to provide a more detailed analysis. The sampling consists of monthly data from January 2005 to December 2021. The main sources of data are Yahoo Finance, Bloomberg and OECD. A detailed view of the data and the precise sources can be found in **Table 1** and **Table 2.**

Table 1 - *Stock market indexes of BRIC*

	Stock market Index	**Definition and Unit of Measure**	**Source**	**Symbol**
Brazil	BOVESPA	Brazil Sao Paulo Stock Exchange Index (in Brazilian Real)	Yahoo Finance	*BVSP*
Russia	IMOEX.ME	Moscow Stock Market index (in Russian Ruble)	Yahoo Finance & Bloomberg	*MOEX*
India	NIFTY 50	National Stock Exchange of India index (in Indian Rupees)	Yahoo Finance & Bloomberg	*NIFTY*
China	SSE Composite	Shanghai Stock exchange index (in Chinese Yuan)	Yahoo Finance	*SHCOMP*

Table 2 - *Macroeconomic variables*

	Macroeconomic variable	Definition and unit of measure	Source	Symbol
Brazil	Interest rate	Brazil Selic Target Rate	Bloomberg	*BIR*
Brazil	Exchange rate	1 USD in Brazilian Real (BRL)	Bloomberg	*BER*
Brazil	Inflation	Consumer Price Index	OECD	*BINF*
Brazil	Money supply	Broad Money Supply (M3)	Bloomberg	*BMS*
Russia	Interest rate	BIS Policy Rates Monthly Data	Bloomberg	*RIR*
Russia	Exchange rate	1 USD in Russian Ruble	Bloomberg	*RER*
Russia	Inflation	Consumer Price Index	OECD	*RINF*
Russia	Money Supply	Narrow Money Supply (M1)	Bloomberg	*RMS*
India	Interest rate	Reserve Bank of India Repo Rate Policy	Bloomberg	*IIR*
India	Exchange rate	1 USD in Indian Rupees	Bloomberg	*IER*
India	Inflation	Consumer Price Index	OECD	*IINF*
India	Money Supply	Broad Money Supply (M3)	Bloomberg	*IMS*
China	Interest rate	China 1 Year Benchmark Lending Rates	Bloomberg	*CIR*
China	Exchange rate	1 USD in Chinese Yuan	Bloomberg	*CER*
China	Inflation	Consumer Price Index	OECD	*CINF*
China	Money Supply	Money Supply (M2)	Bloomberg	*CMS*
International	Oil price	Crude Oil	Trading Economics	*OIL*

3.2.2. BRIC Stock Indexes

3.2.2.1. BOVESPA

Created in 1968, the BOVESPA index, also called IBOV or IBOVESPA, is considered to be the main performance indicator of the stocks in the Brazilian capital market since it represents the behaviour of the most important shares traded on the Bovespa (Fortuna, 2008). Furthermore, For the past 50 years, it has served as a benchmark for investors around the world. According to Pimenta Jr. and Higuchi (2008), the largest stock exchange from Latin America is the BOVESPA (São Paulo Stock Exchange).

There are more than 300 companies listed on the exchange and approximately seventy of them are included in the theoretical portfolio of the index, representing roughly 70% of the exchange's total capitalization. Every four months the theoretical portfolio is updated, for the periods of January to April, May to August, and September to December (Santos, 2021).

The calculation of the index, done in real-time, takes into account all of the trades prices made on the spot market with shares in its portfolio (Santos, 2021). Concretely, the BOVESPA index is the weighted sum of the stock prices included in its theoretical portfolio (Fortuna, 2008).

The following formula – Equation (1) is used to calculate the BOVESPA index (Santos, 2021):

$$T_t = \sum_{i=1}^{n} P_{it}\, Q_{it} \tag{1}$$

where T_t is the BOVESPA Index at instant n ;n is the total number of stocks comprising the theoretical portfolio; P_{it} is the last price of stock i at instant t and Q_{it} is the theoretical quantity of stock i in the portfolio at instant t .

3.2.2.2. MOEX

The MOEX Russia index, also known as IMOEX, is a capitalization-weighted composite index. It means that the value of the index will be dominated by businesses with higher market capitalizations (Ramakrishnan, 2022). The performance of the 50 biggest and most liquid stocks in 10 different industries in Russia is analysed by this index.
One of the famous companies included in this benchmark of the Russian stock market is Gazprom, most known for extracting, processing, and transporting natural gas.

Founded in September 1997 by the Moscow Interbank Currency Exchange (MICEX), the Moscow Exchange (MOEX) was formed after the merging of the two main Russian stock exchanges, the MICEX with the Russian Trading System (RTS) in 2011 (Sakovich, 2021). Later in 2017, the index was officially renamed the MOEX Russia Index. The MOEX represents the biggest exchange of Eastern Europe and controls the Russian securities market (Sakovich, 2021). Six additional exchanges exist; some of them deal in securities, while the majority are devoted to commodities trading.

The MOEX Russia index's total market capitalization as of June 24, 2022, was 11 435 012 981 609 RUB, or roughly 210 billion USD. The MOEX index is calculated in real-time, with a base value equal to 100.

In general, the Russian financial market's capitalisation has been relatively low in recent years. This can be attributed to the exceptionally high demand among investors for a premium for Russian risk given the geopolitical context (Bagautdinova, Kadochnikova & Bakirova, 2020).

3.2.2.3. NIFTY

Launched in 1996, NIFTY is a benchmark based index composed of 50 largest stocks traded on the stock exchange in India out of 1600 stocks. With a total capitalization of over US$2 trillion, it is in the top 15 largest stock exchanges in the world (Girish, 2019). In 2017, about 62.9 percent of all the stocks listed on the NSE India's free-floating market capitalization are represented by the Nifty 50 index (Girish, 2019). It is one of the two most important national indexes, alongside the BSE Sensex (Mary & Radha, 2021). Thirteen sectors are part of the NIFTY : Automobile, Cement and Cement Products, Construction, Consumer goods, Energy,

Fertilizers and Pesticides, Financial Services, IT, Media and Entertainment, Metal, Pharma, Service and Telecom. Financial services and energy are the most represented sectors, with a respective percentage weight of 37.18% and 15.44% (Mary & Radha, 2021).

To be part of NIFTY, there are several criteria required for a company. One of them, for example, is that the trading frequency must be 100% during the last six months. In addition to being domiciled in India and being part of the National Stock Exchange, the company must have stocks with high liquidity (Groww, nd). very six months the index is updated and adds or removes stocks depending on the criteria met and their performance (Groww, nd).

To calculate the index, free-float market capitalization method is used (Mary & Radha, 2021). The following formula – Equation (2) is applied to compute the index value:

$$Index\ value\ = \frac{Current\ market\ value}{Base\ Market\ Capital\ \times Base\ Index\ Value} \quad (2)$$

where the *Current market value* is the product of the shares and the market price per share, the *Base Market Capital* is INR 2.06 trillion and the *Base Index Value* is 1000, with the base year being 1995.

3.2.2.4. SCHOMP

The Shanghai Stock Exchange Composite Index, introduced in 1990, is the oldest and most impactful stock exchange in China. Being a market-cap weighted equity index, the SSE index includes all the A shares and B shares traded on the stock market, displaying the performance of the companies listed on the Shanghai exchange (Chen, 2022). The index was released for the first time in July 1991 (Lin, 2018). A composite index is a statistical instrument that combines a variety of stocks, securities, or indexes to reflect the performance of an entire market or industry sector (Tardi, 2022).

As of July 16, 2022, the total market capitalization of the SSE Composite is 47163.37 RMB billion, which is roughly equivalent to 7000 billion dollars (SHANGHAI STOCK EXCHANGE, n.d.). Furthermore, the number of listed companies on the SSE is equal to 2098. In 2021, financials and real estate were the most represented sectors of the index. One of the main stocks

included are the China National Petroleum and the Industrial and Commercial Bank of China, the biggest bank in the world. Every six months are the component stocks adjusted by the SSE index (Ji & Li, 2021). Each month, the index is updated and rebalanced.

In order to obtain the SSE composite index, the Paasche weighted composite pricing index formula is used. The Equation (3) is written as follows:

$$Current\ index\ =\ \frac{Market\ Cap\ of\ Composite\ Members}{Base\ Period} \times Base\ Value \qquad (3)$$

where the *Market Cap of Composite Members* is the sum of the product of stock price and the number of shares issued, the *Base Period* is the entire market capitalization of all stocks on the base day which is December 19, 1990. Finally, the *Base Value* is equal to 100.

3.2.3. Macroeconomic Variables

3.2.3.1. Exchange Rate

The exchange rate is the value of a national currency in relation to that of another country. It represents the amount of a foreign currency that can be bought with one unit of another currency. The exchange rate of a currency is determined in a market called the "foreign exchange market", also called Forex. Like any competitive market, the foreign exchange market is governed by the law of supply and demand. In other words, the more a currency is in demand in international trade, the higher its rate (and therefore its value) (Chen, 2022).

The exchange rate between two currencies is subject to many influencing factors from a macroeconomic point of view (CentralCharts, 2014). These factors interact with each other and it is their interaction that determines the exchange rate. The exchange rate has a direct impact on the economic growth of a country. It is an element that is closely monitored by the various political and monetary authorities. On a smaller scale, the exchange rate also influences investors who hold assets in a foreign currency (in shares, forex or commodities). The exchange rate can also be a factor for inflation in the country whose exchange rate is falling.

3.2.3.2. Interest Rate

In theory, the interest rate is a percentage calculated on the amount borrowed that a debtor has to pay to the lending financial institution. It represents the remuneration of the loan, i.e. the price or interest to be paid for borrowing money. The interest rate is determined by the central bank of a nation, and each bank uses that rate to define what they can provide. The cost of debt increases when the central bank sets interest rates at a high level. High interest rates deter consumers from taking on debt and reduce consumer demand. Additionally, inflation tends to increase interest rates. The functions of the interest rate are fundamental in modern economies. The interest rate influences the market law of supply and demand. But when it comes to the exchange of capital, interest rate markets are by far the most important in the world, both in terms of volumes traded and in terms of their importance at the macro-economic level (Banton, 2022).

Because borrowers have access to loans at cheap rates, economies are frequently boosted during periods of low interest rates. Low interest rates on savings make it more probable for firms and people to spend money and buy riskier investments like stocks. This spending stimulates the economy and gives the capital markets a boost, which promotes economic growth. Although governments favour lower interest rates, these rates eventually cause market disequilibrium when supply outweighs demand, which results in inflation. Interest rates rise in an inflationary environment, which may be related to Walras' law (Banton, 2022). In general, currencies with a high interest rate will attract investors and currencies with a low interest rate will be abandoned. This is known as the carry trade phenomenon.

3.2.3.3. Inflation Rate

Inflation is a factor in lowering the exchange rate. Inflation causes a currency to lose value. With the same amount of money, it is possible to buy fewer goods and services because of the general rise in prices. There are different indicators to measure inflation. The best known are the consumer price index. Based on a representative basket of goods and services, the Consumer Price Index tracks the overall change in consumer prices over time (Fernando, 2022).

Inflation and the growth of the banking sector and equities market activity have a large and economically significant negative nonlinear link. The marginal effects of inflation on banks loan activity and stock market growth rapidly decline as inflation rises (Boyd, Levine & Smith, 2001). Inflation is often a sign of economic growth within a country. This encourages exports and reduces the amount of debt. On the other hand, if the level of inflation is too high, the country risks overheating and inflation becomes a danger.

3.2.3.4. Money Supply

The total amount of money and other liquid assets in an economy on the measurement date is known as the money supply. Both cash and deposits that can be accessed virtually as quickly as cash are approximately included in the money supply (Investopedia, 2022).

Through a mix of their central banks and treasuries, governments produce coin and paper money. By imposing reserve holding requirements on banks, dictating how to grant credit, and handling other monetary issues, bank regulators have an impact on the amount of money that is accessible to the general people. Few studies such as the one performed by Nizhegorodtsev & Goridko (2015) demonstrated that there is a positive long-term effect of increasing the coefficient of monetization on economic growth. However, there is a point at which monetary expansion carries a risk of rising inflation and other unfavorable effects.

3.2.3.5. Oil Price

The price of oil remains a key determinant of the global economy despite ongoing efforts to reduce its consumption and shift to green energy. The three main factors in determining the price of oil are market supply and demand, extraction costs and market sentiment (Kosakowski, 2022).

The movement of the oil price is usually an important factor indicating inflationary pressure in the economy. Therefore, the oil price can also point to future interest rates and investments of all types (Sadorsky, 1999). Although a change in the oil price affects the economy, a change in the economy will hardly affect the oil price.

3.3. Model

3.3.1. The Multivariate DCC-GARCH Model

High-frequency financial series are characterized by non-stationarity, autocorrelation, heteroskedasticity, thick distribution tails, volatility clusters, leverage, and skewness. To take these phenomena into account, Engle (1982) and Bollerslev (1986) developed the ARCH (AutoRegressive Conditionally Heteroscedastic) and GARCH (Generalized ARCH) models. These GARCH models are an extension of the ARMA model, introduced by Box and Jenkins (1971).

ARCH/GARCH framework has proven to be the most efficient tool in predicting volatility changes. Indeed, these two models are particularly effective in the context of an analysis and prediction of the volatility of the data studied (Robert Engle, 2001). Their characterizations are essentially based on the concept of conditional variance, which depends only on the modulus of past values: the effect on the volatility of the present date of positive and negative past innovations is therefore identical.

The autoregressive conditional heteroskedasticity (ARCH) model, developed by Engle in 1982 has been widely used for many financial return time series. This model establishes an autoregressive structure on conditional variance and allows volatility shocks to persist over time in the financial market (Lamoureux & Lastrapes, 2012). However, it has been proven that the Generalized ARCH (GARCH) model of Bollerslev outperforms the ARCH model by restricting the conditional variance of a time series to depend upon past squared residuals of the process.

In order to perform the multivariate DCC-GARCH model, there are several steps to be done. In the first place, the presence of time-series data requires us to perform stationarity tests. We have to check whether the data are stationary, i.e deterministic, or non-stationary, i.e stochastic. Then, in order to estimate our DCC-GARCH model and to achieve our multiple linear regression, it is mandatory to go through several statistical steps. These different steps are first explained theoretically and their results are detailed in the next sections.

Stationarity is an important concept and a crucial pre-condition in time-series statistical models. In order to produce a stable time series model, stationary data must demonstrate that the associated mean, variance, and auto-covariance on lag variation remain constant whenever it is employed (Febrian & Herwany, 2008). In other words, it means that the statistical characteristics of a time-series are time-invariant (Palachy, 2019). Verbeek (2004) defines this concept as follows: *"Stationary requires that all the moments of the series, and not only the first and second (mean and variance), are unaffected by time"*. There are several reasons behind the stationarity of time-series data. The main reason is that spurious regression can occur in the event of non-stationary data (Febrian & Herwany, 2008). If statistical analyses suggest that two variables are related when there is actually no theoretical relationship between them, then the relationship is claimed to be false.

Different methods can be used to test the stationarity and after a review of the literature we chose to run two unit root tests, the Dickey-Fuller and the KPSS tests. First, the Dickey-Fuller test, developed in 1979 by Dickey and Fuller, consists in testing the null hypothesis that the process is not stationary, which means that a unit root is found in an autoregressive model of a certain time series (Palachy, 2019). If the p-value of the Augmented Dickey-Fuller test is below alpha (generally = 5%), the null hypothesis, i.e. the non-stationarity will have to be rejected. Secondly and unlike the previous test, the KPSS takes as null hypothesis the absence of a unit root, therefore the stationarity of the process (Palachy, 2019). Stationarity is rejected if the p-value of the KPSS test is below alpha. The KPSS test was developed by Kwiatkowski, Phillips, Schmidt and Shin (1992), who give their name to the test.

After looking at the stationarity, it is important to check if temporal dependencies are present in the time series. The ARMA model's objective is to capture and model the linear temporal dependencies between the returns. The first step of this model is to make identify orders p and q with the autocorrelogram for MA(q) and the partial autocorrelogram for AR(p). Then, the ω and θ coefficients for the ARMA(p ,q) model need to be estimated. Finally, an analysis on the residuals should be done to make sure there is no more linear temporal dependence. After modelling the temporal dependencies, the residuals should be white noise and should not include any further dependencies. The Ljung-Box test is efficient to determine if the time

series are autocorrelated (Ljung & Box, 1978). The equation model of Ljung-Box is defined as follows – Equation (4):

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k} \qquad (4)$$

where $\widehat{r_k^2}$ is the estimated autocorrelation of the series at lag k , and m is the number of lags that are tested. The null hypothesis H_0 is rejected (p-value< α) if there are an autocorrelation and H_1 is accepted if there is at least one of the lags is significant. If the null hypothesis of the Ljung-box statistic test is rejected, more lags can be added to the model to have at least one of the lags significant. This kind of test can be called a "porte-manteau" statistic because the alternative hypothesis covers a lot of different options.

In the section on the ARMA model, the homoscedasticity was implied which meant that the conditional variance remained constant across the course of the time series. However, in empirical data, volatility clustering has been more frequently observed. It indicates that high (low) volatility periods frequently follow low (high) volatility periods. More precisely, "volatility clustering", in finance, is the fact that one volatile period tends to be followed by another volatile period, or volatile periods are generally clustered. By intuition, as soon as an important piece of information appears in the financial market, the market will take some time to fully digest the information. Financial series such as stock prices, inflation rate and exchange rates present that phenomenon; values of these series show periods where significant fluctuations can be observed followed by periods where there is a low variation. Statistically, high volatility (variance) today can lead to high volatility tomorrow. For example, on 09/03/2020 the Ibovespa index (Major index of Brazil stock market) lost 13.98% in one day due to COVID-19 event. A few days later, 13/03/2020, the index recovered 13% of its value. To forecast and analyse this volatility, ARCH/GARCH models are the main tools used. These models can describe the evolution of the magnitude of uncertainty , i.e. the time evolution of the average size of squared. Despite the good performance of these models, there is no real consensus on the economic reasons for these clusters (Fabozzi, 2007).

The models are based on the assumption of heteroskedasticity. Heteroscedasticity occurs when the variance of the errors is not the same in all observations made. It refers to the fact that the size of market volatility tends to cluster in periods of high volatility and periods of low volatility, i.e. that the expected size of the error term is not constant (Fabozzi, 2007). In financial data, heteroscedasticity observed over different periods is autocorrelated. Namely, this phenomenon is called the ARCH effect (Abdel-Latif, 2016). The presence of heteroskedasticity makes the regression coefficients for an ordinary least squares regression unbiased, but the confidence intervals and standard errors estimated by conventional procedures will be too narrow, giving a false sense of precision to the analysis. Therefore, ignoring the ARCH effects could be very costly for the portfolio. Indeed, assuming a constant volatility rather than a dynamic one as the ARCH/GARCH model acknowledges, can lead to extreme unexpected losses in the investment portfolio. ARCH/GARCH models will therefore treat the heteroskedasticity as a variance to be modelled rather than a problem to solve.

The ARMA process analysed in the previous part serves as a foundation for the analysis of the ARCH effect. The aim is to remove the time dependency of the location (mean) before addressing the time dependency of the scale (variability). Therefore, an ARMA process will be run before using the GARCH process. Concretely, first the optimal order p_1 and q_1 will be identified thanks to the (partial) autocorrelogram. Then, the parameters of the ARMA (p_1, q_1) model will be estimated. Finally, the Ljung-Box test, as well as (partial) autocorrelogram of the residuals, will be performed to test whether the residuals are white noise or not.

Following this process, we need to see if the times series used contain ARCH effects. Firstly we will look at the autocorrelation function (ACF) and the partial autocorrelation Function (PACF) of squared residuals. Then, a Ljung-Box test on squared observations will be performed to confirm the visual results. In case of ARCH effects, orders p_2 and q_2 will be identified for the GARCH model thanks to the ACF and PACF of the squared residuals. Moreover, the parameters of the GARCH (p_2, q_2) process have to be estimated. The last step is to conduct an ARCH test on the squared residuals of the ARMA (p_1,q_1) − GARCH (p_2, q_2) model. In a nutshell, if there are volatility clusters and therefore ARCH effects, the residuals need to be modelled with a GARCH model whose objective is to capture the heteroscedasticity.

The model used in this thesis is the multivariate GARCH model (MGARCH) because four different variables are used to build the model. The MGARCH model allows us to observe and estimate the effect of interactions between the volatility of the different indexes and to extract the necessary information on the covariance of the volatility of the indexes between them (Andersson-Sall & Lindskog, 2019).

The MGARCH model can be structured as follows – Equation (5):

$$r_t = H_t^{\frac{1}{2}} \eta_t \tag{5}$$

where r_t is a column vector of log returns of the 5 indexes and η_t is an independent and identically distributed vector error, i.e. $E(\eta_t \eta_t^T) = I$. The only element left that we need to identify is the matrix process of H_t. According to the study by Silvennoinen and Teräsvirta (2008), there are four different approaches to estimating this $H_t$factor. The approach we will use in this paper is the Dynamic Conditional Correlation model.

The DCC-GARCH model, presented by Engle and Sheppard (2001), is an extension of the GARCH model that avoids any kind of complexity of the conventional multivariate GARCH model. This model can be viewed as an extension of the DCC-GARCH model, the Constant Conditional Correlation introduced by Bollerslev (1990) but the difference with the DCC-GARCH model is that we can observe the evolution of correlations of the BRIC indexes over time, called time-varying correlation.

The DCC-GARCH model at time *t* can be written as follows – Equation (6)(Engle, 2002):

$$H_t = D_t R_t D_t \tag{6}$$

where H_t is the conditional covariance-variance matrix, R_t represents the conditional correlation matrix. An important assumption of the DCC-GARCH model is that the conditional correlation matrix (R_t) has the same properties as a covariance matrix, it has to be positive definite (Engle & Sheppard, 2001).

D_t is usually seen as univariate GARCH models but can also contains functions of other variables – Equation (7).

$$D_t = diag\{\sqrt{h_{i,t}}\} \tag{7}$$

The elements of D_t are presented in Equation (8) as univariate GARCH models:

$$h_{i,t} = \omega_i + \sum_{p=1}^{P} \alpha_{ip} r_{it-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q} \tag{8}$$

where the restrictions of stationarity of the model and non-negativity of the variance is imposed. Additionally, the parameters α and β are scalar and must individually be greater than zero but $\alpha + \beta < 1$ (Orskaug, 2009). Hence, D_t is positive definite as all the elements on its diagonal are positive.

R_t can be derived as follows in Equation (9):

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{9}$$

where in Equation (10):

$$Q_t = (1 - a - b)\bar{Q} + a\mathcal{E}_{t-1}\mathcal{E}'_{t-1} + bQ_{t-1} \tag{10}$$

, $\bar{Q} = Cov[\mathcal{E}_t \mathcal{E}_t^T] = E[\mathcal{E}_t \mathcal{E}_t^T]$ is the unconditional covariance of the standardized residuals and Q_t^* that is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal – Equation (11):

$$Q_t^* = \begin{pmatrix} \sqrt{q_{11}} & 0 & 0 \\ 0 & \sqrt{q_{22}} & 0 \\ 0 & 0 & \sqrt{q_{33}} \end{pmatrix} \tag{11}$$

The objective of the DCC-GARCH model is to define the two parameters, *a* and *b*. These will be found through the two-step procedures.

The residuals of the univariate GARCH models are estimated in Equation (12) in the first step of estimation by the quasi-likelihood function (Silvennoinen & Teräsvirta, 2008):

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|I_k|) + 2\log(|D_t|) + r_t' D_t^{-1} I_k D_k^{-1} r_t) \quad (12)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|D_t|) + r_t' D_t^{-2} r_t)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \sum_{n=1}^{k}(\log(h_{it} + \frac{r_{it}^2}{h_{it}}))$$

$$= -\frac{1}{2}\sum_{n=1}^{k}(T\ log\ (2\pi) + \sum_{t=1}^{T}(\log\left(h_{it} + \frac{r_{it}^2}{h_{it}}\right))$$

A second likelihood function is generated when the parameters of the dynamic correlation are estimated conditionally on the parameters estimated in the first step.

3.3.2. Multiple Linear Regression Model

The purpose of linear regression is to analyse data in order to determine correlations between two or more variables having a cause-effect relationship, and to make predictions about the dependent variable (Uyanik & Güler, 2013).

Multiple linear regression differs from simple linear regression by including more than one explanatory variable. In other words, a multiple linear regression is composed of one dependent variable, called the response variable, and several independent variables, called the explanatory variables. Multivariate regression analysis is another name for this particular linear regression (Uyanik & Güler, 2013). The term "linear" is still employed since it is claimed that the response variable is related to a linear combination of the explanatory variables (Tranmer & Elliot, 2008). Normal distribution and linearity are ones of the main assumptions of the multivariate regression analysis (Büyüköztürk , 2002).

The equation for the multiple linear regression is expressed in Equation (13):

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_p x_{pi} + e_i \quad (13)$$

where, for $i = n$ observations, y_i is the dependent variable;β_0 being the constant value, or intercept, is equal to *y* when all explanatory variables are equal to 0; β_i corresponds to the parameter and the slope coefficient for each explanatory variable. It represents the amount by which the value of y_i rise, for a one-unit increase in x_i. Then x_i is the independent variable and e_i is the model's error term.

In order to analyse the structure of the causal relationship between the dependent variable and the independent variable, a Granger causality test is used. Causality in the sense of Granger (1969) is an approach to causality that refers not to the theoretical character of causality (cause-effect) but to the predictive character of the eventual cause on the effect. Indeed, according to Granger (1969), the variable X causes the variable Y in the sense of Granger if the past values of X significantly influence the contemporary value of Y. From a statistical point of view, the Granger causality test amounts to a test of the overall significance of the coefficients associated with the past values of the causal variable in the equation for the caused variable. If probability value is less than any α level, then the hypothesis, i.e. the variable X does not cause the variable Y, would be rejected at that level.

4. Analysis and Discussions

4.1. Dependent Variables

4.1.1. Descriptive Statistics

Before analysing our data, several modifications on the database have been made. Across the dataset, many observations had missing values, represented by "NA", which needed to be replaced with rational and relevant values to be able to still draw results from those observations. However, NA values have to be handled in a way that avoid biased results. This was done by replacing the missing values with the most plausible values regarding the other values of the dataset. The missing value was replaced by the mean of the nearest neighbours. Then the date format dd-mm-YY was changed to US format mm-dd-YY so that it will be easier to plot in R Studio. The cleaned database could finally be imported in R Studio. The complete dataset obtained contained four times series of returns of *BVSP, MOEX, NIFTY* and *SHCOMP* and 211 observations.

The **Table 3** summarizes the mean, median, standard deviation, Skewness and Kurtosis of all four numeric variables of the dataset. These figures are used to measure central tendency and dispersion.

Table 3 - *Descriptive statistics of BRIC stock market returns*

	Mean	Median	St.Dev	Skewness	Kurtosis
BVSP	0.9956	0.9930	0.0706	1.5549	7.3139
MOEX	0.9964	0.9862	0.0781	1.9187	7.9363
NIFTY	0.9923	0.9896	0.0658	1.4477	6.4959
SHCOMP	0.9981	0.9934	0.0790	1.0539	3.0893

Standard deviations show us that all variables cover a lot of different values because their standard deviation are pretty high. Overall, it can be observed that all the stock returns have a high volatility.

The skewness and the kurtosis figures are used to examine the normality of the data. The Skewness measures the lack of symmetry across a database. Positive skewness can be observed for all the BRIC returns meaning that the majority of the returns resides left of the mean, i.e. mainly high returns. Regarding Kurtosis, it evaluates if the returns are heavy- or light-tailed compared to normally distributed returns. In our case the returns are quite heavy-tailed meaning that our data tend to have outliers. We have a “leptokurtic” distribution. Some transformations on the returns will have to be done.

4.1.2. DCC-GARCH Models

First, as discussed in the theorical part of the model, the presence of time-series data requires to perform stationarity tests. Hence, two unit root tests are used to examine the stationarity of the times series, the Augmented Dickey-Fuller and the Kwiatkowski-Phillips_Schmidt_Shin (KPSS) tests. Just as a reminder, the non-stationarity will be rejected if the p-value of the Augmented Dickey-Fuller test is below α (generally = 5%) and in the contrary, for the KPSS test, the stationarity will be rejected if the p-value is below α . Since both tests confirm us the non-stationarity of the time-series, a logarithmic transformation is performed on the time series in order to have stationarity processes. To make sure the log returns are efficient, the

two test are computed for a second time and the results prove that the times series are stationary. As opposed to arithmetic returns, working with log-returns has the major advantage that the multiple-period return is simply the sum of all the one-period returns.

After addressing the issue of stationarity, we have to check if there are temporal dependencies in our data. For every of the four BRIC time series, a Box Pierce, also called Ljung-Box Statistics test is performed to verify the temporal dependencies of each of the times series [**Appendix 1**]. By performing a Ljung-Box test on the *SHCOMP* returns, it is observed, because the p-value is below α (5%), that the null hypothesis can be rejected meaning that as there are temporal dependencies between the returns and its past events. Given the ACF and PACF, we start by modelling an ARMA(1,1) model and see whether it is sufficient to remove the temporal dependencies. Finally, the Ljung-Box test confirm us that the ARMA(1,3) the *SHCOMP* returns are now free of temporal dependencies [**Appendix 2.1.**]. Regarding the *MOEX* index returns, temporal dependencies have also been identified using the Ljung-Box test. By looking at the autocorrelogram and partial autocorrelogram, an ARMA(1,1) model is only needed to be fitted into the time series in order to remove the temporal dependencies [**Appendix 2.2.**]. In the case of the *BVSP* and *NIFTY* index returns, the Ljung-Box test allows us to believe that there are no significant temporal dependencies and that there is no need to model the conditional mean with an ARMA model for those index returns. Hence, we subtract the ARMA(p ,q) predictions from the *MOEX* and *SHCOMP* stocks returns to get rid of the linear temporal dependencies in the processes.

Once the ARMA model is done, we need to look at the ARCH effects and see whether a GARCH model should be implemented. We first visually check if any volatility clustering can be noticed by looking at the squared observations of our returns without linear dependency. We also check the ARCH formally with the Ljung-Box test on squared observations [**Appendix 3**].

No ARCH effects are seen in the *BVSP* returns which means that it is not necessary to fit a GARCH model. However, ARCH effects are identifiable for the *NIFTY* returns with the Ljung-Box test. We first determine the optimal orders to fit our GARCH model. Based on the ACF and PACF graphs for the squared residuals, a GARCH(1,1) model is fitted and proves to be successful in capturing the heteroscedasticity in the process [**Appendix 4.1**]. The same applies

to the *SHCOMP* returns, which also has ARCH effects confirmed by the Ljung-Box test. After having fitted a GARCH(1,1) model, we can see that the model is effective in modelling the heteroscedasticity in the process [**Appendix 4.2**]. The *MOEX* returns also exhibited ARCH effects, which is again verified by the Ljung-Box test. By looking at the ACF and PACF graphs for the squared residuals, the optimal orders for our GARCH model is decided. The GARCH(1,8) model is the final model that is successful in modelling the process' heteroscedasticity [**Appendix 4.3**].

Now that we have developed models to account for the heteroscedasticity, we can scale the *BRIC_Ret_CENT* database and finally have a dataset free from temporal dependency and heteroscedasticity. To do so, we divide the processes by the conditional standard deviation modelled in the GARCH models.

We finally have our final time series which is now stationary, with a constant conditional mean, and a constant conditional variance. Since we already checked the constant conditional mean, we just checked the homoscedasticity a last time with the Ljung-Test [**Table 4**].

Table 4 - *Results of the Ljung-test after transformations*

Lags	**P-value**			
	BVSP	**MOEX**	**NIFTY**	**SHCOMP**
4	0.8902	0.1042	0.8709	0.8262
8	0.9715	0.0711	0.2343	0.9839
12	0.9886	0.1709	0.5369	0.7131
16	0.9954	0.2564	0.4995	0.8485
20	0.9996	0.3401	0.5909	0.9144

The Ljung-Tests confirmed us that heteroscedasticity has be removed from the processes.

Now that the data have been correctly adjusted to perform the DCC-GARCH models, we have a cleaned database of 199 observations meaning that our analysis will be done on the following period: January 2005 to July 2021.

First, it is important to check that the parameters [**Table 5**] of the GARCH model verify the conditions stated in the theoretical part in order to be able to estimate the correlations and continue the analysis.

Table 5 - *Parameters estimates of the DCC-GARCH models*

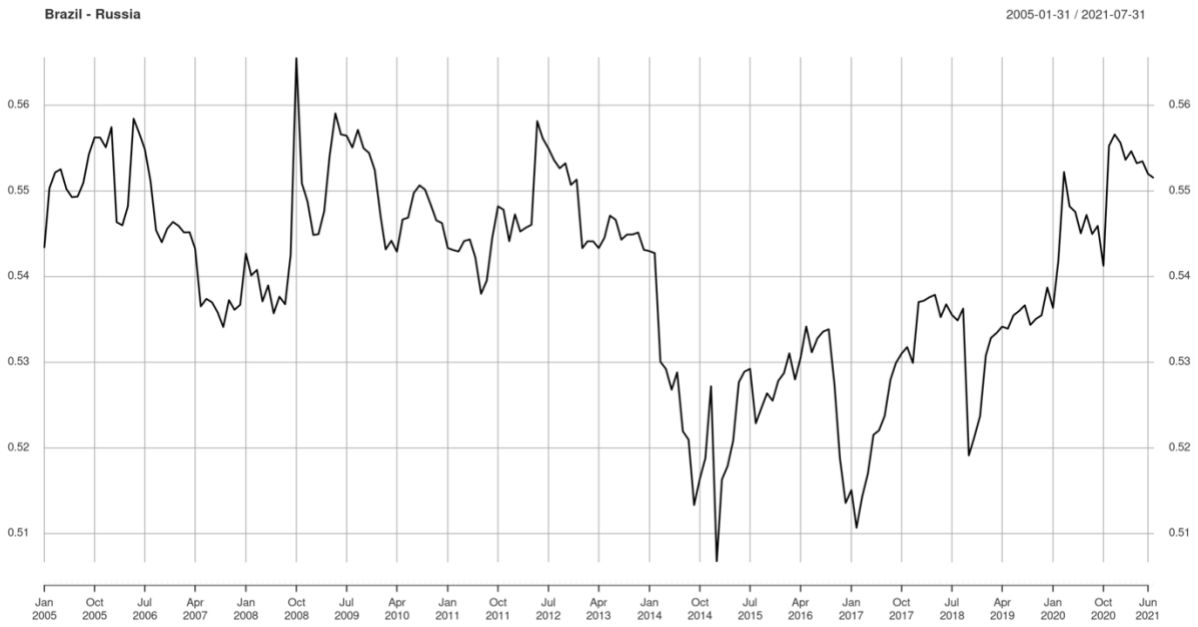
	ω_1	α_1	β_1	ω_2	α_2	β_2	a	b
BVSP-MOEX	0.0011	0	0.9989	0	0	0.9987	0.0237	0.9324
BVSP-NIFTY	0.0011	0.0001	0.9989	0.0003	0.0001	0.9998	0.0128	0.9431
BVSP-SHCOMP	0.0014	0	0.9987	0.0001	0	0.9999	0	0.9204
MOEX-NIFTY	0	0	0.9987	0.0031	0	0.9999	0.0369	0.8988
MOEX-SHCOMP	0.0061	0	0.0087	0.0004	0	0.9999	0.0003	0.9334
NIFTY-SHCOMP	0.0003	0	0.9999	0.0001	0	0.9999	0.0309	0.7499

The coefficients α and β represent the parameters of conditional correlations. For each GARCH modelling, parameter β is close to 1, parameter α is weak and close or equal to 0. The coefficient β shows the degree of conditional correlation between the two indices. The table above shows the existence of a strong conditional correlation between the indices.

The persistence of the conditional correlation is calculated from the sum of α and β. For each modelling, the sum of the two coefficients is smaller than 1. This means that the variance is very persistent for the different yields studied. Indeed, the closer the sum is to unity, the more the volatility persists over time. The results found in our analysis are similar to the results found in the empirical work of Hammoudeh (2009). He also found that the coefficient α is small and close to zero and the coefficient β is close to 1.

Examination of the graphs in the next section shows the evolution of the dynamic correlation between January 2005 and July 2021 for each BRIC stock market return with respect to each other.

Figure 1 - *DCC between Brazilian and Russian stock market returns (BVSP-MOEX)*



Overall, a strong and highly volatile correlation between Brazil and Russia can be observed all over the period observed. This strong correlation may be attributed to the fact that both countries are among the largest exporter and producers in the world (Yuan, Zhangb, Cuia & Wanga, 2021). Tripathy (2015) proves with her study that the Russian and Brazilian stock market were depending on each other and were impacting each other. The 2008 peak of just over 0.56 could have been expected since it is in line with various studies which state that the correlation increased during global crisis (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013; Mishra, 2022; Ngwakwe's, 2020). The strengthening of the correlation in 2020, during the COVID crisis, also supports the findings of studies (Heliodoro et al., 2020).
It can be aligned with the study of Malik et al. (2021) who proved that the two countries are good allies economically, strategically and technologically speaking in times of crisis. Other studies also found that the contagion of the 2008 financial crisis across the market was observed with a high level of severity in the Russian market (Mensi et al., 2017a; Nikkinen et al., 2013). Banerjee & Vashisht (2010) also proved that the pairwise market of Brazil and Russia suffered the most of the crisis.

The dynamic conditional correlation was quite low and highly volatile between 2014 and 2017. Brazil's economy faced severe recession during the 2014-2016 period while Russia's stock market was negatively impacted by the Crimean war and the resulting sanctions received from 2014 to 2017 (Hoffmann & Neuenkirch, 2015; Vartanian et al., 2022; Costola & Lorusso, 2022). This could be of the explanations behind the lower and unstable correlation between their stock markets at that time.

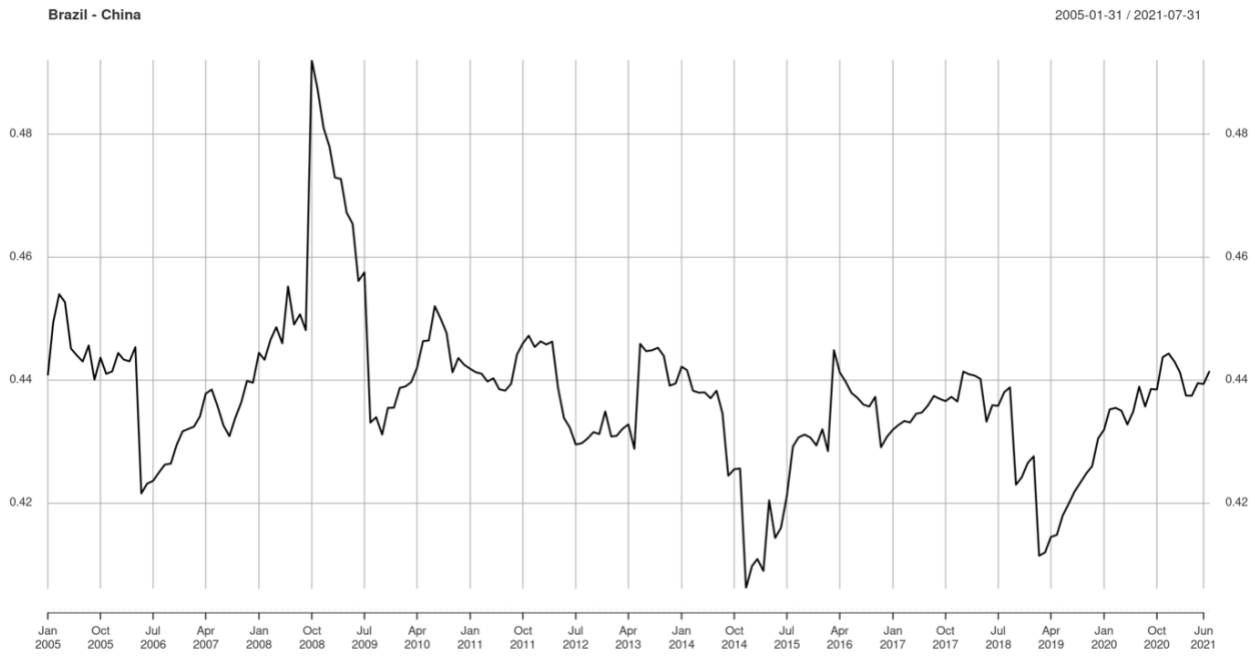
Figure 2 - *DCC between Brazilian and Indian stock market returns (BVSP-NIFTY)*

The correlation between the Indian and Brazilian stock markets is relatively high. The literature (Prakash et al, 2017) has shown us that both countries are highly open, so they are more sensitive to international shocks. Over the 17 years, there is a range of 0.56 and 0.64 with many periods of peaks and troughs. The two highest peaks are observed in 2008 and 2020. These results are in line with previous works (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013; Mishra, 2022; Ngwakwe's, 2020) which found that the integration of the BRIC with each other was higher during the global crisis of 2008 and 2020. Tripathy (2015) found that there is a unidirectional causality between Indian and Brazilian market. Ngwakwe (2020) confirmed the statement showing that, during the COVID-19 crisis, the performance of India's stock market is predictive of the behaviour of the Brazilian stock market. Therefore, an investor in the Brazilian market should therefore pay attention to the Indian stock market development, especially in periods of strong correlation. However, we

notice that for each peak there follows a few years of decrease in the correlation. It is possible that after the crisis, the two countries apply different economic recovery structures which are reflected in their respective returns (Chavali et al., 2021).

Regarding the shocks that one country may have had an effect on the other, it is notifiable that the Brazilian crisis of 2014 and 2016 (Vartanian et al., 2022) may had a negative impact on the correlation between Brazil and India. India would probably have reduced its trade links with Brazil in order to minimise the crisis that the country was experiencing.

Figure 3 - *DCC between Brazilian and Chinese stock market returns (BVSP-SHCOMP)*



The graph shows us that there is only one high peak in the correlation between Brazil and China, it is the 2008 peak with a maximum rate of 50%. This result is again in line with the results of many studies (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013). The lowest correlation is observed in 2014. This finding can be linked with the recession that Brazil faced and with the rise of the Chinese financial bubble, i.e. the significant increase of the stock market index (SSE) (Indrastra, 2017; Vartanian et al., 2022; Indrastra, 2017), their stock returns were highly affected but not in the same way.

During the period studied, it can be seen that, apart from periods of peaks or falls, the correlation interval is between 0.42 and 0.45. For the year 2020, one would have expected a period of increased correlation as predicted by previous studies and by the Chinese origin of the virus. It can be seen that the correlation undergoes a slight increase but not as expected. However, as confirmed by Morales and Gassie-Falwone (2011) and Prakash et al (2017), China is a country with a less open economy and is therefore less integrated with other countries. That is, the shocks that the Chinese economy faces are not directly observable in other economies of the world.

Figure 4 - *DCC between Russian and Indian stock market returns (MOEX-NIFTY)*

In general, the volatility of the correlation is remarkably important. This could be partially explained by the higher volatility of Indian stock cycles that Yadav (2017) argued in his study. Another explanation could be the high bidirectional causality link found by Tripathy (2015) between the two stock markets. The correlation range is just over 0.50 for the greatest peak and under 0.44 for the lowest. As observed above, the peak of the correlation took place in 2008, which follows the trends of the others DCC and is in line with the literature (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013). The strengthening of the correlation in 2020 confirms also the previous literature. The third wave of sanctions against Russia in 2017 following the annexation of Crimea can be a reason for the lowest percentage

of correlation (<0.44) in 2017 since it had negatively impacted the Russian economy (Costola & Lorusso, 2022). There is also a downward trend from 2012 to end 2017. Between 2014 and 2017, Western financial sanctions were imposed to Russia which impacted its economy (Gurvich & Prilepskiy, 2015). This might have had a negative impact on the correlation between the Indian and the Russian stock markets.

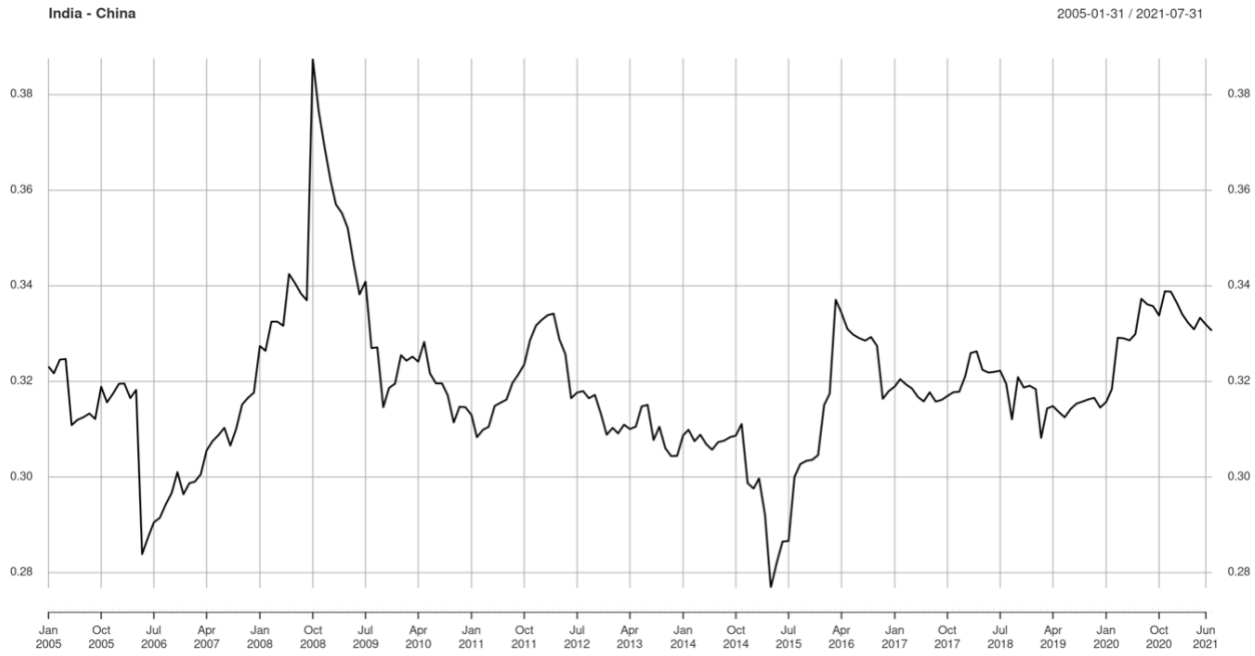
Figure 5 - *DCC between Russian and Chinese stock market returns (MOEX-SHCOMP)*

The correlation between the Russia and Chinese stock markets is the lowest of all the DCC's. Indeed, the highest peak does not exceed 30%, which is relatively low. Russia and China differ on several points that could explain the poor correlation between their stock markets. China is a huge oil importer while Russia is a one of the biggest producers and exporters (Yuan, Zhangb, Cuia & Wanga, 2021). Furthermore, the Russian capital market is much more open and less tightly controlled than the strictly regulated Chinese capital market (Naik & Padhi, 2015). The fact that China is the least integrated of the BRIC nations may also be contributing to this low correlation.

Both increases in correlation during 2008 and 2020 confirm once again that the global financial crisis has strengthened the integration of the BRIC stock markets among themselves (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013). The lowest point in 2014–2015 may have been caused by the Chinese stock market's bubble and/or the Western

financial sanctions imposed on Russia due to the Crimean war of 2014 (Hoffmann & Neuenkirch, 2015; Indrastra, 2017; Gurvich & Prilepskiy, 2015). However, between the end of 2015 and the beginning of 2016, the correlation increased again. This also may be linked to the bursting of the Chinese financial bubble, the Chinese stock market crash seems to have had an effect on the correlation of the two countries.

Figure 6 - *DCC between Indian and Chinese stock market returns (NIFTY-SHCOMP)*



Compared to the other correlations already observed, we notice that the correlation between China and India is relatively weak in general. Overall, the mean range of the DCC is between 0.29 and 0.34. This result is surprising, however, given that the two countries have a number of similarities such as their tax structure (Benerjee & Vashist, 2010). However, it is still important to note that China remains the less integrated country and is relatively unintegrated with the outside world.

The strongest correlation is observed in 2008 during the global financial crisis. Lemoine (2009) observed that India and China did not necessarily suffer from the crisis and were less in recession than other countries. Consequently, both stock markets seem to have held up well and show a stronger correlation at that time with an increase of almost 10%. The lowest correlation point is observed in 2014 (0.27), at the same time as the significant increase of

the Chinese stock market index. The increase in the value of the Chinese index does not seem to have been reflected in the value of the Indian index. However, in 2016, a dramatic increase in the correlation between the Chinese and Indian markets was observed. At that time, the Chinese bubble burst and it seems that the Chinese stock market crash also had an impact on the Indian market (Malik et al., 2021). With regard to the COVID-19 crisis, no sharp increase in DCC is observed. This finding is in agreement with the study of Malik et al. (2021) who observed that the correlation between the two countries did not show a large increase.

To summarize our different DCC results, it is notable that the Dynamic Conditional Correlations between the SHCOMP index and the other three indices (BVSP, MOEX and NIFTY) follow the same trend over the period. It would therefore be interesting to look at the impact that Chinese macroeconomic variables have on these relatively similar correlations. Overall, the correlations with China are relatively smaller than the others, it can be linked to the findings of previous works (Ouattara, 2017; Morales & Gassie-Falzone, 2011) that show that China is the least integrated market of the BRIC.

It can also be interesting to observe that, as it was expected from the literature (Maiti et al, 2022; Nikkinen et al, 2013; Bekiros, 2014; Stuenkel, 2013), for each DCC, the financial crisis of 2008 had a severe positive impact on the integration of the BRIC. The COVID-19 crisis of 2020 also brought an increase in all BRIC countries' correlations, but not as significant as in 2008. As countries reacted differently and not at the same time depending on the progress of the virus and their economic capacity, their level of connectivity was not as high as in 2008. Regarding the domestic crisis that the BRIC members respectively suffered, we note that in general, this attenuates the correlation. Indeed, when a country experiences a domestic financial crisis, it turns out that its trade links with the other BRIC member countries are reduced and consequently a weaker correlation is observed. However, this was not the case in 2016 when China faced a financial crisis, the correlations with the other countries of BRIC increased.

4.2. Independent Variables

4.2.1. Descriptive Statistics

In order to be able to interpret and analyse the correlations between the BRIC stock market returns, five macroeconomic variables were chosen: the interest rate, the exchange rate, the inflation rate, the money supply and the oil price. These five variables were found on Bloomberg and OECD and the sampling consists of monthly data from January 2005 to July 2021.

Since the research focuses mainly on the impact of macroeconomic variables on the correlations between BRIC stock market returns, it is not necessary to do an in-depth descriptive analysis on these variables. However, it is important to note that all variables have been log-transformed in order to reduce the skewness and kurtosis of the distribution of the variables. The log transformation also has the advantage of improving the model and the regression, which makes the residuals less heteroscedastic and closer to the normal distribution.

4.2.2. Correlation between the Macroeconomic Variables

Before assessing the impact of the macroeconomic variables of each country on the correlation between the countries concerned, a correlation analysis between the macroeconomic variables of each country was performed. If a strong correlation is observed between two of them, only one of them will be kept as an independent variable for the linear regression to be performed. Indeed, two variables being highly correlated would not provide more relevant information if both were kept.

The correlations matrix [**Appendix 5**] reveals that there is a strong correlation between two pairs of variables, namely between the *BER* and the *BMS* (0.76) as well as *RER* and *RMS* (0.8). One of the last two can be eliminated from the model because of the strong correlation between the two variables.

4.3. The Influence of Macroeconomic Variables on the DCC's

In total, we performed twelve regressions, two regressions for each dynamic conditional correlation. In this section, the influence of macroeconomics variables, as independent variables, on the dependent variable, i.e. the DCC, will be commented regarding their level of significancy and the sign of their coefficients.

Table 6 - *Results of the multivariate model of DCC of Brazil and Russia*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
BER	0.0979***	0.0968***
BIR	0.0291***	0.0313***
BINF	0.0045	
RER	-0.0375***	-0.0324***
RIR	-0.0203*	-0.0254**
RINF	-0.0049	
OIL	0.0132*	0.0149**
R^2	0.5336	0.5343
Adj. R^2	0.5165	0.5181

A first multiple linear regression is performed with the entire set of variables taken for Brazil and Russia. *BER, BIR & RER* emerge as the most significant variables followed by *RIR* and *OIL*. The p-value of these variables is smaller than α (5%). The null hypothesis that these variables have no effect on the correlation between the stock returns of the two countries can therefore be rejected. The stepwise regression procedure confirms us that the most efficient model, i.e. the model with the highest adjusted McFadden's R-squared multiple determination coefficient, is the regression only composed of the 5 significant variables found through the first regression. The R^2 represents the percentage of initial variability explained by the model and measures the fit between the models and the observed data. The higher it is, the better the model is. On the one hand, the negative coefficients of *RER* (-0.037535) and *RIR* (-0.020365) show a negative impact on the conditional correlation. On the other hand, a

positive impact of *BER* (0.097957), *BIR* (0.029021) and *OIL* (0.013208) on the correlation between Russia and Brazil is detected.

The obtained coefficients show us that if the Brazilian exchange and interest rate increase, the correlation between the Russian and Brazilian stock market increases. The opposite effect is observed with the Russian exchange and interest rate. The literature has shown us the complex nature of the interest rate (Narayan et al, 2014; Bracker et al., 1999). It is therefore advisable for an investor who wants to diversify his stocks in Russia and Brazil to follow the Brazilian interest and exchange rates as these two rates, if they experienced an increase, could increase the risk of the financial portfolio. Indeed, the more correlated his stocks are, the more risky they are. If the investor sees an increase in the Russian interest rate or exchange rate, he would be advised to invest his shares in these two countries as the correlation would probably decrease. Although the literature informs us that BRIC stock markets are not very sensitive to the oil price (Hammoudeh et al., 2012), in the case of the Russian-Brazilian correlation, a significant level of influence of the oil price on this correlation is observed. It would therefore also be relevant for an investor to observe oil price changes before investing.

It is also surprising to observe that both of the inflation rates do not have a significant impact on the dynamic conditional correlation between the stock markets of Brazil and Russia. By looking at the correlation between the two inflation rates, we obtain a correlation of 59% [**Appendix 5**], we therefore expected to see a positive and significant relationship between both of the inflation rates and the correlation. Indeed, Pretorius (2002) found that, if two countries have similar levels of inflation, they will have similar valuations and hence, this will cause stock prices to converse and lead to a higher correlations. It is therefore likely that the other macroeconomic variables in the regression are much more influential, which does not allow inflation rates to impact the correlation.

The results of the Granger causality test [**Appendix 6.1**] demonstrate that the null hypothesis stipulating that the macroeconomic variables do not Granger cause the conditional correlation cannot be rejected.

Table 7 - *Results of the multivariate model of DCC of Brazil and India*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
BER	-0.0021	
BIR	0.0282***	0.0279***
BINF	-0.0010	
IER	0.0922***	0.0887***
IIR	-0.0403***	-0.0397***
IINF	-0.0242***	-0.0242***
IMS	-0.0042*	-0.0040*
OIL	0.0203**	0.0207***
R^2	0.5867	0.5885
Adj. R^2	0.5693	0.5735

Thanks to the stepwise process, we can observe that the model with the highest R-squared (58.65%) was the one without the variables *BINF* and *BER*. This result is also aligned with the outputs of the complete multiple linear regression.

The coefficient and p-value of the variables *BIR* (0.027957), *IER* (0.088715) and OIL (0.020779) indicate a positive and strong relationship between these variables and the correlation between the market stock returns of India and Brazil. An increase of one of these variables will lead to an increase of the integration of Brazilian and Indian stock markets. The significant impact of the Indian exchange rate does not confirm the statement of Narayan et al. (2014) who said that the Indian exchange rate does not seem to be a significant determinant of its correlation. However, it is important to note that they had carried out an analysis with Asian countries and not with Brazil. It would therefore be found that the impact of India's trade rate may have a different impact on its correlation with other Asian countries and Brazil. In the opposite case, the two variables *IIR* (-0.039799) and *IINF* (-0.024206) influence the correlation in a strong and negative way. Here again we can see the complex impact of the two countries' interest rates on the correlation. Looking at previous works (Narod et al., 2022; Volosovych, 2011), we can notice that the latter results confirm the significant impact of inflation on the correlation. The variable *IMS* (-0.004087), being the least influential variable of the model,

presents a negative coefficient, which means that an increase of this variable would lead to a decrease of the DCC Brazil-India (*Cor_BI*). A risk-aware investor will primarily need to consider changes in India's macroeconomic variables in order to assess the risk of a financial portfolio containing Indian and Brazilian equities. He should also be mindful of the Brazilian interest rate and oil price which could increase the risk of his portfolio if these variables were to rise.

The **Appendix 6.2** shows the result of pairwise Granger Causality test. The results demonstrate that the null hypothesis stipulating that the macroeconomic variables do not Granger cause the conditional correlation cannot be rejected.

Table 8 - *Results of the multivariate model of DCC of Brazil and China*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
BER	0.0438**	0.0353***
BIR	0.0309***	0.0271***
BINF	-0.0271***	-0.0261***
CER	-0.1287***	-0.1297***
CIR	-0.0135	
CINF	-0.0141***	-0.0138***
CMS	0.0012	
OIL	0.0097	
R^2	0.341	0.3357
Adj. R^2	0.3133	0.3185

The results of the stepwise procedure on the multiple linear regression show that the most relevant model contains the independent variables *BER, BIR, BINF, CER* and *CINF*. The results of the stepwise procedure on the multiple linear regression show that the most relevant model contains the independent variables BER, BIR, BINF, CER and CINF. However the R-squared is lower compared to the ones of the regressions between Brazil and India and Brazil and Russia with a figure of 33.57%.

By performing a regression composed only of the variables selected by the stepwise procedure, it appears that all variables are highly significant (p-value<0.001). *BINF* (-0.026020), *CER* (-0.12975) and *CINF* (-0.013848) coefficients indicate a negative impact on the conditional correlation. Again, we observe a negative relationship between the inflation rates of China and Brazil with their correlation. These findings are contrary to the results of Bracker et al (1999) who showed that there could be a positive relationship between inflation and the correlation of countries with each other. It would therefore be relevant for an investor to look at the inflation rates of both countries before investing in Brazilian and Chinese stocks. However, the effect of inflation rates is smaller than the impact of the Brazilian exchange rate on correlation. Indeed, the coefficient on China's exchange rate shows us that an increase in the rate would imply a stronger decrease in the correlation compared to the impact of the other variables on it. This result is in line with the work of Tavares (2009) who demonstrated a negative relationship between the exchange rate and the integration of markets between them. It would therefore be more interesting for an investor to focus on the variation of the Chinese exchange rate in order to better assess the risk of his portfolio and the profits he can make.

In the contrary, variables *BER* and *BIR* are positively correlated with the DCC Brazil-China (*Cor_BC*) as their coefficients, respectively 0.035334 and 0.027055, are positive. As with the correlation between Brazil and Russia, an international investor who would move part of his portfolio into Brazilian and Chinese equities must take into account changes in the Brazilian interest rate and exchange rate. An increase in these two rates could slightly increase the risk of his portfolio.

The results of the Granger causality test [**Appendix 6.3**] demonstrate that the null hypothesis stipulating that the macroeconomic variables do not Granger cause the conditional correlation cannot be rejected.

Table 9 - *Results of the multivariate model of DCC of Russia and India*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
RER	-0.0449 **	-0.0455 **
RIR	-0.0043	-0.0714 *
RINF	-0.0076	-0.0078 *
IER	0.1418 ***	0.1389 ***
IIR	0.0181	0.0159
IINF	-0.0392 ***	-0.0395 ***
IMS	0.0034	
OIL	-0.0007	
R^2	0.5591	0.5566
Adj. R^2	0.5405	0.5451

The regression model performed with the entire set of variables of India and Russia demonstrates that only three variables have a significant impact on the dynamic correlation between India and Russia. The variables *IER*, *IINF* and *RER* had indeed p-values under 5%. The only significant variable that has a positive impact on the conditional correlation is the *IER* variable; the other two have a negative effect. In order to identify the subset with the best predictor variables, a stepwise regression was performed. The stepwise regression revealed that the better-fit model should include the *IINF*, *IER*, *RER*, *RINF* and *IIR* variables. The regression's results of this model confirmed that *IINF*, *IER* and *RER* are significant. It also highlights that *RINF* also significantly impacts the DCC India-Russia (*Cor_IR*). Its p-value (0.04453) indeed allows us to reject the null-hypothesis that this variable has no effect on the correlation. The most significant variables of this model are *IINF* and *IER*.

The coefficients of the stepwise model show that the correlation is significantly and negatively impacted by an increase in both inflation variables. This result is consistent with the arguments of several studies arguing that inflation is an important determinant of stock market integration between countries (Volosovych, 2011; Nardo et al., 2022). However, the negative relationship is not in line with Bracker et al's results (1999). Moreover, the results for the exchange rate variables indicate that an increase in these variables significantly

influences the correlation, but in opposing directions; positively for an increase in the Indian exchange rate and negatively for an increase in the Russian one. It is then partially in line with the positive impact of the exchange rate argued by Narayan et al' findings (2014) and with the positive impact expected by Didier et al (2012). Furthermore, the Russian interest rate seems to affect importantly the correlation, which is consistent with Bracker et al (1999), while the Indian interest rate variable is not significant, in line with Lee and Kim's results (2020). Finally, the non-significant impact of the oil variable on the DCC correlation is similar to Hammoudeh et al's finding (2012). This might be surprising since Russia is an oil-exporter and India an oil-importer. Lui et al's results (2020) may help explain this. They found that Russia, in comparison to the other oil-exporting countries, is less dependent to the price of crude oil. Therefore, the co-movements of the stock markets of Russia and oil-importing nations are less impacted by the price of crude oil than the co-movements of the stock markets of other oil-exporting and oil-importing nations.

The results of the Granger causality test [**Appendix 6.4**] demonstrate that the null hypothesis stipulating that the macroeconomic variables do not Granger cause the conditional correlation can only be rejected for the Indian inflation rate.

A conscious investor will need to take into account the evolution of macroeconomic variables in Russia in order to evaluate the risk of a financial portfolio containing Indian and Russian stocks. He should also be aware of the Indian exchange rate and inflation rate, which could increase the risk of his portfolio if this variable were to rise.

Table 10 - *Results of the multivariate model of DCC of Russia and China*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
RER	0.0756 **	0.0751 **
RIR	0.0135	
RINF	-0.0239 *	-0.0177 *
CER	0.2023 ***	0.2213 ***
CIR	0.3577 ***	0.3455 ***
CINF	-0.0453 ***	-0.0448 ***
CMS	-0.0162 ***	-0.0163 ***
OIL	-0.0049	
R^2	0.45	0.4474
Adj. R^2	0.4269	0.4302

The first multiple regression underlines the significance of five factors: *CER*, *CIR*, *RER*, *CINF* and *CMS*. The China-Russia DCC (*Cor_CR*) is affected favourably by the first three of them, while negatively by the last two. The best-fitting model computed thanks to the stepwise regression considers six variables, the five significant from the first multiple regression as well as the *RINF* variable. This model confirmed the significance of the five first variables, all having p-value below 5%. The multiple R-Squared of the stepwise regression indicates that the 44.74% of the fitted data in the regression is explained by the model.

An increase in both inflation variables had a significant and negative impact on the correlation between the Chinese and Russian stock markets. This confirms to us that inflation is important to consider in understanding the integration of stock markets (Volosovych, 2011; Nardo et al, 2022). The relationship's negative sign goes with the results of Narayan et al (2014), even if their results were based on the Chinese and Indian stock markets. However, it disagrees with Bracker et al's finding (1999). Regarding the exchange rate variables, the Chinese and the Russian ones influence both the correlation positively. This disagrees with several studies (Didier et al, 2012; Tavares, 2009). Nevertheless, it is consistent with Narayan et al's results (2014), even though their study was about Asian economies. In the same study, Narayan et al (2014) discovered that there is a positive relationship between interest rate and correlation

between China and India. It is aligned with our finding that a rise in the Chinese interest rate has a favourable and significant impact on the DCC correlation. However, this finding is not in line with Lee and Kim (2020) and Bracker et al (1999).

It is important to note that all Chinese variables are significant. Therefore, an investor must consider the fluctuations in these variables. The benefits of the international diversified portfolio would be increased in the case of an increase in the Chinese and Russian inflations, as well as the Chinese money supply. However, benefits would be reduced when the Chinese and Russian exchange rate increased, as well as the Chinese interest rate.

The results of the Granger causality test [**Appendix 6.5**] demonstrate that the null hypothesis stipulating that the macroeconomic variables do not Granger cause the conditional correlation cannot be rejected.

Table 11 - *Results of the multivariate model of DCC of India and China*

*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

	Full Model	**Stepwise Model**
IER	-0.2129 ***	-0.2012 ***
IIR	0.0005	
IINF	-0.0549 ***	-0.0548 ***
IMS	0.00349	
CER	-0.0137	-0.0167 *
CIR	-0.0812	-0.0714 *
CINF	-0.0453 ***	-0.0448 ***
CMS	-0.0091 ***	-0.0086 ***
OIL	0.0071	
R^2	0.4354	0.4318
Adj. R^2	0.4085	0.4141

The multiple regression model considering all the variables highlights that only four of them are significant, i.e. with a p-value below 5%. These variables are the *CINF*, *CMS*, *IER* and *IINF* and they all negatively impact the conditional correlation. The stepwise regression confirmed

the significance of the four variables found in the first regression by taking them into account in its best performing model, with two other variables being the *CER* and *CIR*. Furthermore, *IINF* and *IER* seem to be the most significant ones since they possess the lowest p-values, respectively 3.03e-12 and 1.69e-07. The multiple R-Squared indicates that the model explains 43.18% of the fitted data in the regression model. The results of the Granger causality test [**Appendix 6.6**] demonstrate that the null hypothesis cannot be rejected.

The negative and significant influence of the Indian exchange rate on the stock markets correlations is in line with several studies (Didier et al, 2012; Tavares, 2009). However, this is not in line with the results of Narayan et al (2014) who found that for India, the exchange rate does not significantly impact its correlations with China. Then, China's interest rate appears to be significant and negatively related to the DCC correlation, while the opposite is observed for the Indian interest rate. This partly goes with Narayan et al (2014) who state that there is a positive relationship between the interest rates and the correlation of the two countries. Furthermore, both coefficients of Indian and Chinese inflation rates demonstrate us that when there is an increase in these variables, the DCC correlation of stock markets will decrease. The significance of these rates is consistent with numerous studies, including Nardo et al (2022). Additionally, the negative coefficient of the relationship confirms the results of Narayan et al. (2014) who found that an increase in inflation affects the integration of Indian and Chinese stock markets. Oil is not significant in explaining the correlation of the two stock markets and this is consistent with the results of Hammoudeh et al (2012). Finally, the negative relationship between the money supply variable and the correlation disagrees with the study of Sutherland (2002).

5. Conclusion

Investors construct their financial portfolios according to their investment horizon, risk aversion, performance and asset diversification. Many studies have shown that building a portfolio of international assets increases diversification, decreases risk and provides better long-term returns (Roll, 1992; Bartram & Dufey, 2001; Segal, 2021). Investors have understood this and many have decided to build an international financial portfolio in order

to best diversify their assets and reduce correlation risk. Previous work shows that developing countries and especially the four major developing countries, i.e. Brazil, Russia, India and China (BRIC), would be profitable markets for building an effective international financial portfolio (Khaki et al., 2020; Ouattarra, 2017; Dong et al., 2020). However, since globalisation, the numerous global financial crisis among others, there has been greater integration between these emerging markets. Many studies have been done on the subject and prove that the integration of stock markets hinders asset diversification and increases portfolio risk (Zayati et al., 2016; King et al., 1994; Arif et al., 2017). However, most of the studies that have been conducted focus only on the evolution of BRIC stock markets and the level of integration between them (Nikkinen et al., 2013; Dong et al., 2020; Malik, Sharma & Kaur, 2021). Very few studies have attempted to link the development of these correlations with macroeconomic variables. This thesis aimed to identify the relationship between certain macroeconomic variables (exchange rate, interest rate, inflation rate, money supply and oil price) and BRIC stock market returns correlation pairs in order to help an investor construct a financial portfolio containing Brazilian, Russian, Indian and Chinese assets with the best diversification and the level of risk he is willing to take.

We studied the conditional dynamic correlations of the BRIC stock market returns between 2005 and 2021 using the GARCH model developed by Engle (2001). From these correlations analysis, we found, for instance, that the correlations of the BRIC stock market returns with each other were relatively volatile and highly sensitive to global stock market shocks and that the integration of the BRIC with each other increased during periods of global crises. However, we observed that during stock market shocks in the Brazilian, Russian or Indian economy, correlations seemed to decrease instead. We also observed that China, despite having the largest economy of the BRIC countries, has the weakest stock market relationship with the three other stock markets. Furthermore, despite its low correlations with the other stock markets, China remains a highly influential country and the stock market shocks it experiences are also observable in the Brazilian, Indian and Russian markets. As expected, the strongest correlations were observed for the most economically open countries. For example, the strongest integrations observed were between India and Brazil and between Brazil and Russia. Brazil seems to be the most integrated country.

We assessed the influence of macroeconomic variables on the dynamic conditional correlations by using the various multiple linear regression model. The results of these regressions showed us that that the impact of macroeconomic variables was present but complex. We observed that it was not possible to assess the positive or negative impact of the exchange rate and interest rate variables. However, we observe a strong influence of these two variables on the integration of the markets between them, so an investor should pay more attention to these variables. We have observed that the relationship between the inflation rate of two countries and the correlation of these two countries with each other is negative. Although inflation seems to decrease the return of the index, this variable seems to decrease the integration of the markets between them. As for the variables money supply and oil price, it was observed that these variables had a mainly positive relationship with the correlations. However, their influence is not as strong as that of the other variables, which leads us to conclude that, between them, they do not make it possible to correctly evaluate the diversification of the assets present in the portfolio of an international investor.

Based on our observations we can therefore conclude that macroeconomic variables (exchange rate, interest rate, inflation rate, money supply an oil price) do indeed have an influence on the integration of BRIC stock markets among themselves. However, we cannot conclude that, for all the macroeconomic variables, they cause the correlations between two countries. This conclusion can only be drawn for the Indian inflation rate, it was observed that it causes the correlation between Russia and India. Therefore, an investor, wishing to assess the correlation between international stock markets, cannot rely solely on the values of the variables considered in this thesis.

One way to go further in our thesis would be to cluster the correlations by industry. This could indeed improve the accuracy of our analysis as the integration of industries within the BRIC is likely to be stronger but also less volatile and some industries may also be more sensitive than others to certain macroeconomic variables. This would thus reduce bias and improve the quality of the results. Therefore, this will require an increase in the database and the accuracy of the outputs.

This thesis aimed to increase the amount of information that can be extracted from the integration of BRIC stock markets by taking the influence of macroeconomic variables into account which it did succeed to confirm in certain ways. However, the path should be further explored.

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7. Appendices

Appendix 1 - *Results of the four Ljung-Box tests without ARMA*

1.1 BVSP

Lags	Stat	p-value
4	6.7223	0.2421
8	11.7597	0.3014
12	18.4337	0.2405
16	23.5118	0.2643
20	24.7317	0.4774

1.2. MOEX

Lags	Stat	p-value
4	17.9858	0.0012
8	22.9708	0.0034
12	23.6624	0.0226
16	28.6279	0.0265
20	29.3951	0.0802

1.3. NIFTY

Lags	Stat	p-value
4	2.4251	0.6581
8	5.0091	0.7564
12	12.7964	0.3841
16	15.5189	0.4869
20	19.6483	0.4801

1.4. SHCOMP

Lags	Stat	p-value
4	15.8874	0.0031
8	19.4659	0.0125
12	22.8673	0.0288
16	42.3158	0.0003
20	47.5246	0.0005

Appendix 2 - *Results of the Ljung-Box tests with ARMA models*

2.2. SCHCOMP – ARMA(1,3)

Lags	Stat	p-value
4	6.6306	0.1567
8	9.1831	0.3271
12	10.4196	0.5791
16	26.2543	0.0515
20	21.2162	0.0523

2.2. MOEX – ARMA(1,1)

Lags	Stat	p-value
4	0.3216	0.9883
8	5.5011	0.7029
12	6.0335	0.9143
16	10.3145	0.8595
20	11.7172	0.9254

Appendix 3 – *Result of Ljung-Box tests - ARCH effects*

3.1. BVSP

Lags	Stat	p-value
4	1.1384	0.8881
8	2.3282	0.9692
12	3.8035	0.9867
16	5.0915	0.9952
20	5.3281	0.9995

3.2. MOEX

Lags	Stat	p-value
4	12.8039	0.0122
8	22.5755	0.0039
12	24.6727	0.0164
16	26.0253	0.0536
20	26.8477	0.1396

3.3. NIFTY

Lags	Stat	p-value
4	6.8285	0.1452
8	23.6751	0.0025
12	30.5861	0.0022
16	32.5162	0.0085
20	33.8532	0.0271

3.4. SHCOMP

Lags	Stat	p-value
4	15.4156	3.9123e-03
8	30.1057	2.0247e-04
12	55.4594	1.4971e-07
16	60.2372	4.7733e-07
20	51.9471	3.5434e-06

Appendix 4 - *Results of the Ljung-Box tests with GARCH models*

4.1. NIFTY – GARCH(1,1)

Lags	Stat	p-value
4	1.4544	0.8346
8	1.7737	0.9871
12	9.2685	0.6798
16	10.7077	0.8271
20	12.3843	0.9022

4.2. SHCOMP – GARCH(1,1)

Lags	Stat	p-value
4	1.4544	0.8346
8	1.7737	0.9871
12	9.2685	0.6798
16	10.7077	0.8271
20	12.3843	0.9022

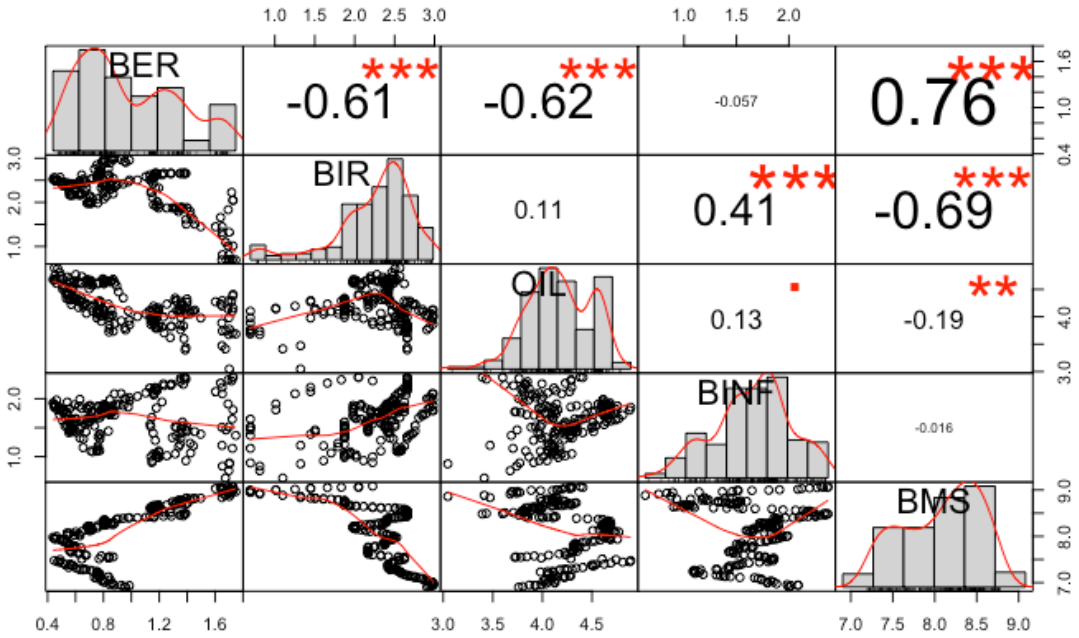
4.2. MOEX – GARCH(1,8)

Lags	Stat	p-value
4	7.4792	0.1126
8	15.2422	0.0546
12	17.8528	0.1202
16	20.4157	0.2021
20	23.9611	0.2441

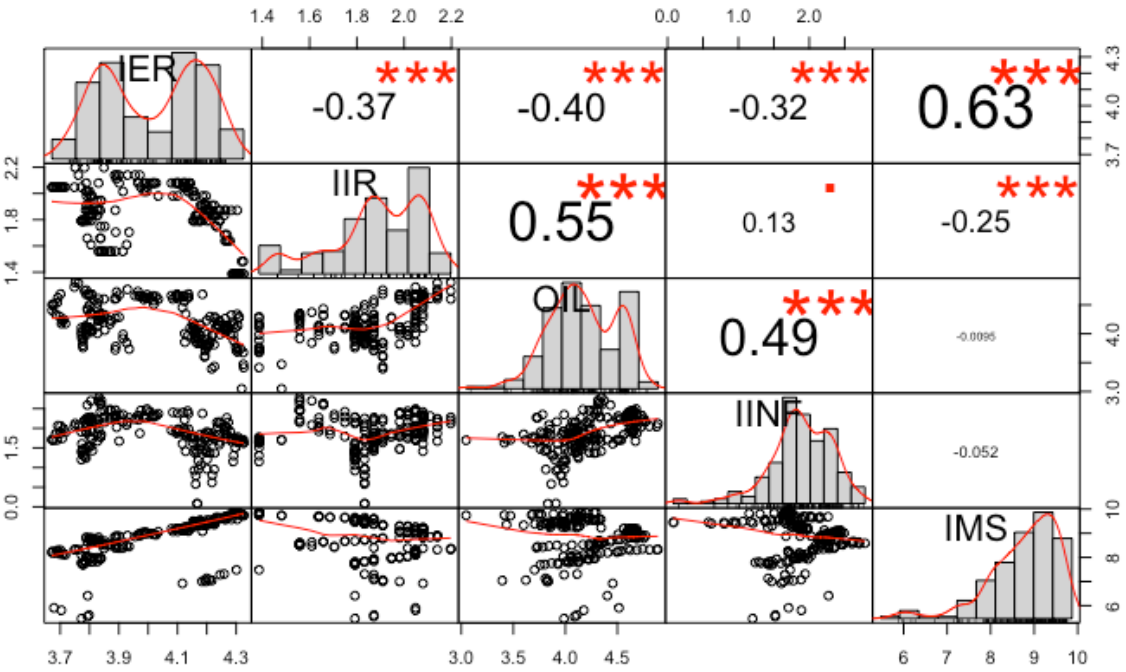
Appendix 5 - *Chart of Correlations between macroeconomic variables*

The larger the font size, the stronger and more significant the correlation.
*** significant at the 0.001 level, ** significant at the 0.01 level, *significant at the 0.05 level

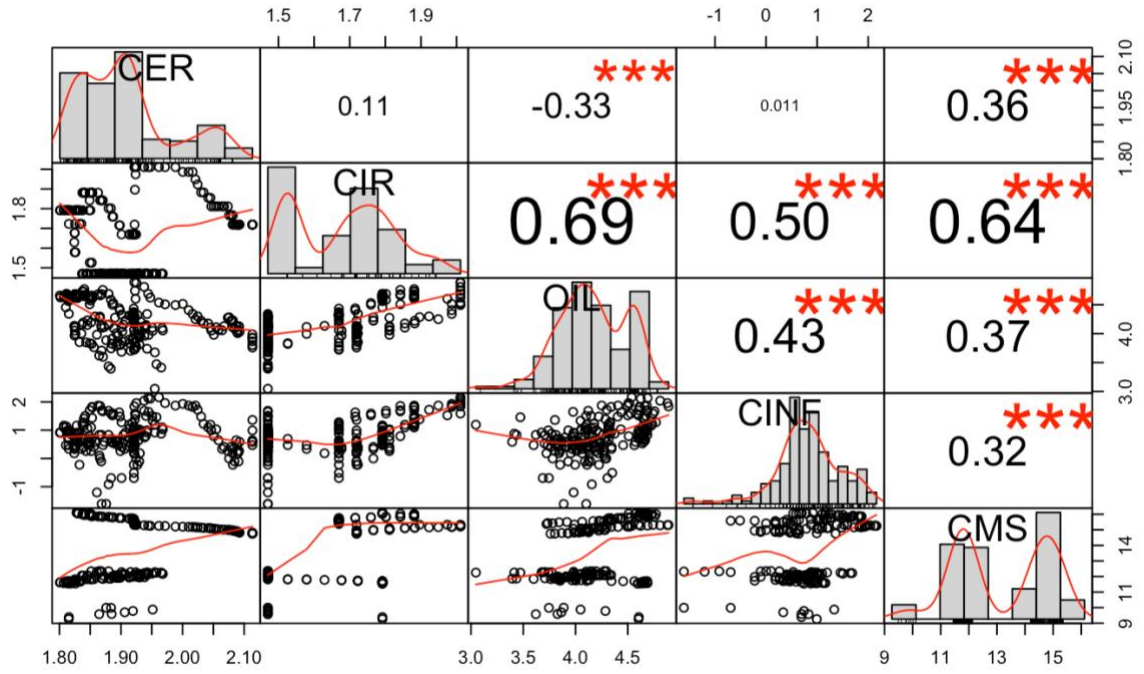
2.1. Brazilian Macroeconomic variables



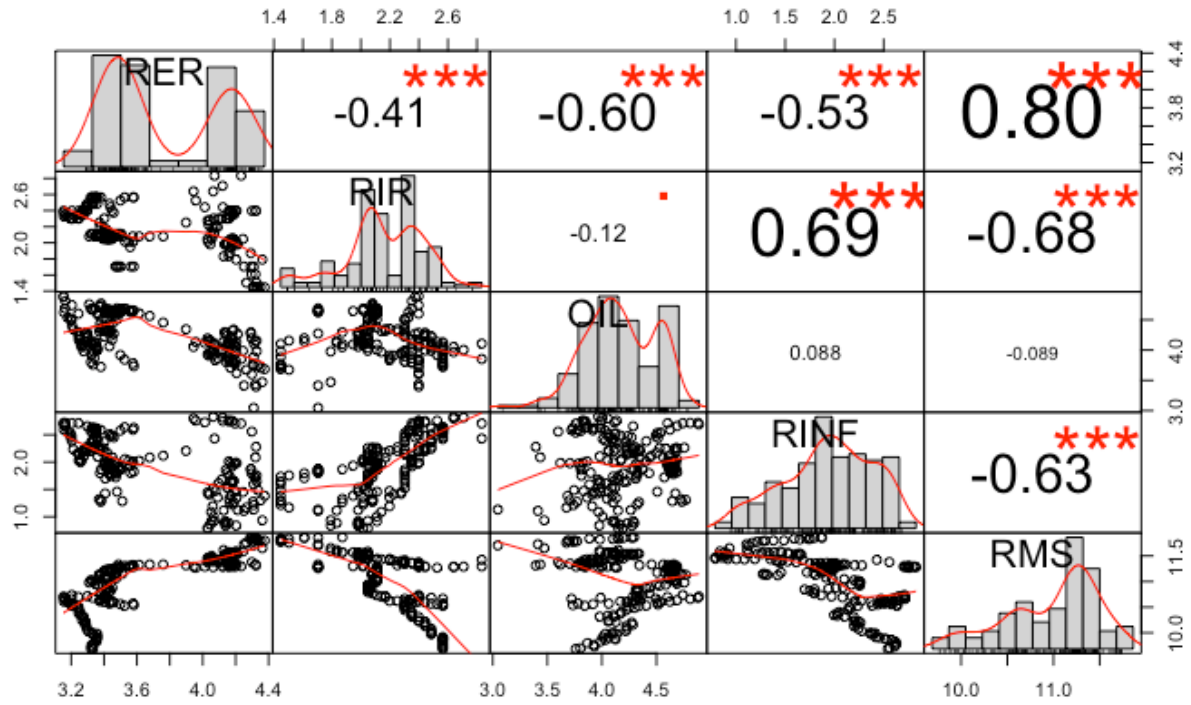
2.2. Indian Macroeconomic variables



2.3. Chinese Macroeconomic variables



2.4. Russian Macroeconomic variables



Appendix 6 - *Granger causality results*

3.1 Brazil-Russia results

Null Hypothesis	F-statistic	P-value
BER does not Granger Cause *Cor_BR*	2.3477	0.07406
BIR does not Granger Cause *Cor_BR*	0.3262	0.8064
BINF does not Granger Cause *Cor_BR*	0.3058	0.8212
RER does not Granger Cause *Cor_BR*	0.9761	0.4051
RIR does not Granger Cause *Cor_BR*	0.9938	0.3969
RINF does not Granger Cause *Cor_BR*	2.6934	0.05742
OIL does not Granger Cause *Cor_BR*	1.6033	0.1901

3.2 Brazil-India results

Null Hypothesis	F-statistic	P-value
BER does not Granger Cause *COR_BI*	0.8489	0.4687
BIR does not Granger Cause *COR_BI*	0.5321	0.6608
BINF does not Granger Cause *COR_BI*	1.2181	0.3044
IER does not Granger Cause *COR_BI*	1.0343	0.3786
IIR does not Granger Cause *COR_BI*	0.7513	0.5229
IINF does not Granger Cause *COR_BI*	0.7165	0.5433
IMS does not Granger Cause *COR_BI*	0.1906	0.9027
OIL does not Granger Cause *COR_BI*	0.8308	0.4784

3.3 Brazil-China results

Null Hypothesis	F-statistic	P-value
BER does not Granger Cause *COR_BC*	0.518	0.6704
BIR does not Granger Cause *COR_BC*	1.4731	0.2233
BINF does not Granger Cause *COR_BC*	1.1652	0.3243
CER does not Granger Cause *COR_BC*	0.6891	0.5597
CIR does not Granger Cause *COR_BC*	1.8736	0.1355
CINF does not Granger Cause *COR_BC*	1.5677	0.1986
CMS does not Granger Cause *COR_BC*	1.3394	0.2629
OIL does not Granger Cause *COR_BC*	0.6026	0.6141

3.4 Russia-India results

Null Hypothesis	F-statistic	P-value
RER does not Granger Cause *Cor_RI*	0.4591	0.7112
RIR does not Granger Cause *Cor_RI*	0.7951	0.498
RINF does not Granger Cause *Cor_RI*	0.8042	0.4929
IER does not Granger Cause *Cor_RI*	0.8075	0.4911
IIR does not Granger Cause *Cor_RI*	0.2098	0.8895
IINF does not Granger Cause *Cor_RI*	4.3502	0.005451 **
OIL does not Granger Cause *Cor_RI*	0.5186	0.6699

3.5 Russia-China results

Null Hypothesis	F-statistic	P-value
RER does not Granger Cause *Cor_RC*	0.7323	0.5339
RIR does not Granger Cause *Cor_RC*	2.0372	0.1101
RINF does not Granger Cause *Cor_RC*	1.2719	0.2853
CER does not Granger Cause *Cor_RC*	0.6355	0.593
CIR does not Granger Cause *Cor_RC*	0.4987	0.6836
CINF does not Granger Cause *Cor_RC*	0.7958	0.4976
OIL does not Granger Cause *Cor_RC*	1.3218	0.2686

3.6 India-China results

Null Hypothesis	F-statistic	P-value
IER does not Granger Cause *Cor_IC*	0.0942	0.9632
IIR does not Granger Cause *Cor_IC*	1.1566	0.3276
IINF does not Granger Cause *Cor_IC*	0.4193	0.7394
IMS does not Granger Cause *Cor_IC*	0.4565	0.713
CER does not Granger Cause *Cor_IC*	0.5561	0.6446
CIR does not Granger Cause *Cor_IC*	0.2776	0.8415
CINF does not Granger Cause *Cor_IC*	0.5698	0.6355
OIL does not Granger Cause *Cor_IC*	1.3234	0.2681

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