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THE EFFECT OF THE FINANCIAL CRISIS ON EMERGING MARKETS. A COMPARATIVE ANALYSIS OF THE STOCK MARKET SITUATION BEFORE AND AFTER

Original scientific paper
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Abstract

In this paper the authors present the findings of an analyses carried out to establish whether the BRIC's stock market returns were affected by the U.S. financial stress during the 2008 Financial Crisis. To do this the authors studied the relationship between the U.S. Stock Markets and the BRIC countries' stock and bond market returns. They carried out a regression analysis which consisted of running an equation of the dependent variable - the BRIC's stock market returns, against a number of regressors -explanatory variables, which include the U.S.' industrial production, the U.S.' unemployment rate, the U.S.' S&P500, the Michigan confidence index, the BRIC's consumer price index, the industrial production, the Gross Domestic Product and the consumer price index of each individual country; Brazil, Russia, India and China respectively. Then the authors used a single-equation time series model to explain spillover effects emanating from the US onto the BRIC markets. They analysed the whole data series from 2003 to 2014. Then sub-divided this data to analyse the post crisis effects on the BRICS equity market. The index of Brazil, Russia, India and China respectively. - BOVESPA (Brazil), MICEX (Russia), NIFTY (India) and China Security Index (CSI300) were the dependent variables of the model. Moreover, the model takes the US stock market index, the S&P500 as a benchmark *variable. Results obtained, revealed that the BRICs were subject to a spillover effect during and following the financial crisis.*

Keywords: BRICS, Financial Crisis, Emerging Markets

1. INTRODUCTION

The Goldman Sachs, 2003 paper "Dreaming with BRICs: the Path to 2050", highlighted that Emerging Markets (EM) are one of the drivers of global growth. Noting that Brazil, Russia, India and China, collectively referred to as BRIC countries, could in the light of the regulations, which are supportive of foreign investment as well as the free flow of capital, further increase their potential development (Bhar & Nikolova, 2008). In fact, BRIC countries represent a class of the middle-income emerging market economy, distinctively large in size, which can prove useful to enhance economic growth in the world economy (Marcelo, Yoshino, & Machado de Sousa, 2013). Therefore, it is important to understand the way regional and global financial events affect emerging market returns and the volatility of returns. Hence, to understand how such markets respond when in financial stress (Bhar & Nikolova, 2008).

This paper focuses on the impact the financial crisis had on BRIC countries, with respect to the United States, the original source of the crisis. The paper analyses the contagion effects of financial shocks from the US to stock and bond markets in BRIC countries and its effect on the volatility of such markets. Moreover, this paper also analyses whether the BRIC countries were affected by US financial stress.

Many investors assume that the inclusion of emerging markets in investment portfolio would enhance their risk-return tradeoff. Research shows that this is in fact true and adding developing economies that are less correlated with advanced economies allows for ideal diversification (Hallinan, 2011). However, in light of the past financial crisis, this is highly debatable. Hence, this paper will also seek to answer questions imposed by the modern portfolio theory, based on the work of Markowitz (1952) and the Capital Asset Pricing Model (CAPM). That is, whether investors can improve their positions by diversifying the portfolio and investing into different classes of financial securities and whether developing countries really serve as diversification opportunities to investors following the financial crisis. (Aloui, Ben Aissa, & Nguyen, 2011).

Since emerging equity markets are undergoing periods of constant change and transformation, understanding the effect of integration with advanced economies such as the U.S., Europe and Japan and assessing the weaknesses of the equity markets in times of financial stress and during regional financial crisis, would prove beneficial to investors, who are constantly seeking new ways of lowering their risks by diversification (Chittedi, 2009).

2. LITERATURE

Between 2006 and 2010, Gross Domestic Product (GDP) growth of the BRICs outperformed growth in advanced economies. During this period, emerging-economic market growth accounted for approximately 60% of worldwide GDP growth. Apart from the fast economic growth, emerging markets showed financial stability and economic resilience during the financial crisis of 2008. However, while GDP output of advanced economies plunged, developing countries output remained constant (World Economic Forum, 2012).

2.1. Contagion

Claessens et al. (2000), define contagion as the intensification of cross-market integration after a shock in a country or group of countries. They explain that contagion is defined by the degree to which stock prices move together across markets relevant to comovement when financial markets are not faced by financial stress. The variables that make a country vulnerable to contagion and through which contagion is spread are still unknown. Hence, it is difficult to propose other policies apart from more rigid financial architecture to effectively reduce and prevent the risks of contagion.

Forbes and Rigobon (1999) examine stock market co-movements. They analysis the different theoretical models as to how linkages between countries can be calculated. Such statistical measures include correlation in asset returns, the probability of a speculative attack and the transmission of shocks or volatility. They also explain what contagion is and develop models on how to interpret spread mechanisms and suggest that the standard tests to examine cross-market correlation in stock market returns is biased and propose a simple method on how to adjust the correlation coefficient from bias. They propose an understanding of why stock markets are integrated during periods of financial stability. To study the spread of the U.S. financial crisis to BRIC countries, Bianconi et al. (2013), use simple unconditional volatility measures, vector autoregressions (VAR), cointegration, and conditional volatility and correlations amongst stock and bond market returns.

Studies conducted by Eichengreen and Park (2008), refer to the recent financial crisis to show that emerging markets where unable to disassociate themselves from the U.S. financial crisis. Although developing markets and their exposure to U.S. financial markets is limited, with enforced regulation on the market, they show that, one cannot imply that the region is without any weakness. They also comment on the impression that China's economy grew so much that it segregates the whole region from U.S. market spillovers. However, they note that although this may contain some truth, one cannot deny that Asia's economy is still linked to the United States both by trade and by stock market co-movements. Dooley and Hutchison (2009), study the spillover effects of the U.S. financial crisis to developing countries. The authors' interest in the topic is related to the fact that emerging markets took upon themselves reforms such as increases in reserves and reduction of government deficits that should have isolated them from financial shocks from other countries. Their paper analysis how emerging markets' CDS spreads were affected by U.S. financial shocks. They study about, what news affected CDS spreads and the magnitude of these news on emerging markets. Their research shows that the U.S. has large economic and statistical influence on emerging markets and that news moved markets consistently. However, the authors are not sure whether the linkages between the U.S. and developing countries have changed or whether the importance of events originating from the United States have changed. This is often referred to as the 'decoupling-recoupling' debate. They report that financial indicators show that emerging markets were decoupled from the United States. It seemed that the growth rates of emerging and advanced economies were heading in opposite directions. However, after the bankruptcy of Lehman Brothers in September 2008, correlations between emerging markets and the U.S. also rose substantially (markets recoupled). The paper also identified that major news, such as the bankruptcy of Lehman Brothers and news on the real U.S. economy affected CDS spreads in emerging markets.

Llaudes et al. (2010), analyse the characteristics of the initial crisis and the heterogeneous transmission amongst emerging markets. The paper studies the impact of the financial crisis on the decline in actual growth and decline in stock markets, as well as the decline in credit growth. Since emerging markets where affected by an external crisis, the paper focuses on exterior vulnerabilities of emerging markets. The paper shows that countries that had linkages with advanced economies and are more open to trade where severely hit by the crisis, They experienced steeper falls in output during the crisis. While, countries that strengthened external weaknesses prior to the financial crisis, later went into recession. They found a significant and a healthy relationship between emerging markets' reserves and their decline in growth during the financial crisis.

Nikkinen et al. (2013) investigated the transmission of the US subprime crisis onto BRIC countries and examined the impact of the financial crisis on the stock markets and equity markets of the industrial and financial sectors. They use a bivariate GARCH-BEKK model utilising daily total return indices and estimate four pair-wise models. They identify the extent of contagion by examining the industrial and financial sectors of BRIC equity markets. Results show that there is evidence of contagion between the US and BRIC markets due to direct linkages both in terms of returns and volatility and that Russia and India's equity returns as well as financial and industrial sector returns where influenced by US equity market movements prior to the financial crisis. They also found clear evidence of contagion, however, the authors show that only Russia's financial sector was severely affected by the fall of the Lehman Brothers.

Zouhair et al. (2014) examine the joint behaviour of US and BRIC equity markets. The authors found strong linkages between both stock markets during the US subprime mortgage crisis. Result show evidence of contagion in Brazil and interdependence between China, India and Russia. The study also shows high correlation coefficients for Brazil, meaning that the economy is integrated with the United States in all periods that were studied. Also, the study addresses the general idea that countries with low integration in the global economy prove to be good diversificiation possibilities. This is the case for India and China which have a low correlation coefficient compared to that of Brazil, these results are in line with studies by Aloui et al. (2011) and Bianconi et al. (2013).

2.2. Cross-Market Linkages and integration

Aloui et al. (2011), examine the cross-market linkages and interdependences between BRIC equity markets and the United States during the financial crisis. The authors find that the dependency on the U.S. is more persistent in countries, which depend on commodity prices such as Brazil and Russia – than for countries which economic growth is dependent on finished products such as China and India. Chittedi (2009) studied the long run co-integration relationship between BRIC countries and the U.S., UK and Japan using the Granger causality, Johansen co-integration and Error correction Mechanism. The authors found that the U.S. and Japan are influencing the Indian stock market due to international trade activities. However, the study states that India is far less influencing the UK, Brazil, China and Russia. They also show that the BRICs and advanced economies where highly co-integrating during the period of the study. Bianconi et al's . (2013) results show that in fact for bond markets, India is isolated from the other BRIC countries.

Morales and Gassie (May 2011) study the relationship between BRIC markets and energy markets. The authors highlight the weak integration levels between the Chinese financial markets, energy markets and the U.S. equity markets. They also show that Brazil, Russia and India are more sensitive to financial shocks arising from the United States as well as energy market instability. Bhar and Nikolova (2008) study the linkages between the BRICs, their regions and the world by using a bivariate EGARCH structure, this allows for time varying condition correlation of index equity returns from such markets. They explain that the proposed model allows researchers to analyse the impact of a number of events on BRIC markets and the correlation equity index returns. The authors found evidence that India is the most integrated country from the BRICs on both regional and global levels, followed by Brazil and Russia. China is the most isolated country and hence the least volatile. This means that China could be a great opportunity for investors to diversify their portfolio due to the close nature of China's financial markets. Results obtained indicate that none of the BRIC countries impact the volatility of world market returns.

2.3. News, Volatility and their effect on correlations

Aggarwal et al. (1999) studied the events that have the largest impact on emerging stock markets volatility. Results show that the periods of greater volatility shifts are inter-related with important country-specific political, social and economic events such as the Mexican Crisis and the Marcos-Aquino conflict in Phillipines.

Bae and Karolyi (1994) results suggest that news from a particular market seem to affect the short-term volatility of stock prices in foreign markets. They studied the relationship of the joint dynamics of the Nikkei stock average and the S&P 500 stock index over the 1988-1992 period. The authors noted that bad news from both local and foreign markets seem to have a bigger impact on return volatility than good news.

Beirne et al. (2009), studied the volatility spillover from advanced economies to emerging economies. They found that that volatility in emerging stock markets tended to be higher in periods where mature markets where in turbulence periods.

Bianconi et al. (2013), explain that the behaviour of asset classes affect the co-integration relationship between U.S. financial stress and BRIC nations. Using Multivariate GARCH models and dynamic conditional correlations, they shed light on the role of news and volatility and explore how these affect the correlations between national stock markets during the global financial crisis. Contrary to what was found by Mun and Brooks (2012), who show that news does not have a significant effect on the correlations and that the majority of correlations are strongly explained by volatility, Bianconi et al. (2013), note that news and volatility are equally important for stock returns but news are less important than the volatility in BRIC markets when referring to bond and stock markets returns altogether.

2.4. Stock and bond market Correlations and Yield Spreads

Baur (2007) shows that in developing countries stock-bond market correlations are highly influenced by cross-country influences rather than stock and bond market interaction. He tests the relationship of cross-country, cross-asset stock and bond market linkages. Results show that U.S stock markets influences stock and bond market returns of the eight developed countries. Aslanidis and Christiansen (2012) adopt quantile regressions to study the realized stock-bond correlation based upon high frequency returns. They explain that when the correlation is highly positive or highly negative, correlation dependence behaves differently.

Bunda et al. (2009) examine the comovement in emerging bond market linking to internal and external factors during high market volatility episodes. They analysis eighteen emerging markets between 1997 and 2008 and proposed a conceptual framework based on emerging market spreads and cumulative correlations. The study sheds light on the drop in emerging markets spreads and the factors that contributed to this. They note that the decline was not only led by external factors but also to the fact that emerging countries improved their country fundamentals. They show that the period between 2003 and 2008 had very low levels of contagion in the bond markets. This period was characterized by the global financial crisis and explain that correlations between bond markets increased after the crisis. They also show that the mentioned phenomenon explains the increase in emerging bond markets' volatility.

Siklos (2011), studies twenty-two emerging markets to understand the determinants of bond yield spreads in the period 1998-2009. He examines the linkage between volatility and bond yield spreads. The study shows that emerging markets aren't all affected in the same way and cannot be treated equally. Results show that Asian bond markets were decoupled from other developing economies during the financial crisis, agreeing with Bianconi et al. (2013) with regards to the isolation of Indian bond markets.

Bianconi et al. (2013), show that BRICs cannot be considered to be isolated from the financial stress posed by the United States. Results show that Brazil and Russia are very much likely to suffer financial stress, however, India is the least correlated market. They also investigate whether emerging markets can prove to be good diversification opportunities for investors. The study shows that during that period, China's stock markets respond less to financial stress when compared to other nations. Also, Indian bond markets seem to be isolated from external factors and hence are less influenced by financial stress and external factors posed by the United States.

3. METHODOLOGY

3.1. Sample selection

The sample data for the whole period, 2003 to 2014, was collected using the Thompson Reuters platform. This data was split into two periods. The first period related to the whole period from 2003 to 2014, the second data period related to the period after the financial crisis between 2009 and 2014. Due to lack of monthly data for the gross domestic product, the researcher chose to use industrial production (IP) as a proxy, since except in the case of Brazil, it correlates well with the former variable. The authors used the Eviews application software to conduct the correlation analysis between the two variables for all countries. Although the authors did not find serious correlation between Brazil's GDP and industrial production, they still felt that this variable was the best proxy to use for GDP data.

3.2. Research Model

The researchers used a single-equation time series model to try and explain spillover effects emanating from the US onto the leading emerging markets. This model was chosen so as to enable them to focus on the first two moments, that is, the mean and the constant variance. The research assumes a normal distribution and does not analyse the skewness and kurtosis of the data. This requires the authors to consider a time-variant variance, which is not possible with other models such as the EGARCH. This would also mean that the third and fourth moments do not affect the analysis of the study.

The researchers first analyse the whole data series, that is from 2003 to 2014. Then analyse the post crisis effects on the emerging equity market. The dependant variable of the model will be the index of Brazil, Russia, India and China respectively. Hence, the authors use the following indices: BOVESPA (Brazil), MICEX (Russia), NIFTY (India) and China Security Index (CSI300).

The model will take the US stock market index- the S&P500 as a benchmark variable. The independent variables included in the model are the US industrial production acting as a substitute to the GDP , the US unemployment rate (UR), US non-farm payrolls (NFP) and the Michigan Confidence Index (MCI) as well as the industrial production of each of the BRIC countries and their consumer price index (CPI). By considering these variables in this research model, the authors can understand whether the BRICs' equity markets were isolated from the US financial stress,

$BOVESPA_{BR} = B_1\ (S\&P500) + B_2\ (IP_{US}) + B_3\ (UR_{US}) + B_4\ (NFP_{US}) + B_5\ (MCI_{US}) + B_6\ (IP_{Br}) + B_7\ (CPI_{Br}) + U$

$NIFTY_{In} = B_1\ (S\&P500) + B_2\ (IP_{US}) + B_3\ (UR_{US}) + B_4\ (NFP_{US}) + B_5\ (MCI_{US}) + B_6\ (IP_{In}) + B_7\ (CPI_{In}) + U$

$MICEX_{Ru} = B_1\ (S\&P500) + B_2\ (IP_{US}) + B_3\ (UR_{US}) + B_4\ (NFP_{US}) + B_5\ (MCI_{US}) + B_6\ (IP_{Ru}) + B_7\ (CPI_{Ru}) + U$

$SHCOMP_{Ch} = B_1\ (S\&P500) + B_2\ (IP_{US}) + B_3\ (UR_{US}) + B_4\ (NFP_{US}) + B_5\ (MCI_{US}) + B_6\ (IP_{Ch}) + B_7\ (CPI_{Ch}) + U$

3.2. Method of Analysis

The authors first plotted the data to determine visually, whether the data collected is stationary or not, and then conducted an augmented Dickey-Fuller unit-root test to test for autocorrelation and whether the variables have a unit root. If the variables had an ADF test statistic lower than the test critical value of 1%, this meant that the data has a unit-root and the variable is non-stationary.

The researchers used the EViews software package to analyse the regression. Through the various tests available on EViews the authors were able to test whether the model is econometrically correct and test it using diagnostic checking. One important aspect of EViews is that it allows the researcher to use regression analysis with the aim to explain how the independent variables affect the dependent variable. The authors used EViews to explain whether the BRIC equity indices where indeed affected by the US financial stress.

They compare the two sub-periods against each other and made reference to the various statistical indicators as shown by the regression. They then tested for the significance of the variables and checked whether these should be included in the model. Variables found to be statistically significant meant that they explained the dependant variable. On the other hand if the variable was not significant, the variable did not have an effect on the stock market. The authors then interpreted the meaning of the coefficient term as well as the p-values and ran a white-test to check for heteroscedasticity, then computed the F-statistic to check whether the regression's variables were jointly statistically significant. Then they checked the R-squared, to see how much of the dependent variable was explained by the model and what was captured by the error term (u).

3.3. Limitations of the theoretical model

The authors note that this model has some limitations that result in endogeneity. The first limitation of the model is 'the omitted variable bias', which generally results from limited sources of data. Clarke (2005) explains that it is difficult to include all the variables that influence the dependant variable in the regression equation, hence, the omitted variable bias is inevitable.

Also, a second limitation to the model, is 'simultaneity', also referred to as 'the direction of causality'. The authors refer to the fact that some independent variables are dependent on the dependant variable, hence, the independent variables can have some correlation with the error term.

As noted above, the authors were also faced with limited data, due to the fact that the GDP variable was only available quarterly or annually. Therefore, they used a proxy for GDP. Moreover, for India's NIFTY stock index the authors only managed to obtain data from 2005, which resulted in fewer observations, limiting the ability to analyse the effect of the financial crisis on India.

4. TESTS AND CONCLUSİONS

4.1. Testing for Stationarity

Figure 4.1.1 and 4.1.2 present a graphical representation of the variables that the researchers used in the theoretical method for the period 2003 to 2014 while 4.1.3 and 4.1.4 represent the variables used for the second data set, 2009-2014. This shows a strong indication of the presence of non-stationary data since trends are noticeable in the presented data.

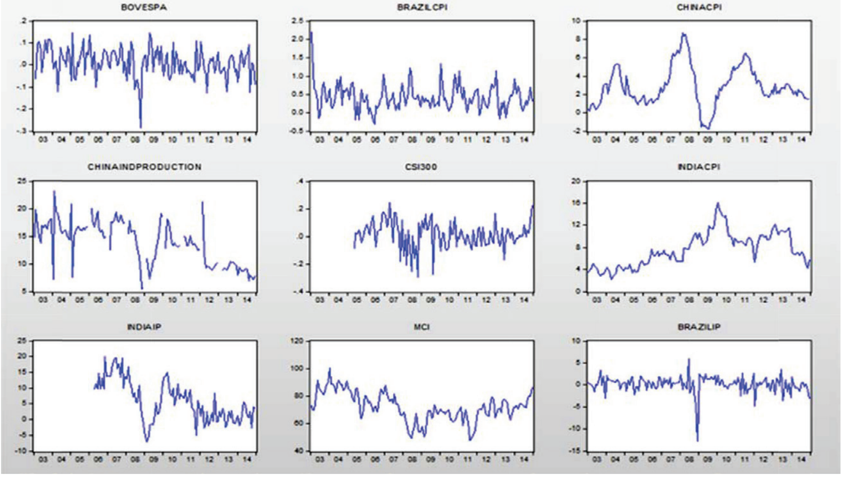

Figure 4.1.1 - Graphical representation of the variables for the period 2003 to 2014

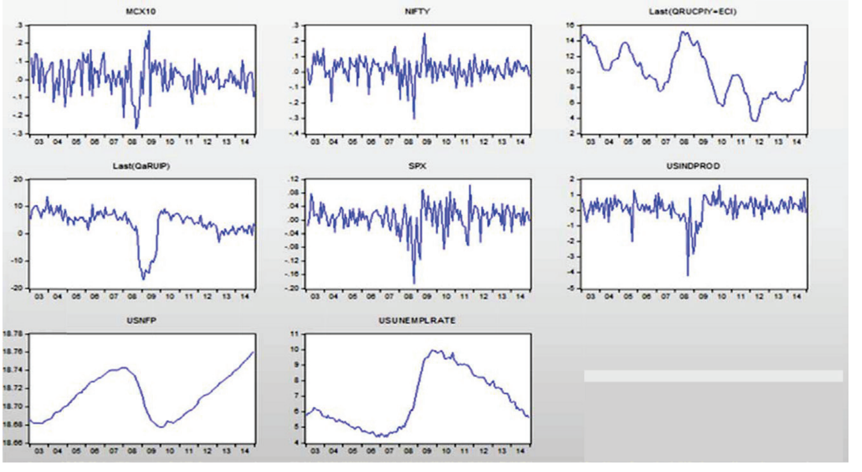

Figure 4.1.2 - Graphical representation of the variables for the period 2003 to 2014

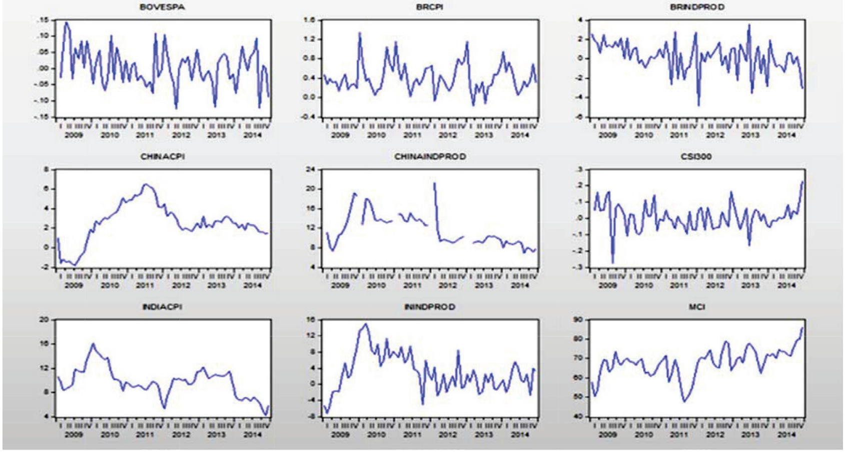

Figure 4.1.3 - Graphical representation of the variables for the period 2009 to 2014

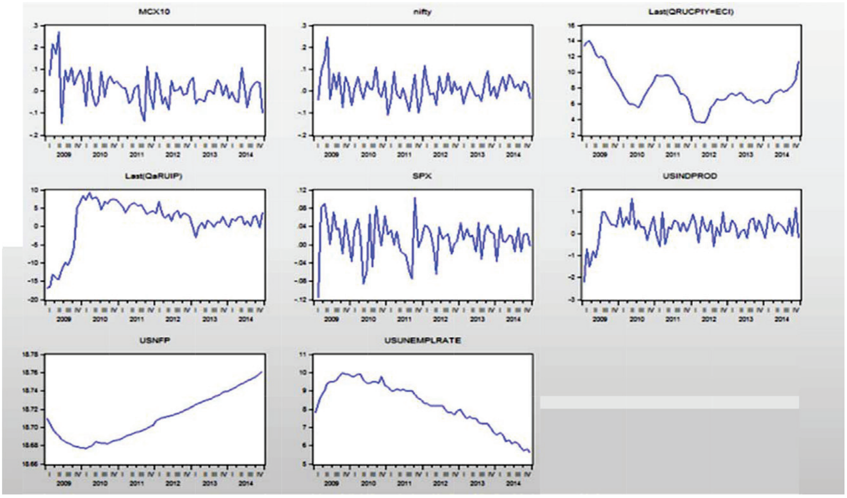

Figure 4.1.4 - Graphical representation of the variables for the period 2009 to 2014

Null Hypothesis: BOVESPA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.628404	0.0000
Test critical values:	1% level	-3.476805	
	5% level	-2.881830	
	10% level	-2.577668	

*MacKinnon (1996) one-sided p-values.

Figure 4.1.5 - The Augmented Dickey-Fuller test

Figure 4.1.5 shows that the variable has a unit root. Table A1.1 and A1.2 (Appendix 1) illustrate the variables that make up the theoretical method and which of these are either stationary or non-stationary as shown by the ADF. Table A1.1 portrays variables from the whole sample, i.e. 2003 to 2014 while table A1.2 shows the second sub-data set, 2009-2014, respectively. It is noted that non-stationary data is not suitable to use in its present form; hence, in order to eliminate this problem the authors took the first differences.

The ADF was re-run once the data was re-arranged by taking the first difference or second differences. The variation in data was found to vary around a constant mean, which gives an indication that stationarity was achieved at 99% confidence level.

4.2. Testing for Heteroscedasticity

Homoscedasticity is a desirable OLS property which states that the variables should have a constant variance ($Var(u_t) = E(u_t) = \delta_2$). Variables not having a constant variance are said to be heteroscedastic, which might be a problem when regressing the equation using OLS, since the constant (C) and the Beta (β) would not have minimum variance, hence are said to be biased. Therefore, the variable is said to be no longer BLUE (Best Linear Unbiased Estimators).

The authors conduct heteroscedasticity tests also known as the White's test to check for heteroscedasticity and remove any interpretational bias. EViews provides the authors with the results which test for heteroscedasticity as well as the auxiliary regression, which is a useful source when determining the source of heteroscedasticity of a multiple variable regression.

In the case of the White's test, the null hypothesis states that there is homoscedasticity, while the alternative hypothesis states that heteroscedasticity is present in the regression. If the p-value are more than 5% or 0.05, it is assumed that there is no presence of heteroscedasticity. On the other hand, if the p-values are lower than 0.05, the data has to be corrected to support the assumption of homoscedasticity. The software package used gives a quick option that adjusts data to account for heteroscedasticity. The results of the White's test for the variables used are shown in appendix 2 (figures A2.1 to A2.8) and most of the data have high p-values, hence the null hypothesis was accepted, meaning that the data is homoscedastic. On the other hand for cases such as India, data were adjusted using heteroscedasticity-consistent standard errors.

In appendix 3 (figures A3.1-A3.4), the authors illustrate how the OLS and standard errors changed after adjusting for heteroscedasticity when compared to that illustrated in appendix 1.

4.3. Result Analysis

Once diagnostic checks were carried out, the authors were able to analyse results from the OLS estimations (Appendix 3).

4.3.1. The OLS's descriptive statistics

4.3.1.1. Brazil

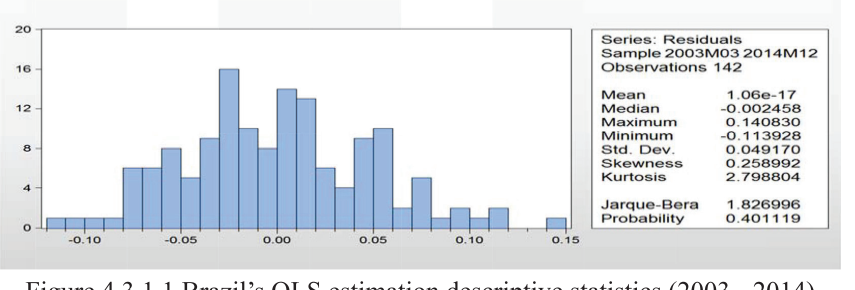

Figure 4.3.1.1 Brazil's OLS estimation descriptive statistics (2003 - 2014)

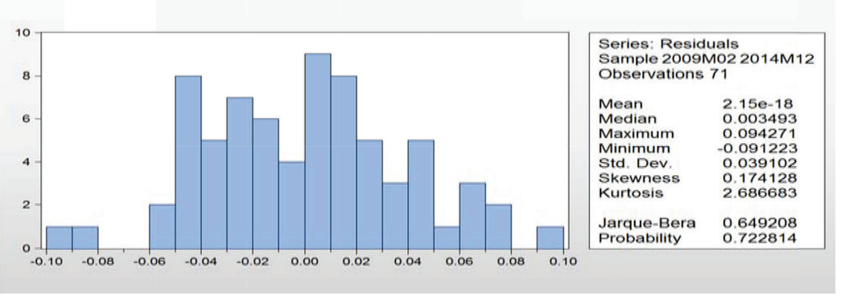

Figure 4.3.1.2 Brazil's post-crisis OLS estimation descriptive statistics (2009 - 2014)

Brazil's data for the whole period is symmetrical with a value of 0.26 and slightly skewed to the right. The kurtosis of Brazil's overall data is 2.8 and is very close to kurtosis of normal distribution (±3.0), however when compared, the estimation's data is flatter than normal distribution with a wider peak, meaning that the data is widely spread around the mean. Further to that, the Jarque-bera test probability well exceed the 0.01 p-value. Therefore the data follows a normal distribution.

Brazil's post-crisis regression, shows descriptive statistics similar to the overall estimation period. The skewness is 0.17, which means that the data is lightly skewed to the right close to symmetry. The kurtosis is 2.69 and when compared to the kurtosis of normal distribution it is found that the data is flatter and widely spread around the mean. The Jarque-Bera test statistic is very low 0.64, however, the p-value is 0.72 which exceeds the 0.01 value. Therefore the data follows a normal distribution.

4.3.2. Russia

When looking at Russia's data for the whole period, the skewness is 0.174. Since skewness is a measure of symmetry, this value shows that practically the data is symmetrical, slightly skewed to the right. The author notes that the kurtosis is very close to the value of 3, this shows that in the case of Russia the data is very close to normal distribution. The Jarque-Bera test p-value is relative high compared to 1%. Therefore the data follows a normal distribution.

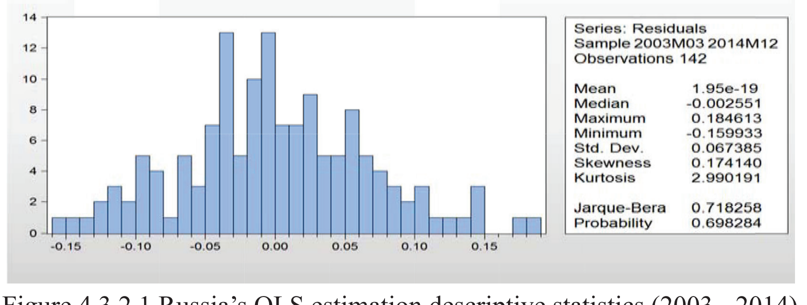

Figure 4.3.2.1 Russia's OLS estimation descriptive statistics (2003 - 2014)

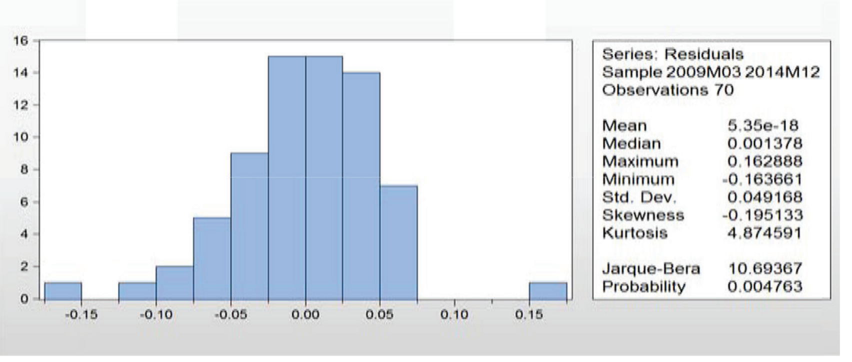

Figure 4.3.2.2 Russia's post-crisis OLS estimation descriptive statistics (2009 - 2014)

Conversely, Russia's post-crisis descriptive statistics are different from the overall period. The author notes a skewness of -0.2, thus showing that the data is practically symmetrical but slightly skewed to the left. The kurtosis is 4.87, higher than the kurtosis of normal distribution (±3.0). This value concludes that Russia's post-crisis distribution has a sharper and higher peak, with longer tails showing that the data is concentrated around the mean.

4.3.3. India

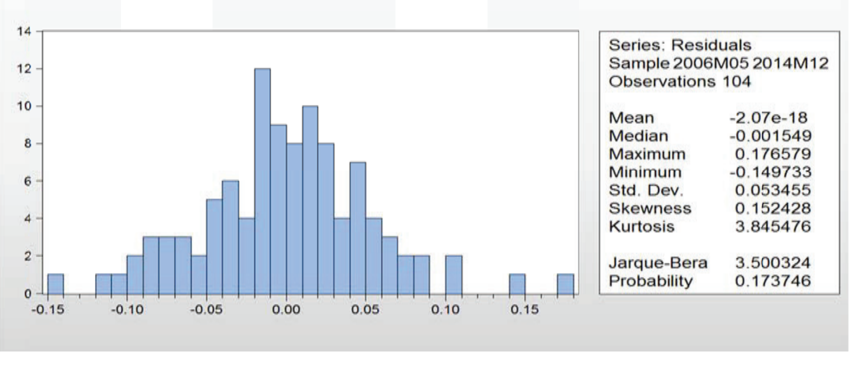

Figure 4.3.3.1 India's OLS estimation descriptive statistics (2003 - 2014)

Figure 4.3.3.1 highlights India's overall descriptive statistics. The skewness value is 0.152 which depicts the data as almost symmetrical and slightly skewed to the right. Comparing the country's kurtosis, 3.85 to normal distribution (±3.0), the author concludes that the distribution's central peak is higher and sharper while it has longer tails. The Jarque-Bera test statistic confirms that the data follows normal distribution since the p-value is 0.174, hence since greater than 0.01. Therefore the data follows a normal distribution.

Furthermore, figure 4.3.3.2 portrays the India's post crisis distribution. The skewness value of 0.57 implies that the distribution is skewed to the right. A kurtosis of 4.82 signifies that the distribution is sharper than normal distribution, with the values concentrated around the mean. The Jarque-Bera probability of 0.001 argues that the data does not follow normal distribution due to its value being less than 0.01. Therefore the data does not follow a normal distribution.

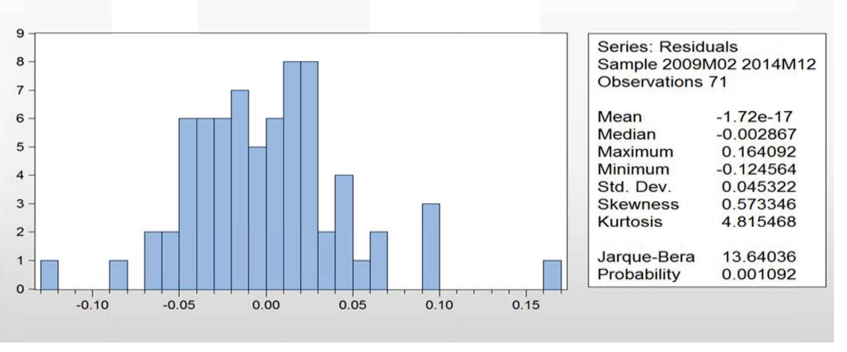

Figure 4.3.3.2 India's post-crisis OLS estimation descriptive statistics (2009 - 2014)

4.3.4. China

With respect to China, the distribution shows a skewness of - 0.247, which shows that the data is skewed to the left. Further to that, when compared to normal distribution's kurtosis (±3.0), a kurtosis of 4.3 shows that the data is concentrated around the mean. The Jarque-Bera test statistic deduces that the data is normally distribution since it has a value of 1.8%. Therefore the data follows a normal distribution.

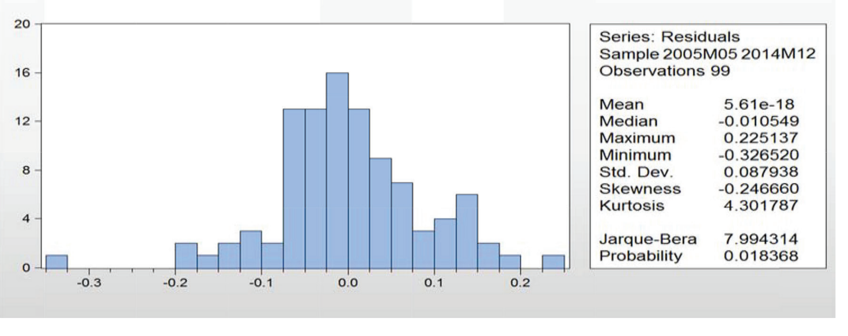

Figure 4.3.4.1 China's OLS estimation descriptive statistics (2003 - 2014)

On the other hand, China's post-crisis distribution has a negative skewness with value of - 0.55, which shows that it is skewed to the left. Further to that, the distribution has a kurtosis of 5.94 which is higher than the kurtosis of normal distribution (±3.0). In turn, this means that the distribution's central peak is higher and sharper, with longer tails and the data is distributed closely to its mean. The Jarque-Bera test statistic concludes that the distribution does not follow normal distribution since it has a p-value lower than 1%.

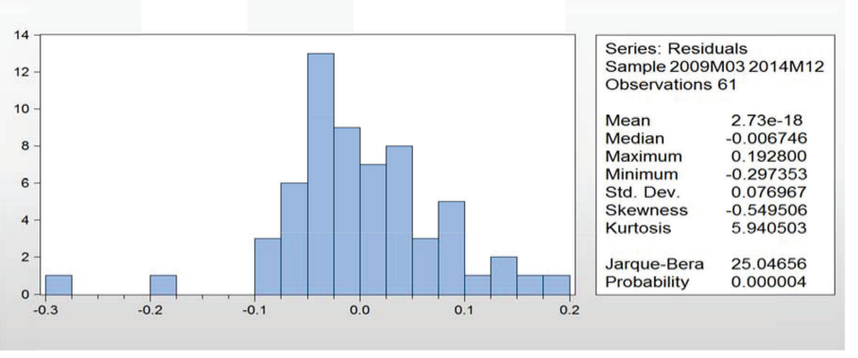

Figure 4.3.4.2 China's post-crisis OLS estimation descriptive statistics (2009 - 2014)

4.3.4. Interpreting the data

The R^2 of the OLS estimations are presented in appendix 3 (Figures A3.1 to A3.8). Figure A3.1 illustrates the Brazilian regression for the overall data period. The authors note that the model explains almost half of the variation in Brazil's stock market returns (45%). Also, since the R^2 increases with the number of variables added to the model regardless of their significance, the adjusted R^2 is given. This shows that the model explains 42% of the total sum of squares. Figure A3.2 shows the post-financial crisis OLS estimation. The R^2 captures 54% of the variation on the dependent variable. This means that 54% of the variation in Brazil's stock market return is captured by the variables present in the model. When looking at the f-statistic, both have a p-value of 0.00. This means that the equation as a whole is statistically significant, in other words, the model makes economic sense.

Figure A3.3 illustrates the R^2 of the Russian OLS estimations, which is 40%, which means that 40% of the variation in Russia's stock market returns between the period 2003 to 2014 is explained by the model. Figure A3.4, shows a R^2 close to 56%, this means that the model explains more than half of the variation in Russia's stock market returns between the period 2009 to 2014. When the researchers reviewed the f-statistics, they could find that both models as a whole are statistically significant, meaning that they have economic meaning.

The authors then considered the R^2 and f-test of the Indian OLS estimations. When interpreting the estimation for both periods shown in figures A3.5 and A3.6, they noted that for the overall data period, the R^2 is 50%, while for during the post-crisis period it was 42%. This means that the model explains 47% and 42% of the total variation in Nifty's stock index returns during both periods, respectively. The F-test in both cases has a p-value less than 0.05 which indicates that all together the model is statistically significant.

Finally, the authors considered the R^2 and f-test of the China's OLS estimations. As noted in figures A3.7 and A3.8, the model only explains 22% for the overall period, and 16% of the total variation in China's stock market returns for the post-crisis period. This means that the researchers left out other important factors that affect China stock market index returns, specifically not including all variables in the model. As with regards the F-test, for the overall data period the model is statistically significant as a whole with a p-value lower than 0.05. Conversely, for the post-crisis analysis, the f-statistic has a p-value of 0.21, thus the model as a whole is not statistically significant.

The authors also looked at the statistical significance of the beta coefficients and compared it to previous research. A variable is said to be statistically significant when the p-value is lower than 0.05. Eichengreen and Park (2008) argue that China' s economy grew so much that the whole region was isolated from the US financial stress. Morales and Gassie (2011) who study the relationship between BRIC financial markets, energy markets and US markets, state that there are weak integration levels between the three markets. The researchers note that the results obtained are not in line with the research carried out by the aforementioned. Table 4.3.4.2 shows China's OLS estimation. This shows that the US S&P500 stock index is individually statistically significant. As a result, this indicates that China's stock market returns are in reality not protected against US financial stress. Also, the researchers found that the relationship between China's stock market returns (CSI300) and US Stock Market returns (S&P500) is in line with findings by previous authors. Showing that the US had a more severe impact during the whole period, which diminished after the financial crisis. Moreover, the paper by Morales and Gassie (2011) concludes that Brazil, Russia and India are more susceptible to US financial shocks. This is in line with the results acquired by the researchers where the SPX variable (S&P500) is statistically significant in all periods, having a p-value of 0.000. Also, the beta coefficients for these countries are quite high in both periods analysed and confirm other author's findings.

The researchers refer back to the paper by Bianconi et al. (2013) since their results are close to the ones shown in this paper. The study conducted by Bianconi et al. (2013) shows that the BRICs cannot be considered as segregated from the financial stress emanating from the United States. Bianconi et al. (2013) state that Brazil and Russia are very likely to suffer from spillovers transmitted from the US, however, it is shown that India is the least correlated market. In addition to that, the authors outline that Russia's Micex stock market returns where affected not only by the US S&P500 stock index but also by the US's unemployment rate. They explain that the US unemployment rate's beta coefficient is in line with the findings of previous authors, hence an increase in US unemployment rate leads to an increase in Russia's stock market returns. In turn, both periods were affected by the unemployment rate on similar levels. The results illustrated in tables 4.3.4.1 and 4.3.4.2 below show that the results obtained are in-line with Bianconi et al.'s (2013) interpretation. However, the researchers' findings about India differ. The results show that India is integrated and affected by the US financial stress as equivalent to Brazil and Russia.

In conclusion, from the results obtained the authors deduce that the US S&P500 stock market index influences the BRICs stock market returns, mainly the BOVESPA, MICEX Index, Russia (MCX10), NIFTY and CSI300 stock returns in both periods. In other words, the BRIC emerging market economies are still not isolated from the major spillover effect transmitted from the US. In reality, irrespective of the volatility in both periods, the US still has a big impact on the stock returns on emerging economies.

Overall Data Period (2003 - 2014)				Post-Crisis (2009 - 2014)			
Brazil BOVESPA Stock index							
Variable	Coefficient	T-Statistic	Prob.	Variable	Coefficient	T-Statistic	Prob.
BRAZILCPI	-0.002104	-0.145520	0.8845	**BRAZILIP**	-0.002477	-0.690912	0.4922
BRAZILIP	0.002249	0.978776	0.3295	**BRCPI**	-0.009795	-0.569444	0.5711
MCID1	-0.001170	-1.374071	0.1717	**MCID1**	-0.001404	-1.298179	0.1990
SPX	1.051280	9.532090	0.0000	**SPX**	0.968971	7.926842	0.0000
USIPD1	-0.007035	-1.455336	0.1479	**USIP**	0.010629	1.017873	0.3126
USNFPD2	1.550167	0.370090	0.7119	**USNFPD1**	-5.443910	-1.509134	0.1363
USURD2	0.015042	0.714451	0.4762	**USURD1**	0.036374	1.045249	0.2999
Russia MIXEC Stock Index							
Variable	Coefficient	T-Statistic	Prob.	Variable	Coefficient	T-Statistic	Prob.
MCID1	-0.001723	-1.470938	0.1437	**MCID1**	0.000324	0.234403	0.8154
RUSSIACPID1	-0.011849	-1.126719	0.2619	**RUCPID2**	-0.025055	-1.986879	0.0514
RUSSIAIPD1	-0.000260	-0.111483	0.9114	**RUIPD1**	0.000415	0.138072	0.8906
SPX	1.192797	7.832829	0.0000	**SPX**	1.166804	6.719209	0.0000
USIPD1	0.005303	0.796590	0.4271	**USIP**	0.021040	1.579396	0.1193
USNFPD2	10.35004	1.837133	0.0684	**USNFPD1**	-6.045096	-1.357391	0.1796
USURD2	0.104705	3.630231	0.0004	**USURD1**	0.119625	2.741262	0.0080

Table 4.3.4.1 Table illustrating the variable's Coefficient and p-values for Brazil and Russia

Overall Data Period (2003 - 2014)				*Post-Crisis (2009 - 2014)*			
India Nlfty Stock Indiex							
Variable	Coefficient	T-Statistic	Prob.	Variable	Coefficient	T-Statistic	Prob.
INDIACPID1	-0.003523	-0.573651	0.5675	**INDIACPID1**	0.003955	0.275282	0.7840
INDIAIPD1	-0.000974	-0.699950	0.4857	**INDIAIPD1**	-0.002014	-2.162429	0.0345
MCID1	0.000358	0.297370	0.7668	**SPX**	0.853469	0.185930	0.8531
SPX	1.064214	8.129393	0.0000	**USIP**	0.009542	7.013752	0.0000
USIPD1	-0.006664	-1.028447	0.3063	**USNFPD1**	-1.913348	1.511546	0.1357
USNFPD2	3.612850	0.530625	0.5969	**USURD1**	0.083317	-1.010172	0.3163
USURD2	0.017425	0.620219	0.5366	**MCID1**	0.000659	2.672864	0.0096
China CSI300 Stock index							
Variable	**Coefficient**	**T-Statistic**	**Prob.**	**Variable**	**Coefficient**	**T-Statistic**	**Prob.**
CHINACPID1	0.034867	1.975855	0.0512	**CHINACPID1**	-0.004313	-0.169454	0.8661
CHINAIPD1	0.005799	0.998926	0.3205	**CHINAIPD1**	0.008180	1.652559	0.1043
MCID1	-0.001104	-0.610118	0.5433	**MCID1**	-0.002578	-1.076604	0.2865
SPX	0.799476	3.436715	0.0009	**SPX**	0.494939	2.501802	0.0155
USIPD1	-0.012912	-1.324507	0.1887	**USIP**	-0.029578	-0.835259	0.4073
USNFPD2	-8.374939	-0.850615	0.3972	**USNFPD1**	-3.087632	-0.333271	0.7402
USURD2	-0.046742	-1.043126	0.2997	**USURD1**	0.003655	0.050898	0.9596

Table 4.3.4.2 Table illustrating the variable's Coefficient and p-values for India and China

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APPENDIX

Appendix 1

1: Stationarity tables

1.1: Data period 2003-2014

Variable	Stationarity
Brazil Bovespa Stock Index	Stationary
Brazil Consumer Price Index	Stationary
Brazil Industrial Production	Stationary
China Industrial Production	Non-stationary
China Consumer Price Index	Non-Stationary
China Composite Stock Index 300	Stationary
India Nifty Stock Index	Stationary
India Consumer Price Index	Non-Stationary
India Industrial Production	Non-Stationary
Russia Micex10 Stock Index	Stationary
Russia Consumer Price Index	Non-Stationary
Russia Industrial Production	Stationary
Michigan Confidence Index	Non-Stationary
S&P500 Stock Index	Stationary
US Industrial Production	Non-Stationary
US Non-Farm Payrolls	Non-Stationary
US Unemployment Rate	Non-Stationary

Table A1.1: Illustrates whether the data of such variables was found to be stationary or non-stationary (2003 to 2014 data sample).

1.2: Data Period 2009 - 2014

Variable	Stationarity
Brazil Bovespa Stock Index	Stationary
Brazil Consumer Price Index	Stationary
Brazil Industrial Production	Stationary
China Industrial Production	Non-stationary
China Consumer Price Index	Non-Stationary
China Composite Stock Index 300	Stationary
India Nifty Stock Index	Stationary
India Consumer Price Index	Non-Stationary
India Industrial Production	Non-Stationary
Russia Micex10 Stock Index	Stationary
Russia Consumer Price Index	Non-Stationary
Russia Industrial Production	Non-Stationary
Michigan Confidence Index	Non-Stationary
S&P500 Stock Index	Stationary
US Industrial Production	Non-Stationary
US Non-Farm Payrolls	Non-Stationary
US Unemployment Rate	Non-Stationary

Table A1.2: Illustrates whether the data of such variables was found to be stationary or non-stationary (2009 to 2014 data sample).

Appendix 2

2: Testing for Heteroscedasticity

2.1: The data period 2003 to 2014

Heteroskedasticity Test: White

F-statistic	1.281013	Prob. F(35,106)	0.1688
Obs*R-squared	42.20913	Prob. Chi-Square(35)	0.1875
Scaled explained SS	33.80595	Prob. Chi-Square(35)	0.5257

Figure A2.1: White's test for Heteroscedasticity (Brazil's 2003-2014 OLS)

Heteroskedasticity Test: White

F-statistic	1.033612	Prob. F(35,106)	0.4340
Obs*R-squared	36.13154	Prob. Chi-Square(35)	0.4155
Scaled explained SS	32.01725	Prob. Chi-Square(35)	0.6129

Figure A2.2: White's test for Heteroscedasticity (Russia's 2003-2014 OLS)

Heteroskedasticity Test: White

F-statistic	1.667062	Prob. F(35,68)	0.0360
Obs*R-squared	48.02723	Prob. Chi-Square(35)	0.0701
Scaled explained SS	58.22216	Prob. Chi-Square(35)	0.0082

Figure A2.3: White's test for Heteroscedasticity (India's 2003-2014 OLS)

Heteroskedasticity Test: White

F-statistic	0.395982	Prob. F(35,63)	0.9981
Obs*R-squared	17.85180	Prob. Chi-Square(35)	0.9928
Scaled explained SS	24.90081	Prob. Chi-Square(35)	0.8972

Figure A2.4: White's test for Heteroscedasticity (China's 2003-2014 OLS)

2.2: The data period 2009 to 2014

Heteroskedasticity Test: White

F-statistic	1.035775	Prob. F(35,35)	0.4589
Obs*R-squared	36.12386	Prob. Chi-Square(35)	0.4159
Scaled explained SS	23.98623	Prob. Chi-Square(35)	0.9200

Figure A2.5: White's test for Heteroscedasticity (Brazil's 2009-2014 OLS)

Heteroskedasticity Test: White

F-statistic	2.021914	Prob. F(35,34)	0.0213
Obs*R-squared	47.28292	Prob. Chi-Square(35)	0.0804
Scaled explained SS	71.86005	Prob. Chi-Square(35)	0.0002

Figure A2.6: White's test for Heteroscedasticity (Russia's 2009-2014 OLS)

Heteroskedasticity Test: White

F-statistic	1.769914	Prob. F(35,35)	0.0479
Obs*R-squared	45.36743	Prob. Chi-Square(35)	0.1127
Scaled explained SS	68.14381	Prob. Chi-Square(35)	0.0007

Figure A2.7: White's test for Heteroscedasticity (India's 2009-2014 OLS)

Heteroskedasticity Test: White

F-statistic	1.101724	Prob. F(35,25)	0.4059
Obs*R-squared	37.00706	Prob. Chi-Square(35)	0.3764
Scaled explained SS	69.01091	Prob. Chi-Square(35)	0.0005

Figure A2.8: White's test for Heteroscedasticity (China's 2009-2014 OLS)

Appendix 3

3: OLS estimations

3.1: Brazil

Dependent Variable: BOVESPA
Method: Least Squares
Date: 04/22/15 Time: 13:33
Sample (adjusted): 2003M03 2014M12
Included observations: 142 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005150	0.007206	0.714664	0.4761
BRAZILCPI	-0.002104	0.014456	-0.145520	0.8845
BRAZILIP	0.002249	0.002298	0.978776	0.3295
MCID1	-0.001170	0.000851	-1.374071	0.1717
SPX	1.051280	0.110289	9.532090	0.0000
USIPD1	-0.007035	0.004834	-1.455336	0.1479
USNFPD2	1.550167	4.188626	0.370090	0.7119
USURD2	0.015042	0.021054	0.714451	0.4762

R-squared	0.449135	Mean dependent var	0.011140
Adjusted R-squared	0.420359	S.D. dependent var	0.066249
S.E. of regression	0.050438	Akaike info criterion	-3.081464
Sum squared resid	0.340892	Schwarz criterion	-2.914938
Log likelihood	226.7839	Hannan-Quinn criter.	-3.013795
F-statistic	15.60771	Durbin-Watson stat	1.467080
Prob(F-statistic)	0.000000		

Figure A3.1: Brazil's OLS estimation for the period 2003 to 2014

Dependent Variable: BOVESPA
Method: Least Squares
Date: 04/16/15 Time: 17:03
Sample (adjusted): 2009M02 2014M12
Included observations: 71 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001943	0.008794	-0.220894	0.8259
BRAZILIP	-0.002477	0.003585	-0.690912	0.4922
BRCPI	-0.009795	0.017201	-0.569444	0.5711
MCID1	-0.001404	0.001082	-1.298179	0.1990
SPX	0.968971	0.122239	7.926842	0.0000
USIP	0.010629	0.010442	1.017873	0.3126
USNFPD1	-5.443910	3.607308	-1.509134	0.1363
USURD1	0.036374	0.034800	1.045249	0.2999

R-squared	0.539475	Mean dependent var	0.003393
Adjusted R-squared	0.488305	S.D. dependent var	0.057620
S.E. of regression	0.041217	Akaike info criterion	-3.434117
Sum squared resid	0.107028	Schwarz criterion	-3.179167
Log likelihood	129.9112	Hannan-Quinn criter.	-3.332732
F-statistic	10.54291	Durbin-Watson stat	1.698699
Prob(F-statistic)	0.000000		

Figure A3.2: Brazil's OLS estimation for the period 2009 to 2014

3.2: Russia

Dependent Variable: MCX10
Method: Least Squares
Date: 04/16/15 Time: 15:56
Sample (adjusted): 2003M03 2014M12
Included observations: 142 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003292	0.005881	0.559656	0.5766
MCID1	-0.001723	0.001171	-1.470938	0.1437
RUSSIACPID1	-0.011849	0.010517	-1.126719	0.2619
RUSSIAIPD1	-0.000260	0.002334	-0.111483	0.9114
SPX	1.192797	0.152282	7.832829	0.0000
USIPD1	0.005303	0.006657	0.796590	0.4271
USNFPD2	10.35004	5.633799	1.837133	0.0684
USURD2	0.104705	0.028843	3.630231	0.0004

R-squared	0.404175	Mean dependent var	0.010923
Adjusted R-squared	0.373049	S.D. dependent var	0.087297
S.E. of regression	0.069122	Akaike info criterion	-2.451192
Sum squared resid	0.640236	Schwarz criterion	-2.284667
Log likelihood	182.0347	Hannan-Quinn criter.	-2.383523
F-statistic	12.98544	Durbin-Watson stat	1.730232
Prob(F-statistic)	0.000000		

Figure A3.3: Russia's OLS estimation for the period 2003 to 2014

Dependent Variable: MCX10
Method: Least Squares
Date: 04/22/15 Time: 12:45
Sample (adjusted): 2009M03 2014M12
Included observations: 70 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.011591	0.051324	-0.225842	0.8221
SPX	1.170345	0.167551	6.985011	0.0000
USIP	0.020406	0.014191	1.438016	0.1555
USNFPD1	-6.186359	6.192871	-0.998948	0.3217
USURD1	0.118419	0.042554	2.782830	0.0071
RUCPID2	-0.025619	0.011630	-2.202743	0.0313
RUIPD1	0.000425	0.002247	0.189195	0.8506
MCI	0.000171	0.000803	0.213439	0.8317

R-squared	0.555604	Mean dependent var	0.012975
Adjusted R-squared	0.505430	S.D. dependent var	0.073768
S.E. of regression	0.051878	Akaike info criterion	-2.972626
Sum squared resid	0.166864	Schwarz criterion	-2.715655
Log likelihood	112.0419	Hannan-Quinn criter.	-2.870554
F-statistic	11.07358	Durbin-Watson stat	2.324549
Prob(F-statistic)	0.000000		

Figure A3.4: Russia's OLS adjusted for heteroscedasticity (2009-2014)

3.3: India

Dependent Variable: NIFTY
Method: Least Squares
Date: 04/22/15 Time: 12:47
Sample (adjusted): 2006M05 2014M12
Included observations: 104 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002610	0.005454	0.478449	0.6334
MCID1	0.000526	0.001155	0.455359	0.6499
INDIACPID1	-0.003896	0.005471	-0.712208	0.4781
INDIAIPD1	-0.000695	0.001338	-0.519171	0.6048
SPX	1.115090	0.132882	8.391583	0.0000
USIPD1	-0.005988	0.006627	-0.903618	0.3685
USNFPD2	2.713074	7.022265	0.386353	0.7001
USURD1	0.061613	0.032736	1.882121	0.0628

R-squared	0.499549	Mean dependent var	0.008126
Adjusted R-squared	0.463058	S.D. dependent var	0.073968
S.E. of regression	0.054201	Akaike info criterion	-2.918424
Sum squared resid	0.282026	Schwarz criterion	-2.715009
Log likelihood	159.7580	Hannan-Quinn criter.	-2.836015
F-statistic	13.68955	Durbin-Watson stat	2.140509
Prob(F-statistic)	0.000000		

Figure A3.5: India's OLS adjusted for heteroscedasticity (2003-2014)

Dependent Variable: NIFTY
Method: Least Squares
Date: 04/22/15 Time: 12:43
Sample (adjusted): 2009M02 2014M12
Included observations: 71 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005530	0.007783	0.710553	0.4800
INDIACPID1	0.003955	0.004660	0.848817	0.3992
INDIAIPD1	-0.002014	0.001239	-1.625738	0.1090
MCID1	0.000659	0.001407	0.468464	0.6411
SPX	0.853469	0.120930	7.057543	0.0000
USIP	0.009542	0.011658	0.818449	0.4162
USNFPD1	-1.913348	3.919234	-0.488194	0.6271
USURD1	0.083317	0.049669	1.677463	0.0984

R-squared	0.421658	Mean dependent var	0.014904
Adjusted R-squared	0.357398	S.D. dependent var	0.059766
S.E. of regression	0.047910	Akaike info criterion	-3.133193
Sum squared resid	0.144606	Schwarz criterion	-2.878243
Log likelihood	119.2283	Hannan-Quinn criter.	-3.031807
F-statistic	6.561726	Durbin-Watson stat	2.117886
Prob(F-statistic)	0.000008		

Figure A3.6: India's OLS adjusted for heteroscedasticity (2009-2014)

3.4: China

Dependent Variable: CSI300
Method: Least Squares
Date: 04/16/15 Time: 15:58
Sample (adjusted): 2005M05 2014M12
Included observations: 99 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004366	0.009350	0.466977	0.6416
CHINACPID1	0.034867	0.017647	1.975855	0.0512
CHINAIPD1	0.005799	0.005805	0.998926	0.3205
MCID1	-0.001104	0.001809	-0.610118	0.5433
SPX	0.799476	0.232628	3.436715	0.0009
USIPD1	-0.012912	0.009748	-1.324507	0.1887
USNFPD2	-8.374939	9.845741	-0.850615	0.3972
USURD2	-0.046742	0.044810	-1.043126	0.2997

R-squared	0.222752	Mean dependent var	0.009049
Adjusted R-squared	0.162964	S.D. dependent var	0.099747
S.E. of regression	0.091258	Akaike info criterion	-1.872896
Sum squared resid	0.757850	Schwarz criterion	-1.663190
Log likelihood	100.7084	Hannan-Quinn criter.	-1.788049
F-statistic	3.725684	Durbin-Watson stat	1.919887
Prob(F-statistic)	0.001370		

Figure A3.7: China's OLS estimation for the period 2003 to 2014

Dependent Variable: CSI300
Method: Least Squares
Date: 04/22/15 Time: 12:46
Sample (adjusted): 2009M03 2014M12
Included observations: 61 after adjustments
White heteroskedasticity-consistent standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012978	0.012487	1.039308	0.3034
CHINACPID1	-0.004313	0.025452	-0.169454	0.8661
CHINAIPD1	0.008180	0.004950	1.652559	0.1043
MCID1	-0.002578	0.002395	-1.076604	0.2865
SPX	0.494939	0.197833	2.501802	0.0155
USIP	-0.029578	0.035411	-0.835259	0.4073
USNFPD1	-3.087632	9.264632	-0.333271	0.7402
USURD1	0.003655	0.071812	0.050898	0.9596

R-squared	0.159710	Mean dependent var	0.007333
Adjusted R-squared	0.048728	S.D. dependent var	0.084355
S.E. of regression	0.082274	Akaike info criterion	-2.035816
Sum squared resid	0.358756	Schwarz criterion	-1.758980
Log likelihood	70.09238	Hannan-Quinn criter.	-1.927321
F-statistic	1.439064	Durbin-Watson stat	2.029503
Prob(F-statistic)	0.209584		

Figure A3.8: China's OLS estimation adjusted for heteroscedasticity (2009 to 2014)