Contagion or decoupling? Evidence from emerging stock markets

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Abstract

With the increased level of interconnectedness among markets around the world, contagion literature has received immeasurable attention from researchers and academics over the years. In order to expand this pool of literature, this study proposes a test to distinguish between interdependence, contagion and the decoupling hypothesis between advanced markets and emerging markets based on entropy theory. The test is applied on time-varying conditional correlations obtained from an asymmetric dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (A-DCC GARCH) model by comparing the extent of correlations over tranquil and turmoil periods across financial crises. In this study, the US and EU are identified as advanced economies and emerging markets are identified by region with the aim to uncover whether they are homogenous or heterogenous as receivers of shocks from advanced economies. Our findings present evidence in support of the decoupling hypothesis in the cases of Brazil and Russia during the GFC and Turkey during the ESDC. Furthermore, strong evidence in support of the existence of contagion effects between advanced and emerging markets is reported and the presence of interdependence was constantly rejected. The findings of this paper provide valuable insights for policy makers, investors and asset managers.

Keywords: Contagion, interdependence, decoupling, A DCC GARCH, entropy test, emerging markets, advanced markets.

1. INTRODUCTION

In the past few decades, the global economy has experienced an increased degree of global interconnectedness of its markets. Owing to this, various financial crises that have occurred over time have been felt across the globe, whereby a developed market sneezes and the rest of the world, or at the very least some parts of it, catch a cold (Read, 2009). This phenomenon has often been used to loosely describe the term “financial contagion”. Defined generally, contagion arises when shocks that occur in one market or nation are transmitted across other markets or nations globally (Kenourgios, Naifar and Dimitriou, 2016). According to Rigobon (2002), contagion is one of the most widely discussed subjects in the field of finance, yet it remains one of the least understood.

While the term has not yet been defined precisely, several authors have attempted to bring more clarity to the concept. Eichengreen, Rose and Wyplosz (1996) define contagion as a large increase in the probability that one country’s crisis would be responsible for the occurrence of a crisis in another country. Similarly, Hamao, Masulis and Ng (1990) also describes contagion as a volatility spillover originating from the crisis country to other economies. According to Forbes and Rigobon (2002) contagion refers to a notable rise in price co-movements across markets resulting from another market’s crisis. Dungey and Gajurel (2014) proceed to explain various layers of financial contagion, namely contagion as the cross-country correlation among nations that is beyond any expected economic fundamentals or contagion as cross-market correlation during periods of crisis in comparison to the linkages during tranquil periods.

The aforementioned definitions constitute two different types of contagion which include “pure or investor-behaviour contagion” and “fundamental-based contagion” (Rigobon, 2002; Dungey and Gajurel, 2014; Bonga-Bonga, 2018). Firstly, pure contagion occurs when financial crises spread across markets as a result of shifts in investor behaviour or changes in their appetite for risk. Thus, an increase in the comovement of asset prices in different markets arises. Without taking into account the respective economic fundamentals of the crisis country involved, international investors are triggered to re-evaluate the risks in their investments. Secondly, fundamental-based contagion occurs when shocks are transmitted from one country to another (or a group of countries) resulting from actual fundamental links, for example through trade (Bonga-Bonga, 2018). As a result of cross-border interactions, when one country experiences a crisis this is quickly transmitted to other countries. Moreover, changes in macroeconomic variables, such as changes in US interest rates and exchange rates, can also impact other nations' economic fundamentals and potentially bring about crises. Although the contagion debate is still ongoing, there is general consensus among most financial economists that contagion did occur during the Mexican (1994 Mexican Peso crisis), Russian (1998 Russian collapse), Asian (1997 Asian financial crisis), 2007 global financial crisis and the 2010 Eurozone debt crisis, to mention but a few.

Following the occurrence of financial crises that have sent great and devastating shocks across financial markets around the world, such as those briefly mentioned above, it comes as no surprise that contagion has gained significant interest over the past years. Several authors have investigated and documented the contagion effects of global crises on various markets. A few notable studies include those of Cho and Parhizgari (2009), Naoui, Khemiri and Liouane (2010), Bekiros (2014), Dungey and Gajurel (2014) and Chittedi (2015). In their quest to investigate the presence of contagion during the 1997 East Asian financial crisis in the case of eight Asian financial markets, Cho and Parhizgari (2009) make use of the dynamic conditional correlation (DCC) GARCH framework. In order to examine whether there is significant dissimilarity in the time-varying correlation coefficients estimated between the tranquil and crisis periods, the authors apply the Wilcoxon test which assumes that the data is normally distributed. The authors' results reveal the existence of contagion in the markets of all countries considered. Furthermore, Chittedi (2015) and Naoui, et al. (2010), also employ the multivariate DCC- GARCH methods. In doing so, they found the presence of contagion effects from the USA to emerging markets such as Malaysia, Mexico, Brazil, Korea, Hong-Kong, Argentina, Singapore and India, respectively.

In contagion literature, there have been studies that have gone a step further to investigate the decoupling hypothesis as well (see Kenourgios, et al., 2016; Bekiros, 2014). Contrary to contagion, decoupling refers to a situation where asset returns that were correlated to other asset classes previously, are no longer moving together (Willett, Liang and Zhang, 2011). The decoupling hypothesis postulates that emerging markets have gained independence from advanced economies over recent years and thus business cycles observed in developed economies will not spill over to emerging markets. According to Wälti (2012), emerging markets have managed to minimise external vulnerabilities through strengthened domestic policies, and factors such as increased domestic demand have lowered the respective contribution of net exports or trade to economic growth. Such developments seem to have resulted in the mitigation of the impact of external shocks to emerging markets. This, in turn has brought about a growing interest around the decoupling hypothesis debate, questioning whether emerging markets have indeed decoupled from developed economies. In addition to investigating the contagion effects of the 2007 global and 2010 Eurozone crises, Kenourgios, et al. (2016) investigated the decoupling hypothesis. With the use of the multivariate APARCH-A-DCC approach. The authors' results failed to show strong supporting evidence of contagion in this regard, yet results supporting the decoupling hypothesis of Islamic securities were obtained. The authors found that, in times of severe financial distress, Islamic equities could provide a cushion against instability and risk. Contrary to this, however, Bekiros (2014) found no supporting evidence for decoupling in the case of the BRIC markets, using vector autoregressions and multivariate GARCH frameworks.

It is important to note that many studies distinguish between contagion and interdependence as far as the cross-transmission of shocks is concerned. For example, Forbes and Rigobon (2002) show that contagion occurs when the magnitude of correlation between markets, i.e. the source and recipient markets, is higher during the crisis period compared to the tranquil period. However, while the magnitude of this correlation is not statistically different during the two periods, the cross-transmission of shocks between markets is dubbed as interdependence. The current strand of literature on the dynamics of contagion focuses on distinguishing between contagion, decoupling and interdependence as far as the cross-transmission of shocks between markets is concerned (see Hemche, Jawadi Maliki and Cheffou, 2016; Çelik (2012) and Bonga-Bonga, 2018). This literature has often distinguished between the three concepts by testing the null hypothesis of interdependence of various correlation coefficients on the basis of first or second moment of distribution of these coefficients. For example, Bonga-Bonga (2018) tested the null hypothesis of the means of correlation coefficient during crisis and tranquil periods to infer contagion or interdependence between BRICS countries. The author made use of t-statistics on the means difference. Similarly, Çelik (2012) and Altun, Çelik and Koç (2019) also made use of t-statistics on mean differences to reach a conclusion.

This paper contributes to the current literature of spillover dynamics mainly by inferring contagion, interdependence and decoupling through testing the density of the correlation distribution rather than using the first two moments of the distribution. Contrary to previous studies, this paper proposes the following contribution: firstly, the paper proposes a test of interdependence based on the distribution of the dynamic correlation series, using the entropy test proposed by Li, Maasoumi and Racine (2009). Secondly, given the importance of crisis periods in assessing contagion dynamics, this paper proposes the use of endogenously determined crisis periods based on the Markov switching technique in addition to the commonly used crisis dates determined by the economic approach. Thirdly, given that the analysis of this paper is based on spillover dynamics between two sources of contagion, the US and EU, and different emerging markets as recipients of contagion, this paper selects emerging markets from different locations with the aim to uncover whether these markets are homogenous with regard to reactions from shocks from advanced economies. In fact, the literature shows that investors often disregard the fundamentals of specific emerging market countries during major crises, and consider them similar, based on perceived macroeconomic weaknesses (Cuadro-Sáez, L., Fratzscher, M. and Thimann, C., 2009). However, other studies support the heterogeneity of emerging market countries. For example, Lawlor (2020) shows that different emerging markets have varying fundamental characteristics that may determine the success of investors' or asset managers' investments. Ignoring the varying characteristics of emerging market countries may be detrimental to asset managers in their role of asset diversification.

It is important to note that distinguishing between the sources of contagion allows this paper to observe whether the type of source market and the related idiosyncratic shocks may determine the extent of vulnerability of the responding emerging markets to these shocks. Thus, by paying attention to the source countries, we observe which markets' shocks are more or less contagious for the emerging markets concerned.

Similar to methods employed by Kenourgios et al. (2016) and Alexakis, Kenourgios and Dimitriou (2016), we also make use of the multivariate asymmetric dynamic conditional correlation GARCH model. However, instead of using tests such as the Wilcoxon test of Cho and Parhizgari (2009), which makes the assumption of normal distribution, or tests such as the

Wald test and t tests that only test the equality of the crisis and tranquil period means (see Caporale, Cipollini and Spagnolo, 2005; Çelik, 2012; Bonga-Bonga, 2018; Altun, Çelik and Koç, 2019), we make use of the “entropy test”. The entropy test by Li, Maasoumi and Racine, 2009 is applied in this paper to propose the test interdependence in the context of the spillover of shocks. We favour the use of this test due to various factors. Firstly, there is no distributional form assumed, so the test statistic is formed using nonparametric density estimation (Robinson, 1991). Entropy-based testing has also been documented to be consistent and, since there is no underlying assumption of a specific probability distribution, it eliminates the possibility of erroneous conclusions resulting from misspecified distributions (see Robinson, 1991; Li et al., 2009; Ruiz-Marín, Matilla-García, Cordoba, Susillo-González, Romo-Astorga, González-Pérez, Ruiz and Gayán, 2010). Secondly, the consistent and nonparametric entropy test is considered favourable for this study due to the fact that, as a test of equality of distributions, it does not only take the means (first moment) into account, but also accounts for the other moments in the density function (Li, et al. 2009). As a large part of contagion literature has often been documented to be directed at highlighting portfolio diversification for investors, we consider the fact that investors and portfolio managers not only look at the first moment of distribution, the expected returns, but also higher moments of distribution. Therefore, the density function of a distribution for testing the null hypothesis of interdependence to infer contagion or decoupling, should rather be used, than some specific moments of a distribution. To the best of our knowledge, this will be the first paper in contagion or decoupling literature to make use of this entropy-based testing. In distinguishing between interdependence, contagion and decoupling experiences in the emerging markets, we make use of daily stock prices over the period 1997-2015, a sample period that covers significant unexpected global events and crises, aiding us in analysing the correlations of interest changing over time.

The remainder of this paper is therefore structured as follows: section 2 reviews the existing literature on contagion and decoupling in various markets, section 3 provides a discussion of the methodology, that is, the econometric techniques employed in the study, followed by section 4 which presents the data used, estimation results and discusses the results obtained. Finally, a conclusion is drawn in section 5.

2. LITERATURE REVIEW

While a vast amount of literature has explored the contagion phenomenon with the use of evidence from various markets across the globe during financial crises, dating back as early as the 1990's, relatively few papers have sought to shed light on the decoupling hypothesis conjointly with contagion and interdependence. Since the early 1990's, the liberalization of capital movements among financial markets has led to their systematic interrelation, resulting in volatility spillovers, contagion or decoupling being observed over time (Bekiros, 2014). Since then, several authors have sought to investigate the contagion effects, the existence or extent of contagion while, in a few cases some have added decoupling in global crises across various markets, countries, or regions.

Among such noteworthy studies is that of Dimitriou, Kenourgios and Simos (2013). In addition to investigating the contagion effects of the different phases of the 2007 global crisis, their study examines the presence of decoupling, using a multivariate FIAPARCH DCC or Fractionally Integrated Asymmetric Power ARCH approach in the case of the US, as the crisis-originating country, and emerging equity markets. The authors do not find evidence of contagion effects for most BRIC countries during the early phases of the crisis; however, the presence of decoupling was inferred. Correlations were seen to recouple following the Lehman Brothers' collapse and this was attributed to a shift in the investors' risk appetite.

Bekiros (2014) also examined the decoupling phenomenon in the case of the BRIC economies, yet during the Eurozone Sovereign Debt crisis. This study explores causality testing, VECH, BEKK, CCC, and DCC GARCH models, and presents no evidence supporting the presence of decoupling, yet strong evidence of contagion effects during the examined period. Samarakoon (2017) also investigates decoupling and contagion effects during the Euro debt crisis; however, among developed and emerging markets. Using the VAR technique, the author's findings are in support of the decoupling view. Also exploring the contagion and decoupling hypotheses in emerging equity markets during the global financial and Eurozone debt crises (GFC and ESDC), Alexakis, Kenourgios and Dimitriou (2016) make use of the asymmetric dynamic conditional correlation (A DCC) multivariate GARCH framework. Varying results were obtained between the two crisis periods, with Latvia and Lithuania experiencing contagion effects during the 2007 global crisis and no contagion effects during the ESDC. On the contrary, Estonia was seen to decouple during the global crisis period, but recouple during the ESDC. The authors attribute these varying results to the macroeconomic and financial characteristics of the Baltic region before the crisis periods. Also, the region adopted the Euro as its currency, which would explain the recoupling during the ESDC. In a similar study, Kenourgios et al. (2016) assess the contagion effects of the ESDC and GFC, however in Islamic developed and emerging financial markets. The study employs the A DCC multivariate GARCH and APARCH models and in doing so, fails to strongly prove contagion exists between conventional and Islamic markets. In actual fact, Kenourgios et al. (2016) provide supporting evidence for the decoupling hypothesis and infer that Islamic markets shield and cushion against instability for investors during crises.

Furthermore, a few studies have taken into consideration the importance and sensitivity of contagion studies to the accuracy of selected crisis dates, and have thus taken to endogenously determine crisis periods, rather than simply taking the dates as published, i.e. the economic approach. These studies have not only determined the entire crisis period, but they went a step further to determine the different phases experienced during the crisis (see Baur, 2012; Dimitriou, Kenourgios and Simos, 2013; Mighri and Mansouri, 2013; Kenourgios and Dimitriou, 2015; Kenourgios et al., 2016). As emerging markets, such as China and Brazil, were seen not to be affected by the spillover of shocks from the US in the initial stages of the crisis, this ignited a new wave of decoupling literature with a breakdown of crisis periods and analyses of the individual phases established. Although a portion of this strand of literature has allowed the study's selected data to determine the crisis dates, it has still often proceeded to conduct the study based solely on the crisis dates obtained through the economic approach rather than the statistical approach, despite the fact that the dates and periods obtained slightly differ. The authors attribute this to Baur (2012), who observes that not using discretion in defining the crisis period can be countered by choosing the appropriate econometric model to estimate when the crisis period will take place in time. Our study remedies this by conducting the analysis at hand based on both the economic approach and statistically obtained crisis periods in the case of emerging markets.

Another notable study that explores both the contagion and decoupling hypotheses is that of Cardona, Gutiérrez and Agudelo (2017). The authors examine both phenomena using the multivariate GARCH BEKK models and Mann Whitney tests and observe a strong presence of contagion effects from the US to Latin American markets. This study provides evidence against the decoupling phenomenon, particularly in the case of the US to Brazil and Mexico. Cardona et al. (2017) go even further to explore the correlation dynamics over time. As one of their hypotheses, the authors compare the Latin American markets' response to the GFC relative to the 1998-1999 emerging market crises and observe a reduction in volatility transmission between the aforementioned events.

Despite the extensive literature available on the contagion phenomenon, the research on financial contagion and decoupling hypotheses during crises has conjointly been explored less and is still growing. Thus, this study aims to bring further clarity to the ongoing debate and contribute to the existing literature in several ways. Firstly, we distinguish between interdependence, financial contagion and decoupling by testing the density of the correlation distribution rather than only using the first two moments of the distribution. Unlike past studies, the study proposes an entropy-based test of interdependence based on the distribution of the dynamic correlation series. No study has ever used the entropy test to infer contagion or interdependence between markets.. Secondly, given that the analysis is based on spillover dynamics between two sources of contagion, the US and EU, and different emerging markets as recipients of contagion, the choice of the different emerging market countries aims to uncover whether these countries are homogenous as recipients of spillover shocks from advanced economies. Thirdly, by differentiating between the source markets, this allows the study to discern if the specifics of the source market play a role in determining the extent of susceptibility of the emerging markets to these volatility transmissions. Fourthly, taking into account the significance and sensitivity of contagion studies to the accuracy of crisis dates in assessing contagion dynamics, this paper distinguishes between the different crisis periods based on economic and statistical approaches. While the economic approach refers to crisis periods determined from specific events, the statistical approach distinguishes the different crisis periods based on the use of the Markov switching technique.

3. METHODOLOGY

This chapter presents a detailed description of the research methodology applied in this study. It is worth noting that the contribution of this paper is to test the null hypothesis of the equality of the distribution of the dynamic correlations before and during crisis periods, which refers to interdependence. The test of entropy is used to this end. The alternative hypotheses to be tested are contagion or decoupling. These occur when the null hypothesis of interdependence is rejected. The methodological approach follows three steps. Firstly, we use the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) class of models, especially the Asymmetric Dynamic Conditional Correlation (ADCC) GARCH, to obtain the dynamic correlations of advanced and emerging stock markets. Then, we apply the test of entropy to the different distributions of the conditional correlation, distinguishing between the periods before and during different crises. All the details are discussed below.

3.1 Multivariate GARCH

The use of multivariate GARCH models has often proved to be an appropriate model choice for the purpose of examining volatility, spillover and correlation dynamics across countless assets, financial markets and economies, dating back as early as the inception of the VECH and BEKK models developed by Bollerslev (1988), and Engle and Kroner (1995), respectively. The limitations inherently found in these models led to the further development of a more suitable class of MGARCH models, namely the constant conditional correlation (CCC) GARCH model introduced by Bollerslev (1990), dynamic conditional correlation (DCC) GARCH by Engle (2002), and finally an extension of the DCC, the asymmetric dynamic conditional correlation (A DCC) GARCH by Capiello, Engle and Sheppard (2006). Through the 2-step procedure embedded in these models, the models allow for the separation of individual conditional variances on the one hand, a conditional correlation matrix on the other and the ability to measure dependence between series (Minović, 2009).

Bollerslev's CCC model assumed the conditional correlations between series to be constant and modelled conditional variances with the use of univariate GARCH. Thus:

$$\rho_t = \rho = [\rho_{ij}], \rho_{ii} = 1 \quad (1)$$

$$\sigma_{ij,t} = \rho_{ij}\sqrt{\sigma_{ii,t}\sigma_{jj,t}} \quad \forall i \neq j \quad (2)$$

With the assumed constant conditional correlations, the conditional covariances are equivalent to the product of the corresponding conditional standard deviations, thus greatly reducing the number of unknown parameters and simplifying the estimation according to Bauwens, Laurent and Rombouts (2006). Through its assumption of constant correlations, the CCC model improves the feasibility of estimating a large model and, by necessitating the univariate conditional variance to be non-zero and a full rank correlation matrix, the estimator's positive definiteness is ensured (Minović, 2009). This was a great stride from the VECH and BEKK models, which showed great difficulty in determining the required restrictions on the parameters to warrant positive definiteness of the conditional covariance as the number of series being modelled grew, even to a reasonable size (Engle and Sheppard, 2001). Additionally, the aforementioned authors describe the individual coefficients of these models as difficult to interpret and discern.

The CCC model is defined as:

$$H_t = D_t R D_t \tag{3}$$

where R is an $N \times N$ time-invariant conditional correlation matrix and D_t represents the $N \times N$ diagonal matrix of the time-varying conditional standard deviations. D_t is discussed further in the section dedicated to the ADCC model.

Although the CCC model was initially favoured and popular in empirical applications due to its simplicity, what made it simple also presented its greatest weakness as the assumption of constant correlations was not actually feasible in reality, especially when applied to highly frequent data-like stock market data, which greatly varies with time. For example, one cannot always expect correlations between markets, assets or economies to remain constant during periods of great economic distress and financial crises. As a remedy to this flaw, Engle (2002) introduced the dynamic conditional correlation model, which accounted for the time-varying correlation between series.

3.2 A DCC GARCH

In order to investigate the contagion effects of financial crises on emerging markets during crisis periods, this study adopts the Asymmetric Dynamic Conditional Correlation (A-DCC) multivariate GARCH approach which was developed by Capiello et al. (2006) as an extension to the DCC model to allow for asymmetry in the time-varying conditional correlations. The method follows a two-stage procedure. Firstly we use asymmetric univariate GARCH models to fit each equity-return time series (Acatrinei, Gorun and Marcu, 2013). The study uses several univariate GARCH models, namely the standard GARCH, GJR GARCH, EGARCH, APARCH models, to mention but a few, with varying error distributions, for example generalized error, student-t and skewed student-t distributions. The most appropriate GARCH specification is then chosen on the basis of criteria such as the Schwarz Bayesian information criteria (BIC) and Akaike information criteria (AIC). Asymmetric GARCH models have often been found to outperform the symmetric group of GARCH models (see Peters, 2001; Alberg, Shalit and Yosef, 2008; Gabriel, 2012; Nugroho, Kurniawati, Panjaitan, Kholil, Susanto and Sasongko, 2019). Hence, asymmetric models make up the greater part of the models we test.

With the use of AIC and BIC, we find the EGARCH models to be the best to fit the equity returns in the study, and thus proceed with obtaining the estimates of their variances using EGARCH and varying error distributions. The EGARCH framework developed by Nelson

(1991) was designed to capture the asymmetry in the volatility in the distribution of each stock market.

Suppose Y_t represents equity returns, then the mean and variance of returns are specified below in equations 4 and 5.

$$y_t = \varphi_0 + \sum_{i=1}^{k} \varphi_i y_{t-i} + \varepsilon_t \tag{4}$$

$$\log(\sigma_t{}^2) = \omega + \sum_{i=1}^{q} (\alpha_i |Z_{t-i} + \gamma_i Z_{t-i}) + \sum_{i=1}^{p} \beta_i \log(\sigma_{t-i}{}^2) \tag{5}$$

where; ε_t denotes the error term, $\sigma_t{}^2$ represents conditional volatility, γ measures the asymmetric effect, ω, α and β represent the constant, ARCH and GARCH effects, respectively, and Z_t denotes the standardized residuals: $Z_t = \frac{\varepsilon_t}{\sigma_t}$.

Equation (5) shows the logarithm of the conditional variance. Due to its logarithm form, the EGARCH(p,q) model removes the need for constraining the parameters of the model while still ensuring the positivity of the conditional variance. This univariate model accounts for the leverage effects.

Having obtained the conditional variance through equation 2, we proceed to the second stage of the process where we use the asymmetric DCC in deriving the time-varying conditional correlation between markets. Let the conditional covariance matrix be denoted as equation (6) below.

$$H_t = E[\varepsilon_t \varepsilon_t{}'] = D_t R_t D_t \tag{6}$$

where, the matrix R_t is the conditional correlation of standardized residuals and D_t represents the diagonal matrix of the time-varying conditional standard deviations determined from equation (5), $D_t = diag(h_{1,t}^{\frac{1}{2}}, h_{2,t}^{\frac{1}{2}}, \ldots h_{k,t}^{\frac{1}{2}})$. We use the standardized residuals, $Z_t = \frac{\varepsilon_t}{\sigma_t}$, to estimate the time-varying correlation matrix and thus obtain the asymmetric dynamic conditional correlation model parameters. The A DCC model was proposed by Cappiello et al. (2006) as an extension to the DCC model, due to the realization that the DCC model failed to capture asymmetric features of the equity markets. Through the estimation of correlation coefficients by using standardized residuals, the model allows for smoothing parameters, news impact, asymmetries in correlation and accounts for heteroskedasticity (Kenourgios et al., 2016). Furthermore, the problem of omitted variable bias is diminished.

Recent literature has shown that the A DCC approach is by far the most appropriate model in estimating variances, covariances and conditional correlation among time series, since it not only accounts for time-varying correlation, but accounts for asymmetry as well (Morema and Bonga-Bonga, 2020). This is unlike the DCC model that only improves the unlikely assumption of constant correlations made by the CCC model, but still fails to capture asymmetry. The evolved A DCC model is thus defined as follows:

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G)\bar{P} + A'_{z_{t-1}z'_{t-1}}A + G'_{\eta_{t-1}\eta'_{t-1}}G + B'Q_{t-1}B \qquad (7)$$

where, $\bar{Q}$ and $\bar{N}$ represent the unconditional covariance matrices of z_t and η_t, respectively, and A, B and G are the k x k parameter matrices. The negative standardized residuals for asymmetric impact η_t are defined by $\eta_{t-1} < 0 = 1$, otherwise 0.

3.3 Testing for interdependence, contagion and decoupling

Having established the conditional correlations between the selected stock markets, we proceed to test the null hypothesis of interdependence between the source market and the selected emerging stock markets by comparing the dynamic correlations of the respective markets during the crisis periods and tranquil periods. To this end, we make use of entropy-based testing, where the null hypothesis postulates the equality of densities of the tranquil and crisis periods. The opposite applies for the alternative hypothesis. Suppose X and Y represent the tranquil period and turmoil period, respectively, then $f(\cdot)$ and $g(\cdot)$ denote the density functions of X and Y, respectively. Thus we test the following null hypothesis:

$$H_o: f(x) = g(x)$$

versus the alternative hypothesis that:

$$H_1: f(x) \neq g(x)$$

where failure to reject the null hypothesis would lead to the inference of interdependence as the correlation during the crisis period would have remained the same as that of the tranquil period. Conversely, when we reject the null hypothesis and infer that the two samples' densities are not equal, we suspect the presence of either contagion effects or decoupling and further seek to examine the two phenomena through the use of regression analysis, where correlation increases or decreases during crises relative to tranquil times, implying contagion or decoupling, respectively.

In order to test for the equality of the univariate densities of X and Y, Maasoumi and Racine (2002) suggest the use of the nonparametric metric entropy measure. Similar to Racine (2012), we compute a normalized Bhattacharya-Matusita-Hellinger's measure to examine the equality of the two samples' densities , given by:

$$S_p = \frac{1}{2}\int (f(x)^{1/2} - f(y)^{1/2})^2 \ dx \tag{8}$$

$$S_p = \frac{1}{2}\int \ (1 - \frac{f(y)^{1/2}}{f(x)^{1/2}})^2 \ dF_x(x) \tag{9}$$

The second expression is in moment form, which can be replaced by a sample average. Although this is a fast and easy way, it can produce inaccurate computations, often used for theoretical developments (Maasoumi and Wang, 2019). We note that, under the null hypothesis, $f(x) = f(y)$ thus $S_p = 0$, otherwise under the alternative hypothesis, $f(x) \neq g(x)$ and $S_p > 0$.

In order to obtain the entropy-test statistic 'S_p', we do not make use of the sample averages as we pursue more accurate computations. The unknown density functions in equations (8) and (9) are substituted by nonparametric kernel-density estimates. The kernel-density estimator is obtained in the steps outlined below.

Since our study uses continuous data, let X be denoted as $X^c \in \mathbb{R}^q$, where X^c is the continuous variable with dimension q, and Y is represented by Y^c with the same dimensions as X. Recall that $f(\cdot)$ and $g(\cdot)$ represent the density functions of X and Y, respectively, and suppose that $\{X_i\}_{i=1}^{n_1}$ and $\{Y_i\}_{i=1}^{n_2}$ are independent and identically distributed (i.i.d) and randomly drawn from the population. Guided by Li, Maasoumi and Racine (2009), we let x_s^c and X_{is}^c represent the sth components of x^c and X_i^c, respectively. Furthermore, x_s and $X_{is}^c \in \mathbb{R}_s^q = \{a_1, a_2, \ldots\ldots a_{c_s}\}$ so that the continuous variable, X^c, takes up values in $\mathbb{R}^q = \prod_{s=1}^{q}\{a_1, a_2, \ldots\ldots a_{c_s}\}$. Let the univariate kernel function for the continuous variable x_s^c be denoted as $\omega\left(\frac{X_{is}^{c}-x_{s}^{c}}{h_s}\right)$, where h_s is the smoothing parameter. Thus, the product kernel associated with the continuous variable component x^c is given as follows:

$$W_{h,x_i,x} = \prod_{s=1}^{q} h_s^{-1}\,\omega\left(\frac{X_{is}^{c}-x_{s}^{c}}{h_s}\right) \qquad (10)$$

The product kernel for continuous variables is generalized and given as:

$$K_{y,x_i,x} = W_{h,x_i,x} \qquad (11)$$

The unknown density functions are thus estimated as:

$$\hat{f}(x) = \frac{1}{n_1}\sum_{i=1}^{n_1} K_{y,x_i,x} \quad ; \quad \hat{g}(y) = \frac{1}{n_2}\sum_{i=1}^{n_2} K_{y,y_i,x} \qquad (12)$$

4. DATA, ESTIMATION AND RESULTS

This chapter presents a discussion of the results we obtain through the estimations conducted following the proposed methodology. In the first section, a detailed description of the data used in the study is provided, following which we also discuss the summary statistics of the variables used. In the second section, we provide and discuss the results obtained from the estimations that have been carried out, extensively providing all necessary interpretations. The dynamic conditional correlations among the countries in the study will be presented. Following this, we conclude the chapter with tests for decoupling or contagion effects among the various markets over the few crisis and tranquil periods covered in the study.

4.1 Data

In examining the decoupling hypothesis and contagion effects of global crises on emerging markets, this study makes use of daily closing stock prices over the period September 1997 to June 2015. The sample was chosen to cover important crisis periods emanating from the US and EU, especially the 2008 global financial crisis and European debt crisis, respectively. There are studies that have documented and questioned the importance of data frequency in hypothesis testing and returns analyses (see Narayan and Sharma, 2015; Bannigidadmath and Narayan, 2016; Kenourgios et al., 2016). Similar to the aforementioned authors who highlight the supremacy of daily data and the wealth of information provided by its use as compared to lower frequencies such as monthly data, our dataset follows a daily frequency.

As said earlier, the selected sample period was found to be ideal for the study as several financial crises, some of which we intend to investigate, occurred during the stipulated time period, with the earliest crisis being explored dating back to as early as 2000. The sample period starts as early as 1997 because, following the decoupling and contagion analysis of the GFC and ESDC, we also find it of interest to observe the development in correlation, contagion or decoupling that has occurred over time. Thus, we also observe two crises that have occurred from the same source, the US market. To this end, we analyse the DOTCOM bubble (2000) and the GFC and observe the behaviour of correlations across both crises. Have the shocks become less or perhaps even more contagious over time? The constraint of the availability of data was also a contributing factor to the chosen sample period, indices selected and crises examined. Nevertheless, our dataset provides the analysis with sufficient observations to observe and examine the decoupling hypothesis or contagion effects of the Global Financial crisis (GFC) and European Sovereign Debt Crisis (ESDC).

In order to represent the crisis-originating countries during the financial crises, we make use of two source markets, namely the USA and the EU stock indices. The source markets were selected in line with an economic approach, with the selection being informed by the economic news and financial events reported in official and reliable sources. As we extend existing literature by distinguishing the contagion or decoupling experiences across regions, it is necessary to have representation of all the regions in the selected markets. The emerging markets under investigation have been selected in such a way that the representation of all regions globally is ensured. We use the following countries' stock indices; Brazil, Russia, India, South Africa and Turkey, to represent the shock-recipient countries in the study. We only consider key emerging markets as these have been found to be the fastest growing economies of particular interest to many international investors across the globe for investment purposes and, as such, this study could be of great interest to them. Table 1 shows the variables (stock indices) used in the study, as well as their classification, that is, source or recipient country.

Table 1: Variables and classification

Variable	Classification
S&P 500 (USA)	Source Market (Developed)
MSCI Euro Index (EU)	Source Market (Developed)
BOVESPA (Brazil)	Recipient Market (Latin American emerging market)
BSESN (India)	Recipient Market (Asian emerging market)
JALSH (South Africa)	Recipient Market (African emerging market)
XU100 (Turkey)	Recipient Market (Middle East emerging market)
MOEX (Russia)	Recipient Market (European emerging market)

Source: Thompson Reuters Eikon, 2021

Our country selection allows us to explore if the region of the emerging market determines whether it is more vulnerable to contagion effects or not. Before proceeding with the necessary estimations, we convert the stock prices obtained using the following computation:

$$R_t = ln\left[\frac{p_t}{p_{t-1}}\right] * 100$$

where returns at time *t* are denoted by R_t; and p_t and p_{t-1} represent the current and previous closing prices, respectively. Due to the fact that there are special events and holidays that result in missing observations, we make use of daily closing prices from the previous day in such instances.

Table 2 below presents the summary statistics of the daily return series of the markets in the study. For the total sample period, we observe higher means in the emerging markets across the world compared to the United States, where the US has a mean of 0.01661and the emerging markets Brazil (0.03262), India (0.04308), South Africa (0.04471), Turkey (0.02276) and Russia (0.06053). Considering the high growth patterns that emerging markets have displayed over the years, particularly in the observation period, it comes as no surprise that these markets would exhibit higher stock return means. Additionally, there are various factors inherent in most emerging markets that make investing in emerging markets come with much greater risks compared to the advanced markets (Karolyi, 2015). These factors include, but are not limited to, rising political or economic instability, the reliability or accuracy of financial reporting, and foreign exchange risks. As a result of the greater associated risks and high growth rates, expected returns are essentially predicted to often be higher in this environment (Leeds, 2015).

Next, we observe a higher standard deviation from the emerging markets in comparison to the advanced market, except in the case of South Africa where its standard deviation (1.230775) is slightly lower than that of the US (1.24642). This implies that the South African market is less volatile than the US market for this specific period. This may be due to the fact that the period of analysis covers instances when then US economy was exposed to global and idiosyncratic crises. This observation warrants testing whether some of the emerging markets were insulated or decoupled from advanced economies. On the other hand, the remaining emerging markets display greater market volatility, with Russia having the most volatile return market (2.677944). To a great extent, equity market return volatility is often expected to be higher in emerging markets than advanced economies for similar reasons as those mentioned previously, for example currency and political or economic risks, among others, in some of the emerging markets. Furthermore, prices are found to swing more in response to good or bad news in emerging markets as compared to those that are advanced (Errunza and Losq, 1987).

When it comes to the distribution of our data, we find the data not to be normally distributed. Using the Jarque-Bera test, where the null hypothesis postulates that our data is normally distributed (with a p- value of 2.2e-16 shown in table 2) we reject the null hypothesis of normality. Furthermore, a skewness of 0 and a kurtosis of 3 would suggest normal distribution but, as illustrated in table 2, most of the markets' data is negatively skewed, with the most negatively skewed being South Africa (-0.4624836). The data also has heavy tails and great peaks suggested by the high kurtosis values (far from 3), with Russia having the highest kurtosis value (15.45325) and South Africa the lowest (6.111185).

Looking at the second and third panels of table 2 which display the descriptive statistics of the tranquil periods vs the crisis periods (total crisis period) as identified by the economic approach, we observe that most of the markets recorded lower means during the crisis period (P_2) than one would expect, except for Turkey and Russia, with reference to panel 3 (ESDC). The markets were in turmoil and achieving low returns. In most cases the mean returns were negative with the lowest average returns recorded by Russia with a whooping low average of -0.1858 (MSCI Euro, -0.0145) and the highest being Brazil with -0.0645 (Turkey, 0.0781) in Panel 2 (and Panel 3, respectively). Moreover, the standard deviation is observed to be greater during the crisis period in comparison to the tranquil period (P_1). As expected, all markets displayed a higher market volatility during P_2, as the crisis was in full swing in both panels. While Russia exhibited the most volatile stock market during the period with a standard deviation of 3.75927 (MSCI Euro, 1.6244), the least volatile market during the crisis was observed to be Turkey with the lowest standard deviation of 1.85465 (South Africa, 1.0193) in Panel 2 (and Panel 3).

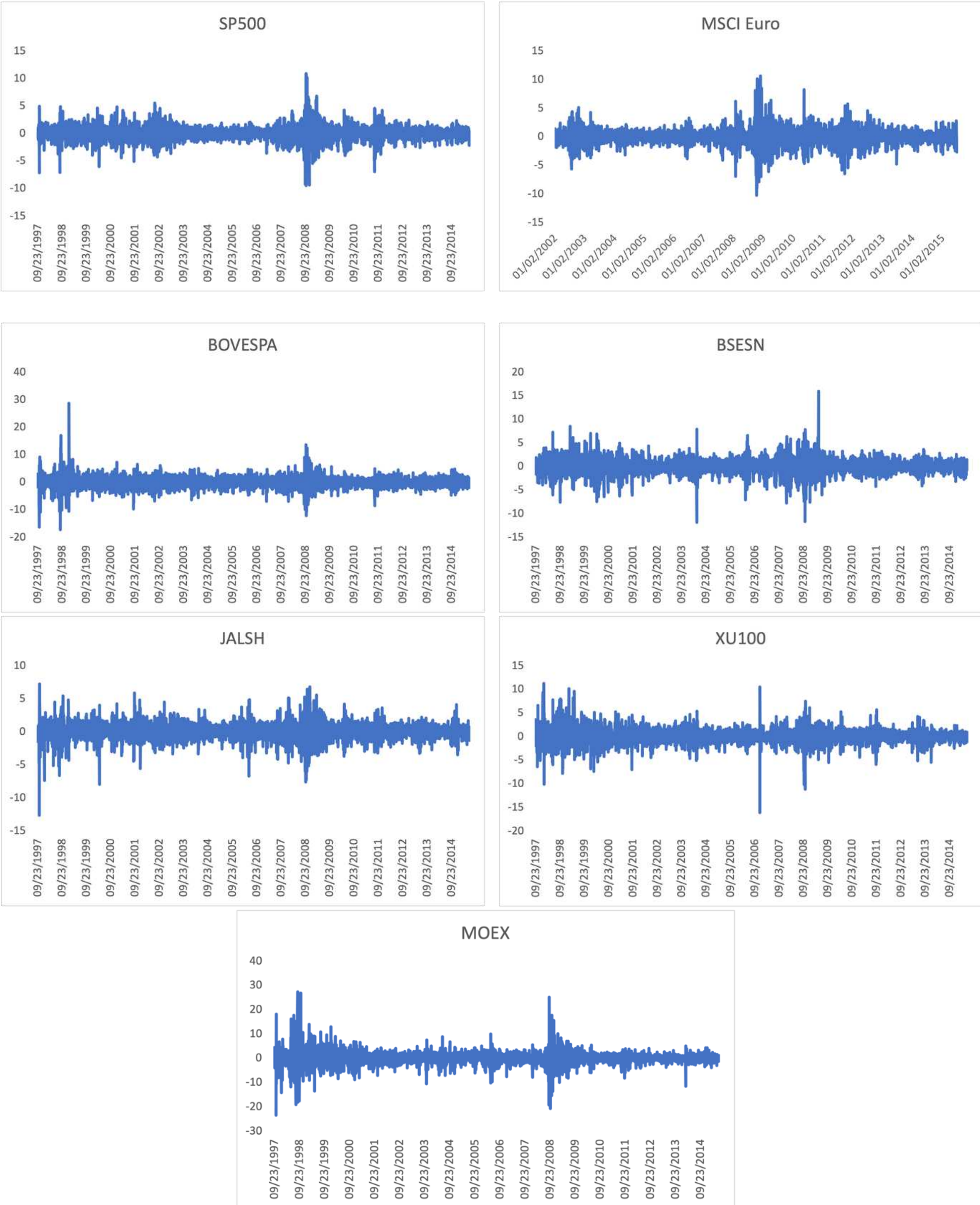
Figure 1 provides illustrations of each market's returns over time, from 1997-2015. We note that there were periods of excess volatility during our periods of interest (2007-2009) and around 2010. We also observe high volatility in the earlier years of the sample period. This could largely be due to the occurrence of the Dotcom bubble, which impacted many markets once again. As the sample period chosen encompasses several crises, some of which this study examines, we do observe some spikes in the market returns over the years. Moreover, we observe how volatile the markets are, with rapid increases and decreases (and significant highs and lows) over time.

Table 2: Daily returns descriptive statistics (Total sample period- P_{total}, Tranquil period- P_1 vs Crisis period- P_2)

	S&P500 (USA)		MSCI (EU)		BOVESPA (Brazil)		BSESN (India)		JALSH (South Africa)		XU100 (Turkey)		MOEX (Russia)	
Panel A.														
	P_{total}		**P_{total}**		**P_{total}**		**P_{total}**		**P_{total}**		**P_{total}**		**P_{total}**	
Min	-9.46951		-10.17826		-17.20824		-11.80918		-12.62563		-16.06325		-23.33561	
Mean	0.01661		0.01170		0.03262		0.04308		0.04471		0.02276		0.06053	
Max	10.95720		10.69806		28.83245		15.98998		7.26802		11.34953		27.50052	
Std. dev.	1.24424		1.416494		2.052856		1.560952		1.230775		1.548809		2.677944	
Skewness	-0.22268		-0.09759713		0.3421395		-0.092872		-0.4624836		-0.01371935		0.1228948	
Kurtosis	8.043964		7.082848		14.58188		6.407174		6.111185		8.598585		15.45325	
Jarque-Bera test	2.2e-16		2.2e-16		2.2e-16		2.2e-16		2.2e-16		2.2e-16		2.2e-16	
Observations	4636		3520		4636		4636		4636		4636		4636	
Panel B.														
GFC	**P_1**	**P_2**			**P_2**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**
Min	-3.53427	-9.4695			-6.85658	-12.096	-7.0033	-11.604	-6.7003	-7.5807	-16.06325	-11.090	-10.1439	-20.657
Mean	0.05292	-0.1382			0.13941	-0.0645	0.1424	-0.1083	0.1282	-0.0778	0.03437	-0.1585	0.15902	-0.1858
Max	2.13358	10.9572			4.84469	13.6782	6.6670	7.9005	4.9173	6.83397	10.57703	7.5488	10.14544	25.2261
Std. dev.	0.631608	2.28816			1.437738	2.84939	1.474624	2.5022	1.211424	2.03510	1.329173	1.85465	2.043946	3.75927
Skewness	-0.45906	-0.03028			-0.26352	0.11553	-0.49801	-0.2091	-0.60054	0.05914	-2.982742	-0.6838	-0.68022	0.18182
Kurtosis	3.042176	4.063984			2.006573	3.47193	3.073194	1.3544	3.780366	1.25614	56.72425	6.03267	4.567242	10.9624
Jarque-Bera test	2.2e-16	2.2e-16			2.2e-16	2.2e-16	2.2e-16	7.441e-09	2.2e-16	3.456e-07	2.2e-16	2.2e-16	2.2e-16	2.2e-16
Observations	435	435			435	435	435	435	435	435	435	435	435	435
Panel C.														
ESDC			**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**	**P_1**	**P_2**
Min			-4.7279	-6.4252	-4.62723	-8.4306	-4.05373	-4.2129	-3.4671	-3.6939	-5.37315	-5.8119	-11.4189	-8.1393
Mean			0.02958	-0.0145	-0.01957	-0.0183	0.055793	0.0112	0.0518	0.0404	0.02505	0.0781	0.01619	0.0202
Max			3.09302	8.3092	4.89879	4.97524	3.703417	3.5181	4.1593	4.2332	4.32343	5.7515	5.12180	5.5070
Std. dev.			0.87897	1.6244	1.36492	1.3926	0.920617	1.1238	0.8246	1.0193	0.9736343	1.1806	1.256416	1.5503
Skewness			-0.2971	-0.0969	0.077721	-0.3676	-0.11674	0.0528	-0.2616	-0.0939	-0.426776	-0.1947	-0.76281	-0.4977
Kurtosis			2.1084	1.8487	0.729938	2.5737	1.759759	0.4189	2.2736	1.2439	4.070614	3.2672	10.05623	2.4035
Jarque-Bera test			2.2e-16	2.2e-16	0.000200	2.2e-16	2.2e-16	0.05515	2.2e-16	3.82e-11	2.2e-16	2.2e-16	2.2e-16	2.2e-16
Observations			714	714	714	714	714	714	714	714	714	714	714	714

Source: Author’s calculations

Figure 1: Stock market returns over time (1997- 2015)



Source: Author's calculations

Similar to previous studies, we also make use of the economic approach in selecting the relevant crisis periods. However, in this instance we go one step further and make use of the statistical approach, as well as an analysis greatly resting on the appropriate selection of crisis and tranquil periods. Guided by these approaches, we use the United States (SP500) to represent the source country during the global financial crisis (GFC, 2007-2009) and the EU to represent the source market during the European Sovereign Debt Crisis (ESDC, 2010- 2012).

Published news and very reliable sources (see, Reserve Bank of Australia, Federal Reserve Board of St Louis, 2009 and Kenourgios and Dimitriou, 2015) describe the global financial crisis as a period of severe stress for banking systems and financial markets across the globe, which began mid 2007and lasted till early 2009. The GFC is reported to have unfolded due to several factors such as immoderate risk-taking as the macroeconomic environment was favourable, and escalated borrowing while there were great policy and regulation errors, but the main catalyst documented appears to have been a plunge in the US housing market. When the economic conditions of the US and other countries were thriving, that is, strong economic growth and low interest, inflation and unemployment rates, there was a significant increase in house prices which led to the expectation that the rising trend in prices would continue to soar. This period saw households and property developers, particularly in the US and some European countries, increasing their borrowing absurdly to invest in the housing market. Unfortunately, this boom period was followed by plummeting prices in the US housing market and a large number of borrowers failing to pay off their loans, which set off a chain of events in the global financial markets and thus catalysed the GFC (2007- 2009). A breakdown of the phases outlined by literature is found in Table 3.

The global financial crisis consequentially led to the European Sovereign Debt Crisis (ESDC) where initially Iceland saw the collapse of its banking system in 2008, serving as the initial trigger of the ESDC (Bonga-Bonga and Manguzvane, 2020). In response to the financial turmoil brought about by the GFC, many European countries resorted to increasing government and deficit spending, which in turn increased their debt relative to their respective GDPs (Bullard, 2010; Federal Reserve Bank of St. Louis, 2010). For example, Greece’s sovereign debt reached an all-time high of 113% of GDP, almost twice the Eurozone limit and a budget deficit of 13.6% of GDP which further exacerbated the ESDC, as news of the Greece debt and deficit exceeding what the previous government had reported spurred fears across countries. Thus, among several factors, the ESDC occurred as a result of institutional failures and exorbitant government debt, and was reported to have occurred over the period 2008-2012, with the peak occurring between 2010 and 2012 (Reuters, 2020). We also provide a breakdown of the phases outlined by Kenourgios (2014) based on timelines established by the European Central Bank (ECB).

Furthermore, we proceed to establish the crisis dates endogenously by employing the Markov Switching Dynamic Regression (MS-DR) model. In a sense, by making use of the statistical approach, we further confirm and examine the robustness of the crisis period identification through the data. One could not stress enough the importance of the appropriate selection of crisis dates, to which the study is greatly sensitive. The MS-DR[1] model is often used with high frequency data as compared to the MS-AR and allows estimated parameters to vary according to, and in the presence of, changing unobservable states (Temkeng and Fofack, 2021). While it is mainly used to describe the series' behaviour while taking into account the presence of changing regimes or structural breaks, in the same breadth the model allows us to actually determine the different regimes in a series. Through the use of this model, we are able to endogenously identify the regimes in our series, and thus obtain the crisis dates (beginning and end dates) which are crucial for the study.

We estimate the following MS-DR equation[2] to identify crisis phases for the source countries, especially phases related to the global financial crisis and the European debt crisis.

$$y_t = v + \alpha y_{t-1} + x'_t\beta + \epsilon_t, \epsilon_t \sim IIN[0, \sigma^2] \quad (13)$$

$$y_t = v(S_t) + \alpha y_{t-1} + x'_t\beta + \epsilon_t, \epsilon_t \sim IIN[0, \sigma^2] \quad (14)$$

where S_t is a random variable that represents the regime in which the process is at time *t* and takes up the value of 1 if the process is in regime 1, and 0 otherwise (in the case of two regimes). Thus, a simple regime-switching model would be written as:

Regime 0: $y_t = v(0) + \alpha y_{t-1} + x'_t\beta + \epsilon_t, \epsilon_t \sim IIN[0, \sigma^2]$

[1] The MS-DR model was developed by Hamilton (1989) as an extension to the MS-AR model to account for the structural breaks in data, making it an ideal model to statistically determine the crisis start and end dates.
[2] y_t is the dependent variable and scalar, x'_t is a vector of explanatory variables which, in this case, would be the lagged y_t values. The intercept is regime dependent and S_t follows a Markov chain, defined by transition probabilities between N regimes. The probability of movement between regimes from one period to another depends on the previous regime (Galyfianakis, Drimbetas and Sariannidis, 2016)

Regime 1: $y_t = v(1) + \alpha y_{t-1} + x'_t\beta + \epsilon_t, \epsilon_t \sim IIN[0, \sigma^2]$

Since the random variable S_t has two possible outcomes, the probabilities of being in a regime can be written as follows:

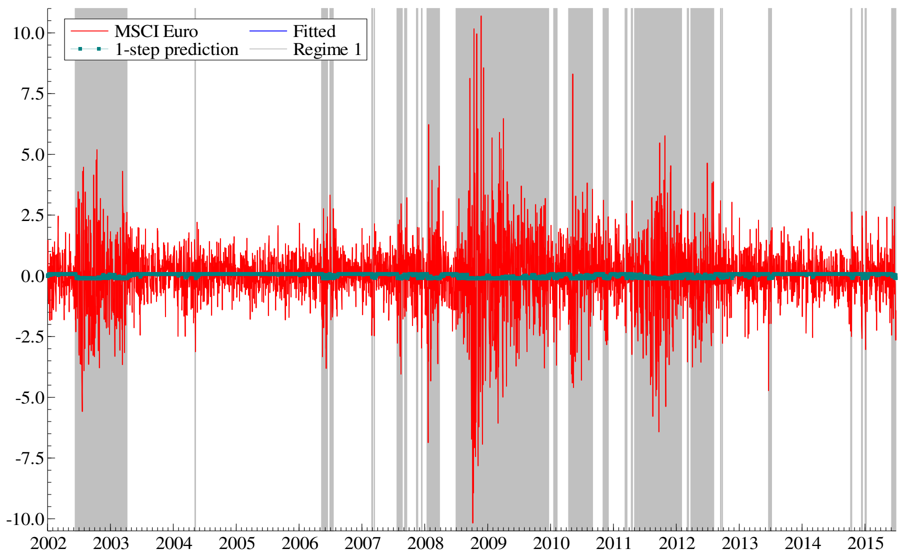
$$\mathrm{P}(\,S_t = 0|I_t)$$

$$\mathrm{P}(\,S_t = 1|I_t) = 1 - \mathrm{P}(\,S_t = 0|I_t)$$

where I_t contains all the information available up to time *t,* such that $I_t = y_{t-1}, y_{t-2}, y_{t-3} \ldots ; x_t$.

The periods of excess equity-market conditional volatilities identified by the MS-DR model make up regime 1 (the volatile regime) and thus identify the turmoil periods. Conversely, where low values of conditional volatilities are recorded, this is found to represent the tranquil periods, that is, regime 0. We identify our crisis sub-periods, where volatilities are in excess of 0.85. The results reported in Figure 2, Figure 3 and Table 3 show that 5 phases are found for each of the crises.

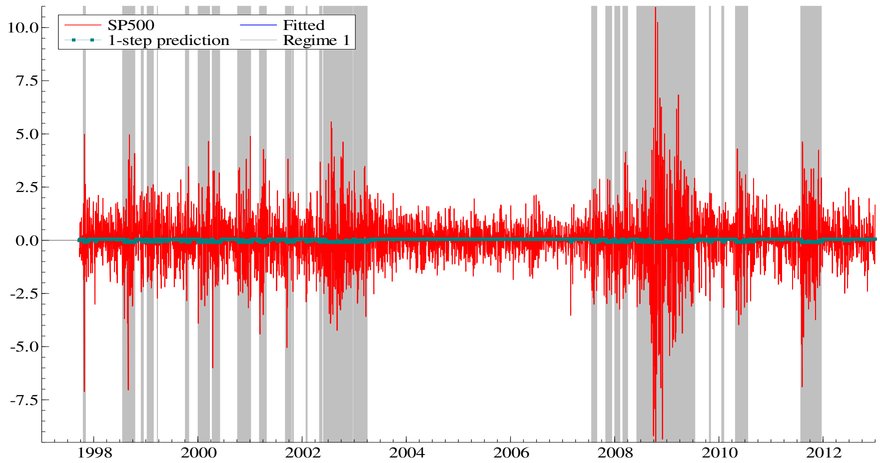
Figure 2: Actual data and estimated high volatility regime (regime1) for Euro



Source: Author's calculations

Note: The grey shaded areas represent the regimes of excess volatilities as identified by the MS-DR model, while the red represents the volatilities.

Figure 3: Actual data and estimated high volatility regime (regime1) for SP500



Source: Author's calculations

Note: The grey shaded areas represent the regimes of excess volatilities as identified by the MS-DR model, while the red represents the conditional volatilities.

Nevertheless, the crisis phases obtained through the statistical approach do actually fall within the entire turmoil period documented by literature and official sources that provide financial and economic news events. Thus, going forward we conduct our analysis using the dates obtained through both approaches. Table 3 provides a depiction of the crisis dates established, for the entire crisis periods and the respective phases identified.

Table 3: GFC and ESDC phases

	GFC	ESDC
Entire crisis period	August 2007- March 2009	November 2009- July 2012
Phases (economic approach)		
Phase 1	1 Aug 2007- 15 Sept 2008 *(dubbed as "initial financial turmoil")*	5 November 2009- 22 April 2010 *(announcement of Greek budget deficit)*
Phase 2	16 Sept 2008- 31 Dec 2008 *(defined as "sharp financial market deterioration")*	23 April 2010- 14 July 2011 *(announcement that the austerity packages were not enough and request for bailout from IMF or EU)*
Phase 3	1 Jan 2009–31 Mar 2009 *(dubbed as "macroeconomic deterioration")*	15 July 2011- onwards *(begins when banking stress tests were published by the European authorities and the first austerity package was announced by Italy)*
Phase 4	1 Apr 2009- 30 Nov 2009 *(described as a phase of "stabilization and tentative signs of recovery")*	
Phases (statistical approach)		
Phase 1	24 Jul 2007- 29 Aug 2007	19 Jan 2010- 8 Feb 2010

Phase 2	31 Oct 2007- 11 Nov 2007	16 Apr 2010- 2 Sept 2010
Phase 3	2 Jan 2008- 6 Feb 2008	2 Nov 2010- 3 Dec 2010
Phase 4	28 Feb 2008- 1 Apr 2008	31 May 2011- 1 Feb 2012
Phase 5	5 Jun 2008- 16 Jul 2009	26 Mar 2012- 6 Aug 2012

Sources: Published news, reliable sources (economic approach) and author's calculations (statistical approach)

4.2 Estimations

Following the transformation of stock prices to returns, we proceed to estimate the asymmetric dynamic conditional correlations between the source and responding markets. We present the results obtained from the univariate EGARCH estimation in the appendix, Table 4 a, where we observe high persistence displayed in the equity indices' volatility as the sum of the highly significant ARCH and GARCH estimated parameters $(\alpha + \beta)$ in each equation is close to unity (1). Additionally, the leverage terms (γ) are statistically significant and positive. This indicates that the volatility in each equity index has an asymmetric response to shocks (positive and negative). Finally, shown in Table 4 a are the results of the Ljung-Box diagnostic test we performed to examine the potential presence of autocorrelations in the series, which are rejected if they have p-values less than 0.05. The estimation results of the A DCC model are illustrated in Tables 4 and 5. Tables 4 and 5 present the A DCC estimates corresponding to the global financial crisis (with the United States as a crisis-originating country or correlations source) and the A DCC estimates corresponding to the Euro Sovereign Debt Crisis (with the EU as a crisis-originating market), respectively. The tables also display the results obtained from conducting the McLeod and Li test[3] with which we investigated the presence of auto-regressive conditional heteroskedasticity (ARCH) effects. With the null hypothesis indicating the absence of ARCH and p-values greater than 0.05, we fail to reject the null hypothesis and infer the presence of ARCH. Thus, we deem the GARCH family of models to be appropriate for our study.

[3] McLeod and Li(10) is the multivariate version of the Ljung-Box statistic by McLeod and Li (1983), for 10 lags in our case. We made use of the AIC and SIC criteria in order to determine the lag length.

Table 4: Multivariate GARCH (A DCC) estimation results

	a_1	b_1	McLeod and Li (10)
US - Brazil	0.026237	0.966704	0.9416
	(0.000000)	(0.000000)	
US - India	0.002266	0.997421	0.7361
	(0.001829)	(0.000000)	
US - SA	0.007092	0.990602	0.5397
	(0.002059)	(0.000000)	
US - Turkey	0.001882	0.996669	0.1586
	(0.062719)	(0.000000)	
US - Russia	0.006864	0.992076	0.2387
	(0.006453)	(0.000000)	

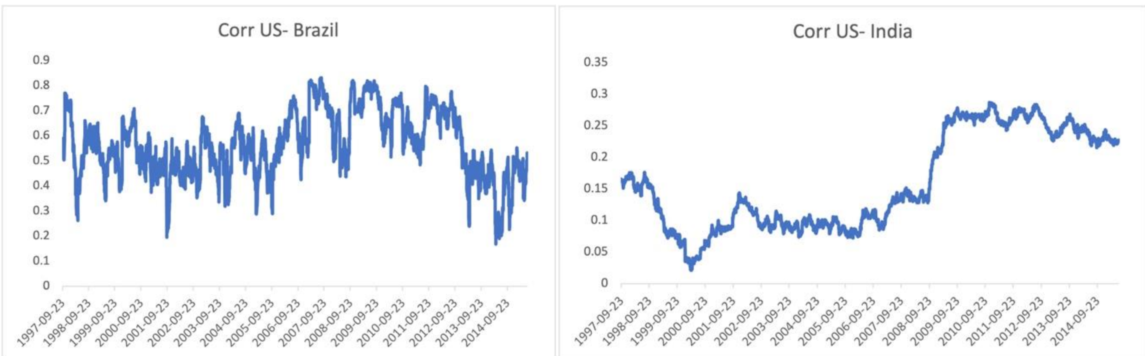
Source: Author's calculations

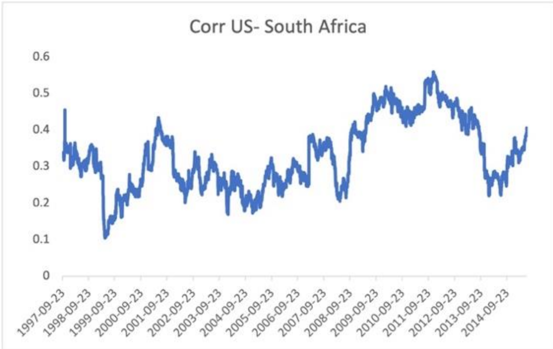
The a_1 parameters are seen to be significant in all market pairs, with a_1 in the case of US - Turkey only being significant at the 10% level of significance. We observe significant and non-negative correlations between the US and the response markets (Brazil, India, South Africa, Turkey and Russia), as the respective p-values, shown in brackets below the estimates, are all below 0.05 or 0.1. Thus, we infer the existence of spillover effects between the US and the above-mentioned markets in the short run. The same applies to the correlations, b_1 , in the long run, for all market pairs in this part of the study. We observe the existence of spillover effects from the US to all the responding markets in the long run as all the p-values (0.000000) corresponding to b_1 are less than 0.05. It is also important to note that the A DCC estimates are below 1, and the sum of a_1 and b_1 are close to unity. Through the estimation of the A DCC model, we obtain and extract the actual correlations (correlation matrix) between the US and the response markets.

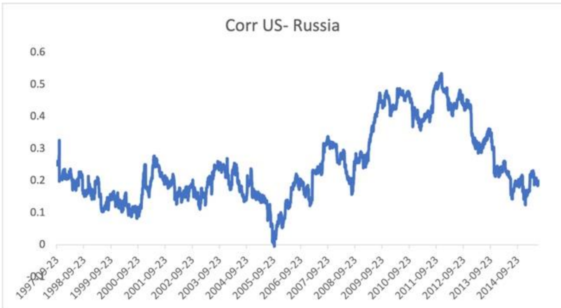
Table 4 also shows the mean of correlations obtained. Following the A DCC estimation, we split the computed correlations into two periods, that is, the crisis period and non-crisis period. Through this, we are able to observe if there have been changes in the average of the correlations before and during the crisis. More specifically, we observe if the correlation between two markets is higher or lower during the turmoil period, as compared to the correlation during the tranquil period. On average, we observe an increase in the correlation mean during the crisis period in comparison to the tranquil period, indicating the possibility of contagion effects existing between the markets.

Figure 4 provides the graphical presentation of the asymmetric dynamic correlations (ADCC) obtained between the US and the emerging markets over the course of the entire sample period, where we observe greatly fluctuating correlations. Of particular interest in Figure 4, is that we observe peaks and troughs during the periods of financial turmoil previously identified in Table 3. For example, in the correlation between the US and South Africa, we find that the two markets initially experienced a decline in correlation at the beginning of the crisis from 0.376755376 in May 2007 to a whopping low of 0.204962606 in May 2008, suggesting that the African emerging market initially decoupled from the giant. However, correlation is seen to be on a constant rise thereafter, even exceeding the levels of correlation observed prior to the subprime crisis, thus suggesting the presence of contagion or spillover effects from the US market to South Africa. The remaining emerging markets' correlation dynamics over the course of the crisis exhibited similar behaviour to that of South Africa, according to Figure 4, whereby the market correlations seemed to decline initially, suggesting insulation. However, the emerging markets eventually felt the adverse impacts. Also comparing the correlation experienced during the DOTCOM crisis of 2000 to that of the GFC, we observe higher correlation heights reached during the latter crisis, contrary to the popular belief that key emerging markets had become less vulnerable to crises originating from advanced markets. Overall, correlations between the US and the emerging markets have increased over time.

Figure 4: Asymmetric dynamic correlations between the US and the emerging markets over time







Source: Author's calculations

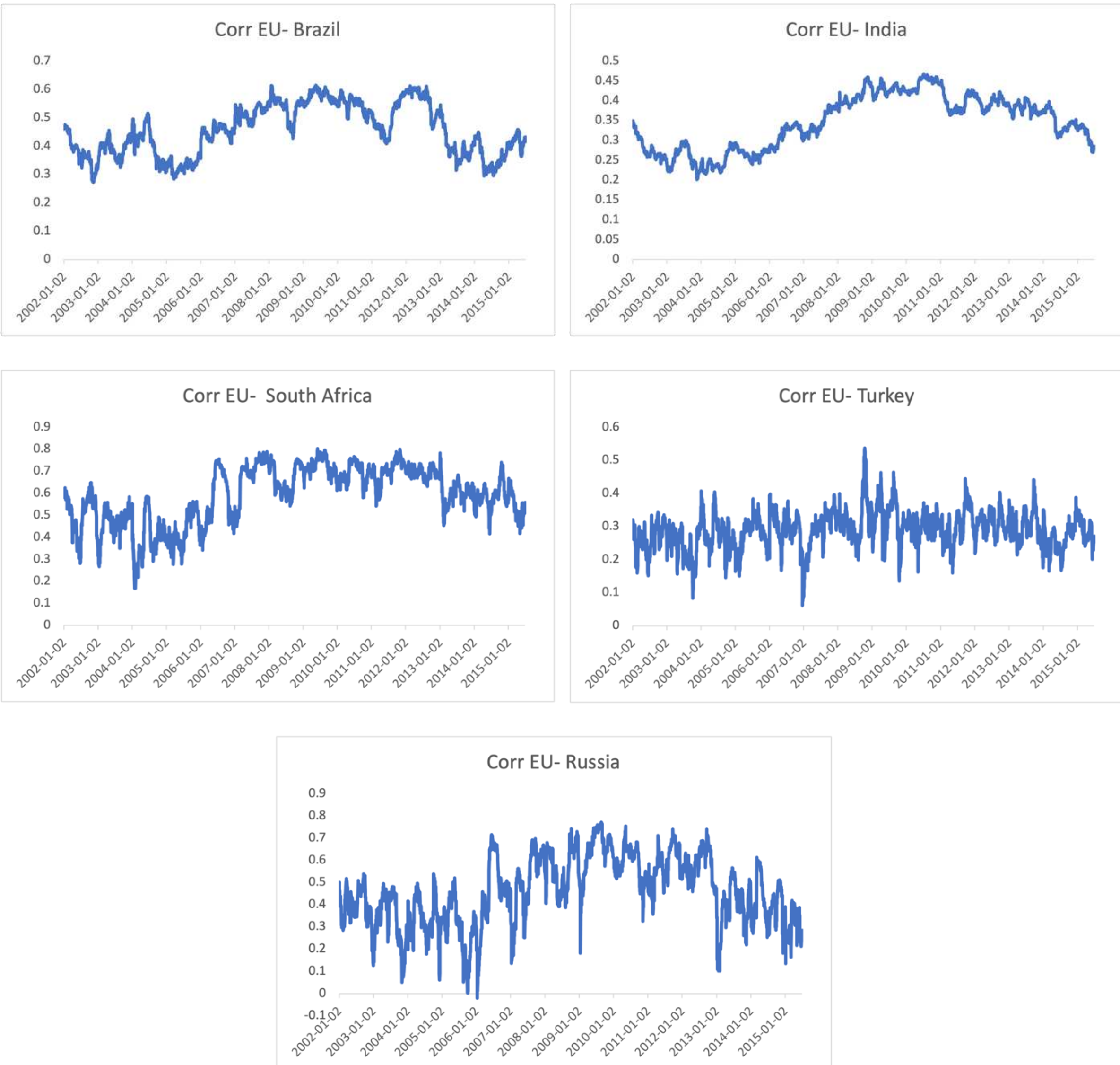
Table 5: Multivariate GARCH (A DCC) estimation results

	a_1	b_1	McLeod and Li (10)
EU - Brazil	0.008205	0.988057	0.1861
	(0.010608)	(0.000000)	
EU - India	0.003512	0.995095	0.7693
	(0.015234)	(0.000000)	
EU - SA	0.023477	0.969148	0.2963
	(0.000006)	(0.000000)	
EU - Turkey	0.018629	0.934944	0.6452
	(0.034997)	(0.000000)	
EU - Russia	0.031463	0.956708	0.1652
	(0.000486)	(0.000000)	

Source: Author's calculations

In the case of EU emerging market pairs, we observe positive and significant short and long run spillover-effect estimates. Both a_1 and b_1 parameters are found to be statistically significant with the p-values obtained all being less than 0.05 and even less than 0.01 for b_1. Thus, we infer that there is correlation between the EU and all emerging markets considered in both the short and long run, as Table 5 suggests positive and significant correlation. The volatility impact is spread or spilt over from the EU to the recipient markets. Like the previous correlation dynamics of the US as a source, we find ourselves with highly fluctuating asymmetric dynamic correlation over the years once again, as displayed in Figure 5. Correlation between the EU and Brazil seems to generally exhibit a downward trend during the ESDC period, increasing thereafter from January 2012. A similar observation is made with regard to EU – India; however only in the earlier phases of the crisis period. Correlation appears to increase from January 2011, mid-crisis. For the South African and Turkish markets, correlation was on an almost instant rise since early in 2010. This could be a result of some of South Africa's major trading partners being part of the EU. Overall, the highest correlation levels seem to be experienced at some points during the ESDC crisis period.

<u>Figure 5: Asymmetric dynamic correlations between the EU and the emerging markets over time</u>



Source: Author's calculations

4.3 Examination of dynamic conditional correlations over turmoil and tranquil periods

We proceed with examining the DCC behaviour during the sample period, particularly focusing on the changes in correlations in the stock markets across tranquil and crisis periods. Firstly, we examine the entire crisis periods relative to the tranquil periods, followed by a similar statistical analysis, yet of the different phases and stages of the crises identified by the economic and statistical approaches, contrary to the bulk of the literature (see Bekiros, 2014; Alexakis et al., 2016; Samarakoon, 2017; Baur, 2020). To this end, we make use of the entropy test of equality to statistically examine the equality or non-equality of the densities of the two periods in question, where the hypothesis is stated as follows:

$$H_o: f(x)^{Crisis} = f(y)^{Non\ Crisis}$$

$$H_1: f(x)^{Crisis} \neq f(y)^{Non\ Crisis}$$

The null hypothesis of the equality of density during crisis and non-crisis periods refers to the concept of interdependence, i.e. markets are interdependent when the density functions of their dynamic correlations are equal during crisis and non-crisis periods. The alternative hypothesis alludes to the differences between the density functions during the two periods, implying either contagion or decoupling. Once the alternative hypothesis is true, a further test is needed to assure whether decoupling or contagion occurs. This is contrary to past studies that link differences in correlation between the crisis and non-crisis periods to contagion effects (see Baur, 2012; Cardona et al., 2017).

The results reported in Table 6 show that the null hypothesis of equality of density function is rejected for all country pairs when considering the entire period of the GFC and ESDC, without accounting for specific phases within these crisis periods.

Table 6: Entropy test statistics (Entire crisis periods for GFC and ESDC)

	Test statistic '*Sp*'	P- value	Outcome
USA - Brazil	0.1992422	2.22e-16 ***	H_o rejected
USA - India	0.1988645	2.22e-16 ***	H_o rejected
USA - South Africa	0.1992422	0.000000 ***	H_o rejected
USA - Turkey	0.1989548	2.22e-16 ***	H_o rejected
USA - Russia	0.196512	0.000000 ***	H_o rejected
EU - Brazil	0.2213491	0.000000 ***	H_o rejected
EU - India	0.1924623	2.22e-16 ***	H_o rejected
EU - South Africa	0.1759779	2.22e-16 ***	H_o rejected
EU - Turkey	0.2112558	0.000000 ***	H_o rejected
EU - Russia	0.206611	2.22e-16 ***	H_o rejected

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level.

In order to distinguish between contagion and decoupling, firstly we introduce the use of dummy variables corresponding to the relevant crises. Where we observe a significant and positive dummy variable coefficient, indicating that during the global financial crisis, correlation between the source and responding markets (ρ_{xy}) is seen to increase, we find evidence in support of the existence of contagion. However, where correlation between the two markets is seen to decline during the crisis, that is, we observe a statistically significant negative dummy variable coefficient, we conclude in support of the decoupling hypothesis. Additionally, where we observe an insignificant dummy variable, and infer no effect of the crisis on correlation, we find the existence of insulation or immunity by the emerging market. We recall that decoupling is observed when market returns that used to be correlated, that is, rise and decline together, begin to make opposite movements, in other words as one market's returns increase, the other market's returns fall. Thus, the correlation between the two markets experiences a decline during a crisis, deviating from the expected or normal correlation (Willett, Liang and Zhang, 2011) Having said this, we consider the pre-crisis period (November 2005-July 2007) as the tranquil period with regard to the GFC. However, we make use of the post-crisis period (September 2012-June 2015) as the period of tranquillity in the case of the

ESDC. This is due to the fact that the pre-crisis period of the ESDC includes the dates corresponding to the GFC and would furnish the study with distorted results. We proceed to estimate the mean equations below:

$$\rho_{xy,t} = \alpha_{xy} + + c_1 DM_{GFC} + c_2 ER_{xy,t} + c_3 IRD_{xy,t} + \varepsilon \qquad (15)$$

$$\rho_{xy,t} = \alpha_{xy} + + c_1 DM_{ESDC} + c_2 ER_{xy,t} + c_3 IRD_{xy,t} + \varepsilon \qquad (16)$$

where, $\rho_{xy,t}$ represents the correlation between the source market "x" and response market "y"; α_{xy} represents the constant term, and DM denotes the dummy variables corresponding to the relevant crises, the GFC and the ESDC. The dummies 1 and 0 are used to represent the crisis period and the non-crisis period, respectively, depending on whether we use an economic or statistical method for identifying crisis periods, as discussed above. Contrary to the few previous studies that incorporated the use of regression analysis after their DCC observations, this is the first paper, to the best of our knowledge, that makes use of control variables that could possibly explain the variation in the correlation between the two markets, going beyond just the mere use of the crisis-related dummy variables. To this end, we implement the use of the exchange rate and interest rate differentials between the two markets at a given time (t), represented by $ER_{xy,t}$ and $IRD_{xy,t}$, respectively. The use of the aforementioned variables in particular, was motivated by Hwang, Min, Kim, and Kim (2013) and Pretorius (2002), where the authors find that exchange market volatility and interest rate differentials between markets, to mention but a few, are some of the determinants driving stock market comovements. Furthermore, in order to enhance the validity of our regression analysis, it is important for the study to include control variables. Through the much needed inclusion of these extraneous variables, we neutralize the potential of obtaining skewed or biased results and the distortion of our primary results of interest (Allen, 2017).

Table 7 and 8 present the results obtained for the GFC and ESDC crises in their entirety, following the estimation of equations (15) and (16). The results provide further clarity to the debate and further ascertain the existence of contagion effects between the market pairs, except in the case of US - Russia, where the Russian stock market appears to have insulated from the US. With a statistically significant DM_{GFC} coefficient of -0.04989, we find that the correlation between the markets of the US and Russia declines during the crisis period as compared to the tranquil period. This finding is not far off from the observation made on the correlation graphs discussed earlier (Figure 4), where the correlation between the US and Russia was seen to decline for some parts of the GFC period. Russia saw their oil prices collapse, export prices and volumes plummet and the withdrawal of capital from the country in the "flight to safety" by investors and creditors taking place during late 2008 (Gaddy and Ickes, 2010). Although the country was adversely impacted in the later stages of the crisis, they were somewhat prepared for external shocks, which greatly contributed to sparing Russia from a much worse outcome. As a resource-dependent nation, Russia's accumulated reserve funds amounting to $225.1 billion provided a cushion against the crisis to some extent (Sutela, 2010). Among other functions, these funds were instrumental in maintaining domestic inflation and demand, thus mitigating the crisis impact to a certain extent. Contrary to the US - Russia case, we find strong evidence in support of the contagion phenomenon in the remaining market pairs, that is, between US and Brazil, India, South Africa and Turkey. We observe positive and significant coefficients indicating that, during the global financial crisis, correlation ($\rho_{xy,t}$) between the US and the four remaining markets rose, and stock market comovements were higher during the crisis as compared to the correlation during periods of no market disturbance, thus signalling and proving the presence of contagion effects.

Table 7: GFC regression analysis (entire crisis period)

	US - Brazil	US - India	US - South Africa	US - Turkey	US - Russia
α_0	0.75749053 (0.000000)***	-0.1710778 (8.591E-34)***	0.2054267 (6.547E-260) ***	0.09508578 (1.385E-297)***	0.30636772 (1.1311E-16)***
DM_{GFC}	0.05059396 (2.7437E-19)***	0.02990513 (2.1013E-19)***	0.03847949 (7.09E-32) ***	0.00841855 (5.1556E-05)***	0.0498957 (5.159E-10)***
Exchange rate	-0.0394569 (5.2727E-36)***	0.00644579 (3.4417E-88)***	0.00729892 (3.4535E-23) ***	0.02187474 (5.3031E-44)***	-0.0020963 (0.09748546) *
Interest rate differential	0.00622531 (1.117E-104)***	-0.0058543 (3.5853E-62)***	-0.0017017 (8.6098E-08) ***	0.00015832 (5.1981E-15)***	-0.018169 (8E-147)***
SE	0.107698	0.06288446	0.09871251	0.04046941	0.11757167
P-value	6.99E-206***	5.103E-232***	1.0375E-77***	1.17E-105***	0.000000***

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

Although Russia seems to have been less scathed by the US subprime crisis, the same cannot be said with the EU as a crisis originating market. This may be due to the different interrelationships Russia has with both source markets. For example, the greater trade relationship Russia has with the EU in comparison to the US would partially explain why

Russia's markets were found to be more vulnerable to shocks originating from the EU. Table 8 shows that most of the emerging markets considered, were affected by the ESDC-related spillover effects, except for Turkey. These market pairs support the existence of contagion with positive and significant DM_{ESDC} coefficients, suggesting that the correlation between the markets increased during the ESDC crisis period compared to the tranquil period. On the other hand, although EU - Turkey appears to be positively related at first glance, the pair's dummy coefficient is insignificant, suggesting that the Turkish market insulated from the EU during the crisis.

Table 8: ESDC regression analysis (entire crisis period)

	EU - Brazil	EU - India	EU - South Africa	EU - Turkey	EU - Russia
α_0	0.6492135	0.10892246	0.29577398	0.32615524	0.6015557
	(0.000000)***	(5.3771E-69)***	(5.951E-138)***	(0.000000)***	(3.024E-202)***
DM_{ESDC}	0.05934492	0.08429326	0.14149668	0.00446084	0.1567137
	(1.9945E-67)***	(6.412E-276)***	(5.226E-189)***	(0.06973659)*	(4.708E-143)***
Exchange rate	-0.0325584	0.00377976	0.02633883	-0.0088868	-0.005272
	(3.0311E-21)***	(1.043E-211)***	(2.519E-176)***	(0.00108001)***	(9.4971E-24)***
Interest rate differential	0.00948557	0.00335053	0.00127841	0.00139337	-0.0105106
	(1.466E-165)***	(4.0995E-16)***	(0.19180879)	(2.2256E-36)***	(3.1155E-33)***
SE	0.06644035	0.0495412	0.10533372	0.05474849	0.13964641
P-value	0.000000***	0.000000***	0.000000***	5.2451E-51***	4.003E-167***

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

Although emerging markets have been documented to have exhibited outstanding economic growth and have been significant drivers of global GDP and growth, the evidence shown in this study challenges the postulation of emerging economies' immunity to shocks emanating from the developed world. We find strong evidence of contagion effects originating from the US or EU to the key emerging markets globally, except for the US - Russia pair in relation to the GFC. The premise of emerging markets escaping vulnerability to spillover effects from advanced economies grew increasingly popular due to the behaviour of the Brazil and Chinese markets during the global financial crisis. Despite the economies being ravaged worldwide, China and Brazil were observed to maintain their comparatively elevated growth rate during the turmoil period. China's unexpected growth rate, while the rest of the world was in severe cold, brought more attention to the decoupling hypothesis which has become more deliberated since then (Li, Willett and Zhang, 2012). However, further studies have since shown that, although China initially seemed to escape the spillover effects from the US, this was short-lived because, as the crisis deepened, not even China could escape the wrath of the GFC. As a result, we find it important to further analyse the crises in phases in addition to the entire crisis period analysis, where we use both the economic and statistical approaches obtained in the sub-periods. We are of the view that studies that only rely on the economic approach do not take into account what the true data tells about that period. Since the statistical approach relies on the data itself, we believe that results obtained from the economic approach alone, without accounting for endogenously detected breaks, can be misleading. Thus, we proceed with a combination of both approaches. Table 9 presents the entropy test results obtained from the economic approach during the GFC and ESDC, respectively. Once again, we begin with the elimination of interdependence between all market pairs through the rejection of the null hypothesis as the test statistic "$S_p \neq 0$", as described earlier, and the p-values being less than 0.05. We infer the absence of interdependence; however, at this point there is no telling whether the emerging markets decoupled from the source countries, or "caught the flu" during the financial crises, as we accept the alternative hypothesis which postulates the non-equality of distributions of the crisis and non-crisis periods in all phases.

Table 9: Entropy test results (economic approach)

		Test statistics '*Sp*'	P- value	Outcome
USA - Brazil	Phase 1:	0.2034821	2.22e-16 ***	H_o rejected
	Phase 2:	0.1954202	2.22e-16 ***	H_o rejected
	Phase 3:	0.2101099	0.000000 ***	H_o rejected
USA - India	Phase 1:	0.1925159	2.22e-16 ***	H_o rejected
	Phase 2:	0.2054686	0.000000 ***	H_o rejected
	Phase 3:	0.1801679	2.22e-16 ***	H_o rejected
USA - South Africa	Phase 1:	0.2178756	0.000000 ***	H_o rejected
	Phase 2:	0.178754	2.22e-16 ***	H_o rejected
	Phase 3:	0.2200741	2.22e-16 ***	H_o rejected
USA - Turkey	Phase 1:	0.2052791	2.22e-16 ***	H_o rejected
	Phase 2:	0.2162047	0.000000 ***	H_o rejected
	Phase 3:	0.2041979	2.22e-16 ***	H_o rejected

USA - Russia	Phase 1:	0.2103451	0.000000 ***	H_o rejected
	Phase 2:	0.20185	2.22e-16 ***	H_o rejected
	Phase 3:	0.1870066	0.000000 ***	H_o rejected
EU - Brazil	Phase 1:	0.2013982	0.000000 ***	H_o rejected
	Phase 2:	0.2024698	2.22e-16 ***	H_o rejected
	Phase 3:	0.1925159	2.22e-16 ***	H_o rejected
EU - India	Phase 1:	0.201031	2.22e-16 ***	H_o rejected
	Phase 2:	0.1881834	2.22e-16 ***	H_o rejected
	Phase 3:	0.1989455	0.000000 ***	H_o rejected
EU - South Africa	Phase 1:	0.1951405	2.22e-16 ***	H_o rejected
	Phase 2:	0.2062592	0.000000 ***	H_o rejected
	Phase 3:	0.1872081	2.22e-16 ***	H_o rejected
EU - Turkey	Phase 1:	0.1802886	0.000000 ***	H_o rejected
	Phase 2:	0.2036417	2.22e-16 ***	H_o rejected
	Phase 3:	0.1926393	2.22e-16 ***	H_o rejected
EU - Russia	Phase 1:	0.1905485	2.22e-16 ***	H_o rejected
	Phase 2:	0.1894249	0.000000 ***	H_o rejected
	Phase 3:	0.2029673	0.000000 ***	H_o rejected

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

In order to determine during which sub-periods the emerging markets exhibited decoupling or contagion effects, we expand equations (15) and (16) to include more dummy variables with 1 corresponding to the crisis sub-periods and zero otherwise.

$$\rho_{xy,t} = \alpha_{xy} + c_1 \sum_{i=1}^{\lambda} DM_{GFC} + c_2 ER_{xy,t} + c_3 IRD_{xy,t} + \varepsilon \qquad (17)$$

$$\rho_{xy,t} = \alpha_{xy} + c_1 \sum_{i=1}^{\lambda} DM_{ESDC} + c_2 ER_{xy,t} + c_3 IRD_{xy,t} + \varepsilon \qquad (18)$$

where, $i = 1, \ldots, \lambda$ represents the number of dummy variables corresponding to the different phases during the relevant crises. Based on the economic approach, $i = 1, \ldots, 3$ (the fourth phase of "stabilization and recovery" is excluded) and based on the statistic approach, $i = 1, \ldots, 5$ for both the GFC and ESDC. Tables 10 and 11 report the results obtained based on the economic approach, and Tables 13 and 14, following the statistic approach for both crises.

With reference to Table 10, the dummy coefficient for the US - Brazil pair is negative during the “initial financial turmoil” sub-period, suggesting that the correlation between the two markets declined during phase 1 in comparison to the tranquil period, however insignificant. Due to the coefficient’s insignificance and negativity, we find that phase 1 of the GFC had no impact on Brazil and infer that Brazil’s market insulated from the US emanating shock. Similar findings are obtained in the case of Turkey and South Africa with negative, and yet significant, coefficients making the decoupling hypothesis to initially hold as the coefficients indicate that correlation between the markets declined during the first sub-period compared to the tranquil period. The opposite can be said for Russia and India, where Table 10 shows that these emerging markets immediately felt the volatility impact emanating from the US. With positive and significant coefficients, we find strong evidence of the presence of contagion effects. While this experience seems to have been short-lived for Russia, as this emerging market later decoupled from the US in the remaining phases of the deepening global financial crisis, India continued to feel the full brunt of the spillover effects from the US market in the final phase with a positive and significant coefficient. Conversely, in the second phase, although a positive coefficient was obtained, the insignificance cannot be ignored which suggests that the phase of “sharp financial market deterioration” had no impact on the correlation between the US and India compared to the tranquil period. Thus, India insulated from the US during phase 2. On the other hand, Brazil, South Africa and Turkey exhibited contagion effects in phases 2 and 3, as the positive and significant coefficients indicated that the correlation increased during the sub-periods compared to the tranquil periods. Phase 2, which was initiated by the Lehman Brothers’ collapse, was detrimental for all equity markets except for India and Russia.

Table 10: GFC regression analysis (economic approach)

	US - Brazil	US - India	US - South Africa	US - Turkey	US - Russia
α_0	0.77367792	-0.1667311	0.22612807	0.09851885	0.02319544
	(0.000000)***	(2.0446E-28)***	(4.554E-123)***	(0.000000)***	(0.57691663)***
$DM_{GFC,1}$	-0.0036838	0.02968052	-0.0285798	-0.0065242	0.04914055
	(0.57673909)	(9.484E-13)***	(2.067E-06)***	(0.00755262)***	(8.8913E-07)***
$DM_{GFC,2}$	0.17308156	0.00995136	0.03417071	0.03109311	-0.1204906
	(2.2055E-45)***	(0.17590405)	(0.00422677)***	(1.619E-11)***	(8.3394E-16)***
$DM_{GFC,3}$	0.13492855	0.05237262	0.02704641	0.0497887	-0.2210546
	(4.662E-24)***	(7.5512E-11)***	(0.03711181)***	(1.2658E-22)***	(3.3205E-44)***

Exchange rate	-0.044899	0.00633479	0.0182704	0.01946067	0.00743625
	(1.7507E-47)***	(1.4974E-75)***	(1.8802E-50)***	(8.2173E-36)***	(1.942E-07)***
Interest rate differential	0.0065552	-0.0060499	0.00505418	0.00017391	-0.0191256
	(3.676E-120)***	(5.3527E-65)	(1.0829E-23)***	(3.211E-18)***	(2.263E-165)***
SE	0.10487855	0.06277711	0.09872266	0.03981979	0.11290405
P-value	1.73E-249	8.764E-233	9.8839E-77	1.133E-131	6.605E-251

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

Compared to the GFC, the emerging markets considered seem to have been more vulnerable to the shocks that originated from the EU during the ESDC, with more evidence of contagion effects established. We obtained positive and significant dummy coefficients during all three phases for the EU and Brazil, India, South Africa, and Russia market pairs displayed in Table 11. We observe that during the crisis sub-periods, correlation increased between the markets as compared to the periods of tranquillity. Thus, we conclude in support of the presence of contagion effects. On the contrary, the results found in the case of the EU - Turkey market pair allow the decoupling hypothesis to hold through the negative (insignificant) phase 1 dummy coefficient and the negative, yet significant, phase 2 dummy coefficient.

Table 11: ESDC regression analysis (economic approach)

	EU - Brazil	EU - India	EU - South Africa	EU - Turkey	EU - Russia
α_0	0.65945353	0.10601597	0.29015018	0.33942379	0.59968117
	(0.000000)***	(6.6203E-66)***	(4.848E-132)***	(0.000000)***	(2.228E-199)***
$DM_{ESDC,1}$	0.06880884	0.0834809	0.10257756	-0.0025006	0.17991653
	(4.4314E-28)***	(6.0216E-71)***	(1.78E-25)***	(0.6256701)	(1.5339E-42)***
$DM_{ESDC,2}$	0.02293735	0.10406578	0.14945174	-0.013092	0.14377266
	(1.7818E-07)***	(1.315E-234)***	(3.616E-114)***	(0.00010564)***	(6.3541E-65)***
$DM_{ESDC,3}$	0.09223161	0.05864846	0.15111135	0.02667543	0.16171822
	(5.1094E-90)***	(1.5977E-66)***	(1.703E-102)***	(6.8028E-14)***	(2.3468E-70)***
Exchange rate	-0.0375013	0.00378595	0.02652683	-0.0142266	-0.0052097
	(4.2474E-28)***	(2.018E-209)***	(9.418E-178)***	(2.5792E-07)***	(5.6117E-23)***
Interest rate differential	0.00912175	0.0027629	0.00069465	0.00154696	-0.0103228
	(6.617E-158)***	(1.1407E-10)***	(0.48106004)***	(5.0357E-44)***	(1.7161E-31)***
SE	0.06490592	0.04870241	0.10506061	0.05417054	0.13955925
P-value	0.000000	0.000000	0.000000	1.5267E-65	4.794E-166

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

Moving on to the statistically or endogenously determined phases, the results reported in Table 12 show that the null hypothesis of the equality of distributions corresponding to the crisis and non-crisis periods is rejected. This applies to all market pairs during the different phases of the GFC and ESDC, respectively. As discussed earlier, the rejection of interdependence does not necessarily inform us of the existence of contagion effects or decoupling between the markets. Thus, we proceed with the regression analysis depicted in Tables 13 and 14 to distinguish contagion or decoupling between the markets.

Table 12: Entropy test results (statistical approach)

		Test statistics '*Sp*'	P- value	Outcome
USA - Brazil	Phase 1:	0.2223439	2.22e-16 ***	H_o rejected
	Phase 2:	0.6681207	2.22e-16 ***	H_o rejected
	Phase 3:	0.9765144	0.000000 ***	H_o rejected
	Phase 4:	0.2120574	2.22e-16 ***	H_o rejected
	Phase 5:	0.4687102	0.000000 ***	H_o rejected
USA - India	Phase 1:	0.2091447	2.22e-16 ***	H_o rejected
	Phase 2:	0.2062592	2.22e-16 ***	H_o rejected
	Phase 3:	0.2120574	0.000000 ***	H_o rejected
	Phase 4:	0.2036417	0.000000 ***	H_o rejected
	Phase 5:	0.1870535	2.22e-16 ***	H_o rejected
USA - South Africa	Phase 1:	0.2032956	0.000000 ***	H_o rejected
	Phase 2:	0.1894249	0.000000 ***	H_o rejected
	Phase 3:	0.2101099	0.000000 ***	H_o rejected
	Phase 4:	0.2200741	0.000000 ***	H_o rejected
	Phase 5:	0.2104964	0.000000 ***	H_o rejected
USA - Turkey	Phase 1:	0.2223439	2.22e-16 ***	H_o rejected
	Phase 2:	0.2120574	2.22e-16 ***	H_o rejected
	Phase 3:	0.2103451	0.000000 ***	H_o rejected
	Phase 4:	0.1801679	2.22e-16 ***	H_o rejected
	Phase 5:	0.2024698	0.000000 ***	H_o rejected
USA - Russia	Phase 1:	0.2060604	0.000000 ***	H_o rejected
	Phase 2:	0.2223439	2.22e-16 ***	H_o rejected
	Phase 3:	0.2178756	2.22e-16 ***	H_o rejected
	Phase 4:	0.1644527	0.000000 ***	H_o rejected
	Phase 5:	0.1881834	0.000000 ***	H_o rejected
EU - Brazil	Phase 1:	0.2032956	0.000000 ***	H_o rejected
	Phase 2:	0.1907429	0.000000 ***	H_o rejected
	Phase 3:	0.2129627	2.22e-16 ***	H_o rejected
	Phase 4:	0.2007392	2.22e-16 ***	H_o rejected
	Phase 5:	0.18313	0.000000 ***	H_o rejected
EU - India	Phase 1:	0.1917481	2.22e-16 ***	H_o rejected
	Phase 2:	0.1911886	0.000000 ***	H_o rejected
	Phase 3:	0.1940323	0.000000 ***	H_o rejected
	Phase 4:	0.2019162	2.22e-16 ***	H_o rejected
	Phase 5:	0.1901609	2.22e-16 ***	H_o rejected
EU - South Africa	Phase 1:	0.2018207	2.22e-16 ***	H_o rejected
	Phase 2:	0.1835359	0.000000 ***	H_o rejected
	Phase 3:	0.2108033	0.000000 ***	H_o rejected
	Phase 4:	0.175078	0.000000 ***	H_o rejected
	Phase 5:	0.2000702	2.22e-16 ***	H_o rejected

Table 12. continued

		Test statistics '*Sp*'	P- value	Outcome
EU - Turkey	Phase 1:	0.1989548	0.000000 ***	H_o rejected
	Phase 2:	0.2079274	2.22e-16 ***	H_o rejected
	Phase 3:	0.1930285	0.000000 ***	H_o rejected
	Phase 4:	0.1940544	0.000000 ***	H_o rejected
	Phase 5:	0.2153276	0.000000 ***	H_o rejected
EU - Russia	Phase 1:	0.196512	2.22e-16 ***	H_o rejected
	Phase 2:	0.2003858	2.22e-16 ***	H_o rejected
	Phase 3:	0.1870974	2.22e-16 ***	H_o rejected
	Phase 4:	0.2185429	0.000000 ***	H_o rejected
	Phase 5:	0.1819469	2.22e-16 ***	H_o rejected

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

In Table 13, we infer the presence of contagion effects in all the crisis phases where US - India is concerned. We observe positive and significant dummy variable coefficients for the pair. The same can be said for the first two phases of the GFC in the case of US - Brazil, first three phases for US - Russia, and the last phase for US - Turkey. In actual fact, the last phase of the GFC seems to have been dire for all the markets except Russia as they certainly felt the spillover effects from the source market, the US. During phase 3 and 4 of the global financial crisis, Brazil and South Africa exhibited decoupling behaviour as the negative coefficients suggest a decline in correlation (an insignificant coefficient suggests zero impact on the correlation) during the crisis periods as compared to the tranquil periods. We find that Turkey completely insulated from the US market during the first 4 phases of the crisis and only succumbed to the negative spillover impact in the final and 5th phase, a combination of negative and insignificant coefficients guiding this conclusion. Furthermore, Russia's market insulation is observed in the last two phases and guided by a similar observation as that of Turkey.

Table 13: GFC regression analysis (statistical approach)

	US - Brazil	US - India	US - South Africa	US - Turkey	US - Russia
Intercept	0.75377281	-0.1503148	0.21990285	0.0959276	0.20344365
	(0.000000)***	(6.9524E-27)***	(2.012E-118)***	(0.000000)***	(1.6179E-11)
$DM_{GFC,1}$	0.18465667	0.05567735	0.00757591	-0.0230984	0.08359866
	(1.1212E-19)***	(4.5118E-06) ***	(0.69181076)	(0.00250967)***	(0.00016313)***
$DM_{GFC,2}$	0.07916516	0.05586833	0.04928584	-0.0008955	0.06249287
	(3.8691E-05) ***	(1.318E-06) ***	(0.00658841)***	(0.90174537)	(0.00339338)***
$DM_{GFC,3}$	-0.0176848	0.04738597	0.00980031	0.00861945	0.09558955
	(0.39068741)	(0.0001286)***	(0.61441901)	(0.26836151)	(2.6757E-05)***
$DM_{GFC,4}$	0.00701396	0.02808854	-0.0768375	0.00751072	0.01905637
	(0.74331571)	(0.02865917) ***	(0.00015227)***	(0.35373342)	(0.42499997)
$DM_{GFC,5}$	0.1050502	0.04346329	0.01866183	0.03484958	-0.1212583
	(7.0154E-59) ***	(3.1292E-29) ***	(0.00426834)***	(2.8814E-45) ***	(4.1288E-49)***
Exchange rate	-0.0409276	0.00594891	0.01883108	0.01981426	0.00133614
	(4.745E-41)***	(1.1416E-76)***	(5.32E-54)***	(7.8659E-38)***	(0.19985118)
Interest rate differential	0.00601103	-0.0060228	0.00509948	0.00015302	-0.0208021
	(2.165E-104)***	(1.6049E-67)***	(7.3635E-24)***	(8.4315E-15)***	(3.516E-196)***
SE	0.10425233	0.06211716	0.09881417	0.03950784	0.11317997
P-value	8.539E-258	5.31E-249	1.0747E-73	1.833E-143	9.256E-246

Source: Author's calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

In the case of the ESDC results displayed in Table 14, the crisis seems to have ravaged through all the emerging markets across regions during most of the crisis sub-periods, with only positive dummy coefficients obtained. However, due to the insignificance in some, we conclude towards market immunity in a few phases. Phase 3 appears to have been the common phase where some evidence of decoupling is observed in the Brazil, Russia and Turkey markets. Moreover, the evidence also indicates the upholding of the decoupling hypothesis during phase 2 of the crisis in the case of EU - Turkey. The remaining phases and markets provide strong evidence of contagion effects, with positive and significant coefficients indicating that the correlation between markets increased during the statistically obtained sub-periods versus the periods of tranquillity. It is important to note briefly that crises are not the only factor that plays a role in explaining the variation in the correlation between all the market pairs considered. In this study we also considered the influence of macroeconomic variables, such as, exchange rates between the markets and the interest rate differential, where we observed negative or positive coefficients interchangeably, however significant in most cases. Overall significance was achieved as the p-values observed remain below 0.05 or close to 0 in all models run.

Table 14: ESDC regression analysis (statistical approach)

	EU - Brazil	EU - India	EU - South Africa	EU - Turkey	EU - Russia
α_0	0.69321599	0.11558727	0.33443991	0.32977139	0.58642092
	(0.000000)***	(1.2774E-66)***	(8.192E-165)***	(0.000000)***	(2.662E-180) ***
$DM_{ESDC,1}$	0.07525547	0.07401748	0.07422926	0.03277883	0.11260497
	(1.4173E-05)***	(1.01E-07)***	(0.00897249)***	(0.02009827)***	(0.00254565) ***
$DM_{ESDC,2}$	0.05841933	0.1276584	0.1772119	9.6443E-05	0.2095044
	(1.2254E-16)***	(8.157E-113)***	(9.3013E-55)***	(0.98634625)	(3.1317E-45) ***
$DM_{ESDC,3}$	0.01321868	0.12251791	0.12434667	0.02112169	0.03021221
	(0.33735716)	(2.3531E-28)***	(3.594E-08) ***	(0.05916379)	(0.30695081)
$DM_{ESDC,4}$	0.0478586	0.04995985	0.14848582	0.02850333	0.16396512
	(1.5968E-18)***	(5.9198E-31)***	(3.3324E-64) ***	(3.8343E-11)***	(1.455E-47)***
$DM_{ESDC,5}$	0.09025856	0.03223726	0.11604533	0.01856492	0.12355319
	(6.5096E-37)***	(1.6528E-08)***	(7.5363E-24) ***	(0.00106904)***	(3.6133E-16) ***
Exchange rate	-0.0477714	0.00365727	0.0251471	-0.0114085	-0.0044778
	(4.0575E-49)***	(2.199E-173)***	(3.026E-151) ***	(3.5223E-05)***	(1.8785E-16) ***
Interest rate differential	0.00909995	0.0012286	0.00365464	0.00137611	-0.0096825
	(4.503E-150)***	(0.00632257)***	(0.00033674)***	(7.8676E-38)***	(2.3784E-26)***
SE	0.06673247	0.05348605	0.10968062	0.05434496	0.14401552
P-value	0.000000	0.000000	3.864E-246	2.5095E-59	1.235E-116

Source: Author’s calculations

Note: *** denotes the rejection of the null hypothesis of equality at 1%, 5% and 10% level

4.4 Discussion of results

These observations come as no surprise and highlight the fact that financial markets have indeed become more integrated, resulting in higher levels of volatility transmissions over the years. Unfortunately, this has adverse implications for the investment strategy of portfolio diversification. Hence, we sought to bring a new understanding to this ongoing debate by providing a regional analysis that could bring new views to portfolio diversification possibilities. Although the markets we explored all seem to have been affected by the crisis at one point or another, we cannot dispute the fact that some markets were more or less affected than others. During the global financial crisis, we observed Russia's stock market to be the most supportive market of the decoupling hypothesis, similar to results obtained by Mensi, Hammoudeh, Nguyen and Kang (2016). While the country may have been hit by the external shocks emanating from the US during the "initial financial turmoil", we observed the market to decouple from the giant market in the later stages of the crisis. This observation remains constant throughout the different approaches used. Using the statistical approach, Russia decoupled from the US in the last two phases, from February 2008 till the end of the crisis and the economic approach saw Russia decouple in the last two phases as well, however, following the Lehman Brothers' collapse in September 2008. Although there may be slight discrepancies in these dates, Russia's decoupling is still established for the most part of the GFC, according to our results. In 2008, Russia had accumulated reserve funds amounting to $225.1 billion which provided a much needed buffer against the crisis shocks. According to Gaddy and Ickes (2010), resource-dependent nations performed slightly better than others during the crisis. Through accumulated reserves, they were able to maintain domestic demand and inflation. Although Russia was initially hit, the country's stocks were able to rebound in the later stages of the crisis and by 2009. Figure 1 can attest to this.

Countries such as Brazil (during the GFC) were seen to decouple in the early stages of the crisis due to the high consumer demand that they had accomplished, which allows for budget surpluses and the accumulation of great amounts of foreign exchange reserves. These serve as a cushion for such markets in crises, and as a result delay the markets' experience of shocks (Dimitriou et al., 2013). Another plausible explanation for the decoupling hypothesis only being seen in the first stages, is the fact that investors could delay in responding to the news of a pending crisis. However, this is short-lived, as eventually international investors change their risk appetite and scramble to offload their assets through sales. Such behaviours explain why contagion effects may not be felt initially, thus indicating decoupling in the early stages of crises. Conversely, the contagion effects observed are often explained by trade characteristics, financial linkages among stock markets and finally, investor behaviour. A country's economic characteristics and financial profiles of the markets also play a role in determining the magnitude of the effects felt. There are many other factors that can explain how shocks are transmitted, or how markets decouple that go beyond this scope. Further research on these factors, expanding on our regional analysis, is encouraged.

The remaining markets in the study seem to have been hit harder by the crisis, with India leading the pack. Using the statistical approach, India was adversely impacted in all 5 phases of the GFC, while the economic approach saw the country weather the storm in phase 2. Nonetheless, we find India to have been the hardest hit market in the study during the GFC. According to Joseph (2009), the country is documented to have been hit through an "abrupt stop" of capital inflows and the slump of both domestic and external demand. India was also hit the hardest by the ESDC along with South Africa, where we observed contagion effects in all 5 phases of the crisis. Considering the EU makes up some of South Africa's major trading partners, this could explain why the African emerging market was more vulnerable to the EU shock as compared to the US originating shock. While Russia seemed to fare well during the GFC, the country was far from immune during the ESDC. The different interrelationships between Russia and the source markets would explain Russia's greater vulnerability to the EU, as compared to the US. For example, Russia's major export partners were more EU countries than those of the US, with the country exporting 80% of its gas to the rest of the EU in the mid 2000s (Mensi et al., 2016). Although our results for the entire crisis period show that none of the emerging markets were immune to the shocks from the EU during the ESDC, we find Turkey to have been the least impacted as the country's stock market decoupled from the EU in phases 2 and 3 of the crisis.

The results obtained in this study should be of interest to investors and asset or portfolio managers, as they further shed light on the importance of portfolio diversification. Our findings suggest that European stocks are worth having in a portfolio as we observed Russia (a market representative of Europe) to be a possible safe haven or cushion against crises to some extent, unless the crisis originates from its own continent. Furthermore, the Russian (European) market was observed to be able to rebound quickly due to the macroeconomic characteristics, among other factors, inherent in its economy. The study provides clear results that some regions may be able to insulate or achieve immunity from external shocks. Thus, we propose to investors and portfolio managers that, in their bid to diversify their portfolios or investments across regions, they should attain an in depth understanding of each market and, in particular, the economy's upswings and downswings, and its vulnerability to financial crises emanating from advanced economies, macroeconomic and financial profiles among other factors. Consideration of such factors would provide insight or best inform which markets may award the best protection to the investor's portfolio during periods of market disturbance or great turmoil.

Additionally, since emerging markets are considered to be key drivers of global economic growth and are becoming increasingly integrated with the world economy, this study should provide guidance to the decision process of markets becoming fully liberated. This study also noted the importance of the markets' financial profiles, trade and financial characteristics. Thus, policy makers should take note of these characteristics when formulating policies. Clearly, as shown in the case of US - Russia or US - Brazil (at the beginning of the crisis), there are some factors that can serve as a cushion to emerging markets during financial crises and prevent them from "catching a cold when another market sneezes". For the sake of policy making, further research on these factors is encouraged.

5. CONCLUSION

In this study, we proposed a test based on entropy theory to distinguish between interdependence, decoupling and contagion when assessing shock spillovers between advanced economies, the US and the EU, and emerging markets, identified by their locations, during important crisis periods. In doing so, we assessed whether emerging markets are homogenous or heterogenous as recipients of shock spillovers from advanced economies. Another important contribution of this study consists of distinguishing between the phases of each crisis based on an economic and statistical framework conjointly. Studies show that the accurate identification of the crisis date is important when assessing the extent of contagion or interdependence between markets or countries (see Baur, 2012; Dimitriou et al., 2013; Kenourgios et al, 2016). It is in that context that our analysis not only assessed the markets' responses to the crises in their entirety, but also examined and documented the markets' various experiences during the different sub-periods of the related financial and economic crises emanating from the US and EU.

The results of the empirical analysis showed that the interrelationships between the US and the emerging markets have actually increased over time. Particularly, we found that the dynamic correlation between the US and emerging economies was higher during the GFC than it was during the DOTCOM bubble burst. This implies that the emerging markets were less impacted by the shocks emanating from the US earlier in the 2000s, as compared to the global financial crisis in the mid 2000s. Moreover, we observed some instances of decoupling in the markets, for instance in the cases of Russia and Brazil during the GFC, and Turkey during the ESDC.

While some evidence of decoupling was found, contagion effects remained largely popular in our findings, especially during the ESDC. Nonetheless, the dissimilarities in the emerging markets' spillover effects witnessed during both crises show that emerging markets are not homogenous as far as shock spillover from advanced economies is concerned. This dissimilarity alludes to the effectiveness of portfolio diversification when investing in emerging markets, as supported by Mensi et al. (2016). We found that emerging markets are not homogenous as recipients of spillover effects (contagion), as is commonly believed. While some may be exposed to the negative spillover effects of financial crises, some were observed to be immune. To contribute to the understanding of which sectors in the stock market actually play a role in the decoupling of some markets, we encourage further research on the topic by disaggregating stock markets in advanced and emerging markets.

References

Acatrinei, M., Gorun, A. and Marcu, N., 2013. A DCC-GARCH Model to Estimate. *Romanian Journal of Economic Forecasting*, *1*(2013), pp.136-148.

Alberg, D., Shalit, H. and Yosef, R., 2008. Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*, *18*(15), pp.1201-1208.

Allen, M. (2017). *The sage encyclopedia of communication research methods* (Vols. 1-4). Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781483381411

Alexakis, P.D., Kenourgios, D. and Dimitriou, D., 2016. On emerging stock market contagion: The Baltic region. *Research in International Business and Finance*, *36*, pp.312-321.

Altun, A.A., Çelik, S. and Koç, Y.D., 2019. Testing for financial contagion: New evidence from the European debt crisis. *Panoeconomicus*, *66*(5), pp.611-632.

Asgharian, H. and Nossman, M., 2011. Risk contagion among international stock markets. *Journal of International Money and Finance*, *30*(1), pp.22-38.

Bannigidadmath, D. and Narayan, P.K., 2016. Stock return predictability and determinants of predictability and profits. *Emerging Markets Review*, *26*, pp.153-173.

Baur, D.G., 2012. Financial contagion and the real economy. *Journal of Banking & Finance*, *36*(10), pp.2680-2692.

Baur, D.G., 2020. Decoupling and contagion: the special case of the eurozone sovereign debt crisis. *International Review of Finance*, *20*(1), pp.133-154.

Bauwens, L., Laurent, S. and Rombouts, J.V., 2006. Multivariate GARCH models: a survey. *Journal of applied econometrics*, *21*(1), pp.79-109.

Bekiros, S.D., 2014. Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis*, *33*, pp.58-69.

Billio, M. and Caporin, M., 2010. Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. *Computational statistics & data analysis*, *54*(11), pp.2443-2458.

Bollerslev, T., 1988. On the correlation structure for the generalized autoregressive conditional heteroskedastic process. *Journal of Time Series Analysis*, *9*(2), pp.121-131.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The Review of Economics and Statistics*, pp.498-505.

Bonga-Bonga, L., 2018. Uncovering equity market contagion among BRICS countries: an application of the multivariate GARCH model. *The Quarterly Review of Economics and Finance*, *67*, pp.36-44.

Bonga-Bonga, L. and Manguzvane, M.M., 2020. Assessing the extent of contagion of sovereign credit risk among BRICS countries. *Economics Bulletin, AccessEcon, 40(2), pp. 1017-1032.*

Bouaziz, M.C., Selmi, N. and Boujelbene, Y., 2012. Contagion effect of the subprime financial crisis: Evidence of DCC multivariate GARCH models. *European Journal of Economics, Finance and Administrative Sciences*, *44*(1), pp.66-76.5

Bullard, J., 2010. Federal Reserve bank of St. Louis. The European Debt Crisis: Lessons for the U.S. https://www.stlouisfed.org/~/media/Files/PDFs/publications/pub_assets/pdf/re/2010/d/pres-mes.pdf

Caporale, G.M., Cipollini, A. and Spagnolo, N., 2005. Testing for contagion: a conditional correlation analysis. *Journal of Empirical Finance*, *12*(3), pp.476-489.

Cappiello, L., Engle, R.F. and Sheppard, K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics*, *4*(4), pp.537-572.

Cardona, L., Gutiérrez, M. and Agudelo, D.A., 2017. Volatility transmission between US and Latin American stock markets: Testing the decoupling hypothesis. *Research in International Business and Finance*, *39*, pp.115-127.

Çelik, S., 2012. The more contagion effect on emerging markets: The evidence of DCC-GARCH model. *Economic Modelling*, *29*(5), pp.1946-1959.

Chittedi, K.R., 2015. Financial crisis and contagion effects to Indian stock market:'DCC–GARCH'analysis. *Global Business Review*, *16*(1), pp.50-60.

Cho, J.H. and Parhizgari, A.M., 2009. East Asian financial contagion under DCC-GARCH. *International Journal of Banking and Finance*, *6*(1), pp.17-30.

Corsetti, G., Pericoli, M. and Sbracia, M., 2005. 'Some contagion, some interdependence': More pitfalls in tests of financial contagion. *Journal of International Money and Finance*, *24*(8), pp.1177-1199.

Cuadro-Sáez, L., Fratzscher, M. and Thimann, C., 2009. The transmission of emerging market shocks to global equity markets. *Journal of Empirical Finance*, *16*(1), pp.2-17.

Dimitriou, D., Kenourgios, D. and Simos, T., 2013. Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis*, *30*, pp.46-56.

Dungey, M. and Gajurel, D., 2014. Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems*, *38*(2), pp.161-177.

Eichengreen, B., Rose, A.K. and Wyplosz, C., 1996. Contagious currency crises (No. w5681). National Bureau of Economic Research.

Engle, R.F. and Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. *Econometric theory*, *11*(1), pp.122-150.

Engle, R.F. and Sheppard, K., 2001. Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. NBER Working Paper 8554, National Bureau of Economic Research.

Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, *20*(3), pp.339-350.

Errunza, V. and Losq, E., 1987. How risky are emerging markets? *Journal of Portfolio Management*, *14*(1), p.62.

Federal Reserve Board of St Louis., Louis, F.R., 2009. The financial crisis: A timeline of events and policy actions. *St. Louis: FRBS*.

Federal Reserve Bank of St. Louis, 2010. The European Debt Crisis: Lessons for the U.S. https://www.stlouisfed.org/~/media/Files/PDFs/publications/pub_assets/pdf/re/2010/d/pres-mes.pdf

Forbes, K.J. and Rigobon, R., 2002. No contagion, only interdependence: measuring stock market comovements. *The Journal of Finance*, *57*(5), pp.2223-2261.

Gabriel, A.S., 2012. Evaluating the forecasting performance of GARCH models. Evidence from Romania. *Procedia-Social and Behavioral Sciences*, *62*, pp.1006-1010.

Gaddy, C.G. and Ickes, B.W., 2010. Russia after the global financial crisis. *Eurasian Geography and Economics*, *51*(3), pp.281-311.

Galyfianakis, G., Drimbetas, E. and Sariannidis, N., 2016. Modeling Energy Prices with a Markov-Switching dynamic regression model: 2005-2015. *Bulletin of Applied Economics*, *3*(1), p.11.

Ghini, A.E. and Saidi, Y., 2015. Financial market contagion during the global financial crisis: evidence from the Moroccan stock market. *International Journal of Financial Markets and Derivatives*, *4*(1), pp.78-95.

Hamao, Y., Masulis, R.W. and Ng, V., 1990. Correlations in price changes and volatility across international stock markets. *The review of financial studies*, *3*(2), pp.281-307.

Hamilton, J.D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, pp.357-384.

Hemche, O., Jawadi, F., Maliki, S.B. and Cheffou, A.I., 2016. On the study of contagion in the context of the subprime crisis: A dynamic conditional correlation–multivariate GARCH approach. *Economic Modelling*, *52*, pp.292-299.

Hwang, I., In, F.H. and Kim, T.S., 2010. "Contagion effects of the US subprime crisis on international stock markets." In: Finance and Corporate Governance Conference 2010 Paper.

Hwang, E., Min, H.G., Kim, B.H. and Kim, H., 2013. Determinants of stock market comovements among US and emerging economies during the US financial crisis. *Economic Modelling*, *35*, pp.338-348.

Joseph, M., 2009, September. Global financial crisis: How was India impacted. Prepared for presentation to InWEnt-DIE Conference on Global Financial Governance—Challenges and Regional Responses.

Karolyi, G.A., 2015. *Cracking the emerging markets enigma*. Financial Management Associati.

Kenourgios, D., 2014. On financial contagion and implied market volatility. *International Review of Financial Analysis*, *34*, pp.21-30.

Kenourgios, D. and Dimitriou, D., 2015. Contagion of the Global Financial Crisis and the real economy: A regional analysis. *Economic Modelling*, *44*, pp.283-293.

Kenourgios, D., Naifar, N. and Dimitriou, D., 2016. Islamic financial markets and global crises: Contagion or decoupling?. *Economic Modelling*, *57*, pp.36-46.

Lawlor, P., 2020. *Not all emerging markets are equal: Tread carefully when chasing returns*. [online] Investec. Available at: https://www.investec.com/en_za/focus/global-investment-strategy-group/not-all-emerging-markets-are-equal-tread-carefully-when-chasing-returns.html

Leeds, R., 2015. *Private equity investing in emerging markets: Opportunities for value creation*. Springer: New York.

Li, Q., Maasoumi, E. and Racine, J.S., 2009. A nonparametric test for equality of distributions with mixed categorical and continuous data. *Journal of Econometrics*, *148*(2), pp.186-200.

Li, L., Willett, T.D. and Zhang, N., 2012. The effects of the global financial crisis on China's financial market and macroeconomy. *Economics Research International*, *2012*, 961964.

Maasoumi, E. and Racine, J., 2002. Entropy and predictability of stock market returns. *Journal of Econometrics*, *107*(1-2), pp.291-312.

Maasoumi, E. and Wang, L., 2019. The gender gap between earnings distributions. *Journal of Political Economy*, *127*(5), pp.2438-2504.

Mahenthiran, S., Gjerde, T. and Silva-Palavecinos, B., 2020. Stock Market Contagion during the Global Financial Crises: Evidence from the Chilean Stock Market. *International Journal of Financial Studies*, *8*(2), p.26.

McLeod, A.I. and Li, W.K., 1983. Diagnostic checking ARMA time series models using squared-residual autocorrelations. *Journal of time series analysis*, *4*(4), pp.269-273.

Mensi, W., Hammoudeh, S., Nguyen, D.K. and Kang, S.H., 2016. Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics & Finance*, *42*, pp.257-276.

Mighri, Z. and Mansouri, F., 2013. Dynamic conditional correlation analysis of stock market contagion: evidence from the 2007-2010 financial crises. *International Journal of Economics and Financial Issues*, *3*(3), pp.637-661.

Minović, J.Z., 2009. Modeling Multivariate Volatility Processes: Theory and Evidence. *Theoretical & Applied Economics*, *16*(5).

Missio, S. and Watzka, S., 2011. Financial contagion and the European debt crisis. CESifo, Munich. Germany. Working Paper 3554.

Morema, K. and Bonga-Bonga, L., 2020. The impact of oil and gold price fluctuations on the South African equity market: volatility spillovers and financial policy implications. *Resources policy*, *68*, p.101740.

Naoui, K., Khemiri, S. and Liouane, N., 2010. Crises and financial contagion: the subprime crisis. *Journal of Business Studies Quarterly*, *2*(1), p.15.

Narayan, P.K. and Sharma, S.S., 2015. Does data frequency matter for the impact of forward premium on spot exchange rate? *International Review of Financial Analysis*, *39*, pp.45-53.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, pp.347-370.

Nugroho, D.B., Kurniawati, D., Panjaitan, L.P., Kholil, Z., Susanto, B. and Sasongko, L.R., 2019, August. Empirical performance of GARCH, GARCH-M, GJR-GARCH and log-GARCH models for returns volatility. In *Journal of Physics: Conference Series* (Vol. 1307, No. 1, p. 012003). IOP Publishing.

Peters, J.P., 2001. Estimating and forecasting volatility of stock indices using asymmetric GARCH models and (Skewed) Student-t densities. *Preprint, University of Liege, Belgium*, *3*, pp.19-34.

Pretorius, E., 2002. Economic determinants of emerging stock market interdependence. *Emerging Markets Review*, *3*(1), pp.84-105.

Racine, J.S., 2012. Entropy-based inference using R and the np package: a primer. *R package vignette, version 0.40-13, URL http://CRAN. R-project. org/package= np*.

Read, C., 2009. “America Sneezes and the World Catches a Cold.” In *Global Financial Meltdown* (pp. 144-148). London: Palgrave Macmillan,.

Reserve Bank of Australia. The Global Financial Crisis. https://www.rba.gov.au/education/resources/explainers/the-global-financial-crisis.html

Reuters., 2020. Pandemic won’t cause euro debt crisis, but a North-South divide. https://www.reuters.com/article/us-health-coronavirus-eu-debt-analysis-idUSKCN2240N6

Rigobon, R., 2002. International Financial Contagion: Theory and Evidence in Evolution. Research Foundation of AIMR. Charlottesville, Virginia:

Robinson, P.M., 1991. Consistent nonparametric entropy-based testing. *The Review of Economic Studies*, *58*(3), pp.437-453.

Ruiz-Marín, M., Matilla-García, M., Cordoba, J.A.G., Susillo-González, J.L., Romo-Astorga, A., González-Pérez, A., Ruiz, A. and Gayán, J., 2010. An entropy test for single-locus genetic association analysis. *BMC genetics*, *11*(1), pp.1-15.

Samarakoon, L.P., 2017. Contagion of the Eurozone debt crisis. *Journal of International Financial Markets, Institutions and Money*, *49*, pp.115-128.

Sutela, P., 2010. Russia’s response to the global financial crisis. *Электронный ресурс].-Режим достуна: http://carnegieendowment. org*.

Temkeng, S.D. and Fofack, A.D., 2021. A Markov-switching dynamic regression analysis of the asymmetries related to the determinants of US crude oil production between 1982 and 2019. *Petroleum Science*, *18*(2), pp.679-686.

Wälti, S., 2012. The myth of decoupling. *Applied Economics*, *44*(26), pp.3407-3419.

Willett, T.D., Liang, P. and Zhang, N. 2011. " Global Contagion and the Decoupling Debate", Chapter 9. In: Cheung, Y.-W., Kakkar, V. and Ma, G. (Eds.) The Evolving Role of Asia in Global Finance. Frontiers of Economics and Globalization, 9, pp.215-234. Bingley: Emerald Group Publishing Limited, https://doi.org/10.1108/S1574-8715(2011)0000009014

Appendix

Table 4a: Univariate EGARCH (1,1) estimation results

Equity Indices	α	β	γ	$\chi(10)^2$ Ljung- Box test	P-value -Diagnostic test
SP500	-0.134446 (0.000000)	0.984116 (0.000000)	0.106849 (0.000000)	56.473	1.674e-08
MSCI Euro	-0.116770 (0.000000)	0.986741 (0.000000)	0.124457 (0.000000)	55.368	2.695e-08
Bovespa	0.080847 (0.000000)	0.980003 (0.000000)	0.136637 (0.000000)	36.428	7.105e-05
Bsesn	-0.101913 (0.000000)	0.977264 (0.000000)	0.179921 (0.000000)	51.497	1.414e-07
Jalsh	-0.073210 (0.000000)	0.982028 (0.000000)	0.143473 (0.000000)	39.686	1.924e-05
XU100	-0.050611 (0.000002)	0.978928 (0.000000)	0.191782 (0.000000)	58.111	8.237e-09
Moex	-0.039302 (0.000025)	0.987829 (0.000000)	0.210850 (0.000000)	51.329	1.519e-07

Source: Author's calculations