ANALYZING ASSET MARKET CONTAGION DURING CRISES FROM EMERGING ASIAN MARKETS TO THE US

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Abstract

This paper investigates whether, during the Asian crisis, the dotcom bubble, and the global crisis, contagion occurred from emerging Asian markets to the US through the stock market. More specifically, this paper explores price comovements between emerging Asian markets (India, Indonesia, the Philippines, Thailand), and two separate control groups (Japan and Europe). The indices selected to represent these markets were the SSEC, BSESN, TOPX, JKSE, SETI, STOXX50, PSI, HSI, and the S&P500. I analyzed a 20-year period from January 1997 to December 2016. The results imply that all markets I studied share interdependence with the US; furthermore, China demonstrates the least amount of price comovements with the US. Finally, I showed that during both the Asian crisis and the dotcom bubble countries such as India, Hong Kong, and Europe, actually de-coupled their markets from the US's.

KEYWORDS: (Contagion, Asian crisis, dotcom bubble, global crisis, price comovements, GARCH, conditional heteroskedasticity, interdependence)
JEL CODES: (A22, C32, E23, E24, E52, G01, G15)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS

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1. Introduction

Stock price comovements have been at the center of modern financial theory for decades, as this question is an important issue for bankers, investors and policymakers alike (Chlibi, Jawadi and Sellami, 2015). The sign and strength of price comovements can directly affect investment and portfolio choices, risk management and diversification benefits (Chlibi, Jawadi and Sellami, 2015). The possibility of discontinuities in international transmission mechanisms in the wake of a crisis is hugely relevant issue. After all, the benefits of diversification for international investors are smaller if cross-country correlations of asset returns are significantly higher in periods of crisis. In this case, portfolio diversification may fail to deliver exactly when its benefits are needed most (Horen, Jager and Klaassen, 2006).

Generally, financial contagion is defined as an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market. There is extensive literature on financial contagion during various crises that occurred in the last three decades (see for example, Horen, Jager and Klaassen, 2006; Kenourgios, 2013; and Deltuvaite, 2017, among others). Most of the earlier research on financial contagion in general has taken the form of cross-country studies aiming to assess whether the occurrence of a crisis in one country or group of countries increases the probability of a crisis in another country. This literature is directed at identifying the linkages through which a crisis spreads without distinguishing between tranquil periods and crisis periods (Horen, Jager and Klaassen, 2006). The early research on the transmission of crises used a range of different methodologies, such as cointegration and vector error correction models,

models of interdependence, ARCH (autoregressive conditionally heteroskedastic) and GARCH (generalized autoregressive conditionally heteroskedastic) specifications, models of asymmetries and nonlinearities, principle components and spillover models and the correlation breakdown analysis (Dungey et al., 2005). More recent transmission studies make a distinct difference between normal interdependence (spillovers), that is the propagation of shocks due to fundamental real and financial linkages that were also prevalent during tranquil times, and contagion, which implies a regime change in the 'factors' driving the transmission of negative shocks (Horen, Jager and Klaassen, 2006).

In this paper I follow the approach of more recent studies. I define contagion as the spread of a shock during a crisis from one country to another beyond any normal interdependencies between the countries (Horen, Jager and Klaassen, 2006). This enables me to distinguish between theories that shocks are transmitted through stable, financial linkages versus theories that argue that investors behave differently during a crisis, leading to the propagation of shocks. Also, the contagion definition provides a relatively straightforward test of contagion, as a significant increase of comovement during a crisis period is evidence of contagion.

Since the publication of the Forbes and Rigobons (2002) paper on Sovereign Credit Risk Co-movements in the Eurozone, scholars have been using more advanced techniques to avoid the restrictions of the approaches mentioned earlier. These are dynamic conditional correlation-DCC models (Chiang, Jeon and Li, 2007; Kenourgios, Samitas and Paltalidis, 2011), regime-switching models (Boyer, Kumagai and Yuan, 2006), and copulas with and without regime-switching

(Okimoto, 2008). However, to employ these models accurately goes beyond the scope of this paper.

The US market is generally considered as the leader market as well as the source of the recent global financial crisis. For these reasons, I evaluate price comovements in the other markets in relation to the US market to test whether the latter did indeed drive the other markets or not. Most literature focuses on the US's interdependence with more developed countries such as Europe or Japan so I decided to expand on this by looking at price comovements in the Asian Emerging Markets in relation to the US. This way, I can see whether investing in emerging markets really does lead to increased portfolio diversification, as a result of their lack of interdependence with the US.

I looked at five emerging Asian markets: China, India, Indonesia, the Philippines, and Thailand. I also include both the European and the Japanese markets in order to identify any differences between interdependence between developed countries versus developed and emerging countries. As I mentioned earlier, early studies of interdependence studied price comovements without identifying whether this transmission mechanism differs between tranquil and crisis periods. Unfortunately, this group typically uses probit/logit and GARCH models (Horen, Jager and Klaassen, 2006). So, in order to account for my definition of financial contagion, I need to expand my GARCH model. I did this by adding dummy variables for each of the three crises within the time period of my study, the Asian currency crisis, the dotcom bubble, and the global crisis of 2008. Next I generated interactive variables between all these dummy variables and each of the indices in my study, that way I can analyze how each index affected the US during each crisis.

The results of this paper demonstrate that all markets I studied share interdependence with the US, implying that international diversification doesn't necessarily decrease a portfolios risk because these markets move more or less in tandem; however, there is still some benefit to diversification since all of the correlations are less than 1. According to my study, China demonstrates the least amount of price comovements with the US so this would be an ideal country for diversification. Finally, I showed that during both the Asian crisis and the dotcom bubble markets in countries such as India, Hong Kong, and Europe, actually de-coupled from the US market. This indicates that during these two crises, portfolio diversification actually was beneficial in maintaining regular returns. I demonstrated that, in general, interdependence exists between the countries included in my study and the US. However, portfolio diversification is beneficial in times of crisis because some markets do tend to de-couple during these periods.

The remainder of this paper is structured as follow. Section 2 presents a brief review of the literature. Section 3 analyzes the data. The model is described in Section 4. The main econometric tests and empirical results are discussed in Section 5. Section 6 concludes.

2. Literature Review

There have been countless research papers over the years that have studied the effects of interdependence and cross-market contagion. Financial contagion is defined as an episode in which there is a significant increase in cross-market linkages after a shock occurs in one market (Forbes and Rigobon, 2002; and Kaminsky, Reinhart and Vegh, 2003, among others). The existence of contagion has been a controversial topic of discussion since the 1980s. A consensus formed as to its existence during the decade starting from 1990 (Koch and Koch 1991), but this was met with criticism and there followed a denial of its existence in the late 1990s and early 2000s (Forbes and Rigobon 2002). Nevertheless, some evidence for its existence during certain periods and in certain markets emerged again in the early 2000s until the present (Rigobon 2003). The sign and intensity of price comovements can directly affect investment and portfolio choices, risk management and diversification benefits (Obstfeld, 1994). From a theoretical point of view, the combination of several phenomena (liberalization, decompartmentalization, desintermediation and deregulation) leads to an increase in price comovements and convergence between financial markets that together result in financial globalization (Chlibi, Jawadi and Sellami, 2015). Liberalization and deregulation similarly affect the process of increased financial globalization because these two phenomena have to led increases in the prevalence of private institutions, as well as a general thinning of the restrictions on these private institutions. Investors are constantly seeking to beat the market and find new, innovative ways to increase returns, while still maintaining a low risk profile. This has resulted in an increased emphasis on portfolio diversification. Disintermediation is the withdrawal of funds from intermediary financial institutions, such as banks and savings and loan associations, to invest them directly. Disintermediation generally leads to investments that yield higher returns because transaction costs are removed. These higher yields give investors more available capital to play around with, which has inevitably led them to expand globally, as they seek to maximize returns while minimizing risk. Financial globalization has accelerated rapidly over the last two decades, due in large part to the implementation of information and communication tools, which has lowered costs to transacting across border, so now the impetus to diversify ones portfolio globally has risen.

The various research papers that have been devoted to studying stock market comovement/contagion can be categorized into three groups. The first group focuses on the existence of financial contagion in international markets. Studies by Peng and Lon Ng (2011), Kenourgios and Christopoulos (2013), and Chlibi and Jawadi (2015) explore the cross-market dependence between various popular world equity indices. Peng and Lon Ng (2011) analyze the cross-market dependence between the S&P 500, NASDAQ 100, DAX 30, FTSE 100, and Nikkei 225, and their corresponding volatility indices (VIX, VXN, VDAX, VFTSE, and VXJ). They proposed a dynamic mixed-copula approach, which is able to capture the time-varying tail dependence coefficient (TDC). Their findings indicate the existence of financial contagion and significant asymmetric TDCs for major international equity markets. In some situations, although contagion cannot be clearly detected by stock index movements, it can be captured by dependence between the volatility indices.

Kenourgios and Christopoulos (2013) investigate the contagion effects of the 2007-2009 global financial crisis across multiple asset markets and different regions. They utilize daily return data of six asset classes: stocks, bonds, commodities, shipping, foreign exchange and real estate. An analysis of financial contagion is provided by estimating and comparing asymmetric conditional correlations among asset markets during stable and turmoil periods. Their results provide evidence on the existence of a channel of information as a contagion mechanism among the US stocks, real estate, commodities and the emerging Brazilian bond index. Chlibi and Jawadi (2015) investigate the hypothesis of stock price comovements between the US market and four different regions (the G6, the BRICS, the MENA region-Middle East North Africa) during calm and crisis periods. They use different econometric approaches (BEKK-GARCH model, cointegration tests, and panel cointegration tests), and check the interdependence of these markets in the short and the long term. Their findings point to the importance of heterogeneity linked to the stock price adjustment process, inviting individual analysis to be carried out according to market specificities in the aim of identifying countries that are sources of investment opportunities. They also highlighted the presence of time-varying stock price comovements that significantly increased after the subprime crisis.

The second group of studies emphasizes structural change. Poshakwale and Mandal (2016) study the economic and non-economic sources of stock return comovements of the emerging Indian equity market and the developed equity markets of the US, UK, Germany, France, Canada and Japan. Their findings show that the probability of extreme comovements in the economic contraction regime is relatively higher than in the economic expansion regime and they show that international interest rates, inflation uncertainty and dividend yields are the main drivers of the asymmetric return comovements. Bekaert and Ehrmann (2011) use the 2007-09 financial crisis as a laboratory to analyze the transmission of crises to country-industry equity portfolios in 55 countries. They use a factor model to predict crisis returns, defining unexplained increases in factor loadings and residual correlations as indicative of contagion. They find statistically significant evidence of contagion from US markets and from the global financial sector, but the effects are economically small. By contrast, they found there has been substantial contagion from domestic equity markets to individual domestic equity portfolios, with its severity inversely related to the quality of countries' economic fundamentals and policies. They found that countries with high political risk, large current account deficits, large unemployment and high government budget deficits experienced a high degree of contagion. They also found that the introduction of debt and deposit guarantees during the crisis helped insulate domestic equity markets to an economically and statistically significant extent from the impact of the crisis through reducing the exposures to global, US and domestic factors.

The third group of studies examines the industry/sector portfolio correlation, rather than aggregate market portfolio correlations (Beckers et al. 1996; Berben and Jansen 2005; Chelly-Steely 2005; Bekaert et al. 2009). These studies are motivated by an observation that if the correlation of market returns across countries is rising, the benefit of portfolio diversification in different countries is declining. The issue then becomes whether the benefit can be achieved by sectoral diversification. Chiang and Lao (2016) investigate the dynamic correlations of Chinese stock returns with those of global markets. To examine the scope of the correlations, they test the correlations at both the market level and the sectoral level. Geographically, they select three major trading partners—Hong Kong, South Korea, and Japan—and more distant markets—Europe and the US; the latter two markets represent more advanced global markets. They derive several important empirical conclusions. First, estimations based on an asymmetric dynamic correlation coefficient model (ADCC) indicate that all dynamic conditional correlations at the market level are time-varying and display structural breaks. Second, the dynamic correlations display smoothing transitional upward changes over time at the market level. The evidence indicates that the stock returns of the financial sector exhibit the highest correlation across countries among 10 sectors. Low correlations are present in the health care, telecommunications, and utilities sectors. The correlations are closely tied to geographic location: the correlation with Hong Kong is the highest, followed by South Korea, Japan, Europe and the US.

Various studies have employed an ever-varying degree of tests to measure the effects of financial contagion. A number of studies (Forbes and Rigobon 2002; Corsetti et al. 2005; Dungey et al. 2005) test for correlation coefficient shift using data from two sub-periods: a tranquil period versus a volatile period. Since these models provide no specific factors to explain the return variations, Bekaert et al. (2005) propose a two-factor asset pricing model or a Fama–French three-factor model to examine equity market contagion in the regions of Europe, Latin America, and Asia during both the Mexican and Asian crises (Chiang and Lao (2016)).

Kenourgios and Christopoulos (2013) take a different approach. To provide an analysis of financial contagion, the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello, Engle and Sheppard (2006), who generalized the DCC-GARCH model of Engle (2002), is employed. Countless other studies use Markov regime-switching models to identify the crisis period endogenously (Boyer, Kumagai and Yuan, 2006; and Dungey et al., 2011). Bekaert and Ehrmann (2011) develop a three-factor model, based on existing fundamentals, to set a benchmark for what global equity market comovements are expected to be. This model distinguishes between a US-specific factor, a global financial factor and a domestic factor. They define contagion as the comovement in excess of that implied by the factor model. Chiang and Lao (2016) believe that current wisdom says that dynamic conditional correlation models (Engle 2002; Cappiello et al. 2006) with asymmetric dynamic conditional correlation (ADCC) should be used to estimate time-varying correlations, since this model is more general and does not suffer from the dimension problem. As Engle proved, DCC models have the flexibility of univariate GARCH models coupled with parsimonious parametric models for the correlations. They are not linear but can often be estimated very simply with univariate or two-step methods based on the likelihood function. It is shown that they perform well in a variety of situations and provide sensible empirical results (Engle, 1999). Peng and Ng (2011) apply a mixed Gumbel-Clayton (MGC) copula approach in their study, as the commonly used t-copula is restricted to symmetry. Moreover, the MGC copula can model the special cases where there is only upper or lower tail dependence, which gives it more flexibility in asymmetric tail dependence modeling compared to the copulas suggested by Patton (2006) and Ammann and Süss (2009).

Since the seminal work of Bollerslev (1990), multivariate GARCH models attracted considerable interest given their direct application in both financial and economic empirical research. By now, they represent a fundamental tool for asset and risk management and are employed in most financial market analyses (Billio and Caporin (2005)). I will be utilizing GARCH models to test the correlations of US stock returns with those of emerging Asian markets. This paper focuses on the US equity market and examines its dynamic movement with six emerging Asian markets: China, India, Indonesia, the Philippines, Hong Kong, and Thailand. I also include both the European and the Japanese markets in order to verify the geographic hypothesis of correlation comovements.

3. Data Analysis

3.1 Data Set

The data consists of monthly closing stock prices for developed and emerging markets, and were obtained from the Thomson Reuters Eikon database. All of the series are expressed in US dollars to avoid exchange bias. The data are classified in three distinct groups: the emerging Asian markets (India, Indonesia, the Philippines, Thailand), and two separate control groups (Japan and Europe). The US index is considered as the benchmark index to evaluate price comovements and financial integration of the other countries in relation to the US. I analyzed a 20-year period from January 1997 to December 2016. The indices I selected for each country were: China, The Shanghai SE Composite Index (SSEC); India, The S&P BSE Sensex Index (BSESN); Japan, The Tokyo Stock Exchange Tokyo Price Index (TOPX); Indonesia, The Jakarta SE Composite Index (JKSE); Thailand, The Stock Exchange of Thailand Index (SETI); Europe, The STOXX Europe 50 EUR Price Index (STOXX50); the Philippines, The Philippine Stock Exchange (PSI); Hong Kong, The Hang Seng Index (HSI); and the US, The S&P500 (S&P500). Following the conventional methodology, asset returns are calculated as the first difference of the natural log of each price index (Kenourgios, Christopoulos and Dimitriou, 2013). I used Stata to analyze the data and computed the descriptive statistics of the stock returns and reported them in Table 1. Next, in order to provide a preliminary overview of price comovements, I computed the pairwise correlations between the various indices and reported them in Table 2.

Table 1 Descriptive Statistics

Country	Obs	Mean	Std. Dev.	Min	Max
USA	239	0.00537	0.044043	-0.16942	0.107723
Thailand	239	0.006351	0.084148	-0.30176	0.328799
Europe	239	0.002915	0.047389	-0.1456	0.116179
Hong Kong	239	0.004735	0.072439	-0.29407	0.288132
Indonesia	239	0.011777	0.078994	-0.31515	0.284274
China	239	0.008164	0.081027	-0.24632	0.320561
India	239	0.011144	0.0704413	-0.2389	0.282551
Japan	239	0.001784	0.051966	-0.20258	0.131416
Philippines	239	0.005411	0.070942	-0.25837	0.393287

Overall, most of the monthly returns in mean are near zero, which would be expected because there are typically small returns for monthly changes. In general, the emerging markets have higher means, reflecting the potential upside in these markets; however, as expected, these markets also possess higher standard deviates, demonstrating the higher volatility and risk present in these markets. Indonesia and India showed the highest means, while Japan and Europe have the lowest means.

Table 2 Coerrelation Coefficients

	US	Thailand	Europe	Hong Kong	Indonesia	China	India	Japan	Philippines
US	1.0000								
Thailand	0.4880	1.0000							
Europe	0.8010	0.3928	1.0000						
Hong Kong	0.6567	0.5292	0.5892	1.0000					
Indonesia	0.4638	0.5857	0.4488	0.4366	1.0000				
China	0.2355	0.1138	0.1901	0.3101	0.1711	1.0000			
India	0.4852	0.3708	0.4087	0.5014	0.4444	0.2745	1.0000		
Japan	0.5523	0.3833	0.5789	0.4565	0.4237	0.2527	0.432	1.0000	
Philippines	0.4778	0.6312	0.3699	0.5363	0.5991	0.1331	0.3786	0.2932	1.0000

Looking at the correlation matrix I can see that Europe and Hong Kong have the highest correlations with the US, 0.8 and 0.7 respectively. This makes sense because I would expect correlations between the US market and developed countries to be higher than those with emerging markets. However, one would expect the correlation between the US and Japan to be higher than the correlation between the US and HK, since Japan is one of the preeminent developed markets, but I don't see this in the correlation matrix. This could be because the Hong Kong dollar is pegged to the US dollar, so policies or events that affect the US dollar directly affect the Hong Kong dollar and their entire economy. As a result, the Hong Kong economy would move relatively in tandem with the US economy. Another interesting thing to note is that China had by far the lowest correlation to the US (0.2), meaning it could be a very good market for portfolio diversification and risk mitigation.

3.2 Dependent Variable

In this paper I define contagion as the spread of a shock during a crisis from one country to another country beyond any normal interdependencies between the countries. To test for contagion, I thus needed a method that could identify a break in the transmission process. Regression models can deal with such breaks. At the same time, they allow us to control for macroeconomic fundamentals, common external shocks, and heteroskedasticity in a straightforward manner (Horen and Klaassen, 2006). As I am interested on the effects of financial contagion in international markets in relation to the US, I used the first difference of the natural log of the S&P500 as my dependent variable. I noted this variable as: r_{us}

3.3 Control Variables

A crisis can be transmitted through two channels: normal links or spillovers and contagion. Crisis spillovers result from links between countries that exist during both tranquil and crisis periods. For example, a major trade partner of a country where a financial crisis has caused a large currency depreciation will experience a decline in its exports to the crisis country and hence a deterioration in its trade account. Investors foresee this, which can cause a decline in asset prices and large capital outflows from the exporting country (Horen and Klaassen, 2006). In contrast to spillovers, contagion only occurs during a crisis. When the S&P500 shows a significant decrease during a crisis period this does not necessarily have to imply that contagion occurred. The increase in comovement during a crisis can also be the result of an increase in similarities of macroeconomic fundamentals or the occurrence of a common external economic shock. To test for the presence of contagion, it is thus important to control for these economic effects. I introduced three explanatory variables as controls. I used the US unemployment rate, federal funds rate, and industrial production index. I obtained this data from the United States Department of Labor Bureau of Labor Statistics and from FRED economic data St. Louis FED. Once again, I used the first difference of the natural log of the US industrial production data; however, since the unemployment rate and federal funds rate are already in percentages I only needed to subtract their values in time t_{t-1} from t to get the percentage point change. These variables will be called:

c_{unem}: unemployment rate control

$c_{indprod}$: industrial production control

$c_{fedfund}$: federal fund rate control

3.4 Dummy Variables

To analyze the effects of various crises on the S&P500 I generated dummy variables for any crises between 1997-2017. The dummy variables include:

Asia crisis: 1997-1998

Dotcom bubble: 1999-2000

Global financial crisis: 2007-2008

These variables will be called:

d_{asia}: Asia crisis

d_{dotcom}: dotcom bubble

d_{global}: global financial crisis

Determining the stationarity of a time series is a key step before embarking on any analysis. The statistical properties of most estimators in time series rely on the data being (weakly) stationary. Loosely speaking, a weakly stationary process is characterized by a time-invariant mean, variance, and autocovariance. In most observed series, however, the presence of a trend component results in the series being nonstationary. Furthermore, the trend can be either deterministic or stochastic, depending on which appropriate transformations must be applied to obtain a stationary series. For example, a stochastic trend, or commonly known as a unit root, is eliminated by differencing the series. A unit root is a feature of processes that evolve through time that can cause problems in statistical inference involving time series models. I can assume that I have loosely corrected for nonstationarity because the asset returns were calculated as the first difference of the natural log of each price index. However, to be sure my time series is indeed weakly stationary I checked for unit roots using two unit root tests: the Augmented Dickey-Fuller test (1981), and the Phillips-Perron test (1988). The results of these tests are displayed in table 3 and table 4.

Table 3 Phillips-Perron Test

Country	Obs	Newey-West lags	Z(rho)	Z(t)	p-value
USA	238	4	-222.712	-14.292	0.000
Thailand	238	4	-224.502	-14.644	0.000
Europe	238	4	-208.482	-13.259	0.000
Hong Kong	238	4	-214.563	-14.352	0.000
Indonesia	238	4	-186.752	-12.895	0.000
China	238	4	-220.324	-13.578	0.000
India	238	4	-241.490	-14.874	0.000
Japan	238	4	-204.330	-12.823	0.000
Philippines	238	4	-196.641	-13.110	0.000

Table 4 Augemented Dickey-Fuller Test

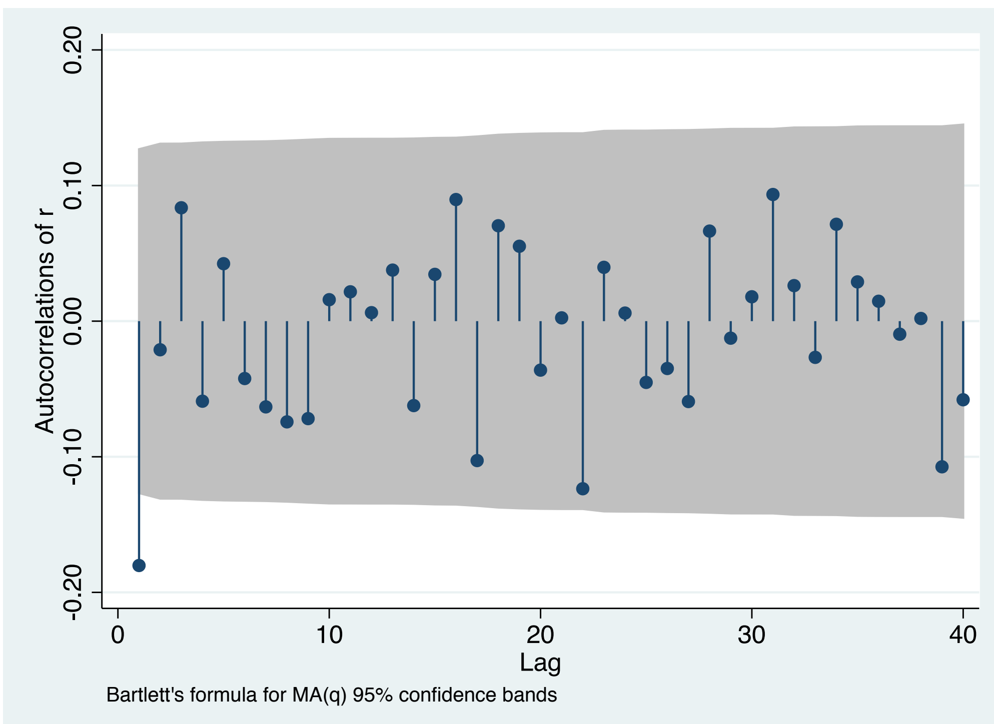
Country	Obs	Z(t)	p-value
USA	238	-14.282	0.000
Thailand	238	-14.648	0.000
Europe	238	-13.206	0.000
Hong Kong	238	-14.379	0.000
Indonesia	238	-12.995	0.000
China	238	-13.454	0.000
India	238	-14.828	0.000
Japan	238	-12.697	0.000
Philippines	238	-13.148	0.000

From these tests I can see that all of my variables pass both the Augmented Dickey-Fuller test and the Phillips-Perron test. I can reject the null hypothesis that my data possesses unit roots and assume that all variables are stationary.

4. The Model

Estimating the model using standard OLS could lead to some problems because the usual standard errors are not valid for two reasons. Using a standard OLS regression with the S&P500 as the dependent variable and all the international markets, controls and dummy variables as the independent variables led to some interesting observations. First, I found evidence of heteroskedasticity in the data, probably resulting from high volatility in financial markets during crisis periods. Second, standard autocorrelation tests indicated that autocorrelation occurred in the residuals, results are displayed in figure 1.

Figure 1 Correlogram of residuals



4.1 Interactive Variables

From the correlogram I could see that there is a lag period of one month, so a more intricate model was necessary to analyze my data. Another potential problem with the use of OLS is that this could lead to inconsistent estimates due to the existence of endogenous regressors and/or omitted variables (Horen and Klaassen, 2006). This is by no means a problem specific to my approach, but affects almost all methodologies applied in the contagion literature because as I demonstrated earlier the residuals' financial return data are almost always autocorrelated. As crises are typically characterized by turmoil in a number of countries, it may well be that events in one country affect the other country while the reverse also occurs. It has been proposed that by focusing exclusively on contagion coming from an individual country, where the crisis originated, limits the endogeneity problem (Horen and Klaassen, 2006). However, employing this method may increase the omitted variable bias in the model because now the regressor coefficients may be over or underestimating the effects of one of the other factors. This could be worse than including all the indices and having larger standard errors because it's hard to determine whether the model over or understated the regressor coefficients, which makes the coefficients much less certain. Including all the indices is less efficient because the standard errors will increase, but including all of them makes the coefficients more reliable. I tested this by running an OLS for each index individually in comparison to the S&P500. I also generated interactive variables between each of the indices and the dummy variables for the various crises in order to see how each index during each crisis affected the US. These variables will be called:

Hong Kong: $i_{hsiasia}$, $i_{hsidotcom}$, $i_{hsiglobal}$

Indonesia: $i_{jkseasia}$, $i_{jksedotcom}$, $i_{jkseglobal}$,

China: $i_{ssecasia}$, $i_{ssecdotcom}$, $i_{ssecglobal}$, India: $i_{bsesnasia}$, $i_{bsesndotcom}$, $i_{bsesnglobal}$,

Japan: $i_{topxasia}$, $i_{topxdotcom}$, $i_{topxglobal}$,

Philippines: $i_{psiasia}$, $i_{psidotcom}$, $i_{psiglobal}$,

Thailand: $i_{setiasia}$, $i_{setidotcom}$, $i_{setiglobal}$,

Europe: $i_{stoxxasia}$, $i_{stoxxdotcom}$, $i_{stoxxglobal}$.

4.2 Regression Formula

Isolating the indices and adding the interactive variables did improve my model so I decided to proceed by testing each index individually in relation to the S&P500. The above-mentioned considerations lead to the following example regression model for the HSI index:

$$r_{us} = \beta_{hk}r_{hk} + \alpha_{unem}c_{unem} + \alpha_{indprod}c_{indprod} + \alpha_{fedfund}c_{fedfund} + \delta_{asia}d_{asia} + \delta_{dotcom}d_{dotcom} + \delta_{global}d_{global} + \gamma_{hsiasia}i_{hsiasia} + \gamma_{hsidotcom}i_{hsidotcom} + \gamma_{hsiglobal}i_{hsiglobal} + \varepsilon_{us} \quad \textbf{(4.2)}$$

Where r_{hk} is the monthly percent change of the HSI and the linkage effect β for the index is the level of interdependence between the Hong Kong markets and the US's. If HK and the US experience price comovements, β is positive. The impact of the macroeconomic fundamentals is captured by α and has a negative expected sign for α_{unem} and $\alpha_{fedfund}$ and a positive expected sign for $\alpha_{indprod}$. The impact of the three crises is captured by δ and has a negative expected sign. The impact of the interactive variables is captured by γ and has an unknown expected value because if the $\gamma's$ are positive, the indices moved together with the S&P500 more during these crises, whereas if they are negative during the crises then the indices were de-coupling during this time period. If contagion takes place from HK to the US during any of these crises, γ is positive. Finally, the mean zero disturbance term is represented by ε_{us}. Because of the reasons mentioned above I moved away from standard OLS models and progressed to a more intricate model to fit my data.

4.3 ARCH/GARCH Models

Due to the contagion reactions in financial markets, consistent price or volatility changes will occur in the same types of financial markets between the same areas, in the same types of financial markets between different areas, or in similar types of financial markets between different areas. Thus, to effectively analyze the contagion reactions and appropriately measure the consistent price volatility in the financial markets I needed a model that could account for this conditional heteroskedasticity (Zhou et al. 2016). A number of researchers have demonstrated that ARCH/GARCH models are useful for estimating comovements in asset returns (Chiang et al. 2007a, b; Yu et al. 2010; Kenourgios et al. 2011; Lahrech and Sylwester 2011), since the model is capable of capturing volatility clustering and of addressing this issue of heteroskedasticity raised by Forbes and Rigobon (2002) (Chiang, Lao, and Xue, 2015).

An ARCH model is a model for the variance of a time series. ARCH models are used to describe a changing, possibly volatile variance. Although an ARCH model could possibly be used to describe a gradually increasing variance over time, most often it is used in situations in which there may be short periods of increased variation. If an autoregressive moving average model (ARMA model) is assumed for the error variance, the model is a generalized autoregressive conditional heteroscedasticity (GARCH) model. A GARCH model uses values of the past squared observations and past variances to model the variance at time *t*. There are many different versions of ARCH and GARCH tests depending on the specification of the model. Which model you use is determined by your data and the ideal lagging period. Since I could assume that my data follows an ARMA model for my error variance, I used a GARCH model. The next step was to determine the autoregressive order (p) and the moving average order (q) and this could be done graphically. To determine the moving average and the autoregressive order I looked back at the correlogram of the residuals I generated earlier, see figure 1. From the correlogram I could see that the optimal lag period is one month, so q/p = 1, therefore all variables were lagged one month. I present the GARCH tests hereafter and discuss the main findings.

5. Results

I estimated the GARCH model over the period February 1997 to December 2016 for all the countries, individually, in relation to the US and reported the results in tables 5-6. Note: I needed to use an ARCH model for the Hang Seng Index because when using a GARCH model a flat log likelihood was encountered, so I couldn't find uphill direction.

5.1 Regression Analysis

Accordingly, I noted some interesting results. First, all the indices' coefficients were significant and, as expected, they were all positive, implying interdependence between these markets. Also, Europe and Hong Kong possessed the largest coefficients, 0.75 and 0.51 respectively, further affirming the pairwise correlations depicted in table 2 and proving that price comovements are most prevalent between the US and Europe and the US and Hong Kong. Furthermore, Japan possessed the third largest coefficient at 0.34, while all the emerging markets demonstrated coefficients below 0.3, with China demonstrating by far the lowest coefficient at 0.09, the second lowest being the Philippines at 0.25. This was also expected as I assumed that the developed markets would possess stronger price comovements with the US whereas the emerging markets would share less interdependence with the US.

Table 5 GARCH Models of Market Returns from 1997m2-2016m12

N=239	US-Thailand	US-Europe	US-HK	US-Indonesia
Country	0.285***	0.747***	0.512***	0.267***
	(5.56)	(16.13)	(11.61)	(5.15)
Asia Crisis	0.0161*	0.00259	0.0206*	0.0222**
	(2.42)	(0.47)	(2.53)	(2.77)
Dotcom Bubble	0.000896	-0.00457	-0.00469	0.00498
	(0.13)	(-0.87)	(-0.76)	(0.72)
Global Crisis	-0.0107	-0.00462	-0.0132	-0.0111
	(-1.60)	(-0.54)	(-1.74)	(-1.92)
Unemployment Rate	-0.0268	-0.0101	-0.0396**	-0.0271
	(-1.62)	(-1.13)	(-2.90)	(-1.62)
Federal Fund Rate	0.0117	-0.0162	0.00389	-0.00211
	(0.88)	(-1.64)	(0.32)	(-0.15)
Industrial Production	-0.425	-0.414**	-0.591*	-0.561
	(-1.45)	(-2.81)	(-2.34)	(-1.70)
Interactive Asia Crisis	-0.0973	-0.155*	-0.237**	-0.0528
	(-1.65)	(-2.09)	(-2.80)	(-0.82)
Interactive Dotcombubble	-0.0513	-0.160*	-0.203*	-0.133
	(-0.52)	(-1.98)	(-2.23)	(-1.48)
Interactive Global Crisis	0.0221	0.149	-0.156	0.0276
	(0.27)	(1.41)	(-1.92)	(0.36)
_cons	0.00446	0.00567**	0.00401	0.00326
	(1.64)	(3.26)	(1.52)	(1.20)
ARCH				
L.arch	0.151*	0.422**	0.109	0.176*
	(2.19)	(3.19)	(1.14)	(2.24)
L.garch	0.810***	0.0160	n/a	0.799***
	(10.08)	(0.11)	n/a	(9.23)
_cons	0.0000570	0.000393***	0.000834***	0.0000447
	(0.99)	(4.80)	(8.23)	(1.04)
t statistics in parentheses	="* p<0.05	** p<0.01	*** p<0.001"	

Table 6 GARCH Models of Market Returns from 1997m2-2016m12

N=239	US-China	US-India	US-Japan	US-Philippines
Country	0.0899* (2.57)	0.268*** (6.11)	0.338*** (6.55)	0.249*** (4.84)
Asia Crisis	0.0250*** (3.66)	0.0176* (2.16)	0.0199** (2.72)	0.0204* (2.21)
Dotcom Bubble	0.00302 (0.39)	0.00859 (1.05)	-0.00238 (-0.36)	0.00494 (0.70)
Global Crisis	-0.0214** (-2.91)	-0.0110* (-2.13)	-0.00194 (-0.31)	-0.00705 (-0.90)
Unemployment Rate	-0.0146 (-0.77)	-0.0281* (-2.02)	-0.0174 (-1.09)	-0.0268 (-1.49)
Federal Fund Rate	-0.00611 (-0.40)	-0.0116 (-0.91)	-0.00546 (-0.45)	-0.00722 (-0.44)
Industrial Production	-0.757** (-2.82)	-0.199 (-0.91)	-0.125 (-0.37)	-0.316 (-1.30)
Interactive Asia Crisis	-0.203 (-1.81)	0.109 (1.21)	0.251* (2.32)	0.0224 (0.31)
Interactive Dotcombubble	-0.0527 (-0.56)	-0.360** (-3.01)	0.0577 (0.25)	-0.0743 (-0.81)
Interactive Global Crisis	0.113 (1.90)	0.106 (1.59)	0.246** (2.66)	0.155 (1.53)
_cons	0.00877** (3.06)	0.00254 (1.13)	0.00461 (1.84)	0.00417 (1.39)
ARCH				
L.arch	0.387** (3.15)	0.221* (2.46)	0.156* (2.04)	0.155 (1.93)
L.garch	0.524*** (4.14)	0.769*** (9.25)	0.811*** (8.98)	0.787*** (7.23)
_cons	0.000232 (1.83)	0.0000377 (1.03)	0.0000459 (0.94)	0.0000837 (1.16)
t statistics in parentheses	="* p<0.05 ** p<0.01 *** p<0.001"			

One explanation for China's extremely low coefficient could be a result of the various difficulties foreigners face when tying to purchase Chinese shares. For a long time foreign institutions weren't allowed to purchase Chinese shares. Since 2003, select foreign institutions are allowed to purchase what are known as A-shares through a program called the Qualified Foreign Institutional Investor (QFII) system. A-shares are shares of mainland China-based companies that trade on the two Chinese stock exchanges, that is, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Because foreign investors are restrained by the QFII system less people manage to invest in China which, as a result, limits the price comovements between the US and China. As China grows from an emergent market to one of the advanced economies of the world, there is a tremendous demand for Chinese equity. Regulators at the stock exchanges continue the ongoing process of attempting to make A-shares more broadly available to foreign investments, but just having the shares recognized by the world's investors has been a struggle. On July 2016, MCSI, a leading provider of investment decision support tools worldwide declined to add mainland-traded Chinese A-shares in its key emerging market index. The main reasons for this were concerns over market accessibility and the monthly limit on capital repatriation for foreigners. In the future Chinese shares could become more available to foreign investors and, as a result, one would expect their interdependence with the US to increase, but as of now I can infer from the data that China's markets are relatively independent of the US.

In general, the dummy variables weren't significant, except for the dummy variable for the Asian crisis, which was significant for every regression except for

Europe's. Interestingly, the coefficient for the Asian crisis was always positive, implying that US stocks actually performed well during the Asian crisis which, upon looking closer at the S&P500 returns during that period, makes sense because the average percent change for that period was a 2.1% increase in the S&P500. The dummy variable for the global crisis was significant only once, during the Indian regression, and had a negative coefficient, but in every other regression it was also negative which is a good sign. It would have been worrying to see any positive values for that coefficient since the global crisis was undoubtedly the worst financial crisis since the Great Depression of the 1930s. I expected the S&P500 to perform poorly during this time period, which my results demonstrate.

The interactive variables were the most interesting. In general, almost half the interactive variables were significant and the other half weren't; however, when they were significant, their coefficients told an interesting story. Looking at the regression for Japan, I found that both the interactive variable for the Asian crisis and the global crisis were significant and had positive coefficients. From this I can assume that the price comovements between the US and Japan increased during both the Asian crisis and the global crisis. This is an interesting find because earlier I noted how throughout the Asian crisis the S&P500 actually experienced a net gain, so one would assume that Japan and the US experienced less price comovements since one would assume that the Japanese markets underperformed during the Asian crisis. Looking closer at the data I found that TOPX was indeed underperforming at that time. The average percent change for that period was a 0.9% decrease, so it's strange that the interactive term shows that during the Asian crisis the US and Japan actually experienced more interdependence because the US experienced a net gain during that period while Japan experienced a net loss during that same period. One possible explanation for this could be that, in general, Japan and the US don't share much interdependence, but during the Asian crisis they could have experienced more price comovements than usual, resulting in a positive coefficient for the interactive variable for the Asian crisis. A positive coefficient for the global crisis makes sense because, even though the crisis began in the US, it quickly spread globally and affected countless markets worldwide. I assumed that during that period a developed country like Japan should move in tandem with the US, and that's what I see here.

As for my regression on India I noticed that the interactive variable for the dotcom bubble was significant and had a negative coefficient, implying that the interdependence between India and the US decreased during the dotcom bubble. This makes sense because the dotcom bubble was largely focused in the US. On April 14, 2000 the S&P500 fell 84%, its third largest daily point loss ever. The stock market crash of 2000–2002 caused the loss of $5 trillion in the market value of companies from March 2000 to October 2002. Many dotcoms ran out of capital and were acquired or liquidated. In response to such a serious market crash, the Indian market could have began de-coupling from the US market. In order to protect itself against potential future losses it is possible that India re-allocated its assets to other, less volatile markets. Another possibility is that the dotcom bubble became such an important driver of the US market that US securities became less dependent on foreign valuations and instead became much more domestically driven. Looking at the other interactive terms for the dotcom bubble I found that all of them were negative, except for the regression for Japan. Even though none of them were significant, this further affirms that the Indian market probably de-coupled from the S&P500 during the dotcom bubble or that the dotcom bubble became such a significant crisis that it began to drive and dictate the direction of the US market. Every market, except Japan, appears to have experienced less price comovements with the US during the dotcom bubble.

Looking at the regression for Hong Kong, I discovered that both the interactive terms for the Asian crisis and the dotcom bubble were significant and had negative coefficients. Once again, I can assume that the interdependence between Hong Kong and the US decreased during both the dotcom bubble and the Asian crisis. These values make sense because, as mentioned previously, the dotcom bubble was largely a US issue so, like India, the Hong Kong market probably de-coupled from the US market or the crisis began to drive the US market in a direction separate from Hong Kong's. The reason a negative coefficient for the Asian crisis also makes sense is largely because of a very similar reason. The Asian financial crisis gripped much of East Asia beginning July 1997 and raised fears of a worldwide economic meltdown due to financial contagion. The crisis started in Thailand with the financial collapse of the Thai baht. As the crisis spread, most of Southeast Asia and Japan saw slumping currencies, devalued stock markets and other asset prices, and a precipitous rise in private debt. Indonesia, South Korea and Thailand were the countries most affected by the crisis. However, Hong Kong, Laos, Malaysia and the Philippines were also hurt by the slump. This could be related to general movement out of emerging markets during the Asian crisis. The US market in response to this spreading financial contagion probably also began de-coupling from that of Hong Kong's or the widespread financial contagion began driving Hong Kong's market in a different direction from the US's, resulting in a negative coefficient for the interactive term for the Asian crisis.

Lastly, I analyzed my regression on Europe. I found that both the interactive terms for the Asian crisis and the dotcom bubble were significant and had negative coefficients. Once again, I can assume that price comovements between Europe and the US decreased during both the Asian crisis and the dotcom bubble. The coefficient for the dotcom bubble makes sense, because of reasons stated earlier, but the coefficient for the Asian crisis is perplexing. It could once again be because Europe, in order to protect against potential future losses due the financial contagion spreading out of Asia, transferred its international assets towards domestic prospects, which led to its de-coupling from the US market as well. In this instance it's hard to see the Asian crisis driving the European market very significantly, so I would hypothesize in this instance that either Europe or the US focused their assets on more domestic prospects rather than international ones.

6. Conclusion

This paper studied the contagion effects of three crises on the US stock market: the Asian currency crisis, the dotcom bubble, and the global crisis of 2008. Furthermore, this paper analyzed the price comovements of six emerging Asian markets and two developed markets toward the US market in the long term. To this end, GARCH models were carried out for China, India, Indonesia, Philippines, Hong Kong, Thailand, Europe, and Japan. This area of investigation is of importance as it can help to enhance portfolio choice, diversification strategies and risk management. I demonstrated that all markets I studied shared some interdependence with the US, implying that international diversification doesn't significantly decrease a portfolios risk because these markets move more or less in tandem; however, there is still some benefit to diversification since all of the correlations are less than 1. According to my study, China demonstrates the least amount of price comovements with the US so this country could provide interesting diversification benefits. Lastly, I showed that during both the Asian crisis and the dotcom bubble markets in countries such as India, Hong Kong and Europe actually de-coupled from the US market. This indicates that portfolio diversification was actually beneficial during these two crises. My study demonstrated that, in general, interdependence exists between the countries included in my study and the US. However, portfolio diversification is beneficial in times of crisis because some markets tend to de-couple during a crisis. This present study can be extended to test Japan and Europe as the dependent variables. This study could also shed light on whether or not, during the crises I studied, the de-coupling of the markets I noticed was a result of investors pulling out of emerging markets and putting their assets into the developed, more stable ones, or whether it was only the US market that de-coupled from the emerging markets and the other developed markets actually did suffer from the financial contagion resulting from these two crises.

7. References

11.1: ARCH/GARCH Models. (n.d.). Retrieved March 07, 2017, from https://onlinecourses.science.psu.edu/stat510/node/78

Aloui, R., Aïssa, M. S., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure. *Journal of Banking & Finance, 35*(1), 130-141. doi:10.1016/j.jbankfin.2010.07.021

Asai, M., & Mcaleer, M. (n.d.). Dynamic Conditional Correlations for Asymmetric Processes. *SSRN Electronic Journal*. doi:10.2139/ssrn.1464325

Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market Integration and Contagion. *The Journal of Business,78*(1), 39-69. doi:10.1086/426519

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2011). Global Crises and Equity Market Contagion. doi:10.3386/w17121

Billio, M., & Caporin, M. (2005). Multivariate Markov switching dynamic conditional correlation GARCH representations for contagion analysis. *Statistical Methods and Applications, 14*(2), 145-161. doi:10.1007/s10260-005-0108-8

Buchholz, M., & Tonzer, L. (2016). Sovereign Credit Risk Co-Movements in the Eurozone: Simple Interdependence or Contagion? *International Finance, 19*(3), 246-268. doi:10.1111/infi.12099

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics, 4*(4), 537-572. doi:10.1093/jjfinec/nbl005

Cheng-Zhi, C., Hong-Lan, M., & Ying, L. (2016). Chinese potato yield projected on ARIMA (Autoregressive Integrated Moving Average) model basis. *Research on Crops, 17*(4), 769. doi:10.5958/2348-7542.2016.00130.3

Chiang, T. C., Lao, L., & Xue, Q. (2015). Comovements between Chinese and global stock markets: Evidence from aggregate and sectoral data. *Review of Quantitative Finance and Accounting, 47*(4), 1003-1042. doi:10.1007/s11156-015-0529-x

Chlibi, S., Jawadi, F., & Sellami, M. (2015). Analyzing Heterogeneous Stock Price Comovements Through Hybrid Approaches. *Open Economies Review, 27*(3), 541-559. doi:10.1007/s11079-015-9381-9

Chow, G. C., Changjiang, L., & Niu, L. (n.d.). Co-Movements of Shanghai and New York Stock Prices by Time-Varying Regressions. *SSRN Electronic Journal*. doi:10.2139/ssrn.1914289

Chittedi, K. R. (n.d.). Interdependence of Global Stock Markets with Special Reference to BRIC Countries. *SSRN Electronic Journal*. doi:10.2139/ssrn.1667862

Deltuvaitė, V. (2016). Cross-Border Contagion Risk Transmission Through Stock Markets Channel: The Case of the Baltic Countries. *Financial Environment and Business Development Eurasian Studies in Business and Economics,* 43-54. doi:10.1007/978-3-319-39919-5_4

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis, 30*, 46-56. doi:10.1016/j.irfa.2013.05.008

Enders, W. (2015). *Applied econometric time series*. Hoboken: Wiley.

Engle, R. F. (n.d.). Dynamic Conditional Correlation - A Simple Class of Multivariate GARCH Models. *SSRN Electronic Journal*. doi:10.2139/ssrn.236998

Forbes, K., & Rigobon, R. (1999). No Contagion, Only Interdependence: Measuring Stock Market Co-movements. doi:10.3386/w7267

Forbes, K., & Rigobon, R. (2001). Measuring Contagion: Conceptual and Empirical Issues. *International Financial Contagion,* 43-66. doi:10.1007/978-1-4757-3314-3_3

Hamilton, J. D. (2012). *Time series analysis*. Kolkata: Levant Books.

Hau, H., & Lai, S. (n.d.). The Role of Equity Funds in the Financial Crisis Propagation. *SSRN Electronic Journal*. doi:10.2139/ssrn.1742065

Horen, N. V., Jager, H., & Klaassen, F. (2006). Foreign Exchange Market Contagion in the Asian Crisis: A Regression-Based Approach. *Review of World Economics, 142*(2), 374-401. doi:10.1007/s10290-006-0072-x

Kenourgios, D., Dimitriou, D., & Christopoulos, A. (2013). Asset Markets Contagion During the Global Financial Crisis. *Multinational Finance Journal, 17*(1/2), 49-76. doi:10.17578/17-1/2-2

Lagoarde-Segot, T., & Lucey, B. M. (2007). International portfolio diversification: Is there a role for the Middle East and North Africa? *Journal of Multinational Financial Management, 17*(5), 401-416. doi:10.1016/j.mulfin.2007.01.001

Li, H. (2007). International linkages of the Chinese stock exchanges: a multivariate GARCH analysis. *Applied Financial Economics, 17*(4), 285-297. doi:10.1080/09603100600675557

Lütkepohl, H. (2009). *Applied time series econometrics*. Cambridge: Cambridge Univ. Press.

Peng, Y., & Ng, W. L. (2011). Analysing financial contagion and asymmetric market dependence with volatility indices via copulas. *Annals of Finance, 8*(1), 49-74. doi:10.1007/s10436-011-0181-y

Poshakwale, S. S., & Mandal, A. (2016). Sources of time varying return comovements during different economic regimes: Evidence from the emerging Indian equity market. *Review of Quantitative Finance and Accounting*. doi:10.1007/s11156-016-0580-2

Ravazzolo, F., & Phylaktis, K. (n.d.). Stock Market Linkages in Emerging Markets: Implications for International Portfolio Diversification. *SSRN Electronic Journal*. doi:10.2139/ssrn.562922

Zhou, W. (2016). Dynamic and Asymmetric Contagion Reactions of Financial Markets During the Last Subprime Crisis. *Computational Economics*. doi:10.1007/s10614-016-9606-z