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Financial Contagion in the 2007-2009 and Eurozone Debt Crises: Mostly Interdependence*

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Abstract:

This study employs a VECH-GARCH model to assess the effects of contagion during the 2007-2009 financial crisis. Weekly stock returns data for five Eurozone countries, the BRICs, and the United States between 2002 and 2013 were used. Several inferences can be drawn from this model. First, there was significant volatility clustering, both with respect to stock returns and bivariate correlations. Second, in the initial stage of both the 2007-2009 crisis and the Eurozone debt crisis, the U.S. stock market was less correlated with the European markets, as investors viewed news as country-specific. Conversely, there were no dynamic changes in correlations between the U.S. stock market returns and those of the BRICs. Third, during the Eurozone debt crisis, the Irish stock returns became slightly more correlated with the returns in other Euro countries, as the crisis was viewed as region-specific due to more integrated financial and trade linkages. Finally, there was strong evidence that quantitative easing increases correlations between international stock returns.

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1. Introduction

Financial crises have played significant roles in shaping the capital markets, particularly with increasing international integration in the late 20th century. Specifically, financial contagion in the 1994 Mexican Peso Crisis, the 1997 Asian Financial Crisis, the dot-com bubble, and more recently, the 2007-2009 recession and the Eurozone crisis, all stemming from one area, have been found to have international consequences.

Contagion, defined by Bekaert et al. (2012) as "shock transmissions that cannot be explained by fundamentals" or "co-movements that are viewed as "excessive,"" is thought to occur for several reasons. Firstly, globalization through trade and financial linkages is often hypothesized as a factor leading to increased contagion. Due to the relationships some countries build with each other through foreign direct investments (FDI) and trade, a financial crisis in one country will reduce international partnerships, and subsequently harm both countries' economies. Furthermore, multinational companies operating in crisis-struck countries will report lower profits, reducing shareholder returns in their home country. Secondly, large negative returns may cause investors to sell financial securities irrationally, ignoring economic fundamentals. Herding behaviours and changes in risk aversion could account for this phenomenon. Moreover, the triggering of margin calls, forcing some investors to sell securities at losses even when their intrinsic values are much higher than the market price, were also found to increase international contagion (Kaminsky et al., 2003). Thirdly, the wake-up call hypothesis suggests that a crisis originating from one market could provide additional information about other markets. This brings to attention weaknesses in similar markets, leading to sell-offs in those regions (Bekaert et al., 2012). Fourthly, a severe price depreciation of securities will decrease the equity of firms holding those distressed assets (Longstaff, 2010). Consequently, companies will be more highly levered, working at inefficient debt to equity ratios.

The globalization argument, though theoretically compelling, was strongly rejected by Bekaert et al. (2012). In the 2007-2009 recession, Bekaert et al. (2012) found that more financially integrated countries often declined less than more independent ones. Their factor loading model determined that contagion from the U.S. markets and the global financial sector existed, although the effects were economically small, and none of it was spread through globalization.[1] Conversely, Mighri and Mansouri

[1] Bekaert et al. (2012)used an OLS estimation model with 25 regressors to estimate the effects of contagion for 415 equity portfolios in 55 countries. If the co-movements between domestic portfolios with U.S. or global factors exceeded the co-movements implied by their model, using pre-crisis data, evidence of contagion existed. However,

(2013) found some evidence of contagion, particularly within emerging markets, during the 2007-2009 financial crisis using a multivariate dynamic conditional covariance GARCH.[2] Contagion was hypothesized to have spread through herding behaviours. Moreover, Longstaff (2010) found strong evidence of financial contagion in the 2007-2009 crisis, primarily carried through the need for liquidity and changes in risk premiums.[3] Risk premiums were also found to have played a large role in spreading contagion during the European debt crisis. Broto and Perez-Quiros (2013)'s dynamic factor model using the Kalman filter found significant time-varying effects on European credit default swaps between 2007 and the end of 2012. More importantly, Broto and Perez-Quiros (2013) found that the source of contagion varied over time. For example, the European debt crisis initially spread through Greece, and was later transmitted by Portugal, Spain, Ireland and Italy (Broto, Perez-Quiros, 2013).

Other authors studying the 1997 Hong Kong stock market crisis also found evidence of contagion. For example, Corsetti et al. (2005) used a Fisher-Z transformation, which accounts for the non-normality of stock returns data. His study found evidence of contagion in some Asian countries. The case for contagion was also backed by Rodriguez (2006), who employed copulas with Markov switching in order to model asymmetric distributions.[4] Chiang et al. (2007)'s study, which provided the template for the aforementioned Mighri and Mansouri (2013) paper, also found evidence of contagion in the Asian markets.

Previous methods of measuring contagion have several disadvantages. Most notably, several authors mentioned the need to account for heteroskedasticity (Forbes, Rigobon, 2001). Since the correlation coefficient between two assets' returns will increase as the variances increase, a higher correlation coefficient will not be sufficient to determine the existence of contagion. After accounting for heteroskedasticity, Forbes and Rigobon (2001) found "no contagion, only interdependence" during the

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Bekaert et al. (2012)'s model did not factor in exogenous changes between the pre-crisis and crisis periods. Furthermore, the model did not account for non-linear relationships, which are typically present in financial data.

[2] Mighri and Mansouri (2013) found evidence of contagion during the 2007-2009 financial crisis, when analyzing daily stock returns data of the U.S., France, Germany, the United Kingdom, the Netherlands, Austria, Brazil, India, Hong Kong, Mexico, Indonesia, Malaysia, Argentina, Denmark, China, Switzerland, and Singapore, from 2003 to 2011.

[3] Longstaff (2010) used a VAR framework to estimate the effects of contagion to asset-backed CDO returns. The VAR framework required structural breaks, that is, Longstaff separated the data to 2006, 2007, and 2008. Moreover, standard errors were assumed to be normally distributed. Forbes and Rigobon (2001) showed that heteroskedasticity likely biases studies towards the conclusion of contagion, which may affect the results obtained in Longstaff's study.

[4] Rodriguez (2006) used copulas, along with his Markov switching model, so that the contagious periods and levels of extreme volatility are determined by the model.

1997 Asian crisis, 1994 Mexican Peso devaluation, and the 1987 U.S. market crash. Earlier models also assumed that financial returns are normally distributed, and that relationships between variables are linear, which are not typically the case in finance. Specifically, Henry (1998) found that negative news affects stock market volatility more than positive news of equal magnitude. Moreover, normality of financial data was strongly rejected by Rodriguez (2007). Finally, the choice of data is subject to selection bias. Due to the lack of a consensus date for the beginning and end of a crisis, authors are able to subjectively choose the timeframe of their data. Although extending the data could lead to less selection bias, Forbes and Rigobon (2001) also stressed the importance for limiting the timeframe of the data. Over time, the transmission of market volatility could change due to factors unrelated to contagion, such as technological advances.

This paper will test for financial contagion during the 2007-2009 crisis from the United States, affecting a group of developed and developing countries. The method used to detect contagion follows from Chiang et al. (2007) and Mighri and Mansouri (2013)'s GARCH models to estimate bivariate correlations. This process accounts for tail dependence, heteroskedasticity, non-linearity, and non-normality of the data (Poon et al., 2003). The data used will be the weekly stock index returns of several Euro countries, the BRICs, and the United States. Despite their inherently smaller sample sizes, weekly data, used in several previous studies, were sufficient to detect contagion.[5]

The analysis in this paper will be based on the assumption of contagion spreading from the United States, which will allow for comparisons with Bekaert et al. (2012) and Longstaff (2010). This study did not find evidence of contagion during the 2007-2009 financial crisis. Throughout the crisis periods, GARCH-adjusted correlation coefficients between the S&P 500 and the stock returns in the Euro and BRIC countries decreased, contrasting with Chiang et al. (2007)'s and Mighri and Mansouri (2013)'s findings. Conversely, the effects of quantitative easing spread internationally. Although international portfolio diversification was still found to be beneficial, other tools, such as volatility indices, were found to be effective tools to hedge risk due to the presence of volatility clustering.

Section 2 will describe the data, outlining descriptive statistics, including simple correlation analysis in Section 2b. Section 3 outlines the VECH-GARCH model that will be used in this study and illustrates the

[5] For example, Edwards and Susmel (2003) found evidence of contagion during the Mexican Peso, Asian financial, and Russian crises with weekly stock returns data and bivariate SWARCH models. However, volatility dependence was short-lived.

results from the returns equations. Section 4 will present the results from correlation analysis, including estimating the effects of quantitative easing, herding and contagion. Finally, Section 5 will conclude.

2. The Data

Similar to Chiang et al. (2007) and Maghri and Mansouri (2013), I will estimate the effects of contagion on equity portfolios. However, returns to stock market indices in this paper will be adjusted for foreign exchange, which has been found to have contagious properties (Gravelle et al., 2006). Unlike most studies which use daily data, the stock returns and exchange rates used in this paper will be based on weekly returns, closing on the last trading day before the weekend. Weekly data will adjust for the fact that markets may not trade based on economic fundamentals on a daily basis due to technical analysis, that is, chart patterns and traders' sentiment. Moreover, weekly data better captures feedback effects due to stock exchanges in different regions having different trading hours. One problem, however, is that using weekly data reduces the sample size, compared to daily returns. Particularly, sample sizes are inherently small during crisis periods, and may limit the robustness of tests, even when daily data is used (Bae et al., 2003). The time period used, from October 4, 2002 to September 13, 2013, begins after the stock market trough, and captures the 2007-2009 financial crisis and subsequent recovery. Whenever data was unavailable, prices and exchange rates were assumed to have stayed the same as the previous week.

The data used will be stock market returns and exchange rates from: the United States; a sub-sample of the developed Eurozone countries, made up of France, Germany, Ireland, Italy and Spain; and developing countries, specifically, the BRICs (Brazil, Russia, India, China).[6] The index chosen was first weighted by market capitalization, and was the index, if available, that held the most number of stocks in each respective country. Stock index and foreign exchange data was found from *Bloomberg*.

To calculate the stock returns, the change in the weekly closing price was given as the first difference of the natural log. The data will be separated into three stages: pre-crisis; crisis; and post-crisis. When the Lehman Brothers declared bankruptcy on September 15, 2008, the S&P 500 fell 4.7%. Although the S&P 500 had already fallen 24% from its peak on October 12, 2007 to September 15, 2008, a one-day drop of that magnitude was never experienced. Lehman's bankruptcy publicly exposed the credit crisis and the

[6] The stock indices chosen for the United States, Germany, Ireland, Italy, Spain, Brazil, Russia, India, China are, respectively, the S&P 500, the HDAX, the ISEQ Overall Index, the FTSE Italia All-Share index, the Madrid Stock Exchange General Index, the Ibovespa Index, MICEX Index, the S&P BSE Sensex Index, and the Shanghai Stock Exchange Composite Index.

fragility of the economy, and thus served as a wake-up call to investors. Naturally, the week starting September 12, 2008 will serve as the beginning of the 'crisis' period. The market subsequently hit a bottom on March 6, 2009, significantly aided by the Federal Reserve's intensified quantitative easing program. This signified the end of the crisis, and the following week, March 13, 2009, was used to begin the 'post-crisis' period.

Table 1 shows descriptive statistics and autocorrelation figures for the sample countries, split into two groups: developed countries, which include the United States, France, Germany, Ireland, Italy, and Spain; and the BRICs. In each country during the crisis period, weekly returns, denominated in U.S. dollars, fell significantly, and the variance increased. Moreover, the average kurtosis fell to 0.9107 during the crisis period, compared to 1.4974 and 1.4662 in the pre and post-crisis periods, respectively. The decreased kurtosis during the crisis period signifies the existence of fat tails, or a higher probability of extreme returns. None of the country's stock index returns exhibited significant autocorrelation.

Table 2 shows similar data as Table 1, except the data does not take into account foreign exchange. The unadjusted data, compared to the currency-adjusted group, generally exhibited lower returns during non-crisis periods and higher returns during the crisis-period. In the crisis periods, the U.S. dollar may have appreciated against other currencies due to a flight to safety, reducing the adjusted returns. As expected, the variances of the adjusted returns were higher than the unadjusted returns' due to currency effects. Finally, 15 of the 24 sub-samples analyzed were characterized by even lower kurtosis, or fatter tails, when the returns were adjusted for currency effects. This is particularly noteworthy during the crisis period, where each sample country's stock returns except China's experienced a drop in kurtosis when foreign exchange was factored. This supports the research by Gravelle et al. (2006) and Bae et al. (2003), who found that contagion occurred in the currency markets. Moreover, the descriptive data illustrates how foreign exchange affects the distributions of stock returns: by denominating the data in USD, the stock returns tend to be even less normal and linear.

The presence of volatility clustering supports the need to account for heteroskedasticity. Appendix 1 illustrates the weekly returns for each country's stock index, adjusted for foreign exchange. It is worth noting that in the second half of 2008, indices in each country were subject to extreme volatility, supporting the existence of contagion.

Table 1: Descriptive statistics on weekly stock returns, adjusted for foreign exchange (10/4/2002 – 9/13/2013)

Pre-Crisis	Mean (%)	Variance	Skewness	Kurtosis	AR(1)
U.S.	0.142	0.034	-0.131	0.941	-0.089
France	0.272	0.056	-0.502	0.988	-0.017
Germany	0.391	0.074	-0.169	0.721	-0.049
Ireland	0.116	0.085	-1.291	5.917	-0.091
Italy	0.157	0.047	-0.517	0.548	0.011
Spain	0.355	0.050	-0.617	0.522	0.041
Brazil	0.797	0.240	-0.336	0.302	-0.105*
China	0.210	0.130	0.021	2.068	0.060
India	0.543	0.113	-0.768	1.622	0.081
Russia	0.525	0.182	-0.722	1.345	0.059
Crisis					
U.S.	-2.299	0.432	-0.137	1.392	-0.112
France	-2.410	0.774	-0.541	1.251	-0.183
Germany	-2.530	0.908	-0.331	0.513	-0.167
Ireland	-3.486	0.894	-1.086	3.569	-0.089
Italy	-3.290	0.815	-0.589	0.206	-0.167
Spain	-2.364	0.803	-0.767	0.903	-0.243
Brazil	-2.510	1.912	-0.313	0.489	-0.253
China	-0.542	0.410	0.210	-0.262	0.143
India	-2.700	0.650	0.011	-0.274	-0.048
Russia	-3.548	1.918	0.694	1.320	-0.057
Post-Crisis					
U.S.	0.383	0.058	0.041	1.713	-0.106*
France	0.255	0.141	-0.534	1.403	-0.056
Germany	0.396	0.136	-0.460	1.481	-0.063
Ireland	0.347	0.126	-0.697	3.045	-0.061
Italy	0.156	0.193	-0.478	0.929	-0.011
Spain	0.113	0.208	-0.414	0.900	-0.054
Brazil	0.175	0.190	-0.058	0.742	-0.022
China	0.077	0.080	0.127	-0.079	-0.024
India	0.279	0.135	0.407	2.088	0.090
Russia	0.354	0.206	-0.436	2.440	0.013

Notes: There were 310 pre-crisis observations for each country except China, which had 308. There were 25 observations during the crisis period and 236 during the post-crisis period. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2: Descriptive statistics on weekly stock returns, in domestic currency (10/4/2002 – 9/13/2013)

Pre-Crisis	Mean (%)	Variance	Skewness	Kurtosis	Difference Means	Difference Variances	Difference Skewness	Difference Kurtosis
U.S.	0.142	0.034	-0.131	0.941	0.000	0.000	0.000	0.000
France	0.150	0.049	-0.288	0.668	0.122	0.007	-0.213	0.320
Germany	0.269	0.069	-0.015	1.289	0.122	0.005	-0.154	-0.568
Ireland	0.035	0.077	-1.014	6.241	0.080	0.008	-0.277	-0.324
Italy	0.050	0.038	-0.622	0.728	0.106	0.009	0.105	-0.180
Spain	0.234	0.040	-0.531	0.327	0.122	0.010	-0.085	0.195
Brazil	0.558	0.125	-0.339	-0.010	0.239	0.115	0.004	0.312
China	0.148	0.130	-0.019	2.223	0.062	0.000	0.040	-0.154
India	0.517	0.094	-0.697	1.254	0.026	0.019	-0.071	0.368
Russia	0.454	0.168	-0.643	1.125	0.071	0.015	-0.080	0.220
Crisis								
U.S.	-2.299	0.432	-0.137	1.392	0.000	0.000	0.000	0.000
France	-1.950	0.580	-0.771	1.980	-0.460	0.194	0.229	-0.729
Germany	-2.070	0.665	-0.352	1.312	-0.460	0.243	0.021	-0.799
Ireland	-3.026	0.806	-0.966	3.212	-0.460	0.088	-0.120	0.357
Italy	-2.830	0.604	-0.867	0.789	-0.460	0.211	0.278	-0.583
Spain	-1.904	0.577	-0.878	1.336	-0.460	0.227	0.111	-0.433
Brazil	-1.294	0.814	-0.041	0.491	-1.217	1.098	-0.272	-0.002
China	-0.541	0.414	0.200	-0.287	-0.001	-0.004	0.009	0.025
India	-2.130	0.463	-0.004	0.026	-0.570	0.187	0.015	-0.300
Russia	-2.244	1.757	0.644	1.411	-1.303	0.161	0.050	-0.091
Post-Crisis								
U.S.	0.383	0.058	0.041	1.713	0.000	0.000	0.000	0.000
France	0.234	0.086	-0.527	1.583	0.021	0.055	-0.007	-0.180
Germany	0.375	0.085	-0.602	2.559	0.021	0.051	0.143	-1.078
Ireland	0.326	0.083	-0.719	2.946	0.021	0.043	0.023	0.098
Italy	0.135	0.126	-0.481	0.932	0.021	0.067	0.003	-0.003
Spain	0.092	0.135	-0.327	0.743	0.021	0.073	-0.087	0.157
Brazil	0.157	0.088	-0.126	0.457	0.017	0.102	0.067	0.285
China	0.030	0.080	0.122	-0.132	0.047	0.000	0.005	0.053
India	0.366	0.081	0.499	2.341	-0.087	0.055	-0.092	-0.253
Russia	0.313	0.123	-0.384	2.415	0.041	0.082	-0.052	0.026

Notes: There were 310 pre-crisis observations for each country except China, which had 308. There were 25 observations during the crisis period and 236 during the post-crisis period. “Difference Means”, “Difference Variances”, “Difference Skewness” and “Difference Kurtosis” are calculated as the currency-adjusted minus unadjusted variable.

2b. Bivariate Correlation Analysis

One simple method of detecting contagion is analyzing bivariate correlation coefficients. The limitation, mentioned by Chiang et al. (2007), is that “the source of contagion has to be identified beforehand.” Fortunately with this study, the main sources of the 2007-2009 crisis could be identified: the mispricing of credit default swaps; the undeserved Aaa credit rating on federal mortgage agencies (Murphy, 2008);

"excessively loose" monetary policy; other policies, including the securitization of mortgage-backed securities, incentivizing leveraged risk-taking; and the rising interest rates leading to the default of the floating-rate mortgage-backed securities (Verick, Islam, 2010). Although there were several factors at play, each originated from the United States. Thus, the pairwise correlations between the U.S. and the other countries will be assessed. Since the pairwise correlation coefficients will increase if the variance of one index increases regardless of the transmission of returns, heteroskedasticity-adjusted correlation coefficients, initially proposed by Forbes and Rigobon (2001),[7] and as in Chiang et al. (2007), will be used.[8] If the bivariate correlation coefficients increased at a statistically significant level, there would be evidence of contagion. To test whether bivariate correlation coefficients were significantly different across the two subsamples, the Fisher z-transformation, used by Chiang et al. (2007) and Corsetti et al. (2005), will be incorporated.[9]

The full results are shown in Table 3. Most notably, the variance during the crisis period was 7.77 times higher than the variance during the non-crisis periods. With such a large increase in variance, bivariate correlation coefficients should be expected to increase significantly. Only China showed a decrease in the unadjusted bivariate correlation coefficient, with the average increase being 0.114. This increase in the correlation coefficient was significant at the 10% level for eight of the nine countries. However, when heteroskedasticity-adjusted bivariate correlation coefficients are taken into account, the contagion hypothesis was rejected. Thus, after taking into account heteroskedasticity, there is little evidence that the pairwise correlations between the United States and other countries during the 2007-2009 crisis increased.

Although there was a general decrease in heteroskedastic-adjusted bivariate correlation coefficients during the crisis period, several other inferences could be made. Despite the lack of a clear relationship between how developed a country is and the change in the unadjusted bivariate correlation coefficient, the more developed countries, i.e. the Euro countries, experienced a sharper drop in bivariate adjusted

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[7] A proof of the bias and Forbes and Rigobon's adjustment can be found in their 2001 paper titled *No Contagion, Only Interdependence: Measuring Stock Market Co-Movements*.

[8] Correlation coefficients were adjusted by using $\rho^* = \rho / [1 + \delta(1 - \rho^2)]^{1/2}$ where $\delta = [Var(r_H) / Var(r_L)] - 1$, ρ is the unadjusted correlation coefficient, and r_H and r_L are the stock market returns in the United States in the high and low volatility periods, respectively.

[9] The test statistic for the null hypothesis of no increase in correlation, initially proposed by Morrison (1983), is $T = (Z_0 - Z_1) / [(1 / (N_0 - 3)) + (1 / (N_1 - 3))]^{1/2}$, where $Z_0 = 1 / 2\ln[(1 + \rho_0) / (1 - \rho_0)]$ and $Z_1 = 1 / 2\ln[(1 + \rho_1) / (1 - \rho_1)]$ are Fisher transformations of correlation coefficients before and after the crisis. This test statistic is still valid for the non-normality of correlation coefficients, and is robust to fat tails.

correlation coefficients during the crisis period. This is due to the developed countries having a higher variance during the crisis period compared to the non-crisis periods.

Table 3: Tests of significant increases in correlation coefficients, with the United States as the source of contagion

United States as Source	Correlation Pre and Post Crisis	Correlation Crisis	Adjusted Correlation during Crisis	Z-statistic (unadjusted)	Z-statistic (adjusted)
France	0.786	0.908	0.571	-2.183**	1.977
Germany	0.796	0.927	0.620	-2.628***	1.732
Ireland	0.654	0.820	0.417	-1.798**	1.618
Italy	0.717	0.860	0.476	-1.891**	1.835
Spain	0.661	0.857	0.471	-2.341***	1.358
Brazil	0.643	0.911	0.577	-3.682***	0.506
China	-0.033	-0.396	-0.137	1.848	0.500
India	0.488	0.669	0.277	-1.323*	1.191
Russia	0.497	0.676	0.282	-1.329*	1.222

Notes: Details of the adjustment of the correlations and Z-statistics can be found in footnotes 7 and 8. The null hypothesis is no increase in correlation. The 1%, 5%, and 10% critical values for a one-sided test of the null are -2.32, -1.64, and -1.28, respectively. Similarly to Table 1, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

One drawback is that contagion could have spread from the United States to another country, and then subsequent volatility transmissions could have taken place. That is, volatility could have been spread indirectly from the United States to other countries, which would not be shown using bivariate correlation analysis. This phenomenon was most prominent in the European sovereign debt crisis, where Bronto and Perez-Quiros (2013)'s dynamic factor model of credit default swaps showed contagion was initially spread by Greece, and later transmitted through Portugal, Spain, Ireland and Italy. Another limitation of simple correlation analysis is that it cannot account for changes in other factors, such as risk-aversion, which are expected to play roles in affecting market movements. These will be accounted for in the next section's VECH-GARCH model.

3. The Multivariate GARCH Model

A more robust method of detecting contagion is through a multivariate GARCH model, which was used by Chiang et al. (2007) in their study of the Asian crisis. More specifically, this paper will use a VECH-GARCH, whereas Chiang et al. (2007) and Mighri and Mansouri (2013) used a dynamic conditional correlation (DCC) GARCH. Unlike the previous method of simply testing for statistically significant changes in the bivariate correlation coefficients during the crisis periods, GARCH will allow us to account for other exogenous variables. Indirect changes in correlation coefficients will also be able to be represented with GARCH.

Moreover, heteroskedasticity, which has been found to put an upward bias on correlation coefficients during crisis-periods (Forbes, Rigobon, 2001), would be directly taken into account within the model. Another advantage with GARCH is that when combined with the use of robust standard errors, we attain quasi-maximum likelihood estimates. Thus, asymmetry and fat tails, which are present in the data, could be modeled (Yan, 2005).

The full derivations of the GARCH model, including the estimations of the bivariate correlations and the conditional covariance matrix with the maximization of a log-likelihood function, are shown in Chiang et al. (2007).

In the first model, the returns equation is estimated as:

(1) $R_t = y_0 + y_1 R_{t-1} + y_2 R_{US,t-1} + e_t$

where $R_t = (R_{1,t}, R_{2,t}, \ldots, R_{n,t})'$; $E_t = (e_{1,t}, e_{2,t}, \ldots, e_{n,t})'$; and $e_t | J_{t-1} \sim N(0, H_t)$

And the variance equations are given by:

(2) $h_{ii,t} = c_i + a_{i,j} h_{i,j,t-1} + b_{i,j} E^2_{i,j,t-1}$, for i = 1, 2, …, 5 and j = 1, 2, …, 5

The one-week lagged VIX was originally used as a proxy for investors' and traders' risk-aversion in the mean equation. Risk-aversion affects both stock returns and foreign exchange. As risk-aversion increases, investors will move money away from stocks, reducing the returns on equity. Moreover, investors will buy U.S. debt, typically viewed as risk-free. This cash inflow will put upward pressure on the U.S. dollar, reducing the currency-adjusted stock returns to non-American stock indices. Despite Bekaert et al. (2012)'s findings, the VIX was not significant in this paper's tests, and was omitted (results are not shown in this paper).

In order to account for the fat tail distribution of equity returns, which was seen with the low kurtosis in the data, robust standard errors were used to attain quasi-maximum likelihood estimates. Table 4 shows the estimates for the returns and variance equations for the Euro countries.

Although the AR(1) term was not statistically significant in the descriptive data, the simple OLS did not take into account non-linearity and non-normality (specifically, the heteroskedasticity) of the data. The AR(1) term was statistically significant in almost half the cases after taking those factors into account with the GARCH model. The previous week's stock returns in the U.S. had statistically significant effects, at the 10% and the 5% levels, on German and Irish stock returns, respectively, and the AR(1) term was statistically significant at the 5% level for those countries. Those terms were not significant for France, Italy, Spain, or the United States.

The lagged GARCH term and the squared residuals were highly significant for each country. Moreover, the persistence (the sum of the *a* and *b* coefficients) was close to one, providing strong evidence of volatility clustering.

Table 4: Estimation results for the VECH-GARCH model for the Euro countries

Mean Equations				Variance Equations			
	Constant	US(-1)	AR(1)	c	a	b	Persistence
France	0.4042***	0.0698	-0.0416	0.3428***	0.0575***	0.9006***	0.9582
	(0.0072)	*(0.2795)*	*(0.1301)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	
Germany	0.4922***	0.1331*	-0.0670**	0.4649***	0.0551***	0.8937***	0.9488
	(0.0021)	*(0.0748)*	*(0.0186)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	
Ireland	0.3959***	0.1503**	-0.0778**	0.2608***	0.0583***	0.9133***	0.9716
	(0.0058)	*(0.0124)*	*(0.0156)*	*(0.0004)*	*(0.0052)*	*(0.0000)*	
Italy	0.2943**	0.0996	-0.0224	0.2762***	0.0580***	0.9097***	0.9677
	(0.0440)	*(0.1013)*	*(0.3815)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	
Spain	0.4265***	0.0432	-0.0180	0.2786***	0.0598***	0.9111***	0.9709
	(0.0080)	*(0.5875)*	*(0.5504)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	
U.S.	0.3055***	-0.0540		0.2350***	0.0679***	0.8779***	0.9458
	(0.0045)	*(0.3008)*		*(0.0000)*	*(0.0000)*	*(0.0000)*	

Notes: The country represents the stock return in each respective country. The p-values are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The returns and variance equations are: $R_t = y_0 + y_1 R_{US,t-1} + y_2 R_{t-1} + E_t$ where $R_t = (R_{1,t}, R_{2,t}, \dots, R_{6,t})'$, $E_t = (E_{1,t}, E_{2,t}, \dots, E_{6,t})'$, $E_t | I_{t-1} \sim N(0,H_t)$; $h_{ii,t} = c_i + a_i h_{ii,t-1} + b_i E^2_{i,t-1}$, i = 1, 2, …, 6

Table 5 shows the return and variance equation estimates for the BRICs—high-growth developing countries. Similarly to the developed Euro countries, returns are fairly unpredictable—the returns in the United States only had statistically significant effects on China and India, and only Brazil's AR(1) term was statistically significant at the 5% level. Similar to the Euro countries, the stock returns in the BRICs exhibited extremely significant lagged GARCH and squared residual terms. However, although persistence was close to unity, volatility clustering was less defined than in the BRICs. This supports the assertion of Allegret and Sand-Zantman (2009) that during volatile periods, a monetary union (the Euro) amplifies the shocks due to inefficient foreign exchange markets in each individual country. However, further research may be required to control for other factors like the 2010-2013 European sovereign debt crisis which could lead to the contrasting conclusion by Caramazza et al. (2000) that exchange rate regimes neither prevented nor amplified contagion.[10]

[10] Both Allegret and Sand-Zantman (2009) and Caramazza et al. (2000)'s studies used probit panel regressions with data from emerging markets. The difference in results may be due to the timeframes of the data. Caramazza et al.

Table 5: Estimation results for the VECH-GARCH model for the BRICs

Mean Equations				Variance Equations			
	Constant	US(-1)	AR(1)	c	a	b	Persistence
Brazil	0.6759***	0.0450	-0.101**	2.0968***	0.1090***	0.8041***	0.9131
	(0.0008)	*(0.6573)*	*(0.0142)*	*(0.0002)*	*(0.0000)*	*(0.0000)*	
China	0.0251	0.1926***	0.0257	0.3634**	0.0790***	0.8877***	0.9667
	(0.8486)	*(0.0007)*	*(0.5860)*	*(0.0357)*	*(0.0008)*	*(0.0000)*	
India	0.5257***	0.1581**	0.0108	0.8574***	0.1123***	0.8247***	0.9370
	(0.0004)	*(0.0227)*	*(0.8253)*	*(0.0003)*	*(0.0000)*	*(0.0000)*	
Russia	0.4981***	0.1042	-0.0703*	1.3768***	0.1086***	0.8314***	0.9400
	(0.0063)	*(0.1340)*	*(0.0620)*	*(0.0002)*	*(0.0000)*	*(0.0000)*	
U.S.	0.3153***	-0.1061**		0.4639***	0.1791***	0.7395***	0.9185
	(0.0001)	*(0.0193)*		*(0.0000)*	*(0.0000)*	*(0.0000)*	

Notes: The country represents the stock return in each respective country. The p-values are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The return and variance equations are: $R_t = y_0 + y_1R_{US,t-1} + y_2R_{t-1} + E_t$ where $R_t = (R_{1,t}, R_{2,t}, \ldots, R_{5,t})'$, $E_t = (E_{1,t}, E_{2,t}, \ldots, E_{5,t})'$, $E_t | I_{t-1} \sim N(0,H_t)$; $h_{ii,t} = c_i + a_ih_{ii,t-1} + b_iE^2_{i,t-1}$, i = 1, 2, …, 5

Consistent with other studies, the AR(1) term was negative in each case for the Euro countries. One hypothesis is that positive feedback trading in developed countries push stock prices above or below fundamental values in the short-term. The following week, markets would be expected to correct, causing the negative value of the AR(1) term. This process is caused by factors such as extrapolative expectations, stop-loss orders, and portfolio insurance (Antinou et al., 2005). Moreover, momentum traders, including the huge rise in high-frequency traders and trading algorithms, may cause extreme volatilities in markets. Finally, when stock prices rise or fall, equity research firms often raise or lower their price targets, respectively, causing additional short-term momentum, leading to profit-taking or bargain-hunting the following week. These activities are far more prevalent in developed countries, where the majority of research firms exist.

4. Dynamic Changes in the Correlation Coefficients Obtained from the VECH-GARCH

Section 4b will analyze dynamic shifts in correlations throughout crises. The following sub-section will report the estimates from the VECH-GARCH, taking into account time-varying dummies. The third part will examine contagion within the Euro countries during the European debt crisis. Finally, sections 4e and 4f will analyze and test for the effects of quantitative easing on correlation coefficients.

(2000) used global stock market returns between 1990 and 1998, encompassing the ERM, Mexican, Asian, and Russian crises. Allegret and Sand-Zantman (2009)'s study was much more focused: the data used was Latin American stock returns between 1991 and 2007, capturing the Mexican Crisis, Argentinean Crisis, ERM and Asian crises.

4b. Different Phases of the Crisis

Along with volatility clustering, changes in bivariate correlation coefficients will be analyzed. Appendices 2A and 2B illustrate the pair-wise conditional correlation coefficients between the United States and the other countries in the sub-sample.

In Chiang et al. (2007)'s study of the Asian crisis, the beginning of an international crisis was marked by decreasing correlations, as investors saw turmoil as merely country-specific events. During the later stages as contagion spread, correlations increased as investors exhibited herding behaviours, withdrawing funds from every region. The contagion may have also been exacerbated by margin calls and portfolio rebalancing in developed countries, and wealth constraints in emerging markets (Boyer et al., 2006). Since U.S. equities are widely held globally, as the value of U.S. equities decreased, brokers would force investors to sell securities globally to maintain liquidity and leverage requirements.

Our results show that a similar pattern could be observed in the 2007-2009 crisis. During the period starting October 2007 to April 2008, the S&P 500 fell 17.5%. The causes for this decrease could have been viewed by investors as mainly U.S.-specific, and consequently, investors reallocated funds from the United States to other countries, decreasing the correlations between the S&P 500 and the stock returns in other countries. For example, the pairwise correlation coefficient between the S&P 500 and Germany's HDAX fell from 0.7805 on October 12, 2007, to 0.5313 on April 4, 2008. As the contagion spread, investors sold their assets in other countries, and bivariate correlations increased, illustrated by the rise in correlations between the S&P 500 and the HDAX from 0.5313 to 0.8748 on October 9, 2009. Subsequently, during the Eurozone debt crisis, the correlation fell from 0.8748 to 0.7367 on February 11, 2011, and has then risen (slightly) to 0.7472 since.

The exception to this pattern was with the correlation between the United States' and China's stock returns. This was not solely due to the Chinese government's deregulation of the RMB, as currency-unadjusted stock returns yielded a similar pattern in correlations. The lack of a strong correlation between Chinese and U.S. stock returns is likely due to China's state-owned enterprises[11] and strict regulations for foreign investments. For example, Australian investments over 248 million AUD must be approved by China's Foreign Investment Review Board, which will reduce China's exposure to international investors, and consequently, international markets (Gordon, Nohen, 2010). Moreover, all

[11] In 2010, there were 26,319 centrally controlled non-financial state-owned enterprises in China. Chen (2013) estimated that those SOEs accounted for nearly 10% of Chinese GDP in 2010.

foreign investors have to obtain approvals by China's State Administration of Foreign Exchange (SAFE) before opening a bank account in China for investments or merger and acquisition activities (White & Case, 2013).[12]

Chiang et al. (2007) mentioned several implications from these results. First, the benefits of international equity portfolio diversification diminish after the beginning of crises due to the increased systemic risk. Second, the volatility of the correlation coefficients presents the need to account for dynamic behaviours in models.

4c. Tests for Contagion during Different Phases of the Financial and Euro Debt Crises

Following the methodologies of Chiang et al. (2007) and Mighri and Mansouri (2013), the multivariate VECH-GARCH model used will incorporate dummy variables to account for the time-varying bivariate correlation coefficients. Thus, the mean equation will be given by:

(3) $$\rho_{ij,t} = C_0 + \alpha_1 DM_1 + \alpha_2 DM_2 + \alpha_3 DM_3 + \alpha_4 DM_4 + \phi_1 \rho_{ij,t-1} + e_{ij,t}$$

where $\rho_{ij,t}$ is the pairwise correlation coefficient between the stock returns in the United States and the stock returns in France, Germany, Ireland, Italy, and Spain in the first model, and Brazil, China, India, and Russia in the second model. DM is a dummy variable equal to 1 during the different phases of the crisis:

DM_1: 10/12/2007 to 4/4/2008, first stage of the 2007-2009 crisis

DM_2: 4/11/2008 to 10/9/2009, second stage of the 2007-2009 crisis

DM_3: 10/16/2009 to 2/11/2011, first stage of the Eurozone crisis

DM_4: 2/18/2011 to 9/13/2013, second stage of the Eurozone crisis

The conditional variance equation is given by:

(4) $$h_{ij,t} = B_0 + A_{i,j} h_{ij,t-1} + B_{i,j} e^2_{ij,t-1} + \chi_1 DM_1 + \chi_2 DM_2 + \chi_3 DM_3 + \chi_4 DM_4$$

The results are presented in Table 7 for the Euro countries and in Table 8 for the BRICs. The AR(1) term in the mean equation was highly significant in each country.

[12] Other regulations include the stipulation that in Chinese-foreign equity joint ventures, the foreign investor must contribute at least 25% of the total capital. Moreover, investors of a Non-legal Person Venture Investment Enterprise must contribute at least $10 million USD for venture investments (Investment Promotion Agency of Ministry of Commerce, 2013)

Table 7: Tests of changes in dynamic correlations between stock returns in the United States and Euro countries

Mean equation	France	Germany	Ireland	Italy	Spain
C_0	0.0638***	0.0586***	0.0417***	0.0608***	0.0816***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
α_1	-0.0211***	-0.0273***	-0.0148***	-0.0293**	-0.0351***
	(0.0041)	*(0.0005)*	*(0.0008)*	*(0.0146)*	*(0.0000)*
α_2	0.0044	0.0032	0.0133	0.0041	-0.0014
	(0.1123)	*(0.2193)*	*(0.1083)*	*(0.1250)*	*(0.6526)*
α_3	-0.0035	-0.0044*	0.0048**	-0.0059**	-0.0198***
	(0.1839)	*(0.0982)*	*(0.0205)*	*(0.0479)*	*(0.0000)*
α_4	-0.0015	-0.0020	0.0081***	-0.0065***	-0.0134***
	(0.3876)	*(0.1571)*	*(0.0000)*	*(0.0004)*	*(0.0000)*
ϕ_1	0.9177***	0.9260***	0.9317***	0.9167***	0.8824***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Variance equation					
B_0	0.0001	0.0000***	0.0000***	0.0000***	0.0001***
	(0.1508)	*(0.0058)*	*(0.0021)*	*(0.0000)*	*(0.0024)*
$A_{i,i}$	0.6647***	0.9295***	0.8609***	0.7684***	0.7520***
	(0.0038)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
$B_{i,i}$	0.0179	0.0343***	0.0754*	0.1326***	0.1380***
	(0.3941)	*(0.0022)*	*(0.0589)*	*(0.0000)*	*(0.0007)*

Notes: The estimates are based on equations 2 and 3 in the text. The p-values are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

During the beginning of the 2007-2009 crisis, bivariate correlations fell in each case (significant at the 5% level) for the Euro countries, indicating that investors thought the recession was a U.S.-specific event. After the first phase, coefficients started to increase, consistent with Chiang et al. (2007) and Mighri and Mansouri (2013)'s studies, although the effects were insignificant at the 10% level. Subsequently, in the first stage of the Eurozone crisis, bivariate correlations decreased for France, Germany, Italy and Spain, supporting the notion that investors believe crises to be country or region-specific events. Contrary to the previous studies, the end of the crisis was marked by further decreases in bivariate correlations in each country except Ireland, which is not consistent with the hypothesis of contagion. Simply put, the European debt crisis may not have had contagious effects on the U.S. stock returns. These results support Chiang et al. (2007)'s assertion that U.S. stock returns affect the stock returns in Asian (international) countries, but Asian (international) stock returns "have no significant dynamic effect on U.S. stock returns."

Originally, the variance equation included the four dummy variables reflecting dynamic changes throughout the crisis. However, none of these were significant at the 10% level, and were omitted. The lack of movement for bivariate correlation coefficients throughout the crisis may indicate investors' growing sophistication. As information becomes more available, markets become more efficient and less volatile. Moreover, investors have become more "rational in analyzing the fundamentals of the individual stock markets rather than adopting the herding behavior after others" (Mighri, Mansouri, 2013). Thus, the previous patterns in correlation coefficients during crises may not hold due to systematic structural technological advances.

There were no consistent signs of dynamic changes in correlation coefficients between the S&P 500 and the stock returns in the BRICs. However, the beginning and end of the Euro crisis had slightly positive effects on the correlations between the U.S. and Russian stock returns, although this may have been due to the emergence of Russian exchange-traded funds[13] (ETFs). The largest U.S.-based Russian ETF, RSX, was created in 2007, exposing Russia to U.S.-specific events such as margin calls. Although RSX began trading in 2007, the bivariate correlations started to rise after investors gained comfort with that ETF in late 2010, when average daily volume started increasing from 1.4 million to 3.4 million in September 2013. So although the increasing correlations coincided with the Eurozone crisis dummy variables, the relationship is likely not causal.

The absence of dynamic changes in correlation coefficients between Brazil, India, and China's stock returns and the S&P 500 indicates that there were no herding or contagion effects. The lack of reliable data and equity research in developing countries may play a role in this. Due to the cost of information, investors may have just viewed emerging markets as a consistently higher beta play on the S&P 500.

The variance equation also supports the previous notion of volatility clustering for correlation coefficients, although the evidence is less robust than in the returns equation in section 3. For the Euro countries, the persistence of the volatility of bivariate correlation coefficients was significant and large in magnitude, with an average persistence of 0.8712. By comparison, persistence in the BRICs averaged 0.8109, including China's, at 1.091. Excluding the outlier China, which is likely to exhibit higher volatility in its correlation coefficient with the U.S. stock returns due to its policies on SOEs and FDI, the average persistence was 0.7176. This implies that there is still persistence in the volatility of correlation coefficients in developed countries with the U.S., but this effect is much weaker in developing countries. This is likely due to investors' views that news in the United States and in Europe is, in the short-term,

[13] ETFs allow investors to purchase shares of a fund that holds assets to reflect the performance of an index it is following. For example, an investor in the United States can easily buy an ETF tracking Brazil's Bovespa stock index in U.S. dollars through their broker, and be indirectly holding Brazilian stocks. Exchange-traded products have grown globally at a 53.9% compound rate between 2000 and 2010 (BlackRock, 2010).

region-specific, causing correlations between those two regions to fluctuate. Conversely, the BRICs may tend to follow the U.S. stock markets more predictably on a weekly basis.

Table 8: Tests of changes in dynamic correlations between stock returns in the United States and the BRICs

Mean equation	Brazil	China	India	Russia
C_0	0.1388***	-0.0166	0.0875***	0.0840***
	(0.0000)	*(0.1154)*	*(0.0000)*	*(0.0000)*
α_1	-0.0060	0.0164	0.0168	0.0070
	(0.9118)	*(0.6813)*	*(0.1608)*	*(0.6973)*
α_2	0.0132	0.0063	0.0020	0.0185
	(0.4749)	*(0.6180)*	*(0.8108)*	*(0.1845)*
α_3	0.0271	-0.0132	0.0108	0.0383*
	(0.2565)	*(0.2189)*	*(0.2745)*	*(0.0511)*
α_4	0.0189	-0.0088	0.0051	0.0262**
	(0.2518)	*(0.3805)*	*(0.4612)*	*(0.0394)*
ϕ_1	0.8059***	0.8871***	0.8176***	0.8103***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Variance equation				
B_0	0.0048	0.0007***	0.0021***	0.0003**
	(0.4009)	*(0.0005)*	*(0.0012)*	*(0.0284)*
$A_{i,i}$	0.7217**	0.9438***	0.3088*	0.9437***
	(0.0332)	*(0.0000)*	*(0.0833)*	*(0.0000)*
$B_{i,i}$	-0.0126	-0.1468***	0.1563***	0.0224**
	(0.2717)	*(0.0000)*	*(0.0000)*	*(0.0195)*

4d. Contagion within European Markets

Given the integration within the Eurozone, this paper will test for the same contagion effects in the Euro countries. The correlations between the returns of Ireland's ISEQ and the stock returns of the other Euro countries, shown in Appendix 2C, will be used. Ireland was used as the comparison country because its yields increased the most at an earlier stage out of the Euro countries in the subsample.

DM_3 and DM_4 are the first and second stages of Ireland's debt crisis, respectively. More specifically, DM_3 is a dummy equal to 1 between October 16, 2009 and May 27, 2011, and DM_4 equals 1 after May 27, 2011. The mean equation is given by:

(5) $$\rho_{ij,t} = C_0 + \alpha_3 DM_3 + \alpha_4 DM_4 + \phi_1 \rho_{ij,t-1} + e_{ij,t}$$

And the conditional variance equation is given by:

(6) $$h_{ij,t} = B_0 + A_{i,j} h_{ij,t-1} + B_{i,j} e^2_{ij,t-1} + \chi_3 DM_3 + \chi_4 DM_4$$

Table 9 shows the results. Similar to the previous models, the AR term was large in value and highly significant. The first stage of the crisis exhibited an increase in correlations between Ireland's stock returns and France and Italy's—contrary to the patterns observed by Chiang et al. (2007) for the Asian crisis. Given the similarities between the European countries, events such as Ireland's debt crisis may not have been seen as country-specific, but region-specific. Slight evidence of contagion in the second stage was shown in France and Germany, where there were statistically significant (at the 10% level) positive changes in pairwise correlations with the ISEQ returns.

Similar to the previous model, the dummy variables in the variance equation were insignificant, and were omitted. The average persistence was 0.7563, providing evidence of volatility clustering with the pairwise correlation coefficients.

Table 9: Tests of changes in dynamic correlations between stock returns in Ireland and the other Euro countries

Mean equation	France	Germany	Italy	Spain
C_0	0.0436***	0.0478***	0.0316***	0.0511***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
α_3	0.0037**	0.0032	0.0050**	0.0006
	(0.0462)	*(0.1969)*	*(0.0403)*	*(0.7943)*
α_4	0.0032*	0.0045*	0.0014	-0.0015
	(0.0808)	*(0.0671)*	*(0.5674)*	*(0.5359)*
ϕ_1	0.9443***	0.9379***	0.9553***	0.9327***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*
Variance equation				
B_0	0.0002*	0.0000	0.0004**	0.0002**
	(0.0571)	*(0.1690)*	*(0.018)*	*(0.0261)*
$A_{i,i}$	0.9703***	0.1716***	0.3388***	0.3456***
	(0.0000)	*(0.0000)*	*(0.0000)*	*0.0002*
$B_{i,i}$	0.0407	0.7903***	0.0371	0.4084***
	(0.4172)	*(0.0000)*	*(0.8004)*	*(0.0000)*

4e. Effects of Quantitative Easing on Bivariate Correlation Coefficients

Along with the pattern of contagion observed by Chiang et al. (2007), the increases in bivariate correlation coefficients between the S&P 500 and other stock indices in October 2008 and May 2010 coincide with the dates the U.S. Federal Reserve started paying interest on reserves, paving the way for more effective monetary policy, i.e. quantitative easing (QE), which began one month later, and the beginning of the Eurozone crisis, respectively. Specifically, on November 25, 2008, the Federal Reserve announced its plans to buy $100 billion U.S. agency debt and $500 billion mortgage-backed securities. This amount was increased on March 18, 2009 to $300 billion in U.S. Treasury securities, $175 billion in

U.S. agency debt, and $1.25 trillion in mortgage-backed securities. QE1 came to an end on August 10, 2010, although maturing assets continued to be replaced with U.S. Treasuries. Between November 3, 2010 and July 2011, the Fed initiated QE2, buying $600 billion in U.S. Treasury securities. A less conventional method, Operation Twist[14], was put in place on September 21, 2011, which ended at the end of 2012. Finally, QE3, that is, the purchasing of $40 billion in Agency mortgage-backed securities per month, was commenced on September 13, 2012. On December 12, 2012, QE3 was expanded to include the purchase of $45 billion of Treasury securities per month. A timeline, reproduced from Labonte (2013), is shown in Table 6. The lowering of interest rates in the U.S. through quantitative easing affects interest rates in every country. U.S. debt is often used as a benchmark for the risk-free rate, and as those rates fall, the yields on other countries' debt will also fall to maintain the risk-premium spread. Thus, given the relationship between interest rates and stock returns, correlations between U.S. and international stock returns will increase (Bae et al., 2003). Subsequently, U.S. and European correlations started to fall at the beginning of the Eurozone crisis, which was largely viewed as solely a Euro event (much like the Asian crisis or the beginning of the 2007-2009 financial crisis). Correlations rose again in 2011, both due to contagion stemming from the Eurozone crisis and the U.S. Federal Reserve's second, and larger, quantitative easing.

4f. Tests for Contagion during Different Phases of the Crisis with Quantitative Easing

The depressed yields on U.S. bonds due to quantitative easing will cause other countries' yields to fall in order to maintain the risk-premium spread. The benefits of low yields, such as increased consumption and higher price multiples on stocks indices, would thus affect all regions, increasing the correlations between the S&P 500 and other stock indices. To incorporate the effects of quantitative easing, the mean equation is now given by:

(7) $$\rho_{ij,t} = C_0 + \alpha_1 DM_1 + \alpha_2 DM_2 + \alpha_3 DM_3 + \alpha_4 DM_4 + \alpha_5 QE + \phi_1 \rho_{ij,t-1} + e_{ij,t}$$

Similar to section 4b, the dummies coincide with the beginning and end of the 2007-2009 crisis and the 2009-2013 Eurozone debt crisis on Ireland:

DM_1: 10/12/2007 to 4/4/2008, first stage of the 2007-2009 crisis

DM_2: 4/11/2008 to 10/9/2009, second stage of the 2007-2009 crisis

[14] Operation Twist was a program which sought to flatten the yield curve and to keep long-term rates low. The Federal Reserve bought $667 billion in long-term Treasury bonds and sold an equivalent amount of shorter-term bonds between September 21, 2011 and December 31, 2012.

DM_3: 10/16/2009 to 2/11/2011, first stage of the Irish Eurozone crisis

DM_4: 2/18/2011 to 9/13/2013, second stage of the Irish Eurozone crisis

QE: 10/3/2008 to 9/13/2013, periods of the Federal Reserve's expansionary monetary policies

And the conditional variance equation is given by:

(8) $$h_{ij,t} = B_0 + A_{i,j}h_{ij,t-1} + B_{i,j}e^2_{ij,t-1} + \chi_1 DM_1 + \chi_2 DM_2 + \chi_3 DM_3 + \chi_4 DM_4 + \chi_5 QE$$

Table 10 shows the results. Two important inferences can be made from the mean equation. First, each of the dummies with the exceptions of the beginning of the 2007-2009 crisis on France, Ireland, and Italian bivariate correlations were significant at the 5% level. Unlike the previous models, each of the time-varying dummies was negative, indicating that the crises did not spread between the U.S. and Euro countries. Moreover, given the significant differences between coefficients in this model compared to the model from section 4a, it can be inferred that policy changes such as QE were positively correlated to the different stages of crises. Thus, the inclusion of the QE term reduced omitted variable bias. Second, there was evidence that the effects of QE had contagious properties, as α_5 (the coefficient representing QE) was positive and statistically significant in each Euro country.

Similar to the previous models of contagion between the U.S. and Euro countries, the volatility of bivariate correlation coefficients was found to be persistent. The average persistence, 0.8794, was similar to the persistence found in the model without QE. However, the time and QE dummies in the variance equation were still extremely insignificant, and were consequently omitted. Thus, QE had no effects on the volatility of correlations. This is likely due to both the increasing efficiency of the markets and the Federal Reserve's transparent communications and guidance about policies.

5. Conclusion

This paper analyzes the transmissions of volatility during the 2007-2009 financial crisis, using a VECH-GARCH model, a methodology similar to the DCC-GARCH proposed by Chiang et al. (2007). After adjusting for heteroskedasticity, this study, using weekly instead of daily stock return data denominated in USD, resulted in a different conclusion than Mighri and Mansouri (2013)'s analysis of the 2007-2009 financial crisis. Some of the difference in results could be due to the contagious properties of foreign exchange, which would reduce bivariate correlations during crises.

Table 6: Timeline of significant Federal Reserve announcements

Date	Announcement
October 6, 2008	Began paying interest on bank reserves.
November 25, 2008	Large scale asset purchases of up to $100 billion of U.S. agency debt and $500 billion of mortgage-backed securities (MBS)
December 16, 2008	Reduced federal funds rate to a range of 0% to 0.25%; anticipated “exceptionally low" federal funds rate would likely be maintained "for some time."
March 18, 2009	Large scale asset purchases which, combined with Nov. 2008 announcement, totaled $300 billion of U.S. Treasury securities, $200 billion of U.S. agency debt (later revised to $175 billion), $1.25 trillion of MBS over about one year (popularly known as "quantitative easing"); anticipated "exceptionally low" federal funds rate would likely be maintained "for an extended period."
August 10, 2010	Following completion of large scale asset purchases, maturing assets would be replaced with U.S. Treasury securities to prevent the balance sheet from shrinking.
November 3, 2010	Large scale asset purchases of $600 billion of U.S. Treasury securities over eight months (popularly known as "QE2").
August 9, 2011	Set a target date (mid-2013) for period Fed anticipated it would keep the federal funds rate at "exceptionally low levels"; the Fed subsequently moved back the target date incrementally to mid-2015
September 21, 2011	Maturity Extension Program (popularly known as “Operation Twist”), under which the Fed purchased $400 billion long-term U.S. Treasury securities, and sold an equivalent amount of short-term Treasury securities over nine months. Began rolling over existing agency debt and MBS into new agency debt and MBS (instead of U.S. Treasury securities)
January 25, 2012	Set “longer-run goal” of 2% inflation; public release of FOMC members forecast of “appropriate” federal funds target.
June 20, 2012	Extended and expanded the Maturity Extension Program to an additional $267 billion of Treasury securities, through the end of 2012.
September 13, 2012	Announced large scale asset purchases of $40 billion of Agency MBS per month for unspecified duration (popularly known as "QE3").
December 12, 2012	Announced that the Fed would continue purchasing $45 billion of Treasury securities per month after the expiration of the Maturity Extension Program; changed the threshold for ending "exceptionally low levels" of the federal funds rate from "at least through mid-2015" to "at least as long as the unemployment rate remains above 6-1/2 percent," contingent on low inflation.

Notes: This table was reproduced from Labonte (2013).

The lack of evidence supporting contagion, that is, dynamic increases in bivariate correlation coefficients throughout a crisis, shows that there are still benefits to international portfolio diversification. In fact, the GARCH models showed that most correlation coefficients between the S&P 500 returns and the stock returns in European countries decreased throughout the crises, implying that investors viewed issues as country-specific events. Correlations with the stock returns of the BRICs, however, had no dynamic changes throughout the crisis periods. The lack of reliable data in the BRICs and the increasing efficiency in markets may play roles in stabilizing pairwise correlations. When analyzing contagion within

Europe during the Eurozone debt crisis, correlations between Irish and other European stock returns increased in most cases, showing investors' views that the crisis in Ireland was affecting the whole Euro-region. Finally, quantitative easing was also shown to have contagious effects throughout Europe, which would diminish some of the gains to international portfolio diversification.

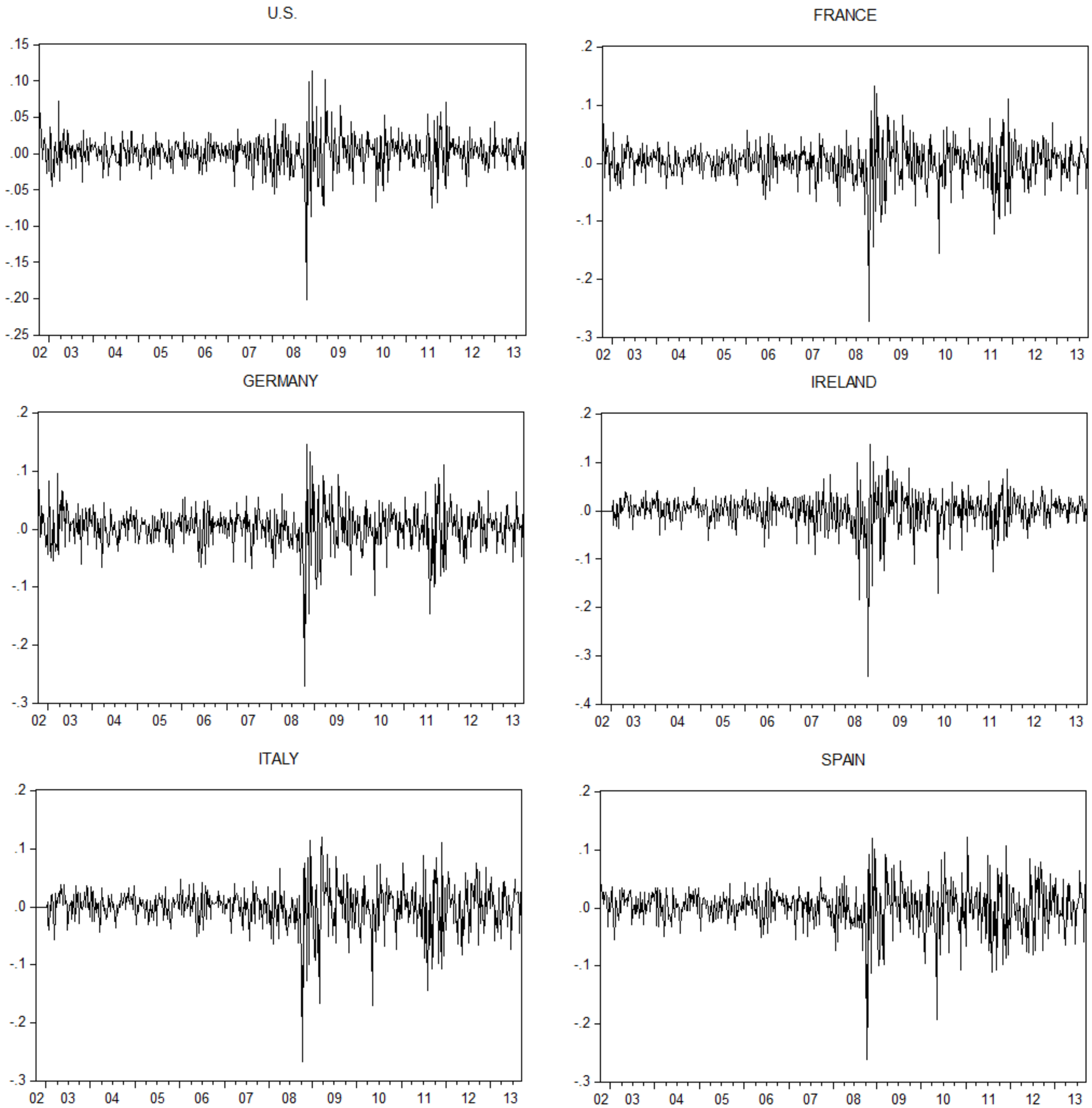
Table 10: Tests of changes in correlations with QE between stock returns in the U.S. and the Euro countries

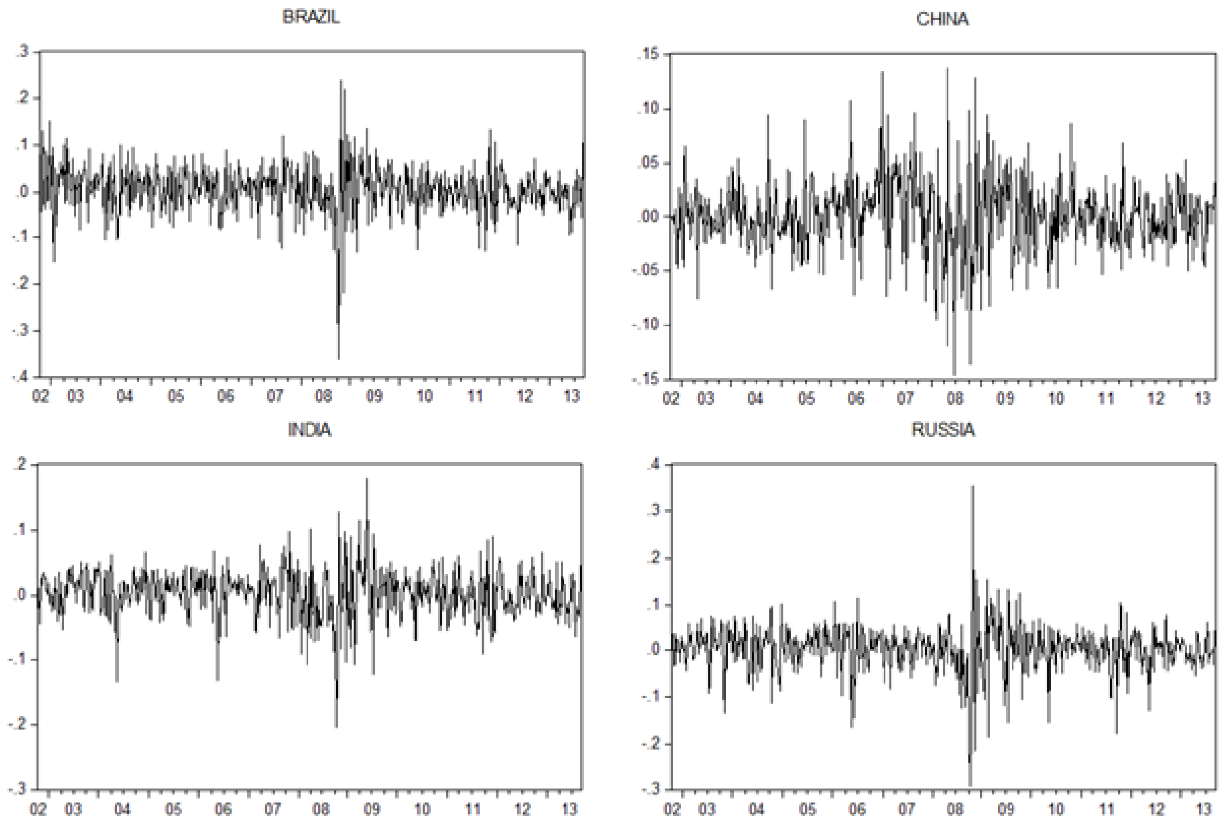
Mean equation	France	Germany	Ireland	Italy	Spain
C_0	0.0682***	0.0842***	0.0421***	0.0587***	0.0725***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
α_1	-0.0061	-0.0180***	-0.0066	-0.0076*	-0.0206**
	(0.1254)	*(0.0012)*	*(0.2049)*	*(0.0784)*	*(0.0224)*
α_2	-0.0119***	-0.0144***	-0.0140***	-0.0136***	-0.0118**
	(0.0012)	*(0.0018)*	*(0.0064)*	*(0.0050)*	*(0.0206)*
α_3	-0.0167***	-0.0187***	-0.0188**	-0.0203***	-0.0252***
	(0.0016)	*(0.0007)*	*(0.0157)*	*(0.0009)*	*(0.0007)*
α_4	-0.0200***	-0.0222***	-0.0170**	-0.0252***	-0.0238***
	(0.0001)	*(0.0000)*	*(0.0257)*	*(0.0000)*	*(0.0002)*
α_5	0.0201***	0.0210***	0.0254***	0.0205***	0.0129**
	(0.0000)	*(0.0000)*	*(0.0008)*	*(0.0002)*	*(0.0247)*
ϕ_1	0.9104***	0.8930***	0.9294***	0.9178***	0.8942***
	(0.0000)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
Variance equation					
B_0	0.0001	0.0000**	0.0000**	0.0001***	0.0000*
	(0.2082)	*(0.0413)*	*(0.0235)*	*(0.0001)*	*(0.0796)*
A_1	0.0399	0.0384*	0.0395*	0.2382***	0.0409**
	(0.1955)	*(0.0503)*	*(0.0554)*	*(0.0001)*	*(0.0129)*
B_1	0.6328**	0.9214***	0.9084***	0.6878***	0.8895***
	(0.0207)	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*

Moreover, it was found that both stock market returns and pairwise correlations exhibited significant and persistent volatility. Although international portfolio diversification can still be used as effective hedges for investors, the increasing use of financially engineered products, particularly volatility indices such as the VIX in the United States and the VSTOXX in Europe, could also serve as effective diversification tools.

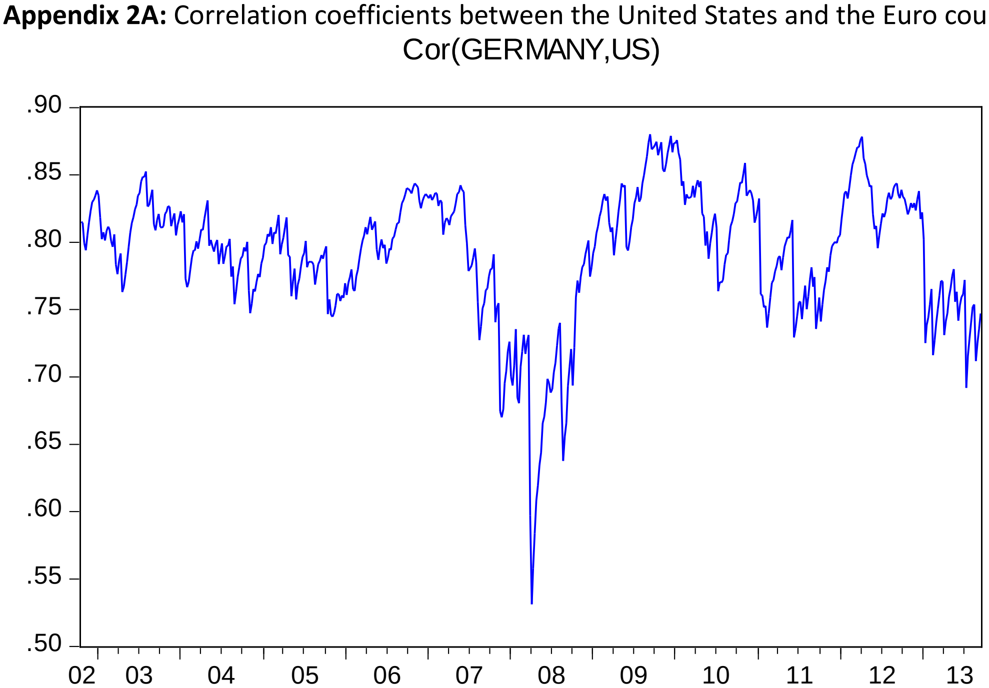
There are two key limitations to this study. First, since the VECH-GARCH model allows for much flexibility, it is possible that more sophisticated models, notably with richer covariance structure, would have produced different results. Second, weekly data significantly reduces the sample size, particularly during the crisis periods. There were only 25 samples for the beginning of the crisis dummy, which may affect the standard errors. Extending the data to capture another crisis, such as the 1999-2001 dot-com bubble, may help to deal with this problem. However, this would need to address the issue of dynamic changes in market volatility transmissions, which is particularly important given the technological advances and the growing sophistication of investors. These issues will be left for future research.

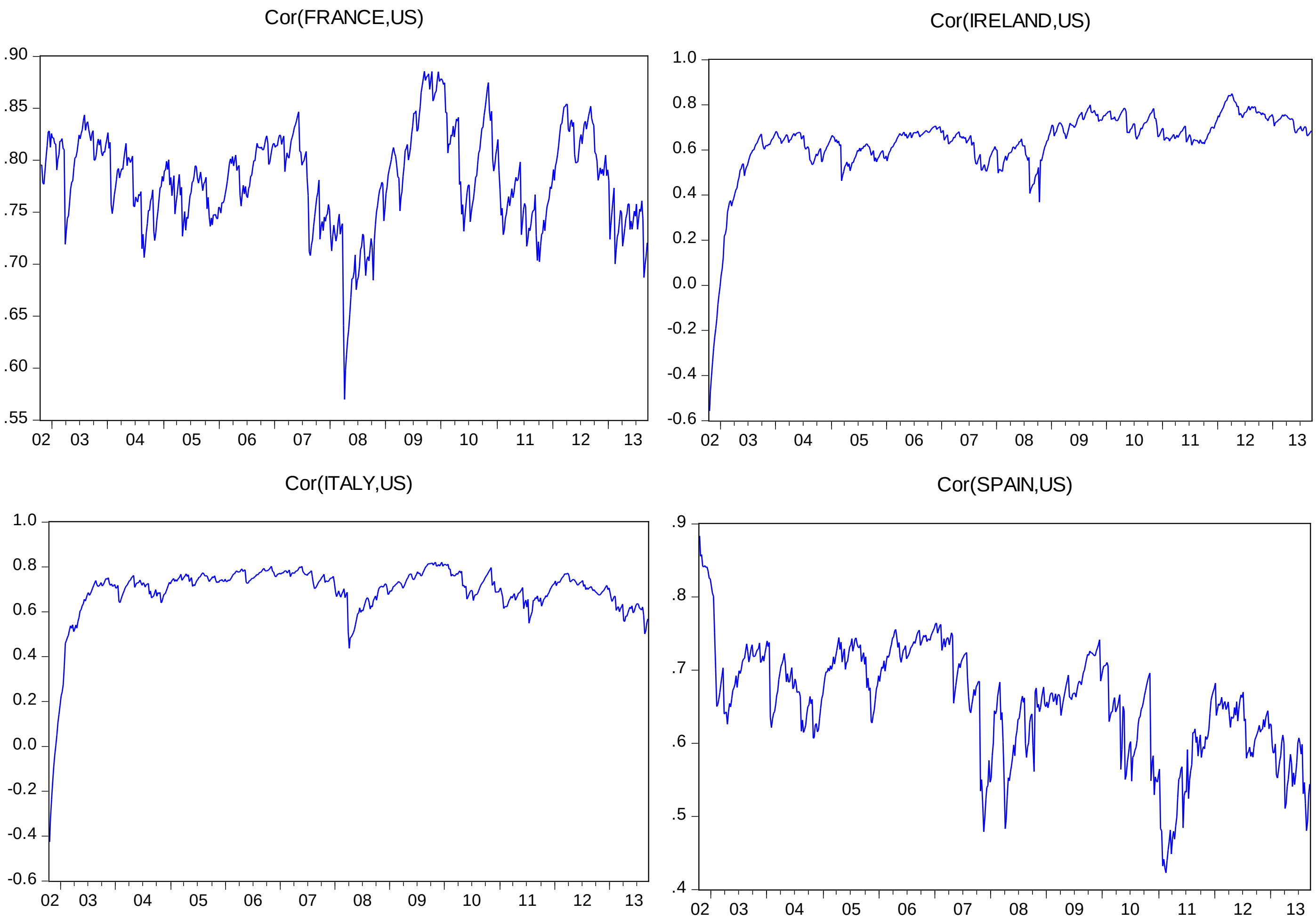
Appendix 1: Weekly stock returns for the sample countries from 10/4/2002 to 9/13/2013



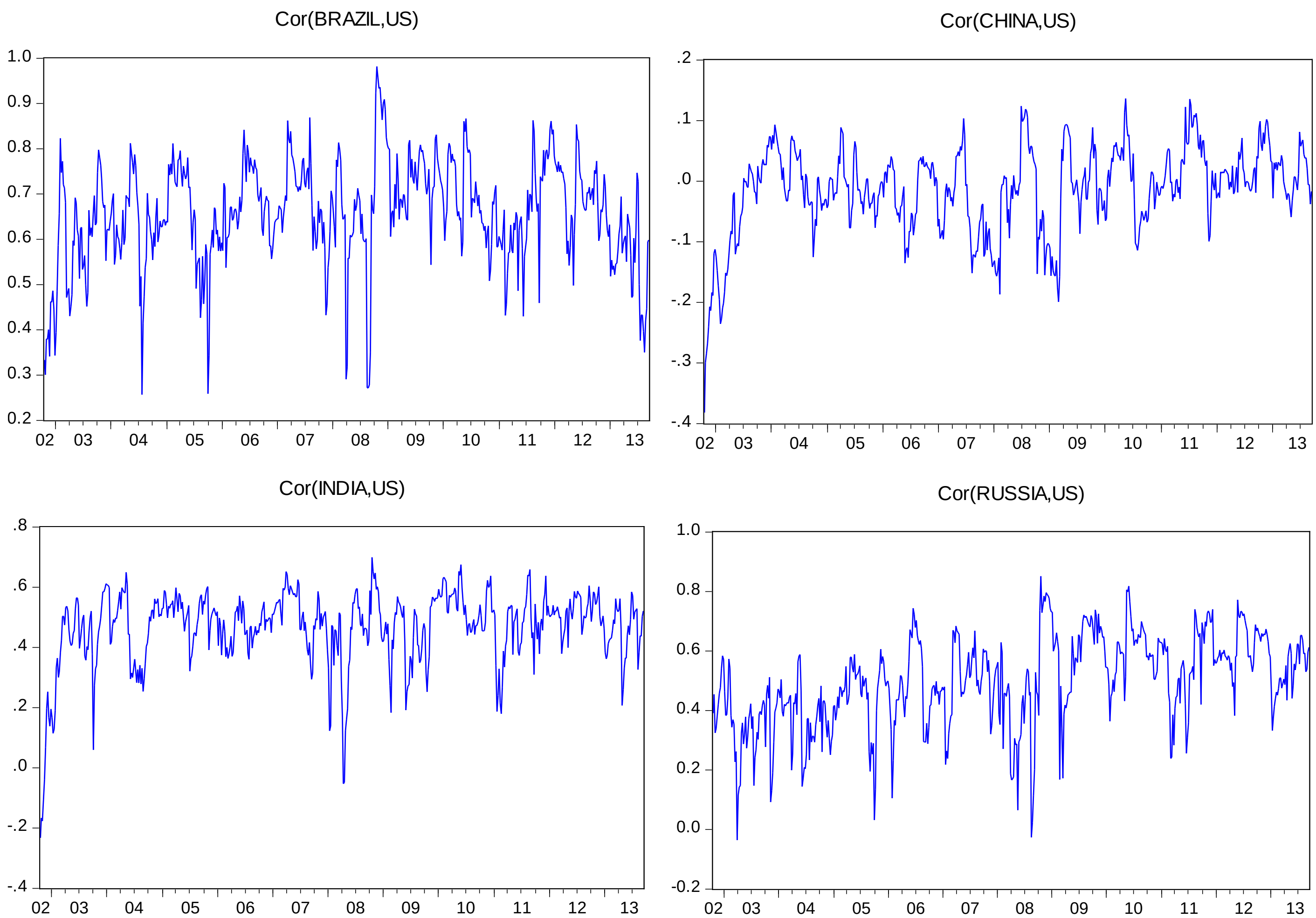


Appendix 2A: Correlation coefficients between the United States and the Euro countries

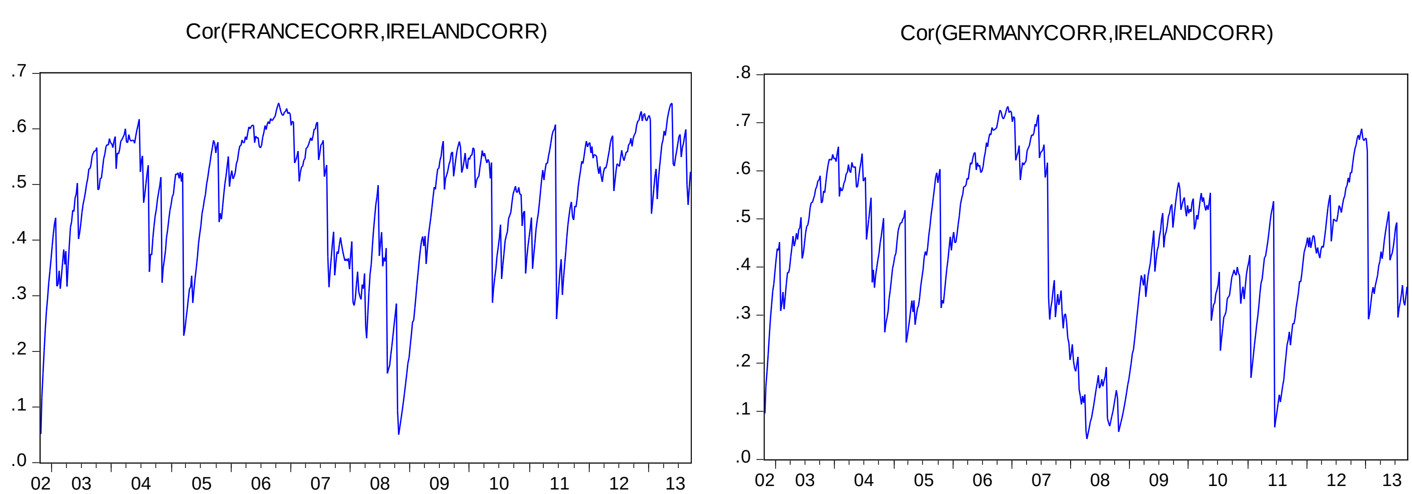


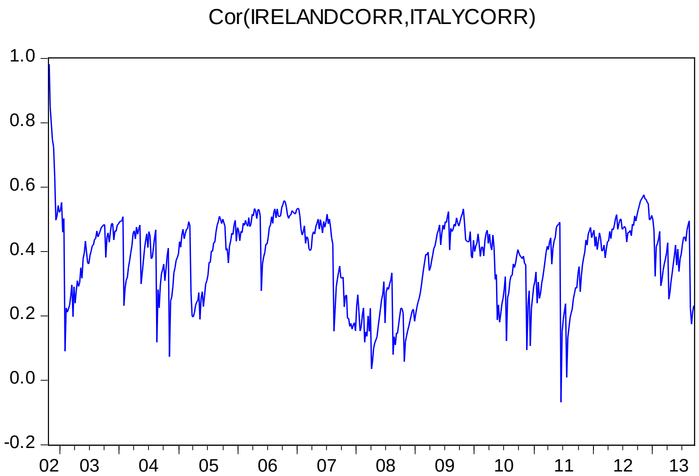

Cor(FRANCE,US)
.90 .85 .80 .75 .70 .65 .60 .55
02 03 04 05 06 07 08 09 10 11 12 13
Cor(IRELAND,US)
1.0 0.8 0.6 0.4 0.2 0.0 -0.2 -0.4 -0.6
02 03 04 05 06 07 08 09 10 11 12 13
Cor(ITALY,US)
1.0 0.8 0.6 0.4 0.2 0.0 -0.2 -0.4 -0.6
02 03 04 05 06 07 08 09 10 11 12 13
Cor(SPAIN,US)
.9 .8 .7 .6 .5 .4
02 03 04 05 06 07 08 09 10 11 12 13

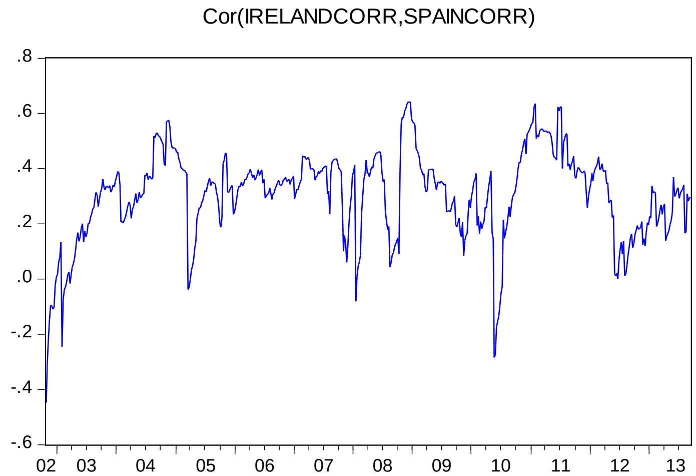
Appendix 2B: Correlation coefficients between the United States and the BRICs



Appendix 2C: Correlation coefficients between Ireland and the other Euro countries




Cor(IRELANDCORR,ITALYCORR)
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
02
03
04
05
06
07
08
09
10
11
12
13


Cor(IRELANDCORR,SPAINCORR)
.8
.6
.4
.2
.0
-.2
-.4
-.6
02
03
04
05
06
07
08
09
10
11
12
13

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