International Stock Market Comovements: What Happened during the Financial Crisis?

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Abstract

We investigate the stock market comovements in Australia, Brazil, Canada, China, Germany, Hong Kong, Japan, Russia, South Africa, the UK, and the USA, both at the market and sectoral level in 2000-2010. Using multivariate GARCH models, our results suggest that the correlation among equity returns during the financial crisis (2008-2010) somewhat increased suggesting that the crisis represented a common shock to all countries. The U.S. stock market is found to be the most correlated with the stock markets in Brazil, Canada and UK. The correlation of U.S. and Chinese stock market is esentially zero before the crisis; it becomes slightly positive during the crisis. The sectoral indices are less correlated than the market indices over the whole period, but again the correlations increase during the crisis.

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1 Introduction

How interdependent are main stock markets around the world? Are they strongly correlated so that the international portfolio diversification is rather cumbersome or are there stock markets, which developments are largely idiosyncratic? And importantly, does the global financial crisis change the comovements of world stock markets? These are the questions that we address in this article.

Shoham and Pelzman (2011) emphasize the global nature of recent financial crisis and discuss why the spillover effects of recent financial crisis were devastating. In this respect, the previous academic research on stock market comovements is voluminous (see, for example, Longin & Solnik (1995), Forbes and Rigobon (2002), Johnson and Soenen (2003), Benelli and Ganguly (2007), among many others). To differentiate our research, we focus on the recent financial crisis and examine the comovements both at market as well as sectoral level (namely, we examine the following sectors: energy, financials, health care, telecommunications, and utilities). We use the daily stock market returns from eleven large countries around the world (Australia, Brazil, Canada, China, Germany, Hong Kong, Japan, Russia, South Africa, the UK, and the USA) in 2000-2010. To assess rigorously the stock market comovements, we employ multivariate GARCH models. This allows us to examine the degree of comovements both across the markets as well as over time.

Our results suggest that the degree of comovements differs across the countries' stock markets. The U.S. stock market is strongly correlated with the stock markets in Brazil, Canada and Germany. On the other hand, the Chinese stock market typically exhibits the lowest correlations with the rest of world, even though there is evidence of of increased integration of Chinese stock market in recent years.

Interestingly, the degree of stock market comovements increase during the recent financial crisis, which is likely to be a consequence of global nature of financial crisis, i.e. all stock markets were hit severely during the crisis. This finding is reconfirmed using the sectoral data. Our results indicate that although the sectoral indices are less correlated than the market indices, the correlation typically increased during the financial crisis, too. In general, our results thus give support to literature that find the increased stock market comovements during the distress.

The article is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes the data. Section 4 presents the multivariate GARCH model. Section 5 gives the results on international stock market comovements. Section 6 concludes. Appendix with additional results follow.

2 Related Literature

We selectively review the related literature in this section. We focus on literature employing multivariate GARCH models with substantial international coverage. There is also related literature investigating the linkages between stock market volatility and macroeconomic conditions, the reader is referred to Engle and Rangel (2008).

King and Wadhwani (1990) focus on explaining uniformity with which the world markets fell in October 1987 after the U.S. stock market crash. They put forward that simultaneous decline in different markets cannot be attributable to fundamentals and that contagion occurs during turmoil period as a result of rational investors operating under asymmetric information. Using the cross-market correlation coefficients they find evidence for contagion in the United States, United Kingdom, and Japan during the period from July 1987 to February 1988. They also conclude that higher volatility generally implies higher correlation among the markets.

Forbes and Rigobon (2002) challenge this finding and show that the correlation coefficients were "biased due to heteroskedasticity in market returns". If the correlation coefficients are corrected for heteroskedasticity, they find no evidence of contagion during the 1997 Asian crisis, 1994 Mexican crisis, and the 1987 U.S. crash. The adjusted unconditional correlation coefficients from January 1986 till December 1987 are 0.53 between the U.S. and Canada, 0.21 between the U.S. and U.K., 0.17 between the U.S. and Germany, 0.14 between the U.S. and Hong Kong, and 0.01 between the U.S. and Japan. Hamao et al. (1990) investigate the U.S., U.K., and Japan markets from April 1985 till March 1988. Using the generalized autoregressive conditional heteroskedastic (GARCH) model they find statistically significant volatility spillovers from the U.S. to Japan and from the U.K. to Japan. The spillovers from Japan to the other two markets are much weaker.

Theodossiou & Lee (1993) examine the weekly returns of the U.S., U.K., Canadian, German, and Japanese stock markets in 1980-1991. Employing multivariate GARCH model, they assess the degree of interdependence among these markets. First, they present cross-border (unconditional) correlations of markets returns. They range from 0.26 between Japan and Canada to 0.57 between the U.S. and Canada. Second, they find statistically significant volatility spillovers from the U.S. to U.K., Canada, Germany, and Japan of which the spillovers to Germany are the weakest. They also find some weak evidence for spillovers from the U.K. to Canada and from Germany to Japan. Third, they conclude that volatility of returns in the U.K. and Canadian markets, unlike for Japanese and German, come in large part from the U.S. stock market. Finally, the German market is found to be the least integrated.

Karolyi (1995) studies the impact of the U.S. shocks on returns and volatility on Canadian stock market for the period from 1981 to 1989. He uses S&P 500 and TSE 300 indices for the U.S. and Canadian market, respectively, and distinguishes stocks that are dually listed on both markets and that are not. First, Karolyi (1995) finds that shocks originated in the U.S. have decreasing impact on returns and volatility of the Canadian market over the studied period. Second, the magnitude and persistence of the U.S. shocks is greater for the Canadian stocks that are not dually listed on both exchanges.

Using the monthly excess returns, Longin and Solnik (1995) study the long-term development of conditional correlations between seven major stock markets (Germany, France, the U.K., the U.S., Switzerland, Japan, and Canada) over the period 1960-1990. First, they calculate the unconditional correlations among the markets over the whole period; the correlations range from the lowest of 0.24 (Germany and Japan) to the highest of 0.71 (Canada and the U.S.) and the average correlation of the U.S. with the remaining six countries is 0.48 (lowest for Japan with the correlation at 0.3). Second, they give evidence that the international conditional correlations rose over the thirty-year period. Third, they find that stock market correlations increase in turbulent times. Finally, they conclude that higher interest rates and dividend yields are supportive for higher correlations.

Johnson and Soenen (2003) use the daily data in 1989-1999 to investigate the integration of equity markets and its driving forces in Argentina, Brazil, Chile, Mexico, Canada, Colombia, Peru, and Venezuela with the U.S. market. First, they find statistically significant comovements of returns between the U.S. stock market and the eight remaining markets; the highest are those of Canada and Mexico. Second, the degree of comovements is found to vary over time with the peak in mid 1990s. Third, their results indicate that bilateral trade intensity with the United States has a positive effect on the comovements, while exchange rate volatility and the higher market capitalization has a negative effect on the comovements.

Worthington and Higgs (2004) examine the spillovers among nine - developed as well as emerging - Asian stock markets (Hong Kong, Japan, Singapore, Indonesia, Korea, Malaysia, the Philippines, Taiwan, and Thailand) in 1988-2000. They find that all the markets are highly integrated. Interestingly, domestic news in the emerging markets play a greater role for the market volatility than domestic news in the developed countries.

Benelli and Ganguly (2007) investigate the linkages between financial markets (stock, currency, and bond markets) in the U.S. and seven Latin American countries (namely, Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela) in 1996-2006. They find that the sensitivity of Latin American stock markets to the U.S. shock increased over the period.

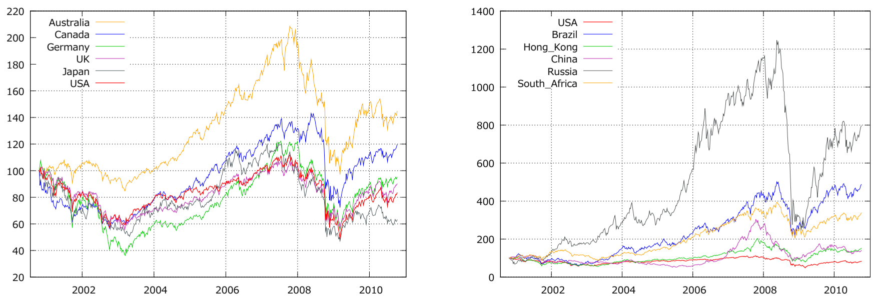
Sun and Zhang (2009) examine the effect of the recent financial crisis originating in the U.S. on the stock markets in China and Hong Kong using the daily data from January 2005 to October 2008. First, they find that although China is not immune to the recent turmoil in the U.S., the price and volatility spillovers from the U.S. to Hong Kong are stronger than those to China. Second, the impact of volatility shocks originating in the U.S. on Hong Kong stock markets is more persistent than on China; the impact of its own volatility, however, is more persistent for China than for Hong Kong.

3 Data

We use the daily data from major national stock market indices of eleven countries: Australia, Brazil, Canada, China, Germany, Hong Kong, Japan, Russia, South Africa, the United Kingdom, and the United States. The choice of our countries is motivated to have global coverage including most financial centers. The data are obtained from *Reuters Wealth Manager* and our aim is to choose the indices that are most comprehensive and representative for the specific country. The sectoral-level indices are obtained from *Datastream.* We focus on the following five sectors: health care, telecommunications, utilities, financials, and energy.

We briefly describe the national indices in this paragraph. The index *ASX 200* comprises 200 largest Australian companies, which account for approximately 78% of Australian equity market capitalization. Brazil is represented by the *Bovespa* index, which comprises about 370 companies and accounts for

Figure 1: Stock markets in 2000-2010



75% of Brazilian equity market capitalization. We use the *TSX Composite Index* for Canada. This index accounts for approximately 70% of equity market capitalization. China is represented by the *SSE Composite Index* comprising 1,500 companies listed on Shanghai Stock Exchange. The *DAX 30* index is used for Germany. It includes 30 large German companies and accounts for approximately 80% of equity market capitalization. Hong Kong is represented by the *Hang Seng* index comprising 45 constituents and accounts for 60% of equity market capitalization. Japan is represented by the well–known index *Nikkei 225*. Russia is represented by the *RTS* index comprising 50 stocks; with the market capitalization of about US$ 200 billion as of December 2010. South Africa is represented by the *JSE Top 40 Tradeable* index comprising 40 largest companies listed on Johannesburg Stock Exchange with approximately US$ 925 billion of market capitalization as of December 2010. The United Kingdom is represented by the *FTSE 100*, which accounts for about 80% of equity market capitalization and the United States are represented by *S&P 500* which accounts for about 75% of market capitalization.[1]

We employ daily closing prices for time period from December 19, 2000 to December 15, 2010 for both market and sectoral indices.[2] The plot of all stock markets is available in Figure 1. All the stock markets were hit substantially by the financial crisis and the (normalized) index value often falls below the level at the beginning of our sample.

For our econometric analysis we study the daily returns, which are represented by continuously compounded rate specified for country i at time t as follows:

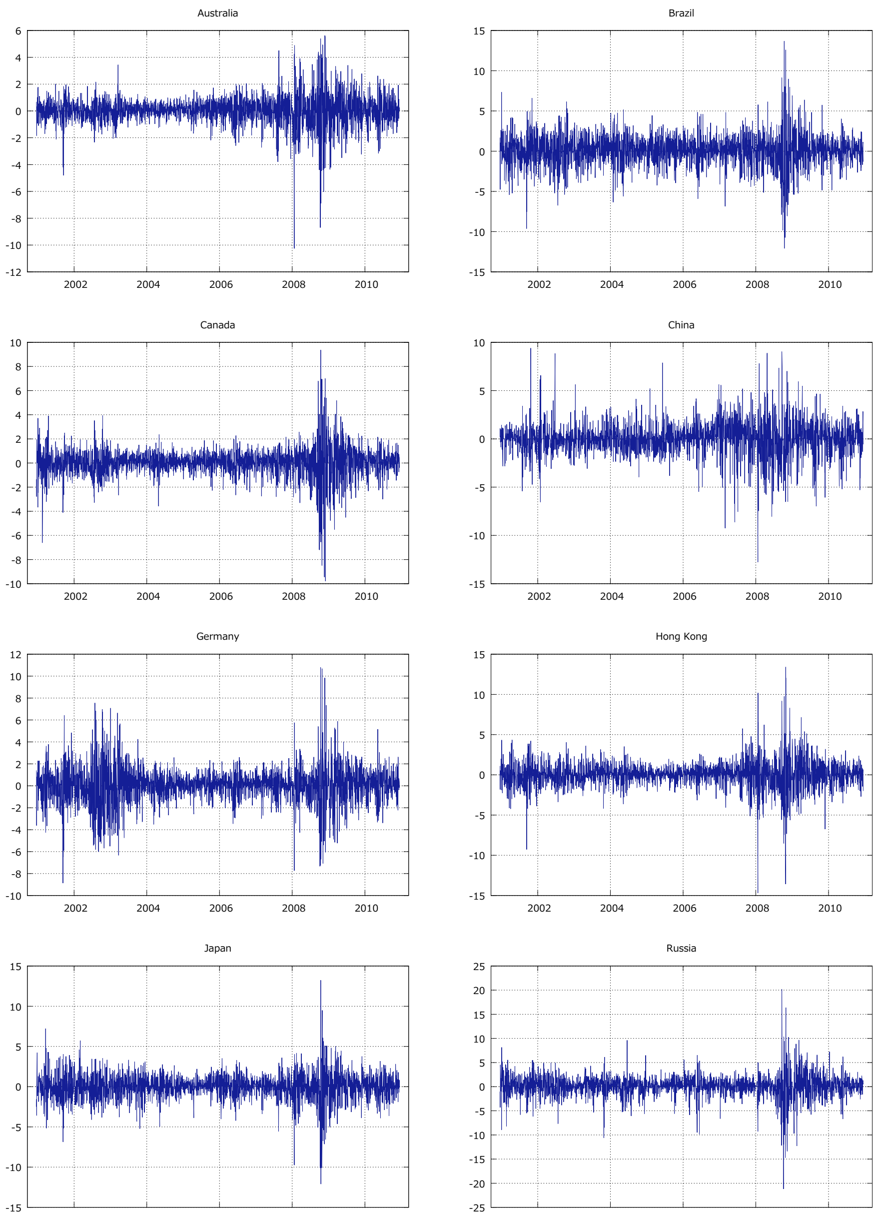
[1]All data about market capitalization are obtained from the web pages of individual stock exchanges and from the World Federation of Exchanges (http://www.world-exchanges.org).

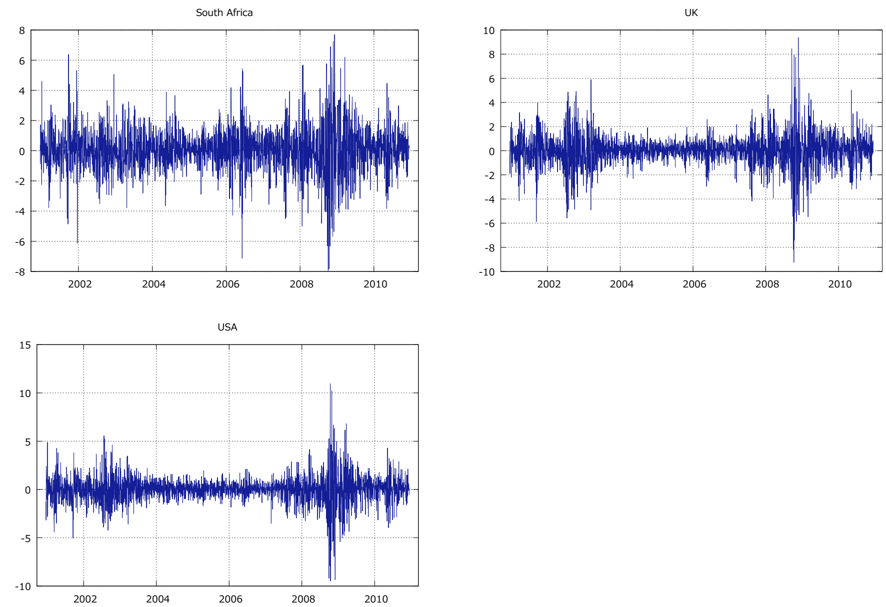
[2]The closing prices are based on local currencies and are not corrected for dividends.

$$r_{i,t} = (ln(p_{i,t}) - ln(p_{i,t-1})) \times 100 \quad (1)$$

The plot of daily returns for each market series is available in Figure 2. The summary statistics for all series is presented in the Appendix. It is noteworthy that unit root (augmented Dickey-Fuller) and stationarity (KPSS) tests were used to assess the degree of integration of all series. We find that the original series in levels are not stationary. To the contrary, the daily returns, $r_{i,t}$, are found stationary.

Figure 2: Daily returns of stock markets





4 Multivariate GARCH model

We use multivariate GARCH model to assess the comovements among stock markets. For the ease of exposition, we present the model for $N = 2$, i.e. two stock markets. See Laurent et al. (2006) for a survey of multivariate GARCH models.

Consider 2 x 1 dimensional vector of daily returns $\boldsymbol{r_t}$. We assume that the mean equation is specified as:

$$\boldsymbol{r_t} = \boldsymbol{\mu} + \boldsymbol{u_t} \tag{2}$$

where $\boldsymbol{\mu}$ is conditional mean vector, i.e. $\mathbb{E}(\boldsymbol{r_t}|\Omega_{t-1}) = \boldsymbol{\mu}$ and

$$\boldsymbol{u_t} = {H_t}^{1/2}\boldsymbol{v_t} \tag{3}$$

where ${H_t}^{1/2}$ is a 2 x 2 conditional variance matrix, i.e. $var(\boldsymbol{r_t}|\Omega_{t-1}) = H_t$, and $\boldsymbol{v_t}$ is a 2 x 1 random vector with the following properties:

$$\mathbb{E}(\boldsymbol{v_t}) = 0 \tag{4}$$

$$var(\boldsymbol{v_t}) = I_N \tag{5}$$

where I_N is a 2 x 2 identity matrix.

The direct generalizations of the variance formula in univariate GARCH model for the multivariate variance-covariance matrix H_t include primarily VECH and BEKK models. The VECH model was introduced by Bollerslev, Engle, and Wooldridge (1988). The specification of the VECH model is as follows:

$$VECH(H_t) = W + A.VECH(\boldsymbol{u_{t-1}u'_{t-1}}) + B.VECH(H_{t-1}), \quad \boldsymbol{u_t}|\Omega_{t-1} \sim N(0, H_t) \tag{6}$$

where $\boldsymbol{u_t}$ is a 2 x 1 disturbance vector, W is a 3 x 1 parameter vector, A and B are 3 x 3 parameter matrices and VECH($\cdot$) stands for the operator that stacks the upper triangular portion of a symmetrical matrix.

The VECH operator transforms a 2 x 2 matrix into a 3 x 1 vector in the following way:

$$VECH(H_t) = VECH\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} = \begin{pmatrix} h_{11,t} \\ h_{22,t} \\ h_{12,t} \end{pmatrix} \tag{7}$$

and analogously for other elements. We can now rewrite it as follows:

$$\begin{pmatrix} h_{11,t} \\ h_{22,t} \\ h_{12,t} \end{pmatrix} = \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} u_{1,t}^2 \\ u_{2,t}^2 \\ u_{1,t}u_{2,t} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{22,t-1} \\ h_{12,t-1} \end{pmatrix} \tag{8}$$

Thus, we have the conditional variance equations for both returns series ($h_{11,t}$ and $h_{22,t}$) and conditional covariance equation between the series ($h_{12,t}$). The drawback of this model is that we have to estimate 21 parameters (3 in matrix W and 9 in each of matrices A and B), which is computationally demanding and risky in the sense that the local instead of global maximum of likelihood function is more likely to be encountered. To account for this problem, several extensions of the VECH models were proposed, such as constant correlation or diagonal multivariate GARCH.

In addition, the VECH model cannot ensure that the covariance matrix H_t is positive definite, which is necessary because variance cannot be less than zero. The BEKK model, as introduced by Engle and Kroner (1995), resolves this drawback. In this model the matrix Ht is defined as:

$$H_t = W'W + A'\boldsymbol{u_{t-1}u'_{t-1}}A + B'H_{t-1}B \tag{9}$$

where A and B are 2 x 2 parameter matrices and W is a 2 x 2 upper triangular parameter matrix.

By rewriting in a more detailed way we get:

$$\begin{aligned}
\begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix} &= \begin{pmatrix} w_{11} & 0 \\ w_{12} & w_{22} \end{pmatrix} \begin{pmatrix} w_{11} & w_{12} \\ 0 & w_{22} \end{pmatrix} \\
&+ \begin{pmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{pmatrix} \begin{pmatrix} u_{1,t-1} \\ u_{2,t-1} \end{pmatrix} \begin{pmatrix} u_{1,t-1} & u_{2,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\
&+ \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \\
&= \begin{pmatrix} w_{11}^2 & w_{11}w_{12} \\ w_{12}w_{11} & w_{12}^2 + w_{22}^2 \end{pmatrix} \\
&+ \begin{pmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{pmatrix} \begin{pmatrix} u_{1,t-1}^2 & u_{1,t-1}u_{2,t-1} \\ u_{2,t-1}u_{1,t-1} & u_{2,t-1}^2 + w_{22}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\
&+ \begin{pmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}
\end{aligned} \tag{10}$$

After multiplication we express the conditional variances and covariance of H_t:

$$\begin{aligned}
h_{11,t} &= w_{11}^2 + (a_{11}u_{1,t-1})^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1}, \\
h_{12,t} &= w_{11}w_{12} + a_{11}a_{12}u_{1,t-1}^2 + u_{1,t-1}u_{2,t-1}(a_{12}a_{21} + a_{11}a_{22}) + a_{21}a_{22}u_{2,t-1}^2 + \\
&\quad b_{11}b_{12}h_{11,t-1} + (b_{11}b_{22} + b_{12}b_{21})h_{12,t-1} + b_{21}b_{22}h_{22,t-1}, \\
h_{22,t} &= (w_{12}^2 + w_{22}^2) + (a_{12}u_{1,t-1} + a_{22}u_{2,t-1})^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + \\
&\quad b_{22}^2 h_{22,t-1}
\end{aligned} \tag{11}$$

The right hand sides of the three equations above contain mainly quadratic terms and the matrix H_t is indeed positive definite even "under very weak conditions," Engle and Kroner (1995). Moreover, the number of parameters to be estimated reduces to eleven, as compared to twenty one in the VECH model.

Note also, that the conditional variances ($h_{11,t}$ and $h_{22,t}$) and the conditional covariance ($h_{12,t}$) depend on lagged values of conditional variances ($h_{11,t-1}$ and $h_{22,t-1}$) and the conditional covariance between the two series ($h_{12,t-1}$) as well as on lagged values of squared disturbances of both series and the cross–products of the disturbances. This feature distinguishes the BEKK–GARCH model from the univariate GARCH model.

Maximum likelihood method is used to estimate the parameters. Assuming the conditional normality, the log–likelihood function has the following form:

$$L(\theta) = -\frac{TN}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log(|H_t| + \boldsymbol{u_t}' {H_t}^{-1} \boldsymbol{u_t}) \tag{12}$$

where θ represents the set of all parameters to be estimated, N is the number of dependent variables (in our case $N = 2$) and T is the number of observations.

Using multivariate GARCH we can model time–varying variances and covariances between stock market returns. We estimate the magnitude of comovements by computing dynamic conditional correlations, which are defined in time t as:

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t} h_{22,t}}} \tag{13}$$

5 Results

This section presents our results on measuring the comovements among stock markets. More specifically, we use the BEKK-GARCH model to receive the time-varying conditional correlations among the stock markets, e.g. $\rho_{12,t}$. The correlations are compared for the 'pre–crisis' period and 'crisis' period. We define the crisis period as starting from the fall of Lehman Brothers (e.g. the mid-September 2008), but the results are robust to alternative specifications of the beginning of crisis.

For the ease of exposition, the daily values of conditional correlations among the stock markets are averaged for the 'pre–crisis' period and 'crisis' period. The detailed results are available in Figure 3 in the Appendix, which show the conditional correlations between the U.S. stock market and all other stock markets (the remaining figures are available upon request).

The results are available in Table 1. For the full sample, we find that U.S.

stock market shows very little correlation with stock markets in China, Australia, and Japan. On the other hand, the U.S. stock market exhibits the highest correlations with Canada, Brazil and Germany. Interestingly, although all correlations increased in the crisis period, the ranking of correlations with U.S. stock market remains largely unchanged. Similarly, the U.K. stock market is found to be the least correlated with stock markets in China, Japan and Australia and most correlated with Germany, South Africa, and the USA. The correlations between the U.K. stock market and remaining countries again increase in all cases (with an exception of Japan) during the crisis. The results for Japan and Hong Kong share a similar pattern, to a large degree. Chinese stock market is typically the least correlated, although some trend towards greater integration is apparent in more recent data. The correlations with the remaining stock markets typically increase during the crisis. On average, the results indicate that the conditional correlations among stock markets increase by about 0.1 during the financial crisis.[3]

The correlations reported in Table 1 are somewhat higher than the results from the previous studies. Forbes and Rigobon (2002) find much lower correlations between the U.S. stock market with the stock markets in the U.K., Germany, and Japan. Similarly, Theodossiou and Lee (1993) report less than half the correlation between German and U.S. stock market compared to what we find. Benelli and Ganguly (2007) estimate the correlation between Brazilian and U.S. stock market to be around 0.4, while our results suggest the values around 0.6. Although we are aware that these studies do not use the identical econometric strategy, the results suggest that the stock market integration increases during the 2000s.

Next, we also examine the comovements among stock markets at the sectoral level. This is much less common, as the studies within this stream of literature typically examine the market-wide indices only (for an analysis of comovements of sectoral indexes, see Rua and Nunes, 2009). Our results are available in Table 2. For the sake of brevity, we present the average correlations between the U.S. and remaining countries. The results suggest that the correlations at the sectoral level are substantially lower than the correlations at the market level. The correlations are especially low for health care and telecommunication sectors. This is not surprising, as these two sectors - and especially health care sector - are typically more regulated than the remaining sectors. Interestingly,

[3]The exception is Japan, the conditional correlations of Japanese stock market with other market have risen only by 0.05 during the crisis.

Table 1: Average correlations between individual stock markets in full period, pre–crisis period, and crisis period.

Full period (12/19/2000 – 12/15/2010)											
	USA	UK	Japan	Hong Kong	Australia	Brazil	Canada	China	Germany	Russia	South Africa
USA	1	0.495	0.132	0.153	0.101	0.587	0.688	0.046	0.566	0.209	0.324
UK	0.495	1	0.289	0.313	0.294	0.390	0.486	0.066	0.797	0.380	0.525
Japan	0.132	0.289	1	0.521	0.522	0.128	0.184	0.170	0.280	0.237	0.306
Hong Kong	0.153	0.313	0.521	1	0.521	0.195	0.233	0.255	0.288	0.325	0.353

Pre–crisis period (12/19/2000 – 09/12/2008)											
	USA	UK	Japan	Hong Kong	Australia	Brazil	Canada	China	Germany	Russia	South Africa
USA	1	0.456	0.131	0.135	0.085	0.553	0.663	0.026	0.538	0.163	0.285
UK	0.456	1	0.294	0.302	0.281	0.354	0.460	0.040	0.778	0.336	0.493
Japan	0.131	0.294	1	0.506	0.488	0.132	0.176	0.137	0.283	0.209	0.295
Hong Kong	0.135	0.302	0.506	1	0.500	0.174	0.220	0.191	0.285	0.305	0.330

Crisis period (09/15/2008 - 12/15/2010)											
	USA	UK	Japan	Hong Kong	Australia	Brazil	Canada	China	Germany	Russia	South Africa
USA	1	0.631	0.138	0.216	0.160	0.702	0.777	0.115	0.663	0.370	0.458
UK	0.631	1	0.273	0.351	0.340	0.514	0.574	0.155	0.865	0.534	0.636
Japan	0.138	0.273	1	0.573	0.640	0.112	0.213	0.285	0.271	0.333	0.346
Hong Kong	0.216	0.351	0.573	1	0.611	0.301	0.302	0.477	0.327	0.426	0.466

although the correlations are not large, they typically tend to increase during the financial crisis. This complies with our results in Table 1.

5 Concluding Remarks

We examine the stock market comovements among eleven countries (Australia, Brazil, Canada, China, Germany, Hong Kong, Japan, Russia, South Africa, the UK, and the USA) in 2000-2010. For this reason, we employ multivariate GARCH models and apply it both to market as well as sectoral stock market returns. We assess the degree of comovements both over time and across different stock markets.

Our results suggest that some stock markets are highly correlated. For example, the average conditional correlation for the U.K. and German stock market is about 0.8, the U.S. and Canadian about 0.7 and the U.S. and Brazilian stock market close to 0.6. On the other hand, Chinese stock market is typically the least correlated with the remaining countries in our sample. However, Chinese market shows the pattern towards higher correlation, for example, its correlation with Hong Kong stock market increases substantially in 2008-2010.

Our results also suggest that the comovements do not differ only across the market, but markedly vary over time, too. In general, our results indicate that the conditional correlations that we receive from the estimation of multivariate GARCH models increase during the financial crisis. This suggests that the financial crisis represented a common shock. This finding is reconfirmed, when we use the stock market returns at the sectoral level. We find that the conditional correlations are much lower at the sectoral level, as compared to the market level. The correlations are low especially for health care and telecommunication sectors, which is likely to be a consequence of greater government regulation in these sectors. Nevertheless, when we examine the correlations over time, our results again show that the correlations increase during the crisis.

In terms of future research, we believe that it would be worthwhile to examine in a more detail the direction of the spread of increased volatility in the financial markets during distress. It would be also interesting to shed light whether the investors distinguished among various emerging markets during the financial crisis. Emerging markets were hit by the crisis with the different intensity and evidence suggests that at least at the beginning of crisis many emerging markets exhibited increased risk premia and volatility in the financial

Table 2: Average correlations between USA and other 10 countries in five industry sectors. *(01/05/2004 - 12/15/2010), **(11/28/2006 - 12/15/2010)

Full period (12/20/2000 – 12/15/2010)	Market	Energy	Financials	Health Care	Telecoms	Utilities
USA-Australia	0.101	0.077	0.043	0.024	0.049	NA
USA-Brazil	0.587	NA	NA	NA	0.247	0.308
USA-Canada	0.688	0.665	0.581	0.359	NA	0.232
USA-China*	0.046	NA	0.061	NA	NA	NA
USA-Germany	0.566	NA	0.347	NA	0.244	0.269
USA-Hong Kong	0.153	NA	0.100	NA	NA	0.078
USA-Japan	0.132	NA	0.091	0.053	0.045	0.047
USA-Russia	0.209	0.102	NA	NA	0.119	NA
USA-South Africa	0.324	0.230	0.215	0.107	0.094	NA
USA-UK**	0.495	0.482	0.457	0.220	NA	0.302
Average	0.330	0.311	0.237	0.152	0.133	0.206

Pre-crisis period (12/20/2000 – 09/12/2008)	Market	Energy	Financials	Health Care	Telecoms	Utilities
USA-Australia	0.085	0.071	0.038	0.027	0.042	NA
USA-Brazil	0.553	NA	NA	NA	0.229	0.276
USA-Canada	0.663	0.645	0.553	0.365	NA	0.204
USA-China	0.026	NA	NA	NA	NA	NA
USA-Germany	0.538	NA	0.315	NA	0.236	0.234
USA-Hong Kong	0.135	NA	0.081	NA	NA	0.049
USA-Japan	0.131	NA	0.088	0.053	0.056	0.051
USA-Russia	0.163	0.086	NA	NA	0.096	NA
USA-South Africa	0.285	0.193	0.185	0.096	0.085	NA
USA-UK	0.456	NA	NA	NA	NA	NA
Average	0.303	0.249	0.210	0.135	0.124	0.163

Crisis period (09/15/2008 – 12/15/2010)	Market	Energy	Financials	Health Care	Telecoms	Utilities
USA-Australia	0.160	0.095	0.062	0.013	0.073	NA
USA-Brazil	0.702	NA	NA	NA	0.310	0.417
USA-Canada	0.777	0.734	0.676	0.337	NA	0.329
USA-China	0.115	NA	0.068	NA	NA	NA
USA-Germany	0.663	NA	0.455	NA	0.270	0.388
USA-Hong Kong	0.216	NA	0.162	NA	NA	0.178
USA-Japan	0.138	NA	0.101	0.054	0.008	0.031
USA-Russia	0.370	0.160	NA	NA	0.197	NA
USA-South Africa	0.458	0.356	0.318	0.143	0.125	NA
USA-UK	0.631	0.508	0.477	0.274	NA	0.311
Average	0.423	0.371	0.290	0.164	0.164	0.276

markets despite at least in some emerging markets macroeconomic fundamentals remained relatively strong.

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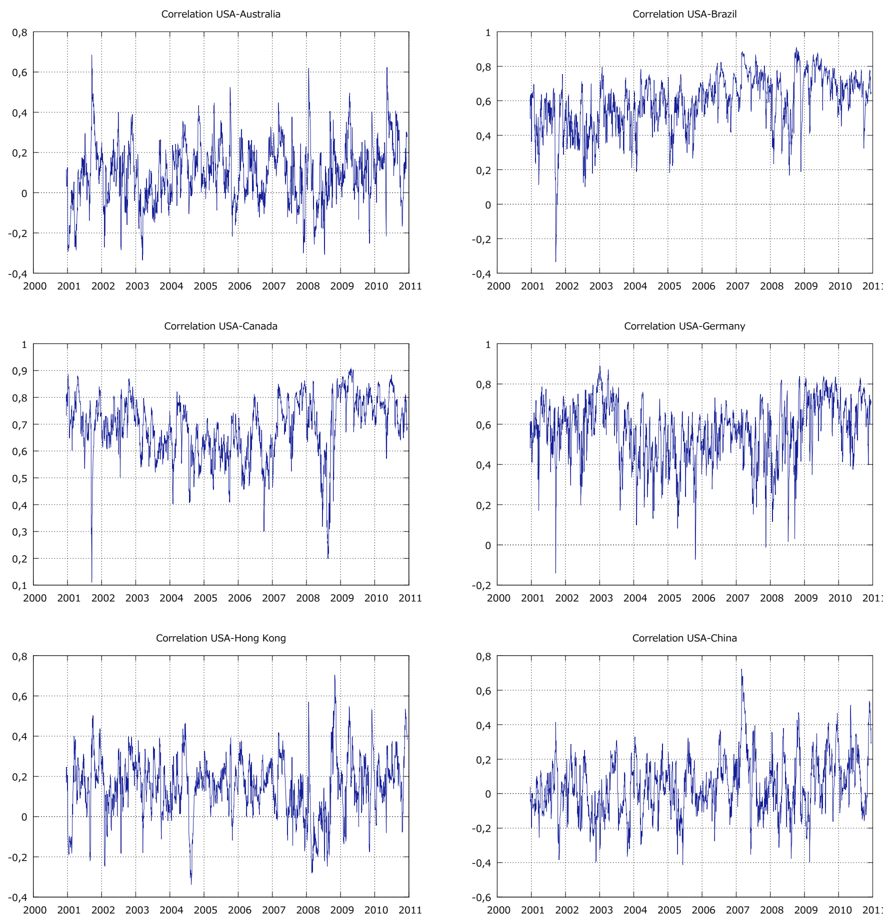
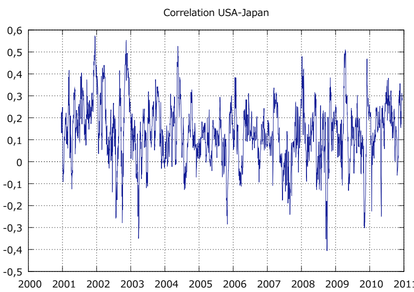
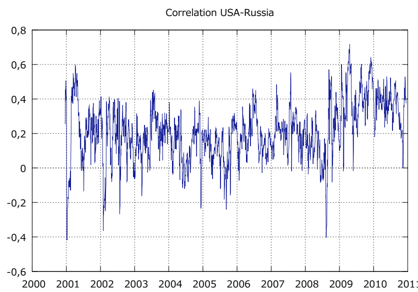
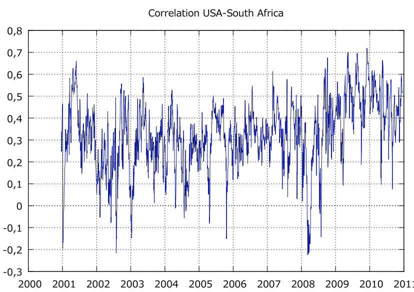
Appendix

Figure 3: The conditional correlation between the U.S. stock market and rest of the world




Correlation USA-Japan
0,6
0,5
0,4
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
-0,4
-0,5
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011


Correlation USA-Russia
0,8
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011


Correlation USA-South Africa
0,8
0,7
0,6
0,5
0,4
0,3
0,2
0,1
0
-0,1
-0,2
-0,3
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011

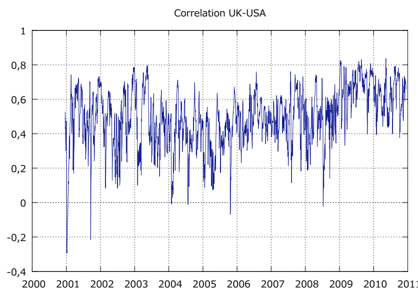

Correlation UK-USA
1
0,8
0,6
0,4
0,2
0
-0,2
-0,4
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011

Table 3: Summary statistics of daily returns for eleven world stock indices

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera stat.	p-value
Australia	0.0152	5.6282	-10.2610	1.0741	-0.6911	8.9271	8683.91	0.0000
Brazil	0.0589	13.6780	-12.0960	1.9336	-0.1213	4.3840	2051.56	0.0000
Canada	0.0150	9.3703	-9.7880	1.2100	-0.6658	10.2370	11340.70	0.0000
China	0.0138	9.4010	-12.7640	1.7067	-0.2494	5.1052	2800.02	0.0000
Germany	0.0037	10.7970	-8.8747	1.6503	0.0221	4.6682	2319.28	0.0000
Hong Kong	0.0166	13.4070	-14.6950	1.6253	-0.1864	10.9570	12790.40	0.0000
Japan	-0.0133	13.2350	-12.1110	1.6074	-0.3553	6.9096	5134.27	0.0000
Russia	0.0983	20.2040	-21.1990	2.2806	-0.5150	10.5140	11877.00	0.0000
South Africa	0.0499	7.7069	-7.9594	1.4610	-0.0701	3.1460	1055.36	0.0000
UK	-0.0024	9.3843	-9.2656	1.3294	-0.0952	6.4345	4409.79	0.0000
USA	-0.0027	10.9570	-9.4695	1.3690	-0.1251	8.2545	7257.61	0.0000