VOLATILITY TRANSMISSION FROM DEVELOPED TO EMERGING STOCK MARKETS: A DIAGONAL BEKK APPROACH

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Economics in the
Economics Department
School of Economics and Regional Studies
at the University of Macedonia

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2019

Abstract

This study investigates the volatility transmission between global stock markets. To achieve our goal, we use daily stock index data covering the time period from 2000 to 2016. Furthermore, we examine the statistical properties of our series as well as the returns correlations, and employ the diagonal parameterization of the BEKK-GARCH model to study the volatility of the global stock market returns. Our results exhibit strong GARCH effects and relatively weaker ARCH effects. We provide evidence that global stock markets are quite integrated, but there is still room for diversification and risk reduction, through the thorough study of the linkages among the markets.

1. Introduction

Globalization is an evident trend worldwide. The last two decades especially, markets seem to have become very integrated, with the rapid development of technology and the removal of cross-border capital flow restrictions. Many international investors nowadays seek to invest in emerging markets for a number of reasons. Investors and portfolio managers could obtain great diversification benefits, which theoretically come with the investment in uncorrelated markets. Another reason is the higher returns that investments in emerging markets offer in order to offset the higher risk, relatively to the returns in developed countries. The global financial crisis of 2007-2008 worked in favor of this trend, since the low interest rates many governments in developed counties enacted to counter the severe effects of the crisis, made many investors to look for higher interest rates in emerging markets. But, international investors and portfolio managers are not the only ones interested in the linkages between different markets. Policy makers should take into account news and developments in markets that are significantly integrated with the domestic one. Therefore, it is obvious that the study of the linkages among different markets is of great importance and great benefits can be derived from such research.

In this study we examine the presence and magnitude of volatility transmission from developed to emerging stock markets. These markets are three of the most influential developed stock markets and four emerging stock markets, two from the euro area and two from Asia. We adopt a long term horizon covering the period from 2000 up to 2016. We even divide our sample into three different sub-periods to capture possible changes in our results due to the global financial crisis. Using daily data we calculate the returns of each stock market during our examined time period, we study their statistical properties, their correlations and we adopt the Diagonal parameterization of the BEKK-GARCH model to examine the stock markets' conditional volatilities and covariances. The severe effects of the global financial crisis on stock markets are apparent in the estimated descriptive statistics. Moreover, the returns between some countries are significant during certain periods. Finally, our results propose the existence of strong GARCH effects in all markets and relatively weaker ARCH effects.

The remainder of this study is organized as follows. Section 2 reviews characteristic examples of researches on this topic in international literature along their main results and defines an important terminology. Section 3 gives a full description of the data we collect as well as the econometric approach we follow on this study. In section 4 we present our empirical results and we discuss on them, while section 5 summarizes and concludes.

2. Literature review and terminology

As we have already mentioned in the introduction, there are many groups of people like investors, financial intermediaries and institutions, as well as governments, policy makers and authorities in general, who have a strong interest to understand the linkages between international stock markets. Those linkages have become stronger due to the constantly increased globalization, especially during the last two decades. So it is no surprise to us that the topic of volatility transmission has been studied by a lot of researchers and there is a great number of studies someone can read to understand this topic in a greater extend. In this section of our study our aim is to present some of those studies, trying to contain as many different variations of these researches as possible, both in terms of sample selection and methodology used to study this phenomenon. But before we further proceed with the presentation of the literature review, we believe it is important to point out some explanatory terms widely used in this dissertation.

2.1 Emerging markets

The expression "emerging markets" is usually used to describe the financial markets located in industrializing or emerging countries around the world. Those countries are considered to be in a transitional phase between developing and developed status and characterized by low-to-middle per capita income. An "emerging market" country is at the same time embarking on an economic reform program that will lead it to stronger and more reliable economic performance levels, as well as transparency and efficiency in the capital market (Chukwuogor, 2007). Emerging markets generally do not have the level of market efficiency and strict standards in accounting and securities regulation as advanced markets (such as the U.S., Europe and Japan), but investors seek them out very often since they experience higher level of economic growth as measured by GDP, and therefore offer higher returns. But, we should not fail to mention that investments in emerging markets come with much greater risk due to political instability, domestic infrastructure problems, currency volatility and limited equity opportunities.

2.2 Interdependence and contagion

Generally, stock market "linkages", "relations" and "interdependence" are used to describe the same phenomenon. However, it is very common to subdivide the terms stock market "linkages" or "relations" into "interdependence" and "contagion" (Jung & Maderitch, 2014). "Interdependence" thereby, is when the movement of one market is affected by the movement of another market. This is a continuous situation that characterizes the related markets, so unexpected phenomena are excluded.

On the other hand, the notion of "contagion" is characterized by strong and sudden changes in measured market linkages. Specifically, by "contagion" we refer to a significant increase in co-movements across markets after a shock (Jung & Maderitsch, 2014). These co-movements can be observed in exchange rates, stock prices, sovereign spreads, and capital flows, and can be translated as the spread of market disturbances. Therefore, financial "contagion" can be a possible risk for countries who are seeking to integrate their financial system with international financial markets and institutions.

2.3 Volatility clustering

Volatility clustering is one of the most important "stylized facts" in financial time series data. Specifically, volatility clustering is the tendency of large changes in prices of financial assets to cluster together, which results to the persistence of these magnitudes of price changes. As noted by Mandelbrot (1963), who was the first one who observed this phenomenon, "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" when it comes to markets.

2.4 Literature review

A large number of papers in the current literature focus on examining the volatility transmission between different financial markets around the globe. Most of them report significant cross-market volatility spillovers among international stock markets due to increased international financial integration (Jung & Maderitsch, 2014). Many authors choose to divide their data into different sub periods, and more specifically, the periods before, during and after the global financial crisis of 2007-2008.

Following this strategy, Vo & Ellis (2018) investigate the interdependence between the Vietnamese stock market, which is an emerging market, and other stock markets of developed countries, namely the US, Hong-Kong and Japan. In order to do that, they collect national stock market index daily data from January 2000 to June 2015, and employ the diagonal presentation of the BEKK-GARCH model to estimate the volatility transmission between those stock markets. They empirically confirm that the Vietnam stock market is strongly influenced by the developed stock markets. Furthermore, seeking to discover if the crisis has affected the stock markets mentioned above and the linkages amongst them, they divide their dataset into sub periods, covering the pre, during and post global financial crisis. Their analysis made clear that the mean returns during the crisis were significantly lower and negative in all countries. Moreover, the correlation coefficients were higher during the crisis and the period after it than they were before.

Jung & Maderitsch (2014) investigate the volatility transmission between the stock markets of Hong-Kong, Japan and U.S. using intra-daily data from 2000 to 2011. Considering the various crisis events contained in their sample, they detected structural breaks in volatility spillovers. However, only a few of these breaks appear to be approximately synchronous across the different markets. Therefore, in contrast to the analysis of Vo & Ellis (2018), they report that splitting the sample according to synchronous break dates and to assess differences in volatility spillovers across the resulting subsamples is not feasible.

Many papers focus on examining the linkages and the volatility transmission between the world's largest economies. For instance, Clements et al. (2015), examine the volatility transmission between the world foreign exchange, equity and bond markets. Using ten minute data from 2005 to 2013 and incorporating a multivariate GARCH model, they investigate the volatility transmission between the financial markets of Japan, Europe and the U.S. Their results indicate that developments in Japan can influence Europe and the United States, as well as similar events in Europe can influence the United States during the same calendar day. Therefore, they state that the meteor shower effect in the transmission of volatility from one region to another during the same calendar day is at least as important as the traditional heat wave effect.

In another study, Lin et al. (1994) use daily data of NIKKEI 225 and S&P500, two of the biggest stock markets in the world. Of particular note is the methodology they employ to model the way investors in one country receive and process information from a foreign country. They used two different approaches. The first approach is an Aggregate-shock model (AS), in which the domestic overnight return depends on the preceding domestic daytime return, the "Monday" dummy and foreign influences. The second approach is a Signal-extraction model (SE), which, as its name implies, proposes to split the unexpected return into two non-relevant shocks, global and local. Their main results show bidirectional cross-market interdependence in returns and volatilities between New York and Tokyo markets. Additionally, they found that the foreign daytime returns can significantly influence the domestic overnight returns, and almost no evidence that lagged return spillovers from New York daytime to Tokyo daytime or vice versa.

A great number of papers focus on financial integration among developed and emerging markets. Chukwuogor (2007) examines the general patterns of stock market returns and their volatility using daily stock indexes of 40 countries classified as developed and emerging for the period 1997 to 2004. During the examined time period, most global stock markets experience positive returns while most of the stock markets with the higher daily returns were emerging markets. In addition, there was presence of the day-of-the-week effect in most of the countries.

Regarding that countries in the European area share strong financial bonds, while some of them have also adopted the same currency and follow the same monetary policy, the examination of the volatility transmission between these countries is another interest chapter in the international literature. Chukwuogor and Feridum (2010) is a characteristic example of scientists who studied this case of volatility transmission. Particularly, in their study they examine the volatility of returns in fifteen emerging and developed European countries. In contrast with other studies, they use the annual percentage changes in the end of year closing values of the European financial stock market indices for the period 1997-2004. This sample has the singularity to contain both the introduction of euro in 2000 and the dotcom crisis of high tech companies in 2001. In order to determine the nature of volatility returns, they used different measures such as the variance, the standard deviations, the kurtosis, the skewness and the coefficient of variation. Their results suggest that there was generally high volatility of returns in the markets during the examined period. In general, the reason for volatility transmission between the European financial markets could be due to the openness of economies, the higher exchange rate stability and the introduction of the euro, which has worked in favor of financial integration.

In the context of Asian markets, Li & Giles (2013) employ an asymmetric BEKK-GARCH model in order to examine the linkages between the US, Japan and six Asian emerging stock markets, namely China, India, Indonesia, Malaysia, the Philippines and Thailand. Their sample covers the period from 1993 to 2012, including both the 1997 Asian financial crisis and the 2007 subprime financial crisis. Instead of examining the return spillovers, they mainly focus on examining the shock and volatility spillovers between the above markets. They further separate their sample into sub periods isolating by this way and examining separately the two major crises, the Asian financial crisis (1997-2001) and the subprime financial crisis (2008-2012). The main results derived from their analysis indicate that the emerging markets are more susceptible to their own past shocks than the developed markets, both for the long run and the short run. Furthermore, they found that the U.S. stock market has unidirectional shock spillovers to both the Japanese and the Asian stock markets. Moreover, they detected significant bidirectional spillovers between the Japanese and the emerging markets during the last five years of their sample.

In another research concerning the Asian equity markets, Sariannidis et al. (2010) explore the extent of contagion and interdependence between the stock exchange markets of India, Singapore and Hong Kong. In order to do that, they collect daily data from 1997 to 2005 and employ a multivariate BEKK GARCH model. Their results indicate that the examined markets are highly integrated and present characteristics that suggest inefficiency and slow absorption of shocks and information, derived mainly from the U.S. stock market.

Beirne et al. (2008) examine the volatility transmission from developed to emerging stock markets giving emphasis to turbulence episodes. Similarly to many other studies, they employ a BEKK GARCH model. They test their model for the period 1993 to 2008 for 41 emerging markets. They find that in most emerging markets the market volatility tends to be higher during turbulence periods in developed markets. However, this increase in volatility was not always statistically significant. Furthermore, not many indications are found to support shifts in conditional correlations between developed and emerging stock markets during crisis episodes in the first ones.

A different approach was followed by Abbas et al. (2013) who employ a bivariate EGARCH model to examine the volatility transmission between some of the major developed stock markets and a number of Asian emerging stock markets. For that purpose they collect daily data from 1997 to 2010 for all the examined stock markets. Bi-directional volatility transmission between India and Pakistan is reported, as well as the fact that India is more speedily integrated with other countries.

3. Data and Methodology

3.1. Data

In this study we use the national stock indices at daily frequency to analyze the returns and examine the linkages between the markets. Particularly, the specific market indices representing each of the countries are as follows: the US S&P500 stock index, the Germany-DAX100 index, the Japan-NIKKEI225 index, the Czech Republic-PX index, the Poland-WIG20 index, the Philippine-PSEI index and the Turkey-XU100 index.

The stock markets we examine in this study are the three major developed world markets and four emerging stock markets, two from the Europe area and two from Asia. Data are collected from Yahoo Finance database. Our data sample covers the period from 3 January 2000 to 29 December 2016, including interesting crisis events such as the 2001 dotcom crisis, as well as the global financial crisis of 2007-2008. High frequency data, such as the daily data we collected are necessary to capture more information about the stock index price changes. Tables 1 to 4 present the descriptive statistics of daily returns for the whole period as well as for the three sub-periods, namely the pre (2000-2006), during (2007-2009) and post crisis (2010-2016) period, while figures 1 and 2 present the daily stock index prices and the daily stock index returns respectively.

We can extract some very interesting results from the first four tables and the first two figures about the statistical properties of our data. All stock market mean returns are lower during the crisis period than the pre-crisis period. Additionally, all mean returns are negative during the global financial crisis except for Turkey (0.0350), but after the crisis all mean returns become higher and positive again, except for the Prague Stock Exchange mean return which is very close to zero (-0.0036) but obviously higher in comparison with its crisis value (-0.0539). So, in contrast to the Vo & Ellis (2018) findings, who report that the mean returns remained lower after the financial crisis, our analysis reveals that the stock markets seem to have recovered from the severe effects of the global financial crisis.

As for the standard deviations, they are all significantly higher during the crisis period, reflecting the uncertainty that characterized the financial markets after the Lehman Brothers bankruptcy. On the other hand, the regulatory reform embedded in the 2010 Dodd-Frank law forced many banks to reduce, and in most cases eliminate their proprietary trading operations. Along with the restriction of the IPO market, and the rise of ETFs, this regulation led to long periods of abnormally low volatility, punctuated by short bursts of panic (such as the European debt crisis in 2011, China's currency devaluation in 2015) (Bob Pisani, 2018, CNBC), which explains the return of stock market standard deviations to their pre-crisis levels.

Of particular note is that all Kurtosis values exceed 5, demonstrating a leptokurtic distribution, a very common result in finance. Since the empirical estimates for kurtosis are all above 3, the value for a Gaussian distribution, the presence of abnormal daily returns is obvious. All stock markets are negatively skewed, revealing that these abnormal returns are generally negative.

Figures 1 and 2 visually confirm the results derived from the descriptive statistics analysis. Specifically, all stock market prices present an extreme fall the periods after the 2001 dotcom crisis and the 2007-2008 global financial crisis. The daily stock market returns present their greatest volatility during these two periods. This highlights the high level of financial integration between the global stock markets, as they seem to be susceptible to the same crisis events.

3.2. Methodology

We log transform our series in order to improve their statistical properties, as suggested by Andersen et al. (2003). Then, we calculate the daily stock returns of these indices as follows:

$$R_t = \log (P_t/P_{t-1})*100 \quad (1)$$

where R_t is the return at time t while P_t and P_{t-1} are the prices at time t and t-1 respectively.

3.2.1. Stationarity

Before we proceed with examining the linkages between the stock markets it is crucial to test our series for stationarity. There are several reasons that make the stationarity or otherwise of a series very important. Brooks (2008), mentions that the stationarity or otherwise of a series can have great impact on its behavior and statistical properties. For example, the persistence of a shock on a series will gradually die out if the series is stationary, while its persistence will be permanent if the series is non-stationary. Additionally, the use of non-stationary data can lead to spurious regressions. Such regressions will have a high R^2 even if the variables are totally unrelated. Consequently, these good looking regressions from the perspective of significant coefficient estimates and high R^2, will be valueless. If the variables in a regression model are not stationary, then it can be proved that the standard assumptions for asymptotic analysis will not be valid. Thus, we cannot validly undertake hypothesis tests about the regression parameters.

Two models have been mainly used to describe the non-stationarity, the random walk model with drift

$$y_t = \mu + y_{t-1} + u_t \quad (2)$$

and the trend stationary process

$$y_t = \mu + \beta_t + u_t \quad (3)$$

where u_t is a disturbance term in both cases.

Those two models require different treatments to induce stationarity. Stochastic non-stationarity, which is described by equation (1), reveals the existence of stochastic trend in the data and first differencing is required. If $\Delta y_t = y_t - y_{t-1}$ and $Ly_t = y_{t-1}$ so that $(1-L)y_t = y_t - Ly_t = y_t - y_{t-1}$, then subtracting y_{t-1} from both sides of equation (1) yields

$$y_t - y_{t-1} = \mu + u_t \quad (4)$$

$$(1 - L)y_t = \mu + u_t \quad (5)$$

$\Delta y_t = \mu + u_t$ (6)

The new variable Δy_t will be stationary. In this case we can say that y_t is integrated of order one, or I(1), since it has to be differenced once in order to get a stationary time series. In general, a series can be I(d), if it must be differenced d times to get a stationary time series. It is evident from the previous equations why y_t is also known as a unit root process, since one root of the characteristic equation will be equal to one.

Deterministic non-stationarity is described by equation (2), the series is trending because it is an explicit function of time and de-trending is required. In this case, any estimations needed would be done to the residuals derived from equation (2), after their trend is removed.

Dickey and Fuller (Fuller 1976; Dickey and Fuller 1979) were the first ones who developed a test for the stationarity of time series. Considering the simple AR(1) process in equation (6), the Dickey Fuller test (DF test) examines the null hypothesis that $\varphi=1$, which would yield that the time series has a unit root and it is non-stationary, against the alternative that $\varphi<1$ which certifies the stationarity of the time series.

$y_t = \varphi y_{t-1} + u_t$ (7)

The t-statistic for the DF test is given by equation (7)

$$T_{\varphi=1}=\frac{\hat{\varphi}-1}{s.e.(\hat{\varphi})} \quad (8)$$

The DF test is generalized into the Augmented Dickey Fuller test (ADF test) to accommodate the general ARIMA and ARMA models. In practice, we usually use the ADF test instead of the DF test. For example, if there are higher-order AR dynamics, we can re-write our model as a function of just y_{t-1} and a series of differenced lag terms.

Phillips and Perron have developed their own model to examine non-stationarity, proposing a test quite similar to the ADF test, with the difference that theirs incorporates an automatic correction to the DF model to allow for autocorrelated residuals. The ADF and the PP tests often give the same conclusions and are widely used in international literature, which is why we also use them in this study to examine the stationarity of our series.

Therefore, the returns were tested for stationarity using the Augmented Dickey-Fuller and the Phillips-Perron unit root tests. Table 5 presents the t-statistics for each series for both tests, as well as the critical values of the tests. As we can see, all t-statistics are much higher than the critical values. Taking these results into account, we can state that the returns are all stationary and suitable for econometric modeling.

3.2.2. Testing for "ARCH effects"

As we discussed earlier in this section, the stock market returns we examine are not normally distributed, which is confirmed both by their descriptive statistics and their graphical presentations. The next step in our research would be to test our data for the so called "ARCH effects", in order to verify whether this class of models is suitable for our data. For that purpose, Engle (1982), proposed the Lagrange Multiplier (LM) test. The test statistic is given by TR^2, where R is the sample multiple correlation coefficient computed from the regression of the squared residuals on a constant and q own lags, and T is the sample size (Wang et al., 2005). Under the null hypothesis, all q lags of squared residuals have coefficient values that are not significantly different from zero (Brooks, 2008), and no ARCH effects are present. If the LM statistic is greater than the critical values, we reject the null hypothesis since past squared residuals affect current residuals, suggesting the existence of ARCH behavior in our data.

So, we performed the Engle (1982) test for the existence of ARCH effects in our data. Initially, each stock market returns series was regressed on a constant term. Then, their squared residuals were regressed on a constant and 1, 4 and 12 own lags. The results are presented in table 6. We can observe that the LM statistic is statistically significant in every case, leading us to the conclusion that there are strong ARCH effects in our data. Thus, an ARCH type model would be appropriate for the modeling of volatility clustering between the examined stock markets. The nature of the ARCH type models as well as their capability of explaining the volatility clustering will be the subject of the following sub-section of this study.

3.2.3. ARCH/GARCH models

Linear models are unable to explain some very common characteristics of financial time series, such as leptokurtosis, the leverage effect, as well as the very important phenomenon of volatility clustering (Brooks, 2008), which has already been explained in our study. Therefore, it is obvious that we cannot use linear models which suppose homoscedasticity, for the modelling of financial time series.

The most popular model for modelling the volatility of financial time series is the autoregressive conditional heteroscedasticity (ARCH) model. Let y_t denote a stationary time series, then consider the typical structural model

$$y_t = \beta_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + u_t \quad (9)$$

where $u_t \sim N(0,\sigma^2_t)$. The conditional variance of u_t can be denoted as σ^2_t:

$$\sigma^2_t = \text{var}(u_t \mid u_{t-1}, u_{t-2}, \dots) = E[(u_t - E(u_t)) \mid u_{t-1}, u_{t-2}, \dots] . \quad (10)$$

Usually we assume that $E(u_t) = 0$, so the above equation takes the form of

$$\sigma^2_t = \text{var}(u_t \mid u_{t-1}, u_{t-2}, \dots) = E[u_t^2 \mid u_{t-1}, u_{t-2}, \dots] . \quad (11)$$

The autocorrelation on volatility is modelled by allowing the conditional variance of the error term, σ_t^2, to depend on the immediately previous value of the squared error (Brooks, 2008)

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (12)$$

The model described by the equations (8) and (10) is an ARCH(1) model, since its conditional variance depends on one lagged squared error. The ARCH model was initially proposed by Engle (1982), and it can be extended in order for the conditional variance to depend on q lagged squared errors

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \dots + \alpha_q u_{t-q}^2 , \quad (13)$$

which is usually referred as an ARCH(q) model. It is very common in the literature to represent the conditional variance as h_t. The complete ARCH(q) model is written as:

$$y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t \qquad u_t \sim \mathrm{N}(0,h_t) \tag{14}$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \ldots + \alpha_q u_{t-q}^2 \tag{15}$$

Although ARCH(q) models analyze the volatility of financial time series, they come with a few drawbacks that make their use quite problematic. More specifically, a researcher who wishes to use an ARCH model faces the problem of choosing the proper value of q, which could in some cases be extremely large, leading to a non-parsimonious model. Furthermore, there is the possibility that the non-negativity constrains are violated, since we demand $\alpha_i \geq 0$ for ∀ i = 0, 1, … , q, in order for the conditional variance to be non-negative.

In order to overcome these problems, Bollerslev (1986) developed the generalized autoregressive conditional heteroscedasticity (GARCH) models, a natural expansion of ARCH models. Their main advantage over ARCH models is that they allow the conditional variance to be dependent upon previous own lags (Brooks, 2008). The simplest GARCH model is the GARCH(1,1) model, in which the conditional variance is written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{16}$$

It can be shown that equation (15) is similar to an ARMA model. It can also be shown that a GARCH(1,1) model is equivalent to an ARCH(∞) model. To see this, just consider the first lag of the conditional variance

$$\sigma_{t-1}^2 = \alpha_0 + \alpha_1 u_{t-2}^2 + \beta_1 \sigma_{t-2}^2 \,. \tag{17}$$

If we substitute equation (16) to equation (15) we take:

$$\sigma_t^2 \; \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_0 \beta_1 + \alpha_1 \beta_1 u_{t-2}^2 + \beta_1^2 \sigma_{t-2}^2 \,. \tag{18}$$

If we continue taking lags of the conditional variance and substituting them to the equation of the conditional variance, we will end up to a form of an infinite order ARCH model.

The GARCH(1,1) model can be extended to a GARCH(p,q) model, where the current conditional variance is parameterized to depend upon q lags of the error term and p previous own lags. In this case, the conditional variance takes the form of:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2$$
(19)

and using sigma notation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \,. \tag{20}$$

The unconditional variance of u_t is constant and is given by

$$\mathrm{Var}\,(u_t) = \frac{\alpha_0 + \beta}{1-(\alpha_1 + \beta)} \tag{21}$$

so long as $\alpha_0 + \beta < 1$. If $\alpha_0 + \beta > 1$ the unconditional variance of u_t is not defined and we have the case characterized as non-stationarity in variance. If $\alpha_0 + \beta = 1$then we have an Integrated GARCH or IGARCH.

There is a vast variety of GARCH parameterizations that have been used in international literature. For the modelling of volatility of financial time series though, the most common models that researchers employ are the VECH and the BEKK model. Of the two most popular parameterizations, we adopted the BEKK parameterization. Li & Giles (2015) report two major disadvantages of the VECH model, specifically, the large number of parameters to be estimated, as well as the difficult the model faces to guarantee the positivity of the covariance matrix. They also state that the VECH model is unable of capturing volatility spillover effects between different markets (Li & Giles, 2015). The parameterization proposed by Engle and Kroner (1995), also known as the BEKK model, uses quadratic forms to ensure positive definiteness, dispenses with the assumption of constant correlation and allows for volatility spillover across markets (Fu et al., 2011). Thus, in the BEKK model the estimated covariance matrix will be positive semi-definite (Sariannidis et al., 2010). In addition, potential asymmetric effects in relationship between returns and volatility can also be captured (Fu et al. , 2011).

In the BEKK(1,1) model, the conditional covariance matrix is defined as:

$$H_t = CC' + A_1 \varepsilon_{t-1} \varepsilon'_{t-1} A'_{t-1} + B_1 H_{t-1} B'_1 \ . \quad (22)$$

If N = 2, then the model in matrix formation is presented as:

$$H_t = CC' + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}'$$

$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-2} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' . \quad (23)$$

In the diagonal form, the BEKK(1,1) model reduces to:

$$H_t = CC' + \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}'$$

$$+ \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-2} \end{bmatrix} \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}'. \quad (24)$$

$$H_{11,t} = c_{11}^2 + a_{11}^2 \varepsilon_{1,t-1}^2 + b_{11}^2 h_{11,t-1} \quad (25)$$

$$H_{12,t} = c_{21} c_{11} + a_{11} a_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + b_{11} b_{22} h_{12,t-1} \quad (26)$$

$$H_{22,t} = c_{22}^2 + a_{22}^2 \varepsilon_{2,t-1}^2 + b_{22}^2 h_{22,t-1} \quad (27)$$

Engle and Kroner (1995) and Kroner and Ng (1998) proposed the use of the full information maximum likelihood method for the estimation of the above system. Let L_t be the log likelihood function (LLF) of observation t, and let n be the number of stock indices. L is the joint log likelihood function (LLF) assuming normally distributed errors, given by:

$$L = \sum_{t=1}^{T} L_t \tag{28}$$

$$L_t = -\frac{n}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t' H_t' \varepsilon_t \ , \tag{29}$$

where T is the number of sample observations. The computer will maximize the function and generate parameter values that maximize the LLF and will construct their standard errors (Brooks, 2008).

4 Empirical results and discussion

First, we study the correlation matrices to examine the integration amongst stock markets. The level of correlation between financial returns and especially stock indices is the most important information in order to define accurate hedging strategies (Curto, J. D., & De Matos). Additionally, the correlation matrices allow us to test whether the correlation is increasing during and after crisis.

Tables 7 to 9 present the correlations between the examined stock markets in our study for the three sub-periods. The first number for every pair is the coefficient value with its probability value beneath it. The first thing we can notice, is that correlation coefficients are not constant over time. In contrast, they significantly vary during different periods. We are mainly interested on the correlations between the developed and emerging markets and how these correlations changed due to the global financial crisis.

The Czech Republic stock market returns were highly correlated with the U.S.A. stock market returns even before crisis breaks out (0.13). This connection amongst the two stock markets maintained during the global financial crisis (0.13), but it became negative (-0.06) during the post crisis period. These results may be explained by the fact that Czech Republic was not much affected by the global financial crisis due to its very stable banking sector, which learned its lessons from the late 1990s crisis in the country. But, during the time the U.S.A. economy was once again developed rapidly, leaving the Lehman Brothers collapse and the financial uncertainty behind for good, in 2012 the Czech Republic economy fell into a recession due both to a slump in the external demand, and the government’s strict measures. Although the recession did not last long and the economy recovered in 2013, we believe it is a major reason that explains the negative correlation coefficient between the U.S.A. and the Czech Republic during this period. The correlation of the Czech Republic stock market returns with the stock market returns of Germany and Japan is not very significant, a surprising event since Germany was traditionally Czech Republic’s biggest trading partner.

As for the other European emerging market, Poland’s stock market returns do not seem to be correlated with the developed markets except for Germany during the post-crisis period (0.04). This could be probably due to the fact that Poland was the only European country that was not affected by the global financial crisis as it presented economic growth during the whole period we examine in this study. Many economists believe that the reason behind this success story is Poland’s large internal market and the business friendly environment. This is probably why WIG20 seems to be the least integrated market.

The Philippine's stock market returns become correlated with the U.S.A. stock market returns only after the global financial crisis, while the Turkey's stock market seems to be the most integrated stock market of our sample. Specifically, XU100 and DAX100 show a significant level of correlation between 2000 and 2006 (0.16), as well as during the period 2010 to 2016 (0.05). Turkey presents a significant correlation with Japan during crisis (0.10), while it presents a small correlation with Philippine before global financial crisis breaks out (0.04).

4.1. BEKK model estimations

In the discussion that follows, we analyze the results that derive from the BEKK models estimations. It must be kept in mind though that the BEKK model is completely different from the linear regression model, with the parameters estimated by the BEKK model being hard to interpret (Li & Giles, 2015). The interpretation we provide in this study rests upon the following general explanations for the diagonal elements of A and B matrices in the BEKK model. On the one hand, the diagonal elements of the matrix A (a_{ij}), measure the effects of own past shocks on the country's own conditional variance. On the other hand, the past volatility effects are measured by matrix B. The diagonal elements of matrix B (b_{ij}) can effectively capture the own past volatility effect on its conditional variance. Very high diagonal elements of the matrix B reveal a common characteristic of financial data, which is the high degree of volatility persistence.

The results from the BEKK(1,1) model estimations are presented by the tables 10 to 13. But before proceeding with the discussion of the results, we should also explain the tables' diarthrosis. Each table has the same structure. The second column of each table presents the estimation of the BEKK model between an emerging market and the DAX100 stock market, while the third and fourth columns present the estimation of the BEKK model between the emerging market and the S&P500 and NIKKEI225 stock markets respectively. Therefore, table 10 presents the BEKK(1,1) model coefficients estimated for the pairs PX-DAX100, PX-S&P500 and PX-NIKKEI225, table 11 presents the BEKK(1,1) model coefficients for the pairs WIG20-DAX100, WIG20-S&P500 and WIG20-NIKKEI225 etc. The same hold for the tables 12 and 13 and the countries Philippines and Turkey. Conditional variances and covariances implied by the diagonal BEKK specification are presented by the equations below each table.

From these empirical results, we report strong evidence of GARCH effects, as well as weak evidence of ARCH effects. Generally, own past shocks are significant for all stock markets examined in this study, revealing the presence of ARCH effects. The small size of ARCH coefficients though, suggests that the stock market returns variances are not likely to vary very significantly under the impulsions of returns innovations. If we compare the magnitude of the estimated coefficients values, then we will discover that in many cases the shock of the emerging stock market has larger effect on its own conditional variance, and the developed stock market has smaller own shock effect. These results indicate that past shocks have larger impact on the volatility of the emerging stock markets than those in the volatility of the developed stock markets (Li & Giles, 2015). This can be explained by the fact that mature stock markets are expected to be less affected by their own past shocks than emerging stock markets.

The estimations between PX stock market and the developed stock markets are quite characteristic examples of the above case. The estimated a_{11} coefficients in the three models estimated between the PX stock market and the developed stock markets are 0.3277, 0.3283 and 0.3169, while the corresponding a_{22} coefficients are 0.2536, 0.2586 and 0.2902. The conditional variance equations derived from the three models reveal that PX stock market derives 10% of its volatility from own past innovations (0.1074, 0.1078, and 0.1004), while the equivalent values for the DAX100, S&P500 and NIKKEI225 stock markets are 0.0643, 0.0668 and 0.0842 respectively.

The same holds for the case of PSEI stock market. The estimated a_{11} coefficients in these three models are 0.2923, 0.2918 and 0.2818. On the other hand, the estimated a_{22} coefficients are 0.2723, 0.2797 and 0.3055. PSEI stock market derives approximately 8% of its conditional variance from own past shocks (0.0854, 0.0851 and 0.0816), while the corresponding values for the developed markets of Germany, U.S.A. and Japan are 0.0403, 0.0782 and 0.0933 respectively. Therefore, the PSEI stock market is more affected by its own innovations than the developed stock markets, with the NIKKEI225 to be the only exception.

WIG20 and XU100, in contrast, seem to perform better than developed stock markets considering the diagonal elements of the matrix A. Specifically, the estimated values of the a_{11} coefficients for the WIG20 stock market are 0.2039, 0.2006 and 0.2009, while the coefficients describing the ARCH effects for the developed stock markets (a_{22}) are obviously higher (0.2879, 0.2986 and 0.3183). This finding is not very surprising, since, as we described earlier in this section of our study, Poland was not significantly affected by the global financial crisis, in contrast to most of the countries which experienced a significant downturn in their economic activity. The variance and covariance equations derived from the tree models reveal that only 4% of WIG20 stock market's conditional variance derives from own past innovations (0.0415, 0.0402 and0.0403), while developed stock markets derive a quite larger percentage of their conditional variance from their own past innovations (0.0829, 0.0891 and 0.1013). Therefore, just like the examination of the stock market returns correlations indicated, these results once again support that the WIG20 stock market is not significantly integrated with the developed stock markets of our study.

As for the XU100 stock market, the a_{11} coefficients are a little smaller than a_{22} coefficients, suggesting that own past shocks (ARCH effects) of XU100 stock market (0.2352, 0.2984 and 0.2300) do not have such great magnitude as those in developed stock markets have (0.2866, 0.3113 and 0.3144). Approximately 5% of XU100 stock market's volatility derives from own past innovations in the BEKK(1,1) models between XU100 and DAX100 and NIKKEI225(0.0553 and 0.0529), but magnitude of the ARCH effect is increased to almost 9% (0.0891) in the BEKK(1,1) model between XU100 and S&P500.

The diagonal elements in the matrix B measure the effect of market's past volatility on its conditional variance (Li & Giles, 2015). All the estimated coefficients on the diagonal of matrix B are statistically significant. Additionally, the values of these estimates are close to one, which indicates a typical characteristic of financial data, the high degree of volatility persistence. The pattern that we are searching for when examining the GARCH effects, is the b_{11} coefficients (which present the GARCH effects for the emerging market) to be lower than the b_{22} coefficients (which present the GARCH effects for the developed market). This feature of the coefficients values indicates that the volatility persistence is lower for the emerging stock markets than for the developed stock markets. If this pattern is spotted in our results, we can state that the emerging stock markets derive relatively less of their volatility persistence from own past volatility than the developed stock markets do. Therefore, emerging stock markets would derive a larger percentage of their conditional variance from exogenous factors, in comparison to the percentage of the developed stock markets' conditional variance derived from exogenous factors.

As the examination of the ARCH effects revealed earlier in this section, the empirical results again are mixed, with the PX and the PSEI stock markets to follow the pattern expected to be seen from an emerging market in the results derived from a BEKK(1,1) model, and the WIG20 and the XU100 stock markets to make the difference by presenting debatable results.

PX presents characteristics of a typical emerging market. The b_{11} coefficients, although they are very high (0.9337, 0.9339 and 0.3981) they are lower than the corresponding b_{22} coefficients (0.9628, 0.9606 and 0.9478 respectively). These coefficients values indicate that in the three BEKK models between the PX stock market and each one of the three developed stock markets, the PX stock market derives 87.18%, 87.21% and 88.01% of the volatility in its conditional variance from its own past volatility. On the other hand, the respective percentages for the developed stock markets are 92.69%, 92.28% and 89.84%.

The same things hold for the PSEI stock market. In this case, the b_{11} coefficients values are 0.9382, 0.9337 and 0.9377, while the b_{22} coefficients are 0.9579, 0.9540 and 0.9432. These values are translated as: 88.02%, 87.18% and 87.93% of the PSEI's conditional volatility depends on its previous own values, while 95.29%, 91.03% and 88.96% of the conditional volatilities of DAX100, S&P500 and NIKKEI225 respectively are derived from their own past values. The cases of these two emerging stock markets present with the best possible way, the vulnerability of the emerging markets and the stability of the developed stock markets.

The other two cases though, are special cases of emerging markets that are very close to be characterized as developed, and the global financial crisis either did not affect them (Poland) or affected them with a significant delay (Turkey) in contrast to most of the other countries. The WIG20 stock market in particular, was not significantly affected by the global financial crisis that is reflected in the estimated coefficients from the BEKK(1,1) models. The three b_{11} coefficients take the values 0.9752, 0.9764 and 0.9761. It is worth mentioned that these are the highest coefficients values from all the diagonal elements of the matrix B in all the estimated models. In these three BEKK(1,1) models, WIG20 derives more than 95% of the volatility in its conditional variance from its own past volatility. These results reveal the low level of integration between the WIG20 and the rest markets, as well as the high level of Poland's dependence on its internal economy. The b_{22} estimated coefficients are 0.9516, 0.9470 and 0.9377, obviously lower than the b_{11} coefficients.

The last emerging stock market, XU100, presents similar behavior to WIG20. The coefficients presenting the GARCH effects in this emerging market are in all estimated models higher than the ones presenting the GARCH effects in the developed markets. Specifically, b_{11} coefficients are 0.9668, 0.9477 and 0.9687, while b_{22} coefficients are 0.9530, 0.9424 and 0.9401. The estimated variance equations suggest that Turkey derives more of its volatility persistence from within the domestic market than the developed markets do.

All the results derived from the estimations of the BEKK(1,1) models are graphically depicted in figures 3 to 21. In figures 3 to 9 where the variances of the stock markets are illustrated, there are obvious extreme picks in all variances during the two major crisis events: the dotcom crisis in 2001 and the global financial crisis of 2007-2008. It is quite impressive that the WIG20 stock market presents the lowest volatility during the whole period. The XU100 stock market also presents very low volatility during the global financial crisis, a period where the volatility and the uncertainty levels dramatically increased all around the world. We can get a very good understanding of the integration amongst stock markets by looking to figures 10 to 21, where the covariances between the stock markets are presented. The graphs again reveal a considerable amount of intense volatility transmission between markets during crisis periods and a significant rise in the co-movements of the stock markets during the dotcom crisis and the global financial crisis. The interpretation of these characteristics in the international literature, lies in the behavior of the international investors and financial institutions.

Last but not least, we should examine the covariance equations derived from the estimations of the BEKK models. Of great importance are the great estimated values that present the influence of lagged covariance to future covariance. All these values are greater than 87%, revealing that previous covariance between countries greatly influences the future covariance level.

5. Conclusions

The main objective of this study was to analyze the volatility transmission, running from mature to emerging stock markets. In order to achieve our goal, we collected daily closing prices for the developed stock markets DAX100, S&P500 and NIKKEI225, as well as for the emerging stock markets PX, WIG20, PSEI and XU100. We examined a long period ranging from 3 January 2000 to 29 December 2016, covering many crisis events and volatile periods. We even separated our data sample into three sub-periods to take into account of the global financial crisis. Those periods were the pre-crisis period, the crisis period and the post-crisis period. We calculated the daily returns of the above indices and examined their statistical properties. The initial analysis made clear that our series are not normally distributed, since they were characterized by negative skewness and leptokurtosis. Negative skewness and leptokurtosis are as well reported by Erten et al. (2012), supporting that their data are not normally distributed and ARCH type models might be applicable. In another study, Curto & De Matos again report abnormal daily returns. Furthermore, all markets presented lower mean returns and higher standard deviations during the crisis period, revealing the severe effects of the global financial crisis to the stock markets worldwide. These results are similar with those of Vo & Ellis (2018), who also report lower mean returns and higher standard deviations during the crisis period for all their examined markets.

Then, we tested for stationarity in our series employing the ADF and the PP unit root tests, which both concluded that all return series were stationary and suitable for econometric modelling. Engle's test for the so called "ARCH effects" made clear that there are significant ARCH effects in our series and therefore an ARCH type model would be the most appropriate for the modelling of our data. Of all the available options, we adopted the diagonal parameterization of the BEKK-GARCH model, which has been found to be the most adequate and has been widely used by many researchers in the international literature to investigate the volatility transmission between different markets.

A BEKK(1,1) model estimated for each pair of developed and emerging stock markets. The estimated coefficients from the BEKK model indicate that own past shocks are significant in all markets, with some of the emerging markets to present higher ARCH effects than developed markets, as a result of the greater persistence of the shocks in the emerging markets. In their research, Erten et al. (2012) report that own volatility spillovers are positive and statistically significant for the markets they examined. However, in our research these findings change for the Poland's stock market which was not significantly affected by the global financial crisis and Turkey's stock market which delayed to present the negative effects derived from the crisis. The PX stock market has the greatest own shock effect (10%) among all the markets we analyzed.

Additionally, the own past volatility effects are highly significant for all cases, and the WIG20 stock market has the highest degree of GARCH effects persistence (95%). The magnitude of the estimated coefficients indicates that all markets present strong GARCH effects, as old news are slowly absorbed by the markets affecting this way the current prices. While the own volatility persistence is lower for some emerging markets than for the developed ones, revealing that a higher percentage in emerging markets' conditional volatility is affected by external factors than the corresponding percentage for the developed markets, Poland and Turkey again diverge from this pattern. In the research done by Erten et al. (2012), the GARCH effects were very high and significant for all markets, results similar to the ones presented in our paper.

The covariance equations derived from the estimations of the BEKK(1,1) models, reveal that past covariance between stock markets significantly affects future covariance, with all the estimated values to be higher than 87%. This great magnitude of the estimated values in covariance equations favors the argument that world stock markets have become extremely integrated.

One noteworthy implication of our study is that stock markets around the world present different levels of integration. While the integration between stock markets seems to be quite high, we estimate that there is still room for diversification. Despite the fact that global financial markets present an increasing level of comovement during times of international financial turmoil, as the covariance figures suggest, these covariances are not constant over time. Therefore, international investors can steal gain diversification benefits including financial assets from the emerging markets in their portfolios, but they should take into account the volatility and correlation linkages among global markets in order to maximize returns and minimize risk. Concluding, economic policy makers, portfolio managers, international investors and traders should always study the linkages between different stock markets before proceeding with the policymaking, the risk evaluation and the hedging strategies.

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Table 1 Descriptive statistics for the whole sample

	DAX100	NIKKEI 225	SP500	PX	WIG20	PSEI	XU100
Mean	0.0130	0.0005	0.0116	0.0169	0.0057	0.0295	0.0394
Median	0.0804	0.0358	0.0477	0.0560	0.0177	0.0090	0.0480
Maximum	10.797	13.234	10.957	12.364	8.1548	16.177	17.773
Minimum	-8.8746	-12.111	-9.4695	-16.185	-8.4427	-13.088	-19.978
Stand Dev	1.5132	1.5043	1.2256	1.3899	1.5052	1.2869	2.1453
Skewness	-0.0672	-0.4371	-0.2001	-0.4719	-0.1629	0.2740	-0.0177
Kurtosis	7.3040	9.5418	11.468	15.754	5.6293	18.639	11.042
Obs	4433	4433	4433	4433	4433	4433	4433

Table 2 Descriptive statistics for the pre-crisis period

	DAX100	NIKKEI 225	SP500	PX	WIG20	PSEI	XU100
Mean	-0.0011	-0.0049	-0.0009	0.0701	0.0330	0.0197	0.0517
Median	0.0787	0.0146	0.0412	0.1087	0.0298	0.0000	0.0114
Maximum	7.5526	5.7352	5.5744	7.0481	6.2460	16.177	17.773
Minimum	-8.8746	-7.2339	-6.0045	-6.1249	-7.705	-6.191	-19.978
Stand Dev	1.5875	1.3362	1.1182	1.2492	1.5472	1.2831	2.6875
Skewness	-0.1088	-0.2786	0.0838	-0.2623	-0.027	1.8684	0.0595
Kurtosis	5.8158	4.6987	5.7131	4.9987	4.3721	28.230	9.3450
Obs	1824	1824	1824	1824	1824	1824	1824

Table 3 Descriptive statistics for the crisis period

	DAX100	NIKKEI 225	SP500	PX	WIG20	PSEI	XU100
Mean	-0.0235	-0.0615	-0.0282	-0.0539	-0.0541	-0.0012	0.0350
Median	0.0687	0.0311	0.0941	-0.0455	-0.0533	0.0000	0.0038
Maximum	10.797	13.234	10.957	12.364	8.1548	9.3652	12.127
Minimum	-7.4334	-12.111	-9.4695	-16.185	-8.4427	-13.088	-9.0138
Stand Dev	1.7983	2.0425	1.8809	2.1958	2.0536	1.7134	2.1256
Skewness	0.2615	-0.3593	-0.1666	-0.3945	-0.1198	-0.7805	-0.0160
Kurtosis	9.2217	9.7329	8.9440	12.395	4.5258	10.382	5.7839
Obs	782	782	782	782	782	782	782

Table 4 Descriptive statistics for the post-crisis period

	DAX100	NIKKEI 225	SP500	PX	WIG20	PSEI	XU100
Mean	0.0428	0.0321	0.0432	-0.0036	0.0040	0.0511	0.0300
Median	0.0930	0.0598	0.0418	0.0251	0.0287	0.0945	0.0803
Maximum	5.2103	7.4261	4.6317	4.4719	4.7223	5.5418	6.8951
Minimum	-7.0672	-11.153	-6.8958	-6.1345	-7.5431	-6.9885	-11.063
Stand Dev	1.2881	1.3874	0.9385	1.0237	1.1423	1.0580	1.4226
Skewness	-0.3146	-0.5480	-0.4684	-0.4169	-0.4479	-0.6382	-0.5865
Kurtosis	5.4624	8.4020	7.7601	5.9235	6.2276	7.5786	7.4757
Obs	1824	1824	1824	1824	1824	1824	1824

Figure 1 Daily stock index prices

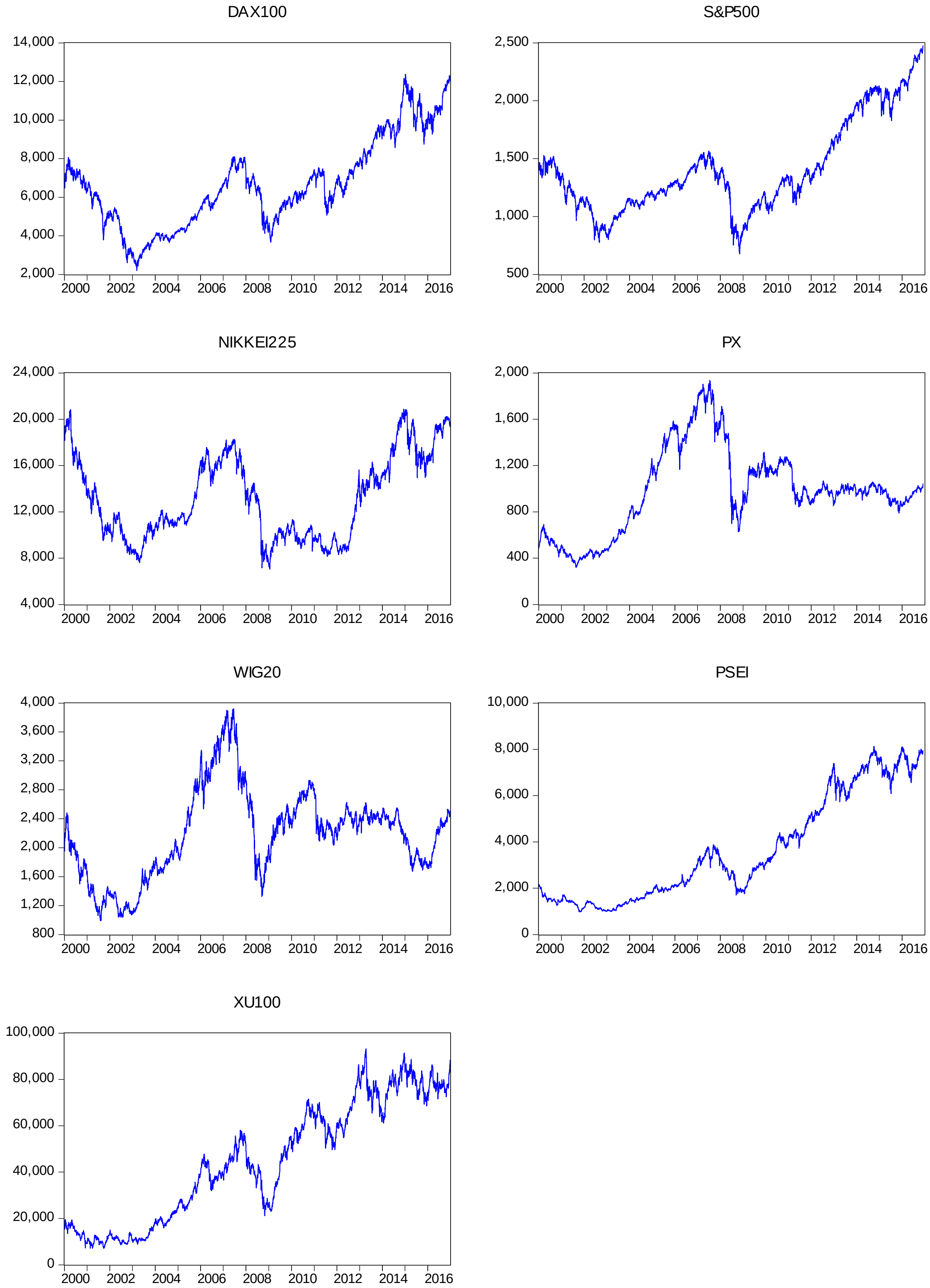

Figure 2 Daily stock index returns

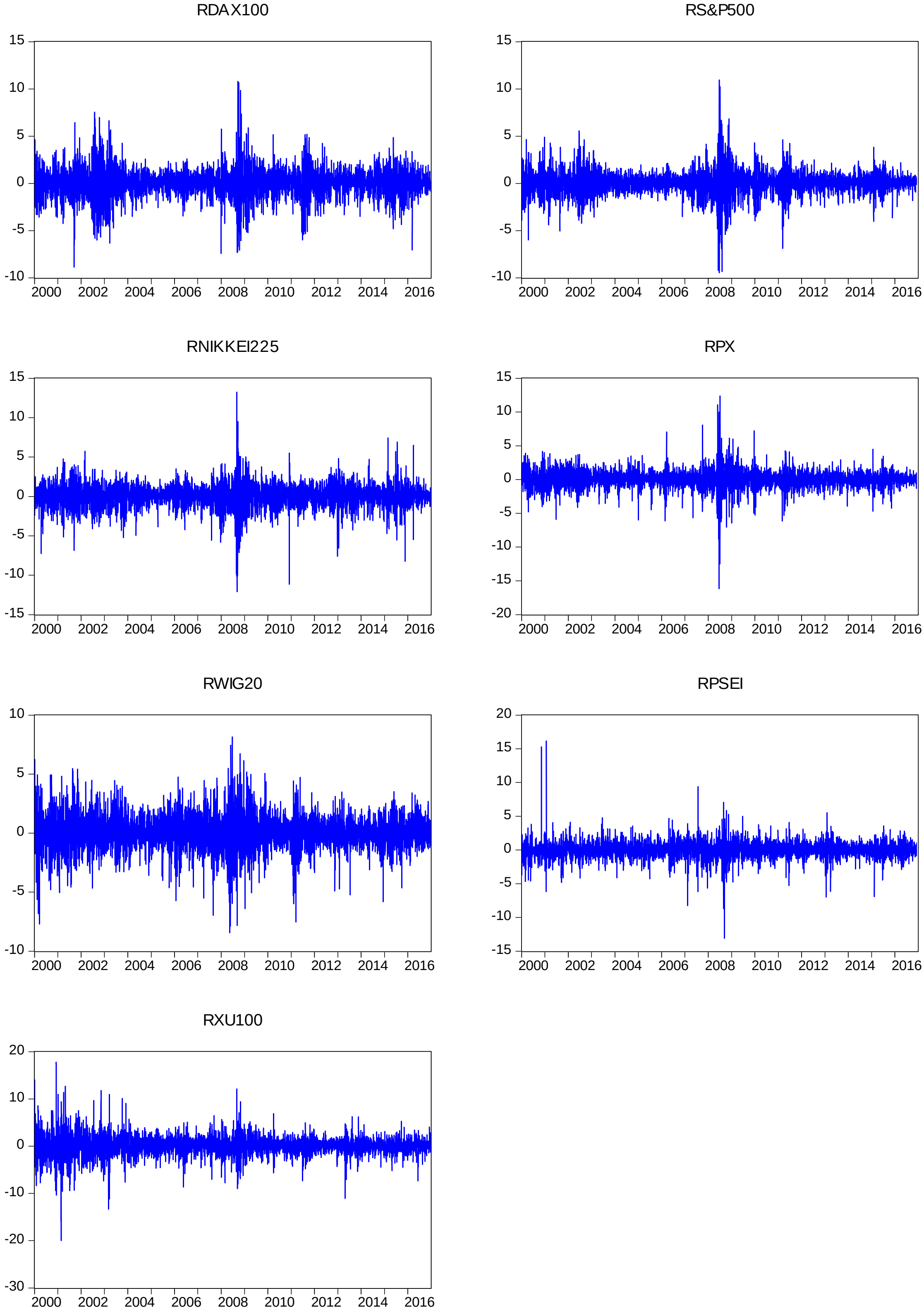

Table 5 Augmented Dickey and Fuller (ADF) and Phillips Perron (PP) tests on the daily stock market returns

Series	ADF	PP
DAX100	-67.35872	-67.46617
NIKKEI225	-68.62716	-68.77266
SP500	-51.89656	-72.73459
PX	-48.55584	-62.97534
WIG20	-64.17946	-64.13689
PSEI	-59.27621	-58.95567
XU100	-66.47599	-66.48827
According to MacKinnon critical values, all stats are significant at 1%		
1% critical value	-3.4316	-3.4316
5% critical value	-2.8619	-2.8619
10% critical value	-2.5670	-2.5670

Table 6 Engle (1982) test for ARCH effects, with p-values in parenthesis.

	LM Statistics		
	1 Lag	4 Lags	12 Lags
DAX100	151.4643	618.2510	860.3312
	(0.0000)	(0.0000)	(0.0000)
S&P500	193.3801	854.4125	1287.932
	(0.0000)	(0.0000)	(0.000)
NIKKEI225	332.0457	920.9986	1042.025
	(0.0000)	(0.0000)	(0.0000)
PX	575.8990	944.7099	1277.106
	(0.0000)	(0.0000)	(0.0000)
WIG20	66.45604	351.4498	552.8837
	(0.000)	(0.0000)	(0.0000)
SPEI	12.00358	112.1521	147.5414
	(0.0005)	(0.0000)	(0.0000)
XU100	377.6461	627.1449	666.9376
	(0.0000)	(0.0000)	(0.0000)

Table 7 Correlations from the pre-crisis period, with probability value under each correlation.

	DAX100	S&P500	NIKKEI225	PX	WIG20	PSEI	WU100
DAX100	1.0000 --						
S&P500	-0.0052 0.8240	1.0000 --					
NIKKEI225	0.3234 0.0000	0.0219 0.3489	1.0000 --				
PX	0.0154 0.5087	0.1365 0.0000	-0.0077 0.7408	1.0000 --			
WIG20	0.0099 0.6706	0.0264 0.2585	-0.0402 0.0856	0.0284 0.2252	1.0000 --		
PSEI	0.0158 0.4975	-0.0102 0.6627	-0.0249 0.2867	-0.0173 0.4591	-0.0279 0.2335	1.0000 --	
XU100	0.1656 0.0000	0.0089 0.7018	0.0548 0.0190	0.0227 0.3315	0.0269 0.2508	0.0460 0.0493	1.0000 --

Table 8 Correlations from the crisis period, with probability value under each correlation.

	DAX100	S&P500	NIKKEI225	PX	WIG20	PSEI	WU100
DAX100	1.0000						
	--						
S&P500	0.0187	1.0000					
	0.6014	--					
NIKKEI225	0.0728	0.0006	1.0000				
	0.0416	0.9854	--				
PX	0.0363	0.1320	-0.0367	1.0000			
	0.3100	0.0002	0.3042	--			
WIG20	0.0009	0.0041	0.0269	0.0069	1.0000		
	0.9792	0.9084	0.4511	0.8453	--		
PSEI	-0.0186	0.0118	-0.0145	0.0418	0.0305	1.0000	
	0.6016	0.7398	0.6853	0.2422	0.3943	--	
XU100	0.0169	-0.0561	0.1011	0.0382	0.0047	-0.0064	1.0000
	0.6360	0.1166	0.0047	0.2857	0.8955	0.8567	--

Table 9 Correlations from the post crisis period, with probability value under each correlation.

	DAX100	S&P500	NIKKEI225	PX	WIG20	PSEI	WU100
DAX100	1.0000						
	--						
S&P500	-0.0035	1.0000					
	0.8786	--					
NIKKEI225	-0.0354	0.0566	1.0000				
	0.1301	0.0155	--				
PX	-0.0310	-0.0630	0.0064	1.0000			
	0.1843	0.0071	0.7826	--			
WIG20	0.0476	0.0101	0.0094	0.0028	1.0000		
	0.0418	0.6646	0.6860	0.9019	--		
PSEI	-0.0191	0.0507	-0.0081	0.0246	-0.0291	1.0000	
	0.4149	0.0303	0.7265	0.2921	0.2142	--	
XU100	0.0559	-0.0078	-0.0027	0.0456	-0.0180	0.0115	1.0000
	0.0168	0.7371	0.9079	0.0512	0.4403	0.6227	--

Table 10 BEKK model estimations between the PX stock market and the developed stock markets, with probability values in parenthesis.

	PX-DAX100	PX-S&P500	PX-NIKKEI225
c_{11}	0.040629 (0.0000)	0.039346 (0.0000)	0.037561 (0.0000)
c_{12}	0.001100 (0.4615)	0.002195 (0.0333)	-5.32E-05 (0.9790)
c_{22}	0.019898 (0.0000)	0.013106 (0.0000)	0.042940 (0.0000)
a_{11}	0.327771 (0.0000)	0.328348 (0.0000)	0.316994 (0.0000)
a_{22}	0.253634 (0.0000)	0.258641 (0.0000)	0.290282 (0.0000)
b_{11}	0.933705 (0.0000)	0.933913 (0.0000)	0.938144 (0.0000)
b_{22}	0.962804 (0.0000)	0.960638 (0.0000)	0.947844 (0.0000)

$H_{t,PX} = 0.0406 + 0.1074\varepsilon^2_{t-1,PX} + 0.8718H_{t-1,PX}$

$H_{t,DAX100} = 0.0198 + 0.0643\varepsilon^2_{t-1,DAX100} + 0.9269H_{t-1,DAX100}$

$Cov_t(H_{PX}, H_{DAX100}) = 0.0010 + 0.0831\varepsilon_{t-1,PX}\varepsilon_{t-1,DAX100} + 0.8989Cov_{t-1}(H_{PX}, H_{DAX100})$

$H_{t,PX} = 0.0393 + 0.1078\varepsilon^2_{t-1,PX} + 0.8721H_{t-1,PX}$

$H_{t,S\&P500} = 0.0131 + 0.0668\varepsilon^2_{t-1,S\&P500} + 0.9228H_{t-1,S\&P500}$

$Cov_t(H_{PX}, H_{S\&P500}) = 0.0021 + 0.0849\varepsilon_{t-1,PX}\varepsilon_{t-1,S\&P500} + 0.8971Cov_{t-1}(H_{PX}, H_{S\&P500})$

$H_{t,PX} = 0.0375 + 0.1004\varepsilon^2_{t-1,PX} + 0.8801H_{t-1,PX}$

$H_{t,NIKKEI225} = 0.0429 + 0.0842\varepsilon^2_{t-1,NIKKEI225} + 0.8984H_{t-1,NIKKEI225}$

$Cov_t(H_{PX}, H_{NIKKEI225}) =$ -5.32e-05 $+ 0.0920\varepsilon_{t-1,PX}\varepsilon_{t-1,NIKKEI225} + 0.8892Cov_{t-1}(H_{PX}, H_{NIKKEI225})$

Table 11 BEKK model estimations between the WIG20 stock market and the developed stock markets, with probability values in parenthesis.

	WIG20-DAX100	WIG20-S&P500	WIG20-NIKKEI225
c_{11}	0.015967 (0.0000)	0.013939 (0.0000)	0.014407 (0.0000)
c_{12}	0.000391 (0.7727)	0.000393 (0.7254)	-0.000448 (0.8178)
c_{22}	0.026029 (0.0000)	0.018271 (0.0000)	0.049034 (0.0000)
a_{11}	0.203952 (0.0000)	0.200681 (0.0000)	0.200983 (0.0000)
a_{22}	0.287931 (0.0000)	0.298663 (0.0000)	0.318343 (0.0000)
b_{11}	0.975202 (0.0000)	0.976427 (0.0000)	0.976181 (0.0000)
b_{22}	0.951640 (0.0000)	0.947031 (0.0000)	0.937746 (0.0000)

$$H_{t,WIG20} = 0.0159 + 0.0415\varepsilon^2_{t-1,WIG20} + 0.9510H_{t-1,WIG20}$$

$$H_{t,DAX100} = 0.0260 + 0.0829\varepsilon^2_{t-1,DAX100} + 0.9056H_{t-1,DAX100}$$

$$Cov_t(H_{WIG20}, H_{DAX100}) = 0.0003 + 0.0587\varepsilon_{t-1,WIG20}\varepsilon_{t-1,DAX100} + 0.9280Cov_{t-1}(H_{WIG20}, H_{DAX100})$$

$$H_{t,WIG20} = 0.0139 + 0.0402\varepsilon^2_{t-1,WIG20} + 0.9534H_{t-1,WIG20}$$

$$H_{t,S\&P500} = 0.0182 + 0.0891\varepsilon^2_{t-1,S\&P500} + 0.8968H_{t-1,S\&P500}$$

$$Cov_t(H_{WIG20}, H_{S\&P500}) = 0.0003 + 0.0599\varepsilon_{t-1,WIG20}\varepsilon_{t-1,S\&P500} + 0.9247Cov_{t-1}(H_{WIG20}, H_{S\&P500})$$

$$H_{t,WIG20} = 0.0144 + 0.0403\varepsilon^2_{t-1,WIG20} + 0.9529H_{t-1,WIG20}$$

$$H_{t,NIKKEI225} = 0.0490 + 0.1013\varepsilon^2_{t-1,NIKKEI225} + 0.8793H_{t-1,NIKKEI225}$$

$$Cov_t(H_{WIG20}, H_{NIKKEI225}) = -0.0004 + 0.0639\varepsilon_{t-1,WIG20}\varepsilon_{t-1,NIKKEI225} + 0.9154Cov_{t-1}(H_{WIG20}, H_{NIKKEI225})$$

Table 12 BEKK model estimations between the PSEI stock market and the developed stock markets, with probability values in parenthesis.

	PSEI-DAX100	PSEI-S&P500	PSEI-NIKKEI225
c_{11}	0.063672 (0.0000)	0.075183 (0.0000)	0.068547 (0.0000)
c_{12}	-0.001607 (0.3999)	0.000274 (0.8585)	-0.001900 (0.3966)
c_{22}	0.020219 (0.0000)	0.014917 (0.0000)	0.044443 (0.0000)
a_{11}	0.292300 (0.0000)	0.291841 (0.0000)	0.286846 (0.0000)
a_{22}	0.272358 (0.0000)	0.279741 (0.0000)	0.305519 (0.0000)
b_{11}	0.938213 (0.0000)	0.933717 (0.0000)	0.937746 (0.0000)
b_{22}	0.957907 (0.0000)	0.954098 (0.0000)	0.943221 (0.0000)

$H_{t,PSEI} = 0.0636 + 0.0854\varepsilon^2_{t-1,PSI} + 0.8802H_{t-1,PSEI}$

$H_{t,DAX100} = 0. + 0.0403\varepsilon^2_{t-1,WIG20} + 0.9529H_{t-1,WIG20}$

$Cov_t(H_{PSEI}, H_{DAX100}) = -O.0016 + 0.0796\varepsilon_{t-1,PSEI}\varepsilon_{t-1,DAX100} + 0.8987Cov_{t-1}(H_{PSEI}, H_{DAX100})$

$H_{t,PSEI} = 0.0751 + 0.0851\varepsilon^2_{t-1,PSEI} + 0.8718H_{t-1,PSEI}$

$H_{t,S\&P500} = 0.0149 + 0.0782\varepsilon^2_{t-1,S\&P500} + 0.9103H_{t-1,S\&P500}$

$Cov_t(H_{PSEI}, H_{S\&P500}) = 0.0002 + 0.0816\varepsilon_{t-1,PSEI}\varepsilon_{t-1,S\&P500} + 0.8908Cov_{t-1}(H_{PSEI}, H_{S\&P500})$

$H_{t,PSEI} = 0.0685 + 0.0822\varepsilon^2_{t-1,PSEI} + 0.8793H_{t-1,PSEI}$

$H_{t,NIKKEI225} = 0.0444 + 0.0933\varepsilon^2_{t-1,NIKKEI225} + 0.8896H_{t-1,NIKKEI225}$

$Cov_t(H_{PSEI}, H_{NIKKEI225}) = -0.0018 + 0.0876\varepsilon_{t-1,PSEI}\varepsilon_{t-1,NIKKEI225} + 0.8845Cov_{t-1}(H_{PSEI}, H_{NIKKEI225})$

Table 13 BEKK model estimations between XU100 and the developed stock markets, with probability values in parenthesis.

	XU100-DAX100	XU100-S&P500	XU100-NIKKEI225
c_{11}	0.042717 (0.0000)	0.060803 (0.0000)	0.037440 (0.0000)
c_{12}	0.003209 (0.0989)	-0.000416 (0.8020)	0.001037 (0.6699)
c_{22}	0.023446 (0.0000)	0.018152 (0.0000)	0.045618 (0.0000)
a_{11}	0.235239 (0.0000)	0.298498 (0.0000)	0.230006 (0.0000)
a_{22}	0.286630 (0.0000)	0.311330 (0.0000)	0.314435 (0.0000)
b_{11}	0.966847 (0.0000)	0.947746 (0.0000)	0.968770 (0.0000)
b_{22}	0.953052 (0.0000)	0.942438 (0.0000)	0.940177 (0.0000)

$$H_{t,XU100} = 0.0427 + 0.0553\varepsilon^2_{t-1,XU100} + 0.9347H_{t-1,XU100}$$

$$H_{t,DAX100} = 0.0234 + 0.0821\varepsilon^2_{t-1,DAX100} + 0.9083H_{t-1,DAX100}$$

$$Cov_t(H_{XU100}, H_{DAX100}) = 0.0032 + \ 0.0674\varepsilon_{t-1,XU100}\varepsilon_{t-1,DAX100} + 0.9214Cov_{t-1}(H_{XU100}, H_{DAX100})$$

$$H_{t,XU100} = 0.0608 + 0.0891\varepsilon^2_{t-1,XU100} + 0.8982H_{t-1,XU100}$$

$$H_{t,S\&P500} = 0.0181 + 0.0969\varepsilon^2_{t-1,S\&P500} + 0.8881H_{t-1,S\&P500}$$

$$Cov_t(H_{XU100}, H_{S\&P500}) = -0.0004 + \ 0.0929\varepsilon_{t-1,XU100}\varepsilon_{t-1,S\&P500} + 0.8931Cov_{t-1}(H_{XU100}, H_{S\&P500})$$

$$H_{t,XU100} = 0.0374 + 0.0529\varepsilon^2_{t-1,XU100} + 0.9385H_{t-1,XU100}$$

$$H_{t,NIKKEI225} = 0.0456 + 0.09881\varepsilon^2_{t-1,NIKKEI225} + 0.8839H_{t-1,NIKKEI225}$$

$$Cov_t(H_{XU100}, H_{NIKKEI225}) = 0.0010 + \ 0.0723\varepsilon_{t-1,XU100}\varepsilon_{t-1,NIKKEI225} + 0.9108Cov_{t-1}(H_{XU100}, H_{NIKKEI225})$$

Figure 3 Conditional variance of DAX100

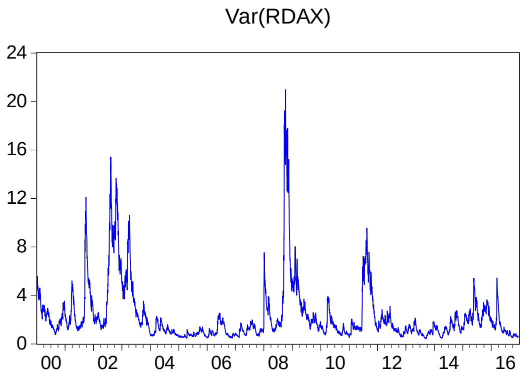

Figure 4 Conditional variance of S&P500

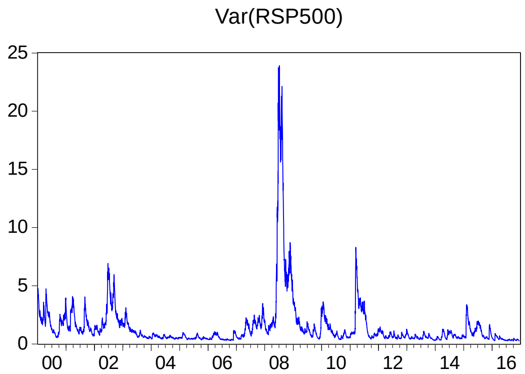

Figure 5 Conditional variance of NIKKEI225

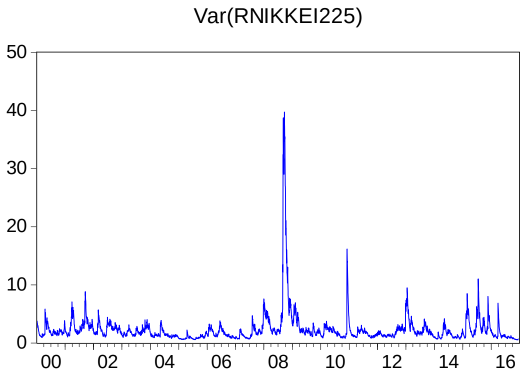

Figure 6 Conditional variance of PX

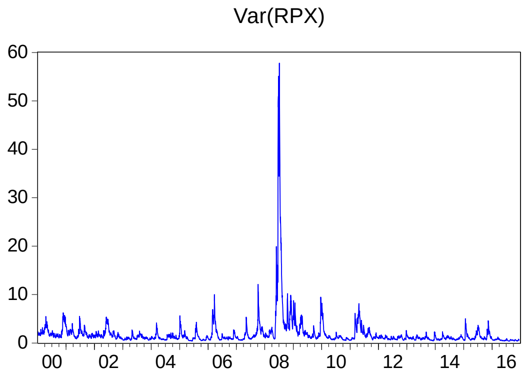

Figure 7 Conditional variance of WIG20

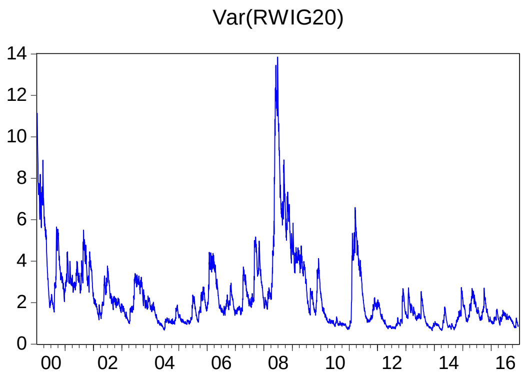

Figure 8 Conditional variance of PSEI

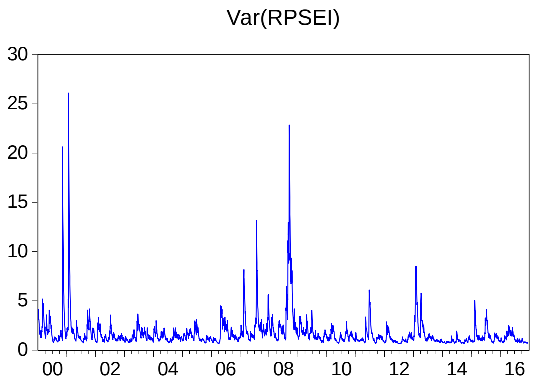

Figure 9 Conditional variance of XU100

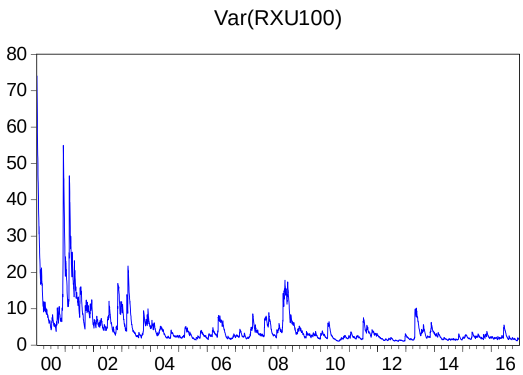

Figure 10 Covariance between PX and DAX100

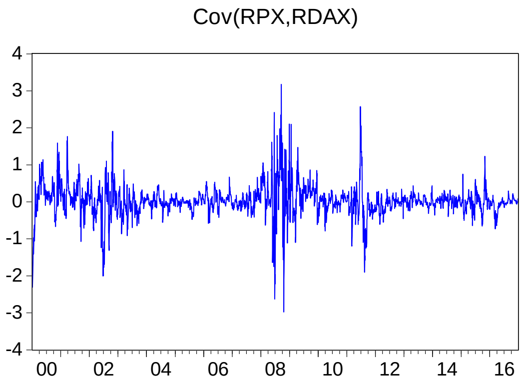

Figure 11 Covariance between PX and S&P500

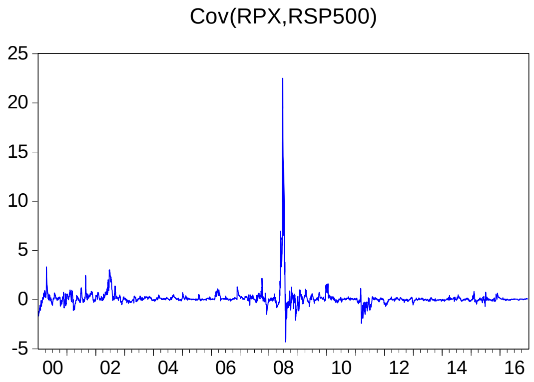

Figure 12 Covariance between PX and NIKKEI225

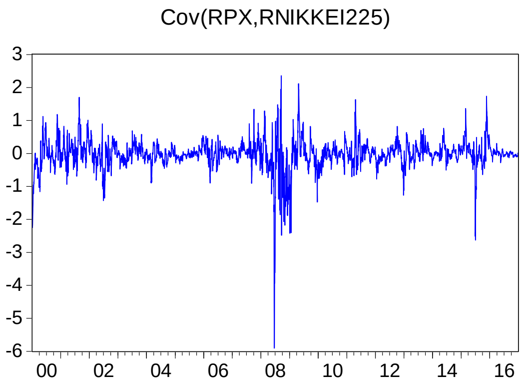

Figure 13 Covariance between WIG20 and DAX100

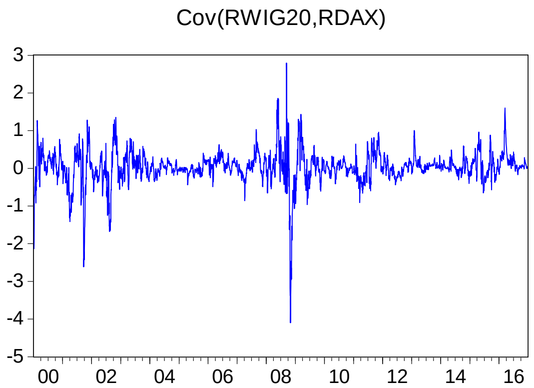

Figure 14 Covariance between WIG20 and S&P500

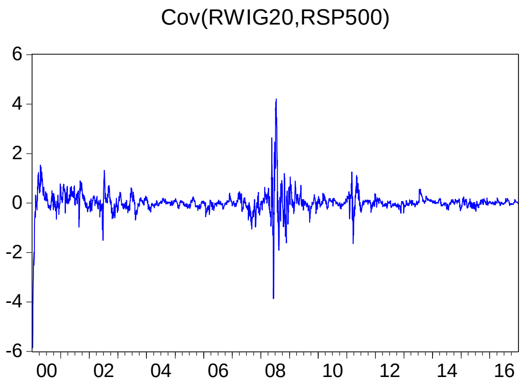

Figure 15 Covariance between WIG20 & NIKKEI225

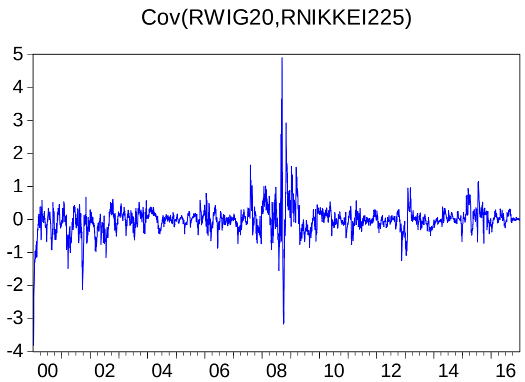

Figure 16 Covariance between PSEI and DAX100

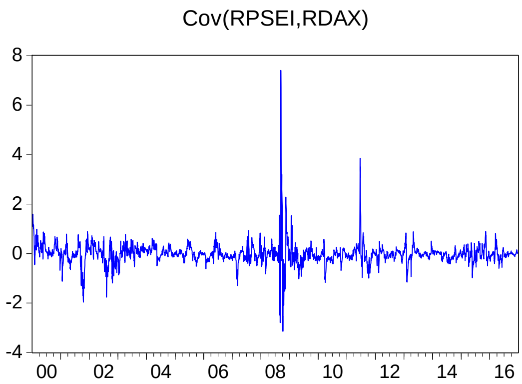

Figure 17 Covariance between PSEI and S&P500

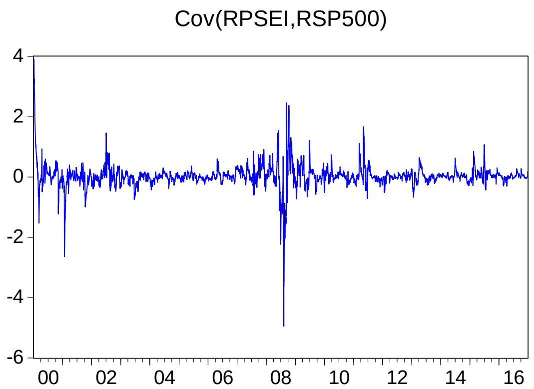

Figure 18 Covariance between PSEI and NIKKEI225

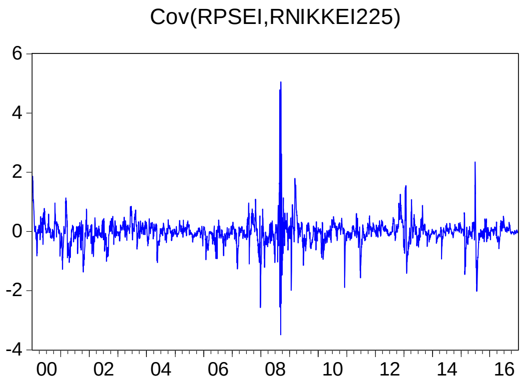

Figure 19 Covariance between XU100 and DAX100

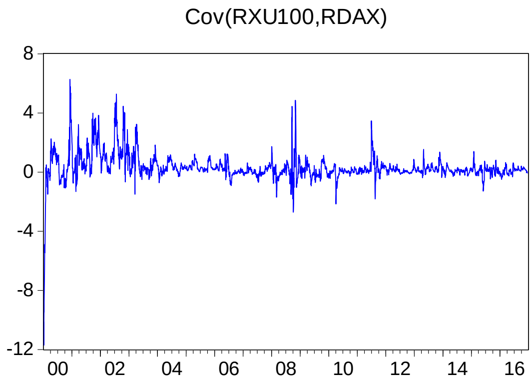

Figure 20 Covariance between XU100 and S&P500

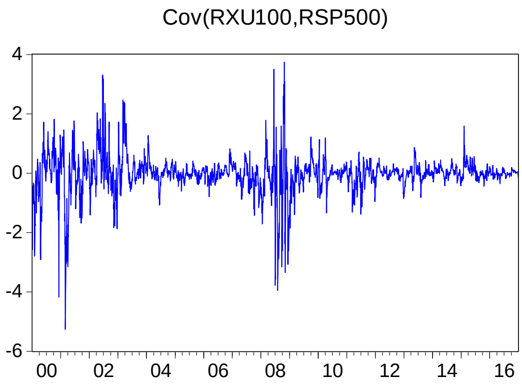

Figure 21 Covariance between XU100 and NIKKEI225