LUND UNIVERSITY
Department of Economics

Master Thesis

June 2009

# ARE INTERNATIONAL STOCK MARKETS INTEGRATED WELL?:

# EVIDENCE FROM THE US, GERMANY AND TURKEY

Author: Naciye SEKERCI Supervisor: Assoc. Prof. Hossein ASGHARIAN

| *Postal address:* | *Visiting address:* | *Phone:* | *Fax:* | *E-mail:* | *Internet:* |
|---|---|---|---|---|---|
| P.O. Box 7082<br>S-220 07 LUND<br>Sweden | Tycho Brahes väg 1 | int +46 46-222 86 50<br>int +46 46-222 00 00 | int +46 46-222 46 13 | nek@nek.lu.se | http://www.nek.lu.se |

**ABSTRACT**

This paper examines the interactions among the three stock markets of the US, Germany and Turkey by applying Vector Autoregressive Model (VAR). Besides causality, impulse response and variance decomposition analyses are done. One of the main findings is that between the US and German stock markets information is transmitted fast and they are quite well integrated. Another result is that, as expected, there is no influence of Turkish index both on the US and German market; on the other hand, these two are exogenous to Turkey. The test results also indicate that the US market affects Turkey more than German index does. Further, it is found that German market can also influence the US index to some extent.

**Keywords:** Financial integration, Vector Autoregressive Model (VAR), causality, impulse response, variance decomposition.

**CONTENTS**

# 1. INTRODUCTION

## 1.1 BACKGROUND

Financial integration has been an attractive topic since it could be observed well after financial liberalization polices became intense in many countries. As a result of free movement of capital, all kind of investments across countries, especially the ones in capital markets; such as equity markets, have increased.

The outcome of the studies examining financial integration can be useful while making investment decisions. If they prove integration between any countries, then we cannot diversify our risks by investing in those countries. As being “homo economicus” people, we should invest in countries which are not highly correlated.

One of the few studies about Turkey’s integration to international arena is done by Kasman, Vardar, Okan and Aksoy (2009). They investigated the stock markets of Turkey and those of some developed and emerging countries; such as the UK, the US, France, Japan, Germany, Argentina, Brazil, Korea, Thailand, China, Malaysia, Russia, Poland and Czech Republic. First, they analyzed the bivariate case at which one can test whether Turkey is cointegrated with any other above-mentioned market and found no long run equilibrium between Turkish market and any other. Furthermore, with a more advanced method, which allows structural break in the cointegrating vector, they showed some evidence of Turkish market’s integration with the US, the UK, France, Germany, Japan, Korea, Thailand, China and Brazil. They suggested that this strong long run relation can be as a result of the increasing amount of foreign capital flows to Turkey since 1980’s when the financial liberalization actions started in Turkey.

There have been some results concerning the role of the US on the world markets. Early in the literature, Eun and Shim (1989) stated that the US is the most exogenous market. What Bessler and Yang (2003) added to this statement is that the innovations from the UK, Hong Kong, France, Switzerland and Germany also affect the US indices, which shows increasing degree of financial integration. They also found that the nine largest equity indices they investigated (Australia, Japan, Hong Kong, the US, Canada, France, the UK, Germany and Switzerland) are cointegrated.

## 1.2 LITERATURE REVIEW

The integration of equity markets is well documented in the literature. However, the results are sometimes not consistent with each other. One of the studies examining the linkages between the US and six biggest European stock markets (the UK, France, Germany, Switzerland, Netherlands and Italy) is Kanas's study (1998). He found no cointegration between those markets. His main finding is that there is even no pairwise cointegration between those European indices and the US, which indicates that this could be a good diversification opportunity for investors. However, Morana and Beltratti (2008) recently concluded in their study that the heterogeneity between the US and Europe has been less now than it used to be.

Especially the emerging and transition markets are of concern to researchers. They tried to examine the correlation among those markets as well as the comovements of them with other international markets. For example, Chen, Firth and Rui (2002) found cointegration among major emerging countries in Latin America. Moreover, Gilmore and McManus (2002) wrote a paper by using the data of the markets of Czech Republic, Hungary and Poland and showed that the correlation between these three Central European markets and the US is relatively low which can be considered as a diversification opportunity for the US investors. They also claimed that there has been an increasing integration of emerging markets with other major markets, such as the US, over time. Another paper about emerging markets is written by Anaruo, Ramchander and Thiewes (2003). In their analysis they use six newly industrialized countries; Hong Kong, India, Korea, Malaysia, Thailand and Singapore, and found some linkages among these markets. Their finding is that the Asian markets react quickly to the innovations in the US and Singapore markets. It can be said that the world markets respond well to each other.

In contrast to the evidences of internationally cointegrated markets, Antell (2002) found no cointegration among international stock markets of the UK, the US, Germany, France, Sweden and Finland.  Moreover, integration is also studied by examining the volatilities of markets. For instance, Scheicher (2001) investigated the comovements of equity markets in Poland, Hungary and Czech Republic, and showed evidence of both global and regional influences for returns while only regional for volatility. Further, the interdependence of markets is analyzed by observing the pre- and post- crashes. In that perspective, Click and Plummer (2005) aimed to see whether there has been an integration in ASEAN-5, which stands for Association of Southeast Asian Nations countries (Indonesia, Malaysia, Singapore, Thailand and Philippines). His finding is that ASEAN-5 has become integrated in the economic sense after the Asian financial crisis starting from July 1, 1998 to December 31, 2002.

## 1.3 PURPOSE OF THE STUDY

The purpose of this paper is to investigate the interactions among the stock markets of the US, Germany and Turkey. In the analysis, thanks to having hourly data, I could take the necessary values of the indexes to be included in the sample. Interactions can be captured better with high frequency data than, for example, with monthly or quarterly basis data.

In the current study, interactions among the indices in all directions are analyzed. More specifically, the causality relations among these markets are looked into more in detail. How fast information can be transmitted between the markets and how much of the variation in one market can be explained by the shock to the other market are examined. It is also aimed to figure out whether any of those markets is exogenous to the others or not.

## 1.4 APPROACH

In this paper, the interactions among the stock markets of the countries included in the research are examined with Vector Autoregressive Model (VAR). It is basically a system of equations. The number of equations is the same as the number of the variables used. In this study, there are three markets to be analyzed, therefore there are three equations. According to VAR, the idea is that the current values of each variable depend on some different combinations of lagged values of all variables. However, in this study there are no different combinations, since it is unrestricted VAR, which means lag length for each equation is same.

In order to facilitate the interpretation of VAR estimation, I also apply three more techniques which are Causality Tests, Impulse Responses and Variance Decompositions. First one is to test whether there is a correlation between the today's value of one market and the past values of the other market. However, Causality test does not tell about the sign of the relation and the duration of the effect. For this reason, Impulse Responses and Variance Decompositions tests are performed. The former one analyzes the responsiveness to the innovations in one market while the latter examines the proportion of the movements in the dependent variables which are because of their own shocks or shocks to the other variables.

## 1.5 CONTRIBUTION

The markets to be examined in this study have some representative characteristics. To represent the US market, Dow Jones Industrial Average is chosen over the other US indexes since DJIA is the widely followed one. DAX (German Stock Index) is used on behalf of the European market. The last index included in the study is ISE National 100 Index which is from an emerging market. While choosing the indexes, such criteria as their relatively high trading volumes and the type of companies whose stocks are traded are also taken into account.

There have not been many studies regarding financial integration that use hourly data. Therefore, this study is aimed to contribute to the literature in that perspective. Under these considerations, by investigating the aforementioned markets, this paper could provide insight to the topic.

## 1.6 OUTLINE

The remaining part of the paper is organized in the way that part 2 discusses financial globalization while in part 3 some key information about the three indices used is presented. Part 4 describes the data and then underlines the important points while getting the data ready to perform the tests. In this part, descriptive statistics results are also presented. Part 5 discusses the theory behind the methodology. The method used is VAR approach which is complemented with Causality, Impulse Response and Variance Decomposition analyses. In order to perform a prudential VAR, the data needs to be checked for the existence of Unit Root and Serial Correlation. In this part, the tests which serve to examine these two issues are outlined with their theories. Besides, the lag length selection process is considered. In Part 6, the empirical results from the tests mentioned above can be found. Finally, all the findings are concluded in part 7 and some further research suggestions are provided in part 8.

Additionally, after references section, in the Appendix, lag length selection results, VAR estimation outputs, Causality tests results and the figures from the Impulse Response and Variance Decomposition analyses are presented.

## 2. FINANCIAL GLOBALIZATION

Arestis and Basu (2004) define *financial globalization* as “the process by which financial markets of various countries of the globe are integrated as one” or maybe as “free movement of finance across national boundaries without facing any restrictions”.[1]

In the past, some sort of unregulated financial globalization movements were observed through 1870s to 1939. Nonetheless, they were hampered due to the reasons; such as, series of banking crisis, stock market collapse (in the late 1920’s) and Great Depression (1929). Thereafter, fixed exchange rate regimes were applied. Furthermore, a variety of controls used to be in force in order to ensure that foreign cash flows were for the benefit of the productivity of domestic economy. Government interventions, whose aim was to stabilize financial system, directly or indirectly, appeared. However, countries experiencing the inefficient results of those interventions have started to liberalize their financial sectors by switching to flexible exchange rates (roughly after 1970’s). This results in “free movement of capital” which is of vital importance in financial globalization process.

According to Fowowe (2008), *financial liberalization* refers to the policies aiming to eradicate the effects of any growth-retarding policies. He states that “interest rate liberalization, abolition of directed credit allocation, bank denationalization, liberalizing entry into the banking sector, and strengthening of prudential regulation” are the implications of financial liberalization.[2] Among them, the primary focus is on the policies regarding the interest rates. Interest rate deregulation suggests that when the rates are up, economic growth is boosted through higher savings and qualified investments.

Literature has revealed that the developments in financial sector have positive impact on economic growth of countries in the long term as well as the volume and efficiency of investments. However, the magnitude of this relation varies across countries depending on the financial policies applied.

[1] Arestis, P. and Basu, S., 2004, *Financial Globalisation and Regulation*, Research in International Business and Finance, 18, 129-140, Pg 129.
[2] Fowowe, B., 2008, *Financial Liberalization Policies and Economic Growth: Panel Data Evidence from Sub-Saharan Africa*, African Development Bank, 549-574, Pg 550.

In literature, it is also documented that in the medium term, financial liberalization increases the fragility of financial system. On the other hand, in the long run it is thought to have some benefits, not been proven yet, though.[3]

Moreover, advocates of financial liberalization claim that reserve and liquidity requirements are considered as taxes for financial intermediaries, which causes to narrow the financial system. When these requirements are removed, financial sector will be deepened. But, as long as they are used by governments for the original purposes -to finance productive public investments-, they still benefit the economic growth and financial development.

According to Arestis and Basu (2004), financial liberalization is a necessary condition for financial globalization, but not sufficient. They also add that globalization process needs to be completed by creating a global institution, which will have a central coordinating role, as well as by having a single currency all over the world.

*Financial integration* definition differs from globalization in the sense that it refers to an individual country's linkages to international financial markets. However, they are rather related. Besides, financial liberalization policies and improvements in information technology (IT) have enabled financial integration to increase more and more.

# 3. OVERVIEW OF STOCK INDEXES

## 3.1 DOW JONES INDUSTRIAL AVERAGE

Dow Jones Industrial Average (DJIA) is the oldest stock market index in continuous use which was introduced by Charles H. Dow on May 26, 1896. It is traded on NYSE which is operated by NYSE Euronext. When it was first founded, it included twelve stocks from important US industries. In 1916, the number increased to twenty and finally it ended up with thirty stocks in 1928.

DJIA is the most widely followed stock market index since October 1, 1928. However, according to some critics like Ric Edelman, it is not an accurate indicator of the overall US market since it is only composed of 30 stocks. Another criticism about the index is that not all the components

[3] Arestis P., Demetriades P., Fattouh B., Mouratidis K. (2002), one of the studies analyzing the impact of financial policies including financial liberalization, claim that the effects of financial liberalization on financial development are ambiguous.

open at the same time in the morning. Therefore, using the opening price of DJIA may be misleading. Additionally, because of the fact that DJIA is a price-weighted average and it "gives relatively higher-priced stocks more influence over the average than their lower-priced counterparts, but takes no account of the relative size or market capitalization of the components", critics also claim that float-adjusted market-value weighted S&P 500 is better representative of the US market.[4]

The trading hours of DJIA are between 9:30 am and 16:00 pm. Besides, the trade volume of DJIA reached almost 673 million and experienced the very low values like 237 million within the three months; 13 March – 13 May, 2009.[5]

### 3.2 DEUTSCHER AKTIEN-INDEX

Deutscher Aktien-Index (DAX), a German Stock Index, started with a base value on December 31, 1987. It has been traded on Frankfurt Stock Exchange which is the largest of Germany's seven stock exchanges. "DAX measures the performance of the Prime Standard's - a market segment of the German Stock Exchange where companies are listed with international transparency standards - 30 largest German companies in terms of order book volume and market capitalization."[6]

Its trading hours start at 9:00 am and end at 17:30 pm. Regarding its trade volume; maximum value for DAX was about 288 million while the lowest was nearly 86 million within the three months; 13 March – 13 May, 2009.[7]

### 3.3 ISE NATIONAL 100 INDEX

Istanbul Stock Exchange (ISE) is the only security exchange corporation in Turkey. ISE National 100 Index is traded on Istanbul Stock Exchange which was established at the end of 1985 and ISE National 100 Index has been calculated since then. Stock trading commenced on January 3, 1986. After October, 1987 the index started to be calculated on daily basis – heretofore it was

---

[4] http://en.wikipedia.org/wiki/Dow_Jones_Industrial_Average#Criticism
[5] This information obtained from http://www.bloomberg.com/apps/cbuilder?ticker1=INDU%3AIND covers only three months just to give some rough idea about the trade volume of the index.
[6] http://en.wikipedia.org/wiki/DAX
[7] Same as Footnote 5, http://www.bloomberg.com/apps/cbuilder?ticker1=DAX%3AIND

weekly. ISE National 100 Index also includes the ISE National 50 and ISE National 30 Index companies and it is also used as a main indicator of the National Market.

One of the major developments about the Istanbul Stock Exchange is that with a Decree, foreign investors have been allowed to trade any type of securities in Turkey and to repatriate the earnings since August 1989. Moreover, in July 1994, daily trading hours were extended to four hours as in two sessions; one between 10:00-12:00 and one between 14:00-16:00. Further, short-selling transactions and margin trading were allowed for all the stocks traded on the ISE's markets starting from August 24, 1999. Before this, authorized ISE members had right to short-sell only the stocks included in ISE National 100 Index. Again, the trading hours on the Stock Market of ISE has been redesigned as 09:00-12:30 for the first session and 14:00-16:30 for the second session, which is 09:30-12:00 and 14:00-17:00 today.

The trade volume of ISE National 100 Index was around at most 1.25 billion and at least 283 million within the three months; 13 March – 13 May, 2009.[8]

## 4. DESCRIPTION OF THE DATA

In the sample, three stock market indices are used. They are Dow Jones Industrial Average (DJIA), the Deutscher Aktien-Index (DAX) and Istanbul Stock Exchange National 100 Index - hereafter ISE 100. DJIA is a price-weighted average of 30 blue-chip stocks that are usually leaders in their own industries. DAX is a total return index of 30 major national blue-chip stocks. Finally, ISE 100 is capitalization-weighted index formed by National Market companies except investment trusts. While ISE 100 is since 1986, there is also ISE 30 which has existed since 1996. ISE 30 is calculated in the same logic. I calculated the correlation between ISE 30 and ISE 100 and found 0.99 which is rather high. Hence, it seems reasonable to include any of them in the study. I choose to work with ISE 100 since its representative power is higher than ISE 30.

The data is hourly basis and covers the period from 22.09.2005 to 06.04.2009. The sample size is 1625. For each day, there are two hourly observations. The series of the equity market indices are obtained from the database called Matrix.

[8] Same as Footnote 5, http://www.bloomberg.com/apps/cbuilder?ticker1=XU100%3AIND

## 4.1 DEALING WITH THE DATA ON AN HOURLY BASIS

Due to the facts that there are time zones and the trading hours of the stock markets are different, time issue should be examined carefully.

Considering the time zones, for DJIA, the East Time of America is used which is five hours later than Greenwich Mean Time, abbreviated as GMT, (GMT -5:00). Frankfurt Stock Exchange, where the stocks of DAX Index are traded, is in the time zone which is one hour ahead of GMT (GMT +1:00). Turkey's time zone is two hours ahead of GMT (GMT +2:00).

In addition to time zone concern, the trading hours are also taken into account. These hours for DJIA is between 9:30 am and 16:00 pm while for DAX, it is between 9:00 am and 17:30 pm. The trading hours of ISE 100 is between 9:30 am and 17:00 pm. **Figure 1** below shows the operating hours of the markets considering the time zones as well. As it can be seen, the period when the three markets are open contemporaneously is between 16:30 pm and 17:00 pm (according to Turkish time zone, GMT +2:00). The figure also reveals the corresponding times at each countries for the trading hours. The ones in bold express the opening and the closing times of the markets.

**Figure 1 The trading hours of the three stock markets**

```
ISE 100

|________|______________________________|________|---------|------------------------------------------|
9:30am   10:00am                        16:30pm  17:00pm   18:30pm                              23:00pm

DAX

         |______________________________|________|_______|------------------------------------------|
         9:00am                         15:30am  16:00pm 17:30pm                                22:00pm
DJIA

                                        |______________|________________________________________|
                                        9:30am         11:30pm                                  16:00pm
```

According to these two pieces of information, the observations to be included in the research are formed. For each day, there are two hourly observations. There are two scenarios; therefore there are two samples that I study with. In both scenarios the first observations are the same. The first observation of the two samples is in the way that yesterday's closing value of DJIA will match today's starting values of DAX and ISE 100. The intuition behind is that when DJIA closes, the time in Germany is 22:00 pm while it is 23:00 pm in Turkey. It means that both markets are already closed. Therefore, the impact of DJIA's closing can be earliest seen in Germany and Turkey the next day. Briefly, the first observation helps to see the effect of yesterday's closing value of DJIA on today's opening values of DAX and ISE 100.

Further, the second observations differ for the two scenarios. To make it clearer, the trading hours of the three stock market indices will be expressed in Turkish time zone from now on.

*In the first scenario*, the opening value of DJIA today is expected to affect the closing of ISE 100 today and the value of DAX today at 17:00 pm according to Turkish time zone. To illustrate, when DJIA starts at 9:30 am, time is 16:30 pm in Turkey at which there is only half an hour left before ISE closes. Since the data is hourly, the earliest observation that can be obtained is at 17:00 pm in Turkey. To sum up for the first scenario, the second observation is:

- DJIA value at 17:00 pm - shows DJIA's opening value,
- DAX value at 17:00 pm - shows just the value of DAX when ISE closes,
- ISE 100 value at 17:00 pm - shows ISE 100's closing value.

The purpose of the first one is that the effects of both DJIA and DAX on ISE 100's closing value may be analyzed better.

*In the second scenario*, the difference is only about DAX. Instead of taking the DAX value at 17:00 pm, I include the "closing" DAX value. DAX ends at 18:30 pm according to time in Turkey. Similarly, the closing time of DAX is taken as the value at 19:00 pm since the data is hourly basis and the earliest observation for DAX that I can have is at 19:00 pm according to Turkish time.

So, in this case, the second observation is:

- DJIA value at 17:00 pm - shows DJIA's opening value,
- DAX value at 19:00 pm - shows the "closing" value of DAX,
- ISE 100 value at 17:00 pm – shows ISE 100's closing value.

The aim in the latter scenario is to be able to test whether DAX can also influence DJIA or not. Briefly, I avoid the implicit assumption that the direction of the influence is always from the US to Europe or to Turkey.

## 4.2 DESCRIPTIVE STATISTICS

**Table 1 Descriptive statistics of the three stock markets**

| | DAX 1 | DAX 2 | DJIA | ISE 100 |
|---|---|---|---|---|
| **Mean** | -7.12E-05 | -6.98E-05 | -0.000169 | -0.000133 |
| **Median** | 0.000596 | 0.000669 | 0.000181 | 0.000577 |
| **Maximum** | 0.102934 | 0.083760 | 0.078677 | 0.098441 |
| **Minimum** | -0.123588 | -0.089103 | -0.065869 | -0.151898 |
| **Std. Dev.** | 0.011765 | 0.011914 | 0.010034 | 0.017014 |
| **Skewness** | -0.589652 | -0.324660 | 0.114430 | -0.567267 |
| **Kurtosis** | 21.08493 | 12.88694 | 13.66163 | 11.15022 |
| **Jarque-Bera** | 22239.16 | 6647.139 | 7699.977 | 4584.756 |
| **Probability** | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **Sum** | -0.115715 | -0.113395 | -0.274862 | -0.215314 |
| **Sum Sq. Dev.** | 0.224801 | 0.230532 | 0.163516 | 0.470113 |

**Table 2 Correlation matrix for scenario 1**

| | DAX | DJIA | ISE 100 |
|---|---|---|---|
| **DAX** | 1.000000 | 0.603510 | 0.247976 |
| **DJIA** | 0.603510 | 1.000000 | 0.167465 |
| **ISE 100** | 0.247976 | 0.167465 | 1.000000 |

**Table 3 Correlation matrix for scenario 2**

| | DAX | DJIA | ISE 100 |
|---|---|---|---|
| **DAX** | 1.000000 | 0.650212 | 0.212583 |
| **DJIA** | 0.650212 | 1.000000 | 0.167465 |
| **ISE 100** | 0.212583 | 0.167465 | 1.000000 |

In order to get a general idea about the data, some statistical properties of the indexes are presented in this section. In **Table 1**, DAX 1 refers to the observations for the first scenario when DAX 2 stands for the second case. The data is in the log return form. The table shows that all of the markets have very low negative mean and especially DAX's mean is rather small. Their low means might be due to having a long observation period (22.09.2005 to 06.04.2009) such that within the period there have been many major events, breaking points and so on. When it comes to volatility, ISE 100 seems more volatile (1.7 %) than the other two whose standard deviations are almost the same (around 1.1 %). This can be because of the fact that Turkey is an emerging market where there is potential for high return due to high risk. On the other hand, the US and Germany, being less risky, are more stable economies.

Furthermore, skewness measures the asymmetry of the distribution of the series around its mean. DAX and ISE have negative skewness which implies that their distributions have a fat tail on the left. On the contrary, DJIA is positively skewed, that is the fatter part of the distribution is on the right. Another property is kurtosis which measures the peakedness or flatness of the distribution. Kurtosis for normally distributed series is 3. According to the table, all of the markets have a kurtosis value greater than 3, which indicates that they all have flat distribution relative to normal (platykurtic).

Jarque-Bera is a test statistic to check whether the series is normally distributed. The clear rejection of the null hypothesis of a normal distribution at 5 % significance level is observed for the three markets which is an expected outcome for time series.

It can be seen clearly in **Table 2** and **3** that DAX and DJIA are highly correlated in both scenarios (60 % and 65 %, respectively). The correlation of ISE 100 with the other two markets indicates that ISE 100 is more correlated with DAX than with DJIA.

When the correlation matrixes are analyzed more, the results may be an evidence of the claim that the two scenarios make difference. The correlation between DJIA and DAX is 60 % in the first scenario while it is 65% in the second one. For the second case, as expected the correlation is higher; since the influence of DAX on DJIA is assumed to exist. Therefore, the closing value of DAX is included in the sample to examine the relation in the direction from Europe to the US. However, it is of course not possible to prove such a relation in that direction just by looking at their correlation. Therefore, further tests will be performed below. Similarly, the linear relationship between DAX and ISE 100 differs for the scenarios. In the first one, their correlation is almost 25% and in the second one 21%. This may be due to again including DAX's closing value in the second scenario. Since, ISE 100 closes before DAX. For this reason, their correlation might decrease in the second case. Again, more advanced methods are required to search for the interactions among them.

# 5. METHODOLOGY

In this part of the paper, the methods used in order to reach the objectives are discussed in the theoretical perspective. Vector Autoregressive Models (VARs) is the one which enables us to examine the interactions among the three stock markets. However, to be able to perform VAR, the time series need to be stationary. Hence, first of all, unit root and stationary tests to search for the existence of stationary are presented. Furthermore, lag length that is included in VAR and the test to check for autocorrelation in the residuals are mentioned. In addition to VAR, the three complementary tests which are Block Significance and Causality Tests, Impulse Responses and Variance Decompositions are discussed.

## 5.1 UNIT ROOT AND STATIONARY TESTS

Financial time series are often non-stationary because of several reasons such as time trends, shocks, bubbles and fads. If the mean, variance and covariance of a series do not depend on time, then it is said to be (weakly or covariance) stationary.

Not all non-stationary series have unit roots. There are two most used types of non-stationarity. The first one is called *"trend stationary"*. Assume a time series which is growing over time. This series is non-stationary since it does not have a constant mean. It might contain a unit root or not. If this series get stationary when a time trend is removed, then it is an example of trend stationary. On the other hand, if a series needs to be differenced in order to become stationary, it is called *"difference stationary"*. Since differencing is required, it contains unit root (Kennedy (2008)).

A difference stationary series is said to be integrated of order d, I(d), if it must be differenced d times before it gets stationary.

According to the efficient markets hypothesis and rational expectations together, asset prices should follow a random walk, which is a common example of non-stationary series, or a random walk with drift. By this way, their differences are unpredictable (Brooks (2008)).

Assume two unrelated series which contain a trend and therefore non-stationary. When we regress a non-stationary variable upon a non-stationary one, we get a *spurious regression*. In such a regression, $t$ and DW statistics and measures like $R^2$ cannot maintain their traditional characteristics (Kennedy (2008)). Statistically, the problem here is the fact that the disturbance term is non-stationary (Verbeek (2008)). The result of a spurious regression is as if there is a meaningful relation between the variables.[9] Toda and Yamamoto (1995) suggested adding an extra lag to solve this problem.

Being stationary or not affects the behaviour and properties of the series. For instance, shocks, which is described as the drastic change or an unexpected change in a variable; in other words, the value of the error term, are one of the factors that are influenced by being stationary. In stationary series, shocks have a transitory effect, which means that they die out as time passes. In contrast, for a non-stationary series, shocks persist infinitely in the system (Brooks (2008)).

In order to check whether a series is stationary or not, there are unit root and stationary tests to be applied. The three examples of these tests will be explained below.

***5.1.1 Dickey – Fuller and Augmented Dickey – Fuller Tests (ADF)***

Consider a simple AR(1) process:

$$y_t = \rho y_{t-1} + x_t'\delta + \epsilon_t, \tag{1}$$

where $x_t$ are optional exogenous variables and they might be composed of a constant, or a constant and trend. $\rho$ and $\delta$ are parameters that are estimated and $\epsilon_t$ is assumed to be a stationary disturbance term.

When we subtract $y_{t-1}$ from both side of the equation (1), we get:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \epsilon_t, \tag{2}$$

where $\alpha$ is equal to ($\rho$-1). The null hypothesis is that the series contains unit root:

$$H_0: \alpha = 0 \tag{3}$$

And the alternative hypothesis is:

$$H_1: \alpha < 0 \tag{4}$$

[9] See Hendry (1980), cumulative rainfall explaining the price levels.

However, there is a problem with the $t$ statistic used. Under the null hypothesis of unit root, $t$ statistic does not follow the conventional Student's $t$ distribution; hence the special critical values are required (Kennedy (2008)).

These special critical values are derived and tabulated by Fuller (1976) and Dickey and Fuller (1981), so they are called DF or Dickey-Fuller Tests.

This simple Dickey-Fuller test is only applicable to AR(1) process. To overcome this problem and make it also valid for the series correlated with higher order of lags, they enhanced the test as Augmented Dickey-Fuller Test (ADF). Violating the assumption of white noise disturbances -in particular, the disturbance terms are not autocorrelated- is avoided with ADF test; since, in ADF test, the dependent variable follows an AR(p) process and p lagged difference terms of the dependent variable are added to the right hand side of the equation (2):

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \epsilon_t + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_p \Delta y_{t-p}, \tag{5}$$

The equation above is used to test the hypotheses (3) and (4) by using again $t$ statistic.

In ADF test, the lag length selection is also an important issue. Since, adding too many lags increases the coefficients standard errors while including too few cannot help to get rid of the autocorrelation in the residuals (Brooks (2008)). Information criteria can be used for deciding on the lag length. This selection should be done in the way that the serial correlation in the residuals is removed.

### *5.1.2 Phillips-Perron Test (PP)*

Phillips-Perron test is an alternative (nonparametric) way of modifying DF statistic. The DF statistic is adjusted before the critical values are consulted. Thus, it allows autocorrelation in the residuals (Kennedy (2008)).

For this method, the equation to be tested is the same as DF, which is presented above in (2). Similar to ADF test, it has to be determined whether to include a constant, a constant and a linear time trend, or neither, in the test regression (Payne and Sahu (2004)).

ADF and PP tests almost always give the same results. However, there have been some criticisms about these tests. The most important one is that the power of both tests is low if the series is stationary with a unit root very close to the non-stationary boundary. For instance, in the equation

(1), if the coefficient ρ is 0.95, then the null hypothesis of unit root ($H_0 : \rho = 1$) should be rejected. However, in particular when the sample size is small, the tests cannot distinguish clearly whether ρ is equal to 1 or 0.95. To deal with this drawback, stationary test; such as KPSS discussed below, can be used (Brooks (2008)).

### *5.1.3 The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test*

KPSS is a stationary test. Its null hypothesis is different from ADF and PP; in that, under the null, series is stationary. And it is tested against the alternative hypothesis of a unit root. Hence, if there is little information in the sample, by default the series is found to be stationary (Brooks (2008)).

Compared to unit root test, in KPSS, the dependent variable is regressed on the exogenous variables composed of a constant, or a constant and trend:[10]

$$y_t = x_t{}'\delta + u_t, \tag{6}$$

LM statistic is calculated:

$$LM = \sum_t {}^{S(t)^2}\!/_{\hat{\sigma}^2} \tag{7}$$

where $\hat{\sigma}^2$ is an estimator for error variance. And S(t) is a cumulative residual function:

$$S(t) = \sum_{r=1}^{t} \hat{u} \tag{8}$$

**Table 4 Comparison of the unit root tests ADF and PP with the stationary test KPSS**

| | ADF & PP | KPSS |
|---|---|---|
| Null Hyp. | $H_0$: $y_t \sim I(1)$ | $H_0$: $y_t \sim I(0)$ |
| Alternative Hyp. | $H_1$: $y_t \sim I(0)$ | $H_1$: $y_t \sim I(1)$ |

[10] EViews 5 User's Guide

In **Table 4**, the null and alternative hypotheses of the three tests are compared. Under the null of ADF and PP tests, series has unit root while it is vice versa for KPSS. If a series is stationary, then ADF and PP tests reject the null while KPSS fails to reject its null.

### 5.2 LAG LENGTH SELECTION

According to financial theory, there is no certain way to determine the lag length for a VAR model. This is, in fact, one of the drawbacks of VAR analysis. There are several approaches for selecting lag length. The most common ones are "*cross-equation restrictions*" and "*information criteria*".

VAR models should be as unrestricted as possible. In a VAR, if the equations have different lag lengths, this model is seen as restricted VAR. Since, some coefficients are set to zero.

One of the disadvantages of cross-equation restrictions -maybe the most important one- is that the $X^2$ test is valid asymptotically only under the assumption that the disturbance terms in each equations are normally distributed. This case is very seldom applicable to financial data (Brooks (2008)).

The alternative approach for VAR lag length selection is to use information criteria. In this method, there is no such an assumption about the distribution of the disturbance terms.

There are two factors considered in information criteria. One of them is the term that is a function of the residual sum of squares (RSS) and the other one is the penalty for the loss of degrees of freedom when extra parameters are added. Adding an extra variable or an additional lag has two results: While RSS decreases, the value of the penalty term increases (Brooks (2008)).

The most common ones are Akaike's (1974) information criterion (AIC), Schwarz's (1978) Bayesian information criterion (SBIC) and the Hannan-Quinn information criterion (HQIC). Algebraically, the multiple versions of the information criteria are:

$$MAIC = log\ |\Sigma| + 2k' / T \tag{9}$$

$$MSBIC = log\ |\Sigma| + (k' / T)log(T) \tag{10}$$

$$MHQIC = log\ |\Sigma| + (2k' / T)log((log(T)) \tag{11}$$

where T is the sample size, Σ is the variance covariance matrix of the disturbance terms and *k'* is the number of explanatory variables in all equations. The values of information criteria are formed up to a pre-specified maximum k lag. The aim is to choose the number of lags which minimizes the value of the information criterion (Brooks (2008)).

It cannot be told whether which criterion is the best one. However, the criteria can be compared somehow. Among the three, SBIC is the most consistent one; but inefficient, while AIC is not that stable; however usually more efficient. Since, SBIC asymptotically chooses the correct lag length when AIC chooses on average too large order (Brooks (2008)).

## 5.3 AUTOCORRELATION LM TEST

One of the diagnostic tools to check the appropriateness of the estimated VAR is residual tests. The residual test for VAR approach is Autocorrelation LM test. It has a multivariate LM test statistics under the null hypothesis of no autocorrelation in the residuals and it tests up to a specified order.

### *5.3.1 Serial Correlation Theory*

If the error terms are correlated with their own past values, then it is said to be that they are "*autocorrelated*" or "*serial correlated*". This situation indicates the violation of one of the CLRM (Classical Linear Regression Model) assumptions, which is "errors are linearly independent of one another, i.e. $cov(u_i, u_j) = 0$".

Ignoring autocorrelation results in inefficient OLS, i.e. the coefficient estimates of OLS will not be BLUE – however still unbiased- anymore even for large samples. As a result, the standard error estimates could be wrong; they are usually understated (Brooks (2008)).

Consider the form below:

$$y_t = x_t'\beta + u_t \tag{12}$$

$$u_t = z_{t-1}'\gamma + \epsilon_t, \tag{13}$$

where β and γ are vector of parameters, $x_t$ is vector of explanatory variables known at time *t*, $z_{t-1}$ is a vector variables observed at time *t-1*(including past values of u, ϵ, or both), $u_t$ is the disturbance term while $\epsilon_t$ is the innovation in the disturbance term.

$u_t$ is called "*unconditional residual*" since it depends on the structural component; $z_{t-1}$, while $\epsilon_t$ refers to "*one-period ahead forecast error*" or the "*prediction error*".[11]

**5.4 VECTOR AUTOREGRESSIVE MODELS (VARs)**

The general model in Box-Jenkins methodology is an ARIMA (*p, d, q*) for the series y:

$$y^*_t = \theta_1 y^*_{t-1} + \theta_2 y^*_{t-2} + \dots + \theta_p y^*_{t-p} + \varepsilon_t + \delta_1 \varepsilon_{t-1} + \delta_2 \varepsilon_{t-2} + \dots + \delta_q \varepsilon_{t-q}, \tag{14}$$

where $\theta$ and $\delta$ are parameters to be estimated and $\varepsilon$ is IID (independently and identically distributed) with zero mean. In this model, y is explained by its own historical values and current and past errors. *p* represents the order of "autoregressive" (AR(*p*)) part of the model while *q* stands for the order of "moving average" (MA(*p*)) dimension of the model. *d* shows how many times the y series is differenced to become stationary ($y^*$) (Kennedy (2008)).

This Box-Jenkins method is enhanced so that it can contain more than one variable. VAR is a simple version of this improvement where MA(*q*) part is eliminated from the model.

For time series modelling, in the simultaneous equations models, economic or financial theory usually gives information about how the relationships between the variables should be. However, theory is sometimes not sufficient. Additionally, since endogenous variables are both side of the equations, inferences and estimation get more difficult.

As an alternative, VAR -non-structural method- can be used which solves the problems above. According to Sims (1980), in a general equilibrium analysis, all economic variables can influence all other ones. It means that all variables are endogenous. Further, VAR allows us to examine the dynamic effect of random disturbances in the system.

In VAR equations of system, all the variables are treated as endogenous. Each variable is explained by its own lagged values as well as the lag values of all the other variables in the model. In each equation, there are same explanatory variables.

Consider a simple version of VAR which is a bivariate case:

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \dots + \beta_{1k} y_{1t-k} + \alpha_{11} y_{2t-1} + \dots + \alpha_{1k} y_{2t-k} + u_{1t} \tag{15}$$

[11] EViews 5 User's Guide

$$y_{2t} = \beta_{20} + \beta_{21}y_{2t-1} + \dots + \beta_{2k}y_{2t-k} + \alpha_{21}y_{1t-1} + \dots + \alpha_{2k}y_{1t-k} + u_{2t}, \tag{16}$$

where $u_{it}$ is a stationary disturbance term, $y_{1t}$ and $y_{2t}$ are two endogenous variables and β and α are parameters to be estimated. The errors have zero mean ($E(u_{it}) = 0$). Moreover, error terms are linearly independent of one another ($E(u_{1t}, u_{2t}) = 0$) (Brooks (2008)). They are also uncorrelated with all of the right hand side variables as well as with their own lagged values.[12]

There is no simultaneity problem in VAR approach since all the right hand side variables are the lagged values of endogenous variables, i.e. they are known at time *t*. Hence, OLS can be used for estimation.

### *5.4.1 VAR with Exogenous Variables (VARX)*

In the VAR representation below, VAR includes exogenous - X variables whose values are determined outside of the system:

$$y_t = A_0 + A_1y_{t-1} + Bx_t + u_{1t}, \tag{17}$$

where $x_t$ is a vector of exogenous variables and *B* is the matrix of the coefficients. In the system, there are no equations where X variables are dependent variables. Hence, this VARX model can be seen as a restricted version of VAR; since the equations for X variables have zero coefficients on the RHS of the equations. For this reason, VARX is against the logic of VAR where no restrictions should be applied.

### *5.4.2 Advantages of VAR*

One of the advantages of VAR is that it has a flexible form and can easily be generated. For instance, moving average dimension, MA(*q*), can be added. Further, the number of variables can be increased. One advanced version of VAR is to include first difference terms and cointegrating relationships (a Vector Error Correction Model-VECM).

Furthermore, in the simultaneous equations structural models, when theory is not enough to determine the relationships between variables, there are identifying restrictions, i.e. the variables should be named as exogenous or not by researcher. Since it is a complicated issue for a researcher, Sims (1980) terms these identifying restrictions as “incredible”. So, in that perspective, VAR is better than simultaneous equations models. In VAR analysis, which

[12] EViews 5 User’s Guide

variables are exogenous or endogenous is not needed to be specified. Since all the variables in the system are endogenous.

Moreover, as it is stated before, in VAR, all the variables depend on their own and also on the other variables' lagged values or combinations of white noise terms. However, univariate ARMA models are constructed so that series is explained only by their own lagged values and combinations of stationary disturbance terms. Thus, VAR has a more flexible structure than univariate ARMA models (Brooks (2008)).

Finally, the lagged values of all the variables in the system are known at time *t*, i.e. they are fixed. Hence, there is no endogeneity problem and OLS is applied for each equation in the system.

### *5.4.3 Disadvantages of VAR*

VAR is a-theoretical approach; hence it consults financial theory very little about how to set the relationships between the variables.

Another controversy about VAR is interpretation of its results. According to Kennedy (2008), the VAR estimation is sensitive to the lag length used and also the number of variables included in the model. He also states that "Since VAR presumes that no variables are exogenous, and that all variables, each with multiple lags, appear in each equation, it usually faces severe degrees of freedom problems. This forces modellers to choose a small set of variables."[13] Further, there is no perfect method to determine the lag length. There are several approaches to decide on length and these methods have their own advantages and disadvantages.

As the number of variables included in the model increases, the number of parameters, of course, increases, too. This results in too many coefficients to appear in the system causing difficulty in interpretation. Consider a system with $g$ variables/equations and k is the number of lags for each variable. The number of parameters is calculated as $(g + kg^2)$ (Brooks (2008)).

Last drawback of VAR method is about stationarity. In VAR analysis, the series have to be stationary. However, financial data usually contains unit root. So, differencing to induce stationarity is applied in order to perform VAR analysis. Some argue that differencing causes loosing long run information in the data. Instead, they suggest another method, VECM, which allows combining levels and the first differences of the series.

[13] Kennedy, P., 2008, 6th Edition, *A Guide to Econometrics*, Blackwell Publishing, the United States of America, Pg 306.

## 5.5 THREE MORE DIFFERENT TECHNIQUES

The interpretation of VAR becomes more difficult when there are many variables involved. Additionally, in the results, some lags can be significant while some are not. Further, lag coefficients sometimes can change sign across the lags. In such situations, there are three complementary methods, discussed below, to facilitate the interpretation of VAR.

### *5.5.1 Block Significance and Causality Tests*

Due to many lags included, it is difficult to see which variables have significant influences on each dependent variable. To deal with this issue, a joint F-test is constructed where the coefficients of a given variable can be tested jointly.

Consider again the equations (15) and (16):

$$y_{1t} = \beta_{10} + \beta_{11} y_{1t-1} + \ldots + \beta_{1k} y_{1t-k} + \alpha_{11} y_{2t-1} + \ldots + \alpha_{1k} y_{2t-k} + u_{1t}$$

$$y_{2t} = \beta_{20} + \beta_{21} y_{2t-1} + \ldots + \beta_{2k} y_{2t-k} + \alpha_{21} y_{1t-1} + \ldots + \alpha_{2k} y_{1t-k} + u_{2t},$$

The null hypothesis of this F-test, for example, for the second equation is that “lags of $y_{1t}$ do not explain current $y_{2t}$” with the implied restrictions such that “$\alpha_{21} = 0$ and ... and $\alpha_{2k} = 0$”. All of the lags of variable $y_{1t}$ are restricted to zero. The test examines how much of the current $y_{2t}$ can be explained by its own lagged values and then whether the model improves when the past values of $y_{1t}$ are added to the system.

This test was formed by Granger (1969); therefore it is called Granger Causality test. It basically tries to answer the question; “Do the changes in $y_1$ cause changes in $y_2$?” If the answer is yes, then it is said that “$y_1$ ‘Granger’ causes $y_2$”, which is a “*unidirectional causality*”. If at the same time $y_2$ Granger causes $y_1$, it is called “*bidirectional causality*”. If the relation is only from $y_1$ to $y_2$, it is stated that $y_1$ is “*strongly exogenous*” in the equation of $y_2$ (Brooks (2008)). We can say that Granger causality test is to examine whether an endogenous variable can be treated as exogenous or not.

However, there are two drawbacks of block F-test. One is that it does not tell about the direction, that is, sign of the causality. The other handicap is that it cannot show how long these effects will last. There are two methods; Impulse Responses and Variance Decompositions, which can deal with these drawbacks.

### *5.5.2 Impulse Responses*

Shock is defined by Brooks (2008) as "It is usually used to denote a change or an unexpected change in a variable or perhaps simply the value of the error term during a particular time period."[14] Effect of a shock to one variable in the VAR system can be transmitted to all of the other variables including itself thanks to the dynamic structure of VAR.

For simplicity, consider again a bivariate VAR model. A unit shock to $y_{1t}$ has effects on both $y_{1t}$ and $y_{2t}$. Impulse response function is a graph showing the effect of an innovation over time. In other words, it traces out the responsiveness of both $y_{1t}$ and $y_{2t}$ variables to the shock applied to $y_{1t}$ (Kennedy (2008)). In practice, VAR has to be expressed in vector moving average (VMA) to generate impulse responses where shocks should die away in the system (Brooks (2008)).

When the disturbance terms of each equation are independent from each other, the interpretation of impulse response in the way that is explained above. However, the error terms may be contemporaneously correlated. If this is the case, transformation P to the innovations applied through EViews to interpret the impulse responses.[15]

It is also possible to create the accumulated responses in EViews. If the series are stationary, the responses will die away to zero while accumulated responses will converge to a non-zero constant as time goes to infinity.[16]

### *5.5.3 Variance Decompositions*

There is a little difference between this method and impulse response. A variable is affected by its own innovations as well as the other variables' innovations. Variance decompositions give the proportions of the movement in one variable, which are because of its own shocks and the shocks to the other variables. Brooks (2008) defines the method as: "Variance decompositions determine how much of the s-step-ahead forecast error variance of a given variable is explained by innovations to each explanatory variable for s = 1, 2,..."[17] This forecast error is a result of the variation in the current and future values of shocks. In line with what is expected, most of the forecast error variance of a variable is usually explained by its "own" innovations. Thanks to

[14] Brooks, C., 2nd Edition, 2008, *Introductory Econometrics for Finance*, Cambridge University Press, United Kingdom, Pg 319.
[15] EViews 5 User's Guide
[16] EViews 5 User's Guide
[17] Brooks, C., 2nd Edition 2008, *Introductory Econometrics for Finance*, Cambridge University Press, United Kingdom, Pg 300.

variance decompositions, the relative importance of a particular variable's shock on each endogenous variable can be analyzed.

The order of the variables is important while performing both impulse responses and variance decompositions. The financial theory should give information about how the order should be. If it does not, the sensitivity analysis can be done by changing the order. Ordering makes difference if the error terms from an estimated equation are correlated (Brooks (2008)).

# 6. EMPIRICAL RESULTS

In this section, the empirical results of the tests are discussed. All the tests are performed by the econometrical software programme EViews.

## 6.1 THE RESULTS OF UNIT ROOT AND STATIONARY TESTS

In order to perform a statistically adequate VAR model, the variables should be checked for stationarity. The two unit root tests (ADF and PP) and one stationary test (KPSS) are applied to both the levels of the indices and the first differences of them.

As it can be observed in **Table 5**[18] below, we cannot reject the null hypotheses of ADF and PP (series has a unit root) for the levels of DJIA, DAX and ISE 100 at 1 % significance level. Since the test statistics of all the series are bigger than the critical values; that is, the test statistics are in the non-rejection area. The critical values for ADF and PP are given as –2.863 at 5 % significance level and –3.434 at 1 % significance level. However, we reject the null hypothesis of unit root for both tests when the indexes are in their first differences.

On the other hand, the null hypothesis of KPSS test (series is stationary) is rejected at 1 % significance level for the levels of the variables. The critical values for KPSS are 0.463 at 5 % and 0.739 at 1 % significance level. When the first differences of the indexes are formed, we cannot the reject the null of stationary at 1 % significance level.

[18] In **Table 5**, DAX 1 stands for the DAX observations for the first scenario while DAX 2 for the second one.

**Table 5 Unit root and stationary tests results**

| | TEST STATISTICS | | |
|---|---|---|---|
| | **ADF** | **PP** | **KPSS** |
| **DJIA Level** | -0,015745 | -0,211866 | 1,139540 |
| **DJIA 1st Diff.** | -23,24975 | -36,8461 | 0,582392 |
| **DAX1 Level** | -0,901797 | -0,901695 | 1,08153 |
| **DAX1 1st Diff.** | -38,02847 | -38,02847 | 0,569364 |
| **DAX2 Level** | -0,826061 | -0,908369 | 1,081404 |
| **DAX2 1st Diff.** | -30,26861 | -37,77216 | 0,578356 |
| **ISE 100 Level** | -1,266814 | -1,197623 | 0,908656 |
| **ISE 100 1st Diff.** | -41,9018 | -41,91555 | 0,282538 |

The results conclude that the series of DJIA, DAX and ISE 100 have unit root at level form. Consequently, the first differences of the series are formed to make them stationary; since the variables have to be stationary for VAR model. After differencing the series once (by clicking "1st difference" option in the unit root test in EViews), the three tests are applied again and found that they do not contain unit root any more.[19]

### 6.2 LAG LENGTH SELECTION RESULTS

Information criteria are used to choose the optimum lag length for the VAR model. If there are no exogenous variables in the VAR, the lag starts at one; otherwise the lag starts at zero. In this study, there is no exogenous variables, thus the lag starts at zero.

SBIC and HQIC consistently offer the same lag length which is four for both scenarios. On the other hand, AIC's choice differs a lot when the maximum lag length is changed manually in EViews while testing for sensitivity. As a result, four lags minimize the values of the information criteria (SBIC and HQIC); hence four lags of each series are determined to be included in the VAR model for both scenarios. The results can be found in **Appendix, Figure 1**.

### 6.3 AUTOCORRELATION LM TEST RESULTS

Before proceed further for the VAR analysis, the residuals have to be jointly tested for any serial correlation. For this purpose, Autocorrelation LM test is conducted.

According to the results, we cannot reject the null hypothesis of no serial correlation in the residuals at 5 % significance level until lag eight for the first scenario. However, at lag four, we

[19] When I apply those three tests to the *log returns* of the series, I get almost the same results.

slightly reject the null. For the second scenario, although the probability of being wrong when we reject the null hypothesis at the fourth lag is not that high, the clear rejection starts again at lag eight.[20]

## 6.4 VAR ESTIMATION

In VAR analysis in this paper, the three variables depend on each other in a way such that there is no restriction on the coefficients. In **Appendix, Figure 3** and **4**, each column refers to an equation in the system. There are three stock market indices in this research; hence, there are three equations. For the lagged values of the variables, the estimated coefficient, its standard error in ( ) and its *t* statistic in [ ] are reported. Additionally, the numbers at the bottom panel reflect the summary statistics for the VAR system as a whole.

According to the tables, the point observed clearly is that in both scenarios we reject the null hypothesis that the coefficient for a particular lagged value of DAX is zero in the equation where DJIA is dependent variable. The null is rejected for each individual lag of DAX in DJIA's equation. Further, all of these significant coefficients have positive sign. This could mean that DAX's past values up to two days positively correlated with DJIA's today's value.

Among the three markets, the US market is the one whose historical values best explain its today's value. Since the number of the significant coefficients - of the DJIA's lags values - is the highest among the three markets. Moreover, as expected, the past values of Turkish index do not have any significant effect on neither the US nor German market.

Apart from the points discussed above, the other results are sort of complicated to interpret. For instance, as it is seen in the findings regarding the following relations; the effects of the past values of DJIA on DAX's today value, of DJIA on ISE 100 and finally of DAX on ISE 100, some coefficients - of the lagged values of the markets - are insignificant. In addition, some of the significant coefficients even change sign.

---

[20] These results may be an evidence of a weak autocorrelation. This situation can have an influence on the ordering of the variables while doing Impulse Response and Variance Decomposition analyses. Therefore, the variables should be ordered carefully in the way that it is consistent with the common sense about international financial markets.

### *6.4.1 Block Significance and Causality Tests Results*

Causality tests are for examining the correlation between the current value of one market with the historical values of the other markets included in the study. It does not mean that movement of one index causes another's movement. It just investigates whether the current value of a certain index can be explained by also the past values of the other markets.

In order to search this relation, Granger Causality tests are performed as both jointly and pairwise. The null hypothesis of the tests is that all four lags (representing two days) of a particular index have no explanatory power in a given equation. The results of these tests can be found in **Appendix, Figures 5-8**. Both scenarios yield almost the same results; hence the interpretations below can be valid for both.

According to the results, it is obviously seen that there is a strong bidirectional Granger causality between the US and German stock markets. We reject the null of no Granger causality in both block and pairwise tests at 1 % significance level for the above-mentioned indices. We can say that the last two days' values of these two indices appear to help in explaining the variations in both markets.

Moreover, the variation in the movement of Turkish market can be explained well by the historical values of both the US and German markets. This relation is in only one direction. As expected, there is no causality streaming from ISE 100 to the other two indices, since we fail to reject the null hypothesis of "ISE 100 does not Granger Cause DJIA/DAX" at 5 % significance level. Causality test is to check whether we can treat an endogenous variable as exogenous. Therefore, it can be concluded that the US and German markets are highly exogenous to Turkey.

When we look at the block test for more specific analysis, we see that ISE 100 – DJIA and ISE 100 – DAX jointly have some explanatory power for German index and the US index, respectively.

### *6.4.2 Impulse Response Results*

Impulse response functions examine the reactions of a particular market to the unanticipated information in each market included in the research. They show how fast information is transmitted across stock markets. In **Appendix, Figure 9** and **10** show the results of the impulse response analysis for the two scenarios, respectively. In the analysis, there are ten periods to observe the responses - meaning five days; since, in the sample there are two observations (hourly) for one day. Before presenting the results, it should be stated that ordering of the variables makes difference. When theory does not tell about ordering, sensitivity analysis is done by changing the order in the “Cholesky Ordering” edit box in EViews. The results presented are in the order of “DJIA DAX ISE 100” which is thought to best fit the general framework of international financial markets.

The figures show the time path of impulse responses of each stock index to a one standard deviation shock to a particular index. Additionally, the graphs contain the plus/minus two standard error bands about the impulse responses. Since the variables are stationary in the study, the responses die away to zero.

When we look at the diagonal graphs in both **Figure 9** and **10**, we see that DJIA and DAX react to their own shocks on the day that the information arrives around 0.009 while Turkey’s reaction to its own innovation is relatively higher (0.016) at t = 1. DJIA and ISE 100 seem that they react to their own innovations in a negative way at some periods; on the other hand, there is almost no negative reaction of DAX to itself. For the three indexes, after period six (3. day), there is nearly no measurable response to their own shocks.

If we compare the graphs for the response of DJIA to DAX’s shock for each scenario, in both scenarios we see that the reaction of the US market is zero on the day that the unexpected news about DAX arrives (t = 1). However, at t = 2, the related impulse response is 0.003 in the first case while it is 0.004 in the second one. Afterwards, the functions start decreasing and die away at around t =7.

When we analyze the reaction of DAX to the DJIA news, for scenario 1 we find that the impulse response of German market to a US shock is 0.007 when the information arrives (t = 1) and 0.02 at t = 2. This can be considered as sort of overreaction and it is corrected with a negative response, -0.001 at t = 3. The negative reaction goes on until t = 6 (the end of the third day) and afterwards there seems almost no response. On the other hand, in the second case, the impulse response of DAX to a one standard deviation DJIA shock is 0.008 at t = 1, which is higher than the first case, and 0 at t = 2. And similarly, there is a negative reaction around -0.001 at t = 3, which continuous until t = 5 (before the third day) and then the impact dies away. Consequently, it is noted that German market strongly response to the US on the day of the shock and most of the adjustments are completed within one day. This strong response of German market to the US news can reflect high degree of financial integration as well as quick transformation of information between the two markets due to their concurrent trading. Since, it is a relatively long period (two hours) when the two indexes are open at the same time.

Further, an interesting point is that shocks to DJIA cause large turbulence to DJIA and shocks to DAX also cause large turbulence to DJIA. So, it can be concluded that DJIA reacts more strongly to shocks than DAX. The initial shock is, of course, the greatest to the market that it hits, however this conclusion is referred to what happens after the first half day. Another remarkable finding is that in general, DAX seems to respond to shocks less dramatically. The response when the news arrives is high but the effect dies away very quickly. There is much more smooth path to equilibrium compared to the responsiveness of the US and Turkish markets.

Moreover, it is obvious in the related graphs that the US and German markets do not react to the unexpected news and events in Turkish stock market for both scenarios.

Finally, impulse response graphs of Turkey to the information about DJIA and DAX provides similar figures in both scenarios. The first reaction is around 0.003 to the shocks of both DJIA and DAX, then the response becomes almost zero at t = 3 for DJIA and at t = 4 for DAX. Afterwards, there are again positive replies until the end of the three days, and no responses since then. Something interesting about ISE 100 is that the response to its own shock is much smoother than the response to the shocks in DAX or DJI. There is not any important difference in the two scenarios.

In general, most of the responses are completed in about three days after the shock occurs.

### *6.4.3 Variance Decomposition Results*

Variance decompositions show how much of the variance of a particular stock market can be explained by the shocks to the other markets as well as by its own shocks. The aim is basically to separate the variation in one variable. In **Appendix, Figures 11** (for the first scenario) and **12** (for the second scenario) represent the variance of stock indices for the next s-step period after being affected by the shocks to each market in the model. Here s value is ten which means five days. Similarly, ordering of the indexes matters. I make the same order as in the impulse response analysis which is “DJIA DAX ISE 100”.

As we can see in **Figure 11**, most of the variation in the US market is due to its own innovations. At the time of the shock (t = 1), the variance of DJIA is 100 % and then it declines to nearly 92 % at t = 3 (two periods after the shock); on the other hand, the remaining part (about 7.5 %) of

DJIA's variance is explained by DAX's shocks. Likewise, **Figure 12** indicates that DJIA's variance function due to itself is again decreasing. However, in this case, the effect of unanticipated information about DAX on DJIA increases. DAX, now, has the explanatory power in the variance of DJIA up to 13.5 % over five days time period. It can be stated that the effect of DAX's shocks in the variance of DJIA is now more in the second scenario. Moreover, as expected, in both scenarios, ISE 100 fails to explain any variation in DJIA.

Looking at the figures for DAX, we observe that innovations in DJIA have rather high ability to explain the movements in DAX (approximately 40 % and 47 % for the first and second scenarios, respectively). When we compare **Figures 11** and **12**, it is seen that in the first scenario the percent of DAX variation due to itself is around 60 %. However, with the second scenario, this amount declines to almost 53 % indicating that the effect of DJIA on DAX is more in the second case. Further, in both scenarios there is no response in the variance of German market movements as a result of the shocks to ISE 100, which is not surprising.

These two outcomes regarding DJIA and DAX might argue that the two scenarios make difference. To make it clearer, in the second case, it is assumed that the interactions can be in each direction; hence the "closing value" of DAX is included in the sample in order to see the effect of DAX on DJIA. We observe that with the second scenario, the ability of DAX's shocks in explaining the movement of DJIA increases. On the contrary, the explanatory power of DJIA's shocks in variance of DAX also increases. To sum up, we observe that some unexpected news, events resulting in drastic changes in the US stock index cause variation in DAX index to some extent between 40 – 47 %. On the other hand, shocks to German market also explain the variation in DJIA between 7.5 – 13.5 %. So, this may indicate that there is a bilateral influence between DJIA and DAX claiming that German index really affects the US market.

Finally, the proportion of the Turkish stock market's movement due to each of the three markets' shocks is examined. And it is found that the variation in ISE 100 due to itself decreases sort of dramatically after period four; that is two days, from nearly 90 % to 80 % for both scenarios. For scenario 1, the remaining part of this variance is constituted by DJIA (in the way that until two days around 4 %; after two days 11%) and DAX (around until two days 4 %; after two days 7 %). In the second case, the remaining variation in ISE 100 after itself are shared among DJIA and DAX; such that, DJIA forms around until two days 3 %; after two days 10 % and DAX constitutes nearly until two days 4 %; after two days 8.5 %. Consequently, DJI can explain the variation in ISE 100 more than DAX can.

## 7. CONCLUSION

The findings reveal that there is a strong bidirectional causality between the US and German markets. Additionally, these two are rather exogenous to Turkish index.

Furthermore, it is found that German index reacts to the unanticipated news or events of the US market a lot, especially on the day that the news arrives while the reaction of the US to German market shocks is moderate. The influential power of German index on the US market is consistent with Bessler and Yang (2003) who claimed that the US market is also influenced by the innovations in Germany, the UK, Switzerland, France and Hong Kong. Besides, the news about the US market can explain the variation in German market well. Similarly, DAX also has some explanatory power in DJIA's movement; however this influence is relatively less. Consequently, it can be concluded that the US and German stock markets are well integrated and the information is transmitted fast between them. Due to the evidence of financial integration of the US and Germany, there seems almost no diversification opportunity by investigating in these countries.

On the other hand, the results for Turkey show that there is no causality in the direction from ISE 100 to neither DJIA nor DAX as well as nearly no response of DJIA and DAX to the information about Turkish market. In addition, ISE 100's innovations have no ability to explain the movements of the other two markets. Turkish index is relatively smaller than the US and German markets. Therefore, it is not expected to influence the others.

Moreover, the results show that the US has dominant causal effects on both German and Turkish markets. It has more influence on Turkish market than DAX does. One of the reasons for this could be that DJIA's closing value affects ISE 100's opening value before DAX opens. Since DAX opens later than ISE 100. Another reason could be due to the number of American individual or institutional investors investing in Turkey. For instance, approximately 64 % of the shares of Turkish index are held by foreign investors.[21] However, we do not how much of this ratio belongs to European and the US investors. Maybe, there are more Americans investing in the shares of ISE 100 than Europeans. If this is the case, therefore, ISE 100 might reflect the general attitude of DJIA. Additionally, DAX is not the only European index that ISE 100 is affected by. There are also other big stock markets; such as CAC 40 (Paris) and MIBTel (Milan) that ISE 100 may be exposed to.

[21] This information is got on the 25th of May, 2009.

Further, there is a substantial interaction between Turkey and the markets of the US and Germany. Turkey is on her way of integration to international financial arena. For instance, the applications which encourage foreign investors and the policies to get harmony with the world, such as IFRS, have facilitated Turkey's integration process. International Accounting Standards Board adopted IFRS (International Financial Reporting Standards) in April, 2001 and the companies listed in Istanbul Stock Exchange have had to prepare IFRS reports since 2006. A similar study to this paper, but, with an old data set of ISE 100 would probably find less interaction between Turkey and the other two markets.

In general, I try to examine the interactions among the three stock markets of the US, Germany and Turkey. The findings above suggest that these three markets are somehow in interactions. It should also be noted that while some test results differ for each scenarios, overall the two scenarios do not make dramatic differences.

## 8. FURTHER ANALYSIS

With more frequent data such as minute basis, the interactions can be captured better, since the concurrent operations of the three markets do not last long. Or the study could include more indexes to be able to generalize the conclusions. Further, the volatility of the markets can be examined as well. Some macroeconomic variables such as interest rate, which is one of the most important factors for financial markets, can also be modelled in the research.

## ACKNOWLEDGEMENTS

I am grateful to my supervisor Assoc. Prof. Hossein ASGHARIAN for his comments and constructive advices. I also would like to thank Prof. Ismail BULMUS, some of the academic staff of Izmir University of Economics and my family for their encouragement and support at the writing process of my thesis.

## REFERENCES


Ahlgren, N., Antell, J., 2002, *Testing for Cointegration between International Stock Prices*, Applied Financial Economics, 12, 851-861.

Anoruo, E., Ramchander, S., Thiewes, H., 2003, *Return Dynamics across the Asian Equity Markets*, Managerial Finance, Volume 29 Number 4.

Arestis, P., Basu, S., 2004, *Financial Globalisation and Regulation*, Research in International Business and Finance, 18, 129-140.

Arestis, P., Demetriades, P., Fattouh, B., Mouratidis, K., 2002, *The Impact of Financial Liberalization Policies on Financial Development: Evidence from Developing Economies*, International Journal of Finance and Economics, 7, 109-121.

Bessler, D.A., Yang, J., 2003, *The Structure of Interdependence in International Stock Markets*, Journal of International Money and Finance, 22, 261-287.

Brooks, C., 2nd Edition, 2008, *Introductory Econometrics for Finance*, Cambridge University Press, United Kingdom.

Chen, G.M., Firth, M., and Rui, O.M., 2002, *Stock Market Linkages: Evidence from Latin America*, Journal of Banking and Finance, 26, 1113–1141.

Click, R.W., Plummer, M.G., 2005, *Stock Market Integration in ASEAN after the Asian Financial Crisis*, Journal of Asian Economics, 16, 5-28.

Eun, C.S., Shim S., 1989, *International Transmission of Stock Market Movements*, Journal of Financial and Quantitative Analysis, Volume 24, Number 2.

Fowowe, B., 2008, *Financial Liberalization Policies and Economic Growth: Panel Data Evidence from Sub-Saharan Africa*, African Development Bank, 549-574.

Gilmore, C.G., and McManus, G.M., 2002, *International Portfolio Diversification: US and Central European Equity Markets*, Emerging Markets Review, 3, 69–83.

Hendry, D.F., 1980, *Econometrics – Alchemy or Science?*, Economica 47, 387-406.

Kanas, A., 1998, *Linkages between the US and European Equity Markets: Further Evidence from Cointegration Tests*, Applied Financial Economics, 8, 607-614.

Kasman, A., Vardar, G., Okan, B., Aksoy, G., 2008, *The Turkish Stock Market Integration with Developed and Emerging Countries' Stock Markets: Evidence from Cointegration Tests with and without Regime Shifts*, Review of Middle East Economics and Finance, Volume 5, Number 1, Article 2.

Kennedy, P., 6th Edition, 2008, *A Guide to Econometrics*, Blackwell Publishing, United States of America.

Morana, C., Beltratti, A., 2008, *Comovements in International Stock Markets*, Journal of International Financial Markets, Institutions and Money, 18, 31-45.

Payne, J.E., Sahu A.P., 2004, *Random Walks, Cointegration and the Transmission of the Shocks across Global Real Estate and Equity Markets*, Journal of Economics and Finance, Volume 28 Number 2, 198.

Scheicher, M., 2001, *The Comovements of Stock Markets in Hungary, Poland and the Czech Republic*, International Journal of Finance and Economics, 6, 27-39.

Sims, C.A., 1980, *Macroeconomics and Reality*, Econometrica 48, 1-48.

Toda, H.Y., Yamamoto, T., 1995, *Statistical Inference in Vector Autoregressions with Possibly Integrated Processes*, Journal of Econometrics, 66, 225-50.

Verbeek, M., 3rd Edition, 2008, *A Guide to Modern Econometrics*, John Wiley & Sons Ltd., Erasmus University Rotterdam.

**Web Sources:**

http://deutsche-boerse.com/dbag/dispatch/en/isg/gdb_navigation/private_investors/20_Equities/20_Indices/10_DAX?module=InOverview_Index&wp=DE0008469008&wplist=DE0008469008&foldertype=_Index

http://en.wikipedia.org/wiki/DAX

http://en.wikipedia.org/wiki/Dow_Jones_Industrial_Average

http://en.wikipedia.org/wiki/Istanbul_Stock_Exchange

http://finance.yahoo.com/intlindices?e=europe

http://www.bloomberg.com/?b=0&Intro=intro3

http://www.djaverages.com/?view=industrial&page=overview

http://www.ise.org/

http://www.ise.org/about/majordev.htm

http://www.nyse.com/marketinfo/indexes/dji.shtml

## APPENDIX

### Figure 1 - VAR Lag Order Selection Criteria Results – Scenario 1

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 14700.51 | NA | 2.44e-12 | -18.22382 | -18.21380 | -18.22010 |
| 1 | 14794.01 | 186.5331 | 2.20e-12 | -18.32859 | -18.28852 | -18.31372 |
| 2 | 14845.57 | 102.6679 | 2.09e-12 | -18.38136 | -18.31124 | -18.35533 |
| 3 | 14880.38 | 69.20433 | 2.02e-12 | -18.41337 | -18.31320 | -18.37619 |
| 4 | 14992.06 | 221.5521 | 1.78e-12 | -18.54068 | -18.41046* | -18.49235* |
| 5 | 14999.97 | 15.66163 | 1.78e-12 | -18.53933 | -18.37906 | -18.47984 |
| 6 | 15004.27 | 8.495069 | 1.79e-12 | -18.53350 | -18.34318 | -18.46286 |
| 7 | 15014.45 | 20.07722 | 1.79e-12 | -18.53496 | -18.31458 | -18.45316 |
| 8 | 15029.76 | 30.15799 | 1.78e-12 | -18.54279 | -18.29237 | -18.44984 |
| 9 | 15036.97 | 14.16506 | 1.78e-12 | -18.54057 | -18.26009 | -18.43646 |
| 10 | 15049.82 | 25.20000* | 1.77e-12* | -18.54534* | -18.23481 | -18.43008 |
| 11 | 15053.74 | 7.680623 | 1.78e-12 | -18.53904 | -18.19846 | -18.41263 |
| 12 | 15060.43 | 13.06511 | 1.79e-12 | -18.53618 | -18.16554 | -18.39860 |

### Figure 2 - VAR Lag Order Selection Criteria Results – Scenario 2

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 14743.92 | NA | 2.32e-12 | -18.27764 | -18.26763 | -18.27393 |
| 1 | 14904.06 | 319.4820 | 1.92e-12 | -18.46504 | -18.42498 | -18.45017 |
| 2 | 14955.15 | 101.7380 | 1.82e-12 | -18.51723 | -18.44711 | -18.49121 |
| 3 | 15009.68 | 108.3887 | 1.72e-12 | -18.57369 | -18.47352 | -18.53651 |
| 4 | 15107.11 | 193.2876 | 1.54e-12 | -18.68334 | -18.55311* | -18.63500* |
| 5 | 15116.13 | 17.85801 | 1.54e-12 | -18.68336 | -18.52308 | -18.62387 |
| 6 | 15119.88 | 7.419602 | 1.55e-12 | -18.67685 | -18.48653 | -18.60621 |
| 7 | 15124.65 | 9.407518 | 1.56e-12 | -18.67161 | -18.45123 | -18.58981 |
| 8 | 15141.79 | 33.74296 | 1.55e-12 | -18.68170 | -18.43127 | -18.58874 |
| 9 | 15147.73 | 11.67748 | 1.55e-12 | -18.67790 | -18.39743 | -18.57380 |
| 10 | 15167.04 | 37.87237 | 1.53e-12 | -18.69068 | -18.38016 | -18.57542 |
| 11 | 15174.42 | 14.44634 | 1.54e-12 | -18.68867 | -18.34809 | -18.56226 |
| 12 | 15188.21 | 26.95960* | 1.53e-12* | -18.69462* | -18.32399 | -18.55705 |

**Figure 3 - VAR Estimation Output – Scenario 1**

| | RETDAX1 | RETDJI | RETISE |
|---|---|---|---|
| RETDAX1(-1) | -0.016156 | 0.279264 | 0.212661 |
| | (0.03257) | (0.02678) | (0.04451) |
| | [-0.49609] | [ 10.4271] | [ 4.77758] |
| RETDAX1(-2) | -0.073556 | 0.153348 | 0.040878 |
| | (0.03451) | (0.02838) | (0.04716) |
| | [-2.13168] | [ 5.40365] | [ 0.86671] |
| RETDAX1(-3) | -0.027632 | 0.065611 | -0.081687 |
| | (0.03477) | (0.02860) | (0.04753) |
| | [-0.79468] | [ 2.29433] | [-1.71872] |
| RETDAX1(-4) | 0.048358 | 0.077153 | 0.262535 |
| | (0.03344) | (0.02750) | (0.04571) |
| | [ 1.44610] | [ 2.80536] | [ 5.74378] |
| RETDJI(-1) | 0.200094 | -0.129115 | -0.004420 |
| | (0.03845) | (0.03162) | (0.05256) |
| | [ 5.20391] | [-4.08298] | [-0.08410] |
| RETDJI(-2) | -0.082931 | -0.273888 | -0.127909 |
| | (0.03963) | (0.03259) | (0.05417) |
| | [-2.09257] | [-8.40309] | [-2.36124] |
| RETDJI(-3) | 0.024621 | -0.075808 | 0.253681 |
| | (0.03958) | (0.03255) | (0.05409) |
| | [ 0.62213] | [-2.32912] | [ 4.68959] |
| RETDJI(-4) | -0.091512 | -0.178500 | 0.298869 |
| | (0.03817) | (0.03140) | (0.05218) |
| | [-2.39718] | [-5.68544] | [ 5.72770] |
| RETISE(-1) | -0.022385 | -0.017002 | -0.138476 |
| | (0.01790) | (0.01472) | (0.02446) |
| | [-1.25067] | [-1.15508] | [-5.66041] |
| RETISE(-2) | 0.023446 | 0.001670 | 0.010857 |
| | (0.01770) | (0.01456) | (0.02420) |
| | [ 1.32436] | [ 0.11468] | [ 0.44868] |
| RETISE(-3) | 0.001996 | 0.020027 | -0.012953 |
| | (0.01770) | (0.01456) | (0.02419) |
| | [ 0.11279] | [ 1.37583] | [-0.53541] |
| RETISE(-4) | 0.004765 | -0.016979 | -0.064810 |
| | (0.01758) | (0.01446) | (0.02403) |

| | | | |
|---|---|---|---|
| | [ 0.27107] | [-1.17453] | [-2.69759] |
| C | -7.93E-05 | -0.000241 | -6.77E-05 |
| | (0.00029) | (0.00024) | (0.00039) |
| | [-0.27537] | [-1.01805] | [-0.17207] |
| R-squared | 0.038783 | 0.107972 | 0.143222 |
| Adj. R-squared | 0.031610 | 0.101315 | 0.136828 |
| Sum sq. resids | 0.215569 | 0.145806 | 0.402745 |
| S.E. equation | 0.011578 | 0.009522 | 0.015826 |
| F-statistic | 5.406580 | 16.21946 | 22.39994 |
| Log likelihood | 4933.835 | 5250.745 | 4427.254 |
| Akaike AIC | -6.071357 | -6.462363 | -5.446334 |
| Schwarz SC | -6.028124 | -6.419130 | -5.403101 |
| Mean dependent | -8.39E-05 | -0.000171 | -0.000137 |
| S.D. dependent | 0.011766 | 0.010045 | 0.017034 |
| Determinant resid covariance (dof adj.) | | 1.72E-12 | |
| Determinant resid covariance | | 1.68E-12 | |
| Log likelihood | | 15073.55 | |
| Akaike information criterion | | -18.54972 | |
| Schwarz criterion | | -18.42002 | |

**Figure 4 - VAR Estimation Output – Scenario 2**

| | RETDAX2 | RETDJI | RETISE |
|---|---|---|---|
| RETDAX2(-1) | 0.099806 | 0.414422 | 0.279706 |
| | (0.03422) | (0.02665) | (0.04560) |
| | [ 2.91662] | [ 15.5529] | [ 6.13456] |
| RETDAX2(-2) | -0.022376 | 0.184050 | 0.123659 |
| | (0.03796) | (0.02956) | (0.05057) |
| | [-0.58952] | [ 6.22723] | [ 2.44511] |
| RETDAX2(-3) | 0.098669 | 0.129366 | -0.131918 |
| | (0.03815) | (0.02970) | (0.05083) |
| | [ 2.58662] | [ 4.35530] | [-2.59545] |
| RETDAX2(-4) | 0.048580 | 0.060269 | 0.246446 |
| | (0.03706) | (0.02886) | (0.04938) |
| | [ 1.31074] | [ 2.08834] | [ 4.99047] |
| RETDJI(-1) | -0.061073 | -0.281120 | -0.115194 |
| | (0.04300) | (0.03348) | (0.05729) |
| | [-1.42041] | [-8.39658] | [-2.01073] |
| RETDJI(-2) | -0.156619 | -0.274494 | -0.122045 |
| | (0.04415) | (0.03438) | (0.05883) |

| | | | |
|---|---|---|---|
| | [-3.54729] | [-7.98419] | [-2.07458] |
| RETDJI(-3) | -0.107767 | -0.097552 | 0.285177 |
| | (0.04394) | (0.03421) | (0.05854) |
| | [-2.45275] | [-2.85136] | [ 4.87127] |
| RETDJI(-4) | -0.068957 | -0.145259 | 0.289251 |
| | (0.04083) | (0.03179) | (0.05440) |
| | [-1.68893] | [-4.56900] | [ 5.31700] |
| RETISE(-1) | -0.006544 | -0.022083 | -0.129960 |
| | (0.01831) | (0.01425) | (0.02439) |
| | [-0.35749] | [-1.54919] | [-5.32807] |
| RETISE(-2) | 0.028418 | -0.006520 | 0.002335 |
| | (0.01796) | (0.01399) | (0.02393) |
| | [ 1.58203] | [-0.46616] | [ 0.09756] |
| RETISE(-3) | -0.007509 | 0.006804 | -0.017289 |
| | (0.01798) | (0.01400) | (0.02396) |
| | [-0.41754] | [ 0.48587] | [-0.72150] |
| RETISE(-4) | 0.000294 | -0.014350 | -0.054442 |
| | (0.01778) | (0.01385) | (0.02370) |
| | [ 0.01656] | [-1.03623] | [-2.29746] |
| C | -0.000130 | -0.000252 | -7.53E-05 |
| | (0.00029) | (0.00023) | (0.00039) |
| | [-0.44367] | [-1.10161] | [-0.19282] |
| R-squared | 0.028027 | 0.170288 | 0.155234 |
| Adj. R-squared | 0.020774 | 0.164096 | 0.148929 |
| Sum sq. resids | 0.223675 | 0.135620 | 0.397099 |
| S.E. equation | 0.011794 | 0.009184 | 0.015715 |
| F-statistic | 3.863959 | 27.50180 | 24.62375 |
| Log likelihood | 4903.916 | 5309.441 | 4438.697 |
| Akaike AIC | -6.034443 | -6.534782 | -5.460453 |
| Schwarz SC | -5.991210 | -6.491549 | -5.417220 |
| Mean dependent | -8.25E-05 | -0.000171 | -0.000137 |
| S.D. dependent | 0.011919 | 0.010045 | 0.017034 |

| | |
|---|---|
| Determinant resid covariance (dof adj.) | 1.49E-12 |
| Determinant resid covariance | 1.46E-12 |
| Log likelihood | 15188.81 |
| Akaike information criterion | -18.69193 |
| Schwarz criterion | -18.56223 |

**Figure 5 - VAR Granger Causality/Block Exogeneity Wald Tests – Scenario 1**

Dependent variable: RETDAX1

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDJI | 43.30804 | 4 | 0.0000 |
| RETISE | 3.697229 | 4 | 0.4485 |
| All | 48.02382 | 8 | 0.0000 |

Dependent variable: RETDJI

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDAX1 | 121.8029 | 4 | 0.0000 |
| RETISE | 4.928412 | 4 | 0.2947 |
| All | 128.3112 | 8 | 0.0000 |

Dependent variable: RETISE

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDAX1 | 69.18626 | 4 | 0.0000 |
| RETDJI | 65.93621 | 4 | 0.0000 |
| All | 257.0194 | 8 | 0.0000 |

**Figure 6 - Pairwise Granger Causality Tests – Scenario 1**

| Null Hypothesis: | Obs | F-Statistic | Probability |
|---|---|---|---|
| RETDJI does not Granger Cause RETDAX1 | 1621 | 11.0837 | 7.2E-09 |
| RETDAX1 does not Granger Cause RETDJI | | 30.8279 | 9.2E-25 |
| RETISE does not Granger Cause RETDAX1 | 1621 | 1.15088 | 0.33088 |
| RETDAX1 does not Granger Cause RETISE | | 46.0033 | 1.2E-36 |
| RETISE does not Granger Cause RETDJI | 1621 | 1.51627 | 0.19490 |
| RETDJI does not Granger Cause RETISE | | 45.1332 | 5.7E-36 |

**Figure 7 - VAR Granger Causality/Block Exogeneity Wald Tests – Scenario 2**

Dependent variable: RETDAX2

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDJI | 16.02839 | 4 | 0.0030 |
| RETISE | 3.107800 | 4 | 0.5400 |
| All | 20.05332 | 8 | 0.0101 |

Dependent variable: RETDJI

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDAX2 | 251.7210 | 4 | 0.0000 |
| RETISE | 4.001011 | 4 | 0.4059 |
| All | 258.7181 | 8 | 0.0000 |

Dependent variable: RETISE

| Excluded | Chi-sq | df | Prob. |
|---|---|---|---|
| RETDAX2 | 93.03378 | 4 | 0.0000 |
| RETDJI | 63.77136 | 4 | 0.0000 |
| All | 283.5377 | 8 | 0.0000 |

**Figure 8 - Pairwise Granger Causality Tests – Scenario 2**

| Null Hypothesis: | Obs | F-Statistic | Probability |
|---|---|---|---|
| RETDJI does not Granger Cause RETDAX2 | 1621 | 4.23872 | 0.00204 |
| RETDAX2 does not Granger Cause RETDJI | | 63.6792 | 4.9E-50 |
| RETISE does not Granger Cause RETDAX2 | 1621 | 0.99878 | 0.40700 |
| RETDAX2 does not Granger Cause RETISE | | 52.9772 | 5.5E-42 |
| RETISE does not Granger Cause RETDJI | 1621 | 1.51627 | 0.19490 |
| RETDJI does not Granger Cause RETISE | | 45.1332 | 5.7E-36 |

## Figure 9 - Impulse Responses – Scenario 1

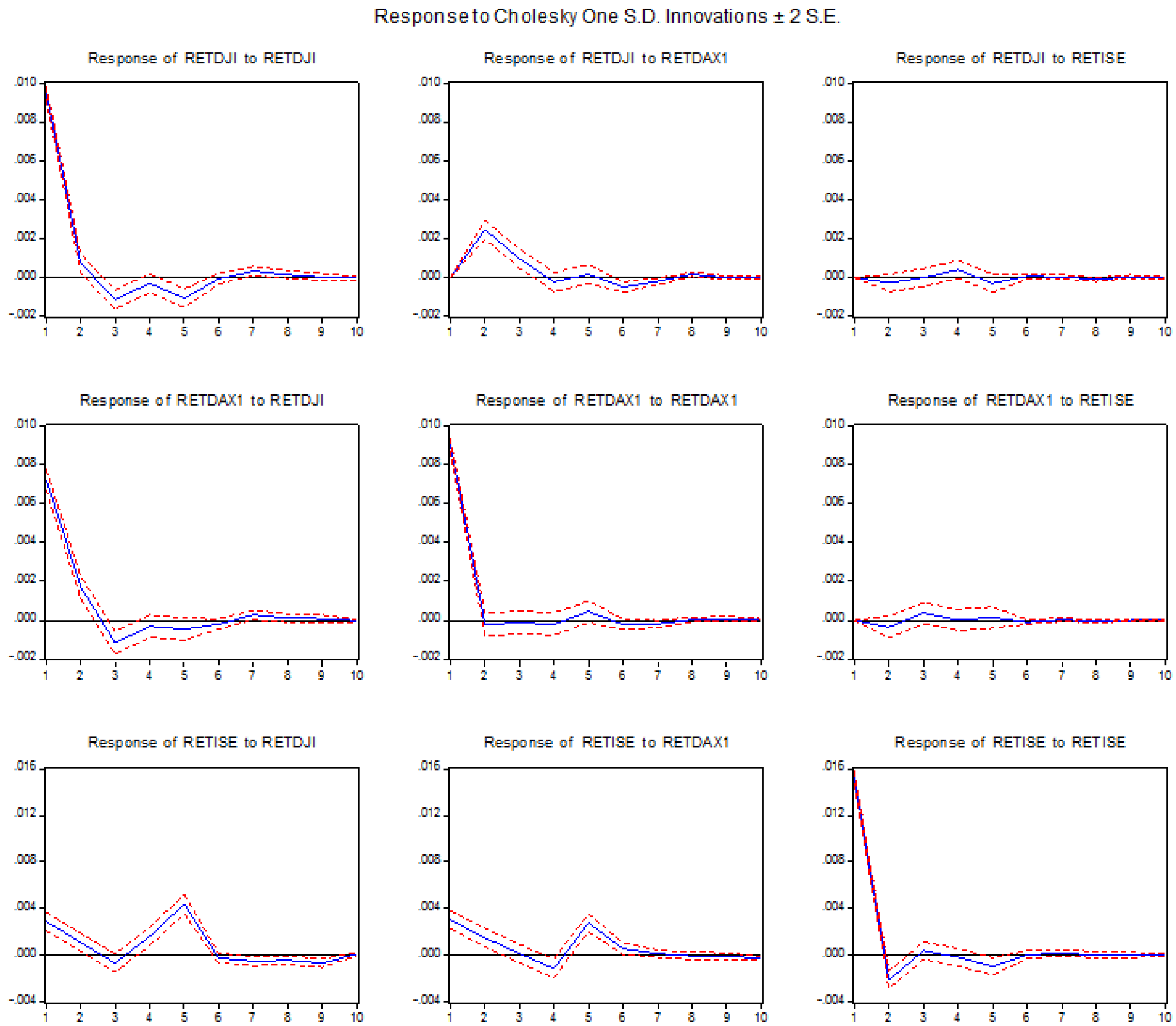

**Figure 10 - Impulse Responses – Scenario 2**

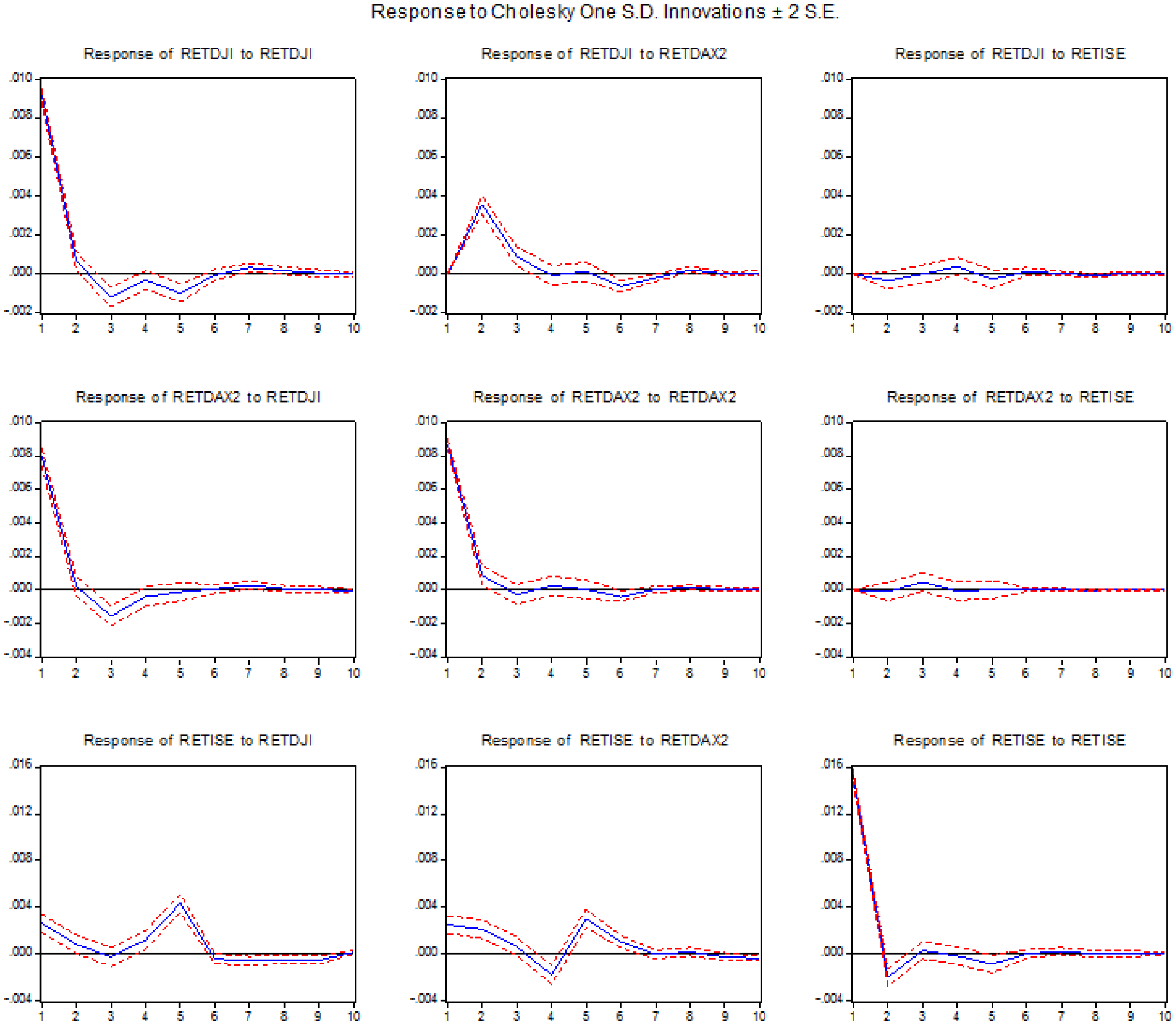

**Figure 11 - Variance Decompositions – Scenario 1**

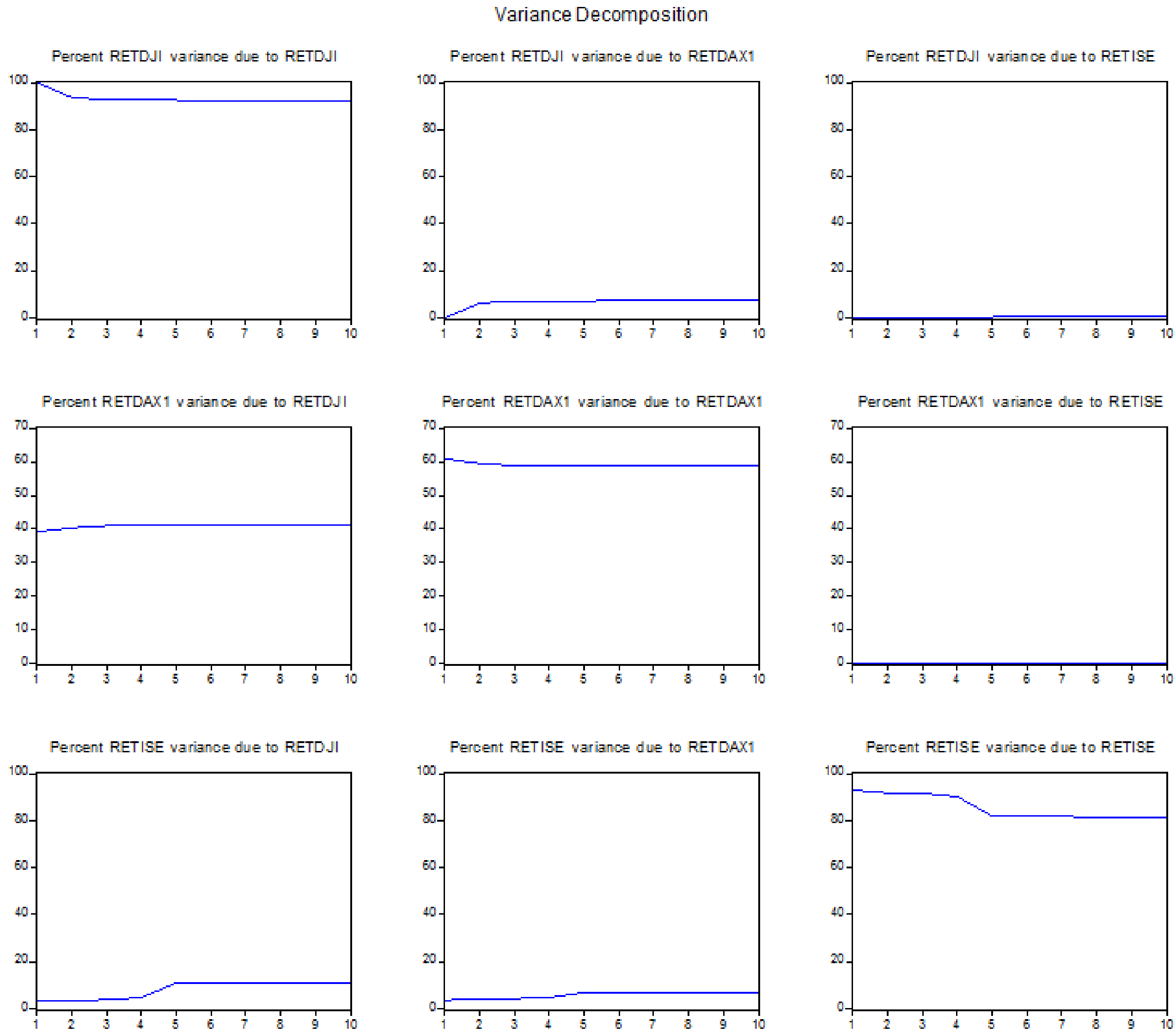

**Figure 12 - Variance Decompositions – Scenario 2**