Hacettepe University Graduate School of Social Sciences

Faculty of Economics and Administrative Sciences

Department of Economics

STOCK MARKETS CONNECTEDNESS

Fatmanur GÜL ORAL

Master's Thesis

Ankara, 2018

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KABUL VE ONAY

Fatmanur GÜL ORAL tarafından hazırlanan "Stock Markets Connectedness" başlıklı bu çalışma, 24 Ocak 2018 tarihinde yapılan savunma sınavı sonucunda başarılı bulunarak jürimiz tarafından yüksek lisans tezi olarak kabul edilmiştir.

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o **Tezimin/Raporumun ....tarihine kadar erişime açılmasını ve fotokopi alınmasını (İç Kapak, Özet, İçindekiler ve Kaynakça hariç) istemiyorum.**
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13 Şubat 2018

Fatmanur GÜL ORAL

ETİK BEYAN

Bu çalışmadaki bütün bilgi ve belgeleri akademik kurallar çerçevesinde elde ettiğimi, görsel, işitsel ve yazılı tüm bilgi ve sonuçları bilimsel ahlak kurallarına uygun olarak sunduğumu, kullandığım verilerde herhangi bir tahrifat yapmadığımı, yararlandığım kaynaklara bilimsel normlara uygun olarak atıfta bulunduğumu, tezimin kaynak gösterilen durumlar dışında özgün olduğunu, Tez Danışmanının **Prof.Dr. İbrahim ÖZKAN** danışmanlığında tarafımdan üretildiğini ve Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Yazım Yönergesine göre yazıldığını beyan ederim.

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ABSTRACT

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The increase in political, economic and financial integration between countries affect the international market linkages. As a result of globalization in finance, a financial crisis occurred in one country can easily spread to other countries. This thesis examines the connectedness between stock markets of both developed and developing countries in different regions. We analyze stock market returns data from January 1, 1997, to August 18, 2017, which include significant turmoil times, and use a new methodology, Diebold and Yilmaz Connectedness Index (2011), to measure static and dynamic connectedness of financial markets. Our results show that the U.S. stock market is the most influencing markets on the other markets in different regions. Additionally, turmoil periods have significant effects on connectedness between stock markets. In conclusion, it is important to monitor and measure stock market connectedness for both portfolio investors and policymakers.

Keywords

Financial market integration, Stock market, Spillover, Conectedness Index, Financial Crisis.

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CHAPTER I

INTRODUCTION

It is possible to encounter connections in all fields of life. However, the connections in finance and macroeconomics are more central than the other areas (Diebold and Yilmaz, 2015).

The links between financial markets have become widespread in the last decades as a result of the globalization efforts since the early 1980s. The key reasons for the markets moving together are the advancement in technology which provides free and easy market information and the decrease in the international investment barriers. The increase in political, economic and financial integration between countries affect the international market linkages. Due to the gradual rise in financial markets correlation, the "global finance" phenomenon occurred (Longin and Solnik, 1995).

Economists and policymakers mostly believe that financial globalization reduces the domestic barriers to international capital flows. Progress to free and fast financial flow gives rise to closely related and interconnected countries. Therefore, a financial crisis occurred in one country can easily spread to other countries (Dymski, 2005). "Globalization makes it impossible for modern societies to collapse in isolation. Any society in turmoil today, no matter how remote can cause trouble for prosperous societies on other continents, and is also subject to their influence (whether helpful or destabilizing)". (Jared Dimon, 2005, preface)

In this context, understanding the financial market relations is important in many aspects. International investors want to know the reasons for the interdependence of markets to notice the risks or gains of international diversification. Likewise, policymakers want to know the reasons for the interdependence of markets to realize the capital flows, in particular, the capital outflows (Pretorius, 2002).

Comovement between financial markets is crucial for decisions of the financial market participants. Comovement of stock market returns is significant for consideration of portfolio risk. Obtaining the optimal portfolio decision, participants choose more independent assets for the diversity of their portfolios, because the effectiveness of diversification decreases as a result of the high correlation between assets (Padhi and Lagesh, 2012). It is also important for governments and international organizations such as IMF. It has a significant role in government and international organization's financial decisions, risk management and distribution of portfolios (Ozer-Imer and Ozkan, 2014).

In 1970s international diversification of portfolios gained popularity because of the low correlation between stock markets. Grubel and Fadner (1971) state that the portfolio holders in the U.S. are interested in foreign assets. According to them, the reason for the increase in benefits of international diversification is due to the reduction in variance of portfolios' expected returns. The reduction occurs because of these two factors: Firstly, foreign asset returns are affected by the business cycle, policies of governments and natural or man made disasters. Secondly, the capital value of assets that change with variation of the exchange rate affect the variance of foreign asset returns.

Solnik (1974) examines the diversification internationally has more benefits than domestically. This is because the international portfolio diversification provides more risk reduction than the domestic one. Solnik shows that the gain from diversification internationally is substantial.

It cannot be exactly said that the domestic diversification does not reduce the risk. As domestic diversification increases, the risk of portfolio decreases. However, this decrease will be less and less with the increase in diversification. The marginal reduction in portfolio risk becomes smaller by adding one more security in the portfolio. The risk cannot drop down from a certain level although the number of securities is large. The reason for that is the stock prices are prone to move together.

The best way to the diversification of portfolio internationally is to select markets from different geography to minimize the risk (Solnik, 1974). Besides the geographical distance, the important thing is the segmentation of financial markets. "A segmented market can offer higher risk-adjustment returns than countries that are more integrated can" (Akdogan, 1996: 34).

In recent decades, the benefit of international diversification reduces due to some institutions and political factors. Exchange rate risk and international monetary instability have an important effect on the reduction of the advantages of international diversification.

For instance, the introduction of the Euro, one of the milestones of global finance, has eliminated the exchange rate risk in European stock markets. It has diminished the differences in investment opportunities between the member countries. Conformity of regulations and social welfare systems in European countries provide fewer market frictions and restrictions to cross-border mobility. Using common currency has affected the dependence or comovement of stock markets in Euro area. Therefore, it affects the portfolio diversification decisions of investors and thus management of asset and management of risk and international asset pricing (Batram et.al., 2007).

After the using common currency in Euro area, the dependence of many financial markets rises. By introduction of Euro, factor risks of many stocks move in the similar direction and the correlations between countries rise over time. It means although diversification is beneficial, diversification in Euro-zone countries has little advantages for investors (Bartram and Karolyi, 2006; Kearney and Poti, 2006; Bartram et al., 2007). Thus, only international diversification is not enough to cope with risk. Diversification against large shocks provides much more benefits to reduce portfolio risk (Karolyi and Stulz, 1996).

The market dependence increased in the relatively large stock markets which have high liquidity and fewer transaction costs. Higher transaction or information costs and less liquidity of market are important factors that affect the market attractiveness to investors. These create the barriers to investment and stronger comovements (Bartman et al., 2007).

Modern economics trends show that economic relations are strongly connected between regions or economic blocks rather than single markets. (Lee and Jeong, 2014). Especially, in last decades, crises spring in a country spills over other countries which are not in the same region. Further, these countries do not have the same economic structure and economic linkage. The apparent reason for propagating of a shock to other regions is trade relations. Additionally, developments in international financial markets and various financial intermediaries are important factors in the transmission of shocks. The decisions of policy-makers also have a crucial role in the transmission of shocks (Pericoli and Sbracia, 2003).

The transmission mechanism is important for explaining the international relation of financial markets because of the following reasons; Firstly it can be used as an indicator of the efficiency of the market. Then, the transmission mechanism is crucial for allocation of a portfolio with information about spillover effect of returns. Lastly, knowledge about volatility spillover effect of returns may help in the financial application based on conditional volatility estimation such as optimizing portfolio and estimating value risk (Harris and Pisedtasalasai, 2006).

Additionally, the feature of transmission process depends on the shock persistence, as a shock can be temporary or permanent (Scheicher, 2001). Chiang (2007) submitted three idiosyncratic crisis transmission phases. The first one is the immediate effect of crises that is observed in sudden increases in dynamic correlation. Then there are herding phases in which dynamic correlation continue to increase. The last one is the post-crisis period, which is the period of the dynamic correlation turning back to initial level. It is worth noting that each country has different economic fundamentals and structures so the same shock could affect countries differently (Hwang et. al., 2013).

All economies experience some crashes and crises in their complex interaction of economic activities. Because of the interconnection across financial markets and increased comovements in crisis periods, avoidance of the crisis is difficult for countries. For this reason, the analysis of crises and comovements is crucial in economics and finance.

The literature about comovement has focused particularly on financial crises. The common view about financial market integration is that the correlation between returns in stock markets rise in the crisis periods.

It is not only during the crisis but also during crashes period, comovements are higher (While the crisis is a period of uncertainty in many markets, a crash related to only one asset or market.) (Kole, 2006, 1-2). Besides the increasing volatility, crises occasionally cause important price changes with clustering tendency (Engle, 1982).

During crises, it is observed that asset price volatility and returns covariance are higher compared to more tranquil periods (Corsetti et.al., 2005). Therefore, stock market comovements increase in time and have high volatility in a financial crisis (Gjka and Horvath, 2013). This is because of the fact that very bad or very good news has a strong effect on financial markets (Avouyi-Dovi, 2004).

Global shocks influence the volatility of markets and their correlations at the same time. Powerful shocks in global factors affect all the stock markets simultaneously (Solnik et.al., 1996). Besides the crisis, important news from major global markets often cause a rapid influence of stock prices on the other markets. In this way, financial crises may expand from one market to other markets of different countries or regions. Intensive relations of crisis market with other markets can conduce to the spread of the crisis, which is often called "financial contagion".

There is no consensus in the literature about the definitions of concepts which indicate the comovements of markets. There are some discussions and models that are devoted concepts. Economists, in general, have used the words such as, "spillover", "contagion", "herding behaviors", when analyzing financial markets, if there are changes with the effect of any events like a crisis, a crash or some other important news on markets. More generally, "contagion and spillovers describe very loosely the phenomenon in which a shock from one country is transmitted to another" (Alter and Beyer,2013: 3). On the other hand terms like "interdependence", "connectedness" are generally used when comovements of markets are high during periods of crisis as well as in stability periods.

To be more specific, there are different descriptions of these concepts in the literature which are as follows; Contagion is essentially a medical term which means "the spread of a medical disease". (Claessens and Forbes, 2001: 1).

According to some economists, contagion is the transmission of a shock from one country to another, even though cross-market linkage does not change significantly. On the contrary, others believed that the definition of contagion related with cross-market relationship is impossible. They think the explanation of spread of a shock is essential and all transmission mechanism cannot compose contagion.

Pretorius (2002) describe the contagion effect as the reason of comovement not explained by economic fundamentals. Pericoli and Sbracia (2003:9-10) compose common definitions that are the most used in the literature: "(i) Contagion is a significant increase in the probability of a crisis in one country, conditional on a crisis occurring in another country. (ii) Contagion occurs when volatility spills over from the crisis country to the financial markets of other countries. (iii) Contagion is a significant increase in co-movements of prices and quantities across markets, conditional on a crisis occurring in one market or a group o markets. (iv) (Shift-)contagion occurs when the transmission channel is different after a shock in one market. (v) Contagion occurs when co-movement cannot be explained by fundamentals."

To sum up, all these definitions describes that contagion occurs after a crisis. Contagion may be defined as the breaks in the international transmission mechanism as a result of an unexpected event in finance. If comovement of asset prices is too different than the envisaged international transmission mechanism, it can be due to the contagion. (Corsetti et.al., 2005).

On the other hand, Forbes and Rigobon (2002) describe the interdependence as the situation having a continuous high level of correlation after the shock in already correlated markets before the shock. Namely, if two markets have high comovement level in stable periods, the increasing of comovement after the shock referred to interdependence instead of contagion.

The important point about interdependence is "a high degree of comovement between countries must exist in economically stable times as well as in crisis period" (Wilson and Zurbruegg, 2004: 403).

While comovement means changes in regimes at the same time in countries, interdependence means "changes in regimes associated with altering the regime in one of the countries" (Gallo and Otranto, 2008: 3012).

There is a tenuous difference between contagion, and spillover (or interdependence, or linkages). This is because, "all are transmission mechanisms whose distinctions are model dependent" (Rigobon, 2016).

As a consequence of all the information, it is crucial to measure and monitor the market relations, "to provide early warning systems for emergent crises, and to track the progress of extant crises" (Diebold and Yilmaz, 2012: 2).

Different types of methodologies have used to measure the market relations in the literature. Most common methods are; Cross-market correlation coefficients method, Autoregressive and General Autoregressive Conditional Heterokedasticity (ARCH or GARCH) models, Dynamic Conditional Correlation models, Spillover Index or Connectedness Index methods.

Most of these studies analyze the stock markets data to investigate the financial market interdependences. "As one of the most important sources of finance for companies, the stock market plays a central role in the market economy. Stocks are priced based on expected future cash flow, which in turn is closely linked to economic activity. The resulting forward-looking perspective makes the stock market the most important barometer of current and expected future economic activity." (Diebold and Yilmaz 2015:84).

In this study, we also analyze the stock market data and use a new methodology, Diebold and Yilmaz Connectedness Index, to measure static and dynamic connectedness of financial markets. We analyze the global stock market returns from January 1, 1997 to August 18, 2017 which include significant turmoil times.

In Chapter 2, we review the literature about financial market relations. Further, we review the literature according to their methodologies that used to analyze the market dependencies.

In Chapter 3, we describe our data and Diebold and Yilmaz Connectedness methodology (2009, 2010, 2011).

In Chapter 4, we interpret our empirical findings obtained from both static (full-sample) and dynamic (rolling-sample) analysis.

Finally, in Chapter 5, we conclude our finding and comment about stock market connectedness.

CHAPTER II

LITERATURE SURVEY

2.1.Brief Review of Literature

The early studies about the relationship between stock markets begin with the study of Granger and Morgenstern (1970) that searches the equity markets relationship. They claim that the financial markets would not be independent during a global financial crisis or a war.

Other early studies search the comovements between equity markets which were continued with Ripley (1973), Lessard (1976), and Panton et.al. (1976). They state that stock price comovement arises from many factors such as trade relations, geographical distances, and institutional, cultural or economic relations. Using factor analysis, Ripley(1973) concludes that the movements in indices of most of the developed countries are unique. Panton and others (1976) use cluster analysis to find the structure of international stock markets and conclude high comovements between equity markets.

Hilliard (1979) examines the comovements in price changes between 10 stock markets during OPEC oil crisis. Using daily closing prices data from July 1973 to April 1974 for analysis, he concludes there is a high correlation between inter-continental stock prices and low correlation between intra-continental stock prices.

The international comovement of stock markets issue became more attractive for researchers, especially after 1987 stock market crash. The 1987 Crash, also known as Black Monday, was one of the severe global events in financial history. Most of the important stock markets were severely affected by this crash all over the world.

Hamao et al. (1990) examine the response of major stock markets to 1987 crash by analyzing pre-crisis and crisis period, which include the data between the years of 1985-

1987. They determine that there are price changes spillover from New York to other markets after the 1987 crash.

King and Wadhwani (1990) study the effect of 1987 U.S. crisis on world stock markets. They use cross-market correlation coefficient to find evidence for contagion. They find that the contagion occurs in the turmoil periods. For the period of July 1987- February 1988 they find evidence for contagion in the U.S., the U.K. and Japan stock markets. They also find that correlations generally increase in high volatility periods.

Lee and Kim (1993) also study the effect of 1987 Crash on some stock markets by employing the correlation coefficient between returns. They use correlation and explanatory factor analysis to investigate the weekly data of 12 stock markets between August 1984 and December 1990. They find that there is a significant rise in the correlation coefficient between markets in the period of the 1987 Crash. In addition, high comovement between stock markets continued after the crash.

At the beginning of the 1990s, economists argue that the comovements between markets are time-varying. Bekaert and Harvey (1995), Longin and Solnik (1995), Karolyi and Stulzi (1996), Solnik et.al. (1996) claim that the stock market integrations vary over time. They all find that the correlation between countries rises in high volatility periods. Also, it increases in high business cycle periods. According to them, this is because of the volatility of national markets and also the interdependence between international stock markets changes in the process of time.

Bekaert and Harvey (1995) analyze stock returns of 12 emerging markets to measure the degree of integration. The analysis covers the years between 1969 and 1975. Their findings show that there is a time-varying integration between emerging markets which means that the degree of market integration changes in time.

Solnik et al. (1996) also find that correlation between countries rise when market volatility increases. Their study focuses on some major stock markets with the US market in the years between 1958-1995, which is a very long period. They find that during this period, the correlation between markets evolves, that is to say, international stock market correlations fluctuate widely over time. They find some peaks in the period that coincide with some global events such as 1987 oil shock.

Karolyi and Stulz (1996) examine the main factors that have an impact on the correlation of international stock returns with using U.S. and Japan stock market data. They find that the large shocks in the broad-based stock market affect the return correlations both in terms of magnitude and persistence. They find strong evidence that if there are large simultaneous return shocks in national markets, the cross-country covariances are higher. These large shocks to stock markets are high as to be global shocks.

At the beginning of the 2000s, the studies on contagion and interdependence accelerated. Most economists have studied whether it is a contagion or an interdependence between stock markets.

According to some economists, contagion is the transmission of a shock from one country to another, even though cross-market linkage does not change significantly. On the contrary, others believed that the definition of contagion related to the cross-market relationship is impossible. They think the explanation of spread of a shock is essential and all transmission mechanism cannot compose contagion.

Forbes and Rigobon (2002) argue that if there is a substantial rise in cross-market linkages after a shock, which occurred in one market, can be described as contagion. For the existence of contagion, the rise in cross-market linkages must occur after a shock. Although there is a high correlation after a shock in two markets, this may not be correlation if these markets have high comovement also in stable periods.

There are many studies in the financial literature that find evidence for contagion (Boyson et al., 2010; Christiansen and Ronaldo, 2009; Chudick and Fratzscher, 2011, Beirne et al., 2008; Dooley and Hutchison, 2009; Kim and Kim, 2011) during the U.S. financial crisis.

Although there is no consensus about what contagion is, most of the authors use the term contagion as opposite of interdependence. Forbes and Rigobon (2001) declared there is "no contagion" between equity markets. After this study, analyzing the existence of contagion became widespread in financial literature.

Forbes and Rigobon (2002) describe interdependence as the situation that there is a continuing high level of correlation after a shock in already correlated markets before the shock. Namely, if two markets have high comovement level in stable periods, the increase of comovement after the shock referred to interdependence instead of contagion. They claim that reason of finding contagion is heteroskedasticity. Since the correlation coefficient depends on volatility, if volatility increases during a crisis, correlation coefficient tends to be increased. Therefore, finding contagion is very neutral if tests do not adjust for this upward bias. When heteroscedasticity problem is solved with adjusted correlation coefficient, contagion case disappears. In other words, if tests are based on conditional correlation coefficient, finding contagion is an obvious result. However, when tests are depended unconditional correlation coefficient, the results show that there is no contagion. It suggests that there is interdependence between stock markets rather than contagion.

They argue that most of the studies about contagion in literature become mistaken when conditional cross-market correlation coefficients are analyzed instead of unconditional coefficients. They claim cross-market correlations tend to be biased upward particularly in crisis time, so they have to be corrected for bias. Therefore, the conditional cross-market correlation coefficients are not applicable to derive the market contagion or interdependence.

Forbes and Rigobon (2002) focus on test for contagion depending cross-market correlation coefficient to show that the tests are biased and failure as a result of heteroscedasticity, which means changes in volatility. Using 28 stock markets data, they analyze the comovements between stock markets during three important turbulence periods, 1997 Asian crisis, 1994 Mexico crisis, and 1987 the U.S. crash. In order to correct this heteroscedasticity problem, they use a new method as calculate the unconditional cross-market correlation coefficient. They calculated both conditional and unconditional cross-market correlation coefficient.

They show that if the correlation coefficients are corrected for heteroscedasticity, there is no evidence for contagion during the 1997 Asian crisis, 1994 Mexico crisis, and 1987 the U.S. crash. Their results show that there is a high level of comovement between stock markets during the crisis as well as tranquil periods, which they call interdependence.

After Forbes and Rigobon (2002) hypothesis of "no contagion, only interdependence", the interdependence term began to be used in literature as opposite to contagion. Wilson and Zurbruegg (2004), Bongfiglioli and Favero (2005), Corsetti et.al. (2005), Cheung et.al (2008), investigated the comovements of markets whether there is contagion or interdependence.

Edward and Susmel (2001) use the stock returns of Latin American and Hong Kong, as a representative Asian market, stock markets to examine comovements in volatility between markets. Using weekly data between 1989-1999, they find significant evidence for interdependence between Latin American stock markets. There is no evidence for contagion behavior of the correlation coefficients, except Mexico. Their results support the existence of interdependence rather than contagion.

Using the Forbes and Rigobon's methodology, Wilson and Zurbruegg (2004) examine the existence of contagion between Thai and some Asia-Pacific property markets during 1997 crisis. By analyzing both conditional and unconditional correlation coefficient, they find evidence for contagion.

Avouyi-Dovi and Neto (2004) analyze the degree of interdependence between France, German, and U.S. equity markets with using daily data from 31 December 1993 to 30 July 2002. They measure the degree of interdependence by the conditional correlations between stock returns. Their empirical findings show that correlations vary over time.

They find there is a close relationship between the correlations and volatility. That is to say, in high volatility periods, the correlations tend to be high; on the other hand, in low volatility periods markets behave more independently.

Corsetti et al. (2005) criticize the results of Forbes and Rigobon (2002) about contagion. They argue that the idea of "no contagion, only interdependence" is doubtful since it considers only common factors, which affect the markets, as an indicator of the increase in variance. They state that higher volatility returns in the turmoil periods can be a result of some country-specific factors as well as common factors. Thus, they use standard factor model of returns to measure interdependence between 17 stock markets after the 1997 Hong Kong stock market crisis. This model provides an opportunity to observe the effect of variance of country-specific shocks besides the variance of common factors. Their results show that there is a contagion from stock market of Hong Kong to some emerging (Singapore, Philippines) and industrial countries (France, Italy, UK). They conclude that when the country-specific factors are ignored, the result of "no contagion" is inevitable.

Bonfiglioli and Favero (2005) explain the comovements between stock markets by separating the interdependence and contagion with the framework of a structural model. Using co-integration analysis, they discriminate the long-run analysis from short-run fluctuations. They analyze the comovement between US and German stock markets in the years between 1980 and 2002. Their findings show that there is not any interdependence between US and German stock markets in the long-run. However, in the short-run the fluctuations of the US stock market spillover the German stock market, which shows there are contagion and interdependence between these markets in the short-run. They argue that these fluctuations of stock markets are relevant to both contagion and interdependence.

Bekaert et. al. (2005) apply a two-factor (global and regional) asset pricing model to stock markets in Europe, Southeast Asia, and Latin America to examine the existence of contagion during the Mexican and Asian crisis (1990s). Their findings show that there is no evidence of contagion arising from the Mexican crisis. However, they find that there is a significant increase in correlation of Asian markets during the Asian crisis.

In 2008, the studies about market interdependence increased and many of studies analyze the effect of 2008 Global Financial Crisis on markets. The Global financial crisis, which is stimulated by the fall in US mortgage market in 2007 and bankruptcy of Lehman Brothers in 2008, is considered as "the most serious global crisis since the Great Depression" (Claessens et.al., 2010).

Sun and Zhang (2009) investigate the effect of the 2008 financial crisis originating in the U.S. on the China and Hong Kong stock markets. They use daily data between January 2005 and October 2008. They find spillovers of price and volatility from the U.S. to Hong Kong. The effect of the crisis on Hong Kong stock market is more continuous than on China.

Kazi et al. (2011) examine the contagion effect based on Global Financial Crisis. Dajcman et.al. (2012) examine the comovements between the UK, Germany, and France stock markets during crucial turmoil periods, such as 1998 Russian Financial Crises, 2001 September 11 attacks, and 2008 Global Financial Crisis, between 1997 and 2010. Lee and Jeong (2014) also examine the influence of global financial crisis (2008) on the financial market integration.

In recent years, the studies about stock market relations are generally based on to measure the relations. Instead of testing contagion or interdependence, they focus on the monitor and measure the interdependences of markets.

Diebold and Yilmaz (2011) used a new term, "connectedness", to describe the relation of financial markets. "Connectedness term exist mostly at the center of modern risk measurement and management. It features prominently in key aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and grid-lock risk (bilateral and multilateral contractual connectedness), and not least, systemic risk (system-wide connectedness). It is also central to understanding underlying fundamental macroeconomic risks, in particular business cycle risk (intra- and inter-country real activity connectedness)" (Diebold and Yilmaz, 2011: 1). Nevertheless, connectedness is a difficult concept to understand and it is not clearly defined and measured.

2.1. Methodological Review

Nature of financial market interdependence has been studied for many years, especially after the 1997 Asian Crisis, by analyzing return or return volatilities (King et al., 1994; Forbes and Rigobon, 2002; Diebold Yilmaz, 2009).

However, like there is no common definition of market movements one could not find a unique measurement to analyze and measure the relation in financial literature. Different methodologies have been applied to measure the relations between stock markets. Although there is a consensus about the strong connection between markets, there are different approaches to measure the connection and to understand the dynamics.

Measuring the degree of a local market integration to world markets is difficult. Some argue that the way of measuring integration is to measure the correlation between the national market return and the world market return. But this way may be defective because if there is a significant difference between industry mixtures of the local country from world industry mixture, it has obtained little correlation although this local country is outstandingly integrated to world markets. On the other hand, some suggest looking for the investment restrictions to measure integration. This is also not a correct way of measurement because each restriction does not have the same importance in all countries (Bekaert and Harvey, 1995).

There are different types of methodologies to measure the market relations in the earlier literature. The most commonly used methods are as follows; cross-market correlation coefficients (King and Wadhwani (1990), Lee and Kim, (1993), Bong and Goldfajn (1999), Forbes and Rigobon (2002), Avouyi-Dovi and Neto (2004), Wilson and Zurbzuegg (2004)), Co-integration analysis (Bonfiglioli and Favero (2005)), AutoRegressive Conditional Heteroskedasticity (ARCH) and Generalized

AutoRegressive Conditional Heteroskedasticity (GARCH) models (Edward and Susmel (2001), Beirne et.al. (2009), Mukherjee and Mishra (2010), Horvarth and Poldauf (2011), Padhi and Lagesh (2012), Bala and Takimoto (2017), Dynamic Conditional Correlation (DCC) models (Cheung et.al. (2008), Lahrech and Sylwester (2011), Kazi et al. (2011), Min and Hwang (2012), Dajcman et.al. (2012), Padhi and Lagesh (2012), Hwang et.al. (2013), Lee and Jeong (2014), Ozer-Imer and Ozkan (2014), Albulescu et.al. (2015)). Besides all these, Co-integration analysis (Bonfiglioli and Favero (2005)), CoVAR Analysis (Adrian and Brunnermeier, (2008)), two-factor asset pricing model (Bekaert et. al. (2005)), Continuous Wavelet Transformation (CWT), Albulescu et.al. (2015) are also used to study stock market dependencies.

By analyzing both conditional and unconditional cross-market correlation coefficient, Forbes and Rigobon (2002) analyze the comovements between 28 stock markets during three important turbulence periods, 1997 Asian crisis, 1994 Mexico crisis, and 1987 the U.S. crash.

Wilson and Zurbruegg (2004) also analyze both conditional and unconditional correlation coefficient to examine the existence of contagion between Thai and some Asia-Pacific property markets during 1997 crisis. They find there is a contagion from Thailand to Hong Kong and Singapore.

Avouyi-Dovi and Neto (2004) analyze the degree of interdependence between France, German, and U.S. equity markets with using daily data from 31 December 1993 to 30 July 2002. They also measure the degree of interdependence by the conditional correlations coefficient between stock returns.

The other methodologies are AutoRegressive Conditional Heteroskedasticity (ARCH) and Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) which are proposed by Engle (1982). These frameworks are most commonly used methods to measure market dependencies. They explicitly deal with time-varying volatility issue. If it is analyzed only one variable (stock market), the ARCH or GARCH models enable to define an equation of the conditional variance.

The ARCH models developed by Engle (1982), are useful for explaining stock market dynamics that are moving simultaneously. The most important thing about ARCH models, they support that variances change over time (Avouyi-Dovi, 2004). Also, GARCH models are suitable to catch the time-varying nature of volatility.

There are many studies in the literature that apply different types of ARCH and GARCH models to analyze market dependencies as BEKK (Baba-Engle-Kraft-Kroner)-GARCH model, Switching ARCH (SWARCH) model, Multivariate GARCH (MGARCH), Exponential GARCH (EGARCH).

Karolyi (1995) examine the effect of U.S. crises on Canadian stock market in the years between 1981-1989. Using bivariate GARCH model, Karolyi analysis the daily returns of stock markets to examine short-run dynamics. They find that the effect of US stock markets on Toronto is smaller and more temporary than results of traditional VAR analysis.

Edward and Susmel (2001) use the stock returns of Latin American and Hong Kong, as a representative Asian market, stock markets to examine comovements in volatility between markets. Using weekly data in 1989-1999, they apply switching ARCH (SWARCH) model to capture the structural change during the crucial events. They find significant evidence for interdependence between Latin American stock markets. They find that there is not contagion behavior of the correlation coefficients, except Mexico. Their results are more supportive of interdependence rather than contagion.

Beirne et.al. (2009) analyze volatility spillover from developed markets to developing markets, investigate the transmission mechanism during turmoil periods in developed markets. By using GARCH-BEKK models, they analyze 41 developing economies from 1996 to 2008. They find spillover parameters change during turbulent periods in developed markets, and spillovers from developed markets affect the dynamics of returns conditional variances in most of developing stock markets.

Mukherjee and Mishra (2010) analyze both return and volatility spillovers between equity markets of India and 12 Asian countries. They use intraday price indices from 1997 to 2008 and apply simple GARCH model to test spillovers. Different from other studies, they test the transmission of markets not only for trading hours but also non-trading hours. They find significant spillover from Asian countries to India, and there is a bi-directional spillovers across Asian countries.

Horvath and Poldauf (2011) examine comovements between the major world stock markets in the years between 2000 and 2010 and especially during 2008 global financial crisis. Because of the conditional correlations among stock markets are time-varying they use the BEKK-GARCH model to analyze the correlations. Their findings show that the correlations between stock markets generally increase in the crisis period. However, the degree of comovements varies across the stock markets. When stock markets of UK and Germany and the US and Canada are highly correlated with each other, Chinese stock market is slightly correlated with the remaining markets.

Padhi and Lagesh (2012) use BEKK-GARCH model to investigate spillover effect between stock markets of emerging Asian countries, India and the US. Their sample covers the daily stock returns from 1994 to 2009.

Bala and Takimoto (2017) investigate volatility spillovers across the stock market of developing and developed countries by applying multivariate GARCH (MGARCH) models. Additionally, they analyze the effects of Global Financial Crisis on stock market volatilities. They find that stock market correlations in developed markets are higher than in developing markets. They also confirmed that stock market correlations increase during high volatility periods.

ARCH and GARCH models are suitable for catch time-varying structure but in the situation of low probability events like international financial crises, they fail to catch the structural changes (Edward and Susmel, 2001). On the other hand, if it is analyzed a number of variables (markets) simultaneously, using the ARCH or GARCH models have some difficulties because of the fact that the number of unknown parameter increases in line with the variables.

Because of volatility clustering, leptokurtosis and time-varying features of financial assets prices, we have some obstacles to obtain a certain estimation of financial comovement and correlations. For this reason, volatility spillover and dynamic conditional correlation should be investigated (Padhi and Lagesh, 2012).

In this context, a number of studies have used some specific models, which provide to decrease the number of parameters while keeping up the dynamic structure of the model. The CCC-ARCH model developed by Bollerslev (1997) consists of time-varying conditional variances and constant correlation. This model provides to reduce the number of parameters however the assumption of constant correlation is unrealistic.

It is needed to consider heteroscedasticity and the dynamic structure of the correlations of stock markets to investigate the comovement or contagion of stock markets (Min and Hwang, 2012). Engle (2001,2002) improves a dynamic model of multivariate GARCH model, DCC-GARCH. This approach supports that the correlation coefficients and conditional variances are time-varying. This approach can describe more realistic than Bollerslev's approach.

DCC model is a flexible approach of univariate GARCH model and uncomplicated approach of general multivariate GARCH model (Padhi and Lagesh, 2012). It is a better predictor to identify the contagion effect than the traditional correlation technique. (Kazi et al.,2011).

The Dynamic Conditional Correlation (DCC) models have widely used in the literature. Some of the studies used different types of DCC model as DCC-MGARCH, DCC-EGARCH.

Cheung et.al. (2008) examine the interdependence between stock markets of some Asian countries and the U.S. The sample period is selected as the period from 1996 to

2008. Because of the time differences between US and Asian stock markets using daily return in the analysis is hard. Thus, they prefer to use weekly returns, which is less noisy than daily returns. They use the DCC and Spillover Index (SI) to measure cross-market interdependence. The results of both analyses show that there is a crucial increase in interdependence between the stock markets during 2008 financial crises. They compare the cross-market correlation coefficients in stable and crisis periods to examine the existence of contagion. Their results show that there is no significant evidence to the existence of contagion. On the other hand, they find evidence for the regional contagion between the Asian stock markets.

Lahrech and Sylwester (2011) use the DCC-MGARCH model and analyze the time variation of correlations between U.S. stock market and some Latin American stock markets in the years between 1988-2004. They find that co-movements between the Latin American equity markets with US equity market have increased in time, though the size and speed of increase differ across countries.

Kazi et al. (2011) examine the contagion effect based on Global Financial Crisis. They investigate the relation of stock markets of US and 16 OECD between the years of 2007-2009 and apply the DCC-GARCH Model. They reach the results of existence of contagion. They find a significant increase in variances during financial crisis period compared to the remained period. There are significant increases in the mean of DCC coefficient between the mentioned countries during the crisis period. These mean and variance analysis shows that there is contagion effect between countries. Additionally, they determine the unconditional correlation coefficient also increases during the crisis period compared to the entire period. This result is similar to findings of Forbes and Rigobon (2002), which state that when defining contagion effect, unconditional correlation coefficient has to be the indicator.

Min and Hwang (2012) use the daily data in 2006-2010 to examine dynamic behavior of stock returns in four OECD countries with the US. They investigate the effect of US financial crises on these OECD stock markets. Like Forbes and Rigobon (2002) they consider the heteroscedasticity and the conditional correlation of stock markets.

Additionally, they consider the dynamic nature of the correlations. They analyze the dynamic conditional correlation of stock market relations by dividing the period into three subsample periods as pre-crisis, the first phase of the crisis and the second phase of crises by using DCC-MGARCH model. They find empirical evidence of contagion from the U.S. to remaining stock markets. Their findings show that correlation increases in the first phase of crisis which remains contagion. In the second phase of crisis, it seems an additional increase, which is named herding behavior, in the correlation for UK, Austria, and Switzerland.

Dajcman et.al. (2012) examine the comovements between the UK, Germany, and France stock markets during crucial turmoil periods, such as 1998 Russian Financial Crises, 2001 September 11 attacks, and 2008 Global Financial Crisis, between 1997 and 2010. Using DCC-GARCH and wavelet analysis, they analyze the daily stock return data. They find that the stock market comovements are scale dependent as well as time-varying. Additionally, their findings show that financial crises in sample period do not uniformly increase the stock markets comovements across all scales. Only, the global financial crisis has slightly and temporary effect on comovements between the stock markets.

Padhi and Lagesh (2012) use BEKK-GARCH model to investigate spillover effect between stock markets of emerging Asian countries, India and the US. Their sample covers the daily stock returns from 1994 to 2009. Additionally, they use DCC model to measure the dynamic conditional correlations of stock markets in the sample. They find volatility spillover between markets. The estimates of DCC-GARCH model show that conditional correlation between stock markets are time-varying.

Hwang et.al. (2013) examine the relationship between stock markets of emerging countries with the U.S. by analyzing the dynamics of daily returns of the stock markets for the period of 2006-2010. Using Bai-Perron test, they state the structural breaks and they examine varied phases of crisis spillover. They find different numbers of structural breaks, which occur different times also, for each country. The results of DCC-EGARCH model show that there is a spillover effect from the U.S. stock market to emerging markets. Additionally, there are important jumps in dynamic conditional correlations in the earlier period of the U.S. financial crisis, which prove the existence of contagion. Meanwhile, they observed herding behaviors between markets.

Lee and Jeong (2014) also examine the influence of 2008 Global Financial Crisis on the financial market integration. They analyze the stock market data of Northeast Asian and European stock markets between the years of 2000 and 2012. They claim that the effect of the financial crisis differs from country to country. The study uses various methodologies to analyze the stock market dynamics. In addition to DCC-MGARCH, they apply Collective Correlation (CCOR), Risk Decomposition, and Generalized Variance (GVAR) models. Their findings show that the process of market integration is dynamic and the effect of the global financial crisis is not same for all stock markets. It changes from market to market. Unlike the previous studies, they show integration increase uniquely only in the crisis period.

Ozer-Imer and Ozkan (2014) investigate the effect of 2008 Global Financial Crisis on the comovements of currencies of 16 countries. Using Dynamic Conditional Correlation model, they estimate the correlation between currency pairs before-during-after the global crisis. The change points of high volatility periods (the start and the end dates of crisis) are different for each market. Not only the starting and ending dates but also the duration of the crisis for each currency differs. Their results show that the volatilities of currencies rise associated with the outbreak of crisis for almost all returns, moreover, for some of the currencies, the volatility at least double during the crisis. They state that there is an adverse relation between the volatility level and period of crisis. The dynamic conditional correlation across returns of currencies firstly increase at the beginning of the crisis, then keep the increased level for a while, and fluctuate smoothly to the end of the crisis.

Albulescu et.al. (2015) investigate the existence of contagion and the dynamic correlation between stock markets of main European stock markets, Germany, France, and the UK by employing daily data in the period October 2009 to August 2013. Using Continuous Wavelet Transformation (CWT), they indicate the comovements in short-run and long-run. This analysis shows stock market of Germany has an impact on France and UK stock markets in the long-run. Additionally, they investigate the effect of European sovereign debt crisis by using dynamic correlation (DCC) analysis. They find that there is a high correlation between stock markets after the debt crisis.

Despite all, correlation-based measurements only measure bi-directional relationships and often tend to the linear Gaussian thinking and reduce them to a limited extent in financial market contexts. Although correlation is certainly a way to measure of connectedness, it does not measure nonlinearities, it measures only linear dependence. Additionally, correlation is also non-directional which means $corr(x, y) = corr(y, x)$. Also, correlation can only measure pairwise connections (Diebold and Yilmaz, 2015).

From all these reasons, Diebold and Yilmaz proposed a new method to measure connectedness which is non-pairwise and yet directional. This methodology, which called Spillover Index, later on, Connectedness Index, is proposed by a series of studies (Diebold and Yilmaz (2009,2010, and 2011).

Firstly, Diebold and Yilmaz (2009) propose a measure of interdependence which is called "spillover index". This method provides a measurement to obtain the return and volatility spillovers, which based on vector autoregressive (VAR) model which is proposed by Engel et al. (1990), however, they focus on variance decompositions. In this approach, they gather the spillover effects of markets and obtain a single spillover measure.

Spillover index can be used to measure return spillovers or volatility spillovers within and across markets, firms, or countries. In addition to all these, the significant feature of this measurement is that "although it conveys useful information, it nevertheless sidesteps the contentious issues associated with definition and existence of episodes of contagion or herd behavior ". (Diebold Yilmaz, 2010: 2).

Using Spillover Index methodology, Diebold and Yilmaz (2009a) analyze nineteen global equity markets. Their sample cover the data from January 1992 to November 2007. In this paper, they formulate and calculate both volatility and return spillovers.

They find evidence of differences in return and volatility spillovers. Thus, they do both unconditional (full-sample) and conditional (dynamic rolling-sample) analysis. They observe a significant level of spillover index in both return and volatilities.

Therefore, unconditionally, return spillovers and volatility spillover are almost of the same size. On the other side, conditionally, dynamics of return and volatility spillovers are different. While return spillovers have an increasing trend, probably as a result of financial market integration in last years, volatility spillovers do not have any trend. In addition, return while return spillovers exhibit no burst, volatility spillovers exhibit clear bursts associated with crises.

Cheung et.al. (2008) use Spillover Index to examine the interdependence between stock markets of East Asian countries and the U.S. The results of both analyses show that there is a crucial increase in interdependence between the stock markets during 2008 financial crises.

Diebold and Yilmaz (2009b) apply Spillover Index methodology to investigate the return and volatility spillovers between major stock markets in the United States from 1992 to 2008.

Then, Diebold and Yilmaz (2010) expand their methodology and by using generalized vector autoregressive framework and they purpose measurements for evaluating both total and directional volatility spillovers. They analyze the volatility spillover between major U.S. asset markets (stock, bond, commodity, and exchange rate) in 1999-2010 by using Spillover Index methodology. They find that volatility spillovers between markets are limited until the 2008 Global Financial Crisis, but they find evidence for spillovers from bond market to other markets after the crisis.

Finally, Diebold and Yilmaz (2011) propose and apply a unified framework, Diebold and Yilmaz Connectedness Index, for "conceptualizing and empirically measuring connectedness" for all levels, pairwise, directional and system-wide, with variance decompositions models. These connectedness measures are closely related to basis connectedness measures used in the network literature. This approach compound the network topology theory and VAR variance-decomposition theory.

In this study, Diebold and Yilmaz analyze the time-varying connectedness between stock return volatilities of important U.S. financial institutions from May 1999 to 2010. They also analyzed stock markets dynamics during Global Financial Crisis by using rolling window estimations.

Schmidbauer et. al. (2013) analyze the stock market connectedness across the major economies by extending the Diebold and Yilmaz (2009, 2011) methodology. They assess the propagation of information across markets. By using daily data from 1997 to 2013, they find an increasing trend in spillover index. In addition, their results show that the system stability of these major stock markets has increased since 2007, although information, or news, is more sudden.

Zhou et.al. (2012) apply Diebold and Yilmaz methodology to measure the volatility spillovers between Chinese and world stock markets from February 1996 to December 2009. They find Chinese equity market has crucial effects on other markets since 2005. In addition, the highest volatility spillover is observed from the U.S. to other markets during the mortgage crisis.

Diebold and Yilmaz (2014) use the Connectedness Index methodology to investigate the average and daily time-varying connectedness between stock return volatilities of main U.S. financial institutions for the period before and during the 2008 Global Financial Crisis. They provide both static and dynamic analysis.

Erkol (2015) measures stock market connectedness with using both Diebold and Yilmaz (2011) and Schmidbauer et. al. (2013) approaches. He compares these two approaches and finds a result that there is a positive correlation between return and volatility spillovers and they have similar behavior, however, during a crisis or a specific event return and volatility spillovers behave differently.

Nguyen (2015) use Diebold and Yilmaz methodology to analyze the volatility spillover between ten main sectors of the U.S. (Energy, Consumer Goods, Healthcare, Oil etc.) in both static and dynamic senses. By using the data from 2001 to 2014, they find the connectedness of these sectors has increased since late 2006. In addition, during 2001 and 2008 Crisis the volatility spillovers between sectors vary.

Demirer et. al. (2015) use Diebold and Yilmaz connectedness measure to analyze connectedness between top 150 banks of the world from 2003 to 2014. As a result of the static analysis, they find that connectedness between banks is related to bank location instead of bank assets. On the other hand, the dynamic analysis shows that connectedness of global banks displays both secular and cyclical variation. The connectedness of global banks changes in accordance with global market integration. Additionally, during crises, global banks connectedness display sharp increases.

Bostancı and Yilmaz (2015) apply Diebold and Yilmaz connectedness methodology to analyze the returns and volatilities of sovereign credit default swaps for some developed and developing countries in 2009-2014.

Chen and Wu (2016) investigate comovements and connectedness of commodity markets in last 1996-2016. They apply DCC model to obtain time-varying dependence structure and apply Diebold and Yilmaz methodology to analyze direction and magnitude of volatility spillovers. They find that comovements and connectedness of commodity markets have increased during the global financial crisis, but afterward, they have returned to initial levels.

Guimaraes-Filho and Hong (2016) analyze dynamic connectedness of Asian stock markets with each other and also with some global stock markets by using Diebold and Yilmaz methodology. They find evidence for large spillovers from Asian stock markets to some global markets. Asian economies, especially China, have crucial effects on other economies including some developed countries.

Diebold and Yilmaz (2016) apply their connectedness methodology to analyze equity return volatility connectedness of important financial institutions in Europe and the United States by using the data from 2004 to 2014. They find that there is clear directional connectedness from the U.S. to Europe during 2007-2008, but this connectedness became bi-directional after the global financial crisis.

CHAPTER III

DATA AND METHODOLOGY

3.1. Data

In our analysis, we use daily-adjusted close prices of 13 stock market indices in local currencies. The sample includes both advanced (Germany, France, United Kingdom, Canada, United States, China, Japan) and emerging economies (Argentina, Brazil, India, Mexico, Spain, Turkey) from different regions of the world. Table 3.1 shows the stock markets that we analyze.

	COUNTRIES	NAMES OF STOCK MARKETS	NAMES OF INDICES
Europe	Turkey	Istanbul Stock Exchange	BIST100
	Spain	Madrid Stock Exchange	IBEX 35
	Germany	Frankfurt Stock Exchange	DAX 30
	France	NYSE Euronext Paris	CAC 40
	UK	London Stock Exchange	FTSE 100
America	Mexico	Mexican Stock Exchange	IPC MEXICO
	Canada	Toronto Stock Exchange	S&P/TSX
	US	New York Stock Exchange	S&P 500
	Brazil	Sao Paulo Stock Exchange	IBOVESPA
	Argentina	Buenos Aires Stock Exchange	MERVAL
Asia	Hong Kong	Hong Kong Stock Exchange	HANG SENG INDEX
	Japan	Tokyo Stock Exchange	NIKKEI 225
	India	Bombay Stock Exchange	SP BSE Sensex

Table 3.2 Stock Markets of Countries

The data are taken from Yahoo Finance and Google Finance and cover the period from 1997/06/01 to 2017/08/18. To analyze stock market connectedness, we calculate the daily returns as the change in daily log closing prices for all indices. Figure 3.1 shows the return series of all stock indices and Appendix 1 has descriptive statistics of all stock markets returns.

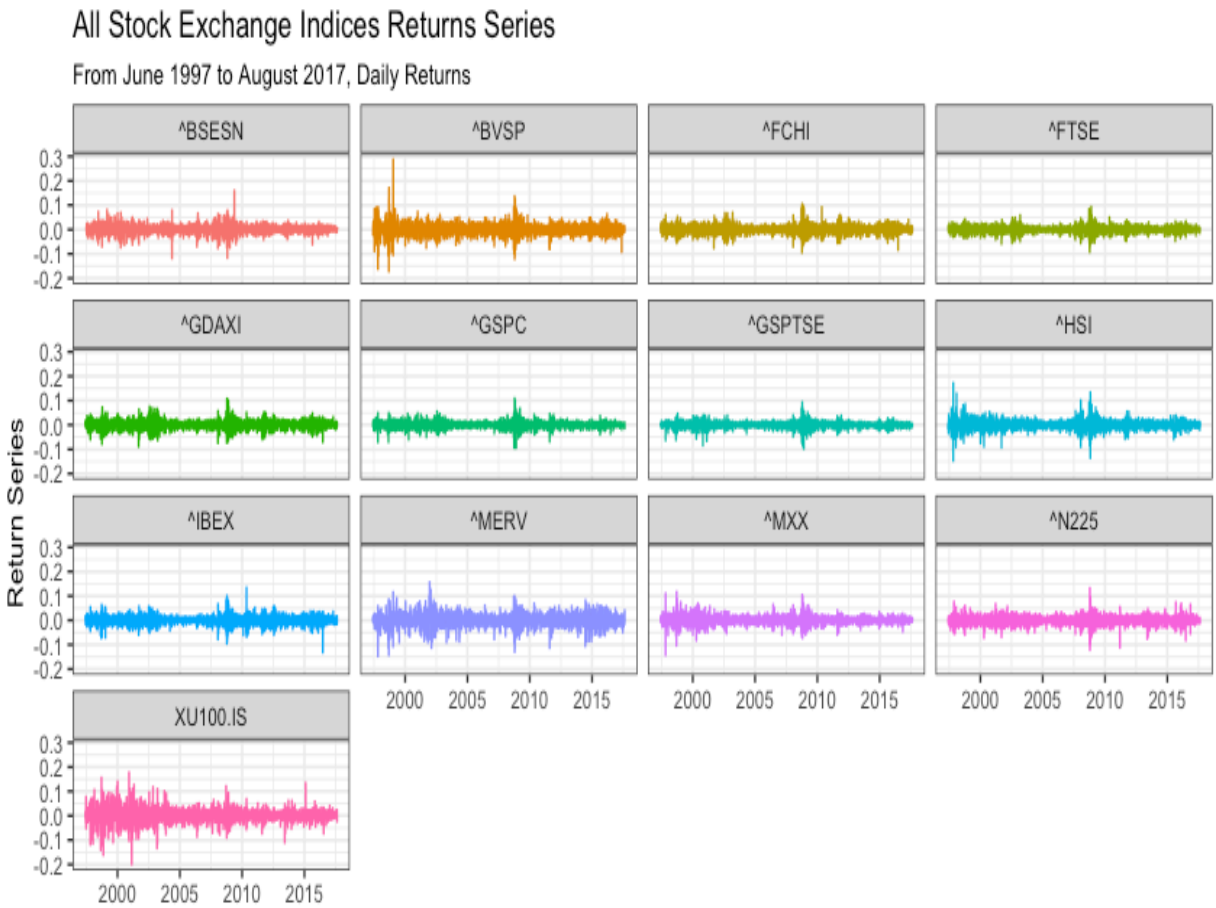

Figure 3.2 All Stock Exchange Indices Returns Series. The indices represented in Yahoo Finance for each stock indices as fallows: ^BSESN (SP BSE Sensex,), ^BVSP (IBOVESPA), ^FCHI(CAC40), ^FTSE (FTSE 100), ^GDAXI (DAX 30), ^GSPC(S&P 500); ^GSPTSE (S&P/TSX), ^HSI (HANG SENG INDEX), ^IBEX (IBEX 35), ^MERV (MERVAL), ^MXX (IPC), ^N225,(NIKKEI 225), XU100.IS (BIST100).

3.2.Methodology

To estimate stock market connectedness, we use Diebold and Yilmaz connectedness measure that is proposed in a series of studies (Diebold and Yilmaz 2009, 2010 and 2011). They measure connectedness in a vector autoregressive (VAR) model using forecast error variance decompositions. This approach measures financial connectedness according to the portions of forecast errors variations attributed to the shocks occurring elsewhere in the system. For each asset i, in an N-variable VAR, the measure of connectedness is the sum of the shares of its forecast error variance coming from shocks to asset j, for all $j \neq i$.

3.2.1.Generalized Forecast Error Variance and Connectedness Measures

The variance decomposition base on a covariance stationary N-variable VAR(p), which represented as:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-1} + \varepsilon_t ,$$

It can rewrite the system into a moving average and representation as:

$$x_t = \sum_{i=0}^{\infty} \mathrm{A}_i \varepsilon_{t-i} ,$$

where the NxN coefficient matrices A_i satisfies that $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for i < 0.

"The moving-average coefficients are key to understanding dynamics. We rely on the variance decompositions, which are transformations of the moving-average coefficients, and which allow us to split the H-step-ahead forecast error variances of each variable into parts attributable to the various system shocks." (Diebold and Yilmaz, 2010: 5)

Variable j's contribution to variable i's H-step-ahead generalized forecast error variance is:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i A_h \sum ej)^2}{\sum_{h=0}^{H-1} (e'_i A_h \sum A'_h ei)^2}$$

where Σ is the covariance matrix for the error vector ε , σ_{jj} is standart deviation of ε_j, the error terms for the j^{th}, and e_i is the selection vector with one for the $i^{th}$and zero elsewhere.

3.2.1.1.Pairwise Directional Connectedness

Since the effects of variables i and variable j to each other are not identical, each entry of the generalized variance decomposition matrix, $\theta_{ij}^{g}(H)$, can be normalized by the row sum,

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}$$

where $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = N$ by construction. $\tilde{\theta}_{ij}^{g}(H)$ is the *pairwise directional connectedness* from j to i at horizon H.

3.2.1.2.Total Directional Connectedness, "To" and "From"

"Total directional connectedness" to firm i from all other firms j is

$$C_{i\leftarrow\blacksquare}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\times 100$$

Similarly, "total directional connectedness" from firm i to all other firms j is

$$C_{\blacksquare\leftarrow i}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}\times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\times 100$$

3.2.1.3.Total (System-Wide) Connectedness

Diebold and Yilmaz describe (2011) the total connectedness as "the ratio of the sum of the off-diagonal elements of the variance decomposition matrix to the sum of all its elements". More simply, it is sum of total directional connectedness either "to" or "from".

$$C(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}$$

3.3.The Connectedness Table

Connectedness table is constituted with the full set of variance decompositions. It provides understanding the connectedness measures and the relationship of these measures. The upper-left block is called "*variance decomposition matrix*," and denoted by $D^H = d_{ij}$. The last column of connectedness table contains row sums which show "from" connectedness, and the bottom row contains column sums which shows "to" connectedness, and lastly, the bottom-right cell contains the grand average which shows total connectedness, in all cases for $i \neq j$.

	x_1	x_2	$\cdots$	x_N	$From\ others$
x_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	$\cdots$	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H, j \neq N$
$To\ others$	$\sum_{i=1}^N d_{i1}^H$ $i \neq 1$	$\sum_{i=1}^N d_{i2}^H$ $i \neq 2$	$\cdots$	$\sum_{i=1}^N d_{iN}^H$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1}^N d_{ij}^H$ $i \neq j$

Table 3.2 Connectedness Table

The "off-diagonal entries" of D^H are the pieces of the N forecast-error variance decompositions. From the connectedness point of view, they represent the "pairwise directional connectedness".

The *pairwise directional connectedness* from j to i is defined as

$C_{i \leftarrow j}^H = d_{ij}$.

In general $C_{i \leftarrow j}^H \neq C_{j \leftarrow i}^H$. Therefore, there are $N^2 - N$ separate measures pairwise directional connectedness measures.

Additionally, the *net pairwise directional connectedness* is defined as

$$C_{ij}^{H} = C_{j \leftarrow i}^{H} - C_{i \leftarrow j}^{H}.$$

There are $\frac{N^2 - N}{2}$ net pairwise directional connectedness measures, similar to bilateral trade balances.

The sums of off-diagonal row and column, namely "from" and "to" in the connectedness table indicate the *total directional connectedness* measures. "The sum of its off-diagonal elements gives the share of the H-step forecast-error variance of variable 1 coming from shocks arising in other variables" (Diebold and Yilmaz, 2011:3). Total directional connectedness from others to i is defined as

$$C^{H}{}_{i \leftarrow \blacksquare} = \sum_{\substack{j=1 \\ j \neq i}}^{N} d_{ij}^{H}$$

and the directional connectedness from others to j is defined as

$$C^{H}{}_{\blacksquare \leftarrow j} = \sum_{\substack{i=1 \\ i \neq j}}^{N} d_{ij}^{H}$$

It is clear that it has to be $2N$ total directional connectedness measures, N “to others,” or “transmitted,” and N “from others,” or “received,” similar to "total exports" and "total imports" for each of a set of N countries.

The *net total directional connectedness* is defined as

$$C^{H}{}_{i} = C^{H}{}_{\blacksquare \leftarrow i} - C^{H}{}_{i \leftarrow \blacksquare}.$$

Additionally, there are N net total directional connectedness measures, similar to the "total trade balances" of each of a set of N countries.

The last connectedness measure is obtained with the sum of all of the off-diagonal entries in D^{H}. The *total connectedness* also equal to the sum of the “from” column or “to” row,

$$C^H = \frac{1}{N}\sum_{\substack{i,j=1 \\ i\neq j}}^{N} d_{ij}^H$$

It is clear that there is only one total connectedness measure since the sum of "from" connectedness and "to" connectedness equal to each other. It analogous to "total world export or import".

3.4.Dynamic Connectedness

The connectedness measure can also calculate for a specific time period. Diebold and Yilmaz (2009, 2010, 2011) apply the rolling-window estimation to capture the time-varying nature of the connectedness.

CHAPTER IV

EMPIRICAL RESULTS

In this study, we apply Diebold and Yilmaz connectedness methodology (2009, 2010, 2011) to daily adjusted close price of stock market returns of 13 countries over the period from January 1, 1997 to August 18, 2017. In accordance with the results of VAR Selection criteria (Akaike Information Criterion), we estimate a VAR(2) model with 10-day forecast horizon. Appendix 2 has the all results for VAR order from 1 to 8.

Dynamic connectedness measures are obtained from the estimation of the VAR(2) model over 200-day rolling windows.

4.1.Static (Full-Sample) Connectedness Analysis

Firstly, we analyze unconditional return connectedness of stock markets. Table 4.1 indicates the connectedness table which shows the connectedness measures between stock markets. The table shows that the U.S. stock market (SP.500 index) has the highest connectedness measures to other stock markets.

	TURKEY BIST.100	U.S. SP.500	UK FTSE.100	JAPAN NIKKEI. 225	HONG KONG HONG.SENG. INDEX	BRAZIL IBOVESPA	ARGENTI NA MERVAL	MEXICO IPC.MEXICO	SPAIN IBEX.35	GERMAN Y DAX	CANADA SP.TSX	INDIA SP.BSE. SENSEX	FRANCE CAC.40
BIST.100	77,81204	10,81681	5,04311	0,6969	0,02663354	2,44595	0,06012	0,733852	0,2818	0,40737	0,3368	0,0955	1,2431
SP.500	0,922801	17,55105	9,80084	1,5418	1,92510764	1,69159	7,7079	4,6646719	0,5074	11,4306	29,5767	0,2557	12,424
FTSE.100	0,055646	**65,58598**	22,3628	1,4656	0,54852946	1,37759	0,08102	1,0195772	2,7865	0,54099	0,4636	0,0076	3,7046
NIKKEI.225	4,714463	**82,0155**	5,30643	1,3633	0,58832989	0,60993	0,2826	0,8687606	1,0726	0,82845	1,00292	1,2068	0,14
HONG.SENG.IN	2,560269	**75,01991**	3,24992	5,1238	0,29570787	5,3838	0,4327	5,6021515	0,0324	0,83251	0,19719	0,4265	0,8432
IBOVESPA	0,073105	22,43278	2,67442	4,605	4,50968565	9,12155	1,71085	3,5571769	3,8611	19,2316	6,06844	9,0599	13,094
MERVAL	1,786939	14,3225	0,062	1,0469	5,51589276	5,59645	43,9438	3,4216784	0,1553	7,80216	9,32245	2,1197	4,9042
IPC.MEXICO	0,98417	36,4627	0,91896	2,0729	1,6665643	5,72037	0,93209	29,719286	0,0676	3,42688	8,7961	2,7142	6,5181
IBEX.35	0,097602	**62,61402**	15,4677	1,1293	0,50088826	5,0771	1,05998	3,6457182	0,6423	0,32137	1,47722	0,0762	7,8906
DAX	0,128997	**60,67825**	22,7807	1,5814	0,17739581	1,17688	0,19568	1,5104657	1,2112	1,178	2,53513	0,184	6,6619
SP.TSX	0,507588	43,28245	7,06175	2,5933	0,88086562	0,26942	0,67746	3,9082912	0,987	6,92764	18,8886	2,2203	11,795
SP.BSE.SENSEX	3,872593	**60,2365**	0,36882	2,2712	0,55931887	10,7048	0,10015	7,1279285	1,0535	0,10642	0,41936	10,021	3,1581
CAC.40	0,070164	**66,97916**	19,2509	1,1167	0,5143533	1,03846	0,21249	0,9635432	2,1499	0,20025	0,85253	0,0522	6,5993
to other (wtih own)	93,58638	**617,9976**	**114,348**	26,608	17,709273	50,2139	57,3968	66,743101	14,809	53,2342	79,9371	28,44	78,977
to others	15,77434	600,4466	91,9856	25,245	17,4135651	41,0924	13,453	37,023815	14,166	52,0562	61,0484	18,419	72,377

Table 4.1. Connectedness Table of Data (VAR(2) model with 10-day forecast horizon.)

We also investigate the network graph to understand the structure of connectedness based on pairwise connectedness measures. Figure 4.1 shows the pairwise connectedness across stock markets. In order to obtain clear display, we ignore the spillovers which below the 10 percent of the highest spillover value (82.68%). In addition, Figure 4.2 shows the more significant connectedness measures which are higher than 16%. The thickness of lines indicates the weight of directional spillovers. The colors of lines changes according to the thickness (from strongest to weakest; purple, green, red, brown, light green, pink, and blue).

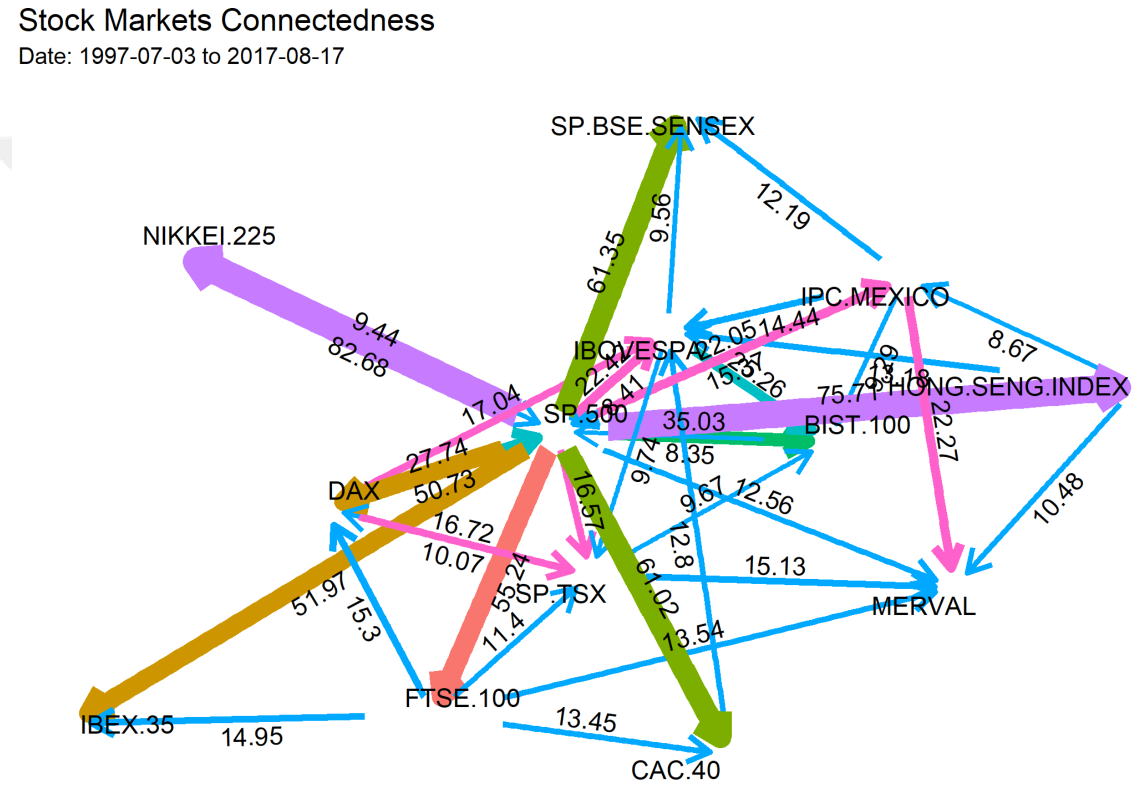

Figure 4.1 Network Connectedness-I Pairwise directional connectedness of returns over full-sample (The spillover measures below the 10 percent of the highest spillover measure are ignored). The countries are represented by stock market indices as follows, Turkey (BIST.100), Spain (IBEX.35), Germany (DAX.30), France (CAC.40), UK (FTSE.100), Mexico (IPC.MEXICO), Canada (SP.TSX), US(SP.500), Brazil (IBOVESPA), Argentina (MERVAL), Hong Kong (HONG.SENG.INDEX), Japan (NIKKEI.225), India (SP.BSE.SENSEX).

The results of the full-sample analysis show that the U.S. stock market (S&P 500 index) is one which is interconnected the other stock markets. The network graph (Figure 4.1) shows that there are significant spillovers "from" U.S. stock market returns to all other stock markets, but only a few of them display significant level spillover "to" U.S. stock market return. Thus, the U.S. has the highest "to" (to others) total directional connectedness measure. It is in the center of the network system.

The highest pairwise directional connectedness is observed from the U.S. to Japan, 82.68%, which means that shocks to Japan stock market are responsible for 82.68 percent of the 10-step-ahead forecast error variances in the U.S. stock market. On the other hand, the pairwise directional connectedness from Japan stock market to the U.S. stock market is 9.44%. It is clearly seen that pairwise directional connectedness from the U.S stock market to Japan stock market is not equal to pairwise directional connectedness from Japan to the U.S. stock market. We can measure the net pairwise directional connectedness from the U.S. to Japan as $C^{10}_{JAPAN \leftarrow US} = 82.68 - 9.44 = 73.24$ % (with 10-day forecast horizon, H=10).

The other pairwise directional connectedness measures "from" the U.S. stock market returns are, the second highest, to Hong Kong (75.71%), and then respectively, to India (61.35%), to France (61.02%), to the U.K. (55.24%), to Spain (51.97%), to Germany (50.73%), to Turkey (35.03%), to Brazil (22.42%), to Mexico (22.05%), to Canada (16.57%), and the lowest, to Argentina (12.56%).

On the other hand, only a few of these countries stock markets returns have a significant level of pairwise directional connectedness "to" the U.S. stock market. Figure 4.2 shows that only German stock market has a measure of pairwise directional connectedness, 27.74%, to the U.S. stock market. Returns of Japan, Brazil, and Turkey stock markets also have measures of pairwise directional connectedness to the U.S. stock market returns but the level of these measures are low, 9.44%, 8.41%, and 8.35%, respectively.

German and the U.K. stock market are other markets which have significant spillovers to other markets returns, which means the "to" directional connectedness measure is higher, German stock market (DAX.30 index) display the highest pairwise directional connectedness measure "to" the U.S. stock market, 27.24%. Additionally, the other pairwise directional connectedness measures "from" German stock markets are obtained to Brazil (17.04%) and to Canada (16.72%) stock markets. On the other hand, the "to" pairwise directional connectedness measures of German stock market are obtained from, with the highest value, the U.S. stock market (50.73%), from the U.K. (15.3%) and from Canada (10.07%) stock markets.

We can calculate the net pairwise directional connectedness from Germany to Canada stock market as $C^{10}_{CAN \leftarrow GER} = 16.72 - 10.07 = 6.65\%$. Also, the net pairwise directional connectedness from Germany to the U.S. stock market is calculated as $C^{10}_{US \leftarrow GER} = 27.24 - 50.73 = -23.49\%$.

The other higher value of the "to" directional connectedness is observed in the U.K. stock market (FTSE.100 index) but at a lower level of measures. The highest pairwise connectedness from the U.K. to others is obtained to German stock market, 15.3%, followed by to Spain (14.95%), to France (13.45%), to Argentina (13.54%) and to Canada (11.4%). On the other hand, the connectedness to the U.K. stock market is only observed from the U.S. stock market with a high value (55.24%).

The Hong Kong stock market (HONG.SENG.INDEX) also has remarkable "to" directional connectedness measure but at very low levels. The highest value of pairwise directional connectedness from Hong Kong stock market is observed to Brazil (13.18%), followed by to Argentina (10.48%), and to Mexico (8.67%). There is not any significant level of directional connectedness measure from others to Hong Kong stock market.

On the other side, Indian stock market (SP.BSE.SANSEX index) has the highest "from" (from others) directional connectedness measure. The highest pairwise directional connectedness to Indian stock market is observed from the U.S. (61.35%) stock market, which is one of the highest values of pairwise directional connectedness measures, followed by Mexico (12.56%), and Brazil (9.56%) stock markets. There is not any significant "to" directional connectedness measure of Indian stock market.

Brazilian stock market (IBOVESPA index) has also higher "from" directional connectedness measures. The highest pairwise directional connectedness to Brazil stock market is observed from the U.S. (22.42%), which is followed by Germany (17.04%), Mexico (14.44%), Hong Kong (13.18%), and France (12.8%) stock markets. Also, there is not any significant "to" directional connectedness measure of Brazilian stock market. Turkish stock market (BIST.100 index) is another stock market that has higher "from" directional pairwise connectedness measure. The highest pairwise directional connectedness to Turkish stock market is observed from the U.S stock market (35.03%) followed by Brazil (25.26%), Canada (9.67%) and Mexico (9.29%). Additionally, Turkish stock market has significant "to" connectedness measures which are obtained to the U.S. stock market (8.35%). Thus, the net pairwise directional connectedness from the U.S. to Turkish stock market is calculated as $C^{10}_{TUR \leftarrow US} = 35.03 - 8.35 = 26.68\%$.

France stock market (CAC.40 index) also has higher "from" directional pairwise connectedness measure. The highest pairwise directional connectedness to French stock market is observed from the U.S stock market (61.02%) which is one of the highest pairwise directional connectedness measures in the analysis. The other pairwise directional connectedness to French stock market is observed from the U.K. stock market (13.45%). French stock market has also "to" directional pairwise connectedness measure which is observed to Brazil stock market (12.8%).

Spain stock market (IBEX.35 index) only have two significant level of "from" directional connectedness measures. The highest pairwise directional connectedness to Spain stock market is observed from the U.S stock market (51.97%) which is one of the highest pairwise directional connectedness measures in the analysis. The other pairwise directional connectedness to Spain stock market is observed from the U.K. stock market (14.95%).

Argentina stock market (MERVAL index) is the other one which has high "from" directional connectedness measure. The highest pairwise directional connectedness to Argentina stock market is observed from Mexico stock market (22.27%) which is followed by Canada (15.13%), the U.K. (13.54%), the U.S. (12.56%), and Hong Kong (10.48) stock markets. Like Brazil, Argentina stock market has not any significant "to" directional connectedness measure.

Canadian stock market (SP.TSX index) also has a significant level "from" directional connectedness measure. The highest pairwise directional connectedness to Canadian stock market is observed from Germany stock market (16.72%) which is followed by the U.S (16.57%), the U.K. (11.4%), and Brazil (9.74%). Canadian stock market has some significant level "to" directional connectedness measures. The pairwise directional connectedness is observed to Argentina (15.13%) and to Turkish (9.67%) stock markets.

The Mexico stock market (IPC.MEXICO index) has almost equal "to" directional connectedness measure and "from" directional connectedness measure. The pairwise directional connectedness from Mexico to Argentina is measured 22.27% and to Turkey is measured 9.29%. On the other hand, The pairwise directional connectedness to Mexico from the U.S. is measured 22.05% and from Hong Kong is measured 8.67%.

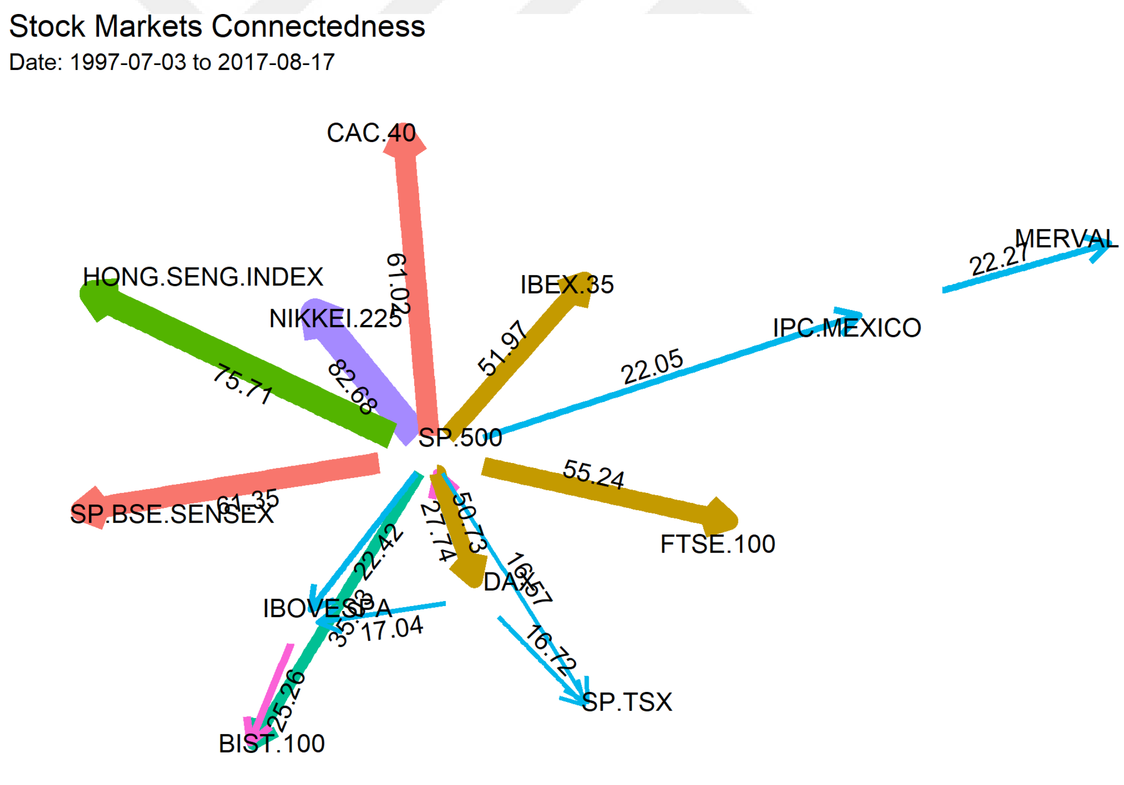

Figure 4.2 Network Connectedness-II The high level of the pairwise directional connectedness measures over the full sample (Spillover measures below 16% are ignored.)

To sum up, the U.S., the U.K, and German stock markets, which are developed markets, have higher "to" connectedness (to others), they also have "from" connectedness, but the significant levels of "from" connectedness of these stock markets mostly obtained from each other. Also, their "from" connectedness measures are lower than "to" connectedness. Thus, when these developed markets have shocks, they generate large "to" connectedness affecting other stock markets.

On the other hand, India, Turkey, Argentina, Spain, and Brazil, which are developing markets, have higher "from" connectedness (from others). Most of these markets do not have a significant level of "to" connectedness to other markets. Some of them have "to connectedness" to only developing markets. Thus, the shock occurred in developed markets can easily spill over to these markets, but the shock occurred in emerging markets spillover to other emerging market economies.

The Europe economies, France, Germany, Spain and the U.K, are highly connected with the U.S stock market. Their significant level of "from" connectedness obtained mostly from the U.S. stock market, and each other's stock markets.

In addition, Indian, Argentina, Brazil and Spain stock markets do not have any significant level of "to" connectedness. Thus, while a shock affects these stock markets, it does not a significant impact on other stock market returns.

On the other side, Hong Kong does not have any significant level of "from" connectedness. Thus, shocks occurred in other economies do not have a significant effect on Hong Kong stock market returns.

4.2.Dynamic (Rolling-Sample) Connectedness Analysis

The full-sample connectedness analysis provides average and unconditional connectedness measures, but it is not suitable to capture the dynamics of connectedness. In this section, we use again VAR(2) model and 10-day forecast horizon for generalized decomposition, but now we estimate 200-day rolling window to capture the dynamics of connectedness. For dynamic analysis, we use same data that we used earlier static analysis.

We analyze the total and pairwise directional connectedness of the U.S. stock market to other stock markets since only the U.S. stock market spillovers to other stock markets and also it has the highest "to" connectedness measure. The directional connectedness from the U.S. stock market to Turkish stock market analyzed in more detail.

4.2.1. Total Connectedness

Figure 4.3. shows the plot of the total return connectedness of stock markets over 200-day-rolling-windows. There are many remarkable features of total return connectedness plot. First, it fluctuates between 80% and 96%, which is relatively high level, over time. It starts approximately 94% in 1997 and fluctuated in the 92%- 96% band until 2001. At the middle of 2001, it decreased sharply to 84%.

There are many cycles in the total return connectedness plot and two of them are more distinct, in the period of September 11, 2011 and at the beginning of 2015. Figure 4.4 shows the dates of crucial historical events. Excluding these bumps, the connectedness index fluctuated approximately in 85%- 95% band.

After 2001 attack and subsequent crisis, there is increasing trend in connectedness index until 2006. The highest value of connectedness index is 96% which is obtained at the begging of 2006. The lowest value of connectedness index is % 81 which is obtained in the middle of 2015.

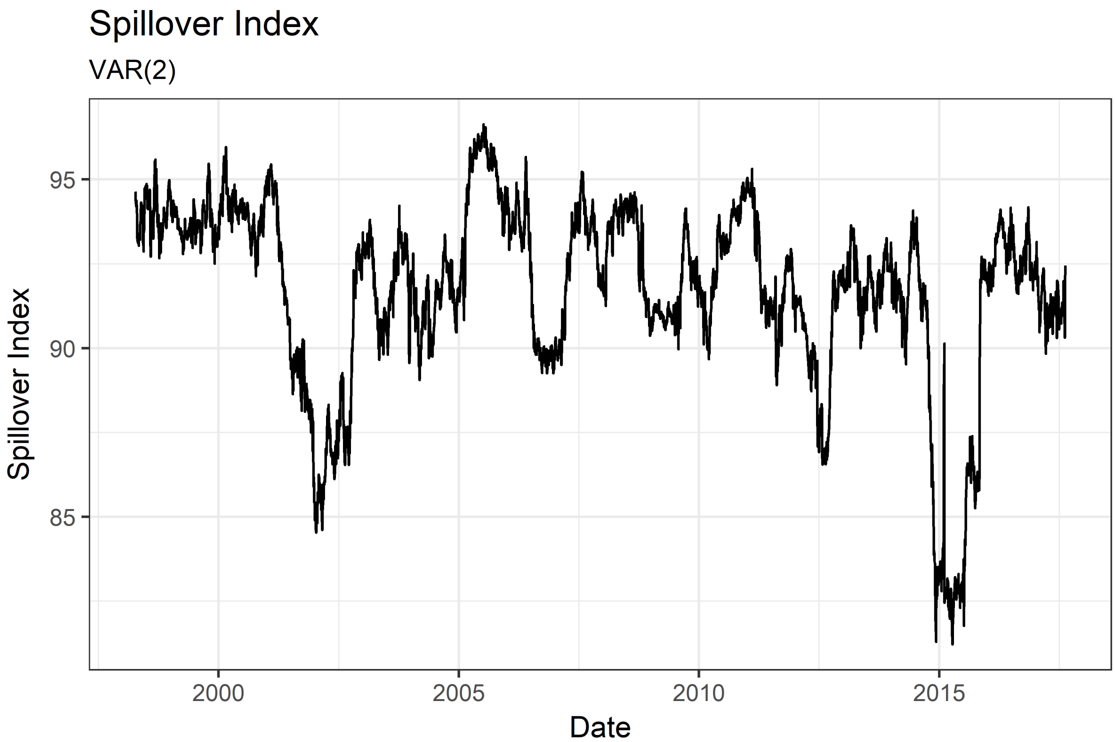

Figure 4.3 Dynamic total stock return connectedness (200-day rolling window). (January 1, 1997- August 18, 2017).

The most remarkable result seen in the plot is connectedness decreases sharply in turmoil periods. This is because the correlation between markets increases in the crisis or crashes times. The plot clearly shows that the spillover index started to decline in the turmoil or crisis periods they increased sharply. The connectedness index decreased to 84% shortly before the September 11 attacks in 2001. September 11 attacks affected adversely the financial markets. At the middle of 2002, the connectedness jumped to 92%. At the beginning of 2007, connectedness index decreased to almost 90% and after Global Financial Crises 2008 it increased to 95%. At the middle of 2012, the index declined to 86% and after European debt crisis (2012), it increased to 93%. Lastly, at the beginning of 2015, the connectedness index decreased to its lowest level, 81%. As seen in Figure 4.4, the decrease of connectedness occurs in consequence of the end of the FED Asset Purchasing Program. Afterwards, at the beginning of 2016, it increased to 92%. This increase occurs as a result of the rise in interest rate in the U.S.

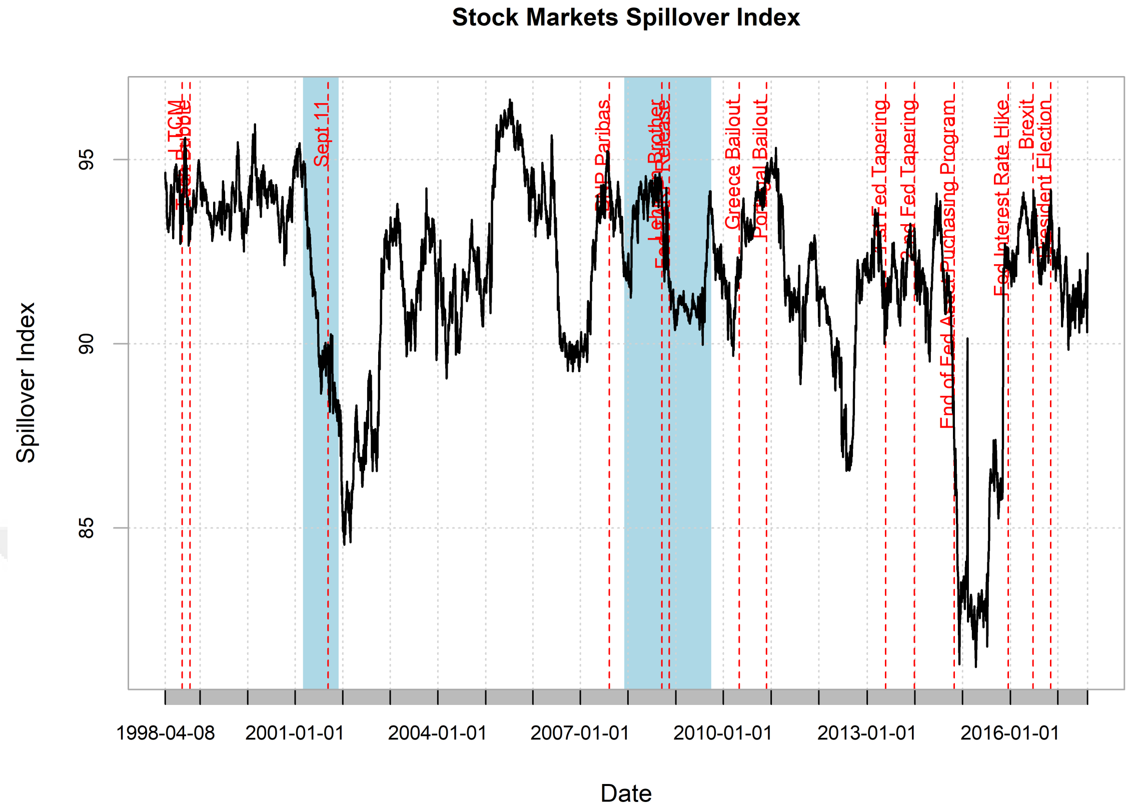

Figure 4.4 Total stock return connectedness during historical events (200-day rolling window). (January 1, 1997-August 18, 2017).

4.2.2. The Pairwise Directional Connectedness from the U.S. to Other Stock Markets

In our previous full-sample analysis, we find that the U.S. stock markets have a significant level of connectedness to all other stock markets. Figure 4.5 shows the dynamic spillovers from the U.S. stock market to all other stock markets in the sample over 200-day rolling window estimations with VAR(2) estimation. All spillover plots show that the "to" connectedness of the U.S. stock market varies over time.

The first plot shows the return connectedness from the U.S. stock market to Turkish stock market. The plot shows a salient feature of the return connectedness which is that there are two important cycles. One of these cycles occurred by the effects of September 11 attack in 2001 and 2007-2009 Global Financial Crisis (We will see more details in sub-section 4.2.2.).

The plot for France stock market shows that the return connectedness from the U.S. has a decreasing trend until the beginning of 2005. The "to" connectedness of the U.S. stock market to France started a high value, approximately 70%. It gradually decreased until the beginning of 2005. Then, it started to increase and reached again high values during global financial crisis period (2007-2009). In the beginning of 2007 it decreases sharply and after the global financial crisis, it increased to a high level. At the beginning of 2015, after FED ends the Asset Purchasing Program, it decreased sharply to a low level. Then the impact of rising interest rates in the U.S. has increased the connectedness from 5% to 55%.

As seen in Figure 4.5, the return connectedness from the U.S. to the European countries, France, Germany, and Spain and the U.K., have almost the same pattern.

The spillover from the U.S. to Germany stock market returns started 55%. Firstly, it decreased sharply in 2001. Then it decreased until the beginning of 2005. Afterwards, it started to increase and reached its high level, approximately 70%, in 2006. At the beginning of 2007, it decreased sharply and it increased during global financial crises period. Like in France returns connectedness, at the beginning of 2015, after FED ends the Asset Purchasing Program, it decreased sharply to almost 0%. Then the impact of rising interest rates in the U.S. has increased the connectedness from to 50%.

The connectedness from the U.S. to U.K stock market returns have decreasing trend until the beginning of 2005. Like in case of France and Germany stock market returns, it decreased sharply at the beginning of 2007 and it increased during global financial crises period. Also, at the beginning of 2015, after FED ends the Asset Purchasing Program, it decreased sharply to almost 0%. Then the impact of rising interest rates in the U.S. has increased the connectedness from to 50%.

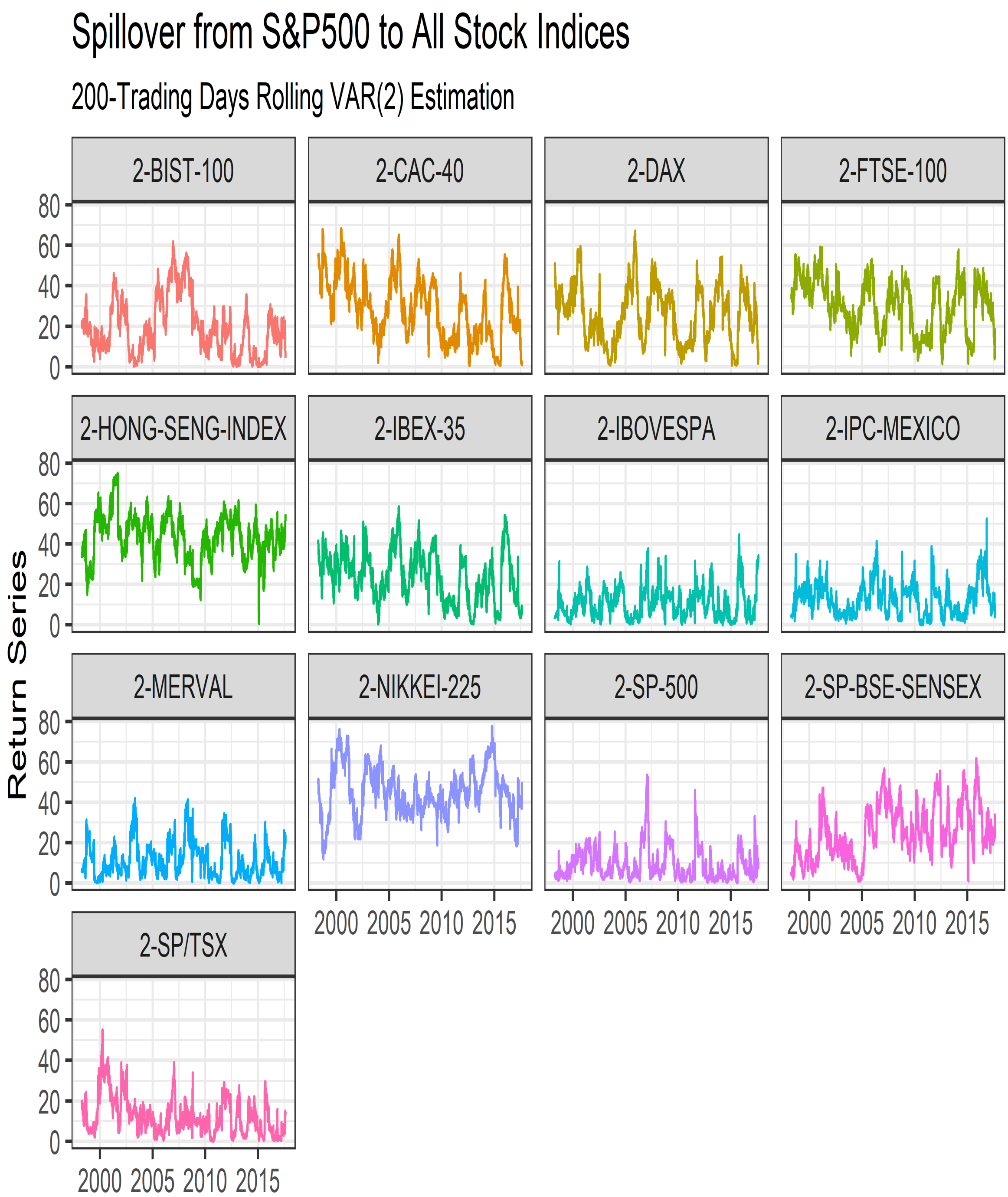

Figure 4.5 Pairwise directional connectedness from U.S. stock market to other stock markets, respectively, Turkey, France, Germany, the U.K., Hong Kong, Spain, Brazil, Mexico, Argentina, Japan, the U.S, India, and Canada. (200-days rolling window).

The return connectedness from the U.S. to Hong Kong and Japan stock market fluctuated relatively high levels comparing to other markets. Both of these connectedness sharply increased in 1997 Asian crisis and increased after global financial crisis periods. Unlike other stock market connectedness, Japan stock market connectedness increase sharply to a high level at the beginning of 2015, with the ends of FED's Asset Purchasing Program.

The return connectedness from the U.S. to Argentina, Brazil, and Mexico stock markets fluctuated in the relatively low band, 0%-40%, comparing to other markets. The plots show they have almost the same pattern.

The return connectedness from the U.S. to Indian stock market increased during Asia crisis period, 2001. Afterwards, it decreased until the beginning of 2005. It increased sharply in 2005 and fluctuated higher level during the global financial crisis period. The highest value of connectedness obtained at the beginning of 2015, with the ends of FED's Asset Purchasing Program.

The return connectedness from the U.S. to Canadian stock markets is relatively high at the beginning of the 2000s. After, it decreased until the September 11 attacks, in these turmoil times the connectedness increased. At the beginning of 2005, the connectedness decreased to a low level. Like all other connectedness, in the global financial crisis times it increased, then it fluctuated in the 0%-20%.

Lastly, we look the own return connectedness of the U.S. stock market. The own connectedness reached its high level during the global financial crisis period (2007-2009). The other high connectedness level observed in 2012, which can be related to European debt crisis (2012). Apart from these, it fluctuates in the 0%-20% band.

4.2.3. The Directional Connectedness from the U.S. to Turkish Stock Market Returns

Now we focus on the first plot which shows the "to" connectedness of the U.S. stock market to Turkish stock market returns. In general, it fluctuated around in the 10%-30% band. In 2001 and 2008 the spillover from U.S stock market to Turkish stock market returns increased. To clear display, Figure 4.6 shows the pairwise directional connectedness from the U.S. stock market to Turkish stock market returns.

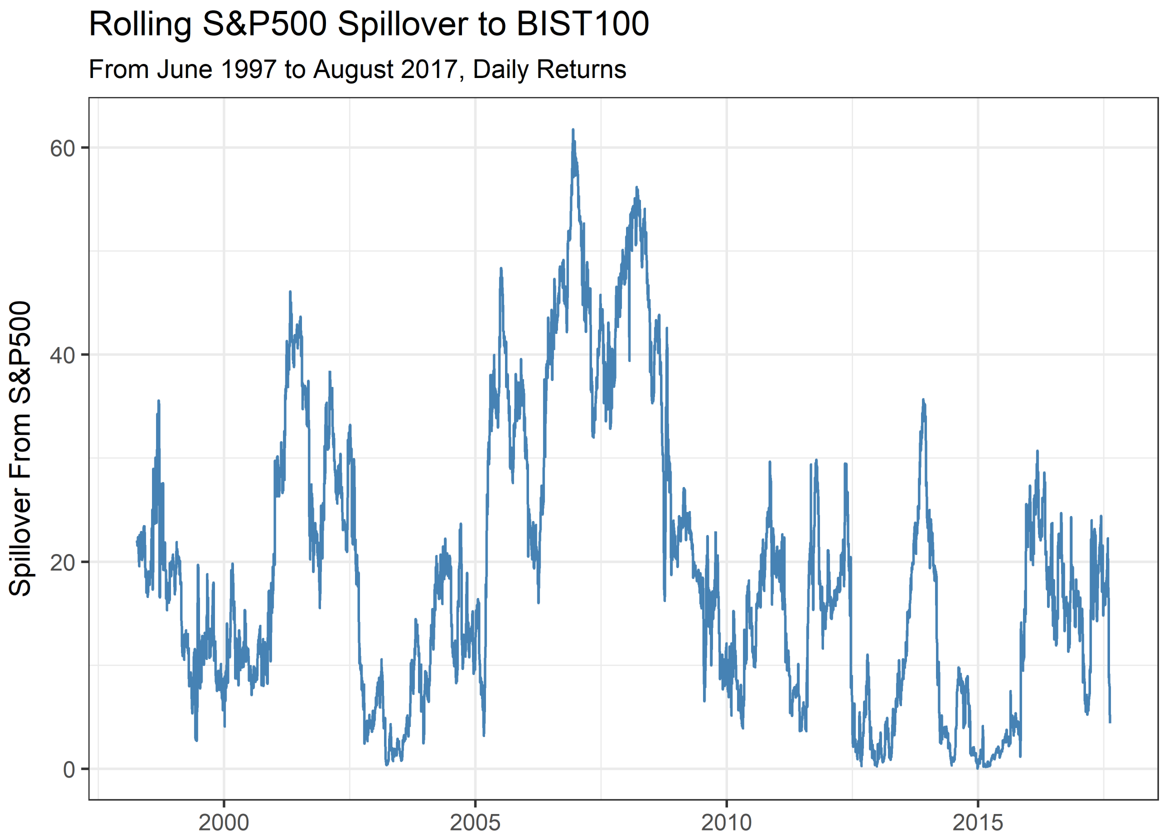

Figure 4.6 Return spillover from U.S. stock market to Turkish stock market (200-day window). (January 1, 1997-August 18, 2017).

The plot shows a salient feature of the return connectedness which is that there are two important cycles. One of these cycles occurred by the effects of September 11 attack in 2001 and 2007-2009 Global Financial Crisis. The first cycle started in 2001 and ended at the middle of 2002. The second cycle started at the begging of 2007 and ended 2009.

The return connectedness from the U.S. to Turkey stock market was 23% in 1997 and jumps to about 38%, probably, since the East Asian crises of 1997. After the Asian crisis, it turned back to about 20% and fluctuated between 5%-20% until 2001. The effect of September 11 attack, the spillover jumped from 12% to %46. At the middle of

2002, it decreased sharply to 2% and fluctuated in the 1%-10% band. Then in 2004 it started to increase and fluctuated in the %10- %20 band until the beginning of 2005. In 2007 the spillover reached its highest level, about 62%. During the Global Crisis 2007-2009, the spillover from the U.S. stock market returns to Turkish stock market returns fluctuated in the highest levels. At the end of global financial crises, the spillover decreased to about 20% which is almost the same level before the global crisis. At the end of 2014 (17-25 December) there was a criminal investigation that involves several key people in the Turkish government so the connectedness increased to 35% . In 2015, it decreased to the %1- %10 band with the effect of FED decision about the end of the Asset Purchasing Program. In the middle of 2015, the interest rate in the U.S financial market increased. Hence, it jumped to 30% and continued to fluctuate in 15%-25% band.

As a result, the return spillover from the U.S. stock market to Turkish stock market changes over time and increases during crisis times. Especially during 2008 global financial crisis, the "to" connectedness index reached its highest level.

CHAPTER V

CONCLUSION

The financial market linkages have become widespread in the last decades as a result of the globalization efforts since the early 1980s. The key reasons for the markets moving together are the advancement in technology which provides free and easy market information and the decrease in the international investment barriers.

Globalization in economy, in particular, in finance, affect the international market linkages and financial markets correlations increases in almost all over the world. Economists and policymakers mostly believe that financial globalization reduces the domestic barriers to international capital flows. Progress to free and fast financial flow gives rise to closely related and interconnected countries. Therefore, a financial crisis occurred in one country can easily spread to other countries (Dymski, 2005).

In recent decades, crises in a country spillover to other countries which are not in the same region. Further, these countries do not have the same economic structure and economic linkage. (Pericoli and Sbracia, 2003). Especially, after the 1987 U.S. crisis, the studies about financial market dependencies accelerated. In particular, economists study how a crisis, which arose in one country or market, spills over the other countries or markets.

Although there is a conflict between describing the relations of markets (is it contagion or interdependence), the common view about financial markets connections is that there is a high comovements (or connections) across financial markets in turmoil periods.

In this context, understanding the financial market interconnections is important in many aspects. Since the stock markets have important role in market economies, analyzing financial market connectedness could be done with analyzing stock markets (Diebold and Yilmaz, 2015).

In this study, we analyze the financial market connectedness with stock markets data. We investigate the return connectedness between both developed and developing stock markets from different regions. We apply Diebold and Yilmaz connectedness index methodology (2009, 2010, 2011) and analysis both static and dynamic return connectedness of stock markets in our sample.

The full-sample analysis shows that the U.S. has the highest "to" (to others) total directional connectedness measure. The U.S. stock market seems as the center of the network system. The developed markets such as the U.S, the U.K, German stock markets have higher "to" connectedness (to others) and, their "from" connectedness measures are lower than "to" connectedness. It means that when these developed markets have shocks, they generate large "to" connectedness affecting other stock markets.

On the other hand, developing economies such as India, Turkey, Argentina, Spain, and Brazil have higher "from" connectedness (from others). Most of these markets do not have a significant level of "to" connectedness to other markets. Some of them have "to connectedness" to only developing markets. It means that the shock occurred in developed markets can easily spill over to these markets, but the shock occurred in emerging markets spillover to other emerging market economies.

Another important result of the full-sample analysis is that the Europe economies, France, Germany, Spain and the U.K, are highly connected with the U.S stock market. Their significant level of "from" connectedness obtained mostly from the U.S. stock market, and each other's stock markets.

In addition, Indian, Argentina, Brazil and Spain stock markets do not have any significant level of "to" connectedness. Thus, while a shock affects these stock markets, it does not a significant impact on other stock market returns.

On the other side, Hong Kong does not have any significant level of "from" connectedness. Thus, shocks occurred in other economies do not have a significant effect on Hong Kong stock market returns.

In the dynamic analysis, we firstly analyze the total connectedness between all stock markets. Then we analyze the pairwise directional connectedness of the U.S. stock market to other stock markets, since only the U.S. stock market spillovers to other stock markets and also it has the highest "to" connectedness measure. Additionally, we analyze the spillovers from the U.S. stock market to Turkish stock market analyzed in more detail.

Dynamic analysis results show that the total connectedness varies over time. Especially, during turmoil periods, the connectedness changes. The most significant events that affect the spillover of the U.S. stock market spillovers are September 11 attacks in 2001, Global Financial Crisis in 2007-2009, the European Debt Crisis in 2012, and Federal Reserve (FED) decisions in 2015.

One of the important results of the dynamic analysis is that the spillovers from the U.S to most of the European countries, France, Germany, Spain, the U.K, display almost same patterns. On the other hand, spillovers from the U.S. to some of the American stock markets; Argentina, Mexico, and Brazil also display same patterns.

Another result of the dynamic analysis is that the European Debt Crisis in 2012 mostly affect the European countries spillovers and the U.S. own spillovers. On the other hand, Asian Crisis in 2001 mostly affects the spillovers to Turkey and to Asian markets, Hong Kong, Japan, India.

To sum up, the U.S. stock market is the most influencing markets on the other markets in different regions. Additionally, turmoil periods have significant effects on connectedness between stock markets.

In conclusion, it is important to monitor and measure stock market connectedness for both portfolio investors and policy makers. Portfolio investors can have information for their portfolio decisions. Policy makers can understand the current situation and apply policies to avoid to effects of crisis or crashes in other markets.

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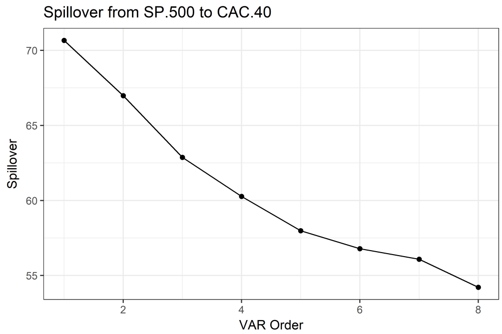
APPENDIX 1:DESCRITIVE ANALYSIS OF STOCK MARKETS' DATA

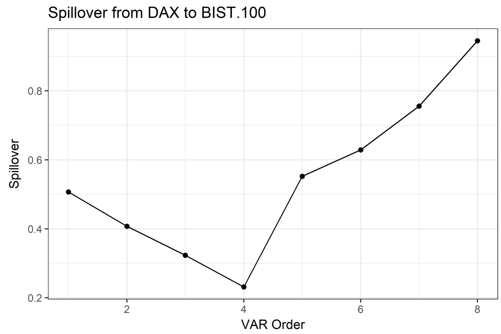
	BIST-100	SP-500	FTSE-100	NIKKEI-225	HANG-SENG-INDEX	IBOVESPA	MERVAL
Observations	4946	5088	5108	4961	4985	5006	4955
NAs	338	196	176	323	299	278	329
Minimum	-0,1998	-0,0947	-0,0926	-0,1211	-0,1473	-0,1721	-0,1476
Quartile 1	-0,0103	-0,0052	-0,0057	-0,0078	-0,0073	-0,0102	-0,0096
Median	0,0005	0,0005	0,0004	0,0003	0,0004	0,0008	0,0011
Arithmetic Mean	0,0008	0,0002	0,0001	0	0,0001	0,0004	0,0007
Geometric Mean	0,0006	0,0001	0	-0,0001	0	0,0001	0,0004
Quartile 3	0,0122	0,006	0,0063	0,0084	0,008	0,0115	0,0116
Maximum	0,1777	0,1096	0,0938	0,1323	0,1725	0,2883	0,1612
SE Mean	0,0003	0,0002	0,0002	0,0002	0,0002	0,0003	0,0003
LCL Mean (0.95)	0,0002	-0,0001	-0,0002	-0,0004	-0,0003	-0,0002	0,0001
UCL Mean (0.95)	0,0015	0,0005	0,0004	0,0004	0,0006	0,0009	0,0013
Variance	0,0006	0,0002	0,0001	0,0002	0,0003	0,0004	0,0005
Stdev	0,0241	0,0122	0,012	0,0154	0,0167	0,0207	0,022
Skewness	-0,0316	-0,2312	-0,1445	-0,3115	0,0996	0,3108	-0,29
Kurtosis	6,7421	7,8977	5,4198	5,5732	10,0122	13,1477	4,6749

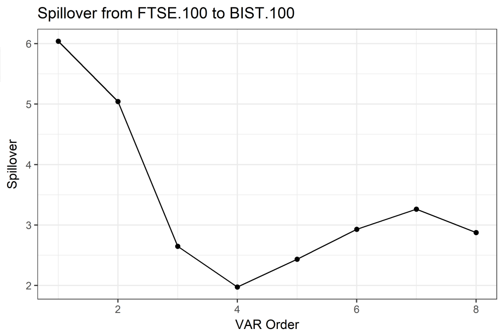
	IPC-MEXICO	IBEX-35	DAX	SP/TSX	SP-BSE-SENSEX	CAC-40
Observations	5069	5119	5131	5122	4962	5154
NAs	215	165	153	162	322	130
Minimum	-0,1431	-0,1319	-0,0887	-0,0979	-0,1181	-0,0947
Quartile 1	-0,0062	-0,0076	-0,0073	-0,0048	-0,0072	-0,007
Median	0,0008	0,0008	0,0009	0,0007	0,0009	0,0004
Arithmetic Mean	0,0005	0,0001	0,0002	0,0002	0,0004	0,0001
Geometric Mean	0,0004	0	0,0001	0,0001	0,0003	0
Quartile 3	0,0075	0,0081	0,0082	0,0058	0,0084	0,0078
Maximum	0,1215	0,1348	0,108	0,0937	0,1599	0,1059
SE Mean	0,0002	0,0002	0,0002	0,0002	0,0002	0,0002
LCL Mean (0.95)	0,0001	-0,0003	-0,0002	-0,0001	0	-0,0003
UCL Mean (0.95)	0,0009	0,0005	0,0007	0,0005	0,0008	0,0005
Variance	0,0002	0,0002	0,0002	0,0001	0,0002	0,0002
Stdev	0,0144	0,0152	0,0154	0,0111	0,0154	0,0147
Skewness	0,0169	-0,127	-0,089	-0,6709	-0,107	-0,0475
Kurtosis	7,815	5,2813	3,9109	9,0328	6,3538	4,432

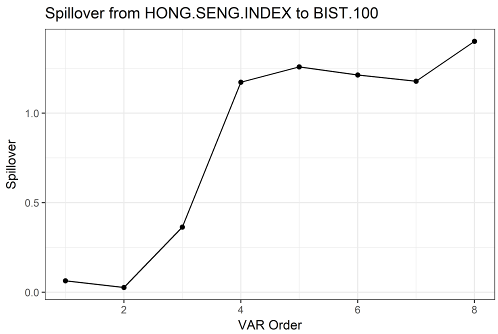
Stdev, standart deviation.

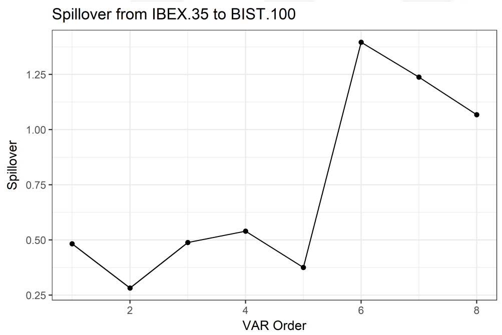
APPENDIX 2:PAIRWISE SPILLOVER TABLES OF VAR(1)-VAR(8) MODEL

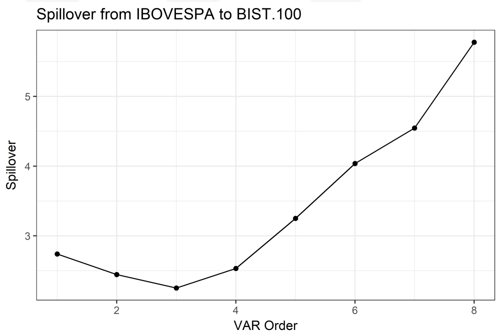


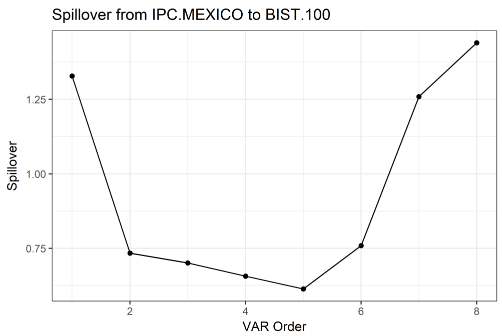


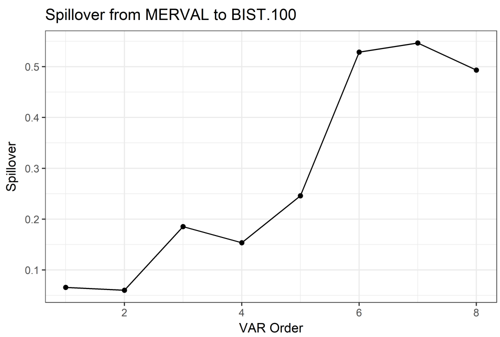


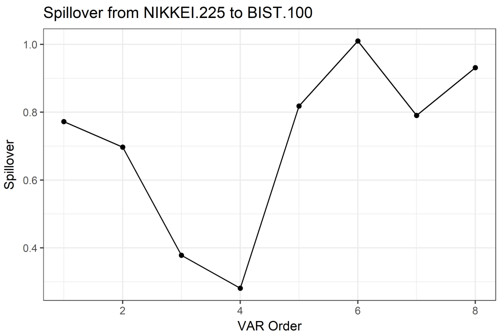


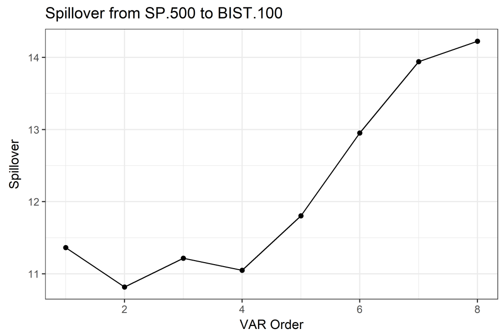


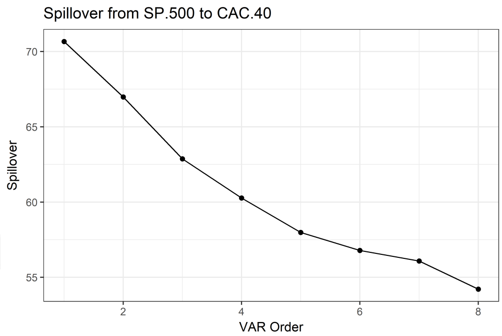


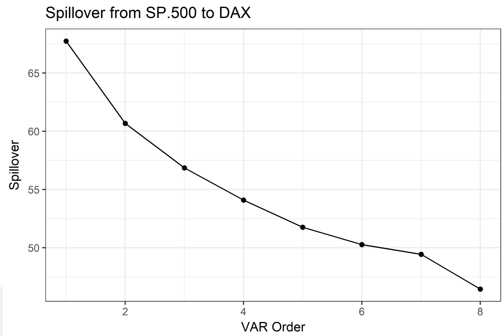


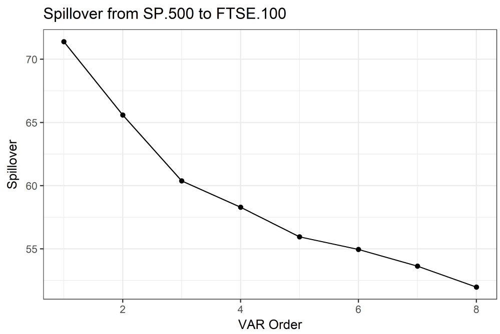


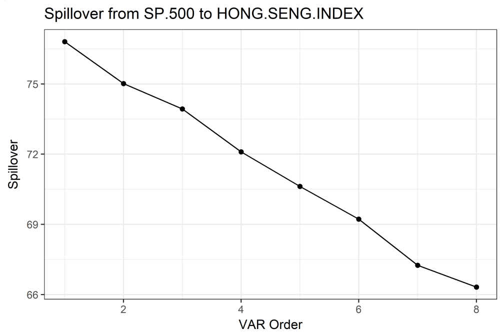

Spillover from NIKKEI.225 to BIST.100
Spillover
VAR Order
0.4
0.6
0.8
1.0
2
4
6
8

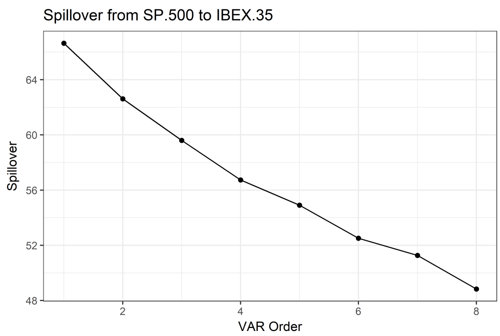

Spillover from SP.500 to BIST.100
Spillover
VAR Order
11
12
13
14
2
4
6
8

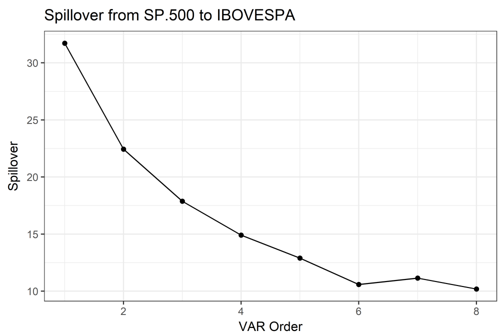

Spillover from SP.500 to CAC.40
Spillover
VAR Order
55
60
65
70
2
4
6
8

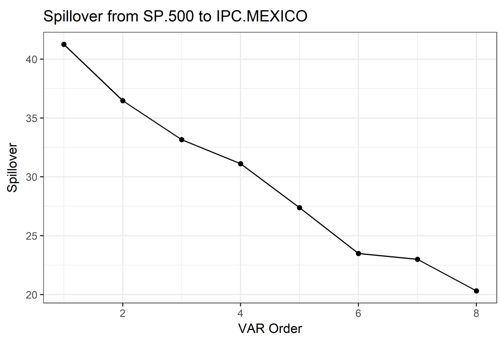

Spillover from SP.500 to DAX
Spillover
VAR Order
50
55
60
65
2
4
6
8

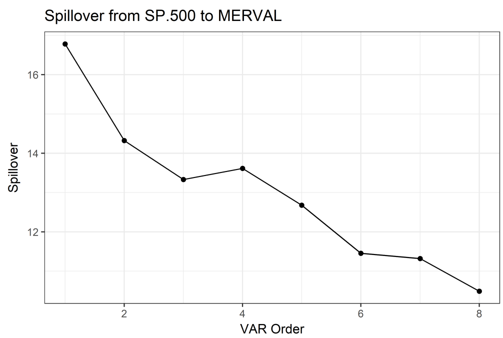

Spillover from SP.500 to FTSE.100
Spillover
VAR Order
55
60
65
70
2
4
6
8

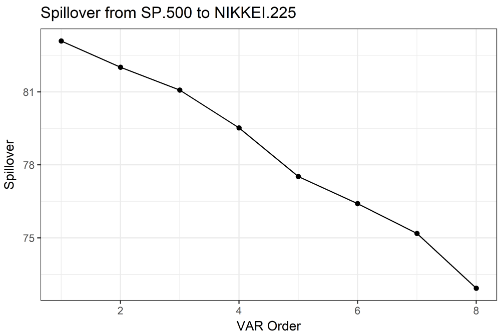

Spillover from SP.500 to HONG.SENG.INDEX
Spillover
VAR Order
66
69
72
75
2
4
6
8

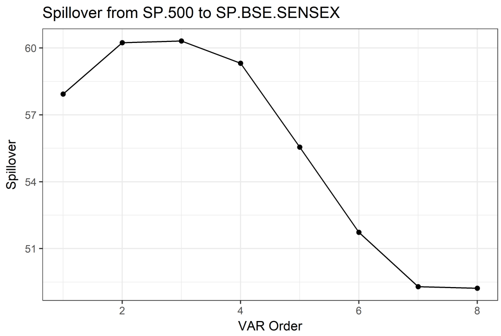

Spillover from SP.500 to IBEX.35
Spillover
VAR Order
48
52
56
60
64
2
4
6
8

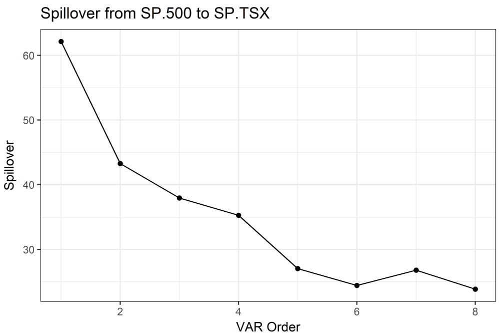

Spillover from SP.500 to IBOVESPA
Spillover
VAR Order
10
15
20
25
30
2
4
6
8

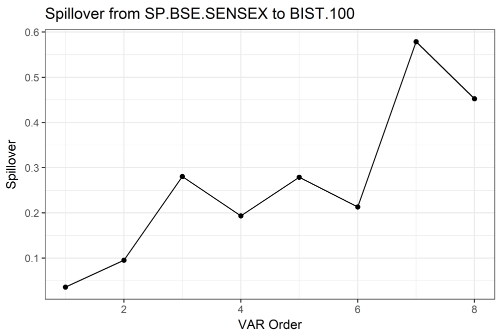

Spillover from SP.500 to IPC.MEXICO
Spillover
VAR Order
20
25
30
35
40
2
4
6
8

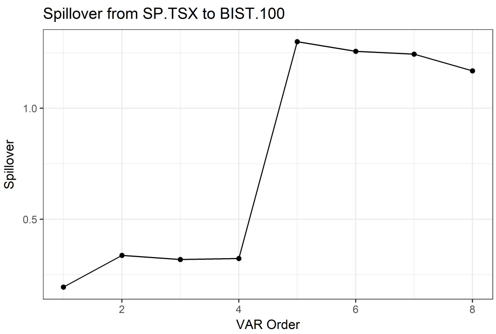

Spillover from SP.500 to MERVAL
Spillover
VAR Order
12
14
16
2
4
6
8


Spillover from SP.500 to NIKKEI.225
Spillover
VAR Order
81
78
75
2
4
6
8


Spillover from SP.500 to SP.BSE.SENSEX
Spillover
VAR Order
60
57
54
51
2
4
6
8


Spillover from SP.500 to SP.TSX
Spillover
VAR Order
60
50
40
30
2
4
6
8


Spillover from SP.BSE.SENSEX to BIST.100
Spillover
VAR Order
0.6
0.5
0.4
0.3
0.2
0.1
2
4
6
8


Spillover from SP.TSX to BIST.100
Spillover
VAR Order
1.0
0.5
2
4
6
8

APPENDIX 3: ORJİNALLİK RAPORU

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
YÜKSEK LİSANS/DOKTORA TEZ ÇALIŞMASI ORJİNALLİK RAPORU

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞI'NA

Tarih: 13/02/2018

Tez Başlığı / Konusu: STOCK MARKETS CONNECTEDNESS

Yukarıda başlığı/konusu gösterilen tez çalışmamın a) Kapak sayfası, b) Giriş, c) Ana bölümler ve d) Sonuç kısımlarından oluşan toplam 53 sayfalık kısmına ilişkin, 13/02/2018 tarihinde şahsım/tez danışmanım tarafından Turnitin adlı intihal tespit programından aşağıda belirtilen filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı %13 'tür.

Uygulanan filtrelemeler:

1- Kabul/Onay ve Bildirim sayfaları hariç,
2- Kaynakça hariç
3- Alıntılar ~~hariç~~/dâhil
4- 5 kelimeden daha az örtüşme içeren metin kısımları hariç

Hacettepe Üniversitesi Sosyal Bilimler Enstitüsü Tez Çalışması Orjinallik Raporu Alınması ve Kullanılması Uygulama Esasları'nı inceledim ve bu Uygulama Esasları'nda belirtilen azami benzerlik oranlarına göre tez çalışmamın herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

13.02.2018

Adı Soyadı:	Fatmanur GÜL ORAL
Öğrenci No:	N12231577
Anabilim Dalı:	İktisat
Programı:	İktisat (İngilizce)
Statüsü:	☒ Y.Lisans ☐ Doktora ☐ Bütünleşik Dr.

DANIŞMAN ONAYI

UYGUNDUR.

Prof. Dr. İbrahim ÖZKAN

(Unvan, Ad Soyad, İmza)

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
THESIS/DISSERTATION ORIGINALITY REPORT

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
TO THE DEPARTMENT OF ECONOMICS

Date: 13/02/2018

Thesis Title / Topic: STOCK MARKETS CONNECTEDNESS

According to the originality report obtained by myself/my thesis advisor by using the Turnitin plagiarism detection software and by applying the filtering options stated below on 13/02/2018 for the total of 53 pages including the a) Title Page, b) Introduction, c) Main Chapters, and d) Conclusion sections of my thesis entitled as above, the similarity index of my thesis is 13 %.

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I declare that I have carefully read Hacettepe University Graduate School of Social Sciences Guidelines for Obtaining and Using Thesis Originality Reports; that according to the maximum similarity index values specified in the Guidelines, my thesis does not include any form of plagiarism; that in any future detection of possible infringement of the regulations I accept all legal responsibility; and that all the information I have provided is correct to the best of my knowledge.

I respectfully submit this for approval.

13.02.2018

Name Surname:	Fatmanur GÜL ORAL
Student No:	N12231577
Department:	Economics
Program:	Economics (English)
Status:	☒ Masters ☐ Ph.D. ☐ Integrated Ph.D.

ADVISOR APPROVAL

APPROVED.

Prof. Dr. İbrahim ÖZKAN

(Title, Name Surname, Signature)

APPENDIX 4: ETİK KURUL İZİN MUAFİYET FORMU

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
TEZ ÇALIŞMASI ETİK KURUL İZİN MUAFİYETİ FORMU

HACETTEPE ÜNİVERSİTESİ
SOSYAL BİLİMLER ENSTİTÜSÜ
İKTİSAT ANABİLİM DALI BAŞKANLIĞI'NA

Tarih: 13/02/2018

Tez Başlığı / Konusu: STOCK MARKETS CONNECTEDNESS

Yukarıda başlığı/konusu gösterilen tez çalışmam:

1. İnsan ve hayvan üzerinde deney niteliği taşımamaktadır,
2. Biyolojik materyal (kan, idrar vb. biyolojik sıvılar ve numuneler) kullanılmasını gerektirmemektedir.
3. Beden bütünlüğüne müdahale içermemektedir.
4. Gözlemsel ve betimsel araştırma (anket, ölçek/skala çalışmaları, dosya taramaları, veri kaynakları taraması, sistem-model geliştirme çalışmaları) niteliğinde değildir.

Hacettepe Üniversitesi Etik Kurullar ve Komisyonlarının Yönergelerini inceledim ve bunlara göre tez çalışmamın yürütülebilmesi için herhangi bir Etik Kuruldan izin alınmasına gerek olmadığını; aksi durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

13.02.2018

Adı Soyadı:	Fatmanur GÜL ORAL
Öğrenci No:	N12231577
Anabilim Dalı:	İktisat
Programı:	İktisat (İngilizce)
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DANIŞMAN GÖRÜŞÜ VE ONAYI

Prof. Dr. İbrahim Özkan

(Unvan, Ad Soyad, İmza)

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Telefon: 0-312-2976860 **Faks:** 0-3122992147 **E-posta:** sosyalbilimler@hacettepe.edu.tr

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
ETHICS BOARD WAIVER FORM FOR THESIS WORK

HACETTEPE UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
ECONOMICS TO THE DEPARTMENT PRESIDENCY

Date: 13/02/2018

Thesis Title / Topic: STOCK MARKETS CONNECTEDNESS

My thesis work related to the title/topic above:

1. Does not perform experimentation on animals or people.
2. Does not necessitate the use of biological material (blood, urine, biological fluids and samples, etc.).
3. Does not involve any interference of the body's integrity.
4. Is not based on observational and descriptive research (survey, measures/scales, data scanning, system-model development).

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I respectfully submit this for approval.

13.02.2018

Name Surname:	Fatmanur GÜL ORAL
Student No:	N12231577
Department:	Economics
Program:	Economics (English)
Status:	☒ Masters ☐ Ph.D. ☐ Integrated Ph.D.

ADVISER COMMENTS AND APPROVAL

Prof. Dr. İbrahim Özkan

(Title, Name Surname, Signature)