Universitat Autònoma de Barcelona

NEW DEVELOPMENTS IN THE MEASUREMENT OF MARKET CONNECTEDNESS

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Part 1

Market Connectedness: Methodology on Spillover and Flow of Information with Return and Volatility Series

Part 2

Turkish and International Stock Markets: A Network Perspective

Part 3

The Russian stock market during the Ukrainian Crisis: A Network Perspective

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Abstract

This dissertation consists of three parts. The aim of this study is to quantify dynamically the market connectedness by using return and volatility spillovers. First part is a methodological study to investigate the market connectedness and explanation of an extended methodology. Return and volatility series is taken into account to compare the different interpretations of market connectedness. The study uses the spillover methodology developed by Diebold and Yilmaz (2009) and the extended version with the focus of flow of information developed by Schmidbauer et al. (2013). The contribution in this case is to discuss how to provide a volatility input series to be used in the explained methodologies. We compare the results of the methodologies using return series and volatility series. A network perspective is used to compute the return and volatility spillovers. Since, quantifying the connectedness is important to evaluate the policy responses and allow an option to policy makers to understand the economy, the last two parts of the study include empirical innovations to discuss the network importance of two countries. In the second part we apply the methodology to Turkish stock market to understand its dynamics since 2000. We construct a network consists of six stock markets and investigate the Turkish economic history by quantifying the market connectedness in the network. We focus on the changes in the market connectedness with a view towards political and economic events. The third one is an examination of Russian stock market during the Ukrainian crisis. We link the shock spillover characteristics of the Russian stock market with different round of sanctions imposed to Russia. We see that distinct spillover patterns exist in different round of sanctions and this help to policy makers to understand the changes in the economy and develop an attitude towards this changes.

Introduction

There is an overwhelming evidence that economic entities are becoming more and more interconnected and the overall degree of international equity market connectedness has been increasing especially over the past two decades. Although, there is an evidence that there is a strong connection among markets, new approaches of measuring and quantifying the connection and understanding its dynamics are still being developed. Quantifying the market connection is substantial to understand the situation of an economy in a network. It has also a crucial role to comment on the effect of political and economic events inside or outside of the country. Analyzing the effect of an event into the economy is very correlated with understanding the dynamics of the market connectedness. Without understanding the strength and the way of this connection, to decide a policy change or to take some precautions is troublesome for an economy. Interconnected economies make use of the dynamics of the market connectedness for appropriate economic policies for the economy. Connectedness has implications for how to quantify it and evaluate policy responses.

The aim of this study is to investigate the market connectedness using two methodologies that we explain below. The contribution in this case is to discuss how to provide the volatility input series to be used in these methodologies. We applied them using return and volatility series to understand the feature of market connectedness. We quantify dynamically the amount of connectedness of different stock markets in a network, using both series, and compare the results obtained from the methodologies. Using the methodology, we discuss the connectedness with a view towards political and economic events and we examine the different economic characters of a chosen country for a specific period. We also link the changes of connectedness during a specific period and economic policy implications of the country, and we examine the relation of the methodology results with important events and breakpoints in the history of the country. Before going through the details of market connectedness, the method and the results we obtained, it is important to understand the idea of connectedness and also the related definitions.

To measure the connection among countries a notion of contagion should be referred to. In the 1990s many experts think that contagion should only be taken into account in case of an emerging markets and it is an issue of the past only. But, when currency devaluations in many countries in the world, for example Thailand's 1997, Russia's 1998 and Turkish financial crisis in 2001 [1], have started to affect global financial markets and contagion became very important issue and entered to the mainstream economic terminology [2]. Dornbusch et al. (2000) defined the contagion "the spread of market disturbances from one country to the other ".

There are many contagion definitions in the literature and all offer their own methodology to quantify it. Karolyi (2003) and Dungey et al. (2005) examine the surveys of definitions and classifications of contagion in their study. According to World Bank[3], "Contagion is the cross-country transmission of shocks or the general cross-country spillover effects. Contagion can take place both during "good" times and "bad" times. Then, contagion does not need to be related to crises. However, contagion has been emphasized during crisis times." Gallo and Otranto (2008) discuss the concepts of "spillover", "contagion" and "interconnectedness" in their study which are generally used synonymously and they establish some practical definitions for them.

Another concept which is very similar to contagion is the "spillover" which started to become a known terminology after the crash of global markets in October 1987. King et al. (1990) investigate the reason of the collapse of world markets in October 1987 and refer to the spillover idea. Hamao, Masulis and Ng (1990) examine the price changes and price volatilities of Tokyo, London and New York stock markets. Another example of an analysis in spillovers is the study of Susmel and Engle (1994) who analyse the return

[1] Didier et al. (2008) and Pinto and Ulatov (2010) offered detailed information about the currency devaluations in many countries in their study.

[2] See Forbes for further information

[3] See http://go.worldbank.org/JIBDRK3YC0, retrieved 2014-04-22

and volatility spillovers between the equity markets of New York and London.

Starting from the October 1987 crisis, the literature of investigation on spillovers within developed economies has improved. Baur and Jung (2006) analyse return and volatility spillovers between US and German stock markets, similarly, Golosnoy et.al. (2015) measure intra-daily volatility spillovers before and during the subprime crisis in US, German and Japanese stock markets. On the other hand, the literature to understand spillovers among developed and emerging economies is still being developed and after the 90s where crisis from emerging economies started to affect the whole world and the literature related with this issue is gradually increasing. For example, Bekiros (2014) investigates volatility spillovers of the US, EU and BRIC markets. Balli et al. (2015) analyse the return and volatility spillovers from developed markets to emerging markets from Asia, Middle East and North Africa region countries.

As we have mentioned above, contagion does not necessarily mean a "bad" effect of an event to the other but the perception is generally in that direction. The concept of interconnectedness identify all this good and bad effects and explains more than contagion.[4] Diebold and Yilmaz (2014) examine the connectedness of major US financial institutions stock return volatilities; Choudhry and Jayasekera (2014), investigate the impact of the 2008 global crisis on spillovers in the European banking industry. Bubak et al. (2011) analyse volatility spillovers between Central European and EUR/USD foreign exchange markets; Hou (2013) examine the spillover effects from the interest rate market to equity markets in euro area.

In a series of papers about market connectedness Diebold and Yilmaz (see, for example, Diebold and Yilmaz (2014)) is not forecast the future returns but rather to assess the degree of market connectedness, operationalized as spillover of shocks occurring in one market to other markets in the form of forecast error variance for that market. They construct a network structure with assets as nodes and analyze how connectedness of a market can be measured by the so-called spillover index capture network effects. When the issue is to discuss the connectedness of markets and investigate the effect of events in one market to the other the first thing that spring to mind is the event study. It elaborates the impact of certain economic and political events on other economic entities, stocks, markets, among others. The motivation why we use the network structure and the spillover index methodology to measure the market connectedness developed byDiebold and Yilmaz (2014) is explained in Introduction chapter of Part 1 but the reason that we count important to measure the market connectedness rather than using the event study method is because of the general phenomenon that markets do not operate in isolation. Unlike the network perspective; in event study, the target assets are usually studied in isolation without considering the prospective ripple effects on others. We know that the markets affected by each other and analyzing one market in isolation is less than what we aim to do in this study. The network perspective and the methodology we extend,

[4] See Forbes (2012) for further information.

facilitate to link the reaction of markets and the impact of the economic and political events of one market into another. We utilize some literature of event study to analyze one market in isolation to understand the effect of an event but for only one market. For example, Gurgul and Machno (2016) study the impact of U.S. macroeconomic data announcements on the prices of the mist liquid shares of the Vienna Stock Exchange. Mandaci (2003) analyses the impact of general elections on Turkish stock market and investigates whether the investors could have abnormal return opportunities in Istanbul Stock Exchange due to general elections in Turkey. Similarly, Mutan et al. (2009) evaluate the impact of various economic and political events, terrorist attacks and natural disasters towards understanding the possible abnormal return opportunities. Chesney et al. (2010) use a more comprehensive set of terrorist attacks data set and evaluate their impacts on stock, bond and commodity markets and want to compare impacts of terrorist attacks with natural disasters and financial crashes. There are great number of studies about event study but as we have mentioned above it is beyond the scope of the present study because they tell less than what we aim to do and take markets into account one by one and analyse the effect of an event in isolation.

The study consists of three chapters. The first one is about the methodology of market connectedness. We explain the spillover methodology developed by Diebold and Yilmaz (2009) which based on the network perspective and return spillover idea. We discuss different methodologies that quantify the amount of connectedness from the literature and explain why we decide on using the network perspective and the advantages of it. Then, we will explain the extended methodology of market connectedness developed by Schmidbauer et al. (2013) where they developed the propagation values to quantify the market connectedness. According to their study using the markov chain approach is better than the base method because in the first one has some limitations on the spillover index. More detailed information is given in Part 1. In Part 1, first we discuss the two methodologies and explain why we use them to quantify the market connectedness. We explain the advantages of using a network perspective rather that analyzing an economy alone. We apply the methodologies by using not only the return series as it has developed before but also the variations of them. To compute the volatility spillovers, we need to obtain the volatility series. The main contribution in this case is to discuss how to provide the volatility input series to use in these two methodologies. We discuss different methods to provide the volatility series and compare the methodologies which uses different volatility series obtained from different methods. We also discuss the results of the methodologies where return series and volatility series is used. We examine different characters of market connectedness which obtained from; using the expectation of the prices and plus using the variations of them. We discuss the advantages of using volatility series instead of return ones and discuss the results results. In Part 1, we apply the methodologies constructing a network of stock markets of six countries chosen and analyze the results.

We measure the connectedness using the stock market data for all chapters of the study because of the advantages to analyse the economic links between two countries on the basis of stock market data, rather than aggregate economic data published by national statistical offices, is that stock market data are readily available, allowing analysis in almost real time.

The second chapter is an empirical paper using the methodology explained in Part 1. We focus on the last 15 years of Turkish economy and investigate the market connectedness of Turkish stock markets within a network of six international stock markets. The aim of the study is to assess the shock spillover characteristics of the Turkish stock market since 2000, by analyzing large-scale political and economic events that have an important role in the Turkish recent past. We use return series and volatility series to apply these methodologies and compare the results obtained from each series. Along with the macroeconomic perspective of Turkish economy there are many events which affects the performance of Turkish economy and growth performance. We will not focus on all important events because the aim of our study is to measure the degree of importance of Turkish stock market in the network evolves and understand the reason of the changes in the connectedness with the help of analysing the effects of events into the Turkish economy. We measure the market connectedness of Turkish stock market and examine how much Turkey is affected by the other network members and similarly how much Turkey affects the other network members with the events that happened in Turkey or outside of the country. For example, how does the relation with other members of the network and Turkey changed after an election? What was the importance of this election? Does market expect this result or is the result surprising for Turkey? We want to discuss the effect of each event an understand the relation of Turkey and other for the last 15 years. By utilizing the political economy studies about Turkish economic periods, we divide the Turkish economic history into sub-periods where each period represents a new era of Turkish history. We link the affects of events and the changes of Turkish market connectedness in the network with the policy implications and changes since 2000. To investigate the connectedness, we use the methodology explained in Part 1. We compute the return and volatility spillovers to see the relation among markets and the propagation value to measure the flow of information. We will also developed a methodology to discuss the different results obtained from the spillover and propagation. We run a regression to discuss the network repercussions of Turkish stock market using this methodology. At the end we reached a strong evidence that each sub-periods has a distinct character in the results of spillovers and propagation value. We found a period-specific behaviour of market connectedness with respect to the new periods in Turkish history. Our study aims to relate the political events and stock market prices and comment on to the political economy using the methodologies. Detailed explanation of the important events and breakpoints of the Turkish history in the literature of political economy will be discussed in Part 2. There is a limited literature about the relation of political and economic events and the stock market changes which was one of the main goal for this part of the study.

The last part is about the Russian stock market during the Ukrainian crisis. In this empirical paper, rather than analyzing a long period of a country as we have done in Part 2 in the case of Turkey, we examine the Russian stock market during the sanctions imposed as a reaction to Russia's alleged role in the Ukrainian crisis. The goal is to quantify the market connectedness of Russian stock market within a network of six members and investigate the shock spillover characteristics of the Russian stock market during these sanctions. As it is explained, in Part 3, in detail, the sanctions that imposed during the period from the beginning of 2014 until mid 2015 have different characteristics and different effects on Russian economy. We are, in particular, interested in detecting these differences between different round of the sanctions using the methodology explained in Part 1 and assessing the impact of political and economic events on them. It turns out that distinct spillover patterns exist in different round of sanctions and with the results that we obtained from the methodologies, we distinguish the different periods of the Russian economy and the degree of importance of Russian stock market in the network.

Part 1: Market Connectedness: Methodology on Spillover and Flow of Information with Return and Volatility Series*

September 2, 2016

Abstract

The goal of the present study is to investigate the market connectedness by using return and return volatility series where we discuss how to obtain the volatility series. First, we explain the two methodologies that we apply in our study: the spillover methodology developed by Diebold and Yilmaz (2009) and an extended methodology with the focus of flow of information developed by Schmidbauer et al. (2013). We apply the methodologies using return and return volatility series to quantify dynamically the amount of market connectedness. We analyze different interpretations of connectedness that comes from either using the expectation of stock market prices or using the variations of them.

We need the volatility series of stock markets to apply the methodologies. So, the purpose of the study is to discuss how to provide volatility input series to be used in this framework, together with applications. We extend the German and Klass (1980) volatility estimation method and explain the intuition behind it. We compare two methodologies for estimating the volatility series; German and Klass (1980) and GARCH approach. Volatility spillovers differs in terms of the estimation methodology we have used and we examine the advantages for each method. For these purpose, we use the stock market data which are; Dow Jones Industrial Average (USA, New York Stock Exchange), FTSE (UK, London Stock Exchange), Nikkei 225 (Japan, Tokyo Stock Exchange), DAX (Germany, Frankfurt Stock Exchange), CAC40 (France, Euronext Paris) for the first part of our empirical results. We also use the stock market of five "Systemic Five" countries (Dow Jones Industrial Average (USA, New York Stock Exchange), FTSE (UK, London Stock Exchange), Euro Stoxx 50 (Euro area), Nikkei 225 (Japan,

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Tokyo Stock Exchange) and SSE Composite (China, Shanghai Stock Exchange)) and we add RTS (Russia, Russian Stock Index) for the second part of our empirical study and interpret the results.

1 Introduction

Connectedness among markets is always an important issue to understand the dynamics of the economies. During 1990's, financial crisis changed their characteristics, especially the propagation of the effects of the crisis and the market connectedness became a crucial issue of the present not only the past and a matter of all economies. After the Great Depression of 1929-1932, the costs and benefits of the financial market integration is started to take on a new significance. Productivity of one country can increase because of an integration with other countries but this is the result of the one side of the coin only. Quantifying the market connectedness help to understand the answer of how crisis are transmitted and what should be done. Also, it allows an option to policy makers to understand how to support an economy in crisis irrespective of the origin of the problem.

To measure the connectedness and understand its feature, we have three different purposes for this paper. First, we measure the connectedness of different stock markets using return spillovers by the methodology of Diebold and Yilmaz (2009). The contribution in this case, will be not only looking on the return spillovers but also discuss the methodologies to measure the connectedness by using volatility-to-volatility spillovers. Diebold and Yilmaz (2009) also applied the spillover methodology by using the volatility series, but in our study we focus on to discuss how to provide volatility input series for the spillover methodology. The details of the method will be explained in the following sections of this paper. To compute the volatility spillovers, we need the daily/weekly volatility series of each market. To do this, we analyse a methodology to obtain the volatility series using the German and Klass (1980) methodology. Below, we will explain the objective of this methodology and the intuition behind it. Then, Schmidbauer et al. (2013) define the propagation value and the entropy idea in their study. They apply the methodology by using return series. The contribution of this study, is to apply the methodology of the propagation value and the entropy idea by using the return volatility series which is obtained from an extended methodology. We construct a network of different stock markets to discuss and compare the results obtained from either return series of volatility series.

One of the approach to measure equity market connectedness, which we have mentioned above, is based on forecast error variance decomposition, developed by Diebold and Yilmaz (2009), and we will discuss the extension of this approach to assess the propagation of information across markets. There are a great number of methods to analysis the market connectedness. One of the method is the balance sheet based measure of interconnectedness which is based on using the balance sheet data and the Global Systemically Important Bank identification methodology to quantify the connectedness.

Another method is quantifying the connectedness using conditional value at risk which utilizing Adrian et al. (2016) methodology. Method uses market data to assess the contribution of an individual financial institution to systemic risk. Chen et al. (2012) uses daily market returns to estimate extreme contributions to toward spillovers.

One way to quantify market connectedness is to estimate the variance of the error when forecasting future return or return volatilities on the asset price. Diebold and Yilmaz (2009) use this idea to develop a network view of markets as nodes and weights determined by variance shares. They decompose the error variances of joint asset return forecasts, using the vector autoregressive (VAR) models. In terms of their approach, the decomposed error variances present a network with assets as nodes and the weights of links between nodes determined by shares of forecast error variance spillovers. Using this methodology, pairwise spillovers can be discussed, but their goal is to go one step further and designate the degree of market connectedness. They suggest a measure for the degree of market connectedness which they call the spillover index. In our study, we set off with the idea of Diebold and Yilmaz (2009) because the method promises more than the others by offering a network perspective. By using the network idea, we analyze the connectedness between markets together and compare the effects to each other. The method captures the different strengths of different connections and so it captures time variation in connectedness. Also, as most studies of connectedness prefer, the method is suitable to evaluate the stock market data which is available at higher frequency and easy to reach. Equity market prices count as price map to expectations about future economic activity to an economy. A network theoretic perspective applied to global financial markets in the methodology. Spillover effects quantify the key measures of connectedness used in the network literature.

Schmidbauer et al. (2013) extend the spillover index methodology and quantify dynamically the amount of connectedness of markets with a focus on the flow of information by using the return series. They use the concepts of propagation value and Kullback-Leibler divergence developed by Demetrius (1974) and Tuljapurkar (1982) to measure the amount of market connectedness dynamically. It measures the amount of information created every period, and measure the relative value of an information in the network. The reason why we do not use the Diebold and Yilmaz (2009) methodology as it is, but we apply an extended methodology is explained in detail in Section 2.2.

The first purpose of the present paper is to use these two methodologies developed by Diebold and Yilmaz (2009) and Schmidbauer et al. (2013) by using weekly return and weekly return volatility series and to interpret the different and similar outcomes of market connectedness in the case of using the expectation and the standard deviation of assets. We analyze the market with respect to different structures, in our case, using the expectation of the prices and plus using the variations of them as a data. Besides the spillover approach we use the definition of propagation value and the entropy methodology to our analysis of measuring the connectedness with return volatility series. We want to compare the results of market connectedness while return series is used and on the other hand, return volatility series is used instead of return. Analyzing not only the return series but also the variations of them will give us an information about how do they complement each other. So, we quantify dynamically the amount of connectedness of markets with a focus on the spillover and the flow of information and apply the methodologies using daily/weekly return and daily/weekly return volatility data. Therefore, this will give a chance to analyze different interpretations of market connectedness that comes from either using the expectation of the prices or using the variations of them.

As it will be explained in Section 3.1.1, we need to obtain the weekly volatility series to compute the volatility spillovers and the propagation value computed by volatility series. So, the main focus of the present study is to discuss how to provide the volatility input series that we apply to the methodologies. We examine the methodological results where different methods are used to obtain the volatility series, together with applications. The methodology uses the Brownian motions idea. We simulate Brownian Motion to have an intuition for the estimation of volatility series. Rather than the German and Klass (1980) approach, we have also calculated the volatility spillover using daily volatility data estimated by the GARCH methodology. One of the purpose of this study is to compare the methodologies of volatility estimation and find the suitable one for our study. We also compared the German and Klass and GARCH approach and analyze them in terms of volatility spillovers and propagation values to discuss the different results obtained from the two methodologies.

The data that we used in this study divided into two parts to measure the connectedness with respect to two different goals. The first method used in the present paper is illustrated using data from the stock markets of five countries: Dow Jones Industrial Average (USA, New York Stock Exchange), FTSE (UK, London Stock Exchange), Nikkei 225 (Japan, Tokyo Stock Exchange), DAX (Germany, Frankfurt Stock Exchange), CAC40 (France, Euronext Paris). The weekly return and weekly return volatility data are used to apply spillover, propagation value, and entropy methodologies.

The second one, uses daily closing quotations of the Russian stock index and the five stock indices representing stock markets in the "Systemic Five" countries. We will compute return spillovers using the same methodology with the first data set, but for the volatility spillovers we will use the GARCH methodology instead of the German and Klass.

R-project (R (2015)) is used to apply the methodologies for both return and return volatility data. Using again R-project, an automatic update system code has written by us and uploaded to the website of `http://financialnetworks.eu/` which updates automatically the spillovers and flow of information and plots the updated figures each day. For now, we constructed four sets of networks using different number of stock market prices and compute the spillovers and propagation values separately. The detailed information about the methodology will be provided in the paper.

This paper is organized as follows. Section 2, describes the methodologies of return spillovers, propagation value and entropy. Section 3 is the methodology of volatility spillovers which we develop. Then, Kullback-Leibler information criterion (KLIC) and

Kolmogorov-Sinai (KS) entropy using volatility series is shown in Section 3.2. The method of obtaining volatility is explained using the idea developed by German and Klass (1980). The formula and the intuition of estimating the volatility series is explained in detail in this section. We have also explained the GARCH methodology of estimating the volatility series. Section 4, describes some properties of the two groups of data and explains how to obtain the daily/weekly return and daily/weekly volatility series. Empirical results of the two methodologies using return series (explained in Section 2) and volatility series (explained in Section 3), are presented in Section 5. Section 5.1 discuss the results of volatility spillover where the volatility series obtained from the methodology using German and Klass (1980) and Section 5.2 discuss the results of the methodology where volatility series obtained by using GARCH. The section also provides a comparison of two spillover results and discuss them. Section 5.3 is the results of the entropy methodology with return and volatility series. Section 6, concludes and discusses suggestions for further research.

2 Methodology I: Measuring return spillovers and shock repercussions

2.1 Return spillovers using forecast error variance decomposition (fevd)

First, we explained the methodology of spillover return series. Given a multivariate N return series, the forecast error variance decomposition (fevd) obtained from fitting vector autoregressive (VAR) models to windows of return data. This methodology can be briefly summarized as follows:

1. Fit a standard VAR (vector autoregressive) model to the series.
2. Establish an n period ahead forecast.
3. Decompose the error variance of the forecast for each component with respect to shocks from the same or other components at time t.
4. Following Diebold and Yilmaz (2009), for each market, arrange the forecast error variance decomposition (fevd).

The decomposition of forecast error variance is given in terms of the structural VAR. A structural VAR model an order of 1 is in the form of

$$\mathtt{B}x_t = \Gamma_0 + \Gamma_1 x_{t-1} + \epsilon_t \tag{1}$$

where ϵ_t is white noise process. This equation can also be written as an MA representation:

$$x_t = \mu + \sum_{i=0}^{\infty} (\mathtt{B}^{-1}\,\Gamma_1)^i\,\mathtt{B}^{-1}\epsilon_{t-i} = \mu + \sum_{i=0}^{\infty} \Phi(i)\epsilon_{t-i} \tag{2}$$

where Φ quantifies responses to shocks of size one standard deviation.

Then in the second step, the variance of the n-period-ahead forecast of x_l can be shown as

$$\operatorname{var}(x_{l,t+n} - \hat{x}_{l,t+n}) = \sum_{k=1}^{N} \sum_{i=0}^{n-1} (\Phi_l^k)^2(i) \tag{3}$$

where $(\Phi_l^k)^2(i)$ designates an impulse response function from series k to series l. (the response of x_{lt} to a shock in $\epsilon_{k,t-i}$, happening i time units earlier)

Next, in the decomposition of the error variance of the forecast, to omit the undesirable dependence on the ordering of markets, a generalized fevd is used, proposed by Pesaran and Shin (1998). They use Cholesky decomposition to identify the impulse response function of a component in the sense that they give the highest priority to that component. In other words: To identify the impulse response function of x_k, use a Cholesky decomposition which allows x_k to have a contemporaneous impact on *all* other components $x_1, \ldots, x_N$.

The fevd is then expressed in terms of the ratios

$$\frac{\sum_{i=0}^{n-1} (\Phi_l^k)^2(i)}{\sum_{k=1}^{N} \sum_{i=0}^{n-1} (\Phi_l^k)^2(i)}, \quad l = 1, \ldots, N. \tag{4}$$

The fevd gives the share of forecast variability in x_l due to shocks in x_k, or, in other words, the return spillovers to volatility since return series is used in the model. After obtaining the fevd for each market, all spillovers can be arranged in the so-called spillover matrix as follows where N=4:

		from return (x_k)			
		x_1	x_2	x_3	x_4
to forecast error variability share in (x_l)	x_1	□	■	■	■
	x_2	■	□	■	■
	x_3	■	■	□	■
	x_4	■	■	■	□

(5)

Each row thus sums up to 1 (or 100%) and provides a breakdown of the forecast error variance of the corresponding stock index return with respect to shock origins in terms of percentages. Each entry in the spillover table is called a directional spillover. Schematically, Diebold and Yilmaz (2009) introduced the spillover index,

$$\frac{\sum \blacksquare}{\sum \blacksquare + \sum \square}. \tag{6}$$

The network structure of the spillover matrix with respect to the propagation of shocks is a broad perspective, using the concepts from population, Markov Chain theory and information theory. The methodology developed by Diebold and Yilmaz (2009) is used in this paper to find supplementary measures of market connectedness using volatility series where we discuss and compare the methodologies of how to obtain the volatility series. More information about the spillover methodology can be found in Diebold and Yilmaz (2009).

2.2 Limitations of the spillover index methodology

Our starting point to measure the market connectedness is the spillover methodology of Diebold and Yilmaz (2009) explained in Section 2.1. Although, the methodology suggests a summary measure for the degree of market connectedness using a network perspective this has some limitations. Schmidbauer et al. (2013) discuss the limitations in their study and extend the methodology. The hypothetical matrices below display three patterns of spillovers of three market and they are particularly different with respect to the involvement of market 1. If the diagonal entry of a spillover matrix is 1 and otherwise zeros in the row, this indicate that the market is entirely exogenous and the forecast error variance can only be explained by market-internal shocks. If the diagonal entry of a spillover matrix is 0 then it means that the market is entirely endogenous and its forecast error variance is completely due to shocks from other markets.

In the first spillover matrix market 1 is exogenous and at the same time it is entirely isolated from other markets. In the second one, the degree of integration with other markets increased. In the last pattern characterizes market 1 as the one with highest own contribution share and also the highest spillover activity to others. In all three cases although there is a diversity of spillover patterns the spillover index is 40% in all three cases. So, the spillover perspective can measure the amount of market connectedness but can not capture alone the diversity of spillover patterns. In the following section we explain the extended methodology developed by Schmidbauer et al. (2013) which uses the idea of eigenvalue structure. In our study, we examine the methodology by applying the volatility series and compare with the results using return series.

$$\underset{(a)}{\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0.4 & 0.6 \\ 0 & 0.6 & 0.4 \end{pmatrix}} \qquad \underset{(b)}{\begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.3 & 0.6 \end{pmatrix}} \qquad \underset{(c)}{\begin{pmatrix} 0.8 & 0.1 & 0.1 \\ 0.4 & 0.5 & 0.1 \\ 0.3 & 0.2 & 0.5 \end{pmatrix}}$$

Table 1: Three different hypothetical spillover patterns

2.3 Shock repercussions and Entropy

2.3.1 Propagation of shocks

The starting point for shock repercussions is the spillover matrix on a given period. As it is described in the previous section row entries characterize the markets' exposition to shocks while the propagation of the shock needs to be read column-wise. The column entries in the spillover matrix can be interpreted as average amount of direct transmission between markets in one-time unit. For instance, in Table 1, the second pattern can be explained as an initial shock of unit size to market 2 will result in a shock of size 0.2 to market 1 and 0.3 to market, while diminishing to size 0.6 in market 2 itself. So, it can be expressed as $\mathbf{M}.(0,1,0)^T = (0.2, 0.6, 0.3)^T$

So the aim is to understand the answer of the question: How are future volatilities across markets affected by a hypothetical shock hitting x_k on day t? How can we measure the strength of market repercussions of a shock?

Let M_t denote the spillover matrix for day t. The propagation of the shock across the markets within day t can take place in a short time interval of unspecified length. The shock propagation (repercussion of the shock) can be modeled as

$$\mathbf{n}_{s+1} = \mathbf{M}_t \cdot \mathbf{n}_s, \quad s = 0, 1, 2, \ldots, \tag{7}$$

where M denotes the spillover matrix of a certain day and n_0 is a unit vector indicating the market from which the shocks come. A hypothetical shock ("news") of unit size to market i on day t can be denoted as $n_0 = (0, \ldots, 0, 1, 0, \ldots, 0)'$. The index s denotes a hypothetical step in information flow, n_s characterizing what remains of the initial shock n_0 across markets after s steps. To investigate the steady-state properties the eigenvalue structure of the matrix $\mathbf{M}_t$ is discussed. If we have network of markets where they are connected within a finite number of transitions Perron-Frobenius theory can be utilized which corresponds the spillover matrix is irreducible and primitive, and its right and left eigenvectors u and v corresponds to the dominant eigenvalue 1, satisfying $u = M.u$ and $v' = v'.M$. The k-th entry of the left eigenvector of the spillover matrix is called the **propagation value** of market k

The left eigenvector v_t, satisfying

$$\mathbf{v}_t' = \mathbf{v}_t' \cdot \mathbf{M}_t \tag{8}$$

called the "propagation values" of markets. The propagation value can be interpreted as the relative value of a shock to market k as seed for future variability in the markets. In other words, it quantifies the strength of repercussions in the system of markets when a hypothetical shock originates from one of the markets. In our study the aim is to measure the propagation value by using the return and volatility series and understand the feature of each series. Detailed information about the methodology is in Schmidbauer et al. (2013). In the next parts of this study, we develop a methodology to compare the results obtained from spillover index and propagation value methodology. The methodology that we develop will be explained in the next two application parts of the study. Our contribution will be, to examine spillovers and propagation values by running a regression. In the next two parts (Turkish and Russian stock market) we run the regression and discuss the outputs.

2.3.2 Relative Market Entropy

The next discussion is about the location of the shock which can be explained using the transition matrices. Schmidbauer et al. (2013) analyze the relative market entropy in their study. The propagation values that is explained above can also be interpreted as stationary distribution of a Markov chain defined on the basis of a spillover matrix. As they mentioned, a spillover matrix is not a suitable transformation matrix, because its *rows* sum up to 1 but its *columns* don't. So, it can be changed by applying the transformation

$$\mathbf{P}_t \;=\; \mathbf{V}_t^{-1} \cdot \mathbf{M}_t' \cdot \mathbf{V}t, \tag{9}$$

where the diagonal matrix V_t contains the left eigenvector v_t (corresponding to eigenvalue 1) of M_t, and after re-scaling:

$$\pi_s' \;=\; \frac{\mathbf{n}_s' \cdot \mathbf{V}_t}{\mathbf{n}_0' \cdot \mathbf{v}_t},$$

then the Markov chain equation emerges:

$$\pi_{s+1}' \;=\; \pi_s' \cdot \mathbf{P}_F, \quad s = 0, 1, 2, \ldots, \tag{10}$$

The transformation is done by using the Markov chain transformation in a population context explained by Tuljapurkar (1982). All details about the transformation can be found in Tuljapurkar (1982).

The idea can be interpreted as follows: On day t, the initial location of a shock in the system is given by π_0 (a unit vector). The shock moves through the system according to the Equation (10). The stationary distribution of shock location is given by the vector of propagation values, which represents the "information equation" or "news balance" among markets on that day.

The next questions can be as follows: How much information is produced by the system of markets from day to day? In other words, how much information is gained from today's to tomorrow's (or next week's in the case of using weekly data) news balance among markets? The question can be answered by applying the concept of Kullback-Leibler divergence (Kullback-Leibler information criterion, KLIC), which measures the entropy of day t with respect to day $t-1$, of the propagation values belonging to day t and day $t+1$. So, the KLIC measures the relative variability of one probability distribution π_a with respect to the variability of a second distribution π_b:

$$\text{KLIC} \;=\; \sum_i \pi_a(i) \cdot \log_2 \left(\frac{\pi_a(i)}{\pi_b(i)} \right); \tag{11}$$

In the concept of market connectedness, KLIC measures the initial information content of a shock (news) with respect to the news balance between markets in the long run. In cases where π_b characterizes the system of markets, KLIC is called the "relative market entropy".

As it is explained at the beginning of this section, a hypothetical shock to a market will change the equilibrium, but then the market will "digest" the shock and reach the equilibrium again. How fast can the market converge back to the equilibrium after being hit by a shock? An appropriate measure for the speed of convergence is the

Kolmogorov-Sinai (KS) entropy. Demetrius (1974) introduced this entropy measure to population theory as"population entropy"; Tuljapurkar (1982) relates it to the rate of convergence of a population. The rate of convergence to equilibrium defined as

$$\text{KS} \;=\; -\sum_{i,j} \pi(i) \cdot \log_2 \left(\mathbf{p}_{ij}^{\mathbf{p}_{ij}} \right). \tag{12}$$

where $\mathbf{p_{ij}}$ denotes the entries in the transition matrix of the Markov chain as in the Equation (10) and $\pi(i)$ are the stationary probabilities. Schmidbauer et al. (2013) examine the concept developed by Tuljapurkar (1982) and adjust the definition in terms of market connectedness.

In Section 5.3 an empirical study is done to examine the results of relative market entropy. The aim to analysis the results, is to understand the idea of entropy using stock markets.We apply the method not only by using the return series but also the volatility series and examine the differences among them.

3 Methodology II: Measuring volatility spillovers and shock repercussions

3.1 Volatility spillovers

Spillovers are important to understand the financial market interdependence. The spillover intensity is time-varying and this time-variation is fairly different for returns vs. volatilities.

The same fevd methodology is used, as it is in the Section 2, to obtain the volatility spillovers. The x_t in the Equation (2) that we meant return is now means volatility. So, we forecast the volatilities instead of returns. As in the return spillovers, where we need daily/weekly return series, in this case we need daily/weekly return volatility series to apply the VAR methodology for producing volatility spillovers. The methodology to obtain the return volatility series using the German and Klass' formula and the intuition behind it is explained in Section 3.1.1 and the method of applying the formula to our data will be explained in Section 4. One of the aim of this study is to compare the results of the spillover and propagation value methodologies where volatility series is obtained by using the extended version of German and Klass (1980) and GARCH methodology.

3.1.1 Obtaining Daily Return Volatilities

There are different estimation methods to obtain the stock return volatility. Our initial point will be the estimation method of German and Klass (1980) and we discuss the intuition behind it. We answer the question that why we can use the estimation method of German and Klass (1980) instead of a GARCH methodology or can we modify the formula in a different way to estimate the volatility series. As, we can see from the Equation 15, the major difference of the two methodologies are, the German and Klass methodology uses only today's information while GARCH uses also the previous information of the stock prices. The methodology of German and Klass (1980) uses the historical opening, closing, high and low prices to estimate the volatility series. The model assumes that security prices are governed by a diffusion process of the form,

$$P(t) = \phi(B(t)) \tag{13}$$

where P is the price, t is time and ϕ is a monotonic time independent transformation where we obtain the maximum and minimum values of B and P. $B(t)$ is a diffusion process with the differential representation

$$dB = \sigma dz \tag{14}$$

where dz is a standard Gauss-Wiener process and σ is an unknown constant to be estimated.

The methodology of German and Klass (1980) covers the usual hypothesis of the geometric Brownian motion of stock prices to estimate the return volatilities of the series. Although, the starting point of the estimation method is the Brownian motion, they mention some limitations of this methodology. They did modifications on the estimation method and use three different estimation methodology. The first one, uses only the opening and closing prices of the stock market data and the other two uses high and low prices in addition to the opening and closing prices. Using also high and low prices in the estimation model, gives us more information about the data, since high and low prices during the trading interval express a continuous information about the prices changes while opening and closing prices are only 'snapshots' of the process. Finally, the formula have the best efficiency factor among the three methodologies is expressed below.

$$\begin{aligned}\hat{\sigma}_t^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] \\ - 0.383(C_t - O_t)^2,\end{aligned} \tag{15}$$

where O_t (H_t, C_t, L_t) is the natural logarithm of the opening price in day i (daily high, Friday closing, daily low) in day t. The methodology of how we implement this formula to obtain the weekly prices, not the daily ones, is explained in Section 4. For simplicity, we call the stock return volatility series as "volatility series" throughout the paper.

Before analyzing the German and Klass (1980) methodology and the way they formulate it more detailed, we explain the intuition of the formula by simulating a Brownian bridge. We use the same approach like in the German and Klass methodology and simulate a Brownian bridge to understand the estimation method better. Brownian Bridge is formulated as follows;

$$X_t = {B_t}^{\mu,\sigma} - t{B_1}^{\mu,\sigma} \tag{16}$$

where B_t is a Brownian motion with μ and dispersion σ, and $0 \leq t \leq 1$.

Obviously, X_0 and X_1 are 0. So, we know the starting and ending points. In contrast to the Brownian motion, we know the ending point of the process which is the closing price in our case. The idea behind simulating Brownian Bridges is that, if we can find a relation between the *sigma* and the maximum and minimum values of the trading day then we can estimate the sigma, since we have the information about the high and low stock prices during the trading day. So, the aim is to answer the following question; Can we find a relation among the maximum and minimum values and the σ value? In other words, is it possible to estimate the σ, using the maximum and minimum value of the stock price. First, we simulate Brownian Bridge where B_ts are normally randomized numbers. We simulate Brownian Bridges using different normally randomized B_ts. Then, we simulate the Brownian Bridge simulations for different σ values. We have Brownian Bridge simulations with different normalized random Brownian motions. So, now we can obtain the maximum and minimum values of the Brownian Bridges for every simulation. Then, we plot the difference of 'maximum-minimum' values for different *sigma*s to see that whether there is a relation among them. We find a linear relation between the 'maximum-minimum' value and the sigma. So, if we know the maximum and minimum value of the Brownian Bridge (which in our case it will be the high and low prices of stock in day i) then using this information we can estimate the *sigma* value. The graph of 'maximum-minimum' for different values of *sigma* is expressed in Figure 1. As we see from the figure only the slope differs in the relation of 'maximum-minimum' values and sigma and there is a linear relationship between 'max-min' and sigma values. We specify an "average" slope to decide the relation and we can use this average slope to estimate the *sigma* value. The histogram of the slope values is given in Figure 2.

As, we can see from the histogram the average of the slopes lies in the interval of (6,7). Obviously, this is not the value we can see in the Formula (15), but, at least it gives us an intuition of the methodology. The simulation details and the data are provided in Appendix A. We have not answered some questions, for instance, what if we have a drift together with the diffusion. In our study we always have a zero mean with different sigma values. So, the results will affect if we have a drift term with the volatility. Second, we want to find a way to estimate the sigma when the day is not finished due to a holiday or another reason. Now, to say something about the sigma our assumptions are made such that the day is complete and will finish at time 1.

To use the methodology for obtaining the volatility series in our analysis, now we explain the details of the methodology. The intuition behind the formula of German and Klass can be summarized as follows:

As we have mentioned above, a geometric Brownian Motion of stock prices is used to obtain the volatility series. The purpose is to obtain the "best" analytic scale-invariant estimator. Best means, when it has minimum variance and it is unbiased. They defined a decision rule if a stock price which considers as a $D(u, d, c)$ where u, d and c represents the maximum, minimum and closing value of the stock for each day, respectively. The properties are hold for the decision rule: $d < c < u and d < 0 < u$. Two conditions of

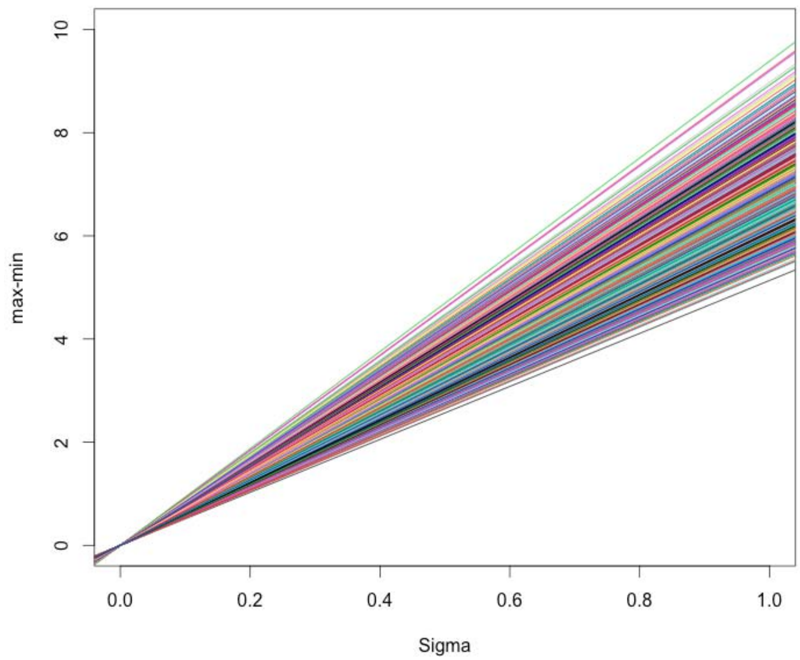

Figure 1: Thousand simulations of Brownian Bridges

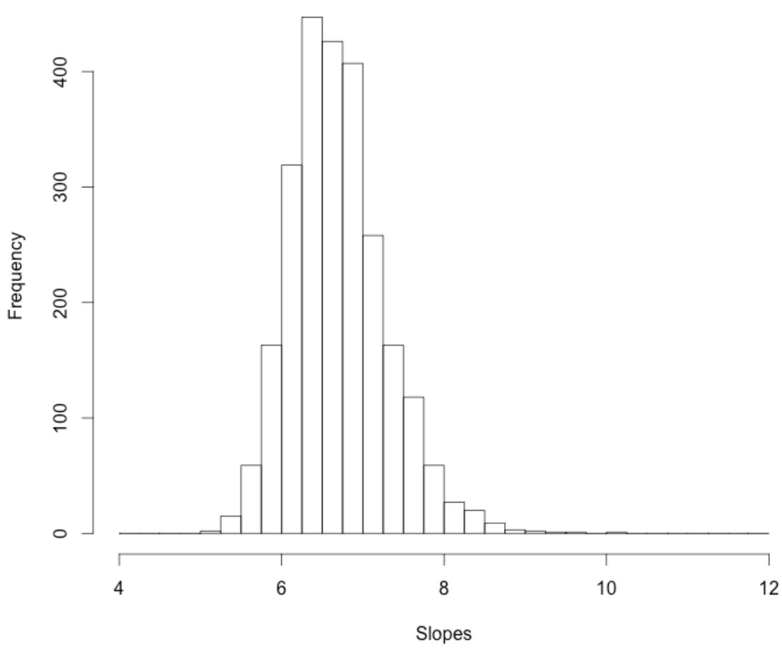

Figure 2: Histogram of Slopes between the 'max-min' and sigma values

Brownian motion is used for the formula: price symmetry and time symmetry. The first one represents that $B(t)$ and $-B(t)$ have the same distribution and the second one where $B(t)$ and $B(1-t)-B(1)$ have identical distributions. By applying these two properties into the decision rule, we have:

$$D(u,d,c) = D(-d,-u,-c) \tag{17}$$

and

$$D(u,d,c) = D(u-c,d-c,-c) \tag{18}$$

Also using the scale-invariance property the following decision rule property holds:

$$D(\theta u,\theta d,\theta c) = \theta^2 D(u,d,c) \tag{19}$$

Then by the scale-invariance property implies that decision rule must be quadratic. Thus, adopting the properties of equation 16 and 17 with the scale invariant property into the decision rule, we have,

$$D(u,d,c) = a_1(u-d)^2 + a_2[c(u+d)-2ud] + [1-(a_1+a_2)4log_e 2 + a_2]c^2 \tag{20}$$

using the Taylor series expansion. Since, $D(u,d,c)$ is unbiased then $E[D(u,d,c)] = \sigma^2$, the forth moment generating function of sigma is:

$$\sigma_4^2 = 0.511(u-d)^2 - 0.019[c(u+d)-2ud] - 0.383c^2 \tag{21}$$

which is the coefficient of the formula in equation 15. The formula considered as a "best" estimator to obtain the volatility series.

3.1.2 Garch Methodology

We will compare the different methodologies of estimating volatility series and discuss them to find the better estimation for our study. For the first step, we will compare the German and Klass (1980) methodology explained in Section 3.1.1 and the Garch methodology. As we have mentioned in the previous section, the Garch methodology uses today's information as well as the previous day's information of the stock prices. Since, the methodology also affected by the previous days, as we expected we found that the volatilities are generally higher than what we have found in the German and Klass methodology. FTSE (UK) and Gdaxi (Germany) stock market volatilities computed with German and Klass, and Garch methodology are shown in Figure 3. In the figure, the red one represents the volatility series obtained from the German and Klass methodology while the black line represents volatility series obtained by applying the Garch methodology. As we can see although the pattern is generally similar for both cases, the level is always different where the red one is higher than the other. To examine which estimation methodology is better for the sake of our project, we will analyze the methodology with the appropriate data in Section 5 and we compare the results with respect to the different volatility series obtained by two methodologies.

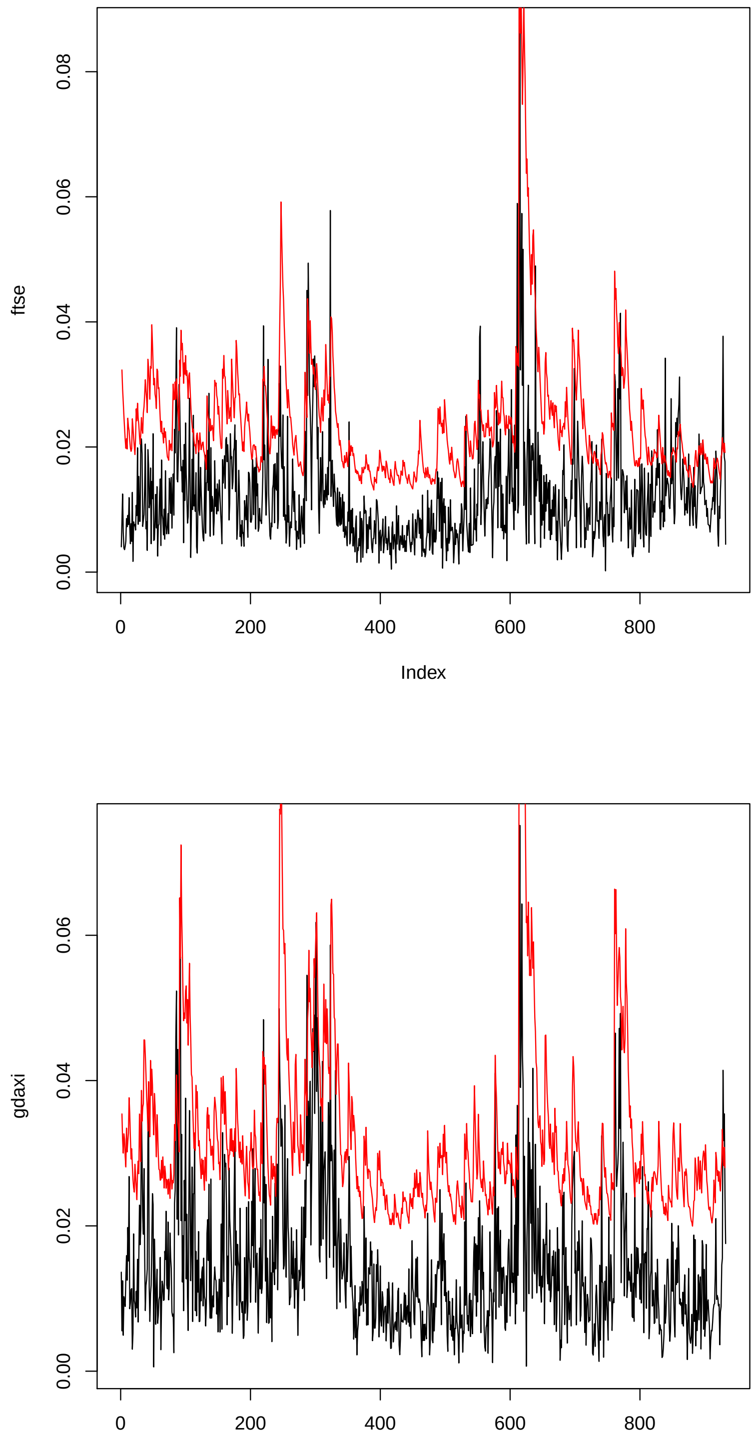

Figure 3: Volatility series by using Garch and German and Klass methodologies

3.2 Shock repercussions and entropy for volatility

The market entropy is a tool to measure the amount of information, created from week to week. Comparing the return KLIC and volatility KLIC is very important to analyze especially the intervals where the behaviour of the two are different. We will see in the Empirical part (Section 5) in detailed that there are different spikes in different times for return and volatility market entropies.

For the KS entropy, which is the speed of convergence back to the equilibrium after a shock, it is shown that return and volatility entropies have different characteristics for some intervals. Especially in the case of some specific events, the speed of information digestion varies in the case of return and volatility KS entropies. On the other hand, the KS entropy has another important characteristic. As it is discussed in Section 5, the overall pattern of KS entropy and spillovers are similar for both return and volatilities.

The same Markov chain approach is used, as in the Section 2.3, to produce the KLIC and KS entropy. The same methodology is used, which is developed by Schmidbauer et al. (2012), using the weekly volatility series obtained from Equation (15) instead of weekly return series.

4 Data

4.1 Data Set I: Data for Return vs. Volatility Spillovers - German and Klass approach

For all methodologies, spillover, propagation value and entropy, are used to see how markets are connected with each other. We apply all methodologies using return and volatility series. For both return and volatility series, 15-year weekly stock market data of five countries are used. They are obtained from daily local-currency stock market indexes from 1997-01-06 to 2013-07-08 taken from Yahoo Finance[1] and Datastream. The stock market indexes of five countries that are used, namely: Dow Jones Industrial Average (USA; in the following called dji), FTSE (UK; ftse), Nikkei 225 (Japan; n225), DAX (Germany; gdaxi), CAC40 (France; fchi). The level series are shown in Figure 4.

To obtain the weekly returns, we calculate the change in log price of close data, Friday-to-Friday. If the price data for Friday are not available due to a holiday, we use Thursday. In the case where Thursday is still not available we use Wednesday. We proceed using this method until we reach an available data in the week. Figure 5 gives an impression of the dynamics of weekly return series as a percentage.

The formula, that is explained in the Section 3 is used to estimate the weekly volatilities. Following German and Klass (1980) and Alizadeh et al. (2002), the underlying daily high/low/open/close data is used to obtain weekly high, low, opening and closing prices to use the values in formula (15). For the weekly closing price, the same method

[1] http://finance.yahoo.com/

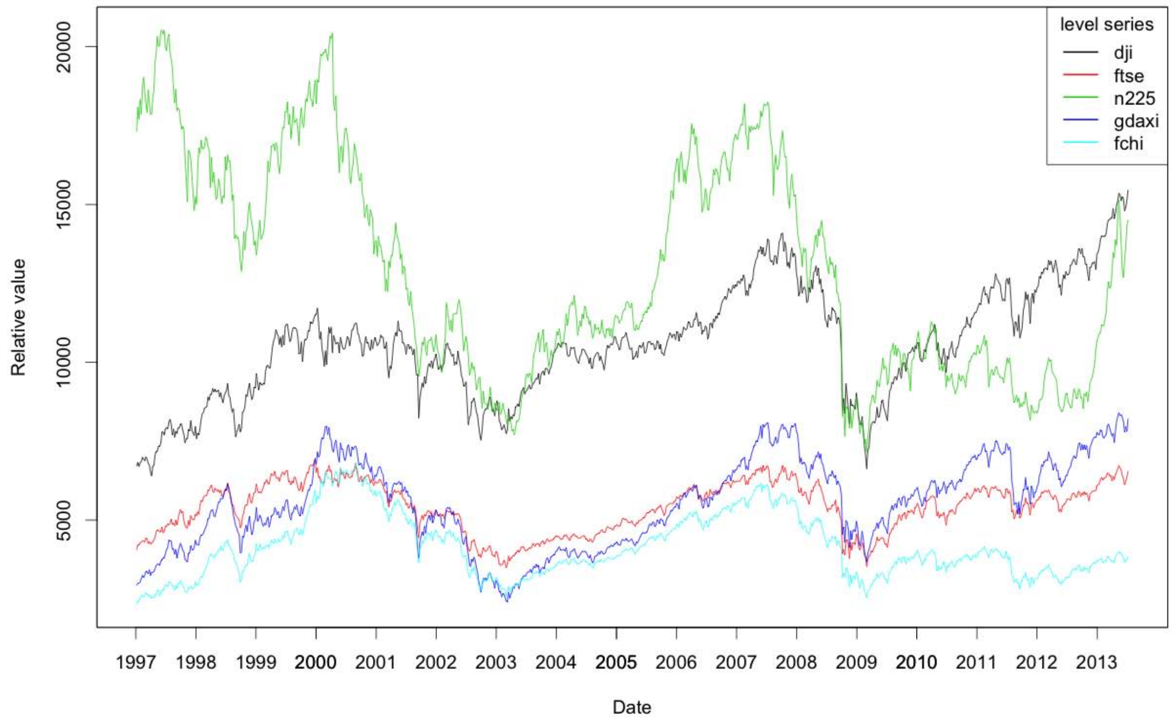

Figure 4: The level series of the stock markets in Data set I

is used as in return: If available, Friday is used as weekly closing price, otherwise the previous available day is used. If available Monday is used as a weekly opening price, otherwise the next available day of the week is used. The highest value from Monday to Friday is used as weekly high price and the lowest value from Monday to Friday is used as weekly low price. Figure 6, gives an impression of the development of weekly volatilities.

4.2 Data set II: Data for Return vs. Volatility Spillovers - using GARCH approach

The second empirical part consists of daily closing quotations of the Russian stock index (rts) and the five stock indices representing stock markets in the "Systemic Five" countries: Dow Jones Industrial Average (USA; in the following called dji), FTSE (UK;ftse), Euro Stoxx 50 (euro area; sx5e), Nikkei 225 (Japan; n225), and SSE Composite (China; spec). The time period begins with 1997-07-03 (the first day for which all six series were available) and ends 2015-05-22. So, we have 4660 observations on total. The level series are shown in Figure 7. We will use the weekly return series with the same methodology used in Session 4.1 and for the volatility estimation we will use GARCH methodology instead of using the German and Klass approach and we will compare the two computing the volatility spillovers. We will also compare the return and volatility spillovers of the

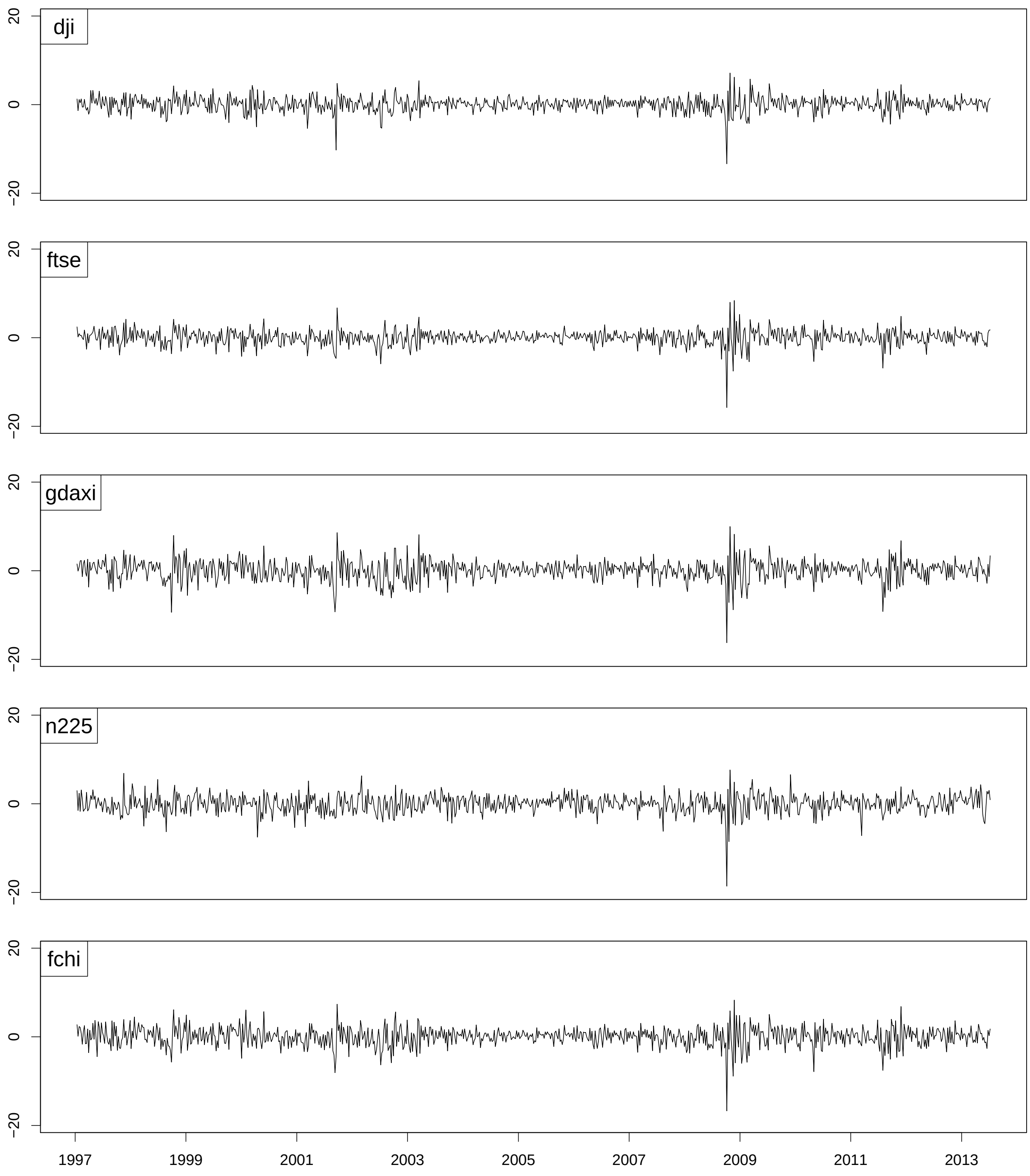

Figure 5: The series of weekly returns of Data set I

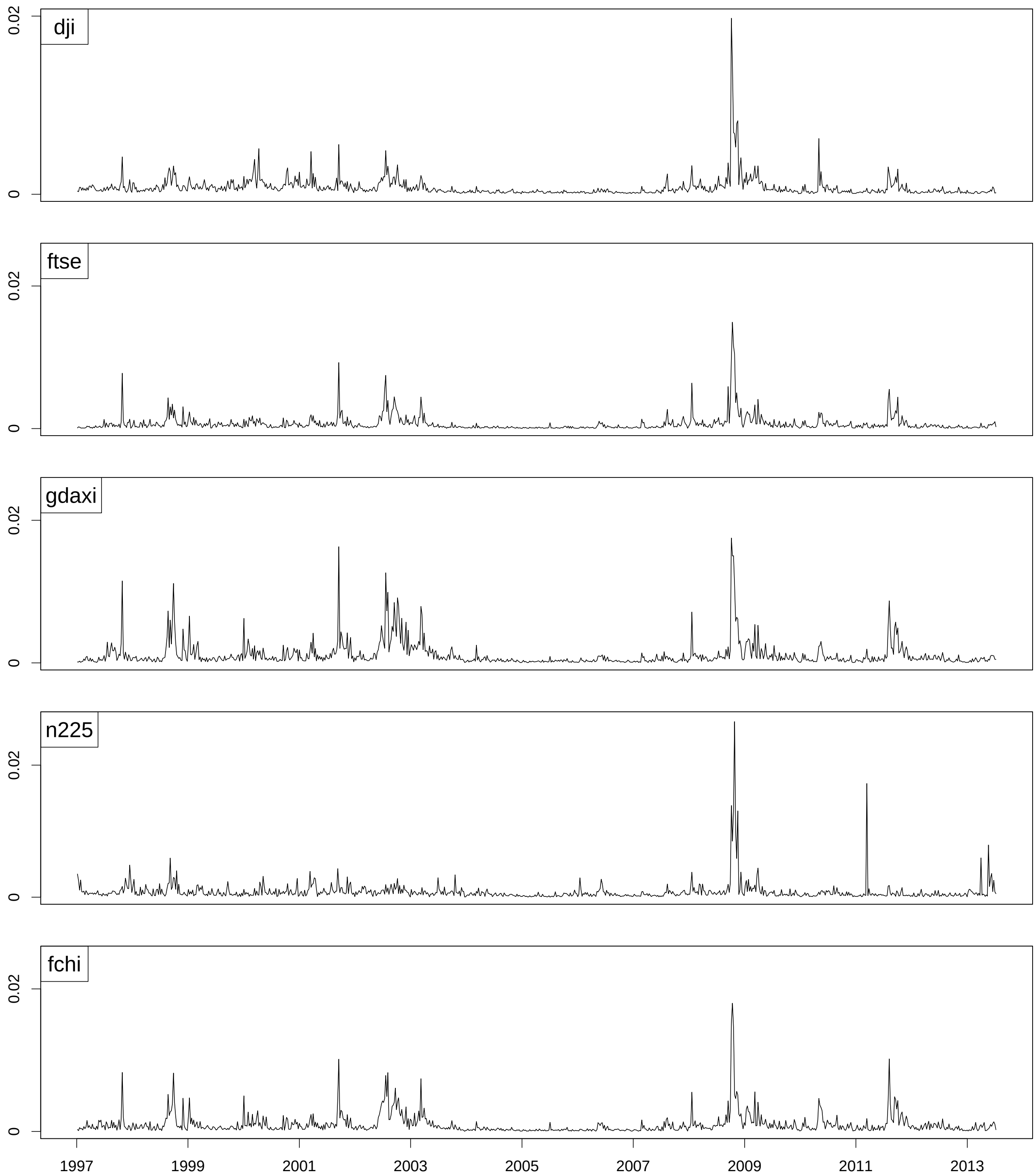

Figure 6: The series of weekly volatilities of Data set I

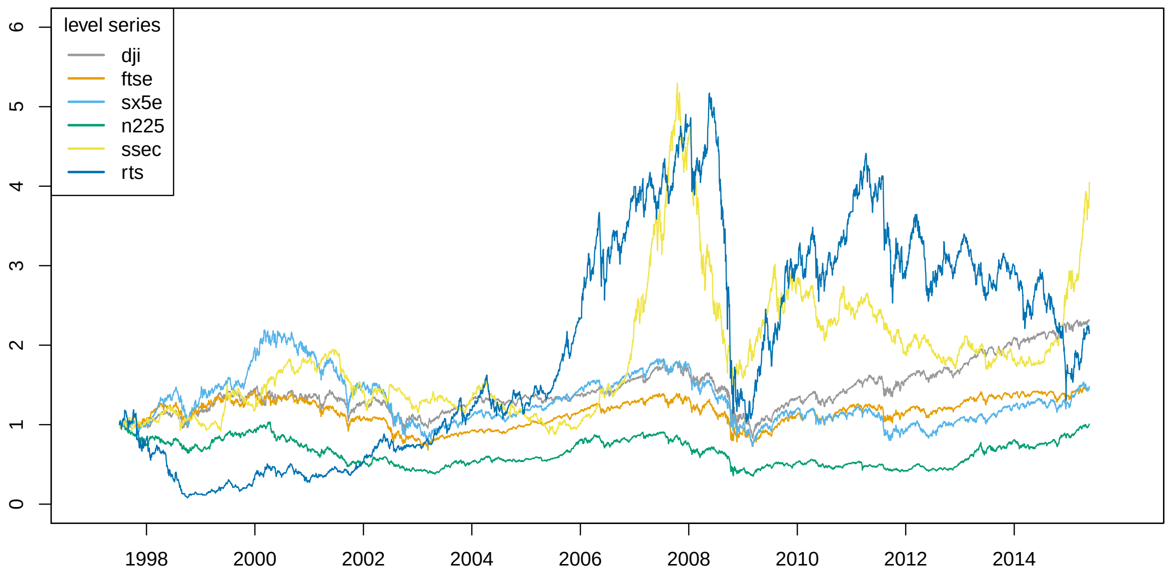

Figure 7: The level series of Systemic Five and Russia: Data set II

data as in Session 4.1.

5 Empirical findings

We divide the empirical findings into two sections. The first one is with the stock market data explained in Section 4.1 where we applied the methodologies explained in Section 2 and 3 by using the method of German and Klass to obtain the volatility series in the case of volatility spillovers and propagation value. After, obtaining the weekly volatility series we apply the spillover and propagation value methodology and discuss the results. We also apply the whole methodology using return series.

The second one uses the stock market data explained in Section 4.2 with "Systemic Five" countries and Russia. We apply same the methodology explained in Section 2 and 3 rather than the previous data set we use the GARCH methodology to obtain volatility series when analyzing the volatility spillovers and propagation value. The methodology for the return spillovers are same for both sections.

Before going through the details of empirical results, an example of a spillover index series is obtained with one of the data set described above using the return series of "Systemic Five" countries. A moving window of 100 days (and n=5) was used for fitting a sequence of VAR models of order 1. The result of spillover index is shown in Figure 8, together with a smoothed version of the series. As we can see market connectedness, has been strongly increasing since 2002, with a shorter period of decline. The reason of this result can be discussed in many ways but it is worth to examine the graph especially in the periods of global events for instance global financial crisis. As we will discuss the

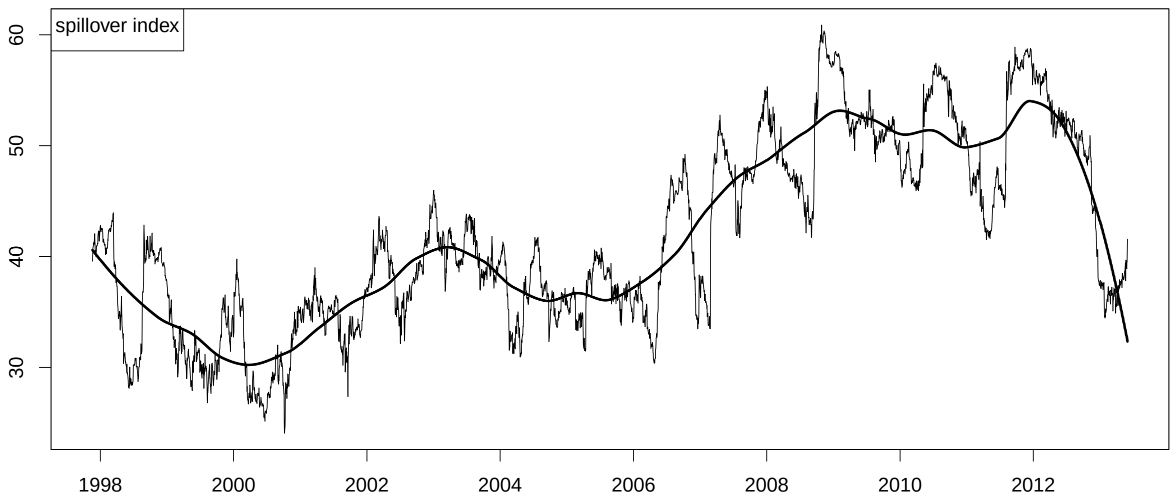

Figure 8: The spillover index series, the case dji/ftse/sx5e/n225/ssec

potential effect of each country, in the case of Turkey and Russia, in Part 2 and 3, some of the countries' network importance increased. This can be explained by an important event that affect one country or the change of the financial situation of one country affects the whole network.

5.1 Directional and overall return and volatility spillovers - German and Klass Methodology for volatility spillover

In this section, we provide an analysis of five countries' stock market weekly sequences of return and volatility spillovers (which means, weekly time series of spillover index values). First, we obtain the spillover matrices which resulted from fitting a sequence of VAR models along the steps outlined in Section 2 for return spillovers and Section 3 for volatility spillovers. Moving windows of 100 weeks and 5-week-ahead forecast are used in the construction of spillover matrices for both return and volatility. The spillover matrix which is shown in matrix (5) expresses the fraction of the forecast error variance of one country due to shocks to another country. The ijth entry of the spillover matrix means estimated contribution *to* the forecast error variance of country i coming *from* shocks to country j.

Each entry in the spillover matrix is called a directional spillover. As an example of the directional volatility spillover, the US case is shown in Figure 9. Assume x_1 in Equation 6 represents the stock market of dji. Since, each entry represents a directional spillover from one market to the other, the total directional spillover from dji to other countries is shown by the black squares of the first column. In other words, if the directional spillover from dji to others is 80%, this can be read as a shock from dji resulting in a volatility shares of 80% to others. On the other hand, the directional

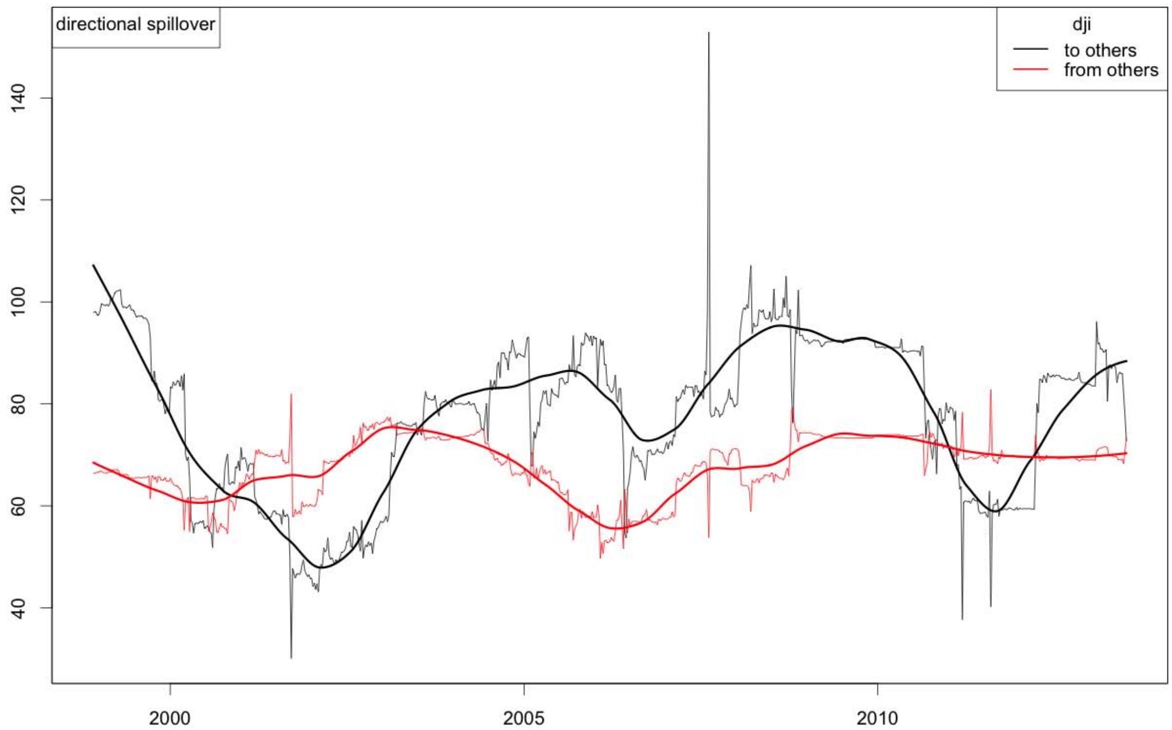

Figure 9: Directional volatility spillover from/to dji using the Data set I (Section 4.1)

spillover from others to dji is shown by the black squares of the first row. The rows of a spillover matrix characterize a market's exposure to shocks. As we can see the early 2000s the spillover that comes *from* US *to* the other markets is less than the spillovers going *to* US *from* others. But, starting from 2004 until nowadays, on general, the spillovers that comes from US to the other markets are higher than the spillovers that come to US from others. It can be said that US is a net sender since mid-2004 in the sense that during the whole period spillovers coming from US are higher than those going to US.

Using the moving window of 100 weeks for fitting a sequence of VARs results in a spillover table for every week. Then using Equation (6) we assess the extent of spillover variation over time via the corresponding time series of spillover indexes. In other words, the spillover table is an 'input-output' decomposition of the spillover index.

Overall, return and volatility spillovers are displayed in Figure 10 and Figure 11, respectively, together with a smoothed version. The spillover index is the division of all black squares to the all directional spillovers, as represented in Equation(6). Figure 10 is the return spillover from 1997 to 2013. The lowest spillover index is in October 2000 and it started to increase steadily to about 75% in October 2008 which is the peak date in the whole interval. After October 2008 it was in a decreasing trend and it currently stands at about 67%.

The volatility spillover graph can be seen in Figure 11. The lowest value in this case is in March 2006 but also in August 2000 the spillover is around 60% which is as low as the minimum value of the spillover series. It started to increase after late 2006 until mid 2010 but unlike the return spillovers it decreased sharply. It currently stands at about 63%.

The comparison between return and volatility spillovers can be seen more precisely in Figure 12. Generally, volatility spillovers are higher than return spillovers until the end of 2006 and they only overlap in the period around mid 2006 which is also the time that volatility is at its lowest value. There are two time intervals that are attracting attention immediately by looking at the figure. From late 2008 to September 2010, both spillovers are in their peak values and move together. Similarly, starting from the beginning of 2011 both but especially volatility spillovers decreased sharply until nowadays. Specific events in these two time intervals have parallel impacts on return and volatility spillovers. On the other hand, there are other time intervals where one affected more than the other. If the effect of a shock stays short, it can be seen more in the volatility spillovers rather than in the return and in such a case it is hard to realize the effect of the shock in the return spillovers. In Figure 13 return spillovers are indicated in the x-axis and volatility spillovers in the y-axis.

In Figure 13, the comparison of return and volatility spillovers are displayed. As it can be seen directly from the graph the values are positively correlated and the volatility spillovers are around 10% higher than return spillovers. There are also outlier values where specific events coincide with a similar date of this outlier values. For instance, the date of terrorist attacks in U.S., September 11, 2001 is an outlier in the graph. The terrorist attacks launched by the Islamic terrorist group al-Qaeda, in the United States in New York City and the Washington, D.C. metropolitan area on Tuesday, September 11, 2001. The subsequent week September 17, 2001 the jump in volatility spillovers can be seen in the figure as an outlier. On 2001-09-17, the volatility spillover was 72.4% whereas the return spillover was 53.9%. Since, in the volatility spillover we look intra week high and low data, the spillover is reflected immediately by the change in the stock market prices due to a shock. The example of September 11 attacks, supports the idea above, the volatility spillover value jumped immediately and stayed high for three more weeks then again entered to the correlated association with return spillover. Unlike in the volatility spillover, there was no jump in the return spillovers. On 2001-09-10, the return spillover was 53.5% and after the attack it was still around 53.9%. Since, for the return spillover the weekly Friday-to-Friday return data is used, the shock might be absorbed by the return spillovers during the week.

September 15, 2008 is the day of Lehman Brothers bankruptcy, which is one of the largest bankruptcies in U.S. history[2]. At the very day of this event, the volatility spillover was 74.6% and the return spillover was 69%. As it can be seen in Figure 13, September 15, 2008 is an outlier value and the effect of the event continues until the end of October. We cannot eliminate the other effects that might cause a jump in volatility spillover during the month, but at least Lehman Brothers bankruptcy induce

[2]http://www.businessinsider.com/largest-bankruptcies-in-american-history-2011-11?op=1

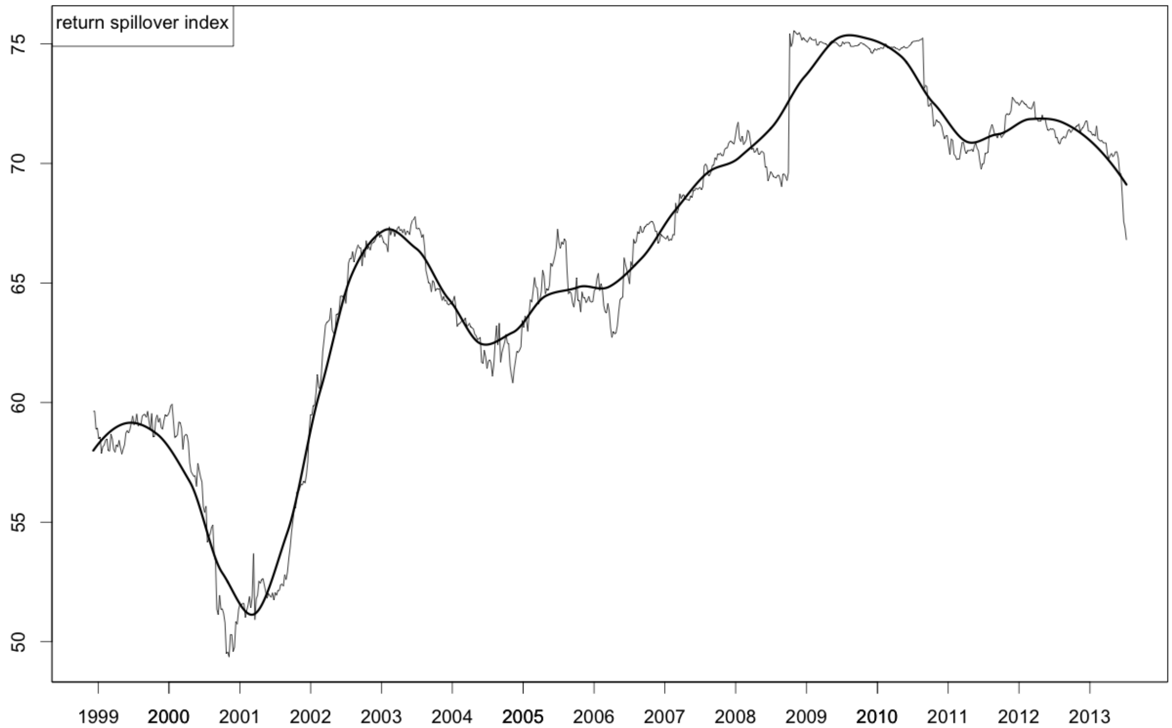

Figure 10: Return spillover index: Network with the stock markets of Data set I

a jump in volatility spillovers even if it might not be the only reason. On 2008-10-06, volatility spillover jumped and the following three weeks stayed high. On the other hand, until the end of September, return spillovers did not increase as much as volatility even though return spillovers are higher than their average value. So, again in the volatility spillover we observe a higher jump then the return spillover after the Lehman Brothers bankruptcy.

Therefore, for these two specific financial events from the history, volatility spillovers are more sensitive to these shocks. The insight is that, many well-known events produced large volatility spillovers, whereas, with a few exceptions, none produced return spillovers. In the identified "crisis" events, volatility spillovers display immediate jump unlike the return spillovers.

5.2 Directional and overall return and volatility spillovers - - GARCH methodology for volatility spillover

The return spillover methodology is the same with the Section 5.1, the only difference is we have daily return series instead of weekly ones within a different network. For the volatility spillovers we have daily volatility series obtained by GARCH methodology explained in Section 3.1.2. We use the daily series of the stock markets of Data set II, presented in Section 4.2. "Systemic Five" countries and Russia is used to apply the

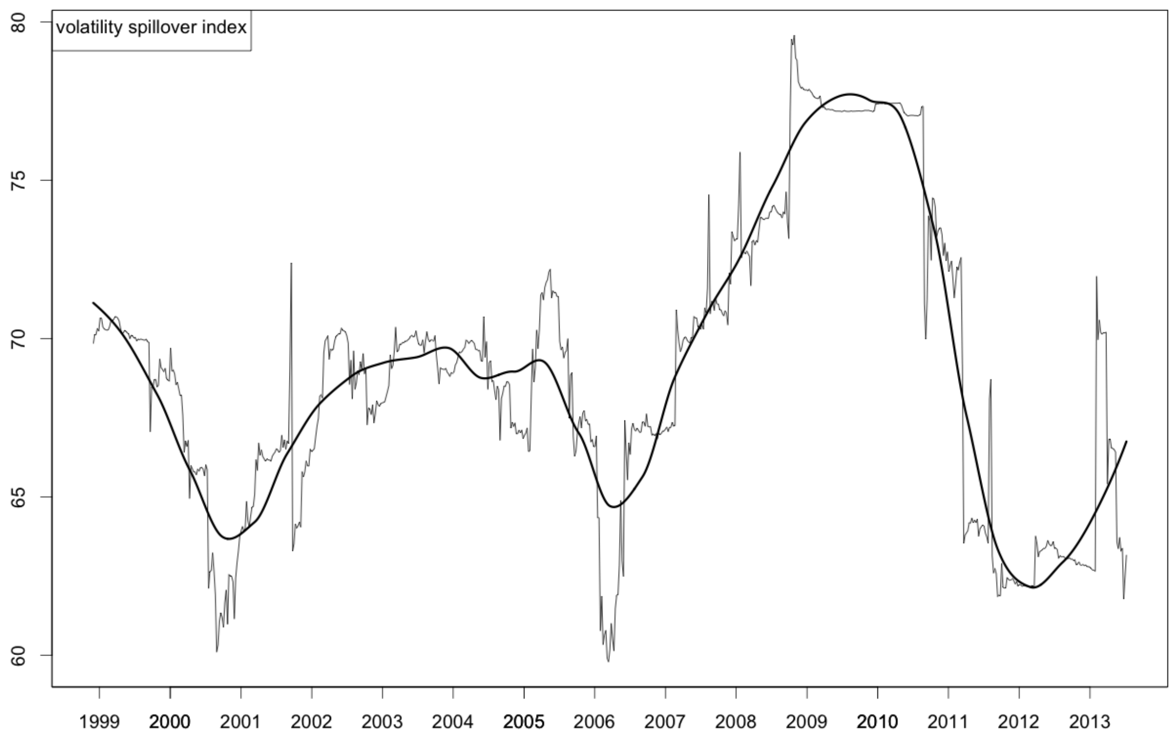

Figure 11: Volatility spillover index: Network with the stock markets of Data set I

Garch methodology and we will focus on the results and graphs of rts as an example. The daily series of direct return spillovers from rts to others and from others to arts are displayed in Figure 14. We can say from the figure that spillovers to rts have always been higher than spillovers from rts. Return spillovers to rts rose sharply on 2014-12-17 the day after the Bank of Russia announced an increase of its key interest rate, the Russian weekly repo rate, from 10.5 to 17 percent as an emergency move to retain the collapse of the rule's value. The big gap in from/to return spillovers lasted for about four months.

Then, we calculated the directional spillovers as we have done for example 1, for both return and volatility spillovers. More specifically, with the daily volatility series that we have obtained from the GARCH methodology, we calculated the volatility spillovers and same methodology as example 1 is used but with daily returns instead of weekly ones, we calculate the return spillovers for stock markets of six countries. Figure 15 displays the directional volatility spillover for the case of Russia. The volatility spillover that comes from Russia to others is less than the spillovers going to Russia from others until the mid 2008. But stating from 2009 the spillovers to Russia from others increased a bit and the effect from Russia to others became smaller. So, we can say that starting from the second half of the period, Russia is a net sender in the sense that during the period spillovers coming from Russia are higher than those going to Russia. But nowadays the spillovers from others to Russia is started to increase again and the net sender situation of Russia started to change.

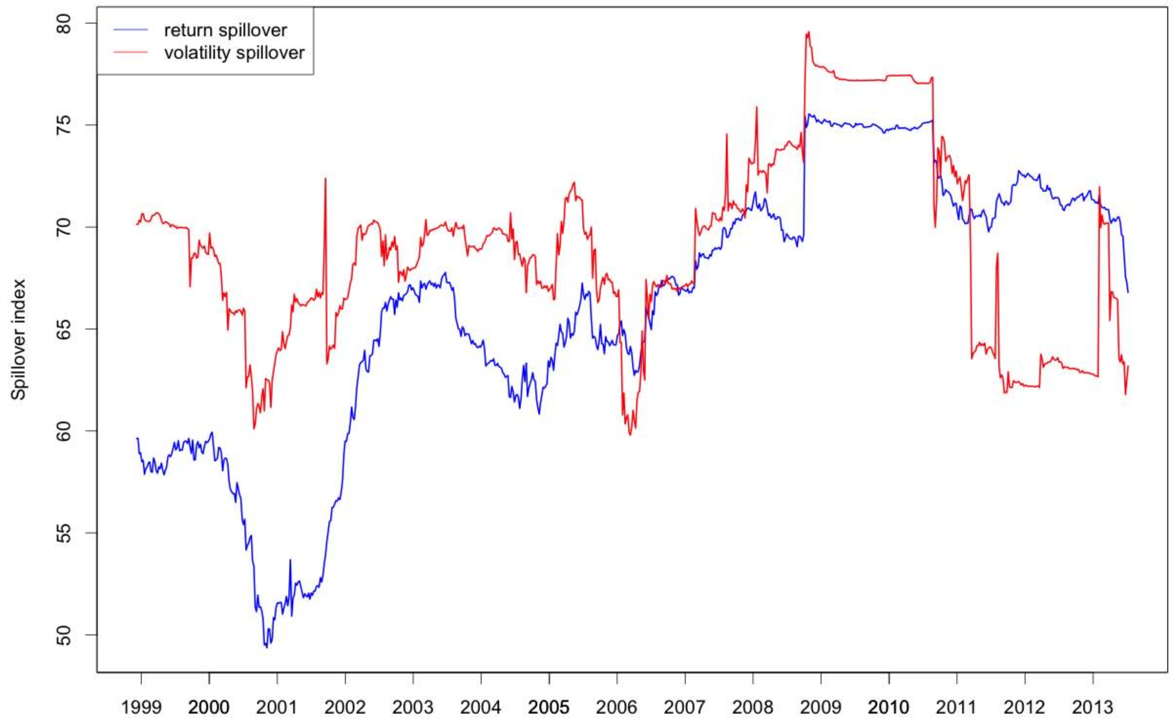

Figure 12: Return and Volatility Spillover Indices: Network with Data set I

The volatility spillover obtained by the GARCH methodology can be seen in Figure (16). The volatility spillover is always in an increasing trend but its peak value was at the beginning of 2007. It is started to decrease starting from 2012 and it continue to decrease. It currently stands at about 35%. Generally, volatility and return spillovers are positively correlated with each other but volatility spillovers are higher than the return ones around 10%.

Propagation values quantify the relative importance of a market to act as a shock propagator. In other words, the propagation value measure the network repercussions of shocks. The propagation values of rts are displayed in Figure 17. The values were gradually increasing since 1997, peaking in early 2012, and have begun to decrease since then especially after 2014-12-17. When we compare the return spillovers and the propagation values especially after December 2014, we can conclude that direct spillovers tended to become more important, while network repercussions of shocks of rts decreased in importance.

5.3 KLIC and KS entropy

- Relative market entropy (KLIC):

The information that is produced by the system of markets from week to week is computed by Kullback-Leibler divergence as it is explained in the Section 2.3. KLIC,

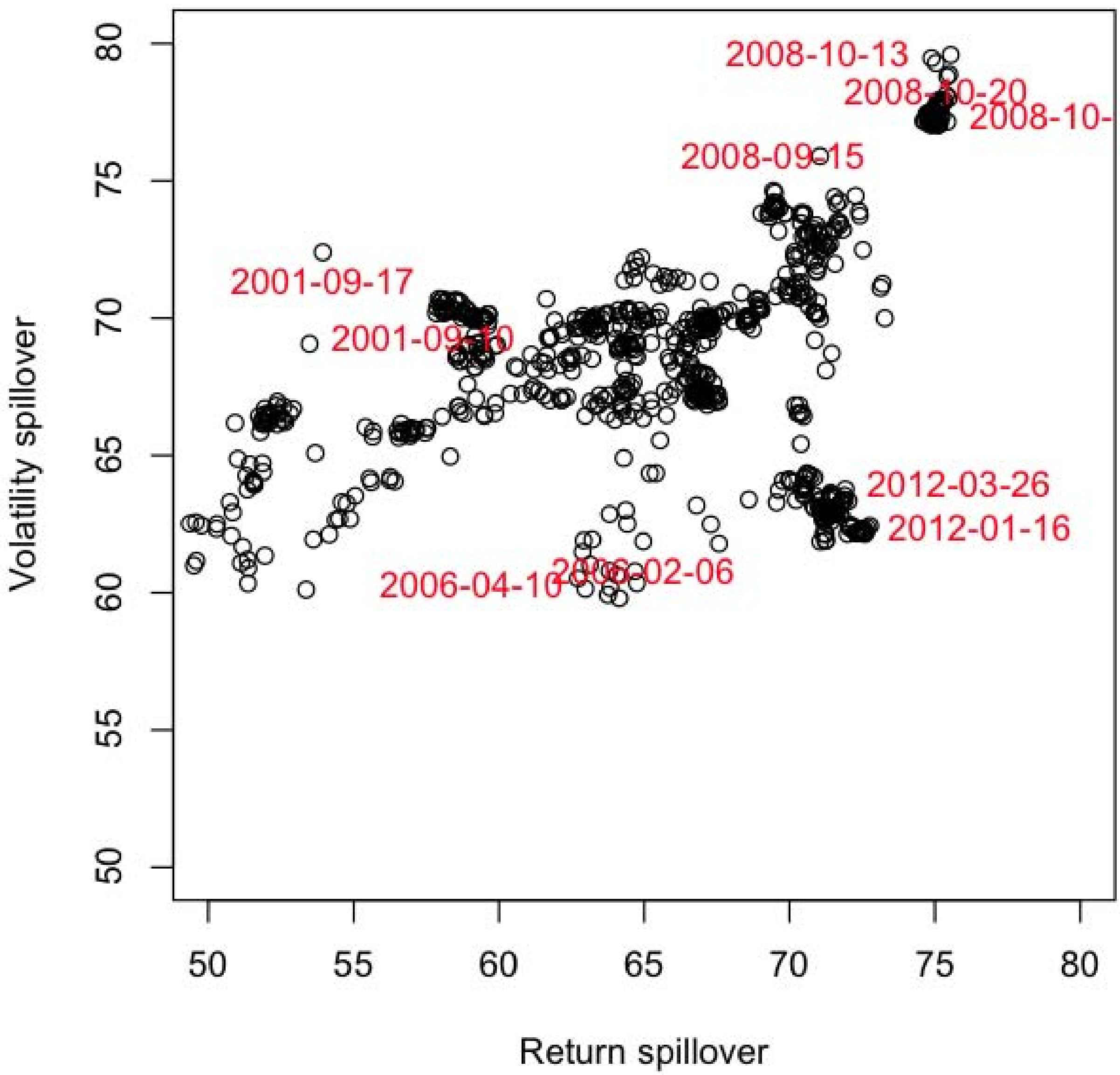

Figure 13: Return vs Volatility Spillovers Indices: Network with Data set I

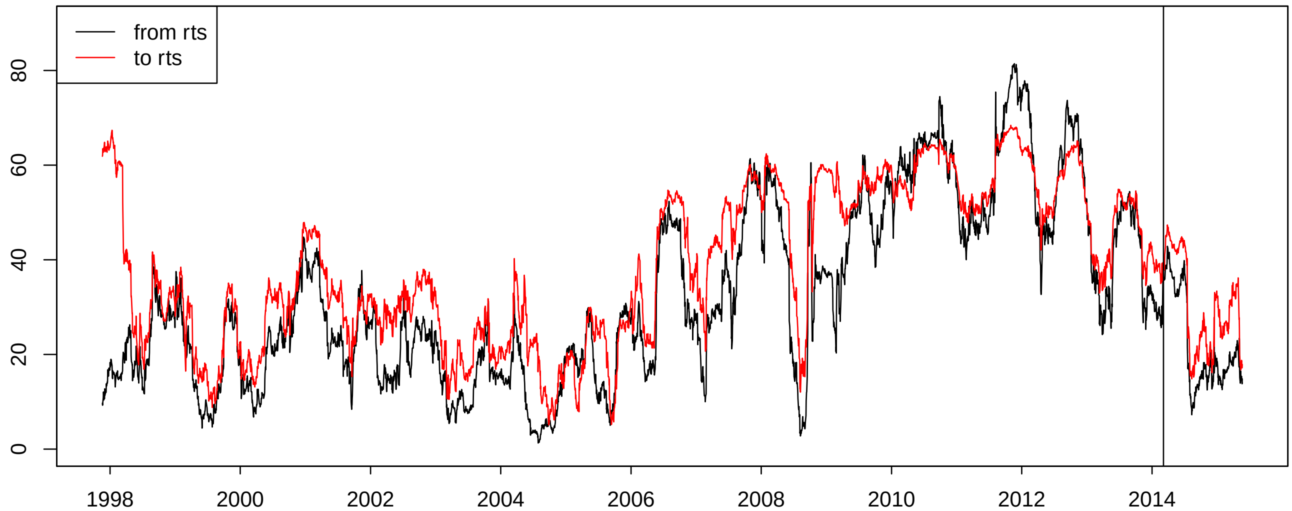

Figure 14: Directional return spillover from/to rts using the Data set II

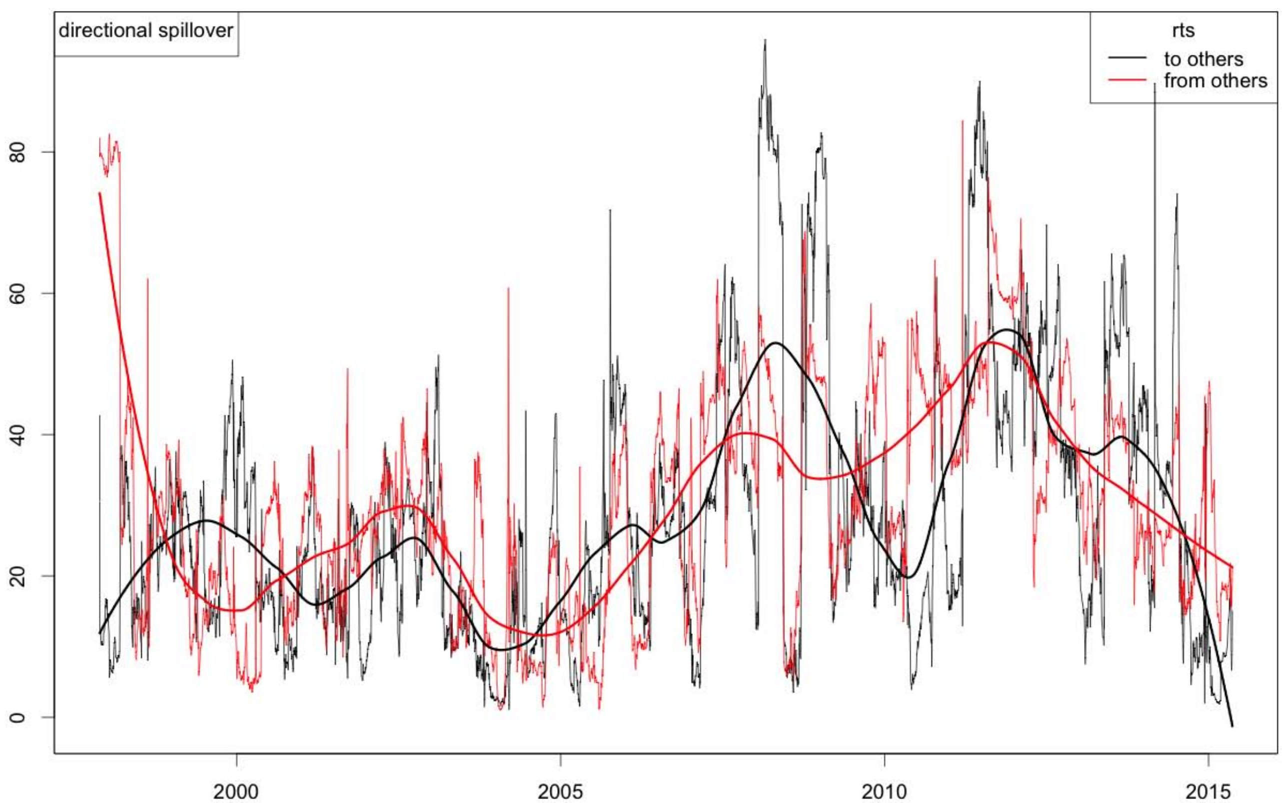

Figure 15: Directional volatility spillover from/to rts using the Data set II

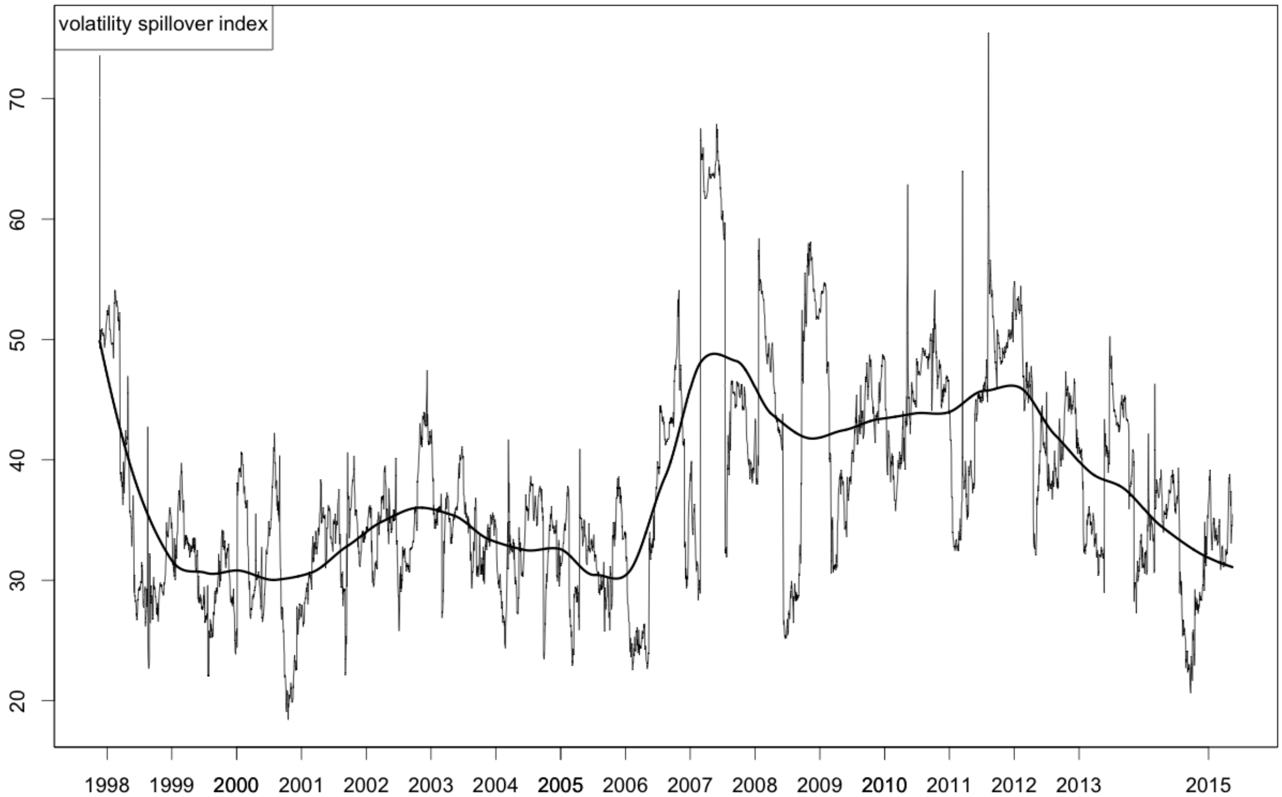

Figure 16: Volatility Spillover index: GARCH methodology using Data set II

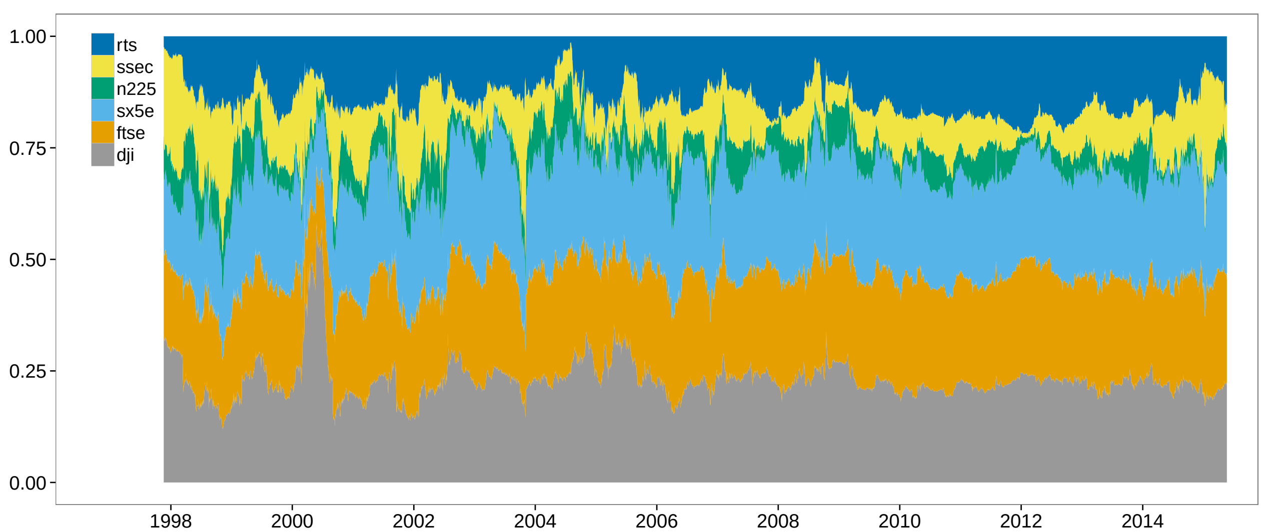

Figure 17: Propagation Value of rts: Network with Data set II

shown in Equation (11) where π_a denotes any initial distribution of a Markov chain and π_b its stationary ("news balance" in our case) distribution, provides a measure of how distant the initial distribution is from equilibrium. From the point of market connectedness, KLIC measures the amount of information created week to week. Figure 18 shows the relative market entropy (KLIC) where the volatility series is obtained by using the German and Klass methodology.

The return KLIC, has an increasing trend until the end if 2004, but then the level of information created started to decrease. On the other hand, the return KLIC spikes have become shorter after 2008 except one big spike at the end of 2009.

In the volatility KLIC, always an increasing trend has seen unlike the return KLIC. Except the big spikes, there are only small jumps in the volatility KLIC. The information that is created is high compared to an average level, especially for the following two cases: The volatility KLIC is at its highest value in 2011-03-21 and the second highest one is at the end of 2007.

Therefore, until the end of 2004 both return and volatility KLICs have an increasing trend but then unlike the volatility KLIC, return started to decrease. So, the magnitude of information gain has increased at the beginning for return but then decreased, whereas the volatility KLIC always increased. Also, in terms of the spikes, the information that is created week to week is higher in the case of volatility. The return KLIC spikes have became shorter after late 2008 and the volatility KLIC values had an increasing spike path, but the last spike was on March, 2011. The magnitude of the information created is huge for volatility but not for the return.

Until now, we have used the Data set I and we obtained the volatility series by using the methodology of German and Klass explained in Section 5.1. Using the second example, which we have explained the details in Section 5.2 by using the daily Data set II, relative market entropy of volatility is shown in Figure 19. In this case, we use the Garch methodology to obtain the volatility series. We can see big spikes especially mid 2010 and at the end of 2014. As we have examined in the spillover part, 2014-12-17 is the day where the interest rates of Russian bank were in a sharp increasing trend and we also observe the effect of this day in our KLIC results which was similar to the spillover results. The magnitude of the information gain increase immediately after the day and a few days later it disappears.

Figure 20 shows the relation of return and volatility relative market entropy values of Data set I by using the German and Klass methodology to obtain the volatility series.. There is a linear association between return and volatility KLIC values. The log values are used for the transformation of scale. As it is seen in the graph, even the volatility KLIC values are in the wider interval than the return KLIC, there is a linear association between two of them. So, we can say that there is a positive correlation between return and volatility entropy values. Is it possible to find an example where the correlation is not positive? We leave this question for future research and try to find an either real or hypothetical example where the correlation is not positive.

- KS entropy:

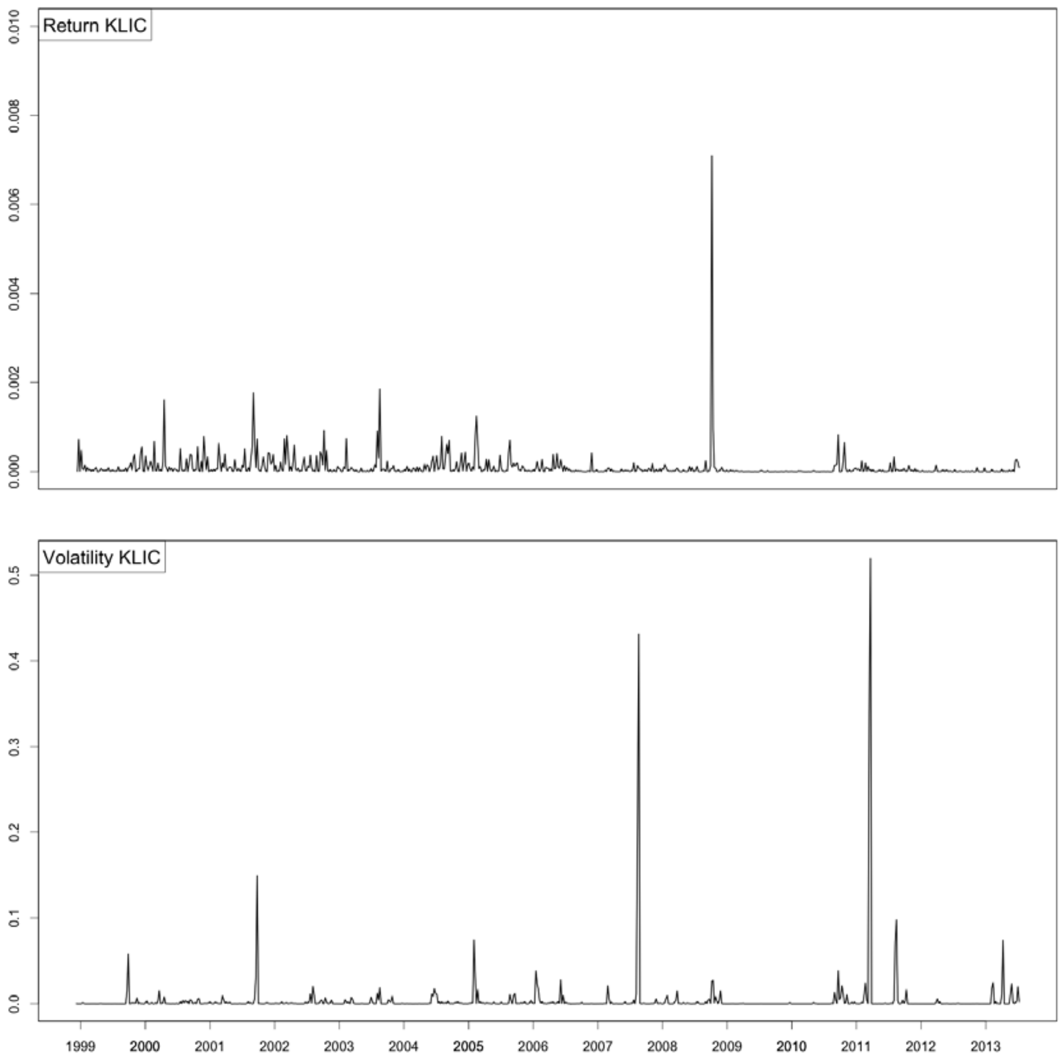

Figure 18: Return and volatility relative market entropy with Data set I

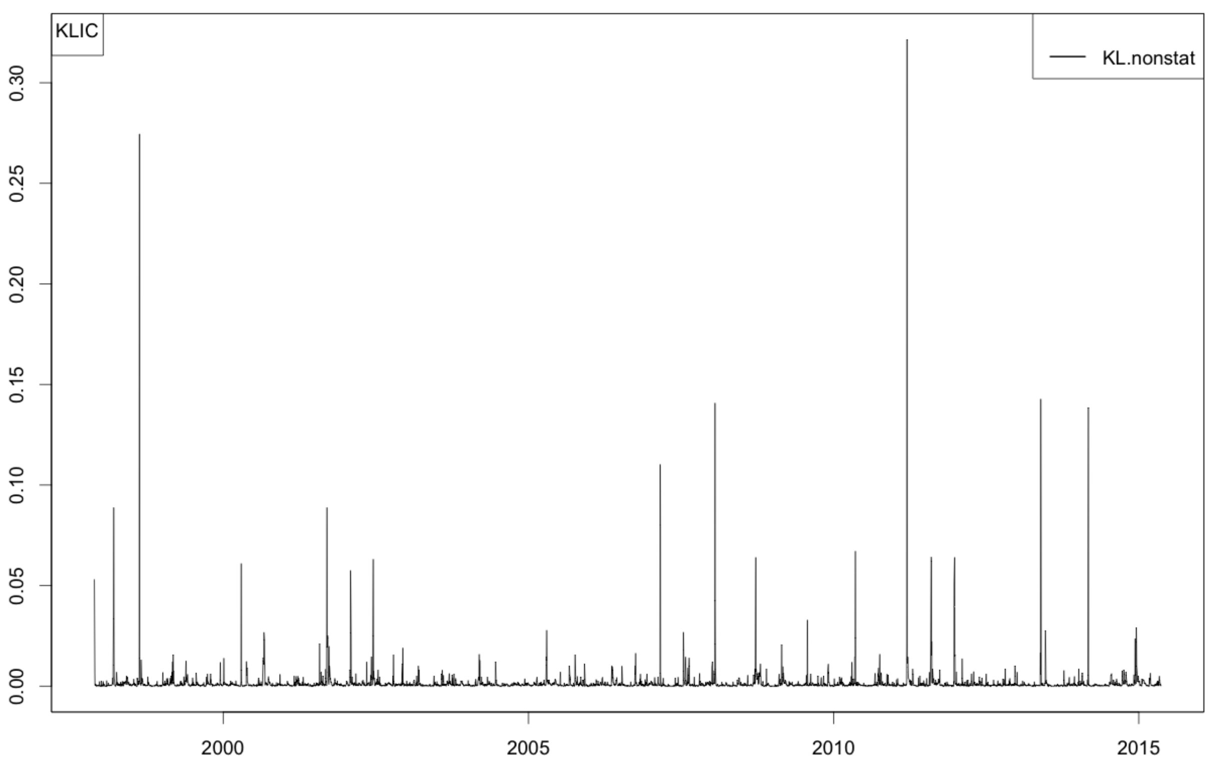

Figure 19: Volatility relative market entropy with Data set II

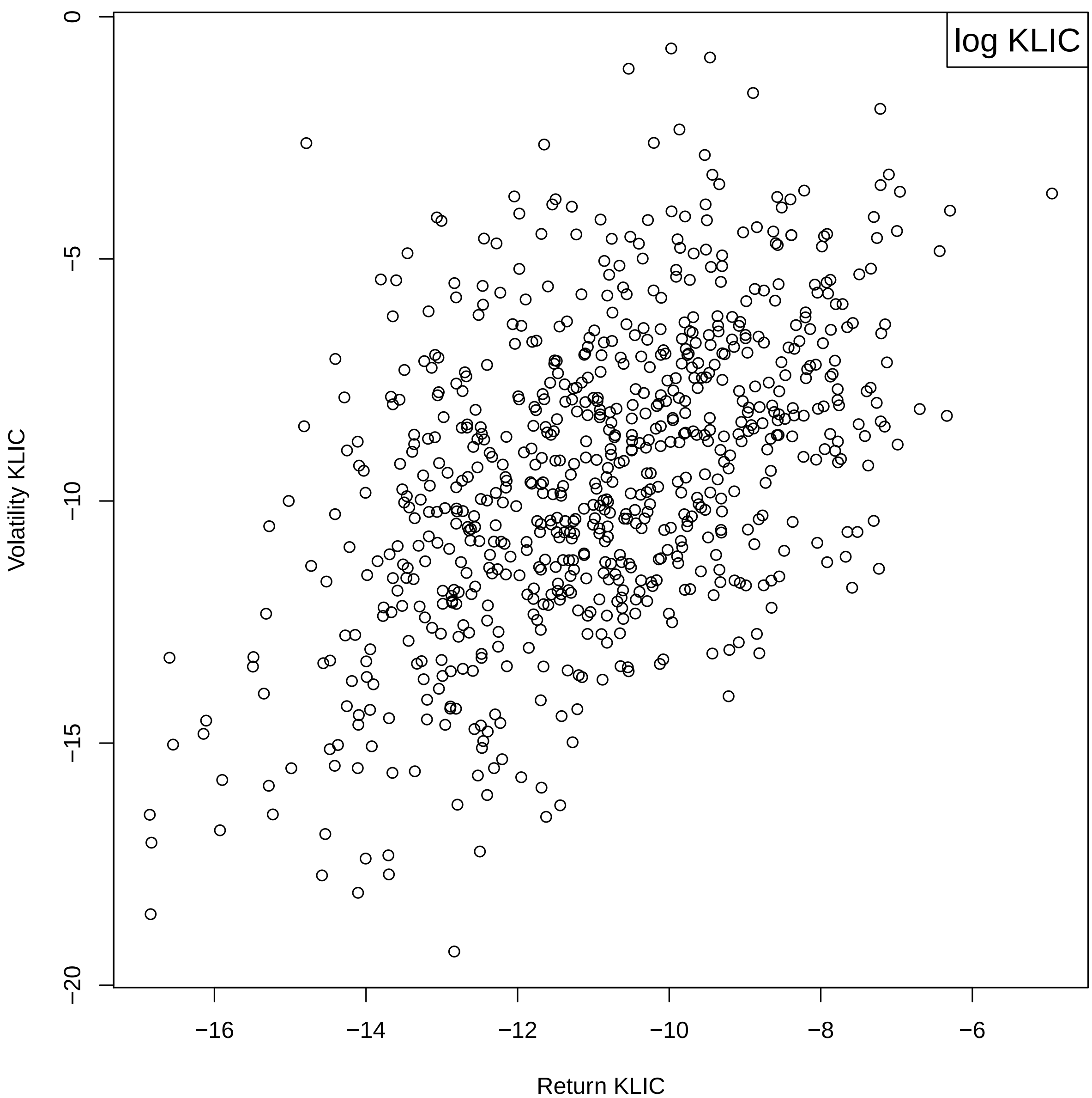

Figure 20: Return vs volatility relative market entropy: Network with Data set I

There is another type of entropy measure which has explained in Section 2.3 as a Kolmogorov-Sinai entropy measure. Demetrius (1974), introduced this entropy measure in population theory and Schmidbauer et al. (2013) adjust it in the field of market connectedness. The idea is to answer the following question: How the speed of convergence to a news balance between markets changed across time if the system is distorted by a shock (news)? In other words, KS entropy measures the speed of information digestion. The KS entropy for return and volatility is shown in Figure 21 where the Data set I is used as a network with German and Klass methodology to obtain the volatility series..

The overall patterns of KS entropy and spillover index are similar, both for returns and volatilities. This relation can be seen by comparing the Figure 21 and Figure 12. The volatility KS entropy is higher than the return KS entropy until 2006, then they overlap. We have seen a similar behaviour in the case of return and volatility spillover indexes. Both return and volatility KS entropies are in their peak values on October 2008 until September 2010 and then both of them decreased sharply. The similar peak dates can be seen in the case of return and volatility spillover indexes.

Figure 22 shows the pattern of return and volatility KS entropies. The points show the return KS entropy in the x-axis and volatility KS entropy in the y-axis. There is a positive correlation in the return and volatility KS entropy, and volatility KS entropy values are generally higher than the return ones.

The specific events that we have discussed in Section 5.1 in terms of the spillover perspective can also be adopted to the KS entropy for returns and volatilities. There are similarities between Figure 22 and Figure 13. Some outlier values are in similar dates in KS entropy and spillover index.

6 Conclusion and Further Research

The first goal of the present study was to compare the results of market connectedness using the spillover and information flow perspective when the return prices and volatilities of them are used. Using both expectation of stock prices and the variations of them, gave us an information about how these two complement each other. So, we analyzed the market with respect to different structures.

We applied spillover index, propagation value and entropy methodologies by using two groups of stock market network. We apply the methodologies to both data sets by using the expectations of the prices and also variations of them. First, we quantify the return spillovers and then we calculate the results of volatility spillovers using two different methods to obtain the volatility series. We reached the result that even the return and volatility spillovers behave similarly and there is a positive correlation among them, at some specific time intervals return spillover and volatility spillover act different. We explained these results in terms of a “crisis” or an important event from the history.

In addition, since we have used the daily/weekly return and daily/weekly volatility series, we needed to obtain the return and volatilities using daily data. We extended the

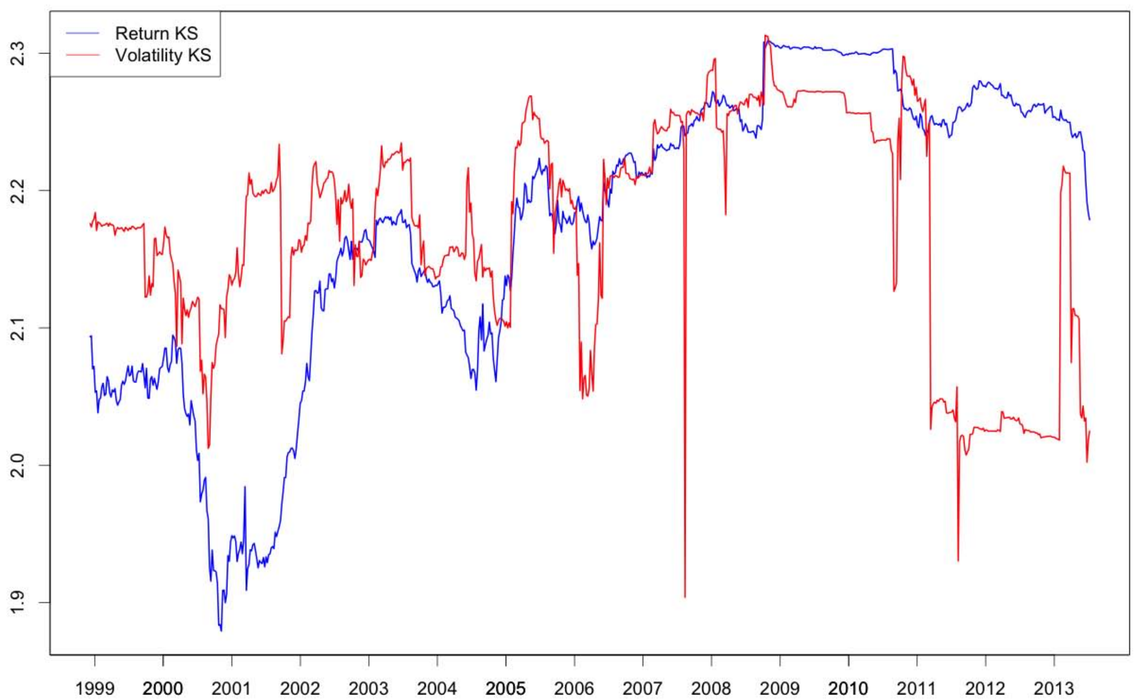

Figure 21: Return and volatility KS entropy: Network with Data set I

methodology of German and Klass (1980) to construct the weekly volatility series and explain the intuition behind the methodology. So, both spillover and information flow perspective depended on return and volatility series that we have obtained using two methodologies explained in the study. Another methodology that we used to obtain the volatility series is the GARCH methodology. We compared the results with German and Klass methodology and discuss the advantages of each of them. We have used two data sets of stock market to examine the different effects of each methodology and compare the two methodologies to calculate the volatility spillovers. So, the purpose of this study was to discuss how to provide the volatility input series while using the spillover and propagation value methodologies. We have seen that the German and Klass methodology was similar to Garch methodology but they obtained a different level of volatility. We have discussed that the German and Klass methodology is better than the Garch with respect to the data they use and it is a better estimation than Garch.

The results obtained from KLIC and KS entropy showed us the information gain comes from either using the return or volatility series. In the KLIC results, the amount of information created week to week had different pattern in the case of return than the volatility. The spikes from the volatility is higher than the spikes coming from return. The magnitude of the information created has been increasing for volatility but in the return there are time intervals where information created has been decreasing. We linked the results of the spillover and entropy where both methodologies used the same stock

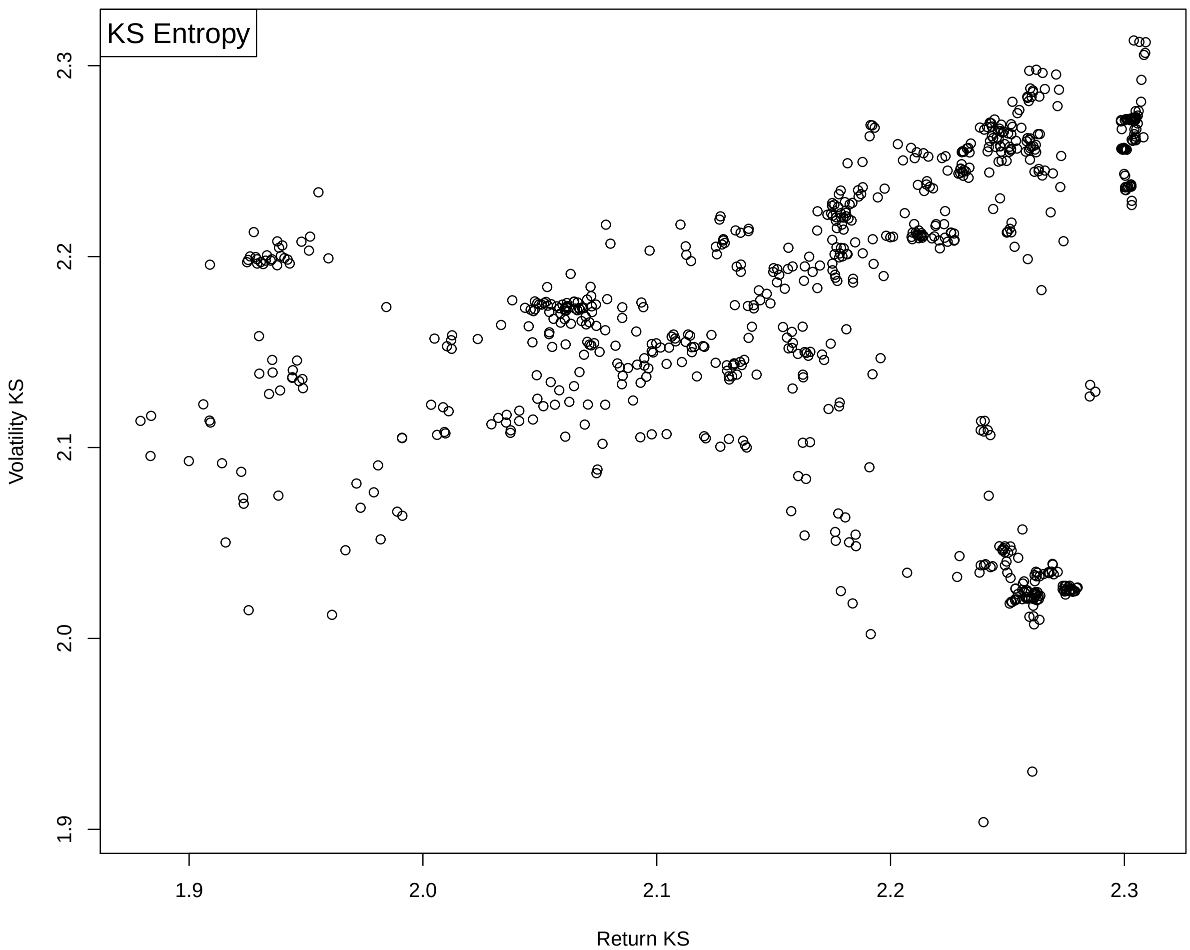

Figure 22: Return vs volatility KS entropy: Network with Data set I

market network.

There is a positive correlation between the values of return market entropy and volatility market entropy. In the further research of this study we will examine the reason of this correlation and create an example where there is no correlation or the correlation is negative. Therefore, we can compare the information created in these two cases where there are positive and negative correlations. In the case of KS entropy, the similar situation like in the spillover index have found. There is a positive relation in the return and volatility KS entropies, but at some specific time intervals the volatility KS entropy, which gives us an information about the shock digestion, is higher than the return KS. We analyzed the reasons of this change as we did in the spillover index.

Finally, we quantified dynamically the market connectedness of two groups of networks. We applied the methodology to both networks by using the return series and also the volatility series. For these two stock market networks, we discussed Garch and the method of German and Klass to obtain the volatility series and discuss the results obtained of them. We focused on comparing the characteristics of the results obtained from the methodologies by using two different stock market networks.

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Part 2:
Turkish and International Stock Markets: A Network Perspective

September 2, 2016

Abstract

The goal of the study is to investigate shock spillover characteristics of the Turkish stock market since 2000, with a view towards large-scale political and economic events. We consider six stock markets, represented by their respective stock indices, namely USA (dji), UK (ftse), the euro area (sx5e), Japan (n225), China (ssec), and Turkey (xu100). Linking these markets together in a network on the basis of vector autoregressive processes, we have measured the following:
(i) direct daily return and volatility spillovers from xu100 to other market indices,
(ii) daily propagation values quantifying the relative importance of the Turkish stock market as a return or volatility shock propagator,
(iii) the amount of network repercussions after a shock in the Turkish stock market. We discuss the network importance of Turkey in 15 years since 2000 and examine the relationship of the methodological results in line with the changes in Turkish economy. We apply the methodologies using return and volatility series to discuss the different aspects of market connectedness. In this case, we obtain the volatility series using a method which is explained in detail in Part 1. We also correlate the policy changes of Turkey for these 15 years and the changes in network repercussions. We divided the 15 years into five subperiods. We concluded that the spillover and propagation values are period specific; each period has its own characteristics. We analyze the impact of important events of Turkish history on spillovers and propagation value of Turkish stock market.

1 Introduction

1.1 Turkish Economy from 2000 to 2015

After the financial crisis in 2001, Turkish economy started to grow rapidly during the next five years. From 2002 to 2006, the GDP growth was almost 6% per annum which is the fastest GDP per capita growth since 1960, according to the study of Acemoglu et al. (2015).

During this five-years period there were remarkable macroeconomic developments and policy changes which affected the rapid growth of Turkish economy. The growth performance brings on relatively high productivity growth, the private investments increased by 10 percentage points after the crisis. These improvements are reflected by some macroeconomic indicators which are important to understand the performance of an economy. For instance, inflation was 80% in 1990s and it decreased until to the single digit numbers at the beginning of 2000s according to the study of Gurkaynak and Boke (2013). Public sector debt also declined sharply after the crisis.

After the recession on 2007, the story has changed and per capita income growth became around 3% which is lower than the growth during 2002-2006. Started with 2007, the growth level in Turkish economy became smaller and with the global crisis hit it remains by low growth during 2008 and 2009. After a sharp decrease in 2009, almost 5%, from the beginning of 2010 the growth was in an increasing trend and the recovery period has started. Economy grew by 9.1% in 2010 which was a surprising result for economists and investors.[1] On the contrary of the pessimist scenario, after the global financial crisis, second quarter of 2009, the recovery period has started immediately. Although the growth is very high during the period of 2010-11, Acemoglu et al. (2015) considers the post-2007 period as a "low quality" period in their study. Starting from 2012, the GDP per capita growth was again in a decreasing trend even it was not as low as during the 2001 and 2007 crisis.

The volatility of GDP growth also indicated that there was a jump in volatility at the beginning of 2000's. The volatility was smaller than before and it was 4.5% in 2001, after the crisis there was a significant increase, during the period 2002-2006, and the growth increased to 5.4%. After a decline in 2007, it was in a declining trend but still not less than 1990s.

Examining only the percentage change of growth is not enough to understand the structure of Turkish economy. It is important to analyse some parameters which have a crucial role in a country's economic performance. By means of these parameters, we will investigate the reasons of the growth change and look to the Turkish economy from a broader perspective. Additionally, we compare the parameters that affect the growth performance of Turkey with other countries' to understand the situation of Turkish economy globally. So, we will not focus on Turkey only in isolation but we will examine Turkey in worldwide context and investigate the Turkish economy relative to the rest of the world.

The role of global effects in Turkey was an important concept to understand a growth performance of Turkey. Instead of GDP per capita, by using Purchasing Power Parity (PPP) it is possible to compare the relative behaviour of Turkey's per capita income with US and Eurozone. In 2002, income per capita of Turkey was much calmer than two systemic five countries, the US and Eurozone. Turkey's per capita income was around 24% of US's and around 32% of Eurozone's per capita income. After a decade, in 2011, the per capita income increased relative to both US and Eurozone and stayed at the level of around 32% and 45%, respectively.[2] So, we clearly conclude that the relative growth performance of Turkey has increased comparing with US and Eurozone.

[1] Source: http://www.mahfiegilmez.com/2015/04/akpnin-ekonomide-13-yl.html; Retrieved 2016-04-20

[2] Source: databank.worldbank.org; Retrieved 2016-04-20

Global business cycles are another important issue to investigate the economic situation of Turkey relative to the rest of the world. Akat et al. (2012) examines in their study the global business cycles characteristic features and they divided these characteristics by two parts and discussed the perspectives. The first one is a real economy side which means if, among the trade partners, a country is in an above-trend growth this is a positive externality for the country and is a plus for the performance of the economy. This is the case for Turkey during the period of 2002-2006. But, with the global financial crisis in 2008, the situation has changed and the trend reversed. So after 2008, there was a below-average growth and above-average volatility for the world economy. According to Akat et al. (2012) "during the financial global crisis especially euro zone is effected and this comprised the market for half of Turkey's exports before the crisis." The second part is the financial side. During the last decade but especially from 2002 to 2006 due to the cheap funding, countries had large external surpluses and then they participate in the liquidity by developed central banks. Akat et al. (2012) explains the situation of Turkey in terms of financial side: "Turkey certainly benefited from these liquidity injections, which easily financed ever-increasing current account deficit of Turkey during the last decade".

There is an another component which related to the economic performance of a country. Foreign direct investment (FDI) is a key component in global economic integration and high FDI inflows improve the economic performance. According to the study of Acemoglu et al. (2015), the FDI inflows of Turkey was 9 billion US dollars during the period of 1980 and 2002. After 2002, the subsequent five years the FDI inflows increased a lot and reached to 110 billon US dollars which was 2.4% of GDP. After 2007 the FDI inflows was still increasing but not as fast as the previous period.

The statements of current account and FDI support our idea that during 2002-2006 due to the long-term financing and FDI inflows the relative growth performance of Turkey was in a good state and post-2007 it changed with short-term flows and the growth of economy became smaller.

In line with the evidences above we can clearly see that even there is a growth in GDP of Turkey in the last decade, the period of 2002-2006 was a period with full of development and as Acemoglu et al. (2015) the period considers as a "high-quality growth period". Instead of this period, the situation has been changed and economy growth became smaller after 2007 and so the authors consider this period as a "low-quality period". The most important difference of "high" and "low" quality periods is the change of the current account and growth performance. During the period 2002-2006 where there is a high growth performance the current account deficit was smaller than the GDP growth and mostly financing the domestic investment. Capital account as a percentage of GDP started to increase after 2002 and in 2006 it was 10% of GDP and then after 2007 the level started to decrease. Post crisis period, after 2007, the growth became smaller with higher current account deficit and a sharp decrease in saving rate and no higher investment comparing with the previous period. In this case, higher capital inflows have been financing by higher consumption. If domestic savings are small the growth can only happen with a foreign capital. But since the capital flows were in a decreasing trend after 2007, one of the solution is to increase the private savings. In 2002, the private savings was 22% but until 2006 it declined. In 2011, it was 13% despite of the recovery period it was the lowest domestic saving rate among large economies.[3] This reverse relationship can be explained by a precautionary savings. Decline in inflation feel households more secure about the future and they decided to save less. Also, households increase their borrowings because of an available cheap credit.

As we have mentioned above, for the capital inflow the liquidity is an important concept but to have an availability of liquidity the domestic factors have a crucial role. First, public services, education, health, level of trust cause an increase in total factor productivity (TFP) which resulted in a high growth rates in the long run. Between 2002 and 2006 about half of the growth in per capita GDP came from TFP growth which was increased by about 3% per year as Acemoglu et al. (2015) mentioned in their study. During this period the level of inequality of income and inequality in access to public services started to decline. The gini coefficient dropped from 42% to 38% in 2003 and 2008, respectively.[4] In addition, the gap of living standards between the big cities and suburbs became smaller. These improvements led to narrow the gap between Turkey and the rest of OECD countries during this period. Since, it is hard to measure these factors the second type of macroeconomic policies need to be discussed.

Stability idea will combine all the factors that we want to mentioned: inflation, interest rate, exchange rate, public debt, external balance all we can call if stability. The price stability is one of the most important stability indicator and is sensitive to the political events. Turkey was faced with a high inflation rate in the 1990s, then after 2001 crisis inflation felt to single digits. Barro (1995) explained the relation of inflation and the growth performance in his study. They displayed that an increase in average inflation by 10 percentage points will lead to an decrease in ratio of investment to GDP and a reduction of real per capita GDP growth by 0.2 to 0.3 percentage points. High inflation increased the uncertainty among investors and especially foreign investment may fall because they interpret the high inflation as a sign of economic instability. High inflation will cause an increase in the amount of public deficit. Private investments will decrease so the interest rates will be affected by this and public deficit will increase. So, depending of the inflation, the economic performance of a country will be affected.

All above macroeconomic parameters had an impact on the growth performance of Turkish economy. The last days of 1999 the economic situation of Turkey was not very decent. To improve the economic performance of Turkish economy, recovery program approved by the government when Bülent Ecevit was a prime minister. They passed the disinflation program with an agreement with IMF. Until on February 2001, where there was a severe attack in the TL[5], the program worked but then with the effect of the crisis Turkey entered to a poor economic performance period. On May 2001, Kemal Derviş, a well-known Turkish economist designed

[3]Source: data.worldbank.org; Retrieved 2016-02-15

[4]source: http://data.worldbank.org/data-catalog/world-development-indicators.World Bank development indicators; Retrieved 2016-02-15

[5]"Growth and economic crises in Turkey: leaving behind a turbulent past?", Mihai Macovei, Economic Papers 386, October 2009

a post-crisis stabilisation process and prepared Turkey's economic recovery program. After AK party came to power, the new government decided to continue with this economic program during three years with an aim of enhancing the Turkeys poor economic performances. Turkish economy grew very fast and this lead to relatively high productivity growth. The private investment increased sharply from an after crisis level of 12% GDP to around 22%. According to Gurkaynak and Boke (2013), during 2002-2006 Turkish economy grew 7,2% GDP on average and this is the most important reason of the success of AK party in the elections of 2007. (AK party won the elections with 40% majority.) Export oriented growth was also increased.

According to an overview about the Turkish economy above, we will focus on the last 15 years of Turkish economy by separating the whole period into five sub-periods. To see the before 2000 and to be able to compare the series we started from the second half of the 1998 but the real analysis will start from the beginning of 2000. Starting from the beginning of 2000, the first period will be until the 2001 crisis. Then, 2002-2006 period will be the second sub period which is the first four years of AKP in power. As we have mentioned above, the Turkish economy started to change in 2007, so we will focus on 2007-2009 period, until the end of global crisis. Then, we call the 2010-2011 period as a recovery period. And, finally the last three years, from 2012 to 2015 which we will examine the important events and discuss the effects on Turkish economy using the methodology that will be explained in Section 3 .

For our study, it is important to sketch the feature and the character of the Turkish economy. Our main goal is to discuss the changes of the network importance of Turkey for each sub periods that we define and link this with the properties of Turkish economy. Each sub period starts and ends with an important change or an important event for Turkish economy, thus, our purpose is to link the results that we obtained with the changes of Turkish economy.

Along with the macroeconomic perspective of Turkish economy political and economic events which affects the performance of Turkish economy and the growth performance is also important to discuss. We believe political and economic events have a significant role in the importance of a country relative to others. An event may change the trajectory of one country by affecting the policy of it and so may change the importance relative to the other countries. We focus on the important events especially for our last sub period, from 2012 to 2015, and we examine the effect of network importance of Turkey by creating a network of six stock markets which will be explained in Section 1.3.

There are several studies in the literature about the hypothesis of political economy that relate political events and stock markets. Our aim is to discuss the methodological results that we obtained about the network importance of Turkey in line with the events which affect the policy of Turkish economy. One of the oldest study about the relation of market moves and the event is the study of Cutler et. al. (1988). They focus on the effect of news on variance in aggregate stock return and examine of the political and world event coincide with the market moves. They found that not all news and events have an impact but some has on market of that country. They claim that relatively small market responses to a news or an event but large market moves often occur on days without any identifiable major news releases. The result is interesting for our study since they compare large and small economies and they analyze the effects of news on different economies. We suggest to examine this differences by using the network importance of a country and we believe network perspective has more results to say about the effects of a news or an event to the market moves. Another example is the study of Chesney et al. (2010). It emphasizes the impact of 77 terrorist attacks on stock, bond and commodity markets. They investigate the effect of terrorist attacks on different areas, such as on global financial markets, travel industry, oil and gas industry, on gold markets and bond markets. In addition, they analyze if the effect of terrorist attacks on financial markets are similar with on natural disasters and financial crashes. At the end, they found that approximately two-thirds of terrorist attacks lead to significant negative impact on at least one stock market. Even they investigate the impact of events on several financial markets, their approach is emphasizing every market separately and evaluate the impact of events on every market. They did not focus on the interaction among financial markets which we are doing with network perspective. The paper of Skoufias (2003) focuses on some of the ex-ante and ex-post strategies that public agencies can adopt. Paper discusses the effects of these strategies in protecting households and their members from the potentially adverse impacts of aggregate economy-wide shocks. For instance, some risk management strategies arrangements and strategies can be used for the protection of households in case of a crisis or a natural disaster. If the crisis affects a specific region of a country new policies can be defined about providing some insurance scheme, some food and nutrition help or a public work such as an infrastructure development project can be one of the possible public sector intervention in response to a crisis. In fact, aggregate shocks may affect market-based mechanisms such as borrowing from formal financial institutions so some policy need to be decided to protect the households from a potential shock. Since our sub periods of Turkish economy includes same type of events like crisis and conflicts we comment on our results in the empirical part of our study (Section 4,5 and 6) when we discuss the results obtained from the methodology of spillover and propagation.

Before applying the methodology and comment on our results, some important events for the Turkish economy is explained that we discuss in our study.

1.2 Events

To understand the impact of an event on other economic entities, event study methodology is used and it has many application areas to analyze the impact of the economic and political events of a country. There are many event studies of Turkey to understand the effect of particular events on the Turkish economy. For instance, Mandaci (2003) analyses the impact of general elections in Turkish stock market between 1991 to 2002. They are based on the studies which indicate that Istanbul stock exchange is not and efficient market and it is affected by the political and economic events. Their starting point is, under efficient market conditions investors could receive abnormal returns in the market and this returns are analyzed before and after the dates of general elections in Turkey. They resulted in that only after some elections investors has been received abnormal returns in the market. Since, our study assumes a network perspective and the purpose is to examine the network importance of Turkish market, an event study literature, for example the study of Mandaci (2003), is related but lesser than our perspective because they examine the stock markets in isolation. So, as we have explained in the Part 1, we don't use the methodology of event study because our purpose is to examine the importance of Turkish stock market with in the network and not only discussing the movements of Turkish market in isolation.

From 2000 to 2015 there are many important events that have an impact on Turkish economy. Especially, for the last three years, we will focus on the impact of these events using our methodologies explained in Section 3 and the application of the methodologies in Section 4, 5 and 6. We investigate the effects of events that are either a big surprise for the Turkish economy or it was an expected event or an expected result like an election etc. We discuss the results of the methodology using these events.

We will specify some of the important events that have happened in Turkey in recent years.[6] We will mention here especially political events and we discuss the results of other types of the events in the empirical parts of the study. The most important events in the year 2013 was the Gezi Park protests and Corruption Scandal:

- Gezi Park Protests (2013-05-31): First wave of demonstrations have started as complaints against the planned construction of a shopping mall and Taksim military barracks in the area of Gezi Park. Following days, the protests became wider and turned to an antigovernment demonstration. The increased tension of the police and protesters led to the protests quickly spreading all over Turkey, and turning into a protests to the country's leaders from just an environmental movement. "This was not an issue of trees any more" and during the demonstrations 44 people had been injured.[7]. After one month, on July 2nd, a Turkish court has canceled the reconstruction of Gezi Parki and the project.[8]

- 17/25 December, 2013, Corruption Scandal: Series of corruption investigations made public on Dec. 17 and 25, 2013, where several key people from Turkish government, including the son of the Prime Minister Recep Tayyip Erdogan, and many businessman have arrested. The investigations counted as the "biggest corruption and bribery scandal in the history of the republic." Observers see this as part of power struggle with former AK Party ally and influential US-based Muslim cleric Fethullah Gulen.[9]

The noticeable events in 2014 are as follows:

- Repo rate increase: On January 28, the one-week repo rate was increased from 4.5% to

[6] "A chronology of key events in Turkey", released 2016-02-15; http://www.bbc.com/news/world-europe-17994865

[7] "Police Storm Park in Istanbul, Setting Off a Night of Chaos", released 2016-01-22; available online at http://www.nytimes.com/2013/06/16/world/europe/protesters-in-turkey.html

[8] "Turkish court blocks disputed park project", released 2016-01-22; available online at http://www.reuters.com/article/us-turkey-court-taksim-idUSBRE9620T220130703

[9] "Highlights of major corruption, bribery operations of Dec. 17, 25", released 2016-01-23; available online at http://www.todayszaman.com/anasayfa_highlights-of-major-corruption-bribery-operations-of-dec-17-25_357703.html

10%, the overnight borrowing rate from 3.5% to 8% and the marginal funding rate from 7.75% to 12%.[10]

- Local Elections: On 30 March 2014, the nationwide local elections were held in Turkey. Prime Minister's party, Justice and Development Party (AKP) performed strongly in the elections and had over 45% of the vote.[11] The local elections were an important test for the AKP after the December 2013 corruption scandal. "One of the most interesting outcomes of the elections, is that despite the recent corruption allegations, leaks and increasing authoritarianism of the prime minister, AKP's voters did not penalize the party."[12]

- First direct presidential election in Turkey: On 10 August 2014, first direct presidential election was held to choose 12th president of Turkey. Recep Tayyip Erdogan was selected the new president of Turkey with 51.95%.[13]

- First operation to arrest the journalist from Gulen movement: On 14 December 2014 Turkish police arrested more than 24 senior journalists and media executives connected with the Gulen movement. operation started with Zaman newspaper. Police was raided the Zaman newspaper and arrested the paper's editor-in-chief Ekrem Dumanli.[14]

  The important events happened in 2015:

- Turkish General Election: On 7 June 2015 Turkish general election took place to choose 550 members to the Grand National Assembly. The pro-Kurdish leftwing People's Democratic Party (HDP) enters parliament at elections where AKP lost its majority in the parliament. Since 2002, this was the first time that Justice and Development party lost its parliamentary majority with a 40.9% of the vote.

- On July 2015, Turkey announces air strikes against Islamic State militant group after suspected IS suicide bomber kills 32 young activists at rally in Suruc, on the Syrian border. [15]

- Turkish General Elections: On 1 Nov 2015, the snap election was held to elect the new parliament of the country. After the election June 2015, the hung parliament's coalition

[10]Official website of Turkish Central Bank, released 2016-01-23; http://www3.tcmb.gov.tr/yillikrapor/2014/en/m-0-2.php#1
[11]"A referendum on Erdogan's rule", released 2016-01-24; http://www.economist.com/blogs/charlemagne/2014/03/turkeys-local-elections
[12]"Turkish local elections: One victor, many losers", released 2016-01-24; http://www.aljazeera.com/indepth/opinion/2014/04/turkish-local-elections-one-vict-20144211532875833.html
[13]"Erdogan emerges victorious in Turkish presidential elections a mid low turnout", released 2016-01-25; http://www.theguardian.com/world/2014/aug/10/turkey-presidential-election-ergodan
[14]Turkey arrests: Raids target Gulen-linked critics of Erdogan, released 2016-01-25; http://www.bbc.com/news/world-europe-30468199
[15]"A chronology of key events in Turkey", released 2016-02-15; http://www.bbc.com/news/world-europe-17994865

negotiations didn't come to a conclusion and the President decided a snap election. The Justice and Development Party regain the Parliamentary majority with 49.5% of the vote. So, AKP regains its parliamentary majority. After the election, Turkey shoots down a Russian military jet on Syria bombing mission. Russia, Turkey's second-largest trading partner, imposes economic sanctions.

1.3 The present study

The goal of this study is to assess the shock spillover characteristics of the Turkish stock market since 2000, with a view towards large-scale political and economic events within a network of six stock markets, each represented by a stock index, namely dji (USA), ftse (UK), sx5e (euro area), n225 (Japan), spec (China), these five entitled the "Systemic Five" economies in IMF (2011b, 2012) spillover reports, and xu100 (Turkey).

The network is defined as a directed weighted graph with the stock indices as nodes and weights given by shock spillovers. This perspective has the advantage of using only data available on a daily basis. A *network* perspective was found useful for our purposes because political and economic events won't affect the Turkish market *in isolation*; markets are actually linked and a network perspective allows to study "event repercussions".

We follow the methodology of Diebold and Yilmaz (2009) for the spillover methodology where we apply the spillover method using return and return volatility series. We examine the results of return and volatility spillovers and link them with the events explained in the previous section. The method of obtaining the volatility series is explained in detail in Part 1. Vector autoregressive (VAR) models fitted to daily stock index returns and volatilities can be used to derive the forecast error variance for each market index in the network, and to decompose this variance with respect to its origin: Which share of stock market volatility is due to shocks in which other stock market? This approach provides a framework to discuss pairwise shock spillovers, arranged in a so-called spillover table, and was proposed by Diebold and Yilmaz (2009, 2012, 2014). The spillover table is updated daily by fitting VAR models to a rolling window of return data. A VAR model can, in this sense, be adapted to measure return- and volatility-to-volatility spillovers in a network analysis. Schmidbauer et al. (2013b) developed an extended methodology to explain the further aspects of spillover tables and show how to define the "propagation value" of a market, which can be interpreted as the relative importance of a market as news propagator and measures an aspect of centrality of the market in the network.

The methodology uses a VAR in daily returns; it can thus assess daily return-to-volatility spillovers (for simplicity, called the *ret2vol* case in the following), that is, it permits to follow the network consequences (in terms of return volatility) of a return shock to a market. It is also possible to fit VAR models to daily return volatilities (instead of returns themselves), and proceed as before; this approach can quantify volatility-to-volatility spillovers (the *vol2vol* case), that is, the network consequences (in terms of volatility risk) of a volatility shock to a market. Both concepts — *ret2vol* as well as *vol2vol* — are used in the present study. The main purpose of our study is to analysis the difference of ret2vol and vol2vol spillovers and also compare them with propagation value to understand the effect of an event into the network importance of Turkish stock market.

More specifically, our study focuses on the following objectives:

1. Assess the magnitude of *direct* daily ret2vol and vol2vol spillovers from the Turkish stock market (that is, from xu100) to other markets (to other nodes) in the network. In this case we use the spillover methodology.

2. Assess the relative importance of the Turkish stock market as a return or volatility shock propagator in the network. This perspective complements objective 1 insofar as it accounts for aftereffects of a one-time shock. Here we use daily propagation values.

3. Provide insight into the network repercussions of an initial shock, that is, into how the network ultimately digests shocks in the Turkish stock market. This amounts to a comparison of network importance (objective 2) and direct spillovers (objective 1). In this case, we develop a methodology to compare the propagation values and direct spillover.

For these three purposes in the volatility case we need to obtain the volatility series. The method to provide the volatility input series is explained in detail in Part 1. Also we explain the method briefly in Section 3.2. By using all results that we obtained from the three methods explained above, we examine the potential effects of political and economic events, by using our sub periods, and we link the results with these events.

Consequently, this paper continues with the empirical data which is the daily stock index quotations from six markets used in the present study in Section 2. In Section 3, we first review the theory underlying the spillover perspective (objective 1 above) and then introduce a new methodology to discuss objectives 2 and 3. The subsequent sections report and discuss empirical results concerning objective 1 (Section 4), objective 2 (Section 5), and objective 3 (Section 6). Section 7 summarizes and concludes the paper. — All computations were carried out with scripts written in R (2015).

2 Data

The empirical starting point of the study consists of daily closing quotations of the Turkish stock index (xu100) and the five stock indices representing stock markets in the "Systemic Five" countries: Dow Jones Industrial Average (USA; dji), FTSE (UK; ftse), Euro Stoxx 50 (euro area; sx5e), Nikkei 225 (Japan; n225), and SSE Composite (China; ssec). The series begin with 1998-03-03 (the first day for which all six series were available) and end with 2016-03-18 (4696 observations). The series of daily simple returns in percent are plotted in Figure 1.

Obtaining daily volatilities is a prerequisite for investigating volatility-to-volatility spillovers. This requires further daily data, namely opening, high, and low, in addition to daily closing quotations.

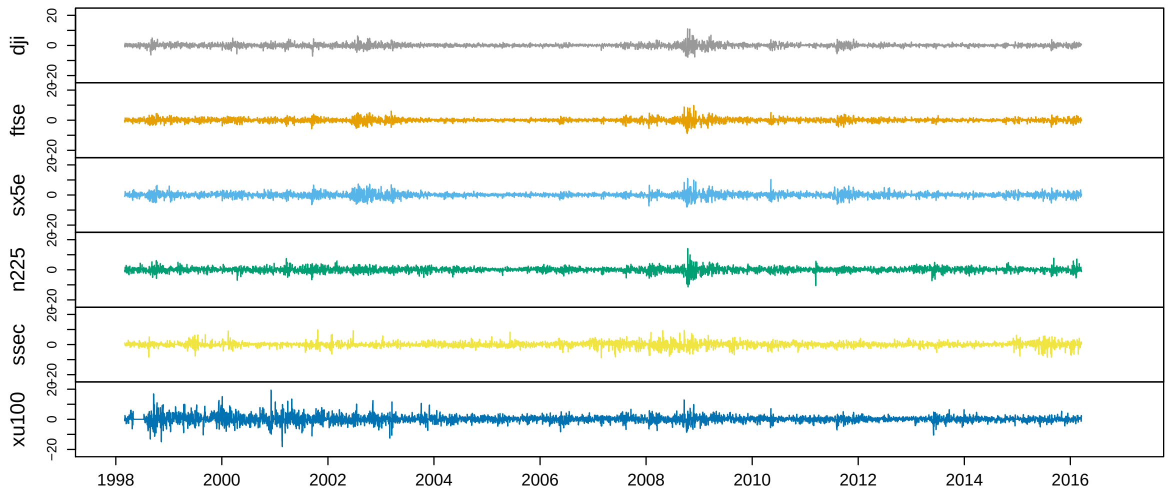

Figure 1: The series of daily returns

3 Measuring spillovers and shock repercussions

3.1 Return-to-volatility spillovers ("ret2vol")

Direct spillovers

Let $(x_{kt})_{t=1,\ldots,T}$, where $k = 1, \ldots, N$, designate N series of daily price changes (simple returns in percent); N is the number of stock markets in the network. The methodology used in the present paper builds on the spillover matrix by Diebold and Yilmaz (2009, 2014) and extensions developed in Schmidbauer et al. (2013b). For a given day t, the spillover matrix is a matrix $\mathbf{M} = (m_{ik})_{i,k=1,\ldots,N}$ (we drop the index t, for ease of exposition) with row sums equal to one, that is, $\sum_{k=1}^{N} m_{ik} = 1$, where each row $(m_{i1}, \ldots, m_{iN})$ provides a breakdown of the forecast error variance of x_i into shares with respect to its origin. In this sense, m_{ik} is the share of variability in x_i due to shocks in x_k. For example, in the case of $N = 3$ markets, a spillover matrix

$$\mathbf{M} = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.3 & 0.6 \end{pmatrix}, \tag{1}$$

means that 60% (20% each) of forecast error variance of x_1 is due to shocks in x_1 itself (shocks in x_2 and x_3, respectively). In other words: 40% of the volatility in market 1 is due to spillovers to market 1 from markets 2 and 3. Considering the first column of $\mathbf{M}$, an "aggregate share" (column sums need not add up to 1) of 0.2 is spilled over from market 1 to markets 2 and 3, making market 1 a net receiver. Market 2 is a net giver.

Direct spillovers from market k (or to market i) are then given by the column (row, respectively) sums in $\mathbf{M}$, excluding the market's spillovers to itself:[16]

$$\text{from market } k \text{ to others: } \sum_{i=1, i\neq k}^{N} m_{ik}; \qquad \text{to market } i \text{ from others: } \sum_{k=1, k\neq i}^{N} m_{ik} \tag{2}$$

In social network terminology, with $\mathbf{M}$ interpreted as adjacency matrix of a weighted directed network of nodes, these aggregates are the from-degree of node k (to-degree of node i, respectively).

For a given day t, the spillover matrix $\mathbf{M}$ is obtained as follows: Fit a standard VAR model of order 1 to the N return series, using data from a window of size 100 (that is, days $t-99, \ldots, t$). We follow Diebold and Yilmaz (2014) which is explained in detail in Part 1, namely: to identify the impulse response function of a component (here, x_k), give highest priority to that component; this removes the dependence on an imposed hierarchy of markets. Forecasting n steps ahead (we use $n = 5$), forecast error variance decomposition (fevd) yields forecast error variance shares $(m_{i1}, \ldots, m_{iN})$. This procedure is then applied for every t, resulting in a sequence of spillover matrices.

Relative importance of a market: propagation values

We only explain a summary of the methodology on propagation values since it is explained in detail in Part 1. Let $\mathbf{M}$ again denote the spillover matrix for day t. We assume that $\mathbf{M}$ contains all relevant, and the most recent available, information about the network. A hypothetical shock ("news", "information") of unit size in market k on day t can be denoted as $n_0 = (0, \ldots, 0, 1, 0, \ldots, 0)'$, where 1 is in the k-th component of n_0. We assume that the propagation of this shock across the markets within day t will take place in short time intervals of unspecified length according to

$$\mathbf{n}_{s+1} = \mathbf{M} \cdot \mathbf{n}_s, \quad s = 0, 1, 2, \ldots \tag{3}$$

(where step $s = 0$ initializes the recursion). The index s in Equation (3) therefore denotes a step in information flow. Moreover, assuming that information flow across markets can proceed instantly on day t, with spillover conditions (given by $\mathbf{M}$) persisting throughout day t, it makes sense to investigate steady-state properties (as $s \to \infty$) of the model defined by Equation (3). This leads to

$$\mathbf{v}' = \mathbf{v}' \cdot \mathbf{M}. \tag{4}$$

When the left eigenvector $\mathbf{v} = (v_1, \ldots, v_N)'$ is normed such that $\sum_{k=1}^{N} v_k = 1$, we call v_k the propagation value of market k. It renders the value of a return shock in market k as seed for future uncertainty in returns across the network of markets:

$$v_k = \sum_{i=1}^{N} m_{ik} \cdot v_i \tag{5}$$

[16] Spillovers from market k to others, plus spillovers to itself, need not sum up to 1.

For $\mathbf{M}$ as in Equation (1), $\mathrm{v}' = (0.2, 0.4, 0.4)$, which means that a shock in market 2 is twice as powerful ($0.4/0.2 = 2$) as a shock in market 1 in terms of creating network volatility. — A similar concept, eigenvector centrality, is also used in social network analysis; see, for example, Bonacich (1987).

Network repercussions of a shock

Quantifying the network repercussions is an methodological innovation different than Part 1 where we explain every steps of the methodology and our contribution about the spillovers and propagation values. Direct spillovers from market k to others measure the *direct* impact of a shock in x_k on day t, without consideration of immediate (that is, also happening on day t) network repercussions of the shock. The propagation value of market k, in contrast, emphasizes the importance of shocks in x_k within the network, including repercussions throughout the network. Owing to different magnitudes, direct spillovers from market k and propagation values of market k cannot be directly compared. However, they can be related to each other via a regression

$$\text{propagation value}_t = \alpha + \beta \cdot \text{spillover}_t + \epsilon_t, \tag{6}$$

where propagation value$_t$ (spillover$_t$) denote the propagation value of market k (direct spillovers from market k, respectively) on day t. The residuals ϵ_t can be interpreted as propagation values (or relative network importance) of market k, from which direct spillovers have been computationally removed. What remains is a measure of network repercussions of a direct spillover, that is: the repercussions of a one-time shock in market k throughout the network, once again assuming that the spillover matrix is the only relevant information structure for a given day. Therefore, ϵ_t indicates which effect is prevailing:

$$\epsilon_t \begin{cases} > 0: & \text{network repercussions are more important than direct spillovers on day } t, \\ < 0: & \text{direct spillovers have little repercussions in the network on day } t. \end{cases} \tag{7}$$

This methodology will be applied in Section 6, where market k designates the Turkish stock market.

3.2 Volatility-to-volatility spillovers (“vol2vol”) and propagation value

The methodology outlined in Section 3.1 can also be applied to a set of series $(x_{kt})_{t=1,\dots,T}$ of daily volatilities, instead of returns (Diebold and Yilmaz, 2009). One difficulty to overcome is that daily volatilities cannot be directly observed and need to be reconstructed. Following Diebold and Yilmaz (2009), we use a method proposed by Garman and Klass (1980), based on the hypothesis that the stock price process is a geometric Brownian motion, to obtain daily variances. Their method results in the following formula which we have discussed in Part 1:

$$\begin{aligned} \hat{\sigma}_t^2 \;=\; & 0.511(H_t - L_t)^2 \\ & -0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] \\ & -0.383(C_t - O_t)^2, \end{aligned} \tag{8}$$

where O_t (H_t, L_t, C_t) designate the natural logarithm of the daily opening price (daily high, daily low, daily closing, respectively) on day t. After obtaining a daily variance series for each market considered, a sequence of spillover matrices — updated daily — can be computed, leading to daily direct spillovers as well as to daily propagation values. In this case, direct spillovers characterize volatility-to-volatility spillovers, while the propagation values quantify the importance of a market with respect to the propagation of a volatility shock across markets, that is, the value of a volatility shock from that market as seed for future uncertainty in volatility across the network of markets.

After obtaining the volatility series using the methodology explained above we apply the methodology of spillover and propagation value using the return volatility series. Also, we quantify the network repercussions of Turkish stock market by using the volatility series and we compare the results of the methodology by using return series and volatility series. The methodology outlined in this section will now be applied to the data described in Section 2. In view of our focus on the Turkish economic history, results will be reported and discussed in the following three sections.

4 Direct spillovers from and to xu100

This section reports the first part of spillover characteristics of the Turkish stock market, namely direct return and volatility spillovers, without considering potential aftereffects of a shock. The subsequent Section 5 and 6 will give more detailed interpretations, using the methodological innovations (propagation values and network repercussions) introduced in Section 3.1 and 3.2. Attention will be given to the following periods and events which have explained above in detail. Same periods also will be examined in Section 5 and 6.

- Period 1 (roughly, July 1998 - end of 2001): Period covers the pre and post periods of crisis in 2001, which started in the first half of 2001. On February 2001 the financial crisis started and on May 2001 a new economic program established to stabilize the post crisis period. In addition, on August 1999, a severe earthquake took place in Turkey with an extensive damage and killing around 17.000 people in terms of reports. Period ends at the beginning of 2002 where the new program endorsed by IMF and World Bank started to affect and some structural changes started.

- Period 2 (roughly, beginning of 2002 - end of 2006): The period was full of development and the growth performance of Turkish economy was very high during these 4 four years. On November 2002, general elections took place in Turkey and AKP was in power in the first time.

- Period 3 (roughly, beginning of 2007 - end of 2009): The period started at the turnover point of Turkish economy which was the beginning of 2007. Almost all economic indicators started to change and the successful days from 2002-2006 has remained behind. One of the most important event for Turkish economy was the investigation into the "Ergenekon" case which was on June 2007. The period continued with the global financial crisis which lasted until the second half of 2009.

- Period 4 (roughly, beginning of 2010 - end of 2012): After the crisis the recovery period has started for the Turkish economy. Even if it was not as good as the 2002-2006 period, the economy started to grow again. On June 2011 parliamentary elections in Turkey took place AKP won the 50% of the votes.

- Period 5 (roughly, beginning of 2013 - beginning of 2016): The growth performance of Turkish economy became smaller. The most important political events happened during this period which are Gezi park protests and 17/25 December corruption scandal had a severe impact on Turkish economy. On March 2014, access to YouTube blocked one day after showing a leaked National Security meeting conversation. A big explosion on May 2014 happened in coal mine in Soma causing an underground mine fire with 311 people killed. We especially analyze the results of this period in the discussion part by discussing the effects of the events.

4.1 The case return-to-volatility (ret2vol)

This section we will examine the results of return-to-volatility spillovers explained in the first part of Section3.1. We discuss the results with the character of Turkish economy which we have discussed in the introduction part. We leave the comparison of the results with important events of Turkish history in the discussion part. The daily series of direct return spillovers from xu100 to others and from others to xu100 are displayed in Figure 2. Return spillovers to xu100 have always been higher than return spillovers from xu100 until the end of 2006. So, the Turkish market has been a net receiver of return shocks before 2007. But after the third period the story has started to change and from xu100 exceeded in some intervals. In period 5, where it started from 2012, Turkish market again became a net receiver with a higher 'to xu100' direct spillovers. In addition, the character of the spillover index was changed after 2007. The whole period can be divided into two sub periods: before and after 2007. Both spillovers were more volatile before 2007 and the connectedness is low during this period. But, after 2007, the fluctuations became smaller and the connectedness increased. Further observations about the period specific direct spillovers are as follows:

- Period 1: The first half of the 1999, both from and to spillovers increased and they moved together. On August 1999, both spillovers went down sharply which coincides with the days of a severe earthquake in Turkey. Until the beginning of 2001 from and to return spillovers are in a similar pattern and both in a very low level. On February 2001, to xu100 received a significant boost, which is the first days of the financial crisis, while spillovers from xu100 was not responded to this event immediately but both started to increase after a couple of days.

- Period 2: The direct spillovers were still in a volatile period. There were no big spikes during this period but from and to spillovers were in an increasing trend and continued to rise until the end of the period. Since, during the whole period to xu100 direct spillovers were higher than from xu100 spillovers, Turkey was a net receiver of return shocks when the Turkish economy was improving and the growth performance was very high.

- Period 3: In the whole period, the spillovers were higher than other periods and at the beginning of 2008 the direct return spillovers were in its peak value. This means that Turkey was much more integrated in this period than before. Since the level was very low before, Turkey started to grown up with the beginning of the third period, on 2007. On mid-2008, there was a sharp decrease on both return spillovers, but especially 'from xu100' was responded more to the shocks. It decreased from 50 to 15 level on mid-2008 where the global financial crisis has just started.

- Period 4: The gap between from and to return spillovers was very narrow in period 4. During the recovery period, the spillovers was lower than period 3 but still with a remarkably high level. Both spillovers decreased on 2011 for a short period of time but at the second half of 2011 it reached again to high levels.

- Period 5: Starting from 2012 the spillovers were in a decreasing trend and the overall period the spillover level was lower than in period 3 and 4. There were two spikes during the whole period where the first one coincides with the Gezi park protests on May 2013 and the second one with the corruption scandal on December 2014 but the responses to this events was not very high for the return spillovers cases.

4.2 The case volatility-to-volatility (vol2vol)

We examine the volatility spillovers using the methodology explained in Section3.2. We leave the comments related with events in the discussion part. The daily series of direct volatility spillovers from xu100 to others and from others to xu100 are displayed in Figure 3. At first view, volatility spillover patterns are more distinct than those of return spillovers. Like in the return case, on general, the Turkish market can be counted as a net receiver of volatility spillover. The pattern of volatility spillovers was very different than the return and some fluctuations can be related with certain events which can not be distinguished in the return spillover case.

- Period 1: As we have mentioned in the return spillovers, in mid-1999 there were a sharp decrease in return spillovers which coincides with the earthquake disaster in Turkey. The sharp decrease was observable in from xu100 volatility spillovers unlike the return. At the beginning of 2000, both volatility spillovers started to increase.

- Period 2: The whole period was with a lot of fluctuations and the direct spillovers was lower comparing with the other periods. From and to direct spillovers were different and they were not move together, so we cannot distinguish if the Turkish market is net receiver or net sender for this period unlike the return case. Starting from 2004 both spillovers started to increase where the growth of the Turkish economy began faster.

- Period 3: With the third period the story has changed and the volatility spillovers had less fluctuations and the level increased. Unlike in the return spillovers, the volatility ones are still distinct and from xu100 spillovers did their peak value in the beginning of 2008. After a sharp increase, both spillovers drop to their average value of this period. The decrease coincides with the days of global financial crisis.

- Period 4: The gap between from and to spillovers was still large and from xu100 spillovers have much more fluctuations than the returns. As we have mentioned in the introduction part we can call the period as a recovery period for Turkish economy. The spillovers were not very high but starting from 2011 they were in an increasing trend.

- Period 5: The from and to spillovers still had fluctuations especially from xu100 spillovers had many. The biggest spike was at the end of May 2013, from xu100 received a significant boost at this date, which is the first weekday after the Gezi park protests. The from and to return spillovers was less responded to this event unlike from volatility spillover. Later 2014, a huge drop happened in both volatility spillovers and it stayed almost the same level for a couple of days and then gradually increased. The drop of spillovers coincides with the date of corruption scandal on December 2014 while the effect was not distinguishable for the return spillovers.

4.3 Discussion

During the whole period, although the return and volatility spillovers had different characters, both has responded to the political and economic events. We can clearly deduce that even return and volatility spillovers had different amount of responses to different events the spillovers are period specific and the political events have impact on the stock market network characteristics. The pattern of return spillovers for from and to xu100 was very similar and they were generally moved in a same direction during the whole period. The ret2vol spillovers indicate that Turkey is much more integrated to the network after 2007, where the level of spillovers increased and there were less fluctuations in direct spillovers. Unlike the return, it is harder to analysis the process of volatility spillovers, from and to xu100 patterns are distinct and they were not move together. But, unlike the return spillovers the responses to a political or economic event is much more clear in the volatility spillover case.

We concluded that there is a correlation between the network characteristics of Turkish stock market and political events that Turkey is affected from. We constructed our sub-periods such that each one starts and ends with an important episode for Turkish economy. It is either be a specific date of an event or a time course where Turkish economy is influenced by them. When analyzing both return and volatility spillover we divide events and the changes of Turkish economy into two parts: first one is the events or changes that were expected by the market and second one that were unanticipated by the market. For example, we see that both return and volatility spillovers react immediately after the earthquake. Even it is not a political event but a natural disaster because the event is a surprise for the investor we see the impact on the market immediately. Similarly, as we have explained, the first elections when AKP won the majority in the parliament was an unexpected event for the market even the date of the election was announced earlier. We conclude that the elections in November 2002 has the most immediate and distinguishable election among other elections in the return and volatility spillovers. Another example is the Gezi park protest which has began at the end of May and it create reactions within a very short period of time. Even it was not a 'surprise' event like an earthquake, the way and the speed of expansion make the event as unexpected which we can see in the return and volatility spillover immediately after the Gezi park protests.

Santa-Clara et.al. (2003) examine the relation of excess return in the stock market and the election dates. Although the method is completely different than ours they found that difference in returns decreases monotonically with the market capitalization of firms. They argue that the amount of the fall is depend on the size of the company and it is also related with the type of the party that won the election. If the difference in returns was expected by the market they see a large price adjustment around the time when it becomes known which party wins the election. Then, as we have observed in many election date cases in the spillover results they also see no such move in prices in this case. As an example for the

Gezi park protests Guidolin et.al. (2010) examine the effect of a conflict on asset markets and they resulted in that it has a significant impact on stock markets. They showed that internal and inter state conflicts has a higher fraction of significance than for international conflicts. We concluded a similar result that Gezi has higher effect on the spillover rather than other international conflict.

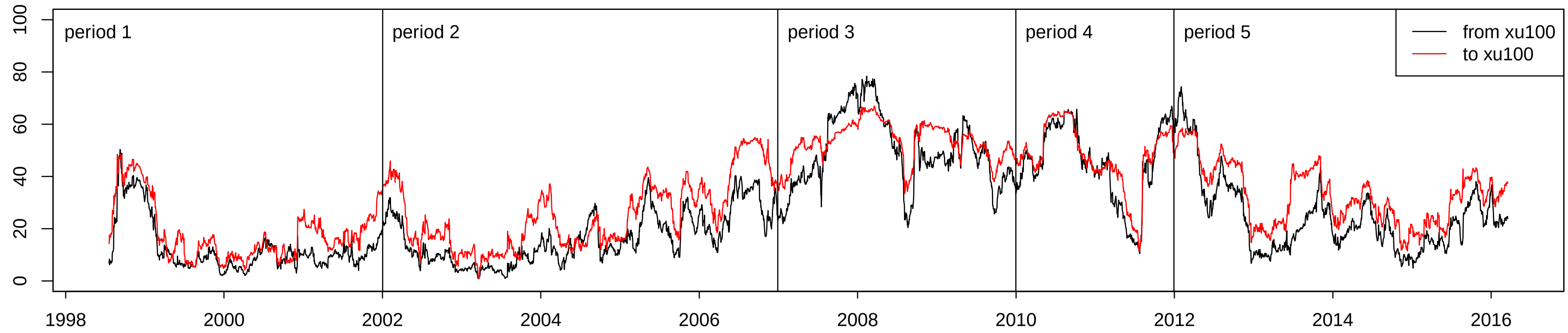

Figure 2: Direct return spillovers (ret2vol) from and to xu100

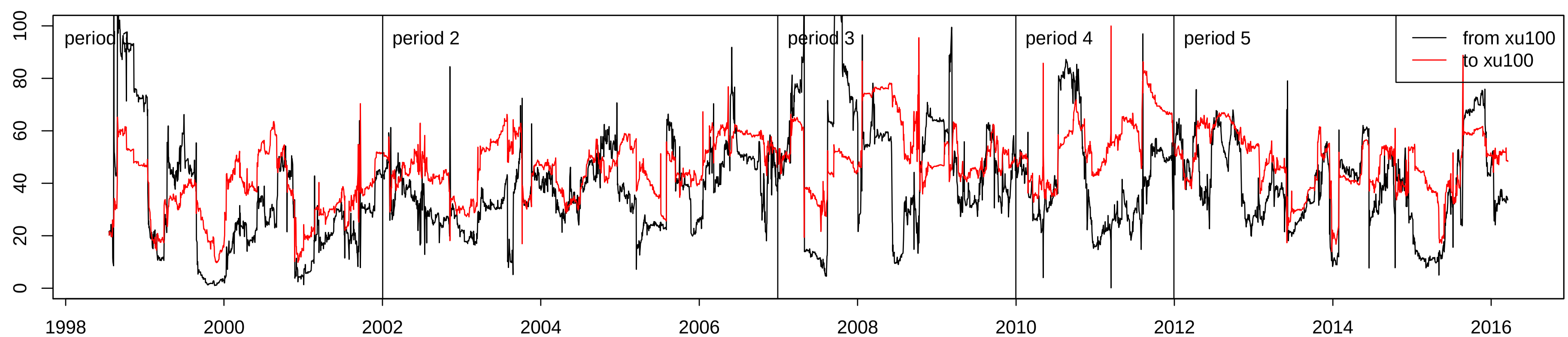

Figure 3: Direct volatility spillovers (vol2vol) from and to xu100

5 Propagation values: relative importance of the Turkish stock market

Similar as in the spillover part we examine the return and volatility propagation values We discuss this focusing on the sub periods of Turkish economy. Then in the discussion part we compare the results that we obtained from the methodology and the selected events. This section reports the second part of spillover characteristics of the Turkish stock market, namely its relative importance as a return (ret2vol) and volatility (vol2vol) shock propagator in the network of the "Systemic Five" plus xu100, measured using the corresponding propagation values. Propagation values of xu100 will be compared and related to those of the "Systemic Five" in the discussion below.

5.1 The case return-to-volatility (ret2vol)

Figure 4 displays the time series of propagation values of xu100 in the ret2vol case, for the period from July 1998 through March 2016. The relative importance of Turkey as a shock spreader are different among periods, so, the network importance of Turkey is period specific. There is a visible structural break in 2007 in the propagation values of ret2vol. The periods after 2007 was more homogeneous than the previous periods. Persistently high levels of network importance of xu100 are observed after 2007 while it was started to decrease after 2014. Detailed explanation about period specific propagation values are as follows:

- Period 1: The network importance of Turkish stock market was not homogeneous in this period. The propagation value was 0.13 on average until the indications of financial crisis has started. In the time of crisis on February 2001 the network importance of xu100 made an abrupt downward shift. Then, just after the government introduced a new economic program endorsed by IMF, the network importance started to increase gradually.

- Period 2: The network importance was in an increasing trend during this period. Before and after the general elections on November 2002, the network importance was very shaky. Starting from the beginning of 2004 the relative network importance of Turkish stock market has started to increase. As we have mentioned above in the high quality growth period, the network importance of Turkey was in an increasing trend especially after the general elections.

- Period 3: There is an important structural difference with the beginning of period 3. As we have explained the reasons in the previous section, after 2007 the economy started to change, the growth in Turkish economy became smaller and with the global crisis hit the growth remained low during 2008-2009. The relative network importance of Turkey became much more homogeneous than the previous two periods. We didn't see fluctuations as in period 1 and 2. During the period, the propagation values were in a high level, 0.18 on average which was one of the highest value from 2000 to 2008. Especially just after the subprime crisis, mid 2007, the network importance of Turkey made an abrupt upward shift. So, what is coming from Turkey was became more important in the third period. The reason of this increase might be because the other countries was also struggling with the global financial crisis, and because the others were shakier, the importance of Turkish stock market was increased.

- Period 4: Starting with the 2010 the recovery days for Turkish economy was started. The propagation value was still homogeneous like the previous period and it remained pretty much constant during the whole period.

- Period 5: At the beginning of the period the network importance of Turkish stock market was in a despising trend, as we know from the economic history that explained in the previous sections the growth performance of Turkish economy is smaller during the beginning of the period. Persistently high levels of network importance of xu100 are observed in the first half of 2014. The maximum network importance for this period was in the beginning of June 2013 which coincides with the Gezi Park protests. Just after the Gezi park protests, the network importance of xu100 rose sharply and during the protests week it stays in a very high level than before. On mid-june the network importance of Turkey falls at the May 2013 level with a little upward shift. On the December 16, the structure of the propagation value has changed and became volatile which coincides with the beginning of the corruption scandal, on December 17. So, for 2013 we resulted in that in two cases the propagation value has an important change in its structure. From mid 2013 the network importance was started to increase even it was more volatile during the corruption scandal, it was in an increasing trend. After December 2014 the propagation value became stable until the beginning of June which coincides with the date of general elections on Turkey. On 2015, the propagation value was in an increasing trend and more volatile. The sharp decline on 2015 coincides the date of general elections on June 2015.

5.2 The case volatility-to-volatility (vol2vol)

The character of the propagation values of xu100 in the vol2vol case was different than the ret2vol. In volatility case the network importance of Turkey has much more fluctuations than the return case. In the first two periods the relative market importance of Turkey has many spikes and it was not homogeneous. After 2007, even the structural break is not clear as in the return case, starting with period 3 the network importance is less heterogeneous.

- Period 1: The network importance of Turkish stock market had many fluctuations in this period. The relative network importance was very little at the beginning of 2000 but it started to increase gradually until the beginning of 2001 where the financial crisis started. The network importance of Turkey was relatively high before the crisis but immediately after the crisis the importance disappeared. Until the beginning of 2002 where the Turkish economy started to improve, the relative network importance of Turkey was not high but after 2002 it entered into an increasing trend.

- Period 2: The network importance was in an increasing trend for the whole period. As in the return case, the relative network importance of Turkey was very shaky, before and after the general elections. Especially after the general elections in 2002 the relative network importance was its highest value from the beginning. Starting from the beginning of 2005 the propagation value was started to rise and became more homogeneous. As we mentioned in the introduction part the economy was in a good situation and the growth rate of Turkey was high during the period of 2002-2006, the network importance of Turkey was increasing in this period. So, among all the countries the importance of Turkish market in the network is more important then in the previous periods.

- Period 3: As we have mentioned above the 2007 was an important year in the Turkish economic history. The successful periods started to became an end with a forthcoming crisis. As in the return case there is a structural change in the network importance of Turkey. The propagation value of Turkey in the volatility case was not calmer as in the return, there were still big spikes but it was more homogeneous. Starting from the mid 2007, the relative importance of Turkey was decreasing which coincides with the subprime crisis. But after 2008, where the global financial crisis has started, although Turkey was also affected from the crisis, the propagation values was increasing. What was coming from Turkey was became more important after the global financial crisis. Since, the other network member was also affected from the financial crisis it worth look at the general relative network importance of all markets and examine the reason of the behaviour of the propagation value in this period. The analysis will be done in the discussion part of this section.

- Period 4: During the recovery days of the Turkey the propagation values was not very high. Staring from mid-2011 it started to increase.

- Period 5: During 2012 the propagation value did not change. Since the beginning of the period the growth performance of Turkish economy became smaller, there were no such big changes in terms of the relative importance. At the first days of June 2013, the relative market importance did a huge jump and the network importance was in its maximum value which is the date of the first weekday after the Gezi park protests. Just after the Gezi park protests the network importance of xu100 rose sharply and during the next two weeks it stayed in a high level. Until the end of 2013 the relative network importance was in a shaky level. During the second half of 2013, the network importance if Turkey was very volatile which period includes the corruption scandal on December 17. Starting from mid 2015 the network importance was in an increasing trend until the beginning of 2016.

5.3 Discussion

We find evidence from the ret2vol and vol2vol propagation values that we can define subperiods where the relative importance of Turkey as a new spreader are distinct. Turkey as a shock spreader changed during the periods. Even the ret2vol and vol2vol propagation values had different pattern in the whole interval they have similarities in terms of breakpoints and responses to shocks. The relative importance of Turkey in the return to volatility case has a visible structural break in 2007 after this date is was more homogeneous than the previous periods. In volatility case, the network importance had more fluctuations than the return case but still the structure changed after 2007 and the responses to some specific events were more clear than the return case. As we have mentioned earlier, Skoufias (2003) examined the impact of a crisis on stock markets. They discuss the strategies that public agencies can adopt on case of a financial crisis. Especially in period 1 and 3 we have two important crises that Turkish economy is affected from. From the results of volatility propagation value, we see the effects of the crisis immediately.

By now, we investigate the network importance of Turkish stock market by only showing the results of Turkey. Now, in Figure 6 and 7 show stacked plots of all the propagation value series in the network of the ”Systemic Five“ plus xu100. By definition, propagation values sum up to 1 each day. By force of these figures, the propagation value of Turkey is examined in a broader perspective since all propagation values of network members are included and the impact of other large-scale events are seen. Considering return shocks, the three Western markets are dominating the network with almost same level of propagation values. Unlike the volatility shock propagation, the return shocks were much more stable and there were less fluctuations. It is hard to distinguish the impact of important events in the return shock propagation. In volatility shock propagation, there are a lot of fluctuations where at the beginning of 2007 there were one of the most observable jump in the propagation value of dji. As we have mentioned in Section 1.2 in mid 2007 the subprime crisis happened and the economic situation of Turkey as well as the other members of the network has started to change. On 2007 the relative importance of dji was increasing until the beginning of 2008 where the global financial crisis has started. On the other hand, in the return shock propagation we can easily argue that after 2007 the relative importance of Turkey has increased. We have known that 2007 is a turnover point for Turkish economic history the successful days between 2002-2006 got behind and a new period started. This situation lasted until the beginning of 2012, then the relative network importance of Turkey was decreased. In the volatility case, as in the return case after 2007 the relative importance of Turkey is increasing but with more fluctuations and the volatility shock propagations are more sensitive to an event rather than the return.

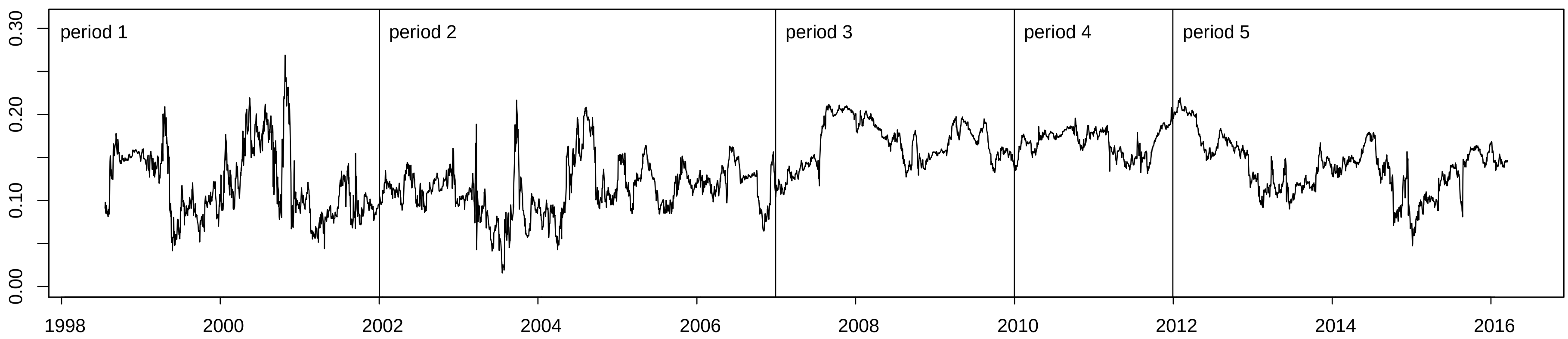

Figure 4: Propagation values of xu100, ret2vol

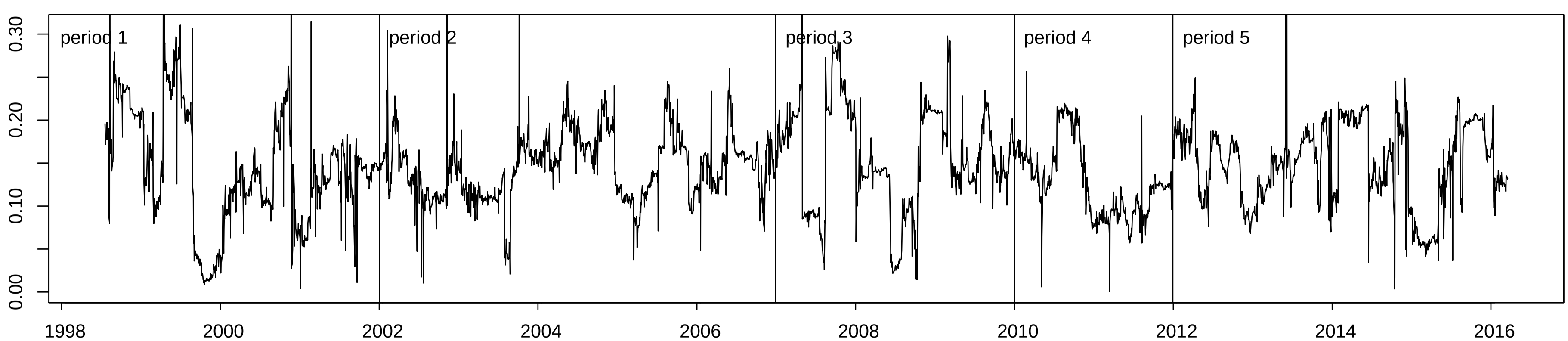

Figure 5: Propagation values of rts, vol2vol

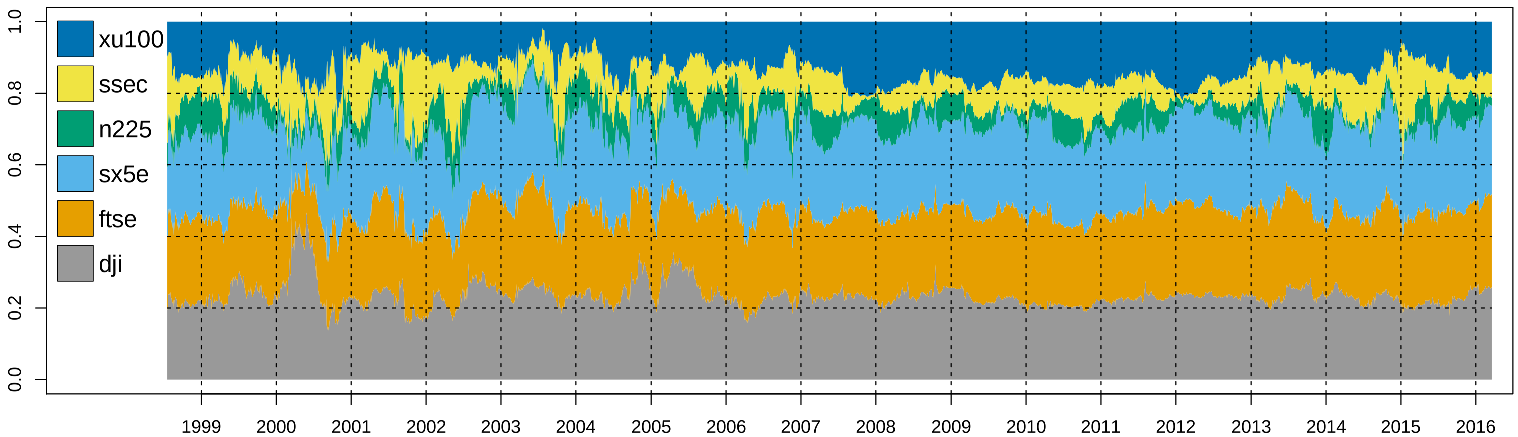

Figure 6: Propagation values, ”Systemic Five“ plus xu100, ret2vol

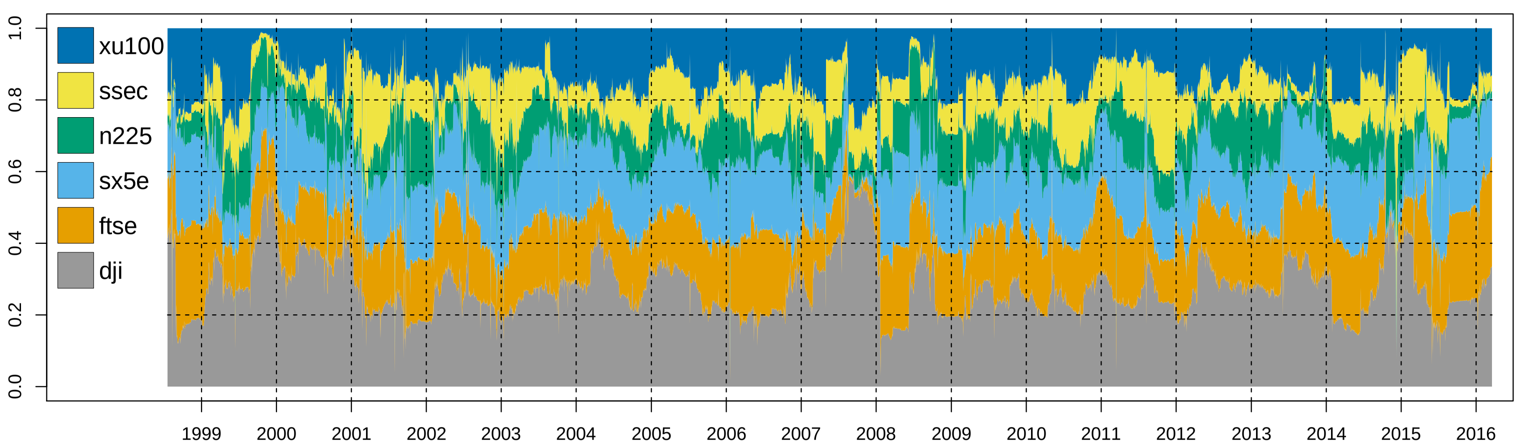

Figure 7: Propagation values, ”Systemic Five“ plus xu100, vol2vol

6 Network repercussions of shocks in the Turkish market

The section reports the third part of spillover characteristics of the Turkish stock market, namely network repercussions of return and volatility shocks in the Turkish market. As we have concluded from the figures of spillover and propagation value that they have similarities in many cases. But also, the pattern of the two differs in many cases in the whole period. Since a direct comparison of both series is not meaningful, we developed a methodology to compare the spillovers and propagation values. We run a regression and the regression residuals are able to release whether direct spillovers or network importance surpass at a given time. A residual close to zero indicates that direct spillovers and network importance are equal, while positive (negative) residuals indicate that network importance (direct spillovers) outweighs directs spillovers (network importance, respectively). The two residual series (ϵ_t), one for each spillover perspective, are plotted in Figures 8 and 9 from 1998 to 2016. The standardized series will be analyzed in the following.

6.1 The case return-to-volatility (ret2vol)

In Figure 8 the network repercussions of return shocks is shown. As in the propagation values and spillover index, we can distinguish two different behaviour in the network repercussion at first sight: before and after 2007. Even if the most visible structural change was before and after 2007, every period has its own character which is explained as follows:

- Period 1: The first period is very shaky in terms of network repercussions and generally it is above the zero level. In first period, the network repercussions of Turkey are generally more important than spillovers from Turkey to others. The beginning of the period the regression residuals was a level of zero but with an increasing trend. Starting from 2000, the network importance increasing so Turkish stock market started to leave effects on the network. Until the end of 2000, the network repercussion of Turkey was always above zero. At the beginning of October 2000, the repercussion of return shock jumped and reached in its maximum level in the whole period. Starting from 2001, which coincides with the beginning of financial crisis, the network repercussions lower and even below zero, which means that direct spillovers from Turkey is dominated but network ignores.

- Period 2: The second period was similar to the first one in terms of fluctuations but the quantity is less than the first one. The repercussions of a return shock from Turkey is not stable during the period from 2002 to 2006. Like in the previous period there are jumps and drops which coincides the shiny periods for the Turkish economy.

- Period 3,4 and 5: There is a huge difference in the network repercussions starting from the third period. The character of repercussions completely changed and it became much more stable than before. There were not big jumps and drops after 2007 and the level is always around zero. So, after 2007, where we know that the economy getting worse comparing with the period 2002-2006, direct spillovers and network importance are on a par and neither of them were dominated.

6.2 The case volatility-to-volatility (vol2vol)

The plot of network repercussions of volatility shocks is shown in Figure 9. Unlike the repercussions in return shocks, the series of regression residuals are close to zero, except a lot of spikes during the period. Although there are more jumps in the volatility case, except the jumps, the residuals are almost always being on the level of zero. The repercussions in volatility case are tend to have big spikes rather than drops. In addition, in the volatility case it is harder to distinguish a structural change among periods as it was in the return case. The period specific vol-to-vol repercussions and examination of booms for each period are as follows:

- Period 1: The whole period the vol-to-vol network repercussions are generally above zero level which means that the network importance is more important than spillovers from Turkey. The biggest spike in this period was in November 22, 2000 with a value of 9.4 and the second one in February 22, 2001 with a value of 4.9. So within the network the importance of Turkey is high especially for this two cases and the network cannot digest this importance immediately. Network was not ready to face with the shock that came from Turkey. The spots with an important jump in network repercussions coincides with the beginning of the financial crisis in Turkey. The second peak in February 22, 2001 was the days of financial crisis where the Turkish economy affected seriously and it produces shocks within the network.

- Period 2: The character of the second period was similar to the previous one, the network repercussions the level is generally close to zero with some spikes during the period. There were two important spikes; the first one was on 2002-11-08 which is just after the general elections in Turkey. On 2002-11-03 was the day of general elections where the Justice and Development Party was in power in the first time. The second day was on 2003-10-07 which coincides with the day of permitting to send troops to Irak was accepted by the Turkish government.

- Period 3 and 4: The character of the network repercussions has changed although it was not as obvious as in the return case. The level was again around zero but unlike the previous period the repercussions was less shaky and the number of jumps are less than the previous periods. The character was similar in period 3 and 4 and there was only one jump on 2007-04-30.

- Period 5: The character was not different than the previous two periods but it was shakier and with more jumps. The most important date of this period was on 2013-05-31 which is the day of Gezi park protests an important day for Turkish history. The network repercussions were at its peak value on 2013-06-03, which is the first week day after the Gezi protests. It was a big surprise for the network and network was not ready for such a huge shock.

stock market	period 1	period 2	period 3	period 4	period 5	total
dji	62.29/0	0/0	0/0	0/0	0/0	12.18/0
ftse	0/10.01	0/0	0/0	0/0	0/0	0/1.96
sx5e	0/7.79	0/0	0/0	0/0	0/0	0/1.52
n225	1.11/0	0.77/0	0/0	0/0	0/0	0.44/0
ssec	3.34/0	1.54/0	0/0	0/0	6.39/0	2.61/0
xu100	24.47/0	0.77/0	0/0	0/0	0/0	5/0

Table 1: Number of exceedances of +4/-4 per thousands in ret2vol case

stock market	period 1	period 2	period 3	period 4	period 5	total
dji	26.7/0	0/0	5.12/0	0/0	0/1.82	6.09/0.44
ftse	0/1.11	0.77/0	0/0	0/0	0/0	0.22/0.22
sx5e	0/1.11	0.77/0.77	0/1.28	0/0	0/0	0.22/0.65
n225	3.34/0	1.54/0	0/0	0/1.92	11.86/0	3.92/0.22
ssec	8.9/0	0.77/0	1.28/0	0/0	6.39/0	3.7/0
xu100	7.79/0	1.54/0	1.28/0	0/0	1.82/0	2.61/0

Table 2: Number of exceedances of +4/-4 per thousands in vol2vol case

6.3 Discussion

To understand the properties of network repercussions of an xu100 return and volatility shock, it is important to examine the behaviour of other countries repercussions in the network. Analyzing the character of repercussion of each countries stock market together with Turkey will give rise to understand better the feature of Turkish economy within the network.

In Table 1 and 2, the number of exceedances of +4/-4 per thousands for each period are shown for all network members. To understand the behaviour of jumps and drops for each network countries and compare the reactions are important for the overall character of the network. As we can see from the table, the European markets do not exceed the positive or negative bound a lot, on the contrary of US and Turkey. The US market has the highest percentage of +4 exceedances, dji has 12 exceedances of +4 in the case of repercussions of a return shock and 6 for volatility shock. On the contrary, the European markets (ftse and sx5e) almost never exceed the level of +4/-4 bound. The situation of the Turkish market is closer to the US case than the European markets. So, European markets did not produce big jumps or drops, on the contrary than US and Turkey. The European markets do not produce shocks. On the other hand, the US and Turkish stock markets produces shocks and the network importance is prevailing since the +4 exceedances is much more than the negative one. So, from the US and Turkish market, surprises came to the network and the network can not digest this information immediately.

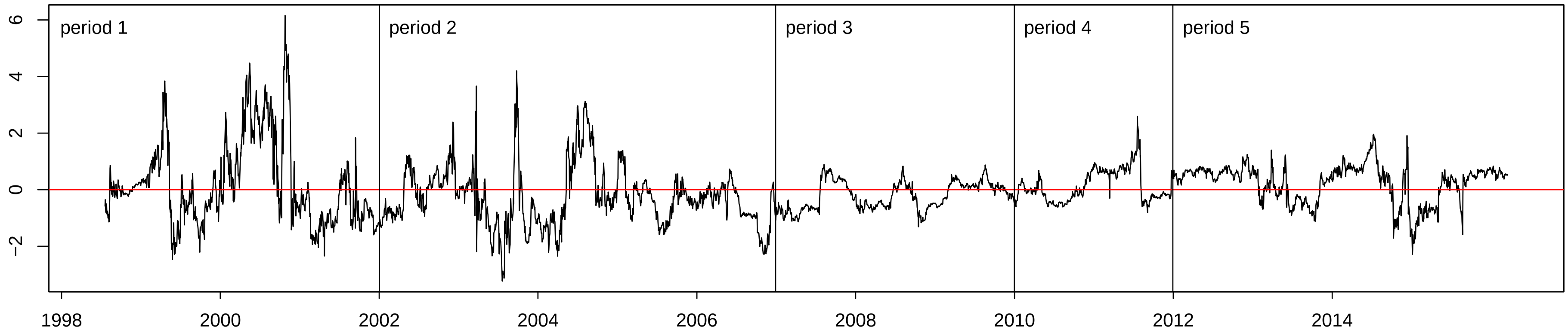

Figure 8: Network repercussions of an xu100 return shock (ret2vol)

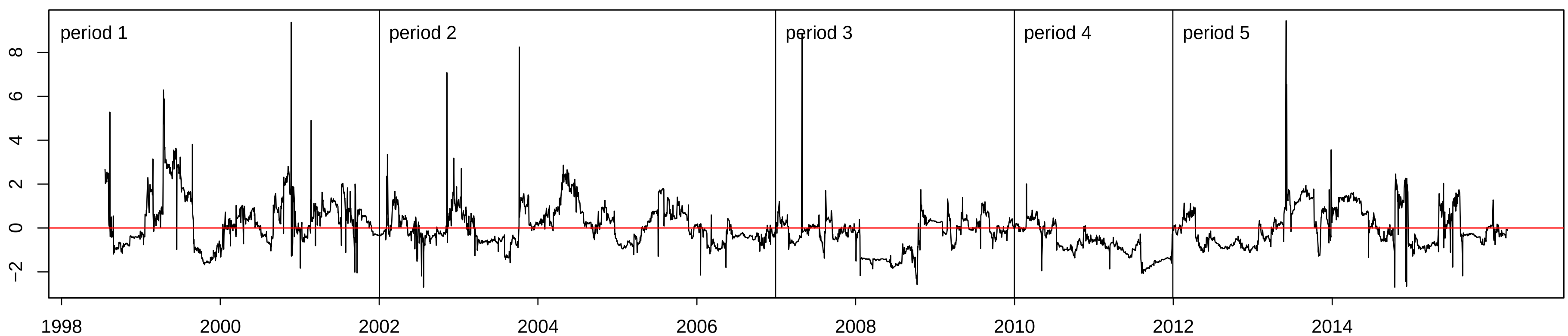

Figure 9: Network repercussions of an xu100 volatility shock (vol2vol)

7 Summary and conclusion

The aim of this study was analyzing the stock market network properties of the ”Systemic Five” plus Turkey, that is: the USA (represented by dji), UK (ftse), the euro area (sx5e), Japan (n225), China (spec), and Turkey (xu100). We investigated the shock spillover characteristics of the Turkish stock market since 2000, with a view towards large-scale political and economic events. For this aim, we divided the 16-year time interval into sub periods according to the breakpoints of Turkish economic history. We examined these sub periods and focused on three objectives: First, accessing the magnitude of direct daily return and volatility spillovers from the Turkish stock market to the other markets in the network. Then, analyzing the relative importance of the Turkish stock market in the network. Finally, investigate how the network digest shocks in the Turkish stock market. For these three purposes we used the important political and economic events of Turkish economy to analyze the results that we obtained from the methodology.

The study uses the methodology by Diebold and Yilmaz (2009,2014) and Schmidbauer et al. (2013b). The Diebold and Yilmaz methodology permits daily screening of network dynamics in terms of direct return-to-volatility and volatility-to-volatility spillovers from and to xu100. The second concept was an extension of the methodology which is called propagation value. It measures the relative importance of the shock in a market as seed for future uncertainty in returns and volatilities across the network.

By applying these methodologies into the network of systemic five plus Turkey, we reached a strong evidence that our partitioning of the time periods is connected with our spillovers and propagation values results. The network properties differ among sub periods and we can interpret these results in terms of the Turkish political and economic history. So, we found a period-specific behaviour of direct spillovers and propagation values with respect to the breakpoint of Turkish history. We also investigated the effect of important political and economic events in the Turkish history and analyze the whole period where an event happened.

Although in the direct spillover analysis the responses of return and volatility spillovers to a shock is different both were sensitive to a shock or an important change in the network. We concluded that after 2007, Turkey is more integrated to the network where the level of spillovers, especially return spillovers, have increased. The important finding from propagation value was there is a visible structural break in 2007 where especially the return spillovers became more homogeneous after 2007. We observed a persistently high level of network importance of xu100 after 2007, which is a turning point of Turkish economic history. To have a comparison among spillovers and propagation value we developed a methodology and run a regression equation to understand the differences of two of them. The network repercussions of shock had two characteristic behaviour where the point they changed is on 2007. The repercussions after 2007 became much more stable than before and especially in volatility part there were some big jumps where important events happened. Investigating the repercussions of all stock markets in the networks was also important to understand Turkey’s situation and make a comparison for the whole network members. The European markets did not create big jumps or drops on the contrary of especially US and then Turkey. So, the characteristics of network repercussions of a shock of Turkey is more similar to US than the European countries. One of the most important result of our study is we did not investigate the Turkish stock market in isolation and comment on the Turkish political and economical events one by one, we approach to the group of stock markets as a network and analyze the characteristics of the network as a whole and focus on the comparison of periods which was partitioned by considering the breakpoints of the Turkish economic history.

Finally, we also believe it is important to apply our methodology and find a correlation between the results and the events. As in Santa-Clara et.al. (2003) mentioned above it is important to discuss the effect of fiscal policy on the economy. We discuss different types of events in the study and classify them in terms the effects to the stock market and examine the reason of this differences among events. There is a large literature on analyzing the impact of monetary policy Rigobon et.al. (2001) on financial markets, however the effect of fiscal and regulatory policies on stock market has been ignored. We examined the events in terms of their types and we analyze the effect of them in terms of regulatory policies by applying the methodologies using return and volatility series.

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Part 3: The Russian stock market during the Ukrainian crisis: A Network Perspective*

September 2, 2016

Abstract

The goal of the present paper is to investigate shock spillover characteristics of the Russian stock market during different rounds of sanctions imposed as a reaction to Russia's alleged role in the Ukrainian crisis.

We consider six stock markets, represented by their respective stock indices, namely USA (dji), UK (ftse), the euro area (sx5e), Japan (n225), China (ssec), and Russia (rts). Linking these markets together in a network on the basis of vector autoregressive processes, we can measure, among others: (i) direct daily return and volatility spillovers from rts to other market indices, (ii) daily propagation values quantifying the relative importance of the Russian stock market as a return or volatility shock propagator, (iii) the amount of network repercussions after a shock. The latter two are methodological innovations.

It turns out that distinct spillover patterns exist in different rounds of sanctions. Large-scale sanctions, beginning in July of 2014, left consequences of shocks from Russia less predictable. While these sanctions reduced the importance of the Russian stock market as a propagator of return shocks, they also increased its importance as a propagator of volatility shocks, thus making the network more vulnerable with respect to volatility shocks from the Russian stock market.

1 Introduction

Russia's economy is of relatively moderate size in terms of aggregate figures. In 2013, Russia's GDP was around 2.8% of the world GDP; the total value of Russia's stock market in 2012 was

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around 1.5% of the world stock market value.[1] Russia's trading volume with the EU was c. EUR 340 bn then[2], and the EU had a GDP of c. EUR 13 500 bn.[3] However, empirical studies have found evidence of strong dependence between Russia as one of the major raw materials exporter along with Brazil of the BRIC (Brazil, Russia, India, China) countries and the US markets, and a significant increase of connectedness among BRIC equity markets and also with equity markets in the developed world beginning in 2005 (see Aloui et al. (2011), Schmidbauer et al. (2013a)).

The recent sanctions against Russia, starting in March 2014, for its alleged role in the Ukrainian crisis and annexation of Crimea[4], may have contributed to structural changes of Russian interconnectedness. Due to the sanctions, Russian companies faced difficulty rolling over debts from Western financial markets.[5] The oil price drop from USD 100 (in June 2014) to USD 60 (in December 2014) further aggravated the situation, distorting the Russian budget balance and weakening the Russian economy significantly. As a result, companies' demand for dollars increased, followed by demand from Russian consumers. This initiated a devaluation and forced the Central Bank of Russia to increase interest rates from 10.5% to 17% in December 2014[6].

There are fears that the ruble's devaluation could have adverse effects on the global economy, as was experienced during the 1998 Russian crisis. Blanchard and Arezki from IMF also warn of the possible side effects of the Russian crisis[7]. On the other hand, there are views suggesting that the likelihood of such a contagious effect has decreased: "One major difference between 1998 and today is that tough sanctions on Moscow have somewhat insulated Western investors from what's ailing Russia..." The sanctions regime has "reduced the risk for financial contagion considerably. This is not 1998. You don't have the same level of interconnectedness," comments Michael Levi, a senior fellow at the Council on Foreign Relations.

[1]Own calculations, based on data provided by the World Bank; see http://data.worldbank.org/data-catalog/GDP-ranking-table, http://data.worldbank.org/indicator/CM.MKT.TRAD.CD. Retrieved 2015-05-21.

[2]"European Union, Trade in goods with Russia", released by the European Commission; available online at http://trade.ec.europa.eu/doclib/docs/2006/september/tradoc_113440.pdf. Retrieved 2015-10-04

[3]See Eurostat database, http://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=tec00001 &language=en; data retrieved 2015-10-04.

[4]For EU sanctions, see http://europa.eu/newsroom/highlights/special-coverage/eu_sanctions/index_en.htm, and for US sanctions, see http://www.state.gov/e/eb/tfs/spi/ukrainerussia/, all retrieved 2015-05-27.

[5]"Western sanctions and rising debts are already strangling the Russian economy", Forbes, 2014-08-28. Available online at http://www.forbes.com/sites/paulroderickgregory/2014/08/28/western-sanctions-and-rising-debts-are-already-strangling-the-russian-economy. Retrieved 2015-09-14.

[6]"Russian central bank raises interest rate to 17% to prevent ruble's collapse", The Guardian, 2014-12-15. Accessible online at http://www.theguardian.com/world/2014/dec/15/russia-interest-rate-rise-17pc-rouble-collapse-oil-price. Retrieved 2015-09-14)

[7]"Oil prices have plunged recently ... One of the lessons from the Great Financial Crisis is that large changes in prices and exchange rates, and the implied increased uncertainty about the position of some firms and some countries, can lead to increases in global risk aversion, with major implications for repricing of risk and for shifts in capital flows. This is all the more true when combined with other developments such as what is happening in Russia. One cannot completely dismiss this tail risk." The Guardian, 2014-12-22. Accessible online at http://www.inkl.com/news/trust-bank-becomes-first-financial-casualty-of-russia-s-currency-crisis. Retrieved 2015-09-14.

(CNNMoney, 2014-12-17, retrieved 2015-05-27).

There are several works which analyse the spillover characteristics of stock market and quantify the market connectedness. We have mentioned in the introduction section of Part I examples from this literature. As we have mentioned generally the studies interested in one economy in isolation and does not study the relation among countries. There are also spillover analysis involving Russia as one of the economies under security. For example, Zivkov et.al. (2015) study the spillover effect of Russia but they are not analyzing the possible effects of the Russian economy on the global economy. We discuss the economic policies in interconnected economies to analyze the situation of Russian economy in the network we constructed. There are studies that examine the policy changes in the interconnected economies. For example, Pitlik (2007) examine the economic policy reform among the OECD countries and they argue that there is a significant interdependence between the monetary and trade policies with the policy choices. We discuss the findings in the result section of our study.

The present study

The goal of our study is to assess the influence of large-scale political and economic events and international sanctions on the importance of the Russian stock market as a news (or shock) propagator within a network of six stock markets, each represented by a stock index, namely Dow Jones Industrial Average (USA), FTSE (UK), Euro Stoxx 50 (euro area), Nikkei 225 (Japan), SSE Composite (China), and RTS (Russia).[8] The network is defined as a directed weighted graph with the stock indices as nodes and weights given by shock spillovers; see the explanations below.

This perspective, which is not making physical spillover channels such as foreign trade explicit, has the advantage of using only data available on a daily basis. A *network* perspective was found useful for our purposes because events and sanctions won't affect the Russian (or any other) market *in isolation*; markets are actually linked and a network perspective allows to study "event repercussions".

The basic idea underlying the methodology used in this study is that the risk associated with investing in a market can be estimated by the variance of the error when forecasting a future return on the market index. Vector autoregressive (VAR) models fitted to daily stock index returns and volatilities can be used to derive the forecast error variance for each market index in the network, and to decompose this variance with respect to its origin: Which share of stock market volatility is due to shocks in which other stock market? This approach provides a framework to discuss pairwise shock spillovers, arranged in a so-called spillover table, and was proposed by Diebold and Yilmaz (2009, 2014). The spillover table is updated daily by fitting VAR models to a rolling window of return data. Schmidbauer et al. (2013b) discuss further aspects of spillover tables and show how to define the "propagation value" of a market, which can be interpreted as the relative importance of a market as news propagator and measures an aspect of centrality of the market in the network.

The methodology, as outlined, uses a VAR in daily returns; it can thus assess daily return-to-volatility spillovers (for simplicity, called the *ret2vol* case in the following), that is, it per-

[8]The former five are dubbed the "Systemic Five" economies in IMF spillover reports IMF (2011, 2012).

mits to trace the network consequences (in terms of return volatility) of a return shock to a market. Again, following Diebold and Yilmaz (2009), it is also possible to fit VAR models to daily return volatilities (instead of returns themselves), and proceed as before; this approach can quantify volatility-to-volatility spillovers (the *vol2vol* case), where in Part 1 we have discussed how to provide the volatility input series, that is, the network consequences (in terms of volatility risk) of a volatility shock to a market. Both concepts — *ret2vol* as well as *vol2vol* — are used in the present study.

More specifically, this study focuses on the following objectives:

1. Assess the magnitude of *direct* daily ret2vol and vol2vol spillovers from the Russian stock market (that is, from rts) to other markets (to other nodes) in the network. For this purpose the spillover index methodology is used.

2. Assess the relative importance of the Russian stock market as a return or volatility shock propagator in the network. This perspective complements objective 1 insofar as it accounts for aftereffects of a one-time shock. This can be achieved using daily propagation values.

3. Provide insight into the network repercussions of an initial shock, that is, into how the network ultimately digests shocks in the Russian stock market. This amounts to a comparison of network importance (objective 2) and direct spillovers (objective 1). We develop a metholody by regressing propagation values on direct spillovers.

We are, in particular, interested in detecting differences between different rounds of the sanctions with respect to these characteristics, and in assessing the impact of political and economic events on them. Consequently, this paper continues with a brief account of the sequence of events and of the international sanctions related with the Ukrainian crisis they entailed, given in Section 2. Short explanation about the daily stock index quotations from six markets is presented in Section 3. In Section 4, we first review the theory underlying the spillover perspective (objective 1 above) and then introduce further methodology to discuss objectives 2 and 3. The subsequent sections report and discuss empirical results concerning objective 1 (Section 5), objective 2 (Section 6), and objective 3 (Section 7). Section 8 summarizes and concludes the paper. — All computations were carried out with scripts written in R (2015).

2 Events and sanctions in connection with the Ukrainian crisis

2.1 Events prior to sanctions

The Ukrainian crisis began in the night of 2013-11-21 with waves of calm protests in Kiev against the then-president of Ukraine who, fancying the prospect of a Russian-led alliance, had suspended an association agreement with the European Union.[9]

On 2014-01-29, Russia "raised the economic pressure on Ukraine", in reversal of its declaration of intention made on an EU-Russia summit the previous day, announcing the suspension of its financial aid commitments to Ukraine, which would be fulfilled "only when we know what economic policies the new government will implement, who will be working there, and what rules they will follow".[10]

The anti-governmental demonstrations in Ukraine resulted in violent clashes with the police on 2014-02-18, known as the "2014 Ukrainian revolution", which led to the ousting of the Ukrainian president two days later and the installation of an interim government.[11] In the aftermath, pro-Russian and anti-revolution protests and activism affected Crimea and parts of eastern and southern Ukraine, while the Olympic Games (2014-02-07 through 2014-02-23) in nearby Sochi, Russia, were about to end. On 2014-02-27, the Supreme Council of Crimea was taken over by unidentified pro-Russian gunmen[12], leading to the installation of a pro-Russian government in Crimea declaring Crimea's independence. On 2014-03-01, the Russian president Vladimir Putin had officially requested (and was granted) parliamentary authorization to "use force in Ukraine to protect Russian interests".[13]

2.2 Implementation of international sanctions

In retrospect, international sanctions imposed so far in connection with the Ukrainian crisis can be grouped into three rounds:

- First round, starting 2014-03-06: The first round of sanctions essentially involves travel bans and asset freezes targeting individuals and entities allegedly instrumental for actions undermining Ukraine's sovereignty.

  On 2014-03-06, through executive order[14], US president Barack Obama stated that events in the Crimean region "…constitute an unusual and extraordinary threat to the national security and foreign policy of the United States…" and ordered the blocking of property of "certain persons contributing to the situation in Ukraine".

[9] "Kiev protesters gather, EU dangles aid promise", Reuters, 2013-12-12; available online at http://www.reuters.com/article/2013/12/12/us-ukraine-idUSBRE9BA04420131212. Retrieved 2015-09-15.

[10] "Russia Defers Aid to Ukraine, and Unrest Persists", The New York Times, 2014-01-29; available online at http://www.nytimes.com/2014/01/30/world/europe/ukraine-protests.html?_r=0. Retrieved 2015-10-04.

[11] "Ukraine crisis: Timeline", BBC news, 2014-11-13; available online at http://www.bbc.com/news/world-middle-east-26248275. Retrieved 2015-09-15.

[12] "How the separatists delivered Crimea to Moscow", Reuters, 2014-03-13; available online at n.reuters.com/article/2014/03/13/ukraine-crisis-russia-aksyonov-idINL6N0M93AH20140313. Retrieved 2015-09-15.

[13] "Ukraine crisis: Timeline", BBC news, 2014-11-13; available online at http://www.bbc.com/news/world-middle-east-26248275. Retrieved 2015-09-15.

[14] "Executive Order – Blocking Property of Certain Persons Contributing to the Situation in Ukraine", released 2014-03-06 by the White House Press Secretary; available online at https://www.whitehouse.gov/the-press-office/2014/03/06/executive-order-blocking-property-certain-persons-contributing-situation. Retrieved 2015-09-14.

A secession referendum, internationally disputed as illegitimate, was held on 2014-03-16, resulting in the Russian annexation of Crimea on 2014-03-18.[15] The involvement of incognito Russian armed forces has been admitted by the Russian president only later, on 2014-04-17.[16,17]

On 2014-03-17, the US extended its list of persons targeted, and also the EU declared sanctions specifically targeted against certain individuals[18,19]. Furthermore, Canada[20], Japan[21] and Australia[22] also imposed sanctions against Russia in the spirit of sanctions of the US and the EU.

- Second round, starting 2014-04-28: The second round of sanctions by the US "... [was] taken in close coordination with the EU."[23] In the second round, in addition to the first-round sanctions, bans on business transactions of several Russian government officials and entities (defense, energy companies and banks) were imposed.[24] The EU extended the list of individuals targeted with a travel ban and a freeze of their assets within the EU.[25]

[15] "Putin signs laws on reunification of Republic of Crimea and Sevastopol with Russia", TASS, 2014-03-21; available online at http://tass.ru/en/russia/724785. Retrieved 2015-09-15.

[16] "Vladimir Putin admits for first time Russian troops took over Crimea, refuses to rule out intervention in Donetsk", National Post, 2014-04-17; available online at http://news.nationalpost.com/news/world/vladimir-putin-admits-for-first-time-russian-troops-took-over-crimea-refuses-to-rule-out-intervention-in-donetsk. Retrieved 2015-09-15.

[17] "Direct line with Vladimir Putin" (in Russian), released on 2014-04-17 by the Kremlin; available online at http://kremlin.ru/events/president/news/20796. Retrieved 2015-09-15.

[18] "Executive Order – Blocking Property of Additional Persons Contributing to the Situation in Ukraine", released 2014-03-17 by the White House Press Secretary; available online at https://www.whitehouse.gov/the-press-office/2014/03/17/executive-order-blocking-property-additional-persons-contributing-situat. Retrieved 2015-09-14.

[19] "Council decision 2014/145/CFSP of 17 March 2014 concerning restrictive measures in respect of actions undermining or threatening the territorial integrity, sovereignty and independence of Ukraine", released 2014-03-17 by the Council of the European Union; available online at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2014:078:0016:0021:EN:PDF. Retrieved 2015-09-14.

[20] "Canadian Sanctions Related to Russia", released 2014-03-17 by the Government of Canada; available online at http://www.international.gc.ca/sanctions/countries-pays/russia-russie.aspx?lang=eng. Retrieved 2015-09-14.

[21] "Statement by the Minister for Foreign Affairs of Japan on the Sanctions against Russia over the situation in Ukraine", released 2014-04-29; available online at http://www.mofa.go.jp/press/release/press4e_000281.html. Retrieved 2015-09-14.

[22] "Sanctions regimes – Russia", released 2014-03-19 by the Australian Government; available online at https://dfat.gov.au/international-relations/security/sanctions/sanctions-regimes/Pages/russia.aspx. Retrieved 2015-09-14.

[23] "Statement Of Treasury Secretary Jacob J. Lew", released 2014-04-28; available online at http://www.treasury.gov/press-center/press-releases/Pages/jl2368.aspx. Retrieved 2015-09-14.

[24] For further details, see "Ukraine and Russia Sanctions", available online at http://www.state.gov/e/eb/tfs/spi/ukrainerussia/, issued by the US Department of State. Retrieved 2015-09-14.

[25] "EU strengthens sanctions against actions undermining Ukraine's territorial integrity", released 2014-04-28 by the Council of the European Union; available online at https://www.consilium.europa.eu/uedocs/cms_Data/docs/pressdata/EN/foraff/142411.pdf. Retrieved 2015-

- Third round, starting 2014-07-16: The third round of sanctions, building upon previous rounds, is marked with the announcement of the US Treasury to take a "broad-based package" of sanctions against certain major Russian financial institutions, energy firms, defense technology entities, as well as on "those undermining Ukraine's sovereignty or misappropriating Ukrainian property".[26]

  The downing of a Malaysian airplane over separatist-held territory in Ukraine on 2014-07-17 worsen the confrontation between Russia and Western countries dramatically. On 2014-07-22, the EU agreed to draft a new list of Russian individuals and entities to be targeted by travel bans and asset freezes. At the same time, the EU threatened to quickly pass on to extensive sectoral "phase three sanctions" if Russia continued its alleged support of separatists, believed to have shot down the plane, and refused to cooperate with an international inquiry.[27] On 2014-07-29, the EU decided that Russia had not complied with these conditions and agreed on sweeping economic sanctions, targeting "economic cooperation and exchanges with Russia", to come into force on 2014-07-31.[28] These sanctions "limited access to EU capital markets for Russian State-owned financial institutions", established an arms embargo and an export ban for sensitive technology and equipment for the oil industry. The US joined the EU with new measures, in particular cutting off three prominent Russian banks from the US economy.[29] Tougher sanctions were also announced by Canada (2014-07-24), Japan (2014-08-05), Norway (2014-08-12), Switzerland (2014-08-14), and Australia (2014-09-01). Alleged evidence of Russia's involvement in separatists' fights led the EU to expand and strengthen sanctions

08-22.

[26]"Announcement of treasury sanctions on entities within the financial services and energy sectors of Russia, against arms or related materiel entities, and those undermining Ukraine's sovereignty", released 2014-07-16 by the US Department of the Treasury; available online at http://www.treasury.gov/press-center/press-releases/Pages/jl2572.aspx. Retrieved 2015-09-14.

[27]"E.U. imposes new sanctions on Russian officials, stops short of tougher penalties", The Washington Post, 2014-07-22; available online at https://www.washingtonpost.com/world/europe/eu-foreign-ministers-confer-on-tougher-sanctions-against-russia/2014/07/22/05e1d794-1197-11e4-8936-26932bcfd6ed_story.html. Retrieved 2015-09-30.

[28]"Statement by the President of the European Council Herman Van Rompuy and the President of the European Commission in the name of the European Union on the agreed additional restrictive measures against Russia", released 2014-07-29; available online at http://europa.eu/newsroom/highlights/special-coverage/eu_sanctions/index_en.htm#6. Retrieved 2015-09-30.

"Council regulation (EU) No 833/2014 of 31 July 2014 concerning restrictive measures in view of Russia's actions destabilising the situation in Ukraine", released 2014-07-31 by the Council of the European Union; available online at http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:JOL_2014_229_R_0001&from=EN. Retrieved 2015-09-14.

[29]"EU and US impose sweeping economic sanctions on Russia", The Guardian, 2014-07-29; available online at http://www.theguardian.com/world/2014/jul/29/economic-sanctions-russia-eu-governments. Retrieved 2015-09-30.

even further on 2014-09-12[30], aligned with the US[31], while Japan implemented stricter sanctions on 2014-09-24. However, reports like that of Russian tanks "crossing border" into eastern Ukraine on 2014-11-07, a few days after the separatists' proposal to establish a "People's Republic", officially "respected" by Russia[32], continued fueling concerns of "Russia's aggression and direct involvement in destabilising Ukraine".

Bans on investments in Crimea were first implemented by the EU on 2014-12-18, and the following day by the US.[33,34] In view of the escalation of violence in Ukraine, the EU Council, on its 2015-01-29 summit in Minsk, decided to extend existing restrictive measures until September 2015, adding to the list of targeted individuals and entities on 2015-02-16.[35,36] Canada followed suit on 2015-02-18. At their 2015-06-07/08 summit, the G7 leaders declared their commitment to uphold sanctions, the duration of which "should be clearly linked to Russia's complete implementation of the Minsk agreements and respect for Ukraine's sovereignty" and to "take further restrictive measures in order to increase cost on Russia should its actions so require".[37]

2.3 Further events in the wake of sanctions

Events with an economic background

In response to the international sanctions, Russia imposed bans on food imports from the sanctioning countries on 2014-08-06.[38]

In December 2014, a vast devaluation seized the already weak ruble. On 2014-12-02,

[30]"Reinforced restrictive measures against Russia", released 2014-09-11 by the Council of the European Union; available online at http://europa.eu/newsroom/highlights/special-coverage/eu_sanctions/index_en.htm#6. Retrieved 2015-09-30.

[31]"Obama says U.S. to outline new Russia sanctions on Friday", Reuters, 2014-09-11; available online at http://www.reuters.com/article/2014/09/11/us-ukraine-crisis-obama-sanctions-idUSKBN0H620I20140911. Retrieved 2015-09-30.

[32]"Ukraine crisis: Tanks 'cross border' from Russia", BBC News 2014-11-07; available online at http://www.bbc.com/news/world-europe-29952505. Retrieved 2015-10-11.

[33]"EU bans investment in Crimea, targets oil sector, cruises", Reuters, 2014-12-18; available online at http://www.reuters.com/article/2014/12/18/us-ukraine-crisis-eu-idUSKBN0JW18020141218. Retrieved 2015-10-07.

[34]"US slaps trade ban on Crimea over Russia "occupation"", The Telegraph, 2014-12-20; available online at http://www.telegraph.co.uk/news/worldnews/europe/ukraine/11305372/US-slaps-trade-ban-on-Crimea-over-Russia-occupation.html. Retrieved 2015-10-07.

[35]Press release by the Foreign Affairs Council, 29/01/2015; available online at http://www.consilium.europa.eu/en/meetings/fac/2015/01/29/. Retrieved 2015-10-07.

[36]"New EU Sanctions Hit 2 Russian Deputy DMs", Defense News, 2015-02-16; available online at http://www.defensenews.com/story/defense/international/europe/2015/02/16/official-new-eu-sanctions-hit-two-russian-deputy-defence-ministers/23527227/. Retrieved 2015-10-07.

[37]"Leaders' Declaration G7 Summit", released on 2015-06-08; available online at https://www.g7germany.de/Content/DE/_Anlagen/G8_G20/2015-06-08-g7-abschluss-eng.html?nn=1281552. Retrieved 2015-10-07.

[38]"Russia hits West with food import ban in sanctions row", released 2014-08-07; available online at http://www.bbc.com/news/world-europe-28687172. Retrieved 2015-08-22.

Russia acknowledged that it "will fall into recession next year, battered by the combination of Western sanctions and a plunge in the price of its oil exports".[39] On 2014-12-09, mingling with the World Bank's revision of its economic outlook for Russia[40], bad news also came from China[41] with which Russia had strengthened its economic ties, particularly in the energy sector, by contracts nominated in rubles and Chinese yuan.[42] A crucial date for the Russian economy was 2014-12-16, increased the Russian weekly repo rate from 10.5% to 17% in an effort to halt the collapse of the ruble. On 2014-12-21, China signaled its commitment to assist Russia overcome its "worst economic crisis since the 1998 default".[43]

On 2015-06-01, the World Bank released more optimistic forecasts for the Russian economy reflecting the stabilization of oil prices.[44] The annual St. Petersburg International Economic Forum, held from 2015-06-18 through 2015-06-20, was used as a platform to "defend Russia as a place to invest" and to declare that the international economic sanctions were "helping Russian businesses to thrive".[45] On this occasion, Russia also declared its willingness to intensify relations with Greece suffering from a severe government-debt crisis. Just one day before the forum opened, the Central Bank of Russia had cut its repo rate down again to 11.5% in an effort to stimulate economic growth.[46]

Events without a direct economic background

In the course of the analysis, two further non-economic events were found to coincide with significant spillover patterns: On Sunday, 2014-10-26, Ukraine's parliamentary elections were won by pro-Western parties.[47]

The Moscow celebrations of the 70th anniversary of the end of World War II, lacking

[39] "Russia warns of recession next year", The Washington Times, 2014-12-02; available online at http://www.washingtontimes.com/news/2014/dec/2/russia-warns-recession-next-year-ruble-falls-recor/?page=all. Retrieved 2015-10-11.

[40] "World Bank Revises Its Growth Projections for Russia for 2015 and 2016", released 2014-12-09 by the World Bank; available online at http://www.worldbank.org/en/news/press-release/2014/12/08/world-bank-revises-its-growth-projections-for-russia-for-2015-and-2016. Retrieved 2015-10-12.

[41] "Shanghai stocks suffer sharpest fall in five years", Financial Times, 2014-12-09; available online at http://www.ft.com/intl/cms/s/0/95372ce6-7f79-11e4-b4f5-00144feabdc0.html?siteedition=intl#axzz3nst55gjh. Retrieved 2015-10-07.

[42] "The Ukraine Crisis Has Accelerated Russia-China Energy Ties", Business Insider, 2014-09-07; available online at http://www.businessinsider.com/the-ukraine-crisis-has-accelerated-russia-china-energy-ties-2014-9?IR=T. Retrieved 2015-10-07.

[43] "Ruble Swap Shows China Challenging IMF as Emergency Lender", Bloomberg, 2014-12-22; available online at http://www.bloomberg.com/news/articles/2014-12-22/yuan-ruble-swap-shows-china-challenging-imf-as-emergency-lender. Retrieved 2015-10-07.

[44] "World Bank Revises Its Growth Projections for Russia for 2015 and 2016", released 2015-06-01 by the World Bank; available online at http://www.worldbank.org/en/news/press-release/2015/06/01/world-bank-revises-its-growth-projections-for-russia-for-2015-and-2016. Retrieved 2015-10-12.

[45] "Russia sanctions helping businesses to thrive", CNBC, 2015-06-18; available online at http://www.cnbc.com/st-petersburg-international-economic-forum/. Retrieved 2015-09-30.

[46] Russian central bank cuts key interest rate to 11.5%", CNBC, 2014-06-15; available online at http://www.cnbc.com/2015/06/15/russia-central-bank-to-cut-but-by-how-much.html. Retrieved 2015-09-30.

[47] "Ukraine elections: Pro-Western parties set for victory", BBC, 2014-10-27; available online at http://www.bbc.com/news/world-europe-29782513. Retrieved 2015-09-30.

period	remarks	begins	ends	mean	sd
0	before 2014	1998-07-20	2013-12-31	0.079	2.418
1	2014, before sanctions	2014-01-01	2014-03-05	−0.406	2.285
2	first round of sanctions	2014-03-06	2014-04-25	−0.127	2.067
3	second round of sanctions	2014-04-28	2014-07-15	0.341	1.390
4	third round of sanctions	2014-07-16	2014-12-15	−0.558	2.009
5	after increase in repo rate	2014-12-16	2015-07-06	0.199	2.840

Table 1: Periods, daily average returns and standard deviations of rts

attendance by most Western leaders due to the ongoing Ukrainian crisis, was announced as the "biggest military parade ever held". Just four days before the Victory Day Parade, on 2015-05-05, a new-generation battle tank had been unveiled to the public.[48]

On 2015-05-22, an EU summit with six former Soviet states ended in Latvia, reconfirming the determination and importance the EU attaches to its "Eastern Partnership".[49] The following Sunday, 2015-05-24, Russia passed a bill which allowed the prosecution of foreign non-governmental organizations labeled as "undesirable".[50] A "blacklist" of European officials with entry ban was revealed a few days later, on 2015-05-29[51] — amid concerns that "Russia masses heavy firepower" on its border to Ukraine.[52]

2.4 Partitioning the time period

The goal of the sanctions was to impose costs on the Russian economy. For our purposes, this leads to the partitioning of the time period under consideration shown in Table 1.[53]

It should be emphasized that this partitioning is apriori in the sense that network properties (reported and analyzed in Sections 5, 6, and 7) are not used in defining sub-periods. At this point, our working hypothesis is that network properties are different in different periods.

[48] "Russia unveils new Armata tank for WW2 victory parade", BBC News, 2015-05-05; available online at http://www.bbc.com/news/world-europe-32478937. Retrieved 2015-09-15.

[49] "Eastern Partnership summit, Riga, 21-22/05/2015", released by the European Council, 2014-05-22; available online at http://www.consilium.europa.eu/en/meetings/international-summit/2015/05/21-22/. Retrieved 2015-09-30.

[50] "Russia's Putin signs law against "undesirable" NGOs", BBC, 2015-05-24; available online at http://www.bbc.com/news/world-europe-32860526. Retrieved 2015-09-30.

[51] "Russia releases 89-name EU travel blacklist", Yahoo! News, 2015-05-29; available online at http://news.yahoo.com/russia-issues-blacklist-bars-eu-politicians-dutch-pm-164848974.html. Retrieved 2015-10-07.

[52] "Exclusive: Russia masses heavy firepower on border with Ukraine — witness", Reuters, 2015-05-27; available online at http://www.reuters.com/article/2015/05/27/us-ukraine-crisis-russia-military-idUSKBN0OC2K820150527. Retrieved 2015-10-08.

[53] 1998-07-20 is the first day for which all measures reported below were available.

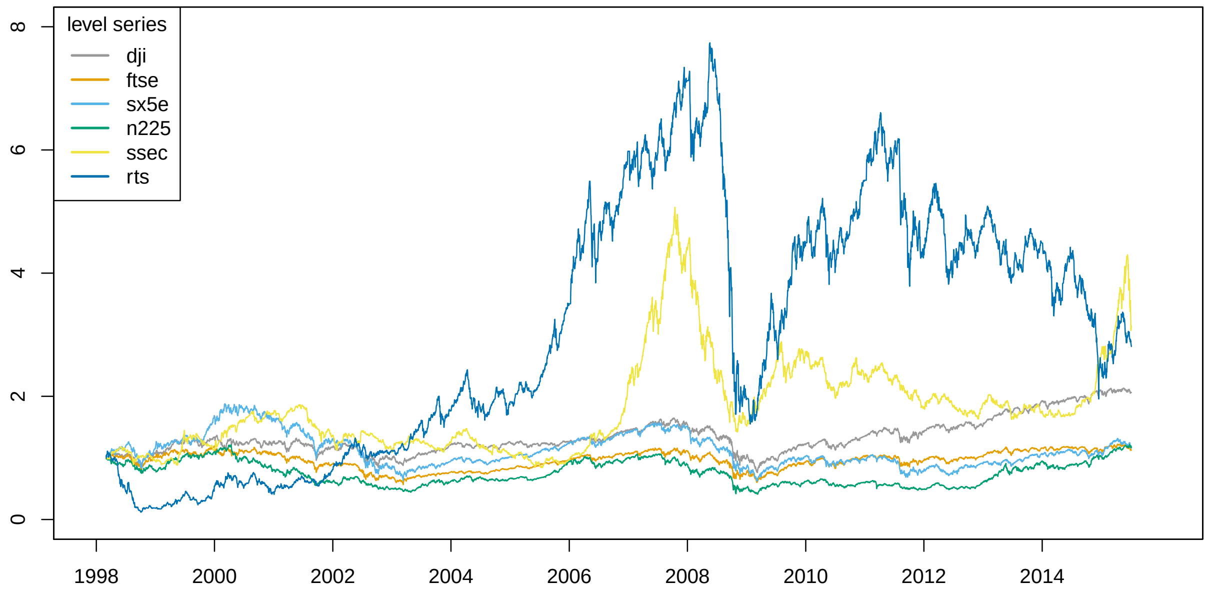

Figure 1: The series of daily levels (with 1998-03-03 $\equiv$ 1)

3 Data

The empirical starting point of the present study consists of daily closing quotations of the Russian stock index (rts) and the five stock indices representing stock markets in the "Systemic Five" countries: Dow Jones Industrial Average (USA; dji), FTSE (UK; ftse), Euro Stoxx 50 (euro area; sx5e), Nikkei 225 (Japan; n225), and SSE Composite (China; ssec). The series begin with 1998-03-03 (the first day for which all six series were available) and end with 2015-07-06 (4556 observations). Table 1 gives daily average returns and standard deviations of rts in each period. The level series of all six stock indices, normed such that 1998-03-03 $\equiv$ 1, are shown in Figure 1; the associated series of daily simple returns in percent are plotted in Figure 2.

Obtaining daily volatilities is a prerequisite for investigating vol2vol spillovers. This requires further daily data, namely opening, high, and low, in addition to daily closing quotations. The corresponding series are not plotted here.

4 Measuring spillovers and shock repercussions

4.1 Return-to-volatility spillovers ("ret2vol")

Direct spillovers

Let $(x_{kt})_{t=1,\dots,T}$, where $k = 1,\dots,N$, designate N series of daily price changes (simple returns in percent); N is the number of stock markets in the network. The methodology used in the present paper builds on the spillover matrix by Diebold and Yilmaz (2009, 2014) and

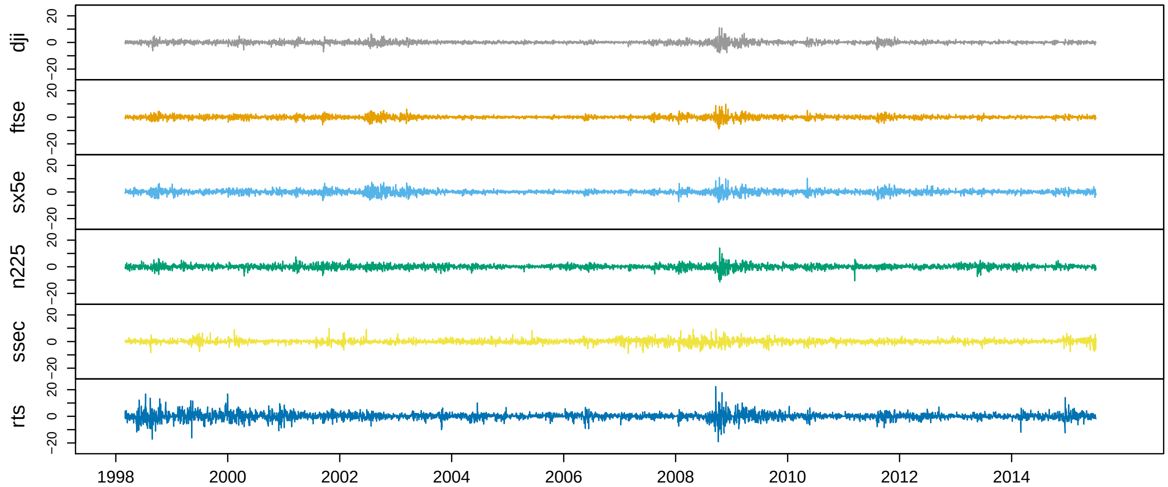

Figure 2: The series of daily returns

extensions developed in Schmidbauer et al. (2013b). For a given day t, the spillover matrix is a matrix $\mathbf{M} = (m_{ik})_{i,k=1,\ldots,N}$ (we drop the index t, for ease of exposition) with row sums equal to one, that is, $\sum_{k=1}^{N} m_{ik} = 1$, where each row $(m_{i1}, \ldots, m_{iN})$ provides a breakdown of the forecast error variance of x_i into shares with respect to its origin. In this sense, m_{ik} is the share of variability in x_i due to shocks in x_k. For example, in the case of $N = 3$ markets, a spillover matrix

$$\mathbf{M} = \begin{pmatrix} 0.6 & 0.2 & 0.2 \\ 0.1 & 0.6 & 0.3 \\ 0.1 & 0.3 & 0.6 \end{pmatrix}, \tag{1}$$

means that 60% (20% each) of forecast error variance of x_1 is due to shocks in x_1 itself (shocks in x_2 and x_3, respectively). In other words: 40% of the volatility in market 1 is due to spillovers to market 1 from markets 2 and 3. Considering the first column of $\mathbf{M}$, an "aggregate share" (column sums need not add up to 1) of 0.2 is spilled over from market 1 to markets 2 and 3, making market 1 a net receiver. Market 2 is a net giver.

Direct spillovers from market k (or to market i) are then given by the column (row, respectively) sums in $\mathbf{M}$, excluding the market's spillovers to itself:[54]

$$\text{from market } k \text{ to others: } \sum_{i=1, i\neq k}^{N} m_{ik}; \qquad \text{to market } i \text{ from others: } \sum_{k=1, k\neq i}^{N} m_{ik} \tag{2}$$

In social network terminology, with $\mathbf{M}$ interpreted as adjacency matrix of a weighted directed network of nodes, these aggregates are the from-degree of node k (to-degree of node i, respectively); see Diebold and Yilmaz (2014).

For a given day t, the spillover matrix $\mathbf{M}$ is obtained as follows: Fit a standard VAR model of order 1 to the N return series, using data from a window of size 100 (that is, days

[54]Spillovers from market k to others, plus spillovers to itself, need not sum up to 1.

$t-99,\ldots,t$). We follow Diebold and Yilmaz (2014) and use an approach suggested by Pesaran and Shin (1998), namely: to identify the impulse response function of a component (here, x_k), give highest priority to that component; this removes the dependence on an imposed hierarchy of markets. Forecasting n steps ahead (we use $n = 5$), forecast error variance decomposition (fevd) yields forecast error variance shares $(m_{i1},\ldots,m_{iN})$. This procedure is then applied for every t, resulting in a sequence of spillover matrices.

Relative importance of a market: propagation values

The network structure of the spillover matrix with respect to the propagation of shocks lends itself to a broader perspective, elaborated in Schmidbauer et al. (2013b). Let $\mathbf{M}$ again denote the spillover matrix for day t. We assume that $\mathbf{M}$ contains all relevant, and the most recent available, information about the network. A hypothetical shock ("news", "information") of unit size in market k on day t can be denoted as $n_0 = (0,\ldots,0,1,0,\ldots,0)'$, where 1 is in the k-th component of n_0. We assume that the propagation of this shock across the markets within day t will take place in short time intervals of unspecified length according to

$$\mathbf{n}_{s+1} = \mathbf{M}\cdot\mathbf{n}_s, \quad s = 0,1,2,\ldots \tag{3}$$

(where step $s = 0$ initializes the recursion). The index s in Equation (3) therefore denotes a step in information flow. Moreover, assuming that information flow across markets can proceed instantly on day t, with spillover conditions (given by $\mathbf{M}$) persisting throughout day t, it makes sense to investigate steady-state properties (as $s \to \infty$) of the model defined by Equation (3). This leads to

$$\mathbf{v}' = \mathbf{v}'\cdot\mathbf{M}. \tag{4}$$

When the left eigenvector $\mathbf{v} = (v_1,\ldots,v_N)'$ is normed such that $\sum_{k=1}^{N} v_k = 1$, we call v_k the propagation value of market k. It renders the value of a return shock in market k as seed for future uncertainty in returns across the network of markets:

$$v_k = \sum_{i=1}^{N} m_{ik}\cdot v_i \tag{5}$$

For $\mathbf{M}$ as in Equation (1), $\mathrm{v}' = (0.2, 0.4, 0.4)$, which means that a shock in market 2 is twice as powerful ($0.4/0.2 = 2$) as a shock in market 1 in terms of creating network volatility. — A similar concept, eigenvector centrality, is also used in social network analysis; see, for example, Bonacich (1987).

Network repercussions of a shock

Direct spillovers from market k to others measure the *direct* impact of a shock in x_k on day t, without consideration of immediate (that is, also happening on day t) network repercussions of the shock. The propagation value of market k, in contrast, emphasizes the importance of shocks in x_k within the network, including repercussions throughout the network. Owing to different magnitudes, direct spillovers from market k and propagation values of market k cannot be directly compared. However, they can be related to each other via a regression

$$\text{propagation value}_t = \alpha + \beta \cdot \text{spillover}_t + \epsilon_t, \tag{6}$$

where propagation value $_t$ (spillover $_t$) denote the propagation value of market k (direct spillovers from market k, respectively) on day t. The residuals ϵ_t can be interpreted as propagation values (or relative network importance) of market k, from which direct spillovers have been computationally removed. What remains is a measure of network repercussions of a direct spillover, that is: the repercussions of a one-time shock in market k throughout the network, once again assuming that the spillover matrix is the only relevant information structure for a given day. Therefore, ϵ_t indicates which effect is prevailing:

$$\epsilon_t \begin{cases} > 0: & \text{network repercussions are more important than direct spillovers on day } t, \\ < 0: & \text{direct spillovers have little repercussions in the network on day } t. \end{cases} \tag{7}$$

This methodology will be applied in Section 7, where market k designates the Russian stock market.

4.2 Volatility-to-volatility spillovers ("vol2vol")

The methodology outlined in Section 4.1 can also be applied to a set of series $(x_{kt})_{t=1,\dots,T}$ of daily volatilities, instead of returns (Diebold and Yilmaz, 2009). One difficulty to overcome is that daily volatilities cannot be directly observed and need to be reconstructed. We use a method proposed by German and Klass (1980), based on the hypothesis that the stock price process is a geometric Brownian motion, to obtain daily variances. As we have discussed in detail the methods how to provide the volatility series, their method results in the following formula:

$$\begin{aligned} \hat{\sigma}_t^2 \;=\; & 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] \\ & -0.383(C_t - O_t)^2, \end{aligned} \tag{8}$$

where O_t (H_t, L_t, C_t) designate the natural logarithm of the daily opening price (daily high, daily low, daily closing, respectively) on day t. After obtaining a daily variance series for each market considered, a sequence of spillover matrices — updated daily — can be computed, leading to daily direct spillovers as well as to daily propagation values. In this case, direct spillovers characterize volatility-to-volatility spillovers, while the propagation values quantify the importance of a market with respect to the propagation of a volatility shock across markets, that is, the value of a volatility shock from that market as seed for future uncertainty in volatility across the network of markets.

The methodology outlined in this section will now be applied to the data described in Section 3. In view of our focus on the Ukrainian crisis,. We report and discuss only the results concerning 2014 and 2015 in the following three sections.

5 Direct spillovers from and to rts

This section reports the first part of spillover characteristics of the Russian stock market, namely direct return and volatility spillovers, without considering potential aftereffects of a shock. Sections 6 and 7 will give more detailed interpretations, using the methodological innovations (propagation values and network repercussions) introduced in Sections 4.1 and 4.2. Particular attention will be given to the following periods and events (cf. Section 2):

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014): Russia increased the economic pressure on Ukraine. The Olympic Games began in Sochi, Russia. In the run-up to the first round of sanctions, Russia's president was granted parliamentary authorization to "use force in Ukraine to protect Russian interests".

- Beginning of period 4 (roughly, 2nd half of July 2014):
  The third round of sanctions entailed extensive sectoral measures targeting Russia's economy on a broad base, while the first and second rounds had imposed travel bans and asset freezes on Russian individuals and entities. The US were the first to take this step. The downing of the Malaysian airplane worsened the relations between Russia and Western countries to the effect that the EU joined, and tightened, economic sanctions two weeks later.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014): Ukraine's parliamentary elections were won by pro-Western parties. Falling crude oil prices leaded Russia to acknowledge that it was heading towards a recession. A ruble crisis was triggered, which finally made the Central Bank of Russia increase the weekly repo rate significantly.

- Later part of period 5 (roughly, May – June 2015):
  Russia's Victory Day Parade in early May was received in the Western world as a show-off of Russian military strength. Later this month, reports that Russia masses military power on its border to Ukraine further strained relations between Russia and the EU. The St. Petersburg International Economic Forum held in mid-June was used as a platform to advertise businesses and investments in Russia.

5.1 The case return-to-volatility (ret2vol)

The daily series of direct return spillovers from rts to others and from others to rts are displayed in Figure 3 for the period from January 2014 through July 2015. Return spillovers to rts have always been higher than return spillovers from rts after the first round of sanctions was imposed. This was also true for a high share of earlier days, so that the Russian market has been a net receiver of return shocks — at least when potential aftereffects of shocks in the network are ignored; cf. Table 2. Periods 2 and 3 can be jointly characterized as having persistently high levels of return spillovers; the latter were lowest throughout period 4, and only period 5 gradually brought them back close to January 2014 levels; cf. Table 3. Further observations:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014): Return spillovers from rts received a significant boost on Monday 2014-03-03, the first trading day after the Russian president had received parliamentary authorization to use military force in Ukraine, while spillovers to rts hardly responded to this event; these gradually increased only later, days after the first round of sanctions had been implemented.

- Beginning of period 4 (roughly, 2nd half of July 2014):
  On 2014-07-18, one day after the downing of the Malaysian plane, both return spillover series plunged towards levels which were below those held in January 2014. The implementation of economic sanctions by the EU on 2014-07-31 coincides with further sliding.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014): The advent of the ruble crisis was accompanied by return spillovers moving closer to each other and, during the most dramatic days in mid-December, on a zigzag course. From 2014-12-16 onwards, the day of the repo rate increase, spillovers from rts started to stabilize, while spillovers to rts rose sharply the following day. An enlarged gap between return spillovers lasted for about four months, with both spillovers gradually increasing.

- Later part of period 5 (roughly, May – June 2015):
  The gap between return spillovers narrowed again with a temporal significant boost in spillovers from rts when Russia unveiled its new battle tank in the run-up to its Victory Day Parade on 2015-05-09. From this time onwards a simultaneous decrease in both series can be observed, with another visible plunge on 2014-05-27, the day when, amid political issues, Russia was reported to mass military force on its border to Ukraine.

5.2 The case volatility-to-volatility (vol2vol)

The daily series of direct volatility spillovers from rts to others and from others to rts are displayed in Figure 4 for the period from January 2014 through July 2015. Volatility spillover patterns are more distinct than those of return spillovers, and they are different. On the whole, the Russian market can be considered a net receiver of volatility spillovers, too; cf. Table 2. However, there are notable exceptions in periods 1, 4 and 5 which can be related to certain events, see below. Periods 2 and 3, as well as the first five months of period 5, witnessed volatility spillovers at the lowest observed levels; cf. Table 3. Interjacent periods and events show the following characteristics:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014):
  During period 1, volatility spillovers from rts had already increased markedly in two steps, namely on 2014-01-29, the day when Russia increased economic pressure on Ukraine, and on 2014-02-06, the day before the the Olympic Games started in Sochi, Russia. The end of period 1 was one of the rare occasions when spillovers from rts exceeded those to rts. Spillovers from rts once again rose sharply after Russia's parliament had given its authorization to use force in Ukraine, only to plunge heavily just before the first round of sanctions was imposed. At the same time, spillovers to rts, which had been more or less stable during period 1, plunged, too.

- Beginning of period 4 (roughly, 2nd half of July 2014):
  The downing of the Malaysian aircraft along with the threat, and final implementation, of economic sanctions by the EU sent volatility spillovers from rts to temporary peaks once again briefly exceeding spillovers to rts, most pronouncedly one day after the implementation. These events declared a period of turbulence, especially for spillovers from rts. Both spillovers were elevated again, and approaching each other.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014):
  Turbulence in volatility spillovers increased towards the end of period 4, when the ruble crisis was becoming obvious. While spillovers to rts spiked with bad news coming in from China on 2014-12-09, spillovers from rts increased dramatically on 2014-12-16, the day of the repo rate increase, to plunge the following day. From then onwards, volatility spillovers started to stabilize at low levels, and with an enlarged gap between them, for the following five months.

- Later part of period 5 (roughly, May – June 2015):
  Again, volatility spillovers switched into turbulence mode in early May, when Russia demonstrated military determination on the occasion of its Victory Day Parade. Spillovers from rts were elevated throughout the month, temporarily exceeding spillovers to rts, amid further military threats from Russia and concerns of the Cold War resurging.

5.3 Discussion

The behavior of both return spillovers (ret2vol) and volatility spillovers (vol2vol) is clearly period-specific, and there is strong evidence that political events impact stock market network characteristics.

Rounds 1 and 2 of the sanctions differ with respect to neither ret2vol nor vol2vol patterns. The character of volatility spillovers, however, changed totally in the aftermath of the implementation of round 3 sanctions, targeting banks and institutions. Volatility spillovers became more unpredictable, while return spillovers plunged to a low but more or less stable level. The increase of the repo rate appears to have had a stabilizing effect on volatility spillovers pushing them back at lower levels. On the other hand, return spillovers were increasing.

Economic sanctions did not isolate Russia, but they did reduce ret2vol spillovers from the Russian stock market. This reduction came at the cost of increased volatility spillovers, and hence vulnerability, increasing the risk across the network.

period	remarks	ret2vol	vol2vol
0	before 2014	0.82	0.70
1	2014, before sanctions	0.98	0.59
2	first round of sanctions	1.00	1.00
3	second round of sanctions	1.00	1.00
4	third round of sanctions	1.00	0.80
5	after increase in repo rate	1.00	0.94

Table 2: Share of days with spillovers to rts exceeding spillovers from rts

		avg spillover…			
		…from rts		…to rts	
period	remarks	ret2vol	vol2vol	ret2vol	vol2vol
0	before 2014	33.35	40.04	38.90	47.08
1	2014, before sanctions	28.52	49.64	37.69	58.17
2	first round of sanctions	37.74	6.57	43.60	24.45
3	second round of sanctions	34.86	10.82	42.81	31.66
4	third round of sanctions	14.71	42.53	21.26	51.73
5	after increase in repo rate	24.56	18.95	33.93	37.75

Table 3: Average daily spillovers from and to rts

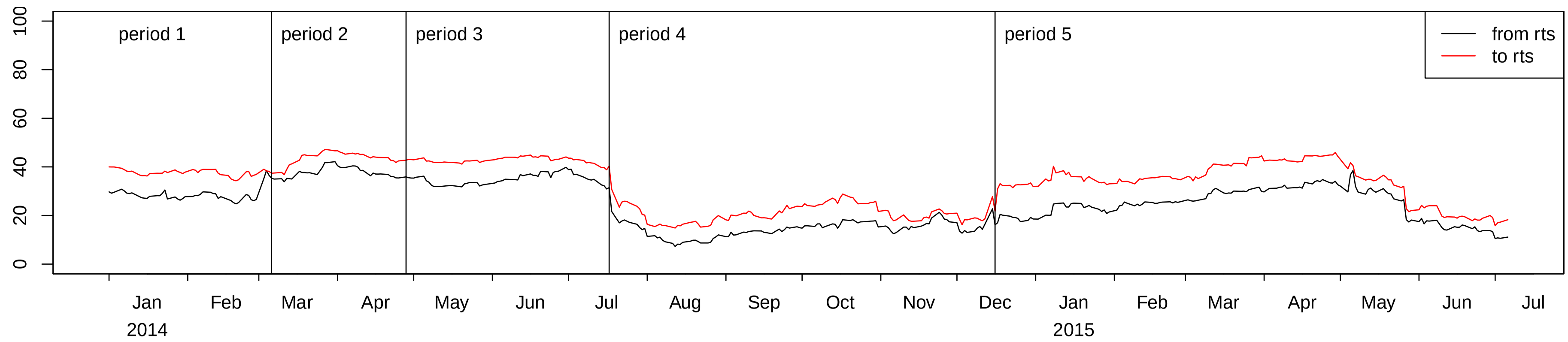

Figure 3: Direct return spillovers (ret2vol) from and to rts

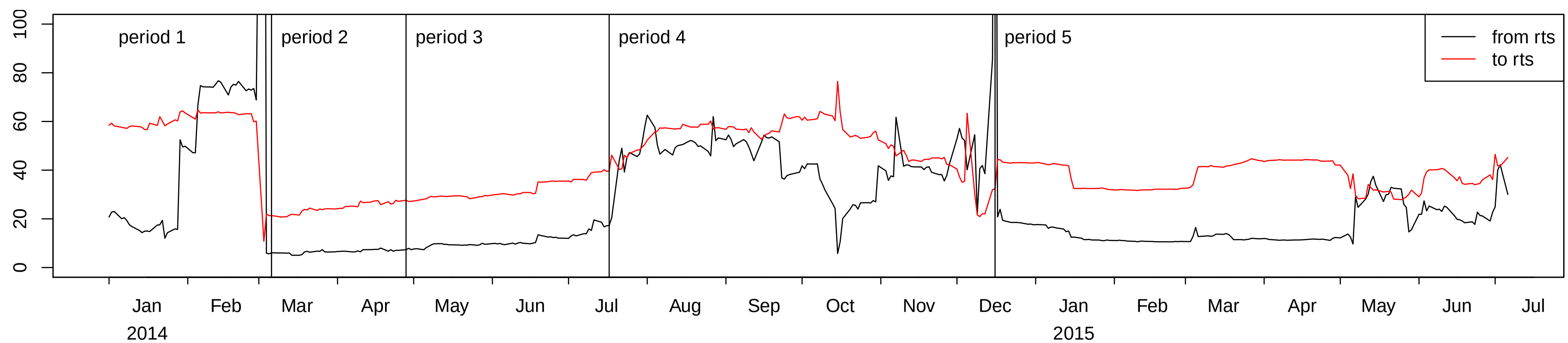

Figure 4: Direct volatility spillovers (vol2vol) from and to rts

6 Propagation values: relative importance of the Russian stock market

This section reports the second part of spillover characteristics of the Russian stock market, namely its relative importance as a return (ret2vol) and volatility (vol2vol) shock propagator in the network of the "Systemic Five" plus rts, measured using the corresponding propagation values. Propagation values of rts will be compared and related to those of the "Systemic Five" in the discussion below.

6.1 The case return-to-volatility (ret2vol)

Figure 5 displays the time series of propagation values of rts in the ret2vol case, for the period from January 2014 through July 2015. Persistently high levels of network importance of rts are observed during periods 2 and 3, while network importance was lowest during the first five months of period 5, unlike direct return spillovers from rts in Section 5; cf. Table 4 for averages. In particular:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014): On the first trading day after the Russian parliament had granted the use of military force in Ukraine, the network importance of rts made an abrupt upward shift. With the implementation of first-round sanctions, it gradually abated to a still high plateau where it remained, more or less constant, throughout periods 2 and 3.

- Beginning of period 4 (roughly, 2nd half of July 2014):
  The onset of economic sanctions by the US was marked by a steady decrease in the network importance of rts, with little flare-ups when the EU finally joined this round on 2014-07-31. On the other hand, the downing of the Malaysian aircraft does not seem to leave any traces. The decrease in network importance continued until mid-August. The network importance of rts hardly reached its January 2014 levels during period 4, though the September expansions of the sanctions as well as the ruble crisis are visible.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014): The dramatic days of the ruble crisis witnessed mild turbulences of the network importance of rts. The Russian repo rate increase, however, coincided with an abrupt and deep plunge in network importance to its lowest level since 2008, while direct spillovers increased, cf. Section 5. In the aftermath, the network importance of rts also started to increase, even if slowly.

- Later part of period 5 (roughly, May – June 2015):
  The run-up to Russia's Victory Day Parade on 2015-05-09 marked an abrupt upward shift in the Russian market's network importance with respect to return shocks. Amid worsening relations between Russia and Western countries, the network importance of rts remained at elevated levels throughout May and June, though direct return spillovers, after a corresponding spike, were on a decrease, cf. Section 5.

6.2 The case volatility-to-volatility (vol2vol)

Figure 6 displays the time series of propagation values of rts in the vol2vol case, for the period from January 2014 through July 2015. The overall pattern is similar to that of direct volatility spillovers from rts in Section 5 (cf. Figure 4), with several notable differences. In detail:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014):
  The pattern of network importance of rts with respect to volatility shocks is similar to that of direct volatility spillovers: a timely coincidence of boosts to a higher plateau and the Russian rise of economic pressure on Ukraine in late January as well as the start of the Olympic Games in early February; and the Russian parliament's authorization to use force in Ukraine and the anticipation of sanctions sent network importance to a roller coaster, too. As a result, however, propagation values did not fall below their January 2014 levels, as did direct spillovers.

- Beginning of period 4 (roughly, 2nd half of July 2014):
  The network importance of rts rose again, unlike direct spillovers, on the occasions of the EU threat to impose sanctions in the immediate aftermath of the downing of the Malaysian aircraft and the sanction's implementation on 2014-07-31. Also, network importance entered a turbulent phase.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014):
  A strong upward shift in network importance of rts with respect to volatility shocks, much more pronounced than for volatility spillovers, coincided with Russia's acknowledgment on 2014-12-02 that it was heading into a recession. News from China refueled concerns and boosted the Russian market's network importance on 2014-12-09. On 2014-12-16, the day of the Russian repo rate increase, the network importance of rts soared dramatically, to plunge to levels last witnessed during periods 2 and 3.

- Later part of period 5 (roughly, May – June 2015):
  The network importance of rts with respect to volatility shocks soared again on 2015-05-07, in the run-up to Russia's Victory Day Parade, to build up even more and peak after the EU's "Eastern Partnership" summit on 2015-05-22, when Russia passed its bill against "undesirable NGOs". Network importance was diminishing again during June 2015.

6.3 Discussion

It turns out empirically that direct spillovers are not the same as propagation values, or relative network importance, for example: ret2vol propagation values fell heavily when the Central Bank of Russia increased the repo rate (2014-12-16), while direct return spillovers rose. Other occasions saw direct spillovers from rts as well as its propagation values increasing, for example: the run-up to Victory Day Parade. This indicates a difference in how the network "digests" return shocks in rts: below- (above-) average network repercussions when the repo rate was increased (in the run-up to Victory Day Parade, respectively). This aspect will be investigated more systematically in Section 7 below.

Although the behavior of ret2vol propagation values depends on the period, the series has much less variability about its average than vol2vol propagation values; it hardly reaches beyond 20% and never moves below 5%. The former series has relatively smaller level shifts, which, however, can be linked to important events, namely the Russian president's parliamentary grant to use force in the Ukraine, the increase in repo rate, and the run-up to the Russian Victory Day Parade. The reaction of vol2vol propagation values to these stimuli has been much larger; the series displays the biggest fluctuations during the third round of sanctions until the repo rate was increased. As in the case of direct spillovers, there is very little difference between the first and second rounds of sanctions. The highest propagation values were the vol2vol propagation values during the onset of the Russian aggression (beyond 80%) and on the very day of the increase in repo rate (more than 60%): This is when a shock to the volatility of the Russian stock market index rts had the relatively strongest impact on the network.

Figures 7 and 8 show stacked plots of all the propagation value series concerning the network of the "Systemic Five" plus rts. By definition, propagation values sum up to 1 each day. These figures allow an assessment of the impact of other large-scale events and thus contribute to the interpretation of the propagation values of rts.

Concerning return shocks, Figure 7 reveals that the propagation values of the three Western markets in the network (represented by dji, ftse, and sx5e) were almost at the same level and more or less uniform across time, with a notable upward bulge at the expense of the Japanese and Chinese markets in February 2014, coinciding with the Ukrainian revolution. This bulge was followed by a fall in early March 2014, mirroring the Russian market's sudden boost in importance. — The Japanese stock market's importance as propagator of return shocks, probably boosted in early 2014 by the introduction of the New Japan Stock Index,[55] almost vanished in early March 2014, to appear again only a year later in March 2015 when a new corporate governance code was to take effect.[56] — News about weak economic indicators in late 2014[57] may have shifted attention to China for some time, which is also clearly visible in Figure 7. Apart from these "Asian effects", however, the pattern of propagation values of the Russian market can be linked to Ukraine- and Russia-related events.

Volatility shock propagation, on the other hand, paints a picture of sharp discontinuities at certain dates, affecting each member in the network; see Figure 8. The spikes relating to the outright Russian threat of military intervention in Ukraine in early March 2014 and the repo rate increase in mid-December 2014 pinpoint the highly prominent role of the Russian

[55] "JPX-Nikkei Index 400", start of calculation 2014-01-06; see Japan Exchange Group at http://www.jpx.co.jp/english/markets/indices/jpx-nikkei400/index.html. Retrieved 2015-09-17.

[56] "Japans reforms push companies to unlock cash", Financial Times, 2015-03-30; available online at http://www.ft.com/intl/cms/s/0/a5699738-ce58-11e4-86fc-00144feab7de.html#axzz3m1slR6H7. Retrieved 2015-09-17.

[57] "China industrial activity shrinks in December, calls grow for more stimulus", Reuters, 2014-12-16; available online at http://www.reuters.com/article/2014/12/16/us-china-economy-pmi-idUSKBN0JU06520141216. Retrieved 2015-09-17.

market as volatility shock propagator in the network, in both cases marking the end of a phase of elevated importance. In the latter case, however, the Russian market's prominence had meanwhile been scaled down and even temporarily interrupted by global growth concerns and a plunge in stock prices in the US in mid-October 2014[58] and in China in early December 2014[59], while the European markets' role was waning. Figure 8 also unveils that the re-boost of the Russian market's importance in early May 2015 was again Russia-related; news about financial reforms in China scaled it down only later in that month.[60]

period	remarks	ret2vol	vol2vol
0	before 2014	0.146	0.143
1	2014, before sanctions	0.143	0.148
2	first round of sanctions	0.180	0.055
3	second round of sanctions	0.177	0.064
4	third round of sanctions	0.135	0.146
5	after increase in repo rate	0.123	0.085

Table 4: Average propagation values, rts

[58] "This is not another financial crisis", CNN Money, 2014-10-15; available online at http://money.cnn.com/2014/10/15/investing/stocks-plunge-not-like-2008/. Retrieved 2015-09-18.

[59] "Shanghai stocks suffer sharpest fall in five years", Financial Times, 2014-12-09; available online at http://www.ft.com/intl/cms/s/0/95372ce6-7f79-11e4-b4f5-00144feabdc0.html#axzz3m1slR6H7. Retrieved 2015-09-18.

[60] "China to allow individuals buy overseas financial assets", Financial Times, 2015-05-29; available online at http://www.ft.com/intl/cms/s/0/5da9f1c4-05b5-11e5-bb7d-00144feabdc0.html#axzz3m1slR6H7. Retrieved 2015-09-18.

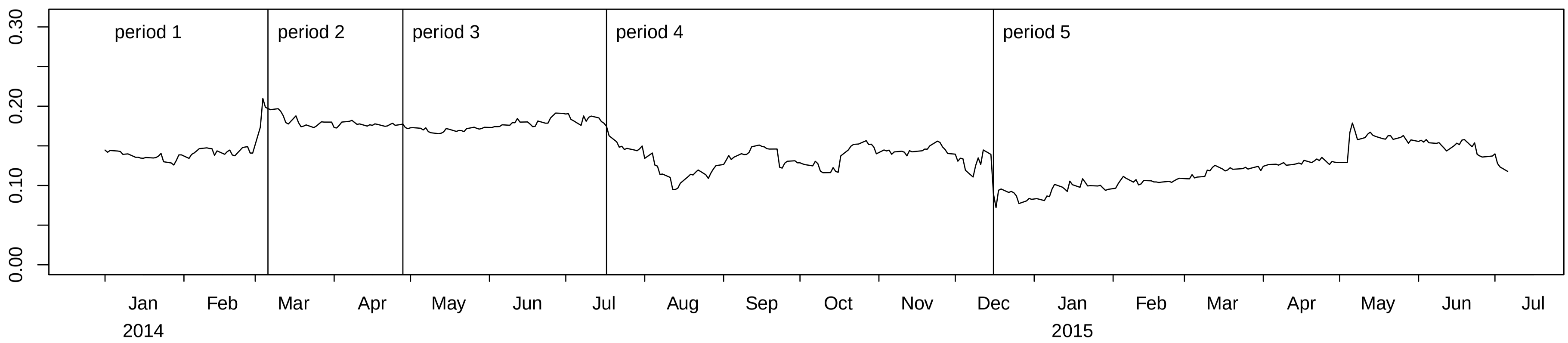

Figure 5: Propagation values of rts, ret2vol

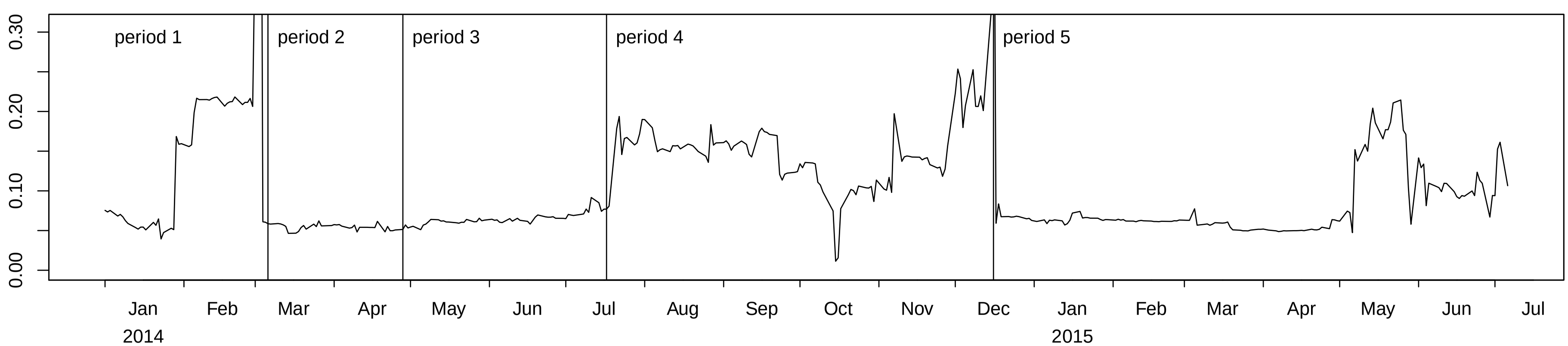

Figure 6: Propagation values of rts, vol2vol

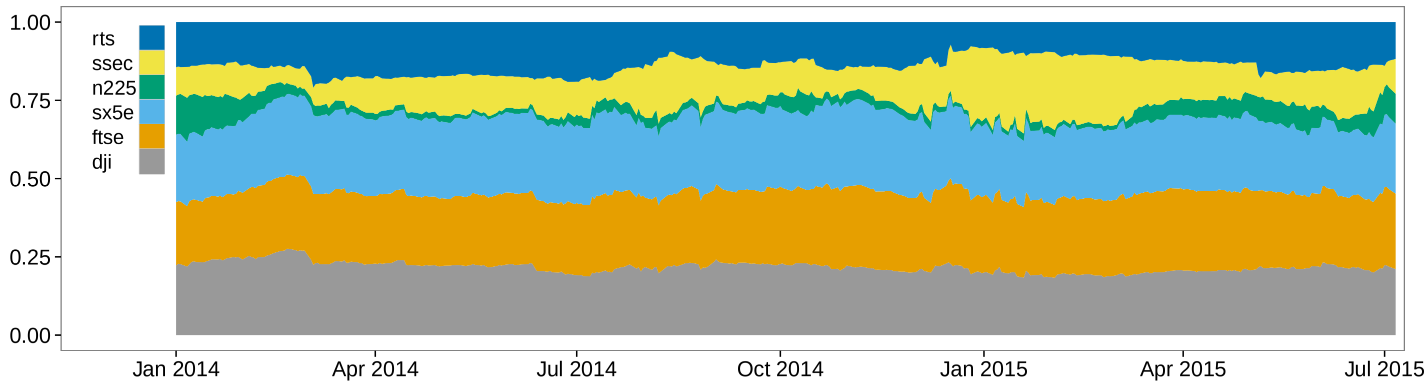

Figure 7: Propagation values, “Systemic Five” plus rts, ret2vol

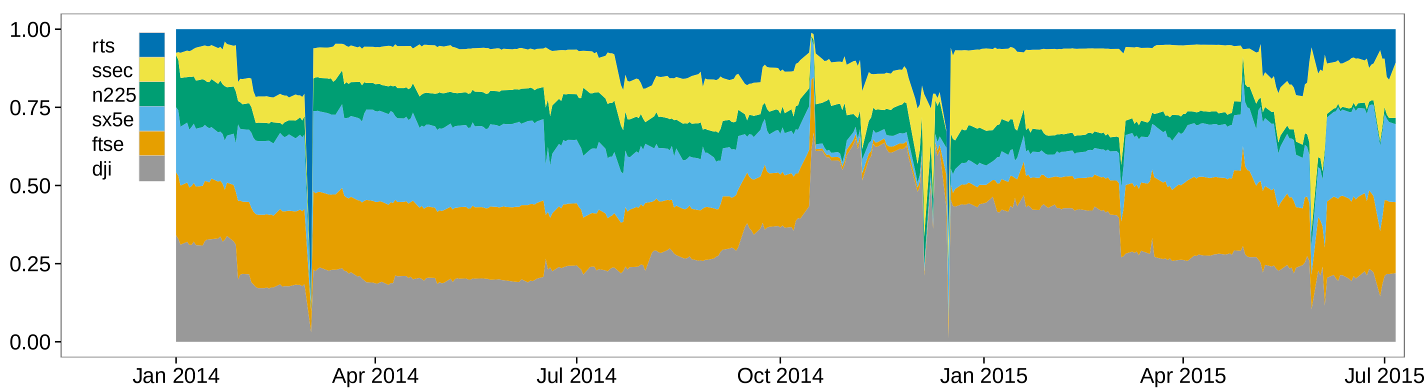

Figure 8: Propagation values, “Systemic Five” plus rts, vol2vol

7 Network repercussions of shocks in the Russian market

This section reports the third part of spillover characteristics of the Russian stock market, namely network repercussions of return and volatility shocks in the Russian market.

Direct spillovers from the Russian market as well as the market's propagation values have a distinct period-specific behavior, and the two series look very similar at first sight, but there are notable differences between them. As was pointed out in Section 4, a direct comparison of both series is not meaningful, while regression residuals are able to unveil whether direct spillovers or network importance prevail at a given time. A residual close to zero indicates that direct spillovers and network importance are on a par, while positive (negative) residuals indicate that network importance (direct spillovers) outweighs direct spillovers (network importance, respectively). The two residual series (ϵ_t), one for each spillover perspective, are plotted in Figures 9 and 10 from 2014 onwards. The series have been standardized over the entire regression period, 1998 through 2015, in order to facilitate the comparison of repercussions from 2014 onwards with long-term repercussions.

7.1 The case return-to-volatility (ret2vol)

A plot of network repercussions of return shocks is shown in Figure 9. Again, periodic-specific behavior is visible: regression residuals are close to zero in period 1; network repercussions were prevailing throughout periods 2, 3 and 4, and direct spillovers dominated during the first five months of period 5. In particular:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014): When the Russian president openly declared his intention of military intervention in Ukraine the first Saturday in March 2014, the anticipation and onset of sanctions the following Thursday had a strong impact on the network in terms of heavy network repercussions of return shocks in the Russian market. This can be inferred from soaring regression residuals at that time. In the aftermath of the implementation of first-round sanctions, network repercussions of return shocks in the Russian market were leveling lower, but were still elevated when compared to those earlier that year. Another peak occurred on 2014-03-17, when sanctions were joined and extended by the EU. Network repercussions tended to grow during the following months.

- Beginning of period 4 (roughly, 2nd half of July 2014):
The beginning of the third round of sanctions, first implemented by the US only, has discontinued the preceding upward trend and entailed diminishing, but rather unstable amounts of network repercussions of return shocks in the Russian market. There was, however, a notable temporal peak in timely coincidence with the EU's implementation of economic sanctions on 2014-07-31.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014): Towards the end of period 4, return shocks in the Russian market started to leave strong effects on the network again, peaking the day after Ukraine's parliamentary election on 2014-10-26, and refueled by concerns over Russia's Ukraine politics. The ruble crisis and Russia's bleak economic outlook in early December sent network repercussions lower, though first intervening efforts by the Central Bank of Russia (a lending-rate increase) may have had a singular boosting effect. A huge temporary drop, taking regression residuals to a level far below zero, can be assigned to the day of the Russian repo rate increase, leaving direct spillovers prevailing for several months.

- Later part of period 5 (roughly, May – June 2015):
  In the run-up to the Russian Victory Day Parade on 2015-05-09, another heavy boost of network repercussions of return shocks in the Russian market occurred, further building up during the subsequent two months and culminating on two occasions: one day in late May amid aggravated concerns of the Cold War resurging, when Russia was reported to mass heavy firepower on its border with Ukraine, and another day in mid-June, on 2015-06-19, when the annual St. Petersburg International Economic Forum just had ended, resulting in, among others, Russia's declared willingness to intensify relations with Greece.

7.2 The case volatility-to-volatility (vol2vol)

The plot in Figure 10 of residuals in the case of a volatility shock in the Russian market reveals: The series of regression residuals is, with a few notable exceptions, close to zero, which shows that (i) there is little difference between the long-term average (1998 through 2015) and the period beginning with 2014, (ii) propagation values with respect to volatility spillovers follow the direct spillovers closely. Particular exceptions are:

- End of period 1 / beginning of period 2 (roughly, late January 2014 – early March 2014):
  The Russian president's openly declared intention of military intervention in Ukraine, just before the sanctions were implemented, is in timely coincidence with rising amounts of network repercussions of volatility shocks in the Russian market.

- Beginning of period 4 (roughly, 2nd half of July 2014):
  Network repercussions of volatility shocks in the Russian market made an abrupt upward shift on 2014-07-21, peaking the following day, when the EU agreed to impose new sanctions on Russia, in particular threatening with economic sanctions if Russia would not use its influence to restrain pro-Russian separatists believed to have downed the Malaysia Airlines flight over Ukraine on 2014-07-17. Network repercussions gradually diminished in the aftermath, with moderate fresh peaks on 2014-07-31 (and on 2014-09-15), that is, on the day (or the first trading day) after economic sanctions were implemented.

- End of period 4 / beginning of period 5 (roughly, late October 2014 – December 2014):
  December 2014 was a month of soaring network repercussions concerning volatility

shocks from rts, with a first spike on 2014-12-02, when Russia acknowledged that it was heading into a recession, and then on 2014-12-09, hitting its maximum, when concerns over Chinese economy and the World Bank's revision of its growth projections for Russia cumulated. The strong network repercussions on the day before the repo rate increase died down abruptly on 2014-12-17, taking residuals temporarily far below zero.

- Later part of period 5 (roughly, May – June 2015):
  Another month of soaring network repercussions was May 2015, with a first abrupt rise on 2015-05-07 in the run-up to the Russian Victory Day Parade, and culminating, on 2015-05-25, the first trading day after Russia's passage of a bill against "undesirable NGOs". Smaller repercussions were prevailing during June.

period	remarks	ret2vol	vol2vol
0	before 2014	−0.031	0.024
1	2014, before sanctions	0.155	−0.452
2	first round of sanctions	1.130	−0.332
3	second round of sanctions	1.187	−0.335
4	third round of sanctions	0.701	−0.075
5	after increase in repo rate	−0.459	−0.257

Table 5: Average residuals

7.3 Discussion

The results of Sections 7.1 and 7.2 reflect an effort to separate network repercussions of a shock in the Russian market from one-time shock spillovers. It has turned out that the ret2vol case is fundamentally different from the vol2vol case. In the ret2vol case, we observe longer-term trends, disrupted on days of important events. In the vol2vol case, on the other hand, we observe relatively short-lived deviations from the long-run average, again coinciding with important events. The conclusion is that the network considered in this study digests volatility shocks more readily than return shocks in the Russian market.

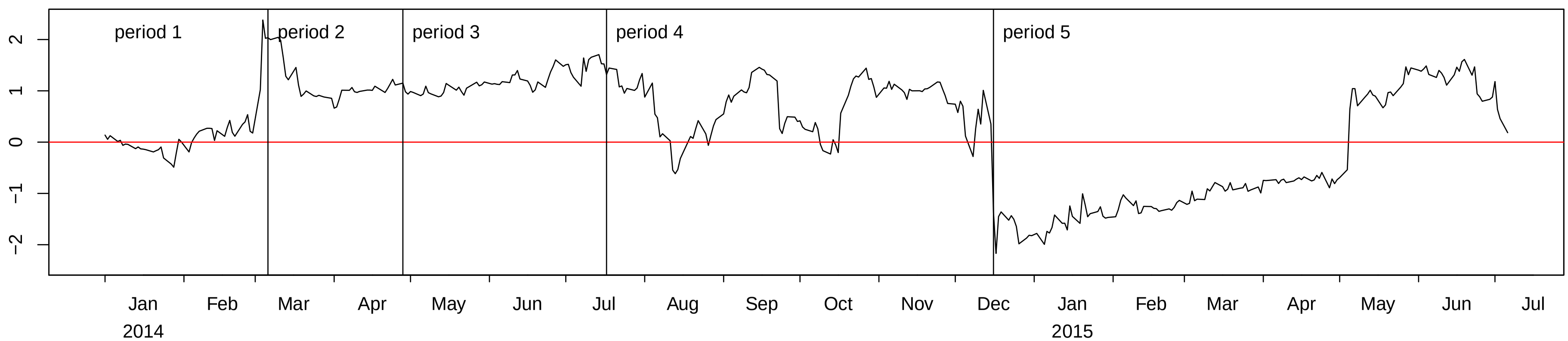

Figure 9: Network repercussions of an rts return shock (ret2vol)

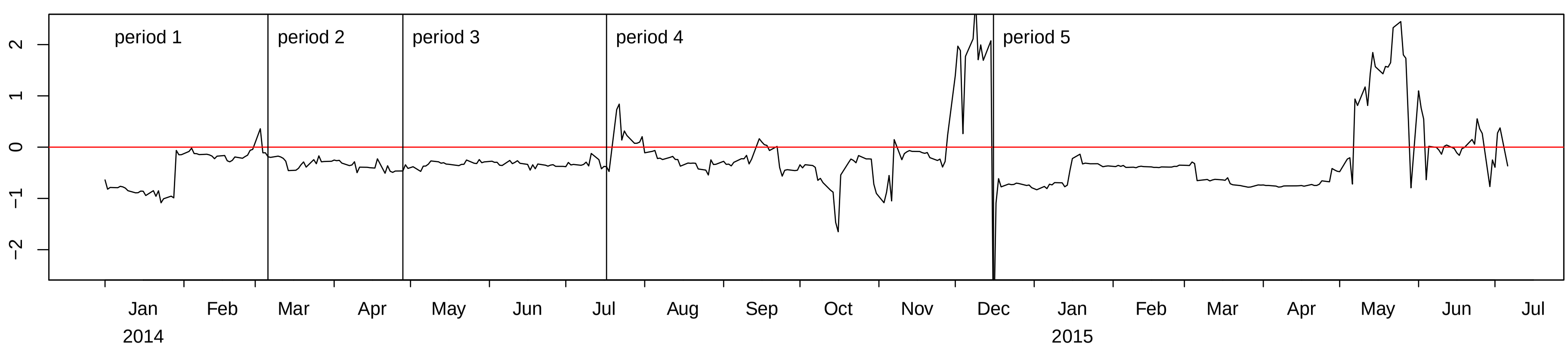

Figure 10: Network repercussions of an rts volatility shock (vol2vol)

8 Summary and conclusions

We studied the stock market network of the "Systemic Five" plus Russia, that is: the USA (represented by dji), the UK (ftse), the euro area (sx5e), Japan (n225), China (ssec), and Russia (rts). In particular focusing on the period from January 2014 through July 2015, we are interested in gauging shock spillover characteristics of the Russian market in the light of events and international sanctions in connection with the Ukrainian crisis, with a focus on detecting differences between different rounds of sanctions.

The methodology of this paper uses, and extends, methodology developed by Diebold and Yilmaz (2009, 2014). It permits daily screening of network dynamics in terms of direct return-to-volatility (and volatility-to-volatility) spillovers from and to rts as well as in terms of repercussions of return (and volatility) shocks coming from rts. The latter is measured by a concept called the propagation value in the present paper; it measures the relative importance of a shock in a market as seed for future uncertainty in returns (and volatilities) across the network. Together with direct spillovers, this also allows an assessment of whether direct spillovers, or network repercussions of shocks, are more important on a given day.

There is strong evidence that political and economic events, along with the international sanctions imposed so far in connection with the Ukrainian crisis, impacted shock spillover characteristics of the Russian stock market.

On the one hand, we found period-specific behavior of direct spillovers and propagation values with respect to rounds of sanctions, concerning both return and volatility shocks in rts. While rounds 1 and 2 of the sanctions hardly differ with respect to their patterns, these change totally with the implementation of economic sanctions in round 3, and again after the Central Bank of Russia increased the weekly repo rate. When round 3 of sanctions began, direct spillovers as well as propagation values from return shocks in rts dropped back to the low levels held before the sanctions began (or to even lower levels), while those from volatility shocks entered a period of turbulence on elevated levels. This period ends abruptly with the day when the Central Bank of Russia increased the repo rate. In the aftermath, the impact of volatility shocks in rts on the network was reduced considerably, while return shocks were becoming more important again, though only with respect to direct spillovers: the propagation value of return (and volatility) shocks in rts initially plunged to its lowest level.

On the other hand, there are five prominent events, among them the repo rate increase, that coincided with a sudden burst or downturn in network repercussions. Russia's propagation values fell heavily when the Central Bank of Russia increased the repo rate, leaving network repercussions far below average. Two other events, of direct economic relevance, with strong impact on volatility shocks and network repercussions were the threat of economic sanctions by the EU after the downing of the Malaysian aircraft in July 2014, and Russia's acknowledgment that it was heading into a recession in early December 2014. The remaining two events, of a more political character, lead to bursts of network repercussions which were particularly pronounced for return shocks: the Russian president's parliamentary pledge and grant to use force in Ukraine in early March 2014, and Russia's activities around the Victory Day Parade in May 2015; no other Victory Day since 1998 had such a big impact. This indicates a difference in how the network "digests" news.

In 2014, Russia's GDP was down by 11.26% compared to 2013[61], and its trading volume with the EU had decreased to c. EUR 300 bn[62]. An analysis of the costs of the trade restrictions between the EU-27 plus Switzerland versus Russia was conducted in a recent study, see Christen et al. (2015). According to them, EU-27 plus Switzerland economies are estimated to incur short-run costs of EUR 34 bn in the value added; similarly, the long-run costs are estimated to amount to EUR 92 bn.

Economic sanctions did not isolate Russia, but they did change its role as a shock propagator in the network of stock markets: They reduced the Russian stock market's relative importance as a propagator of return shocks. We have shown that this reduction came at the cost of increasing the importance of the Russian stock market as a propagator of volatility shocks, thereby increasing the risk across the network. The deterioration of the Russian economy, along with the ruble's depreciation, could be responsible for this phenomenon; indeed, fears of a 1990s type contagion effects were pronounced louder than before. With this observation in mind, it can be concluded that sanctions can be used as a policy tool to impose costs on the sanctioned economy. Sanctions are able to magnify an economy's problems. But this can probably only be achieved at the expense of introducing more volatility into the entire network of stock markets and, in particular, making the network more vulnerable with respect to volatility shocks from the Russian stock market, to the effect that the sanctioning economies are faced with a backlash of their own sanctions.

[61] Own calculations, based on data provided by the World Bank; see http://data.worldbank.org/data-catalog/GDP-ranking-table. Retrieved 2015-05-21.

[62] "European Union, Trade in goods with Russia", released by the European Commission; available online at http://trade.ec.europa.eu/doclib/docs/2006/september/tradoc_113440.pdf. Retrieved 2015-10-04

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Online, http://eaf.ku.edu.tr/sites/eaf.ku.edu.tr/files/erf_wp_1320.pdf

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Appendix A

R-project codes for applying the methodology using return and volatility series:

Codes for obtaining the volatility series:

```
######################################################################
## Update the data
######################################################################

file.name.list =
  c('dji', 'ftse', 'sx5e', 'n225', 'ssec', 'xu100')

index.name.list =
  c('DJIA', '^ftse', '^sx5e', '^n225', '^ssec', '^xu100')

index.file.list = data.frame(file.name = file.name.list, index.name =
index.name.list)

library(tseries)

update = function(file.name, index.name) {
  system(paste('cp ', file.name, '.dat ', file.name, '_old.dat', sep =
''))
  index.old = read.table(paste(file.name, '_old.dat', sep = ''),
header = T)
  date = index.old$date
  last.date = as.character(date[ length(date)] )
  yesterday.date = Sys.Date()-1
    if (last.date == yesterday.date)
    {
      cat(paste('\nThere is no available data to update',
file.name,'\n'))
    }
    else
    {
      x.Open = get.hist.quote(instrument = index.name, start =
last.date, quote = 'Open')
      x.High = get.hist.quote(instrument = index.name, start =
last.date, quote = 'High')
      x.Low = get.hist.quote(instrument = index.name, start =
last.date, quote = 'Low')
      x.Close <- get.hist.quote(instrument = index.name, start =
last.date, quote = 'Close')
      index.new = data.frame(date = row.names(data.frame(x.Close)),
open = data.frame(x.Open)$Open, high = data.frame(x.High)$High, low =
data.frame(x.Low)$Low, close = data.frame(x.Close)$Close)
      index.attached = rbind(index.old, index.new[ -1,] )
      row.names(index.attached) = NULL
      write.table(index.attached, file = paste(file.name, '.dat', sep
= ''), quote = F)
    }
}

for (i in 1:length(index.file.list$file.name))
{
  file.name = as.character(index.file.list$file.name[ i] )
  index.name = as.character(index.file.list$index.name[ i] )
  update(file.name, index.name)
}
```

```
######################################################################
##Define the problems of replication
######################################################################

#Update the problem column with new data

index.name.list = c('dji', 'ftse', 'sx5e', 'n225', 'ssec','xu100')

for (index in index.name.list)
{
file.to.read1 = paste(index, '_with_problem_col.dat', sep = '')
my.problem.data = read.table(file = file.to.read1, header = T)
my.prob.date = my.problem.data$date
last.date1 = as.character(my.prob.date[ length(my.prob.date)] )

file.to.read2 = paste(index, '.dat', sep = '')
my.data = read.table(file = file.to.read2, header = T)
my.date = my.data$date
last.date2 = as.character(my.date[ length(my.date)] )

  if (last.date1 == last.date2)
    {
      cat(paste('\nThere is no new problem col to update',
index,'\n'))
    }
  else
    {
      system(paste('cp ', index, '_with_problem_col.dat ', index,
'_with_problem_col_old.dat', sep = ''))
      data.old = read.table(paste(index, '_with_problem_col_old.dat',
sep = ''), header = T)
      last.date= length(data.old$date)
      my.data.last.date = length(my.data$date)
      my.data.new = my.data[ -c(1:last.date),]
      my.data.new[ ,'problem'] = 0
      for (i in last.date:my.data.last.date){
        if (my.data[ i,-1][ 1]  == my.data[ i,-1][ 2]  && my.data[ i,-1][ 1] ==
my.data[ i,-1][ 3]  && my.data[ i,-1][ 1]  ==my.data[ i,-1][ 4] )
          my.data[ i,-1][ 5]  = 1
      }

index.attached = rbind(data.old, my.data.new)
row.names(index.attached) = NULL
write.table(index.attached, file = paste(index,
'_with_problem_col.dat', sep = ''), quote = F)
    }
}
```

```
######################################################################
##Calculate the daily volatility for each index using
```

```
## 1- German and Klass
## 2- Garch
######################################################################

index.name.list = c('dji','ftse', 'sx5e', 'n225', 'ssec','xu100')

###### German and Klass formula####################################
## Obtaining volatility series using German and Klass methodology ##
####################################################################

germanklass.formula = function(log.open, log.high, log.low, log.close)
{
  germanklass.volatility = 0
  germanklass.volatility = 0.511*((log.high-log.low)^2) -
0.019*((log.close-log.open)*(log.high     + log.low - 2*log.open) -
2*(log.high-log.open)*(log.low - log.open))- 0.383*((log.close-
log.open)^2)
}

###### Garch #########################################################
##Obtaining volatility series using Garch methodology
######################################################################

garch.formula = function(alpha, ret, var.yesterday) {
  est.garch = 0
  est.garch = alpha + 0.05*(ret)^2 + 0.93 * var.yesterday
}


for (index in index.name.list)
{
system(paste('cp ', index, '_daily_volatility.dat ', index,
'_daily_volatility_old.dat', sep = ''))
vol.old = read.table(paste(index, '_daily_volatility_old.dat', sep =
''), header = T)
vol.date = vol.old$date
last.date = as.character(vol.date[ length(vol.date)])
yesterday.date = Sys.Date()-1
  if (last.date == yesterday.date)
    {
      cat(paste('\nThere is no available data to update daily
volatility of', index,'\n'))
    }
  else
    {
      file.to.read = paste(index, '_with_problem_col.dat', sep = '')
      my.data.all = read.table(file = file.to.read, header = T)
      my.date = my.data.all$date
      log.open = log(my.data.all$open)
      log.high = log(my.data.all$high)
      log.low = log(my.data.all$low)
      log.close = log(my.data.all$close)

      ret = diff(log.close)
      alpha = var(ret)*(1-0.05-0.93)

      volatility = numeric(0)
      germanklass.data = numeric(0)
      est.garch = numeric(0)

    for (i in 2:nrow(my.data.all)){
```

```
      if (my.data.all[ i,6] == 0)
        {
        volatility[ i] = germanklass.formula(log.open[ i] , log.high[ i] ,
log.low[ i] , log.close[ i] )
        }
      else
          if (my.data.all[ i,6] == 1) {
          volatility[ i]= garch.formula(alpha, ret[ i] , volatility[ i-1] )
          }
      else
       volatility[ i] = 0
      }
    germanklass.data = data.frame(date = my.date, volatility =
volatility)
    write.table(germanklass.data, file = paste(index,
'_daily_volatility.dat', sep = ''), quote = F)
    }
}

###################################################################
####Compute and plot volatility series using GARCH estimation
###################################################################

index.name.list = c('dji', 'ftse', 'n225', 'gdaxi', 'fchi')

for (index in index.name.list) {
  file.to.read = paste(index, '_weekly_all_data.dat', sep = '')
  my.data.all = read.table(file = file.to.read, header = T)
  my.date = my.data.all$date
  log.open = log(my.data.all$open)
  log.close = log(my.data.all$close)
  log.high = log(my.data.all$high)
  log.low = log(my.data.all$low)


ret = diff(log.close)

library(tseries)
my.data = na.omit(ret)
my.garch = garch(my.data)
my.garch.fitted = na.omit(my.garch)
vol.min = min(my.data)
vol.max = max(my.data)

garch.min = min(na.omit(my.garch.fitted$fi[ ,1] ))
garch.max = max(na.omit(my.garch.fitted$fi[ ,1] ))

my.range = c(min(vol.min, garch.min), max(vol.max, garch.max))

plot(sqrt(vol1$vol1), type = 'l')
lines(my.garch.fitted$fi[ ,1] , type = 'l', ylim = my.range, col =
'red')

}




##################################################################
## Plot all volatilities obtained from
```

```
##the formula of German and Klass
##################################################################

library(zoo)

my.data = read.table('ALL_VOLATILITY_COMBINED.dat', header = T, sep =
' ')

vol.dji = my.data$dji.ret
vol.ftse = my.data$ftse.ret
vol.n225 = my.data$n225.ret
vol.gdaxi = my.data$gdaxi.ret
vol.fchi = my.data$fchi.ret

pdf(file = 'vol_dji.pdf', height = 3.6, width = 16)
  par(mar = c(2,2,0.2,0.2), cex = 1.4)
  plot(zoo(vol.dji, as.Date(my.data$date)),
       ylim = c(0,0.025),
       xaxt = 'n',
       yaxt = 'n',
       xlab = '',
       ylab = 'dji'
       )
#   axis(side = 1, at = as.Date(paste(seq(1998,2012,2),'-01-01', sep =
''), format = "%Y-%m-%d"), labels = seq(1998,2012,2))
  axis(side = 2, at = c(0,0.02), labels = c(0,0.02))
  legend('topleft', title = 'dji', legend = '', y.intersp = 0.2, bg =
'transparent', cex = 1.4)
dev.off()

pdf(file = 'vol_ftse.pdf', height = 3.6, width = 16)
  par(mar = c(2,2,0.2,0.2), cex = 1.4)
  plot(zoo(vol.ftse, as.Date(my.data$date)),
       ylim = c(0,0.025),
       xaxt = 'n',
       yaxt = 'n',
       xlab = '',
       ylab = 'ftse'
       )
#   axis(side = 1, at = as.Date(paste(seq(1998,2012,2),'-01-01', sep =
''), format = "%Y-%m-%d"), labels = seq(1998,2012,2))
  axis(side = 2, at = c(0,0.02), labels = c(0,0.02))
  legend('topleft', title = 'ftse', legend = '', y.intersp = 0.2, bg =
'transparent', cex = 1.4)
dev.off()

pdf(file = 'vol_n225.pdf', height = 3.6, width = 16)
  par(mar = c(2,2,0.2,0.2), cex = 1.4)
  plot(zoo(vol.n225, as.Date(my.data$date)),
       ylim = c(0,0.027),
       xaxt = 'n',
       yaxt = 'n',
       xlab = '',
       ylab = 'n225'
       )
#   axis(side = 1, at = as.Date(paste(seq(1998,2012,2),'-01-01', sep =
''), format = "%Y-%m-%d"), labels = seq(1998,2012,2))
  axis(side = 2, at = c(0,0.02), labels = c(0,0.02))
```

```
  legend('topleft', title = 'n225', legend = '', y.intersp = 0.2, bg =
'transparent', cex = 1.4)
dev.off()

pdf(file = 'vol_gdaxi.pdf', height = 3.6, width = 16)
  par(mar = c(2,2,0.2,0.2), cex = 1.4)
  plot(zoo(vol.gdaxi, as.Date(my.data$date)),
       ylim = c(0,0.025),
       xaxt = 'n',
       yaxt = 'n',
       xlab = '',
       ylab = 'gdaxi'
       )
#   axis(side = 1, at = as.Date(paste(seq(1998,2012,2),'-01-01', sep =
''), format = "%Y-%m-%d"), labels = seq(1998,2012,2))
  axis(side = 2, at = c(0,0.02), labels = c(0,0.02))
  legend('topleft', title = 'gdaxi', legend = '', y.intersp = 0.2, bg
= 'transparent', cex = 1.4)
dev.off()


pdf(file = 'vol_fchi.pdf', height = 3.6, width = 16)
  par(mar = c(2,2,0.2,0.2), cex = 1.4)
  plot(zoo(vol.fchi, as.Date(my.data$date)),
       ylim = c(0,0.025),
       xaxt = 'n',
       yaxt = 'n',
       xlab = '',
       ylab = 'fchi'
       )
  axis(side = 1, at = as.Date(paste(seq(1997,2013,2),'-01-01', sep =
''), format = "%Y-%m-%d"), labels = seq(1997,2013,2))
  axis(side = 2, at = c(0,0.02), labels = c(0,0.02))
  legend('topleft', title = 'fchi', legend = '', y.intersp = 0.2, bg =
'transparent', cex = 1.4)
dev.off()
```

Rest of the R-project codes developed for this thesis and Schmidbauer et.al. (2013b) can be provided upon request.

```
#################################################################
##Simulation of Brownian Bridge to understand the methodology of
##Obtaining volatility series
#################################################################

##Defining the Brownian Bridge

f=10
t=seq(from=0,to=1,length=f)
B=c(0,cumsum(rnorm(f-1,mean=0,sd=sqrt(1/f))))
X=B-t*B[ f]
plot(t,X,type="l")
abline(h=0,lty="dashed")

##################################################################
#Simulating a brownian motion with drift for different sigma values
##################################################################
N = 1000
B = c(0,cumsum(rnorm(N-1,mean=0,sd=sqrt(1/N))))
```

```
brownian.motion = function(b, sigma)
{
  t = seq(from = 0, to = 1, length = N)
  X = b*t + sigma*B #defining brownian motion with drift
  Y = X - t*X[N]    #defining brownian bridge
  plot(t,Y,type = 'l')
  output = data.frame(min = min(Y), max = max(Y))
  return(output)
}

min.max = data.frame(min = numeric(), max = numeric())

for (sigma in seq(0,10,0.1))
{
min.max = rbind(min.max, brownian.motion(0,sigma))
}
sigma.min.max = data.frame(sigma = seq(0,10,0.1) , min.max)
plot(sigma.min.max[ ,1],sigma.min.max[ ,2]) #min
plot(sigma.min.max[ ,1],sigma.min.max[ ,3]) #max


t = 0:1000 #time
random = rnorm (n = length(t)-1, sd = sqrt(sig2))
sig2 = 0.1
#simulate a set of random variables
x = rnorm (n = length(t)-1, sd = sqrt(sig2))
#compute their cumulative sum
x = c(0, cumsum(x))
plot(t, x,type = 'l')#, ylim = c(-2,2))




X <- matrix(0, nsim, length(t))
for (i in 1:nsim) X[i, ] <- c(0, cumsum(rnorm(n = length(t) - 1, sd =
sqrt(sig2))))
plot(t, X[1, ], xlab = "time", ylab = "phenotype", ylim = c(-2, 2),
type = "l")
for (i in 1:nsim) lines(t, X[i, ])



nsim <- 10000
X <- matrix(rnorm(n = nsim * (length(t) - 1), sd = sqrt(sig2)), nsim,
length(t) - 1)
X <- cbind(rep(0, nsim), t(apply(X, 1, cumsum)))
v <- apply(X, 2, var)
plot(t, v, type = "l", xlab = "time", ylab = "variance among
simulations")

###################################################################
#Defining a random sequence
###################################################################


N = 1000
H = numeric()

my.data = data.frame(matrix(ncol = 5, nrow =1000 ))

for (i in 1:5) {
```

```
  H = rbind(H,c(0,cumsum(rnorm(N-1,mean=0,sd=sqrt(1/N)))))
  my.data
}
my.data = data.frame(my.data,my.data[ ,i])


######################################################################
##Simulating 1000 brownian motion with drift for different sigma
##values and looking at the min max differences
#######################################################################


rm(list=ls())

N = 1000

my.slopes = numeric()

brownian.bridge = function(b, sigma)
{
  t = seq(from = 0, to = 1, length = N)
  X = b*t + sigma*rnorm(N)#defining brownian motion with drift
  Y = X - t*X[N]    #defining brownian bridge
  #plot(t,Y,type = 'l')
  output = max(Y) - min(Y)
return(output)
}


for (i in 1:repetitions)  {
  my.slopes = c(my.slopes, brownian.bridge(b = 0, sigma = 1))
}

plot(2,-1, xlim = c(0,1), ylim = c(0,10), pty = 'n', xlab = 'Sigma',
ylab = 'max-min')


for (i in 1:repetitions)  {
  abline(a = 0, b = my.slopes[i], col = i)
}

browser()

hist(my.slopes, breaks = seq(4, 12, by = 0.25), xlab = 'Slopes')


# max.min.diff = numeric()
#
#   for (sigma in seq(0,10,0.1))
#       {
#         max.min.diff = rbind(max.min.diff, brownian.motion(0,sigma))
#       }
#       sigma.min.max = data.frame(sigma = seq(0,10,0.1)
,max.min.diff)
#
# plot(sigma.min.max[ ,1],sigma.min.max[ ,2], xlab = 'Sigma', ylab =
'Max-Min',ylim = c(0,8)) #max-min
#lines(sigma.min.max[ ,1], sigma.min.max[ ,2])
#}
```