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Faculty of Social Sciences

Institute of Economic Studies

Master's Thesis

Frequency Connectedness of Financial, Commodity, and Forex Markets

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Abstract

This Thesis is dedicated to the variance decompositions from the VAR model under the Diebold, Yilmaz (2012) methodology combined with the Baruník, Křehlík (2017) method of frequencies that was used to create traditional and directional spillover tables to be compared under different frequencies. Diverse markets variables were used for the analysis during the period 1/6/1999 to 29/6/2018. The S&P 500 Index represented the financial markets, EUR/USD and YEN/USD represented the Forex markets, and eight types of commodities: Crude Oil, Natural Gas, Gasoline, and Propane represented energy commodities and Corn, Coffee, Wheat, and Soybeans represented food commodities. This analysis contribute to understanding of the dynamic frequency connectedness in case of a differentiated system of markets. The main finding was the strongest short-frequency reaction to shocks in case of all variables, which is opposite behavior than usually observed in banking sector frequency dynamics analyses.

Classication: F12, F21, F23, H25, H71, H87

Keywords: connectedness, financial market, forex market, commodity market, systemic risk, spillovers, frequency analysis

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Abstrakt

Tato diplomová práce je věnována přenosu volatility pomocí dekompozice odchylek z VAR modelu metodou Diebold, Yilmaz (2012) v kombinaci s metodou Baruník, Křehlík (2017) v různých frekvencích v období od 1. 6. 1999 do 29. 6. 2018. Index S&P 500 reprezentuje finanční trhy, EUR/USD a YEN/USD trhy s měnovými kurzy. Ropa, zemní plyn, benzín a propan představovují energetické komodity. Kukuřice, káva, pšenici a sójové boby zastupují potravinářské komodity. Tato empirická studie přispívá k pochopení dynamické spojitosti rozdílných frekvencí v případě diferencovaného systému trhů. Hlavním zjištěním je skutečnost nejsilnější krátkodobé reakce na šoky, která byla pozorována v případě všech proměnných. To je v příkrém rozporu s výsledky klasických analýz frekvenční dynamiky v bankovním sektoru, které byly doposud pozorovány.

Klasifikace: F12, F21, F23, H25, H71, H87

Klíčová slova: finanční trhy, komoditní trhy, provázanost, nejistota, frekvenční analýza

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Motivation The connectedness of financial markets opens an area for research and offers space to move from current standard methods and frameworks of connectedness that use classical tools which overlook some properties and provide aggregate information only such as generalized forecast error variance decompositions (GFEVD) used by Diebold and Yilmaz (2012) to more advanced models because shocks propagate on different horizons and our intention is to see the differences and a topic of dynamics of responses to shocks arise. Ortu et al. (2013) argue that formation of preferences brings different horizons and consumption has to response to shocks.

Hypotheses

Hypothesis #1: FX markets, commodities and financial markets influence each other on both short and long runs with various strengths.

Hypothesis #2: Types of shocks resulting in the short-, medium-, and long-term responses differ.

Hypothesis #3: The hypothesis of Baruník, Křehlík (2018) that shocks with long-term responses transmit across markets with larger strengths, pointing to high long-run systemic risk works for global most liquid financial, commodity, and forex markets.

Methodology We will analyze the frequency connectedness of global data from publicly available databases on forex markets, the commodity market and the financial markets such as Yahoo! And Google Finance. As a main material we are going to use the paper Baruník, Křehlík (2018), which deals with the measurement of the frequency connectedness between the financial variables resulting from the heterogeneous frequency response to shocks in the short-, medium-, and long-term and we will use their R-studio code. We are going to test the frequency connectedness theory for the global liquid real world data and how the length and strengths of the shocks are.

Expected Contribution We will test the connectedness of the acquired data on the mentioned markets so we will be able to come up with the underlying conclusions of their interconnection. The main contribution will be an empirical analysis of highly diverse variables from financial, commodity and forex markets. We will also pay attention to the lengths of these shocks, which have not yet been addressed in this frequency dynamics in the literature besides Baruník, Křehlík (2018) and we would like to come with practical possible causes of these lengths from a macroeconomic point of view.

Outline

1. Introduction and literature review
2. Methodology
3. Empirical analysis on selected real data
4. Conclusion

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Chapter 1

Introduction

Global economic growth has already been renewed since the 2008 crisis. Over the last decade the connectedness of markets has risen in importance. The economic world is changing quickly and with profound results. Why is it important to understand systemic risk through market connectedness? It is important because it may prevent negative economic events such as slow downs and crashes. Financial regulators, bankers, economists, politicians as well as academics are interested in systemic risk. Connectedness is central to risk measurement and management. This covers risks regarding return, default and contractual/activity connectedness. Systemic risk is directly connected to financial markets and various academic works view this topic differently. Correlation-based measures use pairwise association and average correlations, (Engle (2009)) CoVaR; CoVaR (Adrian, Brunnermeier (2008)) or variance decompositions Diebold, Yilmaz (2012), Diebold, Yılmaz (2014). Systemic risk influences the stability of financial markets with high importance on the source of the instability and the frequency responses to the shocks. Baruník, Křehlík (2017) specify those responses as assessing connectedness at different horizons to capture the heterogenous frequency of responses based on divergent expectations.

The purpose of this Thesis is to provide a complex empirical analysis of financial markets, forex markets and commodities in the frequency domain to test whether their dynamic connectedness corresponds to the theory of Baruník, Křehlík (2017). Various empirical methods were developed to describe the volatility of time series in a single complex model. Variance decompositions were the primary methods used to analyze sources of volatility. In this paper we are going to base the analysis of connectedness on variance decompositions specified by Diebold, Yilmaz (2009) and Diebold, Yilmaz (2012). Diebold, Yilmaz (2009) introduced a methodology from a variance decomposition of vector autoregressive model (VAR) to capture the connectedness of one variable explained by other variables. The method is order dependent and does not differentiate any time horizons. Diebold, Yilmaz (2012) introduced a methodology from a variance decomposition of vector autoregressive model with no order dependence but still in a one frequency horizon. Those studies introduced the possibility of measuring the connectedness between financial markets, forexes and commodities. Nevertheless, those studies also measured the impact of shocks to the system of variables with no regard to their length. Is it important to understand not only the level of impact but also the duration of impact of the shocks on the system?

Yes. For systemic risk management purposes it is important to understand the dynamics of the whole system in as much depth as possible and how long it takes for each variable to recover (if ever) and return to normal. This may help to understand and predict market evolution. Baruník, Křehlík (2017) refined variance decompositions and came up with "the frequency dynamics of connectedness" created by different strengths and lengths of shocks to financial markets. Does connectedness really differ in different frequencies? Yes. Baruník, Křehlík (2017) provided an empirical analysis of numerous important U.S. banks that showed significantly different results over different frequencies. The greater the frequency, the stronger the connectedness. Would this work for a different and wider system of variables? That is the research question of our analysis.

In this Thesis we use the Diebold, Yilmaz (2012) methodology combined with the Baruník, Křehlík (2017) method of frequencies. We used realized volatility for the VAR model and variance decompositions. We created traditional and directional spillover tables overall to be compared in different frequencies. We also analyzed total and individual frequency dynamics of all variables. Our chosen frequencies were one week, one month, and one year. 250 windows were used for our rolling sample estimation.

We decided to provide an analysis of the S&P 500 Index representing financial markets, EUR/USD and YEN/USD representing forex markets, and eight types of commodities: Crude Oil, Natural Gas, Gasoline, and Propane representing energy commodities and Corn, Coffee, Wheat, and Soybeans representing food commodities. We created a widely differentiated system where we expected lower connectedness compared to purely financial or banking empirical analyses. We believe this analysis will contribute to the understanding of whether dynamic frequency connectedness differs in the case of a widely differentiated system.

Baruník, Křehlík (2017) considered volatility spillovers as a proxy for uncertainty transmission. We believe that understanding transmission is crucial for risk management. Our data sample covers the period from 1/6/1999 to 29/6/2018. To the best of our knowledge such a diverse markets data analysis in the frequency dynamics domain has not yet been undertaken. We believe that our results might be of interest to economists, investors and regulators of financial and commodity markets.

Our Thesis is structured as follows: Chapter 1 covers introduction, Chapter 2 provides a literature review, Chapter 3 describes the methodology of measuring connectedness primarily based on Diebold, Yilmaz (2009), Diebold, Yilmaz (2012), and Baruník, Křehlík (2017). Chapter 4 covers the institutional background of each of our variables with factors driving their prices. Chapter 5 contains data analysis. Chapter 6 provides empirical results and finally Chapter 7 provides a summary of our findings, discusses results, and suggests possible extensions of our analysis.

Chapter 2

Literature Review

Increasing market connectedness raises an interest of researchers and analyzing methods evolve. Academics try to develop more suitable general frameworks to minimize number of overlooked properties that are sources of systemic risk. This chapter provides a review of the main literature regarding measurement of connectedness.

Linear dependence was firstly measured on 3 time frequencies through a frequency decomposition of a likelihood statistics ratio. (Geweke (1982)) This method soon moved to 2 multiple time frequencies conditional on the 3rd where the distribution measures were approximated by bootstrap and multivariate extensions were created. (Geweke (1984)) Later the method developed into a normal linear regression model approached as a problem in Bayesian inference where the disturbances were calculated using the Monte Carlo simulation. (Geweke (1986)) For all those methods related measures in restrictive environment were used. We decided to use 3 time frequencies of one week, one month, and one year.

A conditional covariance matrix of asset returns using the FACTOR-ARCH model to analyze dynamics between asset risk premia and volatility in a single system was examined later. It was proved by an empirical analysis dedicated to pricing of Treasury bills with an outcome of stable positive results over time. (Engle et al. (1990)) Another approach was built on the structural VAR and spectral decompositions to interpret the impact of changes of one variable on other variables. The empirical section behind analyzed relationship among the time series. The frequency dynamics of the connectedness was specified through variance decompositions based on the frequency responses to shocks. (Stiassny (1996)) A different method estimated the time varying correlations using dynamic conditional correlation (DCC) models that used univariate two step methods based on a likelihood function. Its empirical section tested propriety of the DCC model and the conclusion was a good performance in different situations and feasible results. (Engle (2002)) Correlations of risk management, portfolios and hedging depending on forecast of an asset structure, volatility and correlations within the system and introduction of new methods for estimating dynamic correlations and forecasting correlations and their measurement were examined a few years after. (Engle (2009)) Through the model dynamics of the cross section disturbances of economic time-varying growth was provided an evidence that transitions from low to high income levels were primarily small and sparsely-populated. (Quah et al. (1992)) We analyzed the volatility dynamics through variance decompositions from the VAR model and our empirical analysis was applied to a wider field of markets.

A different approach estimated stochastic volatility models using a price range to prove that the range was of high efficiency volatility but also that it was Gaussian and robust to microstructure noise. The dynamics of daily exchange rate volatility were used to conclude that one single model was not enough to describe the high- and the low- frequency dynamics of volatility. (Alizadeh et al. (2002)) The first sights of need for distinction between the short- and the long-term of the system brought measuring connectedness between the moving average and the error correction representation of consumption, income, wages and prices through the vector autoregression model was proposed. (Engle, Granger (1987)) The VAR and GARCH models were used to explain causes of volatility spillovers in exchange rates. (Engle et al. (1988)) These empirical analyses also remained in a financial and consumption sector but supported the idea to separate frequencies.

The long-term and the short-term effect disturbances on the output variance joint behavior and the moving average representation of the output could be used to interpret fluctuations. The analysis behind focused in an interpretation of fluctuations in a GNP and unemployment. The dynamics present resulted in the short-term disturbances effect that increased steadily over time. (Blanchard, Quah (1989)) The low frequency movements of the dynamics where the long-term changes proved that the stochastic trend of the decompositions and an error to one series could be a shock to the long-term trend were modeled many years later. (Balke, Wohar (2002)) This was an important idea that the long-term lasting shock had the greatest power at low frequencies and could lead to the long-term connectedness if it influenced the other variables.

An academic work leading to the idea of the variance decompositions started by the consumer preference theory already. A vector autoregression model with random coefficients could be used. As a prove was described the unemployment-inflation dynamics after the World War II in the U.S. (Cogley, Sargent (2001)) The model applied the decompositions to a number of consumption-based discounted factor models. The conclusion was an instability of the inflation dynamics in both the short- and the long-run via spectral estimates implied by their time-varying VAR. The consumption-based asset pricing model was used to prove existence of the financial market dynamics as the long-run growth raised equity prices. (Bansal, Yaron (2004)) The investors preference dynamics could be quantified through connectedness of shocks to set the asset pricing through the decompositions. (Dew-Becker, Giglio (2016)) These examples proved suitability of the variance decompositions from the VAR model in the connectedness measure methodology and an importance of the dynamics measure where the results differed in various frequencies.

Impulse-response shocks leading to fluctuations dependent on the connectedness structure was another theory proved by an empirical evidence that analyzed the higher-order interconnections and concluded that the aggregate volatility might be obtained from shocks if the input–output matrix was unrelated to the nature of the aggregate fluctuations. (Acemoglu et al. (2010)) A distinction of the short-term from the long-term movements in connectedness and an introduction of the Vector Error Correction Model (VECM), which was the vector autoregression (VAR) extended by cointegration restrictions for analyzing the dynamic effects of permanent and transitory shocks using the Cholesky decompositions was another method. The impulse-response functions diversified shocks based on a degree of their persistence. The conclusion of an empirical evidence behind proved that if some variables share common stochastic trends then the system of variables was connected by restrictions. If we separate the short- and the long-term shocks, the standard VAR identification tools could be used to make them mutually uncorrelated. (Gonzalo, Ng (2001))

Regarding systemic risk the system-wide connectedness could be examined to identify a gap between an approach of different sources of isolated systemic risk and global measures not connected to any theory. A specific example was testing the gap in order to be fully understood and to provide a guideline for regulating banks and the market with regard to the shocks on the financial market. (Benoit et al. (2017)) The long-run risk valuation model where the consumption growth contained predictable cyclical components was used and provided the main reason to believe that agents operate on different investment horizons based on their preferences. These horizons were represented by frequencies and consumption growth through cyclical components. (Ortu et al. (2013)) The consumption growth could be separated into a variety of frequencies and provided an evidence of the cross-sectional pricing ability of a business cycle component of the consumption growth. (Bandi, Tamoni (2017)) A simple model of systemic risk to demonstrate that each financial institution's contribution to systemic risk could be measured through a different method. The empirical analysis proved the possibility to predict emerging risks such as outcome of stress tests, decline in equity valuation and widening credit default swap spreads. (Acharya et al. (2017)) A measurement of systemic risk and the value at risk of the financial system conditional on institutions being under distress through CoVaR was also proposed. Systemic risk was defined as "*the difference between CoVaR of institutions under distress*" and CoVaR of institutions in "normal situation". (Adrian, Brunnermeier (2008)) A practical application of the methodology predicted more than half of the realized covariance during the financial crisis of 2008. (Adrian, Brunnermeier (2016)) These papers provided an evidence of importance and need to create suitable methods for systemic risk measurement purposes.

Highly important methodology was a spillovers measure based on the forecast error variance decompositions from the vector autoregressions (VAR) depending on Cholesky-factor identification. The resulting variance was variable ordering dependent across identical assets data in different countries and distilled wealth of information into a single spillover measure. The empirical study analyzed 19 global equity markets over the years 1990-2009 and their conclusion was an evidence of divergent behavior in the dynamics of return spillovers. The term "spillover index" was firstly used as a measure of financial market independence in different time horizons. (Diebold, Yilmaz (2009)) Our complete traditional, directional, total and individual dynamics analysis under this methodology is provided in the Appendix section.

The main body of our paper was built up on a spillovers measure, which moved to usage of Cholesky-factor identification of the VAR with resulting variance decompositions invariant to ordering. The original empirical study behind the methodology analyzed daily volatility spillovers across the U.S. stocks, bonds, foreign exchange and commodity markets during 1999-2010 with a conclusion of limited importance of volatility spillovers from the stock market to other markets especially during the financial crisis of 2008. (Diebold, Yilmaz (2012)) We applied this method to a diverse system of financial, commodity and forex markets. We provided complete traditional, directional, total and individual analysis dynamics within this methodology.

Creation of a scale of the short-, medium-, and long-term and a general framework that allowed measurement of the connectedness at different frequencies while their exact length could be chosen were proposed later. Where the strength and length of shocks that impacted the other variables of the system could be measured and compared. The empirical evidence was dedicated to number of U.S. banks where different trends caused various shocks in different frequencies and created systemic risk. (Baruník, Křehlík (2017)) This was the methodology we were mainly building our hypothesis on as well as our empirical analysis was built on this methodology with usage of mentioned orders invariant spillovers measures. (Diebold, Yilmaz (2012))

The focus of Baruník, Křehlík (2017) on the frequency-specific measurement of systemic risk based on different lengths could be compared to Bandi, Tamoni (2017) who separated consumption growth into cyclical components through diversification of betas in different frequencies. However; Baruník, Křehlík (2017) used the spectral representations of the variance decompositions to document the frequency dynamics of the connectedness. Commodity prices driven by consumption naturally generated shocks with heterogeneous frequency responses.

Chapter 3

Methodology

In this section we describe methodological background used for our analysis. Firstly, we counted the realized volatility and established the Vector Autoregressive model (VAR). The methodology of Diebold, Yilmaz (2009) and Diebold, Yilmaz (2012) were followed to define the forecast error variance decomposition (FEVD). Methodology of Baruník, Křehlík (2017) brought Fourier transformation of the impulse-response functions to analyze the FEVD and we showed the decomposed aggregated connectedness to the short-, medium-, and the long-term frequencies.

3.1 Realized Volatility

The realized volatility was counted as:

$$\sigma_n^2 = 1/(m-1)\sum_{i=1}^{m}(u_{n-i}-\bar{u})^2,$$

where $\bar{u}$ was the average daily log return that was assumed to be near enough to 0 to be round of and dropped out. Moreover $1/(m-1)$ was the sample variance estimator where could be used just $1/m$ as a population variance. The simplified version was:

$$\sigma_n^2 = 1/m\sum_{i=1}^{m}u_{n-i}^2.$$

So the daily variance estimate was counted as a square of the $logreturns^2$.

From the daily variances were counted the daily realized volatility the average daily standard deviations by square roots.

3.2 Measuring Connectedness with the Variance Decompositions

The variance decompositions were used for determining how much of the future uncertainty of variable i was due to shocks in variable j so it documented how the variance behave under certain period of time. That provided a useful information for future uncertainty. However; measuring responses to shocks as standard correlation-based measure was not suitable for us as we wanted to document the impact of our variables at diverse frequencies with various strengths.

The connectedness measure of the VAR using the forecast error variance decompositions (GFEVD) was undertaken. The VAR model was used as an underlying model for spillovers theory regarding Diebold, Yilmaz (2012) methodology. The frequency-dependent connectedness was measured from the variance decompositions and frequencies measured by the different periods of time regarding the Baruník, Křehlík (2017) methodology.

3.2.1 Orthogonal Structural System Dependent on Ordering

The volatility spillovers from the variance decompositions allowed to aggregate the total spillovers effect across markets in one order dependent measure. (Engle et al. (1990), Diebold, Yilmaz (2009))

The N-variable dimensional covariance-stationary data-generating process described by the VAR model of order p with orthogonal shocks (the moving average representation of the VAR) exist and was defined as:

$$x_t = \Theta(L)\varepsilon_t,$$

which was a moving average representation of time series specifically first-order two-variable VAR (2x2 parameter matrix of koeficients), x_t represented the realized volatitity and described the vector autoregressive stationary process, and ε_t represented white noise (sometimes referred as unpredictable innovation through which correlation of the model could be tested). (Diebold, Yilmaz (2009) (originally proposed by Sims (1992)))

$$\Theta(L) = \Phi_0 + \Phi_1(L) + \Phi_1(L)^2 + ... \Longrightarrow \Theta(L) = (I - \Phi L)^{-1},$$

could be rewritten as

$$x_t = A(L)u_t,$$

where $A(L) = \Theta(L)Q_t^{-1}; u_t = Q_t\varepsilon_t; E(u_t u_t') = I$, which was a unique lower-triangular Cholesky-factor identification of the covariance matrix where Θ_0 did not need to be diagonal. (Sims (1992))

For this 2x2 matrix corresponding a 1-step-ahead error vector was described as

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

which had the covariance matrix

$$E\Big(e_{t+1,t}e_{t+1,t}^{'} = A_0 A_0^{'}\Big).$$

An order dependent spillover index in simple first-order two-variable case was than

$$C = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_0^{'})} * 100.$$

The simple VAR framework and this Cholesky-factor was orthogonal and dependent on ordering as shocks in the model might be orthogonal to other variables with high importance of identification scheme where the dependence on ordering complicated the measure. Nevertheless; all aspects of the connectedness were contained in this representation while the contemporary aspects in Θ_0 and the dynamic aspects in Θ_1, Θ_2. A problem arised with usage of high number of coefficients in $\Theta_0, \Theta_1, \Theta_2, ...$ so a transformation was needed for better and more compact results, which could be done through the variance decompositions.

The orthogonal structural system identified the uncorrelated structural shocks from correlated assumptions. The main assumptions of the Cholesky-factor identification was the sensitivity to ordering and the generalized variance decomposition (GVD). (Diebold, Yılmaz (2014)) Under the GVD over-identification used to be faced so that the identifying restrictions could not be tested. (Koop et al. (1996), Pesaran et al. (1998))

Find the results of our empirical study based on the Diebold, Yilmaz (2009) methodology dependent on ordering in the Appendix section.

3.2.2 Directional Spillovers Independent on Ordering

The total connectedness was too robust to Cholesky ordering, which means that the range of the total connectedness estimates across ordering was small. (Diebold, Yılmaz (2014)) The new directional spillovers in a generalized VAR framework might eliminate possible dependence of the results dependent on ordering and built on the generalized VAR and the generalized identification. (Koop et al. (1996), Pesaran et al. (1998)) Moreover; a permanent and transitory decomposition theory of both unorthogonzalied and orthogonzalied shocks could be used. (Diebold, Yilmaz (2012), Gonzalo, Ng (2001))

The principle was that instead of using orthogonalized - correlated - shocks historically observed distribution of the errors was used, which caused that the contribution to the variance of the forecast error was not necessarily equal to one. (Diebold, Yilmaz (2012))

The N-variable dimensional covariance-stationary data-generating process described by the VAR model of order p with no orthogonal shocks was

$$var(p), x_t = \sum_{i=1}^{p} \Phi_i x_{t-1} \varepsilon_t \Longrightarrow x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + ... + \Phi_p x_{t-p} + \varepsilon_t,$$

where $x_t = (x_{1t}, ..., x_{Nt})'; t = 1, ..., T; \Phi_1, ..., \Phi_N$ was a coefficient parameters matrix and

$$\varepsilon \sim (0, \sum)$$

was a vector of identically distributed disturbances. The moving average representation was

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i},$$

where the NxN coefficient matrices Ai obeyed recursion $A_i = \Phi_1 A_{i-1} + Phi_2 A_{i-2} + ... + Phi_p A_{i-p}$ with A_0 an NxN identity matrix and $Ai = 0$.

The moving average coefficients (the variance decompositions) were important for dynamics of the system analyzing the forecast error variances of each variable. In this model each variable was regressed on its own p lags and matrices of each coefficients contained complete information about the connection between the variables.

The lag-polynomial matrix was represented as

$$\Phi(L) = [I_N - \Phi_1 L - ... - \Phi_p L^p] \Longrightarrow \Phi(L) x_t = \varepsilon_t,$$

where I_N was an identity matrix and $|\Phi(z)|$ lied outside the unit circle. The vector moving average representation:

$$x_t = \Psi(L)\varepsilon_t,$$

where $\Psi(L) = [\Psi(L)]^{-1}$ was a matrix of infinite lag polynomials and Ψ_h was the moving average coefficients with h=1,...,H horizons. (Pesaran et al. (1998)) The variance decompositions were the transformation of the (NxN) matrix of moving average coefficients Ψ_h at lag h through which could be measured connectedness as contribution of shocks to the system. As the errors were uncorrelated the total covariance matrix of the forecast error conditional at the information in $t-1$ was

$$\Omega_H = \sum_{h=0}^{H} \Psi_h \sum \Psi'_h,$$

where $\sum$ were the covariance matrix errors than the covariance matrix of the conditional forecast error

$$\gamma_t^k(H) = \sum_{h=0}^{H} \Psi_h [\varepsilon_{t+H-h} - E(\varepsilon_{t+H-h}/\varepsilon_{kt+H-h})]$$

with normal distribution

$$\gamma_t^k(H) = \sum_{h=0}^{H} \Psi_h[\varepsilon_{t+H-h} - \sigma_{ii}^{-1}(\varepsilon_{t+H-h}/\varepsilon_{kt+H-h})]$$

then the covariance matrix was

$$\Omega_H^k = \sum_{h=0}^{H} \Psi_h \sum \Psi_h' - \sigma_{ii}^{-1} \sum_{h=0}^{H} \Psi_h(\sum)_{.k}(\sum)_{.k}' \Psi_h'.$$

The main difference from the order dependant methodology was the identification scheme of shocks while calculating the variance decomposition could be described as

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H}((\Psi_h \Sigma)_{j,k})^2}{\sum_{h=0}^{H}(\Psi_h \Sigma \Psi_h')_{j,j}},$$

where $(\theta_H)_{j,k}$ represented the contribution of the kth variable to the variance of the forecast error of j over the horizon H, and Ψ_h was the $(N \times N)$ matrix of moving average coefficients at lag h and $\sigma_{kk} = (\Sigma)_{k,k}$.

$$C_H = \frac{\sum_{j \neq k} \left(\tilde{\theta}_H\right)_{j,k}}{\sum \tilde{\theta}_H} * 100 = \left(1 - \frac{Tr\left\{\tilde{\theta}_H\right\}}{\sum \tilde{\theta}_H}\right) * 100,$$

where C stood for the connectedness measure and $Tr\left\{\tilde{\theta}_H\right\}$ was the trace operator of the θ_H matrix.

Directional Spillovers

The generalized VAR measure allowed to learn about the direction of the volatility spillovers where d_{ij}^H was the $ij - th$ H-step variance decomposition component and each variance decomposition followed $d_{ij}^H,\ i,j = 1,...N,\ j \neq i$. (Diebold, Yilmaz (2012)) The variance decomposition matrix could be denoted as $D^H = d_{ij}^H$. (Diebold, Yılmaz (2014)) The off-diagonal entries of D^H were parts of the N forecast-error variance decompositions of relevance and measured the pairwise directional connectedness from j to i as

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

where

$$C^H_{i\longleftarrow j} \neq C^H_{j\longleftarrow i}$$

in case of not just an individual element D^H but off-diagonal row or column sums.

The total directional connectedness from i variable to j variable was specified as the sum of off-diagonal elements equal to the H-step forecast-error variance where

$$C^H_{i\longleftarrow \bullet} = \sum_{j=1, j\neq i}^{N} d^H_{ji}; C^H_{j\longleftarrow \bullet} = \sum_{i=1, i\neq j}^{N} d^H_{ji}$$

was the grand total of the off-diagonal entries in D^H, which measured the total connectedness as

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

which could be used to obtain the total directional connectedness measures.

Specifically, measuring the directional volatility spillovers obtained to variable i **FROM** all other markets j was represented as

$$C^g_{i\longleftarrow \bullet}(H) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} * 100.$$

Measuring the directional volatility spillovers obtained from variable i **TO** all other markets j was represented as

$$C^g_{\bullet\longrightarrow i}(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} * 100.$$

Than the **NET** volatility was

$$C^g_i(H) = C^g_{\bullet\longrightarrow i} - C^g_{i\longleftarrow \bullet}(H).$$

3.3 Frequency Dynamics

The VAR approximating model was the most commonly used method for the estimation of connectedness in frequency domain. The VAR provided some properties of the relationship between the variables of the frequency domain.

The estimated VAR was often used to compute impulse responses and the forecast error variance decompositions. Linear feedback measures of analysis of the variables relationships properties and their decomposition by frequency could be undertaken. (Geweke (1982), Geweke (1984), Geweke (1986))

Frequencies can be distinguished as the short-, medium-, and long-term. The frequencies responses to shocks show the spectral representation of the variance decompositions. (Baruník, Křehlík (2017))

An estimation of spectral quantities was performed through a Fourier transformation. The estimates of the quantities where the cross-spectral density on the interval $d = (a, b) : a, b \in (-\pi, \pi), a \succ b$ defined as

$$\int_d \Psi(e^{-iw}) \sum \Psi'(e^{+iw}) dw,$$

then estimated as

$$\sum_w \hat{\Psi}(w) \hat{\sum} \hat{\Psi}'(w).$$

The frequency response function $\Psi(e^{-iw}) = \sum_h e^{-iwh} \Psi_h$, which could be obtained as the Fourier transformation of the coefficients Ψ_h, with $i = \sqrt{-1}$ with the spectral density of x_t at frequency w where the Fourier transformation of $MA(\infty)$ filtered series was

$$C_x(w) = \sum_{h=-\infty}^{\infty} E(x_t x_{t-h}^{'}) e^{-iwh} = \Psi(e^{-iw}) \Sigma \Psi^{'}(e^{+iw}).$$

The power spectrum $C_x(w)$ described the distribution of x_t variance over the frequency components w. The generalized causation spectrum over the frequencies $w \in (-\pi, \pi)$ was defined as

$$(f(w))_{j,k} \equiv \frac{\sigma_{kk}^{-1} \mid \Psi(e^{-iw}\Sigma)_{j,k} \mid^2}{(\Psi(e^{-iwh})\Sigma\Psi^{'}(e^{+iw}))_{j,j}},$$

where $\Psi(e^{-iw}) = \sum_h e^{-iwh} \Psi_h$ was the Fourier transformation of the impulse response Ψ_h and $(f(w))_{j,k}$ represented the portion of the spectrum of the jth variable at a given frequency w due to shocks in the kth variable.

The impulse response function depended on the parameters of the model in a complex way and was of a little use in constructing the confidence bands even though the sampling variability accessed by bootstrapping. (Gonzalo, Ng (2001))

The natural decomposition of the variance to frequencies weighted $(f(w))_{j,k}$ by the frequency share of the variance of the jth variable, with the weighting function

$$\Gamma_j(w) = \frac{(\Psi(e^{-iw})\Sigma\Psi'(e^{+iw}))_{j,j}}{\frac{1}{2\pi}(\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda}))_{j,j}d\lambda}.$$

The decomposition of the impulse response function at a given frequency band was then estimated as

$$\hat{\Psi}(d) = \sum_w \hat{\Psi}(w)$$

and

$$C_d^F = C_d^W = C_\infty$$

that could be estimated as

$$(\hat{\theta}_d)_{j,k} = \sum_w \hat{\Gamma}_j(w)(\hat{f})(w)_{j,k},$$

where the estimated generalized causation spectrum was represented as

$$(\hat{f}(w))_{j,k} \equiv \frac{\hat{\sigma}_{kk}^{-1}((\hat{\Psi}(w)\hat{\sum})_{j,k})^2}{(\hat{\Psi}(w)\hat{\sum}\hat{\Psi}'(w))_{jj}},$$

and an estimate

$$\hat{\Gamma}_j(w) = \frac{(\hat{\Psi}(w)\hat{\sum}\hat{\Psi}'(w))_{jj}}{(\Omega)_{j,j}}$$

of the weighting function

$$\Omega = \sum_w \hat{\Psi}(w)\hat{\sum}\hat{\Psi}'(w).$$

Then $\hat{C}^w$ and $\hat{C}^f$ at the given frequency band of interest could be readily derived by plugging $\left\{\tilde{\theta}_d\right\}_{j,k}$ estimated into

$$\left\{\tilde{\theta}_d\right\}_{j,k} = (\theta_d)_{j,k} / \sum_k (\theta_\infty)_{j,k}$$

to get

$$\sum_{w} \hat{\Gamma}_j(w)(\hat{f})(w)_{j,k} = (\theta_d)_{j,k} / \sum_{k} (\theta_\infty)_{j,k}.$$

The spectral representation of the variance decomposition

$$(\theta_\infty)_{j,k} = \frac{1}{2\pi} \int_{-\pi}^{\pi} \Gamma_j(w)(f(w))_{j,k} dw,$$

where $(\Theta_H)_{j,k}$ at $H \to \infty$ in the time domain was an information aggregated through frequencies ignoring heterogeneous frequency responses to shocks and the effect of the whole range of frequencies influence. $\theta_\infty)_{j,k}$.

To diversify the short-, medium-, or the long-term connectedness it was needed to work with the amount of the forecast error variance created on a convex set of frequencies $w \in (a, b)$. The generalized variance decompositions on the specific frequency band d was defined as

$$(\theta_d)_{j,k} = \frac{1}{2\pi} \int \Gamma_j(w)(f(w))_{j,k} dw.$$

The scaled generalized variance decomposition on the frequency band was defined as

$$\left\{\widetilde{\theta}_d\right\}_{j,k} = (\theta_d)_{j,k} / \sum_{k} (\theta_\infty)_{j,k}.$$

Then the within connectedness on the frequency band d of the connectedness effect that occured within the frequency band was weighted by the power of the series on the given frequency band exclusively was then defined as

$$C_d^W = 100 \times \left(1 - \frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum \widetilde{\theta}_d}\right),$$

while the frequency connectedness on the frequency band d that decomposed the overall connectedness into distinct parts that gave the original connectedness measure was then defined as

$$C_d^F = 100 \times \left(\frac{\sum \widetilde{\theta}_d}{\sum \widetilde{\theta}_\infty} - \frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum \widetilde{\theta}_\infty}\right) = C_d^W \times \frac{\sum \widetilde{\theta}_d}{\sum \widetilde{\theta}_\infty},$$

where $Tr.$ was the trace operator, and the $\sum \widetilde{\theta}_d$ marked the sum of all components of the $\widetilde{\theta}_d$ matrix.

Chapter 4

Institutional Background

Commodity markets operate differently on the basis of multiple dependencies. Functionality depends not only on the nature of the commodity and the needs of traders but also on its history. (Nesnidal, Podhajsky (2006)) Commodities in today's world do not lose their importance because the natural resources create the largest non-financial market in the world. More than thirty commodity exchanges (such as New York, London, Tokyo, or Paris) generate each year more than 2.2 trillion Dollars, which is several times more than the stock exchanges do. (Rogers (2008))

The purpose of this chapter is to provide background information of all variables used in the empirical study. Variables chosen were financial market representing S&P 500 Index, two forex markets EURO and YEN and eight types of commodities, namely Crude Oil, Natural Gas, Gasoline, Propane, Corn, Coffee, Wheat and Soybeans, which can be considered as energy and food commodities. Data used for this analysis are daily closing financial statement historical data since 1.6.1999 until 29.6.2018. We focus on the method how the prices are influenced and connected. Moreover; how they react to the shock in the short-, medium-, and the long-term and how their behavior differ.

4.1 Standard & Poor's 500 Index

Background Information

The S&P 500 Index is a member of the S&P Global 1200 family of indices. The S&P 500 Index contains of approximately 500 titles of major US-based companies. It is about 75% of the total US stock market. Through this index it is possible to reliably evaluate the performance of the US stock market. The index can be understood as a value-weighted index, which calculates the representativeness of the branches and it reflects the current economic situation in the USA. It is used by all economists, financial analysts and investors. It has been in use since 1943. (Rejnus (2014))

The smaller companies included in the S&P 500 Index have more favorable position than larger entities as they have higher potential to increase their margins. Moreover; with extending globalization each company exposes itself to a number of macroeconomic factors that affect the economy globally.

Factors Driving Price

According to Agrawal (2016) the most significant determinants affecting the S&P 500 range include, above all, cuts in goods costs, conservative rental growth, S&P 500 structure, permanent interest rate cuts. It turned out that in 2014, as well as in 2004, the reduced cost of goods fallen in total revenues by about 2% during that period. That was also the reason why this variable was the most involved in overall corporate profitability. The index variable is historically the largest source of income erosion, which is a considerable disadvantage. That also includes sales and administration costs, income taxes, depreciation, research and interest costs. (Agrawal (2016))

Other sources have confirmed that the S&P 500 Index is also being affected by such economic variables as GDP or the unemployment rate. The rise in GDP from one period to the next contributes to an increase in the stock market. The explanation is that consumers generally make more purchases, and it probably also leads to higher earnings on the stock market (higher investments). In this case GDP acts as a means of pointing out the purchasing power of investors. In the event that the economy is hit by a higher unemployment rate that influences employees as they do not have any job, which causes worries about redundancy. The financial security of both employed and unemployed decreases, which leads them to smaller investments in the stock market. Investors do not have enough free funds as they need to keep some for their necessary expenses and investments in the stock markets does not belong to necessities. Therefore, the unemployment rate is used as one of the key indicators for investors. The cyclicality of industry can also be mentioned. If the economy thrives well, it is producing cyclical stocks, however; in case of poor economic conditions and in the event of a recession, there are more cyclical stocks than non-cyclical issues. E.g. in the event of a recession during the economic crisis, cyclical stocks were run out three times faster than the S&P 500 Index. (Taublee (2001))

Data

Data of trading the Standard & Poor's 500 Index were downloaded from CBOE. CBOE (2018a): "Cboe is the exclusive home for S&P 500 Index options (SPX). Cboe's suite of S&P 500 products includes the flagship SPX contract – the most-actively traded index option in the U.S. – along with contracts featuring different expirationS (SPXW - Weekly and End-of-Month), exercises (AM and PM), sizes (regular and mini) and trading methods (electronic and open outcry)".

Source: CBOE; Release: Standard & Poor's 500 Index; Units: U.S. Dollars, Not Seasonally Adjusted; Frequency: Daily closing data, Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717. (CBOE (2018b))

4.2 Forex EUR/USD

Background Information

The currency pair USD/EUR is one of the strongest and most traded on forex because the US Dollar is the most traded and it is also currency, which is being the most held. Euro is the second most popular currency in the world. This currency pair thus covers two major economies of the world: European and American -

therefore it represents more than a half of the total trading on forex.

Factors Driving Price

The first factor that influences this currency pair is the trading time that affects volatility. EUR/USD activity slows slightly at midday, then rises in afternoon. That also affects some important institutions such as the European Central Bank and the Federal Reserve System, which has an impact on monetary policy, regulates money supply, interest rates and influences the strength of the currency. One can not fail to mention the political instability deviates this currency pair in a rather significant way. This applies to the European or the US events such as Brexit of 2016, which touched the euro. The elections in particular European countries or the euro-zone crisis may be named among others, which was reflected in the depreciation of the euro. More over while for example the US Treasury Secretary Steven Munchin has said the weaker Dollar is good for the US, it has led to an immediate fall in the US Dollar. (Bobrova (2018))

Data

Source: Board of Governors of the Federal Reserve System (US); Release: H.10 Foreign Exchange Rates; Units: U.S. Dollars to One Euro, Not Seasonally Adjusted; Frequency: Daily; Noon buying rates in New York City for cable transfers payable in foreign currencies. Date: 1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total:4717. (FRED (2018b))

4.3 Forex YEN/USD

Background Information

The YEN/USD exchange rate is the second most traded currency pair, which in 2015 accounted for 18.3% of all forex trades closed and since 2007 the share of closed deals has increased by a whole 5%. Consequently, there is an increasing interest in this currency pair, despite the fact that Japan is not as prevalent in the world trade as it used to be in the past. (Raputa (2015))

Factors Driving Price

Although it has been mentioned above that the currency pair is still in the interest of traders, it has tended to decline during the recent years. The best values were reported in 1985. Local mines relate mainly to 2011, which is directly related to the tragedy of the Fukushima nuclear power plant. Local maxims were reached in 2007 and 2015, which is related to the Asian-Russian financial crisis, the peak of the US mortgage bubble and unprecedented quantitative easing by the Bank of Japan. As Raputa (2015) also mentions, the declining currency pair trend is the natural outcome of the gap between the US and Japanese inflation. That theory is also supported by the 30-year inflation rate, which remains higher in the US than in the case of Japan, and that also reduces the relative US Dollar. This causes an average annual loss of 2.5%. (Raputa (2015))

Data

Source: Board of Governors of the Federal Reserve System (US); Release: H.10 Foreign Exchange Rates; Units: Japanese Yen to One U.S. Dollar; Not Seasonally Adjusted; Frequency: Daily; Noon buying rates in New York City for cable transfers payable in foreign currencies.Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717. (FRED (2018a))

4.4 Gasoline

Background Information

Gasoline is a product made of petroleum. That is why the history of crude oil is closely related. The rise of gasoline is related to the development of industrial oil processing. Gasoline, as a byproduct of oil, was almost negligible in the nineteenth century. Towards the end of the 19th century, following the invention of a passenger car, gasoline was actively used as a fuel for these cars. (EIA.gov (2018)) Petrol is a light distillation fraction of petroleum made up of hydrocarbons. It is distilled at lower temperatures. Industrial gasoline is produced in oil refineries. (vitejtenazemi.cz (2013))

Factors Driving Price

The price of gasoline is influenced by several factors such as a minimum consumption tax according to the Czech National Bank. For the Member States of the European Union, the European Commission Directive stipulates that the minimum consumption tax on unleaded gasoline is set at 0.359 EUR per litter, which is approximately 9 EUR per conversion. However, the real value varies by country, which then raises price jumps. The petrol price is also affected by gross refinery margins. The Czech National Bank adds that the refinery in Europe sets the price of gasoline according to the current prices that are valid on the Rotterdam Commodity Exchange. However, Asian refineries with modern technologies enter the market and rapidly increase their capacities and boosts production. That leads to pressure on gasoline prices in general and leads up to shutting down European refineries as margins remain at a low level. (CNB (2012))

Alexeeva-Talebi (2011) states that the price of gasoline also increases EU emission allowances if the price of that allowance increases, which is reflected in higher gas prices traded on the European commodity market. Wadud et al. (2009) points out that if the emission allowance price increases by 1%, the petrol price will increase by 0.08%. The price of petrol is also directly influenced by rising incomes of the population, as their increase is also reflected in higher petrol consumption.

Data

Source: U.S. Energy Information Administration; Release: Spot Prices; Units: Dollars per Gallon; Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717. (FRED (2018d))

4.5 Natural Gas

Background Information

Natural gas can be described as an indispensable source of energy for society. This is a so-called very hot gas, which can be used in a number of areas - heating, cooking etc. In terms of its properties, the mixture of gaseous hydrocarbons is composed of methane together with other non-hydrocarbon gases. (Budin (2015))

Factors Driving Price

An important factor affecting the price of Natural Gas is the production technology of a shale gas. That may led to an increase in the supply of Natural Gas and, at the same time, to a reduction in its price by more than 50%. This is also related to new technologies in the wind and solar power; the emergence of more efficient batteries and technologies to store energy. These factors will not only reduce demand for oil but also for natural gas in all developed countries, thus slowing demand growth for both commodities in developing countries. (Boeckh (2012))

Data

Source: U.S. Energy Information Administration; Release: Natural Gas Spot and Futures Prices (NYMEX); Units: Dollars per Million BTU; Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717. (FRED (2018c))

4.6 Crude Oil

Background Information

Crude Oil is a raw material and non-renewable natural energy source. As a raw material it has an indirect share in most of the globally produced energy and is also used as a raw material in many industries. Crude Oil is also an important source of transport. (Jenicek, Foltyn (2010))

Factors Driving Price

The price of Crude Oil, like any other commodity, is the result of a mutual interaction between supply and demand. The factors influencing these two parties also have an impact on the price of oil on commodity markets. E.g. according to Benak (2010) weather is a significant factor influencing higher supply. If hurricanes are reported, mining capacities are reduced, resulting in a change of the price of Crude Oil on the market. The author also mentions geopolitical factors such as wars, civil unrest or terrorist attacks. It is also necessary to mention a OPEC's decision on oil production.

Cernoch (2012) mentions that at the beginning of the analyzed period, specifically in 2000 and 2001, the collapse of the price of barrel oil has slowed economic growth in the US; which reduced demand for Crude Oil. The price was also influenced by the threat of war in the context of the US terrorist attack in September 2001. However, in the following year, the price of Crude Oil started to rise. Several important factors and events need to be addressed here. First, it was the strike of the oil company Petroleos de Venezuela, due to the strike the company lost an average production of 3 million barrels per day. That had a major impact on the US, which used to be dependent on Venezuelan oil exports. (ourenergypolicy.org (2014)) The oil supply also fell due to a strike on the Nigeria oil rig, which at the time was one of the world's largest oil producers. (latimes.com (2003))

Considering the world economy growth of 4.2% (worldbank.org (2018)) was recorded in 2004-2007 and the demand for Crude Oil increased. Producers, however, had to maximize production in order to fulfill demand. The other determinants, such as little investments in oil fields and the weak US Dollar lead to the fall of price. (Cernoch (2012))

The year 2008 when the financial crisis began resulted in a steep decline in the Crude Oil prices at the beginning of 2009. The price of a barrel was below 40 Dollar as the demand also declined sharply. In order to support demand growth, OPEC reduced mining quotas, which was evaluated as successful. The price of Crude Oil grew gradually to 115 Dollar per barrel in 2011. The US began to extract unconventional oil from 2008, but it did not show up on the price of crude oil. Although US demand for the year was higher, it was balanced by the reduced demand due to riots in areas where the key oil producers were located. That political instability in Libya lead to limited Crude Oil exports. Libya was at that time one of the largest oil producers in the OPEC cartel. Those mentioned conditions lead to decrease in demand for crude oil, and its price had fallen sharply. However, riots were also recorded in Egypt, which further exacerbated the rise in oil prices due to concerns that Egypt could be cut off respectively the Suez Canal closed, which is crucial for oil exports. (Bednar (2011))

According to Traxler (2012), further reductions in crude oil demand were caused by sanctions imposed on Iraq by the US and the European Union. After these events the oil price remained for a long time at a high price level. It even occurred that Brent had a higher price than WTI oil, despite the fact that WTI oil is of a higher quality. The cause probably remained at the anomaly of standard market power level- in both supply and demand. The higher grew the WTI oil with regard to unconventional mining from shale, the more Brent crude oil fell.

Although military riots in the Middle East caused the rise in crude oil prices in a number of cases, it is not necessarily a rule. An example may be the year 2003, when the invasion of Iraq took place. Just before this event, the price of oil fell by more than 10 Dollar a barrel as a result of the expectation that new oil resources were about to be leveraged into Western countries. Similarly, the same was the result of the terrorist attack in September 2011 (financial markets panic triggered by a drop in oil prices of 6$ to 22$ a barrel). In the case of military intervention in Libya, the oil price dropped by 15$ per barrel. (Colosseum (2013))

Data

Source: U.S. Energy Information Administration; Release: Spot Prices; Units: Dollars per Barrel; Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717. (FRED (2018e))

4.7 Propane

Background Information

Propane is a colorless and highly flammable liquefied gas. It is characterized by the lowest flammability range. It is produced by means of refining and processing of natural gas. It is also one of the main components in liquid petroleum gas (LPG) along with butane. Propane has a wide range of uses such as heating, brazing, heat treatment, and acetylene is replaced with flame cutting. It is also another possible fuel source for passenger cars. It heats industrial buildings or houses. (Linde-gas.cz (2018))

Factors Driving Price

Propane is also a commodity that is derived from other commodities, traded on the global market and its prices often fluctuate, depending on many factors that cannot be always predicted reliably. In this case, the demand for Propane is relatively important. Demand growth occurs especially when people demand heating in their homes. In the US it can be in the event of an extreme winter. Here, basically, two factors combine demand and climatic conditions. Given that the weather has changed a lot in the last few years and the whole world is experiencing various extreme weather fluctuations, it is often unpredictable that the demand for Propane in the last few years is rising, the market reacts by increasing the price of this commodity. (propane101.com (2018))

An example is the turn between years 2013 and 2014, when the price was rising rapidly, due to the fact that the US was in the middle of the winter, and there was also a higher demand for Propane. Moreover, Propane is completely dependent on the price of oil and Natural Gas. If any fluctuations in prices, demand or supply for these two commodities occur, it logically depends on the price of propane. Apart from unexpectedly cold weather, the propane price is also affected by its low inventory. (Klobuchar (2018))

Data

Source: U.S. Energy Information Administration Release: Spot Prices; Units: Dollars per Gallon, Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717 (FRED (2018f))

4.8 Corn

Background Information

Corn is considered to be an agrarian commodity. It is a one-year crop that can reach up to 3 meters. Maize is a plant, which requires sufficient amount of moisture, and is also relatively sensitive to temperature fluctuations. The risks of Corn growing include its susceptibility to soil erosion, the need for special machinery harvesting, the use of herbicides and the possibility of severe damage to wild pigs during cultivation. (Skladanka (2006)) Those risks also need to be reflected in the price development of the commodity.

Not only grains, but also the whole silage plants can be harvested such as maize sticks. It is a commodity with high energy value. The specific use of maize differs according to cultivated types, which can be up to several hundred with respect to different hybrids and modifications. (komodity24.cz (2018))

Factors Driving Price

Fluctuations of corn price are influenced by number of crucial factors, both economic and non-economic determinants. Similarly to other agricultural commodities (wheat, soy or cocoa) it is also very difficult for maize to predict the price of the commodity, as it is influenced by many global factors. For example, population growth, declining oil reserves, weaker agricultural yields due to weather, rising demand for meat, and more. (Rattray (2012))

One of the major influences involved in raising the price of Corn is controversial ethanol production. (komodity24.cz (2018)) In recent years, the volume of Corn used to produce ethanol as an alternative source of fuel has increased. As demand for ethanol increases, there is also a marked increase in demand for maize itself, which also affects the price of that commodity. As a result, farmers are encouraged to raise their crops and therefore the production of maize is increasing. Demand for ethanol, however; shows steeper pace than in case of growing crops. Despite growing area for Corn is extending, the price of corn continues to rise. (Rattray (2012))

In 2005, the price of Corn was very low, ranging from 1.90$ to 2.70 $/ poul. (kurzy.cz (2018)) A significant increase came in 2007 and 2008. However, this was only a short time. This phenomenon occurred for several reasons. Prices did not rise only for maize, but for many other crops, due to poor harvesting and insufficient cereal supplies. (Wisner (2008)) But these were not the only factors others were such as: the rise in oil prices, the depreciation of the US Dollar and the demand for Corn due to the production of ethanol in the United States. (Wiggins et al. (2010))

An important factor on the supply side is the weather. In the event of unexpected flooding or enormous drought the price of Corn responds very quickly. (komodity24.cz (2018)) E.g. in 2012 the price of corn increased rapidly from 5.1$ / pound to 8.2$ / bushel (during July and August of that year). This means a 61% increase in price over a very short period because the volume of US corn was reduced as the Corn Belt area had enormous droughts. US production therefore had to cope with a 13% reduction in production, a sharp decline compared to the average growth rate of maize production at that time (4.86%). (Rattray (2012)) The problem in this situation was that the US cereal stocks were completely inadequate to demand. However, the situation began to calm down after several months, but prices of corn fell to its original price level by the beginning of 2013. (bbc.com (2012))

The price of Corn is also dependent on the demand for meat. This is due to the fact that approximately 40% of the world's maize stocks are used in the form of animal feed. It is mainly used in developing countries. In the future, it is expected that demand for meat will continue to increase especially in South Asia. Rattray (2012) also mentions the political factors influencing maize prices. For example in 2011 policy factors played its role in influencing both supply and demand for agricultural commodities. Arab Spring in 2011 that took place in countries like Tunisia, Egypt, Algeria or Libya affected the demand for grain and wheat across the region. The governments of these states started buying large volumes of Corn and wheat in order to maintain food security, which lead to pressure on prices. Egypt for example bought 120 thousands tons of Corn from the US in mid-February 2011. In a view of fears of oil prices in Libya, the demand for ethanol has increased as an alternative fuel source, which has resulted in higher demand for maize (also wheat and sugar). (Rattray (2012)) It is clear from the above that the determinants of maize prices can not be analyzed in isolation, as these factors interact with each other and result in a greater impact together than each factor should have (the synergy of these factors).

Another important factor is China's demand as China is the largest importer of Corn and oil, which is ultimately reflected in the use of Corn as a form of biofuel. China is also processing bulk stocks of corn for ethanol, with demand rising year after year. The price of corn is also affected by the USD exchange rate, as is the case of wheat. Dollar is considered a reserve currency, and given that stock contracts are traded mainly in Dollars, and the US exported Corn to the entire world, the price of Corn is influenced by the movement of strengthening or weakening of that currency. (commodity.com (2018b))

Data

Source: www.macrotrends.net; Release: Spot Prices; Units: Dollars per pounds, Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717.

4.9 Coffee

Background Information

Coffee is another important commodity that belongs to the category of so called soft drinks. It is a popular drink worldwide, despite its negative effects on human health. As stated in the literature, approximately 2,000 berries or 4,000 grains are needed for half a kilogram of Coffee, and the coffee maker is able to produce at most a kilogram of roasted Coffee per year. In terms of type of Coffee, two basic types of Coffee are distinguished. One is Robusta and the second one is Arabica. On the world commodity markets, both types can be traded, but they are different in both price and quality. (Rogers (2008))

Factors Driving Price

Similarly to other commodities, the price of Coffee is depends on different determinants influencing both supply and demand. However, they are above all climatic phenomena that have a major impact on the supply side in this case. This is due to the conditions for the growth of coffee beans. In order of optimal growth, the weather must not fluctuate extremely. If the drought is too high or the precipitation is too high, the crop is reduced. Like droughts and precipitation, large frosts also cause loss of Coffee, not only for the next but also for the one after the next period. (Rogers (2008))

The price of Coffee also reflects the presence of various natural disasters such as hurricane, tornado, flood or tsunami. Natural disasters influence not only growing of Coffee but also demand for Coffee as people loose their property and shape their current needs. It is also necessary to mention the geopolitical factor. Coffee is mainly grown in developing countries that are more susceptible to quicker and easier political unrest. Political tensions most influence the jump prices of Coffee, whether down or up. (Bojinov (2012))

The price of coffee is also affected by transport costs. Here it is necessary to reflect the fact that Coffee beans are grown mainly in countries such as Brazil, Colombia, Vietnam, Indonesia or West Africa. For exporting to consumer countries, it is necessary to overcome considerable distances, thus increasing transport costs, which must be included in the resulting coffee price. And if the price of oil rises, there are jumps in the price of Coffee. (Rogers (2008))

According to Otava (2018) it is also necessary to keep in mind the changes that occur in the discretionary balance of consumer households. Discretionary balance allows us to focus more on the real household income. This is due to the deduction from their total income of the mandatory expenditure necessary for the operation of the household under all conditions. Rogers (2008) adds that if households do not have enough money for other unnecessary expenses, demand will fall, which necessarily carries a lower price for Coffee.

The role of raising Coffee prices also has its health aspects. It may happen that in case of introducing new health effects of coffee consumption, consumers will evaluate it in a certain way, and their preferences will change - their demand for Coffee will change. Negative data on coffee, unless other conditions change, is affecting declining demand, which is also associated with a fall of coffee prices. The case of positive information it is just the opposite. (Bojinov (2012))

Data

Source: www.macrotrends.net; Release: Spot Prices; Units: Dollars per kg (robusta prices), Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717.

4.10 Wheat

Background Information

Wheat can be considered as a basic agricultural commodity, which is cultivated at all continents except Antarctica (the largest Wheat producer is the European Union, China, USA and Russia). Considering its nutritional value, it is one of the most consumed raw materials in the world. (investujeme.cz (2018)) Not only seeds are grown, but also a whole plant that can be used in agriculture. In large quantities, Wheat is used in the food or pharmaceutical industry. In a smaller percentage also as a source for bioethanol or for biomass. (Likes (2018))

Factors Driving Price

There are several factors affecting price of Wheat. In the first place, we could place a US Dollar exchange rate and because the US exports large quantities of Wheat to other world markets, Wheat is mainly traded in US Dollars. When the US Dollar is boosted, the price of wheat is decreasing, and the opposite price effect is observed when the currency is weakened. Similarly, as with other basic raw materials, the discrepancy between supply and demand has the most impact on the price. When production is increasing and wheat consumption is only slightly growing, world stocks are being filled, which has the effect of pushing down wheat prices. (commodity.com (2018c))

The markets of Asia and Africa are growing, which affects the world demand for Wheat. In addition, the population is rapidly growing in these countries, which is linked to the demand for Wheat. These countries need to increase the volume of basic raw materials, so the most Wheat is ordered from these countries. Moreover that leads to demand pressures in the long run, which also increases the price of wheat. In emerging economies, however; the economy has an unstable nature, which also affects the volatile political situation. In many cases, therefore; the country is wholly inaccurate when it attempts to favor domestic production or introduce high tariffs (India's case), which negatively influences the demand for wheat imports and negatively affects the price of this commodity. (Gabor (2017))

Of course, climate conditions, like other agricultural commodities, can not be ignored. The weather always influences the achieved yields from the farmed area, thus the weather reduces or increases the overall production. Climate factors play a major role in this, as speculators evaluate weather forecasts and predict possible Wheat production. Because meteorological forecasts are relatively inaccurate, speculators have an impact on unjustified volatility. (commodity.com (2018c)) Other experts say that due to the extreme weather in recent years there cannot be made relied production predictions. Extreme weather conditions have worsened production over the last five years, again reflecting the rise in the price of this crop on commodity markets. (Gabor (2017))

In certain periods, the price of Wheat may also be affected by its ban on exports from export countries, due to an increase in the export tax. These measures protect home markets from short-term shocks or food deficiencies. However, these measures are detrimental to the countries where the wheat is imported. In the mid-term, domestic farmers have less incentive to invest in increasing their production, thus increasing domestic imbalances. The wheat price is also affected by the inability of the system to respond flexibly, due to the seasonal harvest of wheat, when producers react with a certain time lag on market signals. (Komise-

Evropskych-Spolecenstvi (2018))

The last factor affecting the Wheat price will be the subsidy for ethanol. The US allows to subsidize maize, which is the main raw material for the production of ethanol added to the fuel. This is the reason why the Wheat production in the US is declining, and farmers prefer to grow corn. Ending subsidies would most likely increase the production of wheat and reduce its cost. (commodity.com (2018c)) However, this is not expected in the years to come, due to an increasing demand for ethanol as an alternative fuel source.

Data

Source: www.macrotrends.net; Release: Spot Prices; Units: Dollars per kg, Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717.

4.11 Soybeans

Background Information

Soy is a legume that has high nutritional value (high protein and oil content), so it is now increasingly demanded among consumers around the world. Out of soybeans is made mainly soybean oil and soybean meat. The use of this crop is mainly in the food industry, partly from soybean oil also produced by bio-fuels. Soy scrap with its high protein content is used as feed for livestock. However, soybean scrap is increasingly demanding by consumers who replace it with meat (vegetarians, vegans). Soy has also been represented in the pharmaceutical industry. (soja.cz (2018))

Factors Driving Price

The Soybeans price is affected by several important factors. It is possible to place US and Brazil production at the first place in the world, since Soybeans are dependent on these markets, which are their largest exporters. Changes in Soybeans conditions in these countries (such as climatic conditions) may affect overall production and Soybeans prices. An example may be the existence of any US flood or hurricane. Soybeans production is reduced immediately and the price goes up. This factor is related to the US Dollar. Here is basically the same situation as Wheat or Corn commodities. Exchange contracts are traded in US Dollars and appreciation or, on the contrary, weakening of the US Dollar is based on decreasing or increasing the price of this crop. (commodity.com (2018a))

Soybeans are considered to be a relatively large exported commodity. Approximately 45% of its production is exported. Compared to other commodities, wheat 23%, in the case of maize 14%. This is why the price of Soybeans is particularly dependent on exports to emerging countries. As the number of people on the continent of Asia and Africa is increasing and more over taken in consideration how rich the emerging economies are, the growing consumption of meat and other food products is expected to grow in demand for crops such as soy so its price increases. (Adeyanju (2014))

In addition to population growth, it is also worth mentioning the ongoing dispute between the US and China, which wants to introduce duties on imported soy from the US as a response to the US steel import duty introduced by the United States. In addition to economic variables, political and geopolitical determinants can also play a role in the cost of Soybeans commodity in long run. (Tan (2018))

Other factor is the existence of substitutes for Soybeans. There is a competition in the oil field not only regarding soy, but also palm, sunflower, oil, rapeseed etc. The price of Soybeans is so dependent on the substitutions and how the demand for them changes over time. There is also no mention of ethanol subsidies. In the US there is a strong subsidy for the production of corn, which is used to produce ethanol as a fuel source. Ending subsidies would also affect SoybeanS production and lowering its price. (commodity.com (2018a))

Like other crops, soybean needs its specific climatic conditions for successful cultivation. Soybeans needs the hottest summer. According to the experience of many farmers, a temperature of between 20°C and 30°C is required for the successful production of soy. Temperatures that fall below 20°C during the summer, or climbed up to over 40°C, will have a negative effect on the growth of Soybeans. An example is, 2009 when Argentina, as the third largest Soybeans producer in the world, experienced the worst drought in the past 50 years in its history. This fact resulted in a rapid decline in crop production in the country, which was reflected in commodity markets in the form of soybean prices. Similar problems were also experienced by Brazil in 2014, which again caused higher prices of the commodity. (Adeyanju (2014))

Data

Source: www.macrotrends.net; Release: Spot Prices; Units: Dollars per kg, Not Seasonally Adjusted; Frequency: Daily; Date:1/6/2018-29/6/2018; data cleaned up for public holidays and all missing observations- used days in total: 4717.

Chapter 5

Data Analysis

The analysis was based on the end-of-the-day data during the business working days beginning 1/6/1999 and ending 29/6/2018. Data were manually put together to match by dates and each day when the value was missing at least for one variable was excluded completely to provide as good analysis as possible. Public holidays that differ via countries were excluded as well as important stock exchange influencing dates such as a week after 11/9/2001 not to cause any estimation bias. Finally, the data span provided a sample of 4717 trading days.

Table 5.1 shows standard descriptive statistic of our variables. Generally, the highest values has S&P 500 Index, followed by YEN and Crude Oil. Soybeans mean keeps also under 10, Wheat and Natural Gas under 5, Corn under 4, the rest around 1. validity is 100% for all variables and 0 missing observations.

Table 5.1: Descriptive Statistics of Historical Prices

Variable	Mean	Sd	Min	Median	Max	Valid	Missing
SPX	1467.92	465.76	676.53	1330.63	2872.87	100%	0
EUR	1.21	0.17	0.83	1.23	1.6	100%	0
YEN	106.42	13.55	75.72	108.72	134.77	100%	0
GASOLINE	1.74	0.77	0.45	1.64	3.66	100%	0
NATURAL GAS	4.63	2.21	1.49	4.02	18.48	100%	0
CRUDE OIL	60.83	27.66	16.57	57.61	145.31	100%	0
PROPANE	0.85	0.36	0.27	0.83	1.98	100%	0
CORN	3.72	1.58	1.75	3.58	8.31	100%	0
COFFEE	1.24	0.49	0.42	1.2	3.06	100%	0
WHEAT	4.9	1.85	2.34	4.66	12.82	100%	0
SOYBEANS	9.08	3.33	4.1	9.4	17.68	100%	0

Source: Author's computations

Chapter 6

Empirical Results

This chapter is dedicated to the measurement of the time-frequency dynamics of connectedness of the data set. As the estimation and computational tool was used the statistical software R and additional supporting packages such as Connectedness Frequency created by Krehlik (2018).

We demonstrate the static analysis of the spillovers covering the realized volatility, the vector auto-regression model, the test for stationarity, the static full-sample spillover analysis of the traditional spillovers table with FALSE Boolean parameter under Diebold, Yilmaz (2012) methodology, test of correlation and the same under Diebold, Yilmaz (2009) methodology in the Appendix to this Thesis. Secondly, the spillovers tables decomposed into frequencies as an analysis of connectedness dynamics with a rolling window of 250 days, which corresponds to about one-year span.

6.1 Realized Volatility

Volatility is latent and needs to be estimated. An optimal approach to our data is realized volatility. The realized volatility was counted in Microsoft Excel as a wealth ration counted as natural log of the relative price change, which is a continuously compounded return. From closing daily data were calculated daily log returns by taking natural log dividing today closing daily data by yesterdays daily closing data. That gave us a series of daily log returns but as a reason of this methodology we lost 1 day of data- the first day 1/6/1999 as our observation began that day and we had no values of the previous day. So for 4717 observations we got 4716 daily natural log returns. The daily variance estimate was counted as a square of the $logreturns^2$. From that we got a series of daily variances, which we were interested for following usage.

By square root of daily variances we counted the daily realized volatility - the average daily standard deviations. It gave us equally weighted daily volatility as each day was taken having the same weight. This could be done due to deleting all dates values that could bring unnatural or outlining values and those values should be counted with different weights. (Bionic-Turtle (2010))

For a preview of an example of the data frame of the realized volatility see the Appendix section.

Table 6.1: Descriptive Statistics of Realized Volatility

Variable	Mean	Sd	1st Qu.	Min	Median	3rd Qu.	Max	Skewness	Kurtosis	Missing
SPX	0.008063	0.01	0.002209	0	0.005388	0.010767	0.104236	3.413961	23.14573	1
EUR	0.005822	0.01	0.000000	0	0.004806	0.008772	0.104236	3.003204	24.0429	1
YEN	0.004758	0	0.001540	0	0.003590	0.006628	0.052157	2.314117	12.99802	1
GASOLINE	0.014824	0.02	0.003396	0	0.009277	0.020619	0.249067	3.173750	23.97007	1
NATURAL GAS	0.028535	0.04	0.007712	0	0.019581	0.036934	0.576663	5.194135	52.32555	1
CRUDE OIL	0.021479	0.03	0.006364	0	0.014758	0.027916	0.525354	6.133972	74.12786	1
PROPANE	0.01648	0.02	0.00000	0	0.01156	0.02302	0.50822	5.489340	86.41214	1
CORN	0.014043	0.02	0.004301	0	0.010152	0.019061	0.207639	3.058090	21.30808	1
COFFEE	0.015731	0.02	0.006042	0	0.012739	0.021979	0.205444	2.625127	18.39028	1
WHEAT	0.014992	0.01	0.005831	0	0.011794	0.020563	0.204412	2.320949	15.75890	1
SOYBEANS	0.011149	0.01	0.003916	0	0.008388	0.015218	0.074108	1.913771	8.02200	1

Source: Author's computations

Table 6.1 shows the standard descriptive statistics of the realized volatility. The highest mean and the quantiles has Natural Gas followed by Crude Oil. Means of all commodities are almost ten times higher compared to the forexes and the Index. The same apply to the median results with an exception of Soybeans.

EUR/USD and Propane have 0 value in their first quantile, while the third quantile keeps the lowest for forex EUR/USD. The lowest maximum value has Soybeans and the minimal value is 0 for all variables.

The highest kurtosis has Propane followed by Crude Oil, while the lowest Soybeans and forex YEN/USD. The most skewed data has Crude Oil followed by Natural as and the less Soybeans.

All values have one missing variable as a consequence of counting variance where the value for the firs date 1/6/1999 could not be counted as we were missing the previous day value as mentioned previously.

Comparing **table 5.1.** data analysis of historical prices to **table 6.1.** data analysis of realized volatility highly differ as expected. From the strongest values of S&P 500 Index transform into the lowest. The strong position of forex YEN/USD historical prices dropped to similar low values as forex EUR/USD. While standard deviation differed in case of prices in case of volatility ranges just between 0 and 0.04. Reason for these outcome is obvious as we were working with square roots.

6.2 Vector Autoregression Model

The Vector Autoregression model (VAR) was used as an underlying model for spillovers theory while it is in general usually used for estimation of linear connectedness between various time series build up on variance decompositions matrix containing complete information about all variables. (Baruník, Křehlík (2017))

Firstly we ran a regression for each of our variables time series of the realized volatility. For our endogenous variables $y_1 - y_{11}$ the coefficient of the VAR was estimated separately for each equation by least-squares methodology.

The number of lags for VAR must be chosen based on criteria provided in R by package vars function "VARselect", which generated the criteria for selection of the best number of lags fitting the model jointly. Our information criteria provided the following results to minimize the mean squared error:

Table 6.2: VARselect

AIC(n)	HQ(n)	SC(n)	FPE(n)
10	3	3	10

Source: Author's computations

Where AIC stands for Akaike information criterion that provided means for model selection and demonstrated how much information was lost. AIC is often similar to FPE as they have similar criteria such as corollary but both estimators often overestimate the true lag order with positive probability. HQ stands for Hannan-Quinn Criterion and SC for Schwarz Criterion (Umidjon et al. (2018)) As AIC and FPE equal and they often overestimate we decided to go for HQ and equal SC with choice of 3 lags.

See the Appendix section for the VAR estimation results and for the VAR estimated coefficients (an example of SPX).

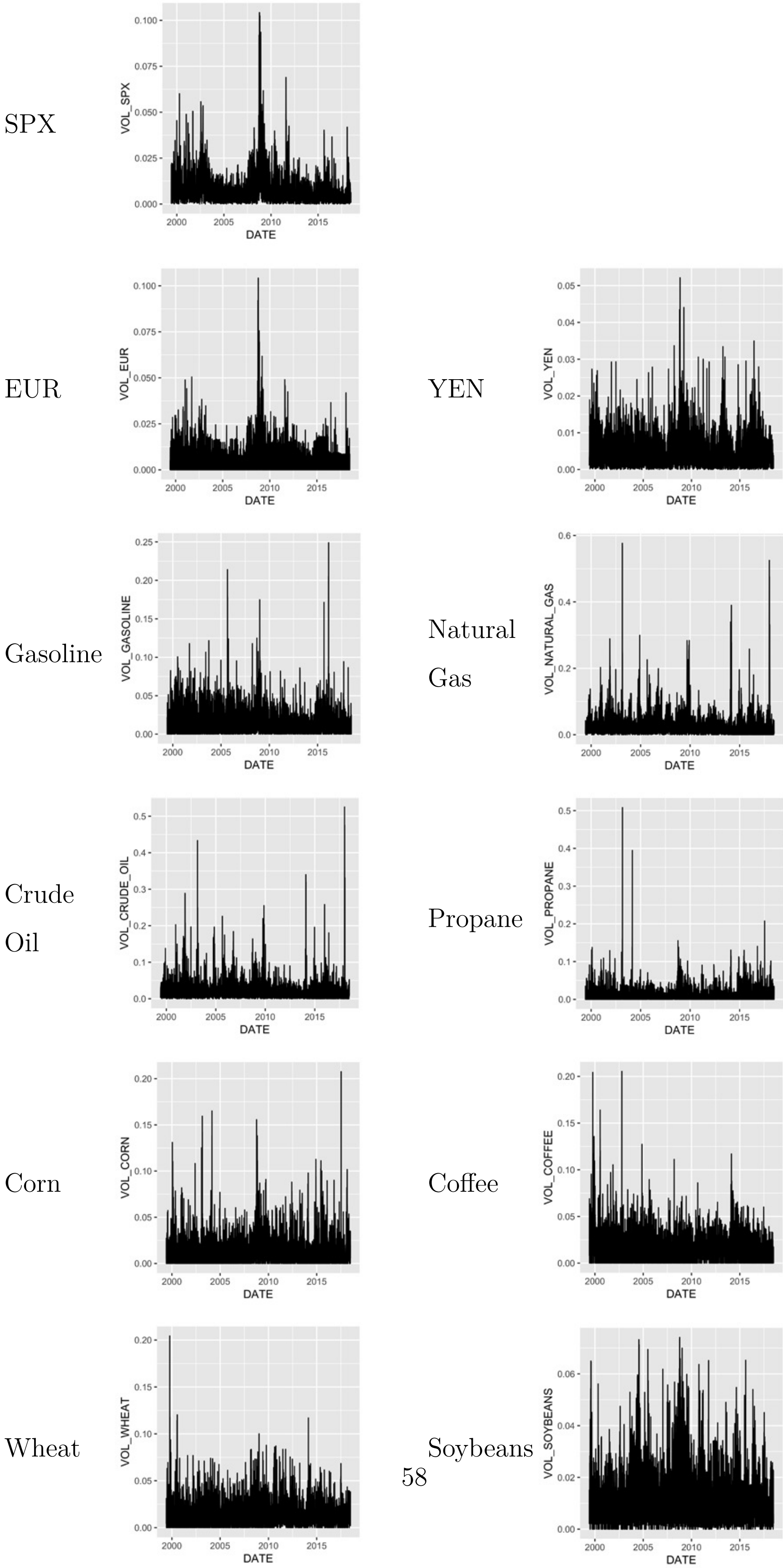
6.3 Stationarity

A test of stationarity helps to avoid false inferences. Stationarity tells whether the variables do not consist of a unit root process as it could bias the OLS estimation of the VAR model. That is meant as no trend or constant variance, autocorrelation or periodic fluctuations over time. In this case we decided for graphic representation of data, which is strong enough for purposes of proving no stationarity evidence for the VAR model. In other cases if needed tests of stationarity such as ADF may be undertaken.

Figure 6.1. displays graphic illustration of the realized volatility that demonstrates the evolution of realized volatility of eleven selected variables over time. All of the data range from zero. S&P 500 Index, EUR/USD and YEN/USD forex, Soybeans keep the lowest just up to maximum value of 0.1 , while Corn, Coffee and Wheat up to double maximum value of 0.2. Gasoline increases up to value 0.25, Crude Oil and Propane to 0.5 and Natural Gas up to 0.6. Generally we can say, that the Index and forexes keeps the lowest, food higher and energy variables at the highest values. Nevertheless; the data show no perpetual or periodical trend over time so they are a prove of no stationarity.

Figure 6.1: Graphic Representation of Realized Volatility

Source: Author's computations



6.4 Traditional & Directional Spillovers Estimation

This section contains results of unconditional volatility connectedness of traditional and directional spillovers measures gained by Diebold, Yilmaz (2012) methodology that builds up on invariant ordering. The Boolean parameter is set as **FALSE**, which caused estimation of the connectedness with the effect of correlation that might influence the whole system.

The coefficient matrices were used for the variance decompositions to obtain the spillovers measure. Here we provided a full-sample analysis of volatility spillovers using the variance decomposition model with 3 lags. All tables were created from author computations using R studio software and results presented are percentages.

Results for the TRUE Boolean parameter are provided in the following section "6.6 Test of Correlation". Results for Diebold, Yilmaz (2009) methodology relying on Cholesky-factor identification of VARs, so the resulting variance decompositions can be dependent on variable ordering for both FALSE and TRUE parameters find in the Appendix to this Thesis.

The traditional volatility spillovers provided an approximate decomposition of the various non-directional volatility spillovers in a single index. The directional connections in realized volatility consist of TO other variables and FROM other variables values. This section presents an estimation of total vector autoregressions of order 3 (selected by Hannan_Quinn and Schwarz Criterion) identified using Cholesky-factor with no importance of ordering. The directional estimation consists not only from TO and FROM values but also NET. The NET value was counted as TO-FROM=NET and its expected value was close to 0 as TO and FROM values usually do not differ significantly.

Table 6.3: Pairwise Spillovers of the DY 2012 Table, BP=False

SPX-EUR	SPX-YEN	SPX-Gasoline	SPX-Natural Gas	SPX-Crude Oil	SPX-Propane	SPX-CORN	SPX-Coffee	SPX-Wheat	SPX-Soybeans
−0.4654625620	−0.1413140456	−0.0697504712	0.0070230920	0.0184369195	−0.0489390228	−0.0241254628	−0.0185102745	−0.0398995008	−0.0801297382
EUR-YEN	EUR-Gasoline	EUR-Natural Gas	EUR-Crude Oil	EUR-Propane	EUR-Corn	EUR-Coffee	EUR-Wheat	EUR-Soybeans	YEN-Gasoline
−0.1098714815	−0.0107649808	0.0022861796	0.0164621766	−0.0278223770	0.0097898514	−0.0104671485	−0.0053414178	−0.0222341444	0.0288313689
YEN-Natural Gas	YEN-Crude Oil	YEN-Propane	YEN-Corn	YEN-Coffee	YEN-Wheat	YEN-Soybeans	Gasoline-Natural Gas	Gasoline-Crude Oil	Gasoline-Propane
0.0008625696	−0.0022003784	0.0086691401	0.0216737928	0.0009004967	0.0084023014	0.0194106535	−0.0084746024	0.0363471755	0.0064391384
Gasoline-Corn	Gasoline-Coffee	Gasoline-Wheat	Gasoline-Soybeans	N.Gas-C.Oil	Natural Gas-Propane	Natural Gas-Corn	Natural Gas-Coffee	Natural Gas-Wheat	Natural Gas-Soybeans
0.0074061743	−0.0355329413	−0.0161827652	−0.0084093306	−0.1253765843	−0.1747002313	−0.0286748839	−0.0042079855	0.0056315496	0.0047030725
Crude Oil-Propane	Crude Oil-Corn	Crude Oil-Coffee	Crude Oil-Wheat	Crude Oil-Soybeans	Propane-Corn	Propane-Coffee	Propane-Wheat	Propane-Soybeans	Corn-Coffee
−0.0858441394	−0.0243337986	−0.0118783608	−0.0007222705	−0.0018764855	0.0600257809	0.0005899337	−0.0153756797	−0.0007475155	−0.0005988771
Corn-Wheat	Corn-Soybeans	Coffee-Wheat	Coffee-Soybeans	Wheat-Soybeans					
−0.0294197682	−0.1179528274	0.0819831232	0.0008854498	−0.0415083316					

Source: Author's computations

Table 6.3 contains off-diagonal values only and the most of the values are negative and all keeps really low. The highest is $\tilde{C}^H_{Coffee \leftarrow Wheat} = 0.08\%$ followed by $\tilde{C}^H_{Propane \leftarrow Corn} = 0.06\%$. The low connectedness between our variables could be expected as they are highly diverse.

Table 6.4: TO Spillovers of the DY 2012 Table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
2.67036	2.10371	0.55600	0.91269	2.38414	2.70399	1.76029	2.63751	1.35233	2.08330	0.99011

Table 6.5: FROM Spillovers of the DY 2012 Table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
1.80769	2.41121	0.89373	0.94597	2.05981	2.63567	2.12698	2.46778	1.51490	2.05271	1.23797

Table 6.6: NET Spillovers of the DY 2012 Table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
0.86267	−0.30750	−0.33773	−0.03328	0.32432	0.06832	−0.36669	0.16973	−0.16257	0.03058	−0.24786

Tables 6.4, 6.5, 6.6 YEN/USD, Soybeans, and surprisingly also Gasoline keeps TO and FROM spillovers at the lowest levels. The highest NET value has the S&P Index followed by Natural Gas and all others also remain under 1%. 6 values keep in negative values, which means that our system of variables have slightly higher impact FROM other variables than TO other variables.

For all results of the FALSE parameters under the methodology Diebold, Yilmaz (2009) dependent to ordering find result in the Appendix section. Generally can be concluded, that results slightly differ in case of Diebold, Yilmaz (2009) and the pairwise spillovers were lower while for directional spillover higher. That means the order of variables influence the overall connectedness measure.

6.5 Frequency Connectedness

This section presents spillover tables under the methodology of Baruník, Křehlík (2017), which decompose the spillovers into frequencies. As previously we use Diebold, Yilmaz (2012) methodology and the Boolean parameter **FALSE**. For the TRUE Boolean parameter under DY 2012 methodology see section "6.6. Test of Correlation". For results under the methodology DY 2009 with both FALSE and TRUE parameters see the Appendix section.

For the frequency analysis purposes bounds were chosen to demonstrate one week (band: 1 day to 5 days: short-term frequency), one month (band: 5 days to 22 days: medium-term frequency) and one year (band: over 33 days: long-term frequency). The estimation was run with different bounds separately. The following sections were divided per frequencies.

ONE WEEK Estimation

Table 6.7: The spillover table for band: 1 days to 5 days. Short-term frequency - BK2012 - BP=False, TO estimation; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	37.08	5.31	0.15	0.08	0.02	0.12	0.06	0.11	0.05	0.13	0.09
EUR	7.94	54.55	0.81	1.40	0.06	0.50	0.21	0.59	0.07	0.16	0.22
YEN	0.80	0.92	67.07	0.73	0.03	0.11	0.15	0.15	0.24	0.22	0.19
GASOLINE	0.29	1.45	0.71	67.38	0.05	1.84	0.85	0.35	0.08	0.25	0.22
NATURAL GAS	0.01	0.04	0.02	0.02	40.34	11.42	0.17	0.02	0.09	0.11	0.03
CRUDE OIL	0.07	0.26	0.08	1.48	11.56	53.39	0.79	0.26	0.11	0.21	0.13
PROPANE	0.11	0.18	0.12	0.72	0.26	0.70	48.61	8.93	0.09	0.05	0.18
CORN	0.15	0.49	0.12	0.25	0.07	0.37	9.25	56.47	0.11	3.00	3.50
COFFEE	0.10	0.17	0.18	0.22	0.10	0.09	0.09	0.13	59.48	10.06	0.30
WHEAT	0.20	0.09	0.16	0.24	0.02	0.09	0.21	3.30	9.88	60.30	2.08
SOYBEANS	0.31	0.22	0.18	0.21	0.04	0.17	0.11	3.85	0.32	2.16	61.04

Table 6.7 represents the short-run frequency. The highest off-diagonal values has $\tilde{C}^H_{CRUDEOil\leftarrow NATURALGas} = 11.56\%$ followed by $\tilde{C}^H_{Coffee\leftarrow Wheat} = 10.06\%$. The most of other values are close to 0.

ONE MONTH Estimation

Table 6.8: The spillover table for band: 5 days to 22 days. Medium-term frequency - BK2012 - BP=False; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	23.04	5.00	0.60	0.30	0.03	0.21	0.10	0.29	0.01	0.00	0.18
EUR	6.27	11.43	0.27	0.08	0.01	0.11	0.10	0.28	0.01	0.01	0.16
YEN	1.04	0.88	15.90	0.47	0.00	0.03	0.14	0.24	0.03	0.09	0.38
GASOLINE	0.60	0.13	0.33	13.97	0.01	0.84	0.29	0.02	0.03	0.02	0.08
NATURAL GAS	0.01	0.01	0.00	0.07	21.27	5.49	0.24	0.03	0.04	0.00	0.05
CRUDE OIL	0.15	0.18	0.07	0.77	6.33	10.93	0.35	0.06	0.03	0.00	0.02
PROPANE	0.32	0.27	0.09	0.28	1.07	0.77	18.30	3.89	0.02	0.01	0.02
CORN	0.40	0.28	0.12	0.02	0.14	0.12	3.28	11.09	0.03	0.72	0.94
COFFEE	0.10	0.02	0.06	0.17	0.06	0.11	0.01	0.02	16.47	2.89	0.07
WHEAT	0.19	0.07	0.05	0.12	0.02	0.07	0.01	0.71	2.47	12.12	0.54
SOYBEANS	0.49	0.27	0.25	0.11	0.02	0.01	0.06	1.49	0.05	0.77	17.16

Table 6.8 represents the medium-run frequency. The highest off-diagonal values has $\tilde{C}^{H}_{CrudeOil \leftarrow NaturalGas} = 6.33\%$ followed by $\tilde{C}^{H}_{EUR \leftarrow SPX} = 6.27\%$. The most of other values are close to 0.

ONE YEAR Estimation

Table 6.9: The spillover table for band: 22 days to Inf days. Long-term frequency - BK2012 - BP=False; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	20.00	4.88	0.67	0.44	0.04	0.26	0.12	0.36	0.01	0.00	0.24
EUR	6.10	7.50	0.31	0.12	0.01	0.16	0.09	0.29	0.00	0.01	0.17
YEN	1.14	0.79	7.19	0.41	0.00	0.04	0.09	0.19	0.00	0.04	0.28
GASOLINE	0.71	0.15	0.25	8.25	0.01	0.57	0.18	0.02	0.01	0.00	0.05
NATURAL GAS	0.00	0.00	0.00	0.08	15.73	4.37	0.24	0.02	0.03	0.00	0.04
CRUDE OIL	0.17	0.15	0.06	0.60	4.76	6.69	0.27	0.05	0.02	0.00	0.00
PROPANE	0.39	0.26	0.08	0.25	1.25	0.89	9.69	2.19	0.00	0.00	0.00
CORN	0.48	0.29	0.10	0.03	0.17	0.15	1.83	5.30	0.01	0.28	0.44
COFFEE	0.07	0.01	0.03	0.12	0.04	0.08	0.01	0.00	7.38	1.33	0.02
WHEAT	0.18	0.07	0.04	0.10	0.02	0.06	0.01	0.31	1.02	5.00	0.25
SOYBEANS	0.59	0.30	0.20	0.12	0.01	0.00	0.04	0.85	0.01	0.40	8.19

Table 6.9 represents the long-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 6.10\%$ followed by $\tilde{C}^H_{SPX \leftarrow EUR} = 4.88\%$. The most of other values are very close to 0.

Conclusions

To sum up our results we must conclude that the longer the frequency the lower the spillovers. That is very surprising result as our expectation and our 3rd Hypothesis were that longer frequencies would result in higher effects of impact of shock on the system and its connectedness. This expectations were build on literature dedicated to analysis of frequency connectedness such as Baruník, Křehlík (2017), which estimate number the most liquid US banks. The contribution of our analysis was to test those theories on diverse markets data such as financial, forex and energy and food commodities markets. It is understandable that the connectedness among these markets is lower compare to the banking sector or to any other -one sector oriented analysis. Considering these facts our results are not surprising anymore. Our diverse set of market variables behaved differently and the connectedness was stronger in the short-run compared to the medium- and the long-run.

Nevertheless; in all frequencies the highest connectedness had EUR/USD with the S&P Index and Crude Oil with Natural Gas. Stronger connectedness compared to the others has also Wheat with Coffee and Yen with the S&P Index. For all results of the FALSE parameter under the methodology Diebold, Yilmaz (2009) dependent to ordering find result in the Appendix section. Generally can be concluded that results slightly differ and in the case of Diebold, Yilmaz (2009) were higher. That means the order dependence impact also the overall connectedness frequency measure.

6.6 Test of Correlation

This section provides results for Diebold, Yilmaz (2012) methodology with the **TRUE** Boolean parameter as a test of correlation. This results were compared to the results of the Diebold, Yilmaz (2012) methodology with the FALSE Boolean parameter. The results should slightly differ just as we expected some correlation effect, moreover; we expected that analysis with the TRUE Boolean parameter should have slightly higher results as we expected that correlation deflect the results from the analysis with the FALSE Boolean parameter closer to 0.

The spillovers were counted as the contribution of the diagonal elements of the FEVD to the total sum of the matrix. The diagonal values are always the highest percentage of the entire tables and represents self correlation. Method used reminds the vector autoregressions of order 3 (selected by Hannan_Quinn and Schwarz Criterion) identified using Cholesky-factor with no importance of ordering.

In case of both the off-diagonal column/row sums gave the value for counting the spillover index while the column/row sums including diagonal gives denominator of the spillover index. It is interesting to compare the values gained by both methodologies.

Table 6.10 shows regarding the traditional estimation that the highest off-diagonal connectedness have $\tilde{C}^H_{CrudeOil \leftarrow NaturalGas} = 22.65\%$ followed by $\tilde{C}^H_{NaturalGas \leftarrow CrudeOil} = 21.27\%$, $\tilde{C}^H_{EUR \leftarrow SPX} = 20.31\%$, $\tilde{C}^H_{SPX \leftarrow eur} = 15.19\%$. All of the traditional gross values are way higher compared to the analysis with the FALSE parameter. That means the correlation very strongly deflect the connectedness to 0. All directional spillovers equal in case of the FALSE and the TRUE parameters.

table 6.11 contains the total spillover index counted as total TO-FROM=NET divided by the number of 11 variables and can be compare to the results under dependence on variable ordering of the method of Diebold, Yilmaz (2009) in the Appendix section.

Table 6.10: Spillovers Table - DY2012 Methodology, BP=TRUE; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans	FROM
SPX	80.12	15.19	1.41	0.83	0.10	0.60	0.28	0.76	0.07	0.13	0.51	1.81
EUR	20.31	73.48	1.39	1.61	0.08	0.77	0.40	1.16	0.08	0.17	0.55	2.41
YEN	2.97	2.59	90.17	1.61	0.04	0.18	0.39	0.58	0.28	0.35	0.85	0.89
Gasoline	1.60	1.73	1.29	89.59	0.08	3.25	1.32	0.39	0.12	0.28	0.35	0.95
Natural Gas	0.02	0.06	0.03	0.17	77.34	21.27	0.65	0.07	0.16	0.12	0.12	2.06
Crude Oil	0.39	0.58	0.21	2.85	22.65	71.01	1.42	0.37	0.15	0.21	0.16	2.64
Propane	0.82	0.71	0.29	1.25	2.57	2.36	76.60	15.02	0.12	0.06	0.21	2.13
Corn	1.03	1.06	0.34	0.31	0.38	0.64	14.36	72.85	0.15	4.00	4.89	2.47
Coffee	0.28	0.20	0.27	0.51	0.20	0.28	0.11	0.15	83.34	14.27	0.39	1.51
Wheat	0.57	0.23	0.25	0.46	0.05	0.22	0.23	4.32	13.37	77.42	2.87	2.05
Soybeans	1.39	0.80	0.64	0.44	0.07	0.18	0.22	6.18	0.38	3.33	86.38	1.24
TO	2.67	2.10	0.56	0.91	2.38	2.70	1.76	2.64	1.35	2.08	0.99	20.15

Table 6.11: DY 2012 Spillover Index

Spillover Index	20,15/11=	1,83%

ONE WEEK Estimation

Table 6.12: The spillover table for band: 1 days to 5 days. Short-term frequency - BK2012 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	47.30	0.14	0.09	0.03	0.11	0.26	0.02	0.03	0.02	0.15	0.02
EUR	5.43	69.53	0.02	1.61	0.12	0.71	0.05	0.22	0.03	0.13	0.05
YEN	0.90	0.06	72.97	0.06	0.05	0.03	0.07	0.04	0.06	0.14	0.07
GASOLINE	0.25	0.85	0.09	72.75	0.24	1.72	0.01	0.16	0.07	0.19	0.01
NATURAL GAS	0.01	0.03	0.04	0.10	50.72	0.68	0.02	0.01	0.02	0.15	0.03
CRUDE OIL	0.04	0.10	0.02	1.38	3.91	75.99	0.07	0.11	0.01	0.15	0.09
PROPANE	0.13	0.07	0.03	0.02	0.40	0.12	62.79	0.45	0.04	0.10	0.12
CORN	0.14	0.05	0.04	0.42	0.46	0.86	0.66	77.44	0.08	0.15	0.20
COFFEE	0.12	0.17	0.01	0.30	0.06	0.09	0.04	0.08	70.78	0.10	0.06
WHEAT	0.22	0.06	0.04	0.41	0.06	0.23	0.30	0.06	0.37	77.15	0.07
SOYBEANS	0.48	0.09	0.05	0.03	0.06	0.07	0.00	0.06	0.06	0.08	70.13

Table 6.12 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the TRUE Boolean parameter and traditional and gross directional estimation in the short-run frequency. The highest off-diagonal values has $\tilde{C}^{H}_{EUR \leftarrow SPX} = 5.43\%$ followed by $\tilde{C}^{H}_{CrudeOil \leftarrow NaturalGas} = 3.91\%$. The most of other values are close to 0.

ONE MONTH Estimation

Table 6.13: The spillover table for band: 5 days to 22 days. Medium-term frequency - BK2012 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	26.98	0.26	0.26	0.15	0.01	0.17	0.02	0.11	0.04	0.04	0.04
EUR	3.06	10.22	0.02	0.06	0.01	0.06	0.01	0.08	0.02	0.00	0.02
YEN	0.59	0.07	16.52	0.11	0.00	0.01	0.01	0.03	0.03	0.01	0.13
GASOLINE	0.38	0.03	0.01	14.14	0.01	0.13	0.00	0.01	0.01	0.05	0.00
NATURAL GAS	0.00	0.02	0.00	0.07	27.67	0.04	0.03	0.01	0.00	0.01	0.10
CRUDE OIL	0.11	0.02	0.01	0.27	2.11	9.01	0.01	0.02	0.00	0.02	0.06
PROPANE	0.19	0.03	0.01	0.02	1.03	0.00	21.92	0.10	0.04	0.01	0.12
CORN	0.28	0.02	0.03	0.00	0.13	0.02	0.40	12.18	0.12	0.04	0.02
COFFEE	0.08	0.01	0.00	0.09	0.00	0.03	0.00	0.06	19.20	0.02	0.00
WHEAT	0.17	0.00	0.00	0.09	0.00	0.03	0.00	0.00	0.03	14.50	0.00
SOYBEANS	0.31	0.02	0.07	0.03	0.02	0.03	0.00	0.03	0.06	0.04	18.97

Table 6.13 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2012) methodology with true Boolean parameter and traditional and gross directional estimation in the medium-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 3.06\%$ followed by $\tilde{C}^H_{CrudeOil \leftarrow NaturalGas} = 2.11\%$. The most of other values are close to 0.

ONE YEAR Estimation

Table 6.14: The spillover table for band: 22 days to Inf days. Long-term frequency - BK2009 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	22.55	0.28	0.26	0.20	0.00	0.18	0.02	0.14	0.05	0.04	0.04
EUR	3.21	5.03	0.03	0.09	0.00	0.06	0.01	0.07	0.03	0.00	0.02
YEN	0.70	0.06	7.04	0.10	0.00	0.00	0.00	0.03	0.02	0.00	0.08
GASOLINE	0.45	0.03	0.01	8.20	0.01	0.10	0.00	0.01	0.01	0.04	0.00
NATURAL GAS	0.01	0.01	0.00	0.08	19.98	0.00	0.04	0.01	0.00	0.00	0.10
CRUDE OIL	0.13	0.01	0.01	0.23	1.76	4.30	0.01	0.01	0.00	0.01	0.05
PROPANE	0.24	0.02	0.01	0.02	0.99	0.01	10.75	0.09	0.03	0.01	0.10
CORN	0.34	0.01	0.03	0.01	0.14	0.00	0.22	5.42	0.08	0.01	0.01
COFFEE	0.06	0.00	0.00	0.07	0.00	0.02	0.00	0.03	8.47	0.01	0.00
WHEAT	0.16	0.00	0.00	0.07	0.00	0.02	0.00	0.00	0.01	5.94	0.00
SOYBEANS	0.39	0.02	0.06	0.03	0.01	0.01	0.00	0.02	0.04	0.02	8.71

Table 6.14 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with true Boolean parameter and traditional and gross directional estimation in the long-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR\leftarrow SPX} = 3.21\%$ followed by $\tilde{C}^H_{YEN\leftarrow SPX} = 0.70\%$. The most of other values are very close to 0.

The frequency dynamics analysis showed the same trend as analysis with the FALSE parameter. The strongest connectedness was in case of the short-term, while significantly lower in the medium- and even lower in the long-term. As well the results of the highest connectedness was between EUR/USD and the S&P Index, followed by Crude Oil and Natural Gas.

If our results would be exactly similar to the analysis with the FALSE parameter that would be a prove of no correlation. Nevertheless; all our values were higher here compared to result of the FALSE parameter so our conclusion is an evidence of an impact of correlation on the system.

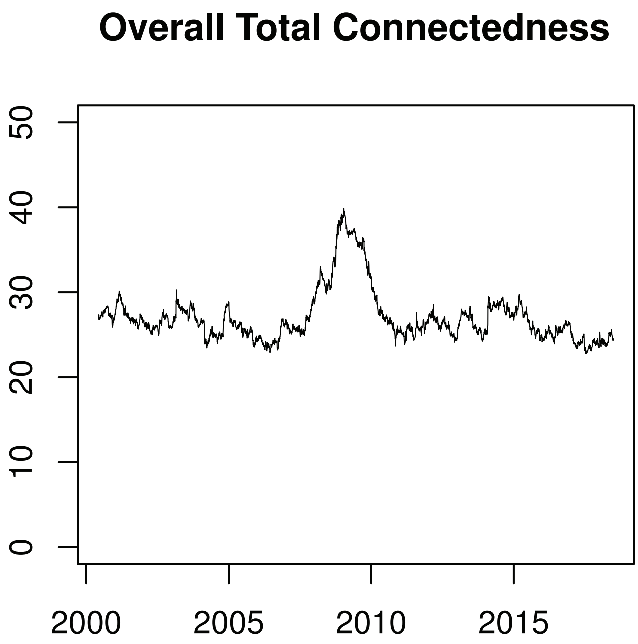
For all the results of the TRUE parameter under the methodology Diebold, Yilmaz (2009) dependent to ordering find result in the Appendix to this Thesis. Generally can be concluded, that results in the case of the Diebold, Yilmaz (2009) methodology were exactly similar. That means the order dependent method with the TRUE parameter do not impact the overall frequency connectedness measure. That means the results differ for different Boolean parameters.

6.7 Dynamics of Connectedness: The Rolling Widow Estimation

The entire spillover estimation provided an average variable behaviour summary, nevertheless; missed potential movements in the spillovers. Usage of the rolling window estimation over time series brigs dynamics of the connectedness based on the methodology Diebold, Yilmaz (2012). The estimation was performed under parameters of 3 lags and 250 windows, which means that our graphs moved by 249 dates drop from moving window by $-seq(1:(W-1))$.

Figure 6.2 shows the dynamic analysis of total connectedness that gives a general overview of events that may influenced the volatility connectedness of our variables. The rolling distribution of the total directional connectedness was plotted by using the time series of volatility of daily closing values. Several cycles in the total spillover plot might be identified. Mainly the crisis of 2008 brought a huge increase from around 25% to almost 40% and started in early 2007 already with sub-prime crisis and came back to normal around 2010, but this swing was

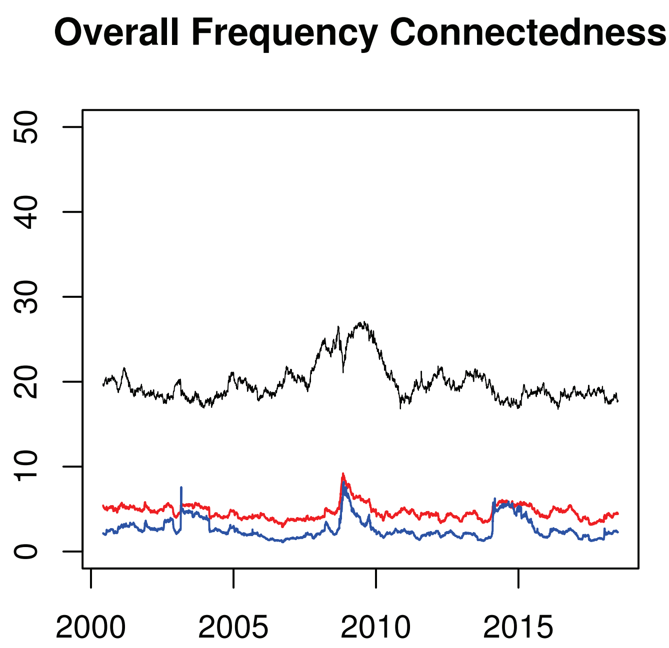
Figure 6.2: Overall Total Connectedness



discussed many times. Lets have a look at smaller cycles ranging more or less between 20% to 30%.

- 2000 the dot-com bubble that had a serious impact on the total volatility connectedness of the financial stocks
- 2001 the terrorist attack and fall of the Twins followed by the Nasdaq and other stock exchanges and recession in the following week after the attack and in late 2001 again increased connectedness trend due to the Enron and MCI WorldCom scandal
- 2003 an invasion of Iraq, which let to a little increase followed by a slight decline
- 2005 FED announced change in interest rates, which let to changes in volatility of prices of commodities
- 2007-2008 the financial crisis
- 2011-2013 the European debt crisis

Figure 6.3: Overall Frequency Connectedness



Nowadays the Index is hitting the bottom of our observed period and is around 23%. Generally; we can say that in our sample data there were not observable those events mainly but were there many little cycles that were probably mostly caused by monetary policy changes and their impact on interest rates.

Figure 6.3 shows the overall total connectedness in frequencies, where the black line represents the short-term, the red line the medium-term and the blue one the long-term connectedness. The short-term connectedness reminds closest in its value to the total connectednes (Figure 6.2.) and ranges between 18% to 28% with more or less similar deflections. Nevertheless; the medium-term and the long-term keep very low compared to the short-term and ranges between 0% to 8%, while the medium-term is the flattest one and the long-term creates in fact just 3 cycles: around 2003, 2008, 2014.

This result supports our conclusion from the frequency spillover tables. Our results were similar, the strongest connectedness was observed in the case of the short-term frequency, while the medium- and long-term were closer to each other and closer to 0. That support our theory that because our variables diverse so much in their market fields they are the most connected just in a the short-run while in the long-run they incline to very low or almost 0 connectedness. That is a second prove against our hypothesis previous to our empirical analysis.

Both the overall total spillover plot and the overall frequency connectedness plot discarded directional information, lets have a look at “Directional TO Others” (row sum) and “Directional FROM Others” (column sum) in separate frequency graphs.

Figure 6.4 and **6.5** represent the "TO" connectedness. It is very interesting how differently our variables behave. All stay in low values between 0% and 4%. In general we can watch the same trend when the short-term keeps above the others and is more dynamic compare to flatter medium- and the long-run. Also the short-run differs the most for all variables. Lets mention a few of the most interesting outcomes.

The S&P 500 Index was the most influenced in the medium- and the long-run during the financial crisis of 2008 when its values increased to the same maximum level of the short-run around 2%. Natural Gas and Propane have very similar outcome for the medium- and the long-term while their long-run differ very much. Crude Oil fluctuate the most of all in all terms. We can also conclude that in "TO others" behaviour our food section consisting of Corn, Coffee, Wheat and Soybeans behave more similar to each other in all terms compare the the rest of variables.

Figures 6.6 and **6.7** show the "FROM" connectedness. All variables vary between 0% and 3.5% so in general a bit lower compared to "TO". Also the trend of lower medium- and the long-run reminding lower compare to the short-term, which is also more dynamic. Graphs are very similar to "TO" outcome, the main differences are in Gasoline where the 2008 swing is less obvious and the medium- and the long-term were before 2008 almost flat. Crude Oil is a bit less dynamic and Propane has in medium and long-run higher values. The food section reminds also very similar and keeps the same, just Wheat and Coffee are a bit flatter.

Figures 6.8 and **6.9** represent the "NET" connectedness ("TO"-"FROM"). Here we get to negative numbers, which means higher influence "FROM other" variables than "TO other" variables. Our all lines represent different lengths cross each other variables and range between -1% to 1.5%, while the short-run reminds the most dynamic. Also the outcome does not copy our event structure anymore. Also the food does not remind very similar to each other. Interesting to mention is that our forex EUR/USD ranges the most in the short-run compared to the other variables while Wheat and Soybeans keep slightly higher in the medium- and the long-term compared to the short. To sum up, all "NET" graphs keep close to 0%, which means no big differences between "TO" and "FROM".

Figure 6.10 presents summary graphs where all previously presented graphs are always combined in just one picture. That helps us to compare that "TO" is the most ranging and medium and long-term frequencies keeping lower. "FROM" ranging less and medium and long-term frequencies keeping lower as well while "NET" keeps around 0% and all frequencies blend.

Overall; all of the graphs support our previous frequency spillover tables results. Both directional graphs TO and FROM demonstrates the strongest connectedness in short-term, nevertheless; in TO case more than in FROM case. Lower and close to 0 in the medium- and the long-term. NET values range around 0 as previously and as expected.

Figure 6.4: Individual Graphic Representation of TO Connectedness; Source: Author's computations

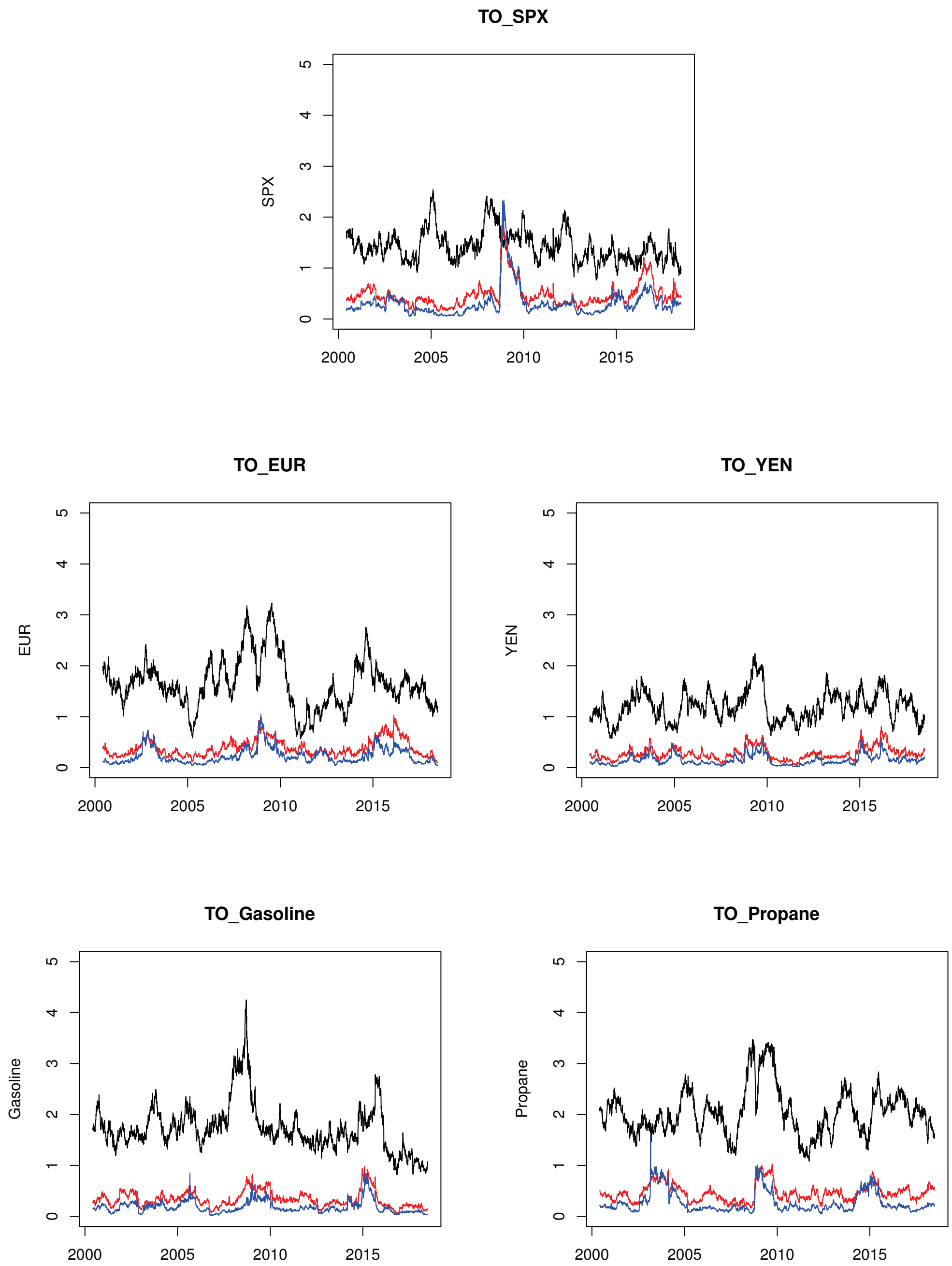


Figure 6.5: Individual Graphic Representation of TO Connectedness - continue

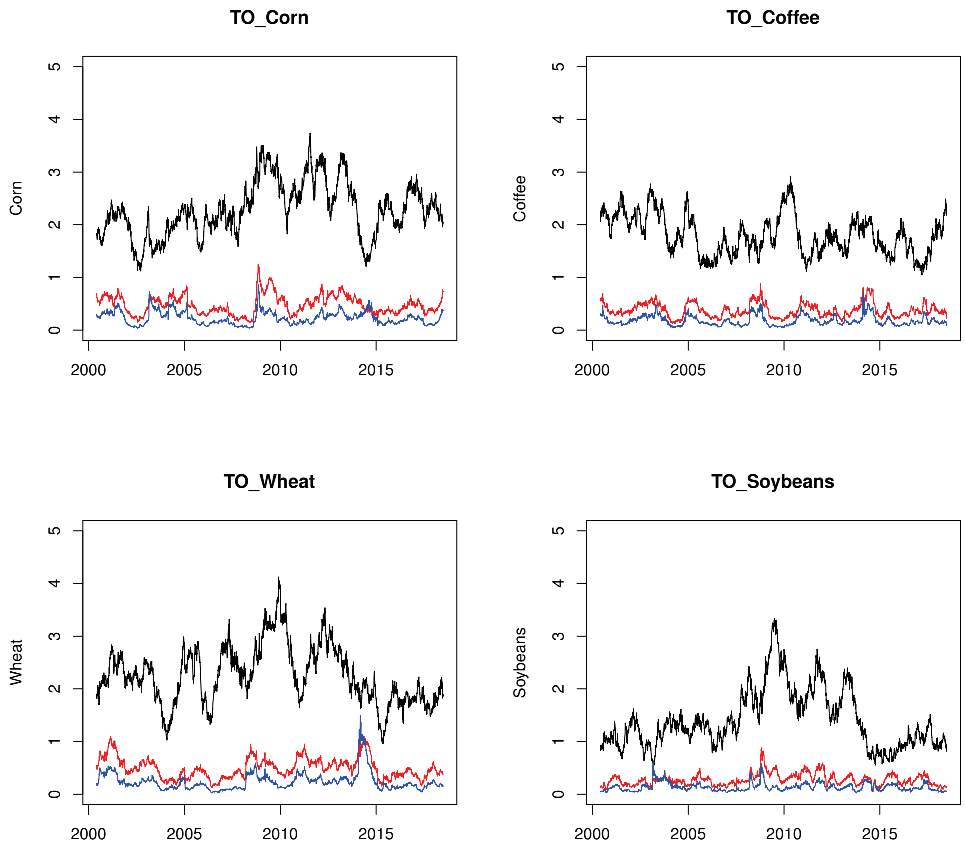


Figure 6.6: Individual Graphic Representation of FROM Connectedness; Source: Author's computations

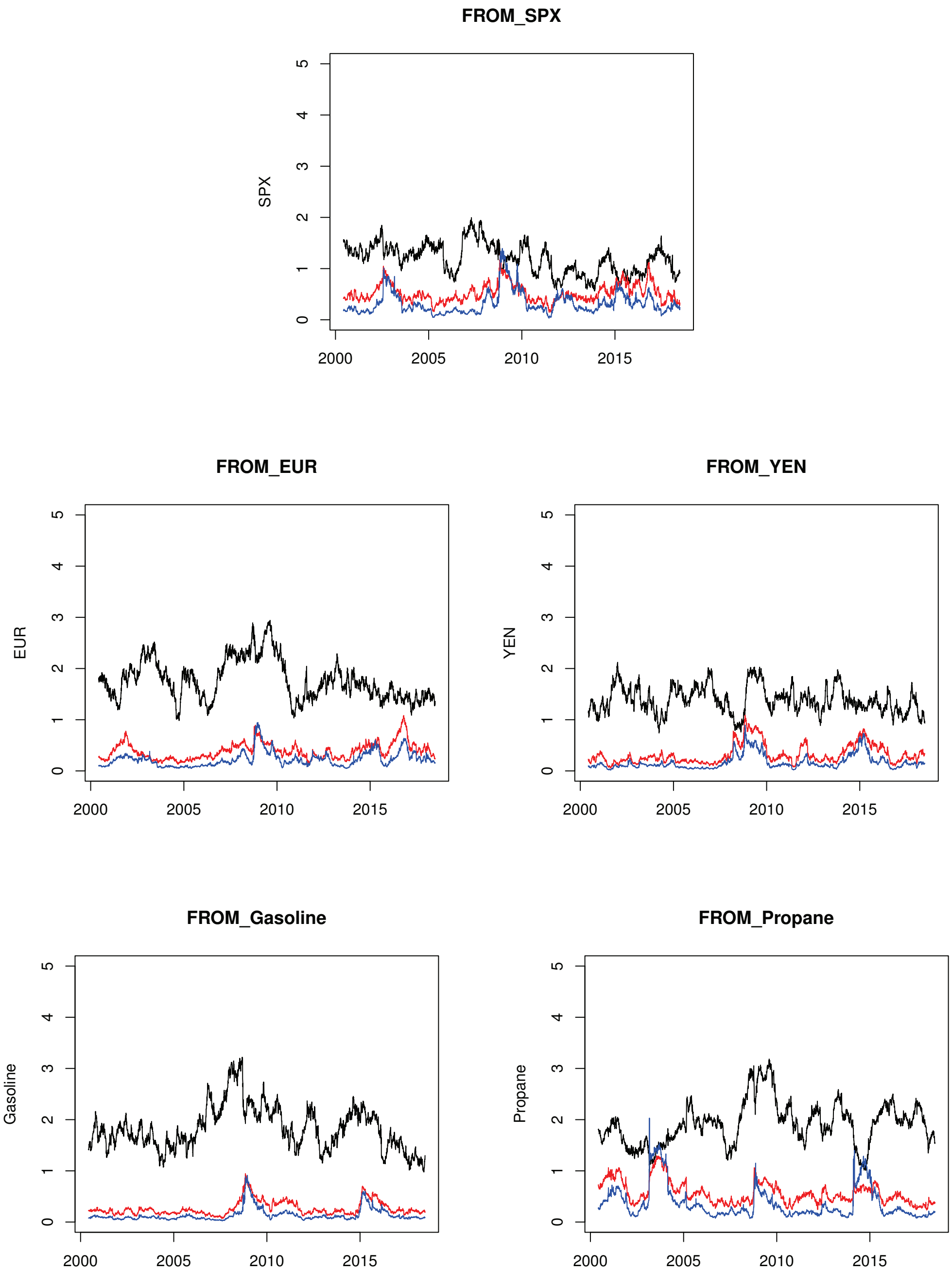


Figure 6.7: Individual Graphic Representation of FROM Connectedness - continue

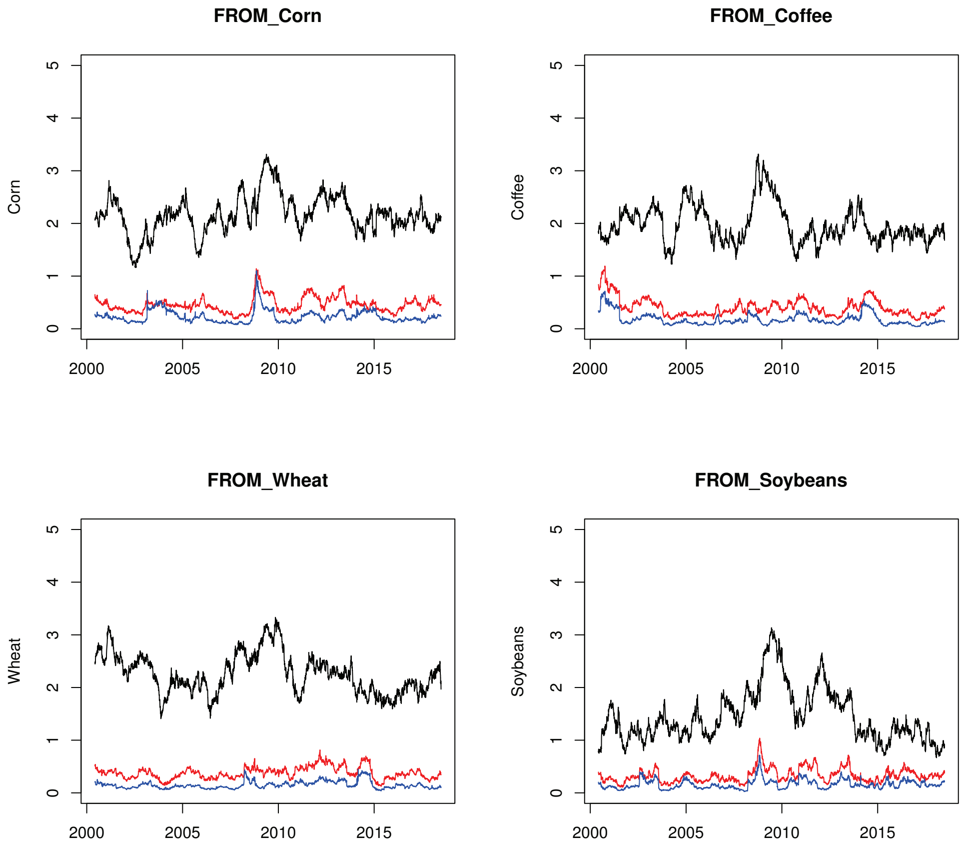


Figure 6.8: Individual Graphic Representation of NET Connectedness; Source: Author's computations

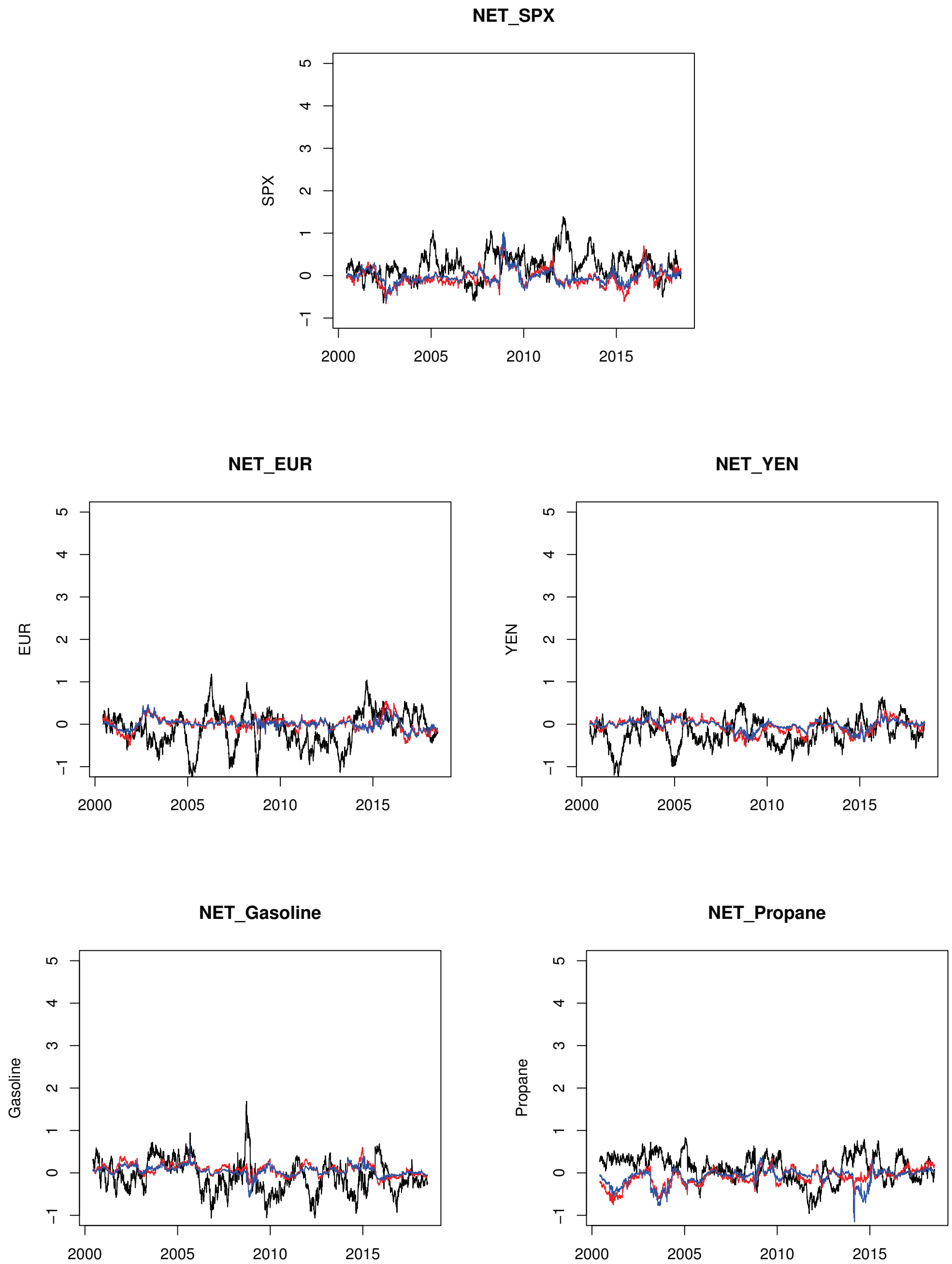


Figure 6.9: Individual Graphic Representation of NET Connectedness - continue; Source: Author's computations

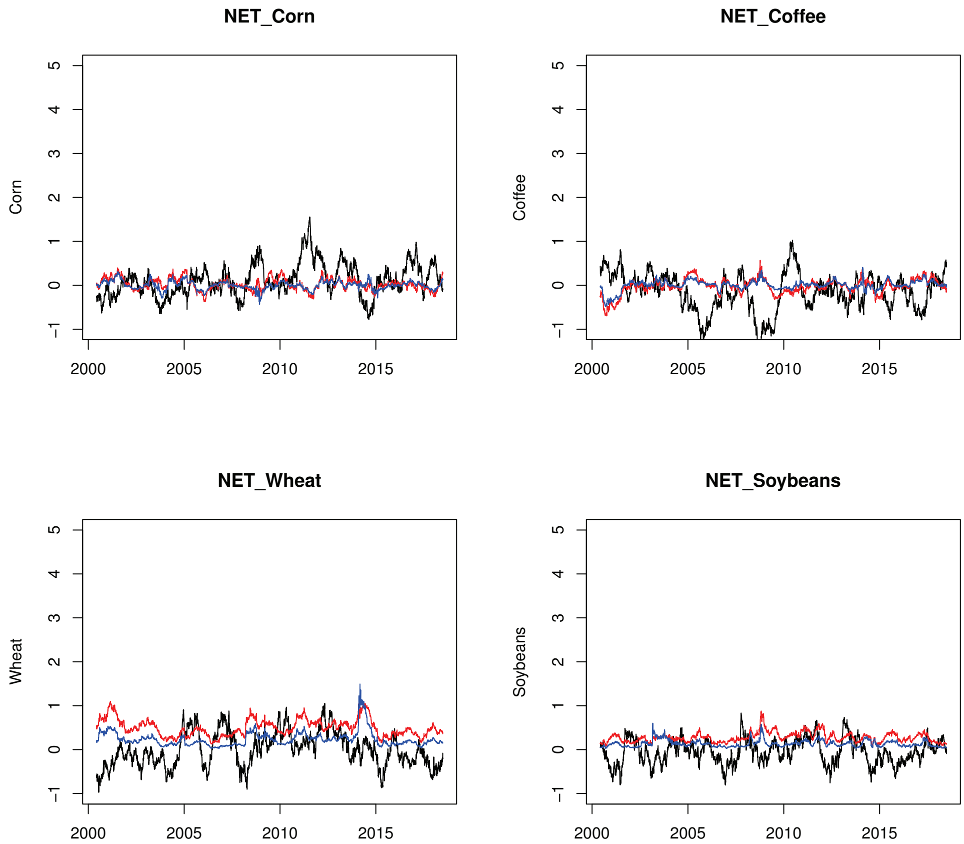
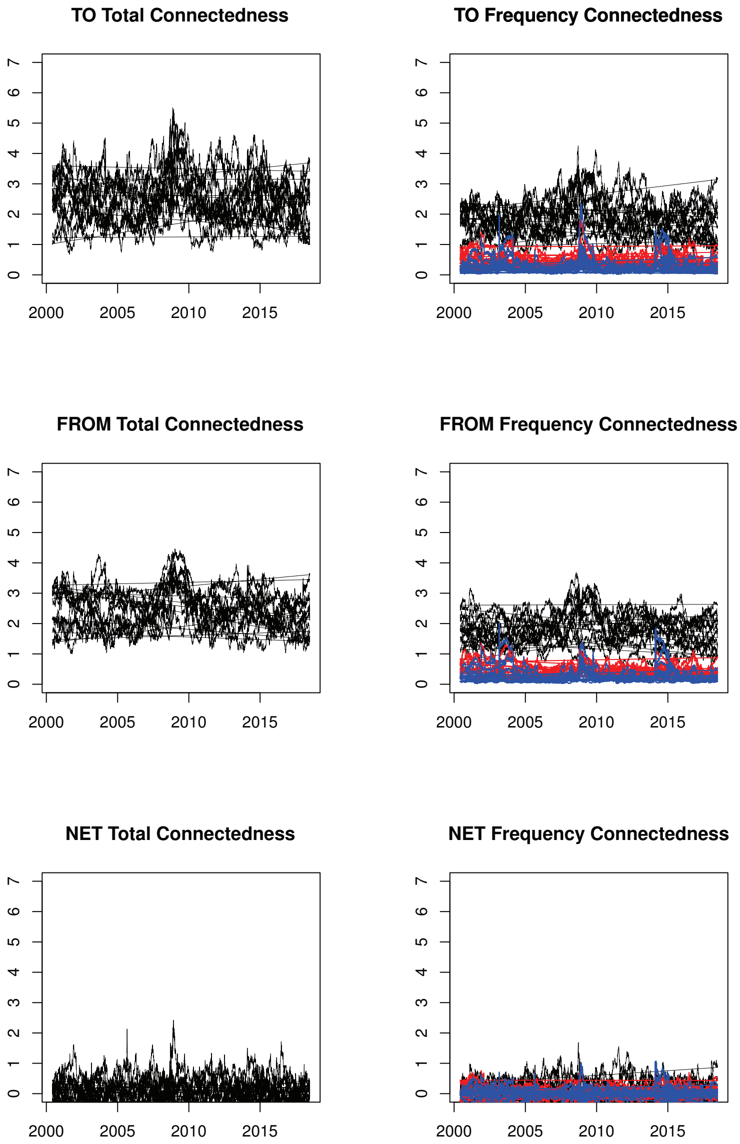


Figure 6.10: Summary Graphic Representation of Connectedness; Source: Author's computations



Chapter 7

Conclusions

The analysis of volatility connectedness provides a tool to view market risk transmission for the purposes of risk management, portfolio diversification and market regulation. The main contribution of this analysis has been to test how closely are highly diverse variables representing financial markets, forexes, and commodities connected in the overall and frequency domains. The analysis of frequency volatility spillovers was based on variance decompositions from vector autoregressions based on daily closing prices of the S&P 500 Index, YEN/USD forex, EUR/USD forex, Gasoline, Natural Gas, Crude Oil, Propane, Corn, Coffee, Wheat, and Soybeans during the period 1/6/1999 - 29/6/2018.

For analysis purposes we used R studio software and its supporting packages such as the Frequency Connectedness. The analysis was performed using a generalized vector autoregressive framework in which are forecast error variance decompositions invariant to ordering under the methodology of Diebold, Yilmaz (2012). The main analysis was run with a FALSE Boolean parameter. The test of correlation was undertaken by running the analysis with a TRUE Boolean parameter. As the results differed (specifically were higher under a TRUE parameter) we provided the evidence of correlation in the dataset.

The results of the main traditional and directional spillovers analysis were as following: the traditional pairwise correlation of variables ranged between the lowest -0.47% of the pair SPX-EUR and the highest 0.08% of Coffee-Wheat. Directional TO other variables and FROM other variables ranged between the lowest 0.91% TO Gasoline and the highest 2.6% FROM SPX. The NET spillover kept close to 0 as expected, which indicates that TO and FROM spillovers were at similar levels. In the frequency domain we showed the strongest connectedness on the one week short-term estimation (ranging between 0.02% between SPX and Natural Gas and 11.56% between Crude Oil and Natural Gas), lower in the case of one month medium-term estimation (ranging between 0.01% between number of variables and 6.33% between Crude Oil and Natural Gas) and the lowest in the case of the one year long-term estimation (ranging between 0.01% between number of variables and 6.10% between EUR and SPX). This results were very surprising and did not corroborate our Hypothesis 3 that shocks with long-term responses transmit across markets with greater strengths, pointing to high long-run systemic risk. This works for the globally most liquid financial, commodity, and forex markets. This theory was not corroborated but the exact opposite trend was observed. Our Hypothesis 1 that FX markets, commodities and financial markets influence each other on both short- and long- runs with various strengths and Hypothesis 2 that types of shocks resulting in the short-, medium-, and long-term responses differ were corroborated as different shocks were observed in this analysis with different impacts on all variables with different strengths and lengths. This means not only, for example, that the financial crisis of 2008 caused changes in connectedness. Also the terrorist attack of 2001 influenced all variables in our sample, and each differently.

The dynamics of connectedness was analyzed through the rolling window estimation that decomposed the spillover index into all of the forecast error variance components for one variable coming from shocks to the other variable. The entire sample and the time variation was tracked by the rolling 250 window estimation. Our findings again proved a relationship between all variables. In general the strongest reaction of all variables was to the global financial crisis of 2008. Both the overall and individual directional frequency connectedness corroborated our Hypotheses 1 and 2 while it did not corroborate our 3rd Hypothesis.

Overall, all our frequency results, both spillover tables and dynamic graphic representations showed that the greater strengths have shocks in the short-term. As mentioned previously, the probable reason is that Baruník, Křehlík (2017) ran their empirical analysis on the most important American Banks. However, our series of variables was largely diverse and was connected only at low levels compared to the banking sector moreover the strongest in the short-run. In the long-run the connectedness was close to 0. The main conclusion is that in the short-term, the reaction of all variables to any shock is stronger compared to the medium- and the long-term. The short-term is also the most ranging in the case of all variables. The main contribution of the Thesis was the provision of evidence of a connectedness measurement mostly in the short-term between highly diverse variables representing financial, forex and commodity markets.

In the Appendix to this Thesis you will find the results of the complete analyses under Diebold, Yilmaz (2009) order variant methodology. The results obtained were higher compared to our original analysis, so an order dependence was proved in the system.

The analysis in this Thesis gave just a small insight into volatility connectedness among diverse system of markets representing variables. It suggests a new theory that, in the wide system, the strongest connectedness can be observed in the short-term while in the long-term the connectedness is getting closer to 0. This new theory demands further investigation.

Firstly, as we are using just day closing prices so it would be great to use high frequency data and run the same analysis under the same methodology. Secondly, it would be interesting to use a larger dataset or a different but also diverse system of markets to prove our theory or, even better, to run two datasets separately: one on the banking sector and the second one on widely diverse markets to prove they behave differently. Thirdly, our results could be used for risk management purposes or they could be compared to the results of other methods of measuring connectedness.

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Acronyms

VAR: the Vector Autoregressive Model

VECM: the Vector Error Correction Model

(G)FEVD: the (general) forecast error variance decomposition

GVD: the generalized variance decomposition

CoVaR: the conditional value at risk

DY 2009: Diebold, Yilmaz (2009)

DY 2012: Diebold, Yilmaz (2012)

BP: Boolean parameter

SPX: S&P 500 Index

YEN: YEN/USD forex

EUR: EUR/USD forex

LPG: liquid petroleum gas

Appendix

7.0.1 The Data Frame

Table 7.1: Preview of the data frame - Realized Volatilities; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
0.00042486299	0.00000000000	0.0010760254	0.0219789067	0.008510690	0.0024110922	0.00000000	0.004618946	0.008230499	0.003960401	0.002181026
0.02147542463	0.00000000000	0.0032246090	0.00000000000	0.004246291	0.0119690238	0.03509132	0.027274418	0.008163311	0.031130919	0.015135424
0.00508589632	0.00508589632	0.0029673612	0.0029673612	0.017167804	0.0171678036	0.0000000000	0.0000000000	0.024692613	0.024692613	0.002148229
0.00508589632	0.00000000000	0.0040248114	0.0210534092	0.042379223	0.0311905068	0.03390155	0.009009070	0.068992871	0.003883500	0.006430890
0.00099394159	0.00966191091	0.0055898214	0.0206192872	0.012526260	0.0140570209	0.00000000	0.000000000	0.055059777	0.011696040	0.002134473
0.01206975659	0.01206975659	0.0118580103	0.0118580103	0.004192878	0.0041928783	0.00000000	0.000000000	0.000000000	0.000000000	0.006376217

7.0.2 VAR

Table 7.2: VAR Estimation Results; Source: Author's computations

Endogenous variables:	SPX, EUR, YEN, Gasoline Natural Gas, Crude Oil, Propane Corn, Coffee, Wheat, Soybeans
Deterministic variables:	const
Sample size:	4713
Log Likelihood:	154136.948
Roots of the characteristic polynomial:	0.7987, 0.775, 0.775, 0.7527, 0.6616 0.6318, 0.6318, 0.5897, 0.5659 0.5659 0.5446, 0.5446, 0.5346, 0.5346, 0.4998 0.4998, 0.4957, 0.4957, 0.4554, 0.4554 0.4398, 0.4398, 0.4262, 0.4262, 0.402 0.3793, 0.3793, 0.3781, 0.3781, 0.3353 0.3353, 0.243, 0.243
call:	VAR(y = volatilities, p = 3, type = "const")

As a specific example of VAR estimated coefficient find result for the S&P 500 Index results:

Table 7.3: VAR: estimated coefficients for SPX, preview. Source: Author's computations

	estimate:
	std.error
SPX.l1	0.4874587
	(0.0155959)
EUR.l1	0.0586682
	(0.0184352)
YEN.l1	0.0693522
	(0.0257301)
GASOLINE.l1	0.0086103
	(0.0066996)
NATURAL GAS.l1	0.0054695
	(0.0039756)
CRUDE OIL.l1	0.0010703
	(0.0051118)
PROPANE.l1	−0.0074712
	(0.0061719)
CORN.l1	0.0118080
	(0.0086751)
COFFEE.l1	−0.0102154
	(0.0077073)
WHEAT.l1	−0.0072076
	(0.0092318)
SOYBEANS.l1	0.0059126
	(0.0115014)
Observations	4,714
R^2	0.3362
Adjusted R^2	0.3316
Residual Std. Error	0.007596 (df = 4679)

7.0.3 Results of the Diebold, Yilmaz (2009) Methodology

Traditional Spillover Analysis

FALSE Boolean parameter

Table 8.4 represents the pairwise directional connectedness measures or spillovers table based on the Diebold, Yilmaz (2009) methodology with the FALSE Boolean parameter and the traditional estimation. The diagonal values are missing and the most of the values are negative and the highest is $\tilde{C}^H_{Propane \leftarrow Soybeans} = 0.018\%$ followed by $\tilde{C}^H_{Propane \leftarrow Coffee} = 0.006\%$. While compared to the main analysis under the methodology Diebold, Yilmaz (2012) this values are lower while the main analysis have higher values. As the values differ it is a prove that data are order sensitive.

Tables 8.5, 8.6, 8.7 represent the spillovers tables based on the Diebold, Yilmaz (2009) methodology with the FALSE Boolean parameter and the directional estimation. The highest NET value has N.Gas followed by SPX. Over a half of the NET values are negative while the lowest value has Crude Oil. Those negative value means that over a half variables has stronger impact TO others than they are being impacted FROM others.

While compared to the main analysis under the Diebold, Yilmaz (2012) methodology this values are slightly higher. As the values differ it is a prove that data are order sensitive.

Table 7.4: Pairwise spillovers of the DY 2009 table, BP=False

SPX-EUR	SPX-YEN	SPX-Gasoline	SPX-Natural Gas	SPX-Crude Oil	SPX-Propane	SPX-CORN	SPX-Coffee	SPX-Wheat	SPX-Soybeans
−2.115415451	−0.223469453	−0.110434915	0.003558727	−0.007823829	−0.092001198	−0.103188765	−0.013017590	−0.051030421	−0.135864551
EUR-YEN	EUR-Gasoline	EUR-Natural Gas	EUR-Crude Oil	EUR-Propane	EUR-Corn	EUR-Coffee	EUR-Wheat	EUR-Soybeans	YEN-Gasoline
−0.131089431	−0.001541607	−0.001966087	0.001019093	−0.038649234	−0.045066151	−0.009962268	0.001809812	−0.032455368	−0.097580956
YEN-Natural Gas	YEN-Crude Oil	YEN-Propane	YEN-Corn	YEN-Coffee	YEN-Wheat	YEN-Soybeans	Gasoline-N.Gas	Gasoline-C.Oil	Gasoline-Propane
−0.000661723	−0.013642032	−0.014579600	−0.011670852	−0.020597302	−0.014371008	−0.026252115	−0.014137836	−0.198560896	−0.131443621
Gasoline-Corn	Gasoline-Coffee	Gasoline-Wheat	Gasoline-Soybeans	Natural Gas-Crude Oil	Natural Gas-Propane	Natural Gas-Corn	Natural Gas-Coffee	Natural Gas-Wheat	Natural Gas-Soybeans
−0.012124017	−0.044926758	−0.027285749	−0.035823724	−2.574522073	−0.272201656	−0.042679039	−0.018853825	0.005841473	0.011818480
Crude Oil-Propane	Crude Oil-Corn	Crude Oil-Coffee	Crude Oil-Wheat	Crude Oil-Soybeans	Propane-Corn	Propane-Coffee	Propane-Wheat	Propane-Soybeans	Corn-Coffee
−0.072922675	−0.071516217	−0.009131317	−0.008798119	0.006704270	−1.620599499	0.006410222	−0.012388527	0.017954900	0.003259868
Corn-Wheat	Corn-Soybeans	Coffee-Wheat	Coffe-Soybeans	Wheat-Soybeans					
−0.547201495	−0.626395576	−1.462552736	−0.023286380	−0.120995970					

Source: Author's computations

Table 7.5: TO spillovers of the DY 2009 table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
3.12975	0.58391	0.36511	0.85129	2.99901	0.47143	1.71019	1.33597	1.56342	0.24439	0.13165

Table 7.6: FROM spillovers of the DY 2009 table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
0.28106	2.44142	0.52031	0.59655	0.12162	3.10930	0.72337	2.07247	0.18440	2.23937	1.09625

Table 7.7: NET spillovers of the DY 2009 table, BP=False; Source: Author's computations

SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
2.84869	−1.85751	−0.15520	0.25475	2.87739	−2.63787	0.98683	−0.73651	1.37902	−1.99498	−0.96460

TRUE Boolean parameter

Table 8.8 represents the spillovers table based on the Diebold, Yilmaz (2009) methodology with the TRUE Boolean parameter. Regarding the traditional estimation the highest off-diagonal connectedness has $\tilde{C}^{H}_{CrudeOil \leftarrow NaturalGas} = 28.82\%$ followed by $\tilde{C}^{H}_{EUR \leftarrow SPX} = 24.03\%$, $\tilde{C}^{H}_{Corn \leftarrow Propane} = 18.07\%$, $\tilde{C}^{H}_{Wheat \leftarrow Coffee} = 16.18\%$. Interesting is that almost all of the other values are lower that 1% or around 3%. Regarding the gross directional estimation the highest TO value has SPX 3.13% followed by 3% of Natural Gas, the rest of variables has values around 1%. FROM value 3.11% Crude Oil followed by 2.44% of EUR, there we can observe in general slightly higher values compared to TO.

While comparing to the correlation test under methodology Diebold, Yilmaz (2012) this values are slightly lower. As the values differ it is a prove that data are order sensitive.

Table 7.8: Spillovers Table - DY 2009 methodology, BP=TRUE; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans	FROM
SPX	96.91	0.76	0.71	0.48	0.07	0.42	0.01	0.22	0.18	0.16	0.08	0.28
EUR	24.03	73.14	0.13	1.50	0.04	0.60	0.01	0.30	0.07	0.11	0.08	2.44
YEN	3.17	1.57	94.28	0.28	0.03	0.02	0.08	0.16	0.05	0.12	0.24	0.52
Gasoline	1.70	1.51	1.35	93.44	0.07	1.41	0.01	0.22	0.05	0.22	0.01	0.60
Natural Gas	0.03	0.06	0.04	0.22	98.66	0.50	0.13	0.00	0.02	0.13	0.21	0.12
Crude Oil	0.51	0.58	0.17	3.60	28.82	65.80	0.06	0.11	0.03	0.14	0.19	3.11
Propane	1.03	0.44	0.24	1.46	3.12	0.87	92.04	0.25	0.14	0.12	0.30	0.72
Corn	1.35	0.79	0.29	0.36	0.47	0.89	18.07	77.20	0.16	0.20	0.21	2.07
Coffee	0.33	0.18	0.28	0.55	0.23	0.13	0.07	0.12	97.97	0.09	0.06	0.18
Wheat	0.72	0.09	0.28	0.52	0.06	0.23	0.26	6.22	16.18	75.37	0.07	2.24
Soybeans	1.58	0.44	0.53	0.40	0.08	0.12	0.10	7.10	0.31	1.40	87.94	1.10
TO	3.13	0.58	0.37	0.85	3.00	0.47	1.71	1.34	1.56	0.24	0.13	13.39

Table 7.9: DY 2009 Spillover Index

Spillover Index	13,39/11=	1,22%

Frequency Connectedness

FALSE Boolean parameter

Table 8.10 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the FALSE Boolean parameter and the traditional and the gross directional estimation in the short-run frequency. The highest off-diagonal values has $\tilde{C}^H_{CrudeOil \leftarrow NaturalGas} = 14.73\%$ followed by $\tilde{C}^H_{Wheat \leftarrow Coffee} = 12.04\%$. The most of other values are close to 0.

Table 8.11 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the FALSE Boolean parameter and the traditional and the gross directional estimation in the medium-run frequency. The highest off-diagonal values has $\tilde{C}^H_{CrudeOil \leftarrow N.Gas} = 8.04\%$ followed by $\tilde{C}^H_{EUR \leftarrow SPX} = 7.42\%$. The most of other values are close to 0.

Table 8.12 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the FALSE Boolean parameter and the traditional and the gross directional estimation in the long-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 7.22\%$ followed by $\tilde{C}^H_{CrudeOil \leftarrow N.Gas} = 6.04\%$. The most of other values are very close to 0.

While compared to the correlation test under the methodology of Diebold, Yilmaz (2012) this values are higher.

ONE WEEK Estimation

Table 7.10: The spillover table for band: 1 days to 5 days. Short-term frequency - BK2009 - BP=False, ; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	44.85	0.13	0.10	0.05	0.02	0.18	0.01	0.02	0.04	0.12	0.02
EUR	9.39	59.90	0.05	1.31	0.03	0.51	0.01	0.15	0.02	0.11	0.05
YEN	0.85	0.88	70.82	0.05	0.03	0.02	0.05	0.05	0.02	0.11	0.06
GASOLINE	0.31	1.50	0.83	70.60	0.05	1.25	0.01	0.22	0.05	0.15	0.01
NATURAL GAS	0.01	0.04	0.03	0.03	51.44	0.47	0.03	0.00	0.02	0.11	0.03
CRUDE OIL	0.09	0.37	0.07	1.90	14.73	55.95	0.03	0.10	0.02	0.11	0.09
PROPANE	0.14	0.19	0.11	0.87	0.31	0.54	59.28	0.20	0.04	0.09	0.10
CORN	0.20	0.54	0.11	0.32	0.09	0.84	11.91	62.11	0.04	0.15	0.18
COFFEE	0.12	0.18	0.19	0.25	0.11	0.06	0.07	0.09	70.07	0.07	0.05
WHEAT	0.26	0.06	0.19	0.29	0.03	0.18	0.26	4.81	12.04	59.51	0.06
SOYBEANS	0.35	0.26	0.16	0.23	0.04	0.11	0.06	4.57	0.27	0.84	63.06

ONE MONTH Estimation

Table 7.11: The spillover table for band: 5 days to 22 days. Medium-term frequency- BK2009 - BP=False; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	27.87	0.30	0.30	0.18	0.02	0.12	0.00	0.09	0.07	0.02	0.03
EUR	7.42	8.77	0.03	0.07	0.00	0.04	0.00	0.07	0.03	0.00	0.01
YEN	1.10	0.41	16.33	0.11	0.00	0.01	0.02	0.06	0.02	0.01	0.11
GASOLINE	0.64	0.01	0.31	14.42	0.01	0.09	0.00	0.00	0.00	0.04	0.00
NATURAL GAS	0.01	0.01	0.00	0.09	27.14	0.03	0.05	0.00	0.00	0.01	0.09
CRUDE OIL	0.19	0.14	0.05	0.96	8.04	6.66	0.02	0.00	0.00	0.02	0.06
PROPANE	0.40	0.14	0.07	0.31	1.30	0.20	21.80	0.03	0.06	0.01	0.11
CORN	0.53	0.14	0.10	0.02	0.18	0.02	4.06	10.46	0.07	0.04	0.02
COFFEE	0.12	0.00	0.06	0.17	0.07	0.04	0.00	0.03	19.30	0.02	0.00
WHEAT	0.24	0.02	0.05	0.13	0.02	0.03	0.00	1.00	2.95	11.24	0.00
SOYBEANS	0.56	0.09	0.22	0.08	0.03	0.00	0.03	1.65	0.03	0.36	17.06

ONE YEAR Estimation

Table 7.12: The spillover table for band: 22 days to Inf days. Long-term frequency- BK2009 - BP=False; Source: Author's computations

	SPX	EUR	YEN	Gasoline	NATURAL Gas	CRUDE Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	24.19	0.33	0.31	0.25	0.02	0.13	0.00	0.11	0.08	0.02	0.03
EUR	7.22	4.48	0.05	0.11	0.00	0.04	0.00	0.07	0.03	0.00	0.02
YEN	1.21	0.29	7.13	0.11	0.00	0.00	0.01	0.05	0.02	0.00	0.07
GASOLINE	0.75	0.00	0.22	8.41	0.01	0.07	0.00	0.00	0.00	0.03	0.00
NATURAL GAS	0.00	0.00	0.00	0.10	20.08	0.00	0.05	0.00	0.00	0.00	0.09
CRUDE OIL	0.22	0.08	0.05	0.73	6.04	3.19	0.02	0.00	0.00	0.01	0.05
PROPANE	0.49	0.11	0.06	0.27	1.52	0.13	10.97	0.02	0.04	0.01	0.09
CORN	0.63	0.12	0.08	0.02	0.21	0.03	2.10	4.63	0.05	0.01	0.01
COFFEE	0.09	0.00	0.03	0.12	0.04	0.03	0.00	0.01	8.61	0.01	0.00
WHEAT	0.23	0.01	0.04	0.10	0.02	0.03	0.00	0.41	1.19	4.61	0.00
SOYBEANS	0.67	0.09	0.16	0.09	0.02	0.00	0.02	0.88	0.00	0.20	7.83

TRUE Boolean parameter

Table 8.13 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the TRUE Boolean parameter and the traditional and the gross directional estimation in the short-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 5.43\%$ followed by $\tilde{C}^H_{C.Oil \leftarrow N.Gas} = 3.91\%$. The most of other values are close to 0.

Table 8.14 represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the TRUE Boolean parameter and the traditional and the gross directional estimation in the medium-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 3.06\%$ followed by $\tilde{C}^H_{C.Oil \leftarrow N.Gas} = 2.11\%$. The most of other values are close to 0.

Table 8.15represents the pairwise directional connectedness measures based on the Diebold, Yilmaz (2009) methodology with the TRUE Boolean parameter and the traditional and the gross directional estimation in the long-run frequency. The highest off-diagonal values has $\tilde{C}^H_{EUR \leftarrow SPX} = 3.21\%$ followed by $\tilde{C}^H_{YEN \leftarrow SPX} = 0.70\%$. The most of other values are very close to 0.

ONE WEEK Estimation

Table 7.13: The spillover table for band: 1 days to 5 days. Short-term frequency - BK2009 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	47.30	0.14	0.09	0.03	0.11	0.26	0.02	0.03	0.02	0.15	0.02
EUR	5.43	69.53	0.02	1.61	0.12	0.71	0.05	0.22	0.03	0.13	0.05
YEN	0.90	0.06	72.97	0.06	0.05	0.03	0.07	0.04	0.06	0.14	0.07
GASOLINE	0.25	0.85	0.09	72.75	0.24	1.72	0.01	0.16	0.07	0.19	0.01
NATURAL GAS	0.01	0.03	0.04	0.10	50.72	0.68	0.02	0.01	0.02	0.15	0.03
CRUDE OIL	0.04	0.10	0.02	1.38	3.91	75.99	0.07	0.11	0.01	0.15	0.09
PROPANE	0.13	0.07	0.03	0.02	0.40	0.12	62.79	0.45	0.04	0.10	0.12
CORN	0.14	0.05	0.04	0.42	0.46	0.86	0.66	77.44	0.08	0.15	0.20
COFFEE	0.12	0.17	0.01	0.30	0.06	0.09	0.04	0.08	70.78	0.10	0.06
WHEAT	0.22	0.06	0.04	0.41	0.06	0.23	0.30	0.06	0.37	77.15	0.07
SOYBEANS	0.48	0.09	0.05	0.03	0.06	0.07	0.00	0.06	0.06	0.08	70.13

ONE MONTH Estimation

Table 7.14: The spillover table for band: 5 days to 22 days. Medium-term frequency - BK2009 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	26.98	0.26	0.26	0.15	0.01	0.17	0.02	0.11	0.04	0.04	0.04
EUR	3.06	10.22	0.02	0.06	0.01	0.06	0.01	0.08	0.02	0.00	0.02
YEN	0.59	0.07	16.52	0.11	0.00	0.01	0.01	0.03	0.03	0.01	0.13
GASOLINE	0.38	0.03	0.01	14.14	0.01	0.13	0.00	0.01	0.01	0.05	0.00
NATURAL GAS	0.00	0.02	0.00	0.07	27.67	0.04	0.03	0.01	0.00	0.01	0.10
CRUDE OIL	0.11	0.02	0.01	0.27	2.11	9.01	0.01	0.02	0.00	0.02	0.06
PROPANE	0.19	0.03	0.01	0.02	1.03	0.00	21.92	0.10	0.04	0.01	0.12
CORN	0.28	0.02	0.03	0.00	0.13	0.02	0.40	12.18	0.12	0.04	0.02
COFFEE	0.08	0.01	0.00	0.09	0.00	0.03	0.00	0.06	19.20	0.02	0.00
WHEAT	0.17	0.00	0.00	0.09	0.00	0.03	0.00	0.00	0.03	14.50	0.00
SOYBEANS	0.31	0.02	0.07	0.03	0.02	0.03	0.00	0.03	0.06	0.04	18.97

Table 7.15: The spillover table for band: 22 days to Inf days. Long-term frequency - BK2009 - BP=True; Source: Author's computations

	SPX	EUR	YEN	Gasoline	Natural Gas	Crude Oil	Propane	Corn	Coffee	Wheat	Soybeans
SPX	22.55	0.28	0.26	0.20	0.00	0.18	0.02	0.14	0.05	0.04	0.04
EUR	3.21	5.03	0.03	0.09	0.00	0.06	0.01	0.07	0.03	0.00	0.02
YEN	0.70	0.06	7.04	0.10	0.00	0.00	0.00	0.03	0.02	0.00	0.08
GASOLINE	0.45	0.03	0.01	8.20	0.01	0.10	0.00	0.01	0.01	0.04	0.00
NATURAL GAS	0.01	0.01	0.00	0.08	19.98	0.00	0.04	0.01	0.00	0.00	0.10
CRUDE OIL	0.13	0.01	0.01	0.23	1.76	4.30	0.01	0.01	0.00	0.01	0.05
PROPANE	0.24	0.02	0.01	0.02	0.99	0.01	10.75	0.09	0.03	0.01	0.10
CORN	0.34	0.01	0.03	0.01	0.14	0.00	0.22	5.42	0.08	0.01	0.01
COFFEE	0.06	0.00	0.00	0.07	0.00	0.02	0.00	0.03	8.47	0.01	0.00
WHEAT	0.16	0.00	0.00	0.07	0.00	0.02	0.00	0.00	0.01	5.94	0.00
SOYBEANS	0.39	0.02	0.06	0.03	0.01	0.01	0.00	0.02	0.04	0.02	8.71

7.0.4 Appendix Summary

The short-term frequency estimation. The traditional estimation results for Diebold, Yilmaz (2009) and Diebold, Yilmaz (2012) with the TRUE Boolean parameter were exactly the same while differed when the Boolean parameter was FALSE. Generally all off-diagonal results ranged between 0.01% and 14.73%.

The medium-run frequency estimation. The traditional estimation results for Diebold, Yilmaz (2009) and Diebold, Yilmaz (2012) with the TRUE Boolean parameter were again exactly the same while differed when the Boolean parameter FALSE. Generally all off-diagonal results ranged between 0.00% and 8.04% which was lower compared to the short-term frequency maximum 14.73%.

The long-run frequency estimation. The traditional estimation results for Diebold, Yilmaz (2009) and Diebold, Yilmaz (2012) with the TRUE Boolean parameter were again exactly the same while differed when the Boolean parameter was FALSE. Generally all off-diagonal results ranged between 0.00% and 7.22% which was not far from the medium-run frequency results 8.04%, nevertheless; all other off-diagonal values were way closer so 0%.

While compared to the correlation test under the methodology Diebold, Yilmaz (2012) this values were exactly similar to the Diebold, Yilmaz (2009) methodology with the TRUE parameter. That is a prove that in case of no correlation included in the system results do not differ under order dependent or independent methods.