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Asset Prices, Network Connectedness, and Risk Premium

Master's thesis

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Declaration of Authorship

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Prague, May 5, 2020

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Abstract

This diploma thesis introduces the measures of network connectedness in the context of asset pricing. It proposes an asset pricing model in which the factor of connectedness is included as one of the risk factors together with the three Fama-French factors. The goal of the analysis is to examine whether the connectedness represents a significant risk factor that should be considered while determining the risk premium of the portfolio in different sectors in the market. Using the realized volatilities and returns of 496 assets of SP 500 index over the period 2005 – 2018, that are divided into 11 sectors, we firstly determine the linkages of connectedness between the assets in the same sector. Applying Fama-MacBeth two-step regression model, we explore the significance of the connectedness factor for the determination of the risk premium. We argue that the sector overall connectedness represents a significant risk in most of the sectors and should be therefore taken into account by the investors in all sectors. Moreover, the total directional connectedness that captures the spillover of shocks to one asset from the other assets in the sector, is a significant risk factor that should increase the risk premium of the portfolio, especially in sectors such as the financial, health care, consumer and real estate sector.

JEL Classification	G10, G11, G12, C13, C58
Keywords	financial network, connectedness, risk premium, asset prices, risk factors

Title	Asset Prices, Network Connectedness, and Risk Premium

Abstrakt

Tato diplomová práce se zabývá propojeností sítě a jejího vlivu v oblasti oceňování akcií. Práce navrhuje model oceňování akcií, který zahrnuje faktor propojenosti jako jeden z rizikových faktorů společně se třemi Fama-French faktory. Cílem analýzy je zjistit, zda propojenost představuje signifikantní faktor rizikovosti, který by měl být brán v úvahu při určování výše rizikové prémie portfolia v různých sektorech na trhu. Za použití realizovaných volatilit a výnosů 496 akcií zahrnutých v SP 500 indexu v období 2005 až 2018, které jsou pro účely analýzy rozděleny do 11 sektorů, určíme nejdříve propojenost mezi akciemi v jednotlivých sektorech. Aplikováním Fama-MacBeth dvoufázového regresního modelu, je pak zjišťována signifikance faktoru propojenosti pro určování rizikové prémie napříč jednotlivými sektory. Z výsledků vyplývá, že faktor celkové propojenosti sektoru představuje významný faktor rizika v mnoha sektorech. Celkovou propojenost systému by proto měli investoři zohlednit napříč všemi sektory při stanovování rizika. Celková směrová propojenost, která zachycuje propojenost spojenou s přeléváním šoků z ostatních akcií v daném sektoru na danou akcii, je významným rizikovým faktorem, který by měl zvyšovat rizikovou prémii portfolia, a to zejména v sektorech jako je finanční, zdravotnický, spotřebitelský sektor a sektor nemovitostí.

Klasifikace JEL G10, G11, G12, C13, C58

Klíčová slova finanční síť, propojenost, riziková prémie, ceny akcií, faktory rizika

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Acronyms

CAPM Capital Asset Pricing Model

HML High Minus Low (Value Premium)

FROM Total Directional From Connectedness

MKT Excess Return on the Market Portfolio

NET Total Directional Net Connectedness

OLS Ordinary Least Squares

RS Realized Semivariance

RV Realized Variance

SMB Small Minus Big (Size Premium)

TO Total Directional To Connectedness

VAR Vector Autoregression

Master's Thesis Proposal

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Proposed topic	Asset Prices, Network Connectedness, and Risk Premium

Motivation The current economic literature focuses its interest more and more frequently on the topic of connectedness relating the time-varying network of relationships. The presently available academic papers provide the information concerning the econometric connectedness measures. The phenomenon of connectedness is nowadays studied in financial risk management as a determinant of the market risk and macroeconomic risks. The network of connectedness can be estimated by the variance decompositions from a vector autoregression approximating model introduced by Diebold and Yilmaz (2012). This approach using the variance decompositions is often used in modern econometrics since it provides the information including the future uncertainty of a particular variable due to shocks in another variable. Moreover, this method can be used to measure the connectedness of the system of many variables using the aggregated information in variance decompositions.

The purpose of this thesis is to investigate how the connectedness among assets should be priced by investors across different sectors i.e. what risk premium investors should request. The main hypothesis of this work is that the stronger the connectedness, the higher the risk and hence higher compensation required by investors (risk premium). The aim of the thesis is also to explore how the risk premium differs across different sectors because the currently available literature does not provide such comparison.

The main motivation for this thesis is to contribute to the expanding number of the academic papers regarding the connectedness and to enrich it with the analysis examining the size of the risk premium taking the connectedness of the asset prices at different sectors into the consideration. Using the publicly available asset prices, I would like to estimate the connectedness among the individual asset prices and use this network of relationships as one of the determining factor in the risk premium regression. I believe that this work could be not only interesting for the readers but also useful for the investors in the decision-making process of the portfolio composition.

Hypotheses

Hypothesis #1: A portfolio connectedness is priced in asset returns.

Hypothesis #2: Investors at different sectors require different risk premium for bearing connectedness risk.

Hypothesis #3: Connectedness is a factor that approximates risk in financial markets well.

Methodology In this diploma thesis, I will estimate the connectedness for the particularly chosen asset prices of approximately 500 companies i.e. I will try to find out how the shock in one asset price affects the other asset prices in the portfolio and construct the network showing these relationships. Then I will use the factor of connectedness as one of the criterions for evaluation of the risk premium i.e. as a factor for risk pricing. All these procedures will be applied for 11 different sectors and their results will be compared afterwards.

According to Diebold and Yilmaz (2012), connectedness measures based on variance decompositions tell us how much of entity's future uncertainty is caused due to the shocks arising from another entity. In this work, I will use VAR model in order to estimate the coefficients through moving average. Moreover, the variance decomposition including also the contribution of shocks to the system will show us how the shock into the price of one variable affects the price of the other variable.

For clarity and better visualisation, I will create a table from the obtained values of connectedness where higher values will signify stronger connectedness among the asset prices indicating higher risk of the overall portfolio. Furthermore, from this table we will be able to say how the shock in one of the asset prices from the portfolio affects the prices of the other assets in the portfolio.

Using the estimated values of the connectedness among particular asset prices in the portfolio from the constructed table and factors from Fama-French three- factor model including market risk, the outperformance of small versus big companies, and the outperformance of high book/market versus small book/market companies, I will estimate the most probable value of the risk premium for the investor.

Expected Contribution Diebold and Yilmaz (2014) suggested that the literatures of connectedness, networks and asset pricing should be all considered together while using network perspectives in economic context. Diebold and Yilmaz (2009) introduced the method of connectedness using generalized forecast error variance decompositions, which they more elaborated in their later works (2012, 2014). According to Herskovic (2018), there exists only a limited amount of academic works focusing on sectoral linkages implications on asset pricing. Herskovic (2018) investigated the asset pricing in multisector model, but he did not included the connectedness as a factor affecting the size of the risk premium.

The purpose of diploma thesis is to contribute to currently available economic literature by showing how the connectedness among the asset prices in the portfolio influences the risk premium if the market prices are set correctly across different sectors. The thesis will work with the data of approximately 500 companies from the period 2005-2018 which will be divided based on the sectors. By using the real asset prices data, this work aims to support the idea that the stronger is the connectedness among the asset prices, the higher is the potential risk of the portfolio and therefore there should be higher risk premium for the investors. The main contribution of the thesis will be the comparison of the required risk premium concerning besides the other factors the connectedness risk across 11 different sectors because current literature have not provided such analysis yet.

I believe that the findings of this thesis working with the factor of connectedness between assets prices can be useful for the potential investors at different sectors in their decision-making process of the portfolio compositions.

Outline

1. Introduction of the topic and review of the currently available literature: studying and summarizing the existing papers concerning the topics of connectedness (measures and main findings), network theory (findings and methodology) and asset pricing theory and models (CAPM, Fama- French factors models)

2. Methodology: introducing the methods used in the thesis and explaining the reasons why these methods were found suitable for the analysis

3. Empirical analysis of real data: description of the data, introduction of the examined sectors, creating the models, estimating the models, interpretation and discussion of the results

4. Conclusion:summary of the results and main findings of the work - rejecting or approving the hypothesis

Core bibliography

1. AHERN, Kenneth R. Network centrality and the cross section of stock returns. Available at SSRN 2197370, 2013.

2. BARUNIK, Jozef; KREHLIK, Tomas. Measuring the frequency dynamics of financial and macroeconomic connectedness. FinMaP-Working Paper, 2016.

3. BILLIO, Monica, et al. The impact of network connectivity on factor exposures, asset pricing and portfolio diversification. 2016.

4. BILLIO, Monica, et al. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of financial economics, 2012, 104.3: 535-559.

5. BURASCHI, A.; TEBALDI, C. Asset pricing in network economies with systemic risk. 2017.

6. COCHRANE, John H. Asset pricing: Revised edition. Princeton university press, 2009.

7. DIEBOLD, Francis X.; YILMAZ, Kamil. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 2009, 119.534: 158-171.

8. DIEBOLD, Francis X.; YILMAZ, Kamil. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 2009, 119.534: 158-171.

Author Supervisor

Chapter 1

Introduction

Financial market interdependence represents an important part of the systemic risk analysis, therefore the characterization of the interdependence has become one of the main objectives of the economic literature. Over the last decades, the descriptive measures of the interconnection of the financial markets went through a significant transformation. A growing literature examines the role of interconnections between firms and sectors as a potential mechanism for shock propagation across the whole economy with the goal to identify and measure possible sources of the systemic risk. The current economic literature focuses its interest more and more frequently on the topic of connectedness relating the time-varying network of relationships. Connectedness measures signify the characteristics of financial system linkages, their direction and strength. The recent academic papers suggest that this measure serves as an appropriate framework to capture the systemic risk, since it provides valuable information about the connectedness of the system, among all see Allen and Babus (2009); Yilmaz (2010); Diebold and Yilmaz (2014) and Baruník et al. (2018).

One of the main problems in asset pricing and finance generally is to understand and determine the differences in the expected asset returns. In the past, many academic researches aimed to explain these differences through finding the risk factors that affect the asset returns. As noted in Cochrane (2005), there is a persisting need for a better understanding of the determinants of the systematic risk. The phenomenon of connectedness is nowadays studied in financial risk management as a determinant of the market risk and macroeconomic risks. The network literature claims that the presence of the network linkages between companies, industries, and countries can change the microeconomic shocks into aggregate fluctuations. In addition, the linkages between the individual assets in a network usually have a direction, so the issue is even more complex, because there is difference whether a link goes from asset i to asset j or the other way around. Moreover, as mentioned by Baruník et al. (2018), the concept of network connectedness is still not completely defined and the impact of network on the economy is not fully understood. There exist several contributions to the literature of network analysis, among all see Diebold and Yilmaz (2009), (2014); Acemoglu et al. (2012); Billio et al. (2016) and Baruník et al. (2018).

The most prominent works concerning the connectedness and its measures using generalized forecast error variance decompositions were introduced by Diebold and Yilmaz (2009) and later elaborated in their papers (2012) and (2014). Moreover, Diebold and Yilmaz (2014) suggested that the literature of connectedness and networks may find its use in other fields such as asset pricing, portfolio management or policy. As noted in Herskovic (2018), there exists only a limited amount of academic works focusing on sectoral linkages implications on asset pricing. The main purpose and motivation of this diploma thesis is to contribute to currently available economic literature regarding the connectedness by showing how the connectedness linkages among the assets in the system influence the risk premium across different sectors.

Our main hypothesis is that a portfolio connectedness is priced in asset returns. We aim to analyse whether the connectedness of assets should be priced in the risk premium, since we argue that the connectedness linkages between assets represent a significant risk factor for the overall portfolio and should be therefore reflected in the risk premium. The economic intuition behind this statement is that higher connectedness leads generally to higher risk, which should be taken into account while determining the risk premium. Moreover, this work examines whether the investors at different sectors should require different risk premium for bearing connectedness risk. For analyzing this hypothesis, we perform the analysis on 11 different sectors. Furthermore, we are interested whether the connectedness is a factor that approximates risk in financial markets well. By conducting the sector analysis, we explore the situation in 11 sectors thanks to which we can approximate the connectedness risk in the whole market.

The thesis is structured as follows. Chapter 2 briefly summarizes the existing literature that concerns and relates the phenomena of connectedness, networks, and asset pricing. Chapter 3 provides the conceptual framework of connectedness measures, network concepts and the asset pricing models.

Firstly, we focus on the connectedness tables based on the variance decompositions and we describe the computations of spillover index. Secondly, we present the system-wide connectedness measure and the total directional connectedness measures. Lastly, we introduce the ideas behind the Capital asset pricing model (CAPM), Fama-French factor models, and Fama-MacBeth two-step regression model, which is later used in the empirical part of the thesis. Chapter 4 displays all examined data, its description and summary statistics. Chapter 5 shows the results from our data analysis following the introduced methodology. Finally, chapter 6 summarize our main findings and conclusions that can be inferred from the sector analyses. Furthermore, we provide suggestions for future research.

Chapter 2

Literature Review

As proposed by Diebold and Yilmaz (2014), the literature of connectedness and networks may find its use in other fields such as asset pricing, which aims to determine which risks represent truly systematic risk, and therefore, should be priced. However, current literature provides only very few researches that connect the literature of connectedness, networks, and asset pricing, which is the main goal and contribution of this diploma thesis. This chapter focuses on presenting the connectedness, network, and asset pricing theories, and frequently used approaches, which have been introduced in the existing economic literature. The main purpose of this part is to provide the reader the theoretical knowledge which will be later applied on the examined dataset in order to confirm or reject our hypothesis.

This chapter is divided into three main sections that provide a review of currently available economic papers and literature. First section introduces the topic of connectedness and spillovers among the financial variables, overview of the most significant existing works in current economic literature concerning this topic and the conceptual frameworks used in contemporary academic papers. Second section presents the theory of networks, most prominent works in this field and the commonly used methodological approaches for constructing the network. Last section of this chapter summarizes the most famous portfolio theories and it concentrates on asset pricing, risk premium settings and their link to connectedness and network literature. In addition, it provides brief introduction of applications of Capital Asset Pricing Model (CAPM)and Fama-French factors models using the network as a risk factor. This part serves mainly for better understanding of the empirical part of this diploma thesis.

2.1 Spillovers and Connectedness

"Issues of connectedness arise everywhere in modern life, from power grids to social networks, and nowhere are they more central thank in finance and macroeconomics - two areas that are themselves intimately connected (Diebold and Yilmaz, 2015, page xi)."

Due to the fact that the financial market interdependence represents one of the most important part of the systemic risk analysis, the characterization of the interdependence has become one of the main objectives of the empirical literature. Over the last decades, the descriptive measures of the interconnection of the financial markets went through a significant transformation. The phenomenon of connectedness has been described by using different academic terms such as co-movement of market, volatility transmission mechanism (characterized by spillover index), and most recently by the volatility connectedness measures. All of these terms are more or less synonyms concerning the same phenomenon.

The concept of connectedness of financial markets represent an interest of many areas of research. It is considered as central concern for modern risk measurement and risk management as well as for portfolio allocation (Baruník and Křehlík, 2018). It is linked to the credit risk (default connectedness), market risk (return connectedness and portfolio concentration), counter-party and gridlock risk (bilateral and multilateral contractual connectedness) as well as to systemic risk (system-wide connectedness). In addition, understanding of connectedness implications is also crucial for explaining macroeconomic risks such as business cycle risk (Diebold and Yilmaz, 2014).

The volatility spillovers across the financial as well as other markets are higher in magnitude, when the high market interdependence is present. Moreover, the correlation of market returns is larger when the volatility increases. Hence the high volatility periods are connected with market downturns or crashes (WU, 2001). Crisis development associated with market volatility spreads expeditiously across markets. The volatility is transmitted across market via spillovers which exhibit asymmetries and signify negative correlation of past returns with present volatility (Bekaert and Wu, 2000). These asymmetries are thought to originate from qualitative disparities connected with bad and good uncertainty. Since both volatility and spillovers serve as informative measures related to risk valuation and portfolio diversification approaches, asymmetries should be properly controlled for (Garcia and Tsafack, 2011).

The phenomenon of connectedness still remains elusive due to incomplete definition and poor measures as noted by Diebold and Yilmaz (2014). To the most widespread measures in this respect belong the correlation-based measures focusing on pairwise associations. This concept is close to the linear Gaussian thinking which limits their value in financial market field. Other often used approaches in this context are equi-correlation approach (using the average pairwise correlation), CoVaR or marginal expected shortfall (MES) using the association between overall market and individual-firm movements. Unfortunately, these measures capture slightly different phenomena (Diebold and Yilmaz, 2014).

The measures of the gross and net directional spillover were proposed by Diebold and Yilmaz (2009). Using the generalized vector autoregressive framework, Diebold and Yilmaz (2009) argued that these measures do not depend on the ordering used for volatility forecast error variance decompositions. In this paper, authors focused on the nature of cross-market volatility transmission with the goal to characterize daily volatility spillovers across U.S. financial markets during the period from 1999 to 2010. In comparison with other authors studying the volatility spillovers (e.g., Engle et al. 1990; Edwards and Susmel, 2001), Diebold and Yilmaz (2009) used a different approach for analysing this phenomenon. The main difference of this approach is that it offers continuously-varying indexes and examines econometrically a huge number of assets. The authors showed that despite the fact that the financial markets exhibited significant volatility fluctuations during the whole examined period, the volatility spillovers remained mostly limited until the year 2007, when the global financial crisis erupted. However, higher intensity of the crisis caused higher volatility spillovers.

In order to show that volatility and returns spillovers act differently during the crisis and non-crises periods, Yilmaz (2010) applied the Diebold-Yilmaz spillover index approach to the main 10 East Asian stock markets. This paper examined the behaviour of return and volatility spillovers in East Asian region during the years 1992 - 2009. Plotting the volatility spillovers proved that during the major crisis, there was a burst in volatility spillovers rather than returns spillovers in the markets. Yilmaz (2010) also pointed out that due to the increasing market integration of Asian stock markets during the studied period, the markets became more interdependent which results in higher return spillovers. Therefore, he argued that the systemic nature of the global financial crisis refers to the burst in returns spillover index. During the financial crisis in 2008, the index in the examined area reached the highest level.

Simple measure framework concerning the relationships between asset returns and asset volatilities was introduced by Diebold and Yilmaz (2013). In their work, they focused on the return spillovers and volatility spillovers using the variance decomposition in vector regressions. They argued that their definition of measures conveys valuable information while avoiding vigorously discussed concept of episodes of "contagion". This paper works with not only the crisis but also non-crisis episodes while taking into account both trends and bursts in spillovers. To support their claims, they analysed the data of 19 global equity markets, using the period of more than 20 years. The results showed that there exists a divergent behavior in dynamics of return and volatility spillovers. The main finding of the work was that the return spillovers display no bursts and increasing trend which is considered to be a result of increasing financial market integration over the past years. On the other hand, the analysis revealed that the volatility spillovers display no trend and bursts associated with the "crisis" events. Therefore, the authors claimed that it is important for the future analysis to distinguish between return and volatility spillovers.

To reveal the network linkages among the publicly-traded subsets of banks, Demirer et al. (2018) worked with the data of world's top 150 banks between the years 2003 - 2014. In this paper, the so called lasso methods were applied with the goal to estimate the static connectedness network using the full-sample estimation. Moreover, they used rolling-window estimation in order to find dynamic network connectedness. In static case, they came to the conclusion that global banking connectedness is related to the bank location, but not to bank assets. In dynamic case, authors concluded that global banking connectedness displays both secular and cyclical variation. *"The secular variation corresponds to gradual increases/decreases during episodes of gradual increases/decreases in global market integration. The cyclical variation corresponds to sharp increases during crises, involving mostly cross-country, as opposed to within-country, bank linkages (Demirer et al., 2018, page 1)."*

Another application of the connectedness measures using the Diebold - Yilmaz Spillover (Connectedness) index framework is introduced in the paper of Bilgin and Yilmaz (2018). This paper presents the analysis of transmission of producer price inflation. It works with the monthly data from the industries in the United States between years 1947 - 2018 using the generalized variance decompositions from vector autoregression. The authors came to the conclusion that producer price inflation connectedness across industries is caused by the system-wide connectedness of the input-output networks. The results showed that the input-output network and the inflation connectedness are stronger during the aggregate supply shocks and weaker during the aggregate demand shock. These conclusions coming from the static as well as dynamic analyses of inflation connectedness are similar to those of Acemoglu et al. (2012) who argued that supply shocks are transmitted from downstream industries, and demand shocks from upstream industries through the input-output networks linkages. Another significant result of this paper is that the increase in system-wide connectedness in the United States in 2018 was caused by the U.S. President Donald Trump's decision of imposing additional tariffs i.e. by shocks mostly transmitted from tariff-targeted industries.

Furthermore, in order to estimate the network structure of global sovereign credit risk, Bostanci and Yilmaz (2020) applied Diebold-Yilmaz spillover index methodology on sovereign credit default swaps (SCDSs). The authors used elastic estimation method with the goal to estimate network of daily SCDS returns and volatilities of examined 38 countries. The results showed that the network of returns and volatilities differs in structure. Moreover, the global factors play more important role than domestic factors in pinpointing of SDCS returns and volatilities. Emerging market countries represent the key determinants of connectedness of sovereign credit risk shocks, while the developed and problematic countries account only for a small share in the determination.

In addition to the spillover index created by Diebold and Yilmaz (2009), which depends on the ordering of the variables in the VAR model, Klößner and Wagner (2014) came up with the idea of new algorithm for faster calculating the spillover index's maximum and minimum. Analyzing the same dataset of Diebold and Yilmaz (2009), but using the new algorithm, Klößner and Wagner (2014) argued that using small number of permutations in order to estimate the range of the spillover index results in underestimating the true range.

Spillovers of policy uncertainty was the main interest of Klößner and Sekkel (2014). They measured the spillovers using the Spillover index created by Diebold and Yilmaz (2009) and the algorithm introduced by Klößner and Wagner (2014) using the idea of Economic Policy Uncertainty Index of Baker et al. (2016). For the analysis, they used monthly data of 6 developed countries from January 1997 to September 2013. They concluded that spillovers accounts for more than one-fourth of the dynamics of policy uncertainty, while this fraction can reach even one-half during the period of financial crisis. The paper found that since the time of the financial crisis, significantly large fraction of spillovers is caused by United States and the United Kingdom,however, the other examined countries are all net receivers of policy uncertainty shocks.

Another approach of measuring the financial connectedness in the US economy was suggested in the paper of Uluceviz and Yilmaz (2018), who examined how the shocks to the real and financial sectors in United States are connected to each other. The real side of the United States economy is represented in the DYCI analysis by the ADS index created by Aruoba et al. (2009). The financial side is represented by range-based volatilities of returns in different financial markets (stock, bond and foreign exchange market). In order to reveal the shock dynamics and interactions of real and financial sides, ADS index and the market return volatilities are then applied to Diebold- Yilmaz framework. The paper concludes that shocks to real sector of economy results in connectedness consequences on the financial sector. Furthermore, when the real activity index (derived from dynamic factor model of the real side) was included to represent the real sector, the direction of net connectedness changed to positive net connectedness between financial markets and the real side of the United States economy.

In addition to the previously mentioned approaches, Cotter et al. (2017) created a new methodology to study the spillovers between the real and financial side of the economy using the mixed-frequency modelling approach. This approach allows to use directly high-frequency financial and low- frequency macroeconomic data series without data aggregation and loss of information. This paper showed that analysing the macro-financial spillovers using the mixed-frequency approach leads typically to higher estimated spillovers than by using common-frequency approach. It also revealed that financial markets transmit the shocks to the real side of the economy. However, the bond and equity market behave heterogeneously in transmitting and receiving shocks to the non-financial side.

Another paper inspired by the Diebold and Yilmaz (2014) methodology is the Demirer et al. (2019) paper. This study developed a volatility connectedness index applying Diebold-Yilmaz framework on the daily stock prices of 40 large US financial institutions. Using the data of non-financial US companies, the authors estimated the contemporaneous return sensitivity to this index. The analysis revealed that the firms' returns significantly vary depending on positive or negative exposures to financial connectedness. As stressed by the authors, applying the bivariate portfolio tests showed robustness of abnormal returns to book-to-market ratio, market beta, size, and idiosyncratic volatility. Asymmetric abnormal returns are mainly driven by firm whose correlation between returns and index is negative.

2.2 Network Literature

Economic research papers on networks provide insights into the application of network analysis to financial systems. Even though that there are a lot of academic papers linking the network analysis to the financial systems, the literature focusing on this concept is still in its early stage. The currently available researches investigating the network theory focus mostly on the issues such as financial stability and contagion. Furthermore, most of the academic papers examine the effects of networks rather than the formation of networks. Jackson (2005) contributed to the network literature by broad survey of different concepts of network formation. As pointed by Diebold and Yilmaz (2014), connectedness measures based on variance decompositions are closely related to the modern network theory, in particular to recently-proposed measures of systemic risk.

The network representation of financial systems captures the structure of connections among the financial institutions. The concept of network is generally described as collection of nodes and the links between them. The so called nodes can represent individuals, firms, countries as well as collections of such entities. Any link between two nodes describes their direct relationship. For instance, the link between countries can be a mutual agreement on free trade or defense pact. In financial systems' network, the nodes represent financial institutions, while the connections are caused by banks' mutual exposures. For this reason, economists argue that network theory can serve as a conceptual framework for analyzing and describing the various patterns of connections. A concept of network in financial system is useful for assessing financial stability and capturing the externalities stemming from the risk that single institution can cause to entire system. Regulations imposed on the individual institutions and considerations of account vulnerabilities stemming from network interdependencies may help preventing the local crisis from expanding to global crisis (Allen and Babus, 2009).

In general, network theory analyses the process of the network formation and the effect of the structure of the network. The formation process highlights the differences between socially desirable outcomes and outcomes resulting from individual self-interested actions. The network formation studies the process of forming the connections among financial institutions. As noted in Allen and Babus (2009), deeper understanding of how financial institutions form connections if they are exposed to the risk of contagion, can provide new information on the systemic risk. Risk sharing can be then considered as one of the main driving factors in forming connections between financial institutions. In case that the risk related to lending funds in the interbank market is too high, the links between institutions bring more costs in proportion to benefits. In such case, network formation game provides empty network i.e. the banks disagree to form a link with each other.

The effect of structure captures the factors linked with social efficiency and examines the fixed network processes. For example, it studies the impact of financial network structure on the response of the bank to contagion. Allen and Babus (2009) argued that different network structures respond in different way to propagation of shocks. However, the system fragility is dependent on the network's location of institution that was originally affected. Thus, certain structures of network of the financial institutions can gain additional benefits from exploiting the position as intermediaries between other institutions. Moreover, in microfinance the structure of network can also affect the effectiveness of mutual monitoring in enforcing risk-sharing agreements.

Current literature applies the network theory to a wide range of situations. In addition to the labor markets, the economists have examined framework of network theory in markets in general. The Arrow - Debreu model of economy works with the assumptions that in centralized markets the agents interact anonymously and the prices are formed according to independent decision-making process. In other case, markets are not centralized and include complex structure of bilateral relationships and trades. Some researchers (Durlauf 1996, Ellison 1993) pointed out that some agents choose to interact only with the neighbours in the network rather than with all agents in the economy. Corominas-Bosch (1999) proposed bargaining model in which buyers and sellers are linked by the exogenously connected network. The model assumes that buyers and sellers, who are connected by a link, transact a purchase with each other. However, the agent that has more links, has several possibilities of transactions. Hence, the bargaining power of buyers and sellers is basically determined by structure of network. Similarly, Gale and Kariv (2003) examined the effect of intermediation between sellers and buyers on network. In this concept, the traders are organized in incomplete framework of network.

Although that one might argue that the incomplete network is a source of potential friction, the authors proved that the trade is nonetheless efficient and the convergence of prices to the equilibrium takes place very fast.

The network structures under which the bilateral insurance framework is self-enforced were examined by Bloch and Jackson (2006). The paper claims that network connections play two main roles - provision of insurance (tool for transfers) and monitoring (stream of information). The monitoring punishes the individuals who deviate from the insurance scheme by excluding them. Individuals are therefore more likely to deflect under intermediate level of connectedness, whereas under thickly or thinly connected levels the insurance schemes are self-enforceable.

Moreover, Bramoulle and Kranton (2007) investigated the formation of risk-sharing networks. They showed that efficient networks include full insurance and connect indirectly all individuals if the distribution of income shocks is random in the population. Nevertheless, the network links fewer individuals in the equilibrium and yields the outcomes with asymmetric risk sharing. In addition, the results of studying the community risk sharing suggest that under idiosyncratic and community-level shocks, networks involving all agents within a village yield usually lower welfare than networks connecting communities.

As suggested by Ahern (2013), more central industries in intersectoral trade gain higher stock than the less central industries. The study shows that the result is economically substantial and robust when leverage, firm size, standard asset pricing factors, industrial concentration, and other return determinants are controlled for. Furthermore, the sector-specific shocks aggregate into macroeconomic fluctuations, which stand behind the findings. In case of the stock returns, systematic risk originates from idiosyncratic shocks that spillover from one industry to the others through the intersectoral trade. Therefore, stocks in more central industries have greater systematic risk and gain higher returns due to its greater exposure to idiosyncratic shocks.

2.2.1 Network Centrality

Network centrality measures are often considered as an industry's exposure to the random shocks. In the current literature, it is frequently assumed that more central industries face greater risks, and hence, earn higher stock returns (Ahern, 2013). This hypothesis has two main assumptions. Firstly, the aggregated shocks start as idiosyncratic events. Contrary to the general notion that aggregate shocks simultaneously have effect on all sectors, it is probable, that demand shock as well as technological and shocks of natural resources originate in one single sector. For instance, macroeconomic events such as interest rate or currency shocks affect directly certain industries (e.g. banking industry) rather than industries such as legal services or car repair shops. Secondly, random local shocks do not cancel out. One might argue that positive shock in one industry is cancelled out by a negative shock in another industry i.e. on average, the economy stays unaffected. However, this argument assumes uniformness and randomness between the sector networks of connections, which is usually not true. The conducted studies (Ahern and Harford, 2014; Acemoglu et al., 2012) showed that the network of sectors is asymmetric with non-uniform connections. The random shocks to sectors do not cancel each other, but they might even aggregate and form wide-spread events in the economy. Since the local shocks do not cancel out each other, it is often hypothesized that more central industries in the SAM (spillover asymmetry matrix) network are more exposed to the systematic risk, and therefore, should gain higher stock returns.

To present the network of connections, the literature often use Social Accounting Matrix, which shows the circular flow of transactions between a complete set of economic agents, including factors of production (capital and labor), institutions (government, households and firms) and production activities. This matrix can be considered as expanded input-output (IO) table that presents connections between capital account, government and foreign sector. Each row of the matrix represents the receipts of an agent and each column represents the expenditures. For each economic agent, the receipts are equal expenditures (Ahern, 2013).

The oil shocks can serve as an illustrative example demonstrating how the shocks in one sector lead to aggregate effects. Despite of the fact that oil shocks are reckoned as systematic risks, they originate locally. Oil extraction firms are generally first to be hit by the oil shocks, but the shock spillovers also quickly to refineries since the oil is the main input in gasoline. Hence, the prices of gas have effect not only on the transportation and delivery services, but also on general consumers. The oil shocks can be thus considered as sequential shocks which affect all sectors because the oil-related products are important intermediary inputs in the economy. It is often claimed that all sectors are connected to some degree, so every sector can influence the whole economy.

2.2.2 Network Concepts

The economic model of networks explains the social and economic phenomena by the choices of the rational agents. According to the model, the agent's choice whether to connect or not to connect with other agent is given by comparing costs and benefits resulting from this connection (the cost-benefit analysis). The model assumes that there is a function that determines the agent's benefits, which depend on the relative position in the connections network. Thus, the externalities among agents are network dependent. It is believed that the individuals form connections with respect to the potential benefits. These relationships are then modelled through a game of network formation.

In the past few years, different concepts of bilateral connections formation have been elaborated assuming agent's awareness of the network shape from which their benefits are derived. The difficulty of the bilateral connection is caused by the fact that both sides have to consent to the interaction. Thus, non-cooperative concepts such as Nash equilibrium do not help to solve the problem of formation network game. Jackson and Wolinski (1996) suggested simpler approach of looking directly at stable networks. They argued that network is considered to be pairwise stable if it satisfies the following two assumptions. Firstly, the formation of the link between any two individuals, which is absent from the network, cannot be beneficial to both of them. Secondly, by deleting the present link between two individuals in the network, neither of the individuals gains strict benefit.

Moreover, another connection game was suggested by Bloch and Jackson (2007). Players demand or offer the transfers according to their preferred links. This allows players to contribute to the formation of particularly chosen links. In case that the mutual consent is not necessary for the formation, and the agents can unilaterally form new links, this concept is close to the Nash equilibrium (Bala and Goyal, 2000).

In addition to static equilibrium approaches, some authors provides also studies with dynamic processes in which the network gradually evolves in time (Jackson and Watts, 2002; Page et al., 2005). In this concept, players can add or remove the links in each period based on their myopic considerations of potential payoffs.

Moreover, some models do not only look on the network formation game but also study the behavior in networks. These studies claim that choices of the individuals are significantly impacted by patterns of connections between individuals. They use the theoretical game tools in order to measure how the expected payoff affects the choices made by the linked individuals. The existing studies provide the information of the effects of network structure on beliefs, dependence of investments in public goods on the network or learning strategies in networks. Galeotti and Goyal (2007) proposed a theoretical model for analyzing strategic interactions considering the neighbourhood structure. Furthermore, there exists the models of networks in the non-economic literature as well. The academic researches provide a set of common properties used for the description of real-world networks for example metabolic network, transmission of infections etc. These models usually exhibit similar characteristics - a small-word property (i.e. the distance (number of links) between two nodes in the social network is on average very low), unequal degree distribution (i.e. high inequality in number of nodes links), and high clustering (i.e. high tendency of linked nodes to have more neighbours).

2.3 Asset Pricing

"Asset pricing theory tries to understand the prices or values of claims to uncertain payments. A low price implies a high rate of return, so one can also think of the theory as explaining why some assets pay higher average returns than others (Cochrane, 2005, page 8)."

As noted in Cochrane (2005), in order to value an asset one has to take into consideration the delay and the risk. The effects of time are considered to be not that difficult to account for. However, the corrections of the risk are essential for determination of the values of the assets. Therefore, the main challenges of the asset pricing are the uncertainty and corrections for risk.

One of the main questions of the asset pricing is: "What determines the risk premium of an asset". Asset pricing theory is based on concept that price equals expected discounted payoff. The asset pricing theory works with two main approaches: absolute pricing and relative pricing. The absolute pricing approach is commonly used in the asset pricing theory. In absolute pricing, each of the asset prices is set based on its exposure to macroeconomic risk. The most well-known models using this approach are consumption-based models and general equilibrium models. These concepts explain why the prices are what they are, and predict the changes in prices caused by the policy changes. On the other hand, relative pricing focuses on the prices of others assets in order to learn something about some particular asset's value. In this approach, the information of fundamental risk factors is rarely used. Typical example of this model is Black-Scholes option pricing (Cochrane, 2005). However, in many application the asset pricing problems are solved using both approaches rather than using just one of the pure approaches. The choice of approaches depends on asset question and on the purpose of calculation. The paradigms of absolute approaches are the CAPM model and the factor models. These models price assets relative to risk factors without considering determinants of market or factor risk premia and betas (Cochrane, 2005).

The main task of absolute pricing is to explain and measure the sources of macroeconomic or aggregate risk that affect the value of asset prices. This is also a central task for researchers who want to understand the fundamentals in macroeconomics and finance. For instance, expected returns differ across assets as well as within time. These changes are connected to macroeconomic variables or variables forecasting the macroeconomic events. That is why a lot of models signify that factors of recession and financial distress lie behind asset prices. The results suggest that the risk premium of stock is larger and varies more than the interest rate. Due to this fact, lining investment up with interest rate is considered to be useless because most of the variation in the cost of capital stems from changing risk premium. In comparison with standard macroeconomic model, asset pricing models predict that people care about business cycles in order to prevent from substantial fall in return premia during recessions (Cochrane, 2005).

The currently available literature, which applies theory of networks to finance and macroeconomics, has been concentrating mainly on documentation of stylized facts and creation of microfoundation for business cycles and other macroeconomic phenomena. However, there is only a limited amount of academic works focusing on sectoral linkages implications on asset pricing (Herskovic et al., 2018).

As noted by Ahern (2013), the industries, which have more central network position, earn on average higher returns. The relationship between the size of firm's distribution and level of firm's volatility using the network model of customer-supplier was examined by Herskovic et al. (2018). However, this work does not consider the asset pricing implications of customer-supplier model linkages. In addition, the paper of Herskovic et al. (2016) presents commonly used factor structure in idiosyncratic firm-level return volatility and describes how the idiosyncratic volatility factor is priced.

The asset pricing in multisector model, where the sectors are linked through an input-output network, was studied by Herskovic et al. (2018). The study suggests that the source of systematic risk, which is reflected in equilibrium asset prices, is caused by the changes in the network. Moreover, there are two main properties of the network that affect the asset prices, namely network sparsity and network concentration. Network concentration measures to which extent the output in equilibrium is dominated by large sectors. The equilibrium output share of each sector identifies the importance of given sector to the other sectors. The output has high equilibrium share provided that the output is used by the other sector in large amount. Network sparsity is a measure of distribution of linkages across sectors. The number of linkages signifies the flow of input in the economy and shows the importance of each input to particular sector. A network that has fewer but stronger linkages is denoted as high sparsity network. In such a network, firms count only on few input sources. The structure of the network determines these two production-based asset pricing factors. These factors can be calculated from input-output data and they characterize attributes of the linkages between sectors based on the fundamentals of the economic system. Therefore, network sparsity and concentration are sufficient statistics for determination of aggregate risk. Thus, even though that the network of input-output has more dimensions, for the analysis of assessing systematic risk, it is enough to concentrate only on these mentioned characteristics (Herskovic et al., 2018).

In addition, the asset pricing in economies with large information networks was examined by Ozsoylev and Walden (2011). It shows that the network theory can work as a useful tool for understanding how the information translate into the asset prices. The social networks as well as the information networks have been used in many researchers (Cohen et al. (2008); Hong et al. (2004)) with the purpose to explain the investors' decisions and portfolio performance. As claimed by Ozsoylev and Walden (2011), the price volatility as well as average expected profits are a non-monotone function of network connectedness. Furthermore, the distribution of profits among the investors is related to the information network's properties.

2.3.1 Asset Pricing and Network as Risk Factor

An interesting study concerning the effect of network in the asset pricing was introduced by Billio et al. (2016), who analysed the impact of network connectivity on factor exposures using the variation of traditional CAPM model. This paper contributes to both, network as well as asset pricing literature, by extending the classic factor-based asset pricing model by the network connections in linear factor models. Such model captures then the impact of the contemporaneous links that are present across assets and are determined in the network of connectedness. As noted in Billio et al. (2016), networks bring the information of the links existence as well as the information of the intensity of the links between particular assets. Therefore the combination of the systematic and idiosyncratic risks together with network risk introduce the cross-dependence information to model. Moreover, the effect of diversification is reduced if the network connections are present.

The asset pricing model introduced by Billio et al. (2016) assumes that the interconnection and links between the risky assets are captured by the network. Therefore, the network relations are expected to represent the actual states between the examined assets. The existence of the interconnections signifies the exposure of risky assets to the movements of the other risky assets. Furthermore, the interconnections of risky assets vary with other assets, which cause an additional form of heterogeneity together with those related to various exposures to common risk factors and to different level of idiosyncratic shocks.

Billio et al. (2016) defined the model capturing the network exposure as follows

$$A(R_t - E[R_t]) = \overline{\beta} F_t + \eta_t \tag{2.1}$$

where A represents a parameter matrix capturing the relations across assets and the coexistence of the common factors, η_t represents the covariance matrix capturing the structural idiosyncratic risk, R_t represents set of risk assets returns, F_t stands for observable zero-mean risk factors and β is a matrix of parameters monitoring the exposure of the risky assets to the common factors. Such model enables to recover a risk decomposition similar to the one for the standard linear factor model equation:

$$R_t = \alpha + \beta F_t + \epsilon_t \tag{2.2}$$

Chapter 3

Methodology

This chapter presents the theoretical background and the applied methodology used throughout the empirical part of the thesis. It is divided into three main section regarding the methodologies of the three main theory concepts which will be later merged together and mutually used for analysis confirming or rejecting the hypothesis. The first part concerns the connectedness methodology approaches. Firstly, it introduces the connectedness tables and the main mathematical and econometric ideas behind the connectedness measures using the variance decompositions. Secondly, the main ideas behind the spillover index and connectedness measures are introduced. Then this section discusses the realized volatility and its decomposition into realized semivariances. The second part explains the interdependence of financial markets using the theories of networks and describes the way how the networks are constructed. Third part introduces the asset pricing models, namely CAPM, Fama-French model and Fama-MacBeth model. The Fama-MacBeth model is discussed in more detail, since the used model in this diploma thesis is based mainly on the ideas of this model.

In the existing researches, the term *connectedness* is often used in the meaning of the economic system's interdependence. In this diploma thesis, the term connectedness will refer to the robust measures based on variance decompositions proposed by Diebold and Yilmaz (2009). Throughout this chapter the employed connectedness measurement and methodology follow the ideas suggested by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2014) and the framework of generalized vector autoregressive model, more specifically the variance decomposition method. This method allows us to measure the amount of information that one variable brings to other variables in the regression. Moreover, it also demonstrates the fraction of the forecast error variance of each of the variables that can be explained by exogenous shocks to the other variables. This approach enables to estimate the system-wide as well as total directional volatility connectedness (Diebold and Yilmaz, 2014).

Since this diploma thesis merges the literatures of connectedness, networks and time series, which all have their own terminology, it is useful to point out the terms that are used as synonyms throughout this work in order to avoid the confusion. The terms *connectedness matrix* (connectedness literature introduced by Diebold and Yilmaz (2009)), *adjacency matrix* (literature of networks) and *variance decomposition* (literature of time series) come from different literatures but they are concerning same phenomenon, and therefore, they are used interchangeably in the text.

3.1 Connectedness Methodology

The main approaches used in this diploma thesis proceed from the suggestions of Diebold and Yilmaz which were firstly introduced in their academic paper released in 2009, and later further specified and elaborated in papers published in 2012 and 2014. The leading advantages of this econometric approach are that there are minimum model assumptions, and the only needed data for estimation are the daily prices. Moreover, this methodology provides weighted directed network.

Diebold and Yilmaz (2009) proposed the so called *Spillover index*, a simple quantitative measure concerning the financial market interdependence, together with spillover tables and spillover plots. They argued that spillover intensity varies over time and that time-variation is not same for returns and volatilities. The return and volatility spillovers measurement is based on vector autoregressive models (VAR) introduced by Engle et al. (1990). Diebold and Yilmaz (2009) used the concept of variance decompositions for calculations, because this approach allows aggregation of spillovers effects across markets into single spillover measure while keeping the valuable information.

Diebold and Yilmaz (2014) introduced several connectedness measures using the concept of variance decompositions. They used the unified framework in order to conceptualize and measure the connectedness at different levels (from pairwise to system-wide connectedness) applying variance decompositions. Using the daily time-varying connectedness of recent stock returns volatilities of US financial institutions, they showed that variance decompositions are related to the key measures of connectedness which are often applied in the network literature.

3.1.1 Connectedness Table

The variance decomposition identifies the amount of information that each variable contributes to other variables in autoregression. In other words, it indicates the size of forecast error variance of each of the variables which results from the exogenous shocks to the other variables. Diebold and Yilmaz (2014) proposed the connectedness measure approach proceeding from assessing the proportions of forecast error variation in different locations due to shocks originating “elsewhere”. This approach is linked to the econometric concept of decomposition variance. The H-step forecast error variance share d_{ij} is understood as the fraction of *i's* H-step forecast error variance due to shocks in variable *j*. Connectedness table is then defined as the full set of variance decompositions. The system of connectedness measures from simple pairwise to system-wide system can be seen in the Figure 3.1. It depicts the various connectedness measures and their mutual relationships. The variance decompositions are shown in the main upper-left NxN block. The upper-left block is called *variance decomposition matrix*. The rightmost column of the connectedness table contains row sums, the leftmost column contains column sums and bottom-right element includes the average for i ≠ j.

Figure 3.1: Connectedness Table

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

Source: Diebold and Yilmaz, 2014, page 3

3.1.2 Spillover Index

The initial idea of spillover index, created by Diebold and Yilmaz (2009), is based on the variance decomposition of the forecast errors in a vector autoregressive model (VAR). It shows how much of the H-step-ahead forecast error variance of some asset i is caused by the changes in another asset j. Therefore it represents a simple way of measuring volatility spillovers (Baruník et al., 2016). However, this approach has some substantial drawbacks, both methodological and substantive. Firstly, the original idea of variance decompositions uses the Cholesky factorization of the covariance matrix of the VAR residuals. This fact may result in the dependence of the variance decomposition results, which can affect the ordering of variables in the underlying VAR process. Furthermore, the original framework of spillover index enables us to measure only the total spillovers i.e. only the transmission from one market to other markets or vice versa. However, it does not allow us to measure the directional spillovers, which tell us how the volatility from one given market i is transmitted to another specific market j or vice versa. Secondly, the application of methodology is considered to be to some extent limited because it only regards the spillovers across identical assets in different countries. It does not concern the other types of spillovers such spillovers of different assets within one country or spillovers across asset classes (e.g. between bond and stock markets within one country). The researchers are especially interested in the spillovers across asset classes since they are the key factor for analysing the recent global financial crisis which is believed to originate in credit market and later spilled to other markets. Fortunately, these limitations were later solved by Diebold and Yilmaz (2012) by instead of using Cholesky factor orthogonalization, the generalized vector autoregressive model is employed. By following directly variance decomposition in the generalized VAR framework, the forecast error variance decomposition is invariant to the variable ordering. Moreover, this approach allows to measure both, total and directional volatility spillovers.

Total spillover index proposed by Diebold and Yilmaz (2012) consists of two parts - cross variance shares (spillovers) and own variance shares. Cross variance shares are understood as fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_j , for i; j = 1,2, ..., N such that i and j are not equal. On the other hand, own variance shares are understood as fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_i, for i = 1, 2, ..., N. More details about the construction of the total spillover index can be found in Baruník et al. (2016). The spillover index is defined by Diebold and Yilmaz (2012) as a measure of the spillover contribution (originating from volatility shocks across four asset classes) to the total forecast error variance.

$$S^H = 100 \times \frac{1}{N} \sum_{i,j=1, i \neq j}^{N} \overline{w}_{ij}^H \tag{3.1}$$

3.1.3 Directional Spillovers and Net Spillovers

Although it is important to examine the total volatility spillover index in order to understand how the shocks to volatility spillover across the asset classes, by using the generalized VAR framework the so called *directional spillovers* can be identified. This method allows us to decompose the total spillovers into spillovers coming *from* the observed assets and spillovers coming *to* the observed assets i.e. it tells us the direction of volatility spillovers (Diebold and Yilmaz, 2012). The directional volatility spillovers caused by asset i and transmitted to the other assets j (*TO spillovers*) are defined as follows:

$$S_{i \to \bullet}^H = 100 \times \frac{1}{N} \sum_{i,j=1, i \neq j}^{N} \overline{w}_{ji}^H \tag{3.2}$$

Similarly, the directional spillovers received by asset i from the other assets j (*FROM spillovers*) are defined as follows:

$$S_{i \leftarrow \bullet}^H = 100 \times \frac{1}{N} \sum_{i,j=1, i \neq j}^{N} \overline{w}_{ij}^H \tag{3.3}$$

Once the directional spillovers are obtained, the simple measures of *net spillovers* can be derived. As suggested by Diebold and Yilmaz (2012), the net spillovers can be computed as a difference between gross volatility shocks transmitted to and received from other assets

$$S_i^H = S_{i \to \bullet}^H - S_{i \leftarrow \bullet}^H \tag{3.4}$$

The already mentioned measures describe the contribution of each asset to the volatility of the other assets in net terms (Baruník et al., 2016). The net pairwise spillovers between assets i and j are then calculated as the gross shocks translated from asset i to asset j minus gross shocks from asset j to asset i:

$$S_{ij}^H = 100 \times \frac{1}{N} (\overline{w}_{ji}^H - \overline{w}_{ij}^H) \tag{3.5}$$

3.1.4 Realized Volatility and Realized Semivariances

In order to describe the asymmetries in spillovers which originate from qualitatively different variations in asset prices which correspond to bad and good volatility, the idea of realized semivariances is often used. Realized semivariances estimate the changes in asset prices and show the direction of this change. Negative realized semivariance measures the negative change in prices or returns, while the positive semivariance measures the positive changes in these variables. Therefore the asymmetry in spillovers mainly captures the qualitative rather than quantitative changes in variation. The realized semivariances measure the volatility that takes the volatility asymmetries into account (Baruník et al., 2016). As noted in Barndorff-Nielsen et al. (2010), the realized variance can be decomposed into positive realized and negative realized semivariances as follows:

$$RV = RS^{+} + RS^{-} \tag{3.6}$$

$$RS^{+} = \sum_{i=1}^{n} r_i^2 I_{[r>0]} \tag{3.7}$$

$$RS^{-} = \sum_{i=1}^{n} r_i^2 I_{[r<0]} \tag{3.8}$$

where RS^{+} and RS^{-} represent the positive and negative semivariances, respectively. From the equation above, it can be seen that the realized semivariances cover a complete decomposition of realized variance and can be used as a measure of downside and upside risk. This decomposition works for any n. RS^{-} measures the downside risk and detects the variation caused by decrease of prices of the assets, whereas RS^{+} captures the variation caused by increase in prices. RS^{-} also shows the fact that future volatility is more dependent on the past negative returns. Furthermore, RS^{+} and RS^{-} correspond to the positive and negative states of the given variable and therefore serve as a proxy for good and bad volatility. The drawback of the realized semivariances lies in the the fact, that the behaviour of RS is limited.

Despite the universality of spillover index introduced by Diebold and Yilmaz (2009), it does not recognize the potential asymmetry in spillovers that arises due to good and bad uncertainty. The bad uncertainty is defined as the volatility that is connected with negative evolution in quantities (e.g. returns) and the good uncertainty is understood as volatility that brings positive shocks to these variables (Segal et al., 2015). Baruník et al. (2016) contributed to this topic by fitting the N- variable vector autoregression model to the semivariances instead of to the volatility. This approach enables to focus on the individual effects i.e. on the effect of volatility of one asset on the other assets' volatilities, while distinguishing between negative and positive shocks on the asset prices. Particularly, this method allows to account for spillovers caused by negative returns ($S-$), positive returns ($S+$), as well as for directional spillovers originating from volatility caused by negative returns ($S^-_{i\leftarrow\bullet}, S^-_{i\rightarrow\bullet}$) and positive returns ($S^+_{i\leftarrow\bullet}, S^+_{i\rightarrow\bullet}$).

Baruník et al. (2016) also proposed an extension of this methodology thanks to which it is possible to isolate asymmetric volatility spillovers by replacing the vector of volatilities $RV_t = (RV_{1t}; ...; RV_{nt})'$ by vector of positive semivariances: $RS^+_t = (RS^+_{1t}; ...; RS^+_{nt})'$ or by the vector of negative semivariances: $RS^-_t = (RS^-_{1t}; ...; RS^-_{nt})'$. This method also enables to differentiate the effects caused by positive and negative shocks on volatility spillovers. This idea therefore makes possible to test which type of volatility affects more the volatility spillover transmission and also to compare the magnitudes of the effects.

As suggested by Baruník et al. (2016), the spillover asymmetry measure (SAM) is defined as the difference between negative and positive spillovers as follows:

$$SAM = S^+ - S^- \tag{3.9}$$

where S^+ and S^- represent the volatility spillovers connected with positive and negative semivariances RS^+ and RS^-, with H-step-ahead forecast at time t. The main advantage of this measure is the straightforward interpretation of the results. The SAM is equal to zero, if the spillovers coming from RS^+ and RS^- have the same magnitude. The SAM < 0, if the spillovers coming from RS^- are larger than the spillovers coming from RS^+ and vice versa.

3.2 Financial Network Methodolology

The theory of networks follows primarily two methodological approaches. First approach originates in the literature of network economics and involves microeconomic perspective on the agent's behavior which is assumed to be driven by incentives. The second approach follows statistical physics literature and it is considered as more mechanical since it includes various stochastic procedures.

Connectedness can be understood as a speed of global communication which results in spread of information, news as well as financial crisis. These facts produce networks that include the behavior of groups of people, the incentives, and most importantly links that connect everything. In such interconnected world, the decisions of one person have consequences on the outcomes of others (Easley and Kleinberg, 2010). To explore the important financial phenomena, the commonly used approach is to analyze the linkages within and across different financial systems. The system of linkages then creates corresponding network.

3.2.1 Formal Representation of Network

Formally, the network is represented by nodes which are linked into a total set of nodes that forms the network. In financial systems, the network structure is formed from the nodes, each of them representing an asset or value of either financial or non-financial institutions. It is often argued that through the system of network, shock to one node transmits to the other connected nodes. Generally, the networks are represented graphically for better understanding. Nonetheless, networks are frequently displayed as square matrix known in network literature as *adjacency matrix*. Usually the network N is composed of N nodes and L represents the number of links between the nodes.

Let W be the N-dimensional square matrix, where N is the number of financial assets/companies in the network i.e. N represents the number of nodes. Each w_{ij} represents potential connection (links) between asset i and asset j. A zero entry signifies that the particular two assets are not connected, whereas non-zero entry signifies connection between given two assets.

Let present some illustrative example for better understanding. From matrix W (Equation 3.10), it can be seen that there are only zero elements on the diagonal, which indicate that no asset influences itself. This matrix is not symmetric since for example the first element is connected to the fourth element, but not vice versa. The network also shows the directions of the links. The network is said to be symmetric, if the links are bidirectional. In general, non-zero element w_{ij} signifies asset j affects asset i, i.e. there is a link between asset i and asset j.

$$\boldsymbol{W} = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix} \tag{3.10}$$

Furthermore, matrices similar to given matrix W are commonly used in other statistical and economic applications associated with spatial statistics and econometrics. In these specific fields, the nodes neighbour with each other in physical way (for example buildings, villages, cities or regions). The matrix W then represents the neighbouring connections. Such matrices are usually called spatial matrices and are normally row-normalized. Furthermore, the matrix W contains only zero elements on the diagonal by the convention in spatial statistics and econometrics (Billio at al., 2016).

Matrix representing the financial networks can be considered as a financial parallel of spatial matrix. In such matrix, the neighbouring relationships are the outcomes of specific model, measurement approach of estimation. In graphical projection of the network, the neighbours represent the connected nodes such as assets or firms. As stressed by Billio et al. (2016), the concept of "first-order contiguity" is followed, if the matrix monitors only the connection between assets i.e. the entry represents the connection and denotes that the given two assets are neighbours. Moreover, by convention in spatial statistics and econometrics, there are only zero elements on the main diagonal of the matrix W. Such matrix, which monitors the network connections, provides relevant information of the evolution of asset returns.

In order to properly understand the network, it is useful to graphically describe it. For this reason, the following Table 3.1 provides an explanation of the main attributes of the network, namely size of the node, location of the node, node color and the thickness of the connectedness lines. Table 3.1 also explains other important terms that are essential for understanding the network theory, concretely the degree of node, strength of the node and the node clustering.

The centrality of the network is calculated from the adjacency matrix of the network graph. The commonly used method to measure the centrality is to use the degree of node, which measures the number of edges that link the particular node with the others. However, there are some other methods that are more informative since they work with the weights attributes of the edges. Since the network centrality determines the agent's exposure to the random shocks coming from the network, it is argued that the more central is the agent, the greater is the risk and the higher is the stock return (Ahern, 2013).

Table 3.1: Network Attributes

Attributes	**Explanation**
Node size	The size of node is usually determined from the *TO* spillover, because it captures the sources of systemic risk in the studied system. Size of the node can also be defined as the size of the asset.
Node location	The location of the node expresses the average pairwise directional connectedness. The particular position is determined from the connectedness tables and by using the adjacency matrices.
Node colour	The colour of node shows the origins of the volatility connectedness. Each node and its edges (connections) are assigned with the same colour. This approach enables to recognize the spread of the volatility connectedness.
Thickness of line	The thickness of each line represents the strength of the connections between the assets (the pairwise directional connectedness).
Node degree	The degree of node tells us the number of adjacent edges of particular node and it is considered as a main indicator for the node's centrality.
Node strength	The strength of node indicates the value of total effect that the particular node has on the system.
Node clustering	The node clustering is given by the clustering coefficient that gives us the information about the number of the node's linkages and their strength.

Source: Demirer (2018), Buraschi and Tebaldi (2017)

3.3 Asset Pricing Models

Linear return models have been widely used in the financial economic literature and had a significant effect on researchers. However, since the introduction of the multifactor generalizations of the capital asset pricing models (CAPM), which attracted huge interest in the last decades, the multifactor models became as widespread as the single-factor models. The first multifactor model was purposed by Ross (1977), Arbitrage Price Theory (APT) model. Other commonly used methods in pricing include the developments of Fama and French (1992), and Cahart (1997), concerning the three-factor and four-factor CAPM models. This diploma thesis works with the multifactor asset pricing model based on the Fama and MacBeth (1973) two-step regression model, using the Fama-French factors and connectedness as risk factors determining the risk premium.

3.3.1 Capital Asset Pricing Model

Capital Asset Pricing Model (CAPM) is said to be the first and most widely used model in the asset pricing. Cochrane (2005) provided detail derivations of the CAPM model for exponential utility, normal distributions; two-period quadratic utility; log utility; quadratic value function, dynamic programming. In his book, Cochrane (2005) defines the CAPM model as:

$$m = a + bR^w \tag{3.11}$$

where m is the discount factor, R^w is the wealth portfolio return, a and b are free parameters.

As noted by Cochrane (2005), thinking in terms of discount factors is usually easier than thinking in terms of portfolios. Cochrane (2005) argues that insisting on the fact that there is positive discount factor is less difficult than checking that every possible portfolio (dominating to the others) has larger price.

The following equation 3.12 shows how the CAPM ties the discount factor to the return on the wealth portfolio. The function is linear:

$$m_{t+1} = a + bR^W_{t+1} \tag{3.12}$$

The CAPM is frequently stated in expected return form:

$$E(R^i) = \alpha + \beta_{i,R^W}[E(R^w) - \alpha] \tag{3.13}$$

The central aasumption of the CAPM is that the market portfolio is mean-variance efficient. The CAPM model also assumes that there is a positive relationship between expected returns on securities and their market betas (risk premiums) i.e. the higher is beta, the higher is the expected return. However, the serious problem of this model is that the risks of the stock are multidimensional i.e. beta does not explain whole cross-section of the average stock returns. There are also some empirical contradictions to CAPM, namely size effect (Banz, 1981), leverage effect (Bhandari, 1988) and existence of other variables related to stock returns such as for example earnings-price, book-to-market equity or market equity.

3.3.2 Fama-French Three Factor Model

Fama-French Three Factor Model, introduced by Fama and French (1992), is considered as one of the first and also one of the most used asset pricing models based on multiple factors. Fama and French (1992) evaluated the joint role of different characteristics of stocks. The factors, which they primarily studied in their work, are size, book-to-market equity, earnings-to-price ratio and leverage. The Fama-French model is regarded as a milestone and benchmark framework for the asset pricing models. As concluded by Fama and French (1992), the relationship between average return and the size of the stock is negative and robust to the inclusion of other variables. Moreover, there is a positive correlation between the average return and book-to-market equity. This work also revealed that the combination of book-to-market equity and size absorbs the role of leverage and earnings-to-price in the average returns of stocks.

The following equation 3.14 specifies the main idea:

$$E(R^i) - R_f = \beta_i^w[E(R_m) - R_f] + \beta_i^{smb}E(R_{smb}) + \beta_i^{hml}E(R_{hml}) + \epsilon_i^{FF} \tag{3.14}$$

where R^{smb} represents the return of the small stocks minus the return of the large stocks, and R^{hml} represents the return of stocks with high book-to-market values minus the return of stocks with low book-to-market values. For the purpose of testing the validity of the model, Fama and French (1992) used two linear regressions. First regression relates to the CAPM (Equation 3.15) and the second one applies Three-Factor Model (Equation 3.16).

$$E(R^i) - R_f = \alpha_i^{CAPM} + \beta_i^w [E(R_m) - R_f] + \epsilon_i^{CAPM} \tag{3.15}$$

$$E(R^i) - R_f = \alpha_i^{FF} + \beta_i^w [E(R_m) - R_f] + \beta_i^{smb} E(R_{smb}) + \beta_i^{hml} E(R_{hml}) + \epsilon_i^{FF} \tag{3.16}$$

3.3.3 Fama-MacBeth Two-Step Regression

Like many other theories, also the CAPM suffers from fair share of problems. These problems were already recognized by Lintner (1965), whose study found statistically insignificant relationship between market betas and expected returns. Black et al. (1972) claimed that the bias of the regression coefficients result from the errors-in-variables problem. Solution to this problem was provided by Fama and MacBeth (1973). This approach significantly contributed to the testing of hypothesis in asset pricing literature. It is used for estimating the parameters for asset pricing models such as CAPM.

One of the main goals of the asset pricing theories is to explain the asset returns using the risk factors. These factors are associated with the macroeconomic phenomena (e.g. consumer inflation, unemployment rate, etc.) as well as financial factors such as firm size. The Fama-MacBeth two-step regression is considered as useful way of testing how these factors affect the overall portfolio or the asset returns. The purpose of this approach is to determine the premium corresponding with the exposure to these factors i.e. Fama-MacBeth regression estimates the asset's betas (factor exposures) and risk premia for any risk factors that are assumed to determine asset prices.

The parameters of the regression are estimated in two steps. Firstly, each portfolio's asset return is regressed on the time series of particular risk factors in order to determine the exposure of each return to the risk factors i.e. the asset's beta is obtained for each risk factor. Secondly, the cross-section of portfolio returns is regressed on the asset's betas to determine the risk premium for each risk factor (Hoechle, 2011).

Let assume n portfolio or asset returns and m risk factors. In the first step, the factor exposures βs are estimated by conducting n regressions. Each time, each portfolio or asset return is regressed on m factors. The corresponding regression equations are defined as follows:

$$\begin{aligned} R_{1,t} &= \alpha_1 + \beta_{1,F_1} F_{1,t} + \beta_{1,F_2} F_{2,t} + ... + \beta_{1,F_m} F_{m,t} + \epsilon_{1,t} \\ R_{2,t} &= \alpha_2 + \beta_{2,F_1} F_{1,t} + \beta_{2,F_2} F_{2,t} + ... + \beta_{2,F_m} F_{m,t} + \epsilon_{2,t} \\ &\cdots \\ R_{n,t} &= \alpha_n + \beta_{n,F_1} F_{1,t} + \beta_{n,F_2} F_{2,t} + ... + \beta_{n,F_m} F_{m,t} + \epsilon_{n,t} \end{aligned} \tag{3.17}$$

where $R_{i,t}$ represents return of portfolio or asset i at time t for i= 1,...,n; t=1,...,T; $F_{j,t}$ is the risk factor j at time t for j=1, ..., m; β_{i,F_j} stands for the risk factor exposure and expresses how the individual returns are exposed to the risk factors. To determine the exposure of each portfolio's return to a particular set of risk factors, same factors F_j are used in each of the regressions.

In the second step, T cross-sectional regressions of the returns are calculated using the m estimates of the βs ($= \hat{\beta}$) that were estimated in the first step. This time each regression uses the same βs calculated in the first step, because the main purpose is to examine the exposure of the n returns to the m factor loadings over time. The new set of regressions look as follows:

$$\begin{aligned} R_{i,1} &= \gamma_{1,0} + \gamma_{1,1} \hat{\beta}_{i,F_1} + \gamma_{1,2} \hat{\beta}_{i,F_2} + ... + \gamma_{1,m} \hat{\beta}_{i,F_m} + \epsilon_{i,1} \\ R_{i,2} &= \gamma_{2,0} + \gamma_{2,1} \hat{\beta}_{i,F_1} + \gamma_{2,2} \hat{\beta}_{i,F_2} + ... + \gamma_{2,m} \hat{\beta}_{i,F_m} + \epsilon_{i,2} \\ &\cdots \\ R_{i,T} &= \gamma_{T,0} + \gamma_{T,1} \hat{\beta}_{i,F_1} + \gamma_{T,2} \hat{\beta}_{i,F_2} + ... + \gamma_{T,m} \hat{\beta}_{i,F_m} + \epsilon_{i,T} \end{aligned} \tag{3.18}$$

where the return R are same as in the first step, γ represents the regression coefficients that are used to compute the risk premium for each factor.

Finally, there are $m + 1$ series γ (including the constant) of length T for each factor. Let assume that ϵ is i.i.d. The risk premium γ_m for factor F_m is calculated by averaging the m^{th} γ over T.

Another possible approach is to replace the second step with T regressions by a single cross-sectional regression of n portfolio returns (averaged over time) and to regress the average returns on m factor exposures with lengths n from the first step. This regression is defined as follows:

$$\overline{R}_i = \gamma_0 + \gamma_1 \hat{\beta}_{i,F_1} + \gamma_2 \hat{\beta}_{i,F_2} + ... + \gamma_m \hat{\beta}_{i,F_m} + \epsilon_i \tag{3.19}$$

Chapter 4

Data

The empirical part of this diploma thesis works with the daily data of 496 assets included in the SP 500 index. Using two datasets of returns and realized volatilities of these assets, the thesis aims to examine the volatility connectedness and return connectedness and to estimate the effect of the connectedness linkages between the assets on the risk premium. In other words, the goal of the thesis is to study how the market's volatility of one asset is transmitted to the other assets in the system (such as market, sectors or portfolios), and particularly how this transmission affects the overall level of the portfolio risk.

The examined datasets consist of data of 496 companies which were divided into 11 groups based on the sector in which the studied companies run their business. The analysed dataset of stock returns was obtained from the stock exchange which provided the data to Charles University in Prague. The data spans from July 1, 2005 to December 31, 2018, i.e. the dataset includes 3 280 trading days. Our dataset therefore covers the pre-crisis period, the global financial crisis of 2008 as well as the after-crisis period. Thus it includes the information concerning the market development during both stable periods and financial crises. This work provides the analyses working with two datasets - the asset realized volatilities and the asset returns. Results of both assets' measures are provided in order to compare the differences between the volatility connectedness and return connectedness in 11 different sectors.

The examined sectors include Consumer sector (divided into two subgroups- Discretionary and Staples), Health Care sector, Industry sector, Sector of Information Technology, Sector of Materials, Real Estate sector, Financial sector, Energy sector, Sector of Telecommunications and Sector of Utilities. The overview of the sectors, their code and the number of companies in individual sectors can be found in the Table 4.1. From this table, it can be seen that the sample of telecommunication sector is very limited and its results can be therefore misleading. For the proper analysis of the situation in this sector, larger sample would be definitely more informative. Otherwise, we argue that the datasets of the other sectors are sufficient to provide the valid results and conclusions for our hypotheses.

Table 4.1: Overview of Analysed Sectors

Sector	*Code*	*Total*
Consumer Discretionary	COND	73
Consumer Staples	CONS	34
Health Care	HLTH	53
Industry	INDU	73
Information Technology	INFT	67
Materials	MATR	33
Real Estate	REAS	29
Financials	SPF	66
Energy	SPN	36
Telecommunication	TELS	6
Utility	UTIL	26

As stressed by Diebold and Yilmaz (2009), the results of connectedness measures calculated from the returns are less informative than the results calculated from the volatilities in terms of the connectedness dynamics. We conduct the analysis for both, returns and realized volatilities, in order to see the differences in results of connectedness and to confirm the conclusions of Diebold and Yilmaz (2009). However, in the interpretations and conclusions we focus mainly on the volatility connectedness. Volatility connectedness provides us the dynamics associated with the shock events and brings more information that enable us to confirm or reject our hypotheses, and hence, we consider it as more suitable for the connectedness analysis.

The original dataset, which was provided to Charles University in Prague by the stock exchange, includes one-minute stock return data of the companies included in the SP 500 index during the examined period. From these data, the daily returns were calculated together with the realized variances by the Institute of Economic Studies, Faculty of Social Sciences, Charles University (IES FSV UK). Due to the fact that the SP 500 index changes frequently in time, the newly created dataset includes only those companies which were frequently present in the index during the examined period and showed sufficient liquidity during that time. As sufficiently liquid companies were considered such companies who had at least five active hours of trading during the trading days. The log returns were obtained on the one-minute data, which were then accumulated for one day. The daily data were computed then as a difference of the values of the opening returns and closing returns at the stock exchange. The realized variances were obtained using the five-minute data. All of the processes were conducted by the researchers at the IES FSV UK and their modified daily data are the source for this diploma thesis. The summary statistics of the dataset of asset returns and asset realized volatilities for the individual sector are provided in the Table 4.2. and Table 4.3.

Table 4.2: Summary Statistics of Sectors - Realized Volatilities

Sector	Min.	$1^{st}Qu.$	Median	Mean	$3^{st}Qu.$	Max.
Consumer Discretionary	0.0027	0.0105	0.0143	0.0177	0.0207	0.4124
Consumer Staples	0.0019	0.0075	0.0098	0.0121	0.0137	0.3218
Health Care	0.0000	0.0090	0.0120	0.0149	0.0169	0.3788
Industry	0.0019	0.0097	0.0132	0.0164	0.0190	0.5328
Information Technology	0.0012	0.0101	0.0137	0.0162	0.0189	0.2909
Materials	0.0029	0.0105	0.0145	0.0189	0.0211	0.2617
Real Estate	0.0024	0.0092	0.0119	0.0159	0.0174	0.4155
Financials	0.0012	0.0087	0.0120	0.0167	0.0181	0.9656
Energy	0.0029	0.0123	0.0168	0.0199	0.0234	0.4761
Telecommunication	0.0033	0.0092	0.0138	0.0177	0.0219	0.1864
Utility	0.0027	0.0078	0.0098	0.0116	0.0130	0.1912

From the summary statistics tables, it can be seen that the daily returns in the sectors (Table 4.3) are quite comparable in magnitude with one another over the examined period. The same is true for the daily realized volatilities across the sectors (Table 4.2). In terms of the extreme values, we can see that the financial sector shows the most extreme minimum and maximum in both returns and realized volatilities. The highest mean of realized volatilities can be found in the energy sector (0.0198) and the lowest mean of realized volatilities in the sector of utilities (0.0116). The sector of information technology together with the real estate sector indicate the highest mean returns (0.0004 and 0.0003 respectively). The lowest mean return is in the sector of telecommunications (-0.0007).

Table 4.3: Summary Statistics of Sectors - Returns

Sector	Min.	$1^{st}Qu.$	Median	Mean	$3^{st}Qu.$	Max.
Consumer Discretionary	-0.3830	-0.0091	0.0000	0.0007	0.0092	0.6309
Consumer Staples	-0.2222	-0.0059	0.0003	0.0002	0.0065	0.2962
Health Care	-0.3757	-0.0072	0.0003	0.0003	0.0080	0.3565
Industry	-0.5520	-0.0081	0.0003	0.0001	0.0086	0.3629
Information Technology	-0.3719	-0.0080	0.0005	0.0004	0.0090	0.3280
Materials	-0.3109	-0.0091	0.0000	-0.0001	0.0091	0.2815
Real Estate	-0.4396	-0.0078	0.0005	0.0003	0.0086	0.2942
Financials	-0.7765	-0.0076	0.0002	-0.0001	0.0078	0.8205
Energy	-0.4129	-0.0109	0.0000	-0.0003	0.0106	0.3466
Telecommunication	-0.3004	-0.0089	-0.0002	-0.0007	0.0078	0.1953
Utility	-0.2001	-0.0059	0.0003	0.00012	0.0065	0.1741

This diploma thesis uses the daily returns data and the daily realized volatilities of 496 companies divided into 11 sectors. We calculate the realized volatilities by extracting the root of the realized variances as follows:

$$RVol_t = \sqrt{RV_t} \tag{4.1}$$

Finally, as proposed by Diebold and Yilmaz (2014) and Baruník et al. (2018), we use the log transformation of the realized volatilities in order to maintain the log-normality of the data for the VAR estimation, which we need as an assumption for the calculation of the connectedness measures.

Due to the extensiveness of the dataset of some sectors, the LASSO (least absolute shrinkage and selection operator) method is applied. LASSO is a regression analysis method that does both variable selection and regularization. It improves the accuracy and interpretability of the predictions which are produced by the statistical model (Tibshirani, 1996). This method is frequently used in case of problems with dimensions that are often present while using VAR. It shrinks the coefficients that do not provide any information to zero. The obtained matrix of results then includes a lot of zero coefficients. The nonzero coefficients show the informative links.

For the estimation of factor pricing in the Fama-MacBeth regression framework, we use the the daily realized volatilities/returns data and the three Fama-French factors - the excess return on the value-weighted equity market portfolio, the Small minus Big portfolio, and High minus Low value premium. We obtained the Fama-French factors from the website of Kenneth French. This dataset includes daily values of these three factors that span from July 1, 1926 to February 29, 2020. For the purpose of our analysis, we adjust the dataset so that it includes the period that coincides with the period of the asset dataset in order to facilitate some comparisons i.e. the period starts from July 1, 2005 and ends by December 31, 2018. Table 4.4 provides the overall overview of the information about the used datasets which are merged and analysed in the Chapter 5.

Table 4.4: Information about Analysed Datasets

	Start Date	End Date	Observations	Number of Assets
Asset volatilities	01-07-2005	31-12-2018	3 280	496
Asset returns	01-07-2005	31-12-2018	3 280	496
MKT	01-07-2005	31-12-2018	3 280	496
SMB	01-07-2005	31-12-2018	3 280	496
HML	01-07-2005	31-12-2018	3 280	496

According to Kenneth French website, the Fama-French factors are constructed using combinations of the six value-weighted portfolios formed on size (small/large) and book-to-market (value/neutral/growth). Small Minus Big (SMB) represents the average return on the three small portfolios minus the average return on the three big portfolios. It is defined as follows:

$$\begin{aligned} SMB = &\frac{1}{3}(SmallValue + SmallNeutral + SmallGrowth) \\ &-\frac{1}{3}(BigValue + BigNeutral + BigGrowth) \end{aligned} \tag{4.2}$$

High Minus Low (HML) is defined as the average return on the two value portfolios minus the average return on the two growth portfolios:

$$SMB = \frac{1}{2}(SmallValue + BigValue) - \frac{1}{2}(SmallValue + BigValue) \tag{4.3}$$

The excess return of the market on the risk-free rate (MKT) is the value-weighted returns of all CRSP firms incorporated in the US and listed on the NYSE, NASDAQ, or AMEX. It is defined as :

$$MKT = R_m - R_f \tag{4.4}$$

where R_f is the simple risk-free rate equivalent to a one-month Treasury bill rate (Kenneth French, website). The summary statistic of the Fama-French factors can be found in Table 4.5.

Table 4.5: Summary Statistics of Fama-French Factors

Sector	Min.	$1^{st}Qu.$	Median	Mean	$3^{st}Qu.$	Max.
MKT	-8.9500	-0.4100	0.0700	0.03636	0.5500	11.3500
SMB	-3.7500	-0.3300	0.0100	0.00549	0.3300	3.81000
HML	-4.2400	-0.3000	-0.0200	-0.00377	0.2600	4.83000

To analyse the correlation of the market factors, we calculate the correlation matrix. The correlation matrix generally shows the correlation coefficient between the variables and it is used for summarizing the data. The correlation matrix is symmetric and the main diagonal shows that each variable is perfectly correlated with itself. From the correlation matrix of the three Fama-French factors concerning the correlation of the market (Table 4.6), we can see that there is a positive correlation between market excess return and HML (approximately 37%), and between market excess return and SMB (16%), and negative correlation between the SMB and HML (9%).

Table 4.6: Correlation Matrix of Fama-French Factors

Factors	MKT	SMB	HML
MKT	1.0000	0.1637	0.3694
SMB	0.1637	1.0000	-0.0879
HML	0.3694	-0.0879	1.0000

Chapter 5

Results

This chapter provides the calculated connectedness measures of the assets for the examined sectors, graphical representation of the sector connectedness tables using the heat maps, and finally the application of estimated connectedness measures as one of the risk factors in Fama-MacBeth factor model with the goal to determine the significance of connectedness linkages between the assets on the overall level of risk. The chapter is divided into three main subsections.

First section 5.1. provides the information about the connectedness analysis using the variance decomposition approach and it describes the results from the connectedness tables in each of the studied sectors. Due to the extensiveness of the connectedness tables, this section includes the graphical representations of the connectedness linkages across the sectors using the heat maps. Moreover, it shows the results of overall connectedness across the sectors and examines the directional connectedness measures by analyzing the net transmitters and net receivers in each sector. The second section 5.2. presents the asset pricing analysis using different connectedness measures as a risk factor for determining the factors that significantly affect the risk premium of the portfolio in different market sectors, namely it works with the *overall connectedness*, *FROM connectedness* and *TO connectedness*. All of these measures together with the three Fama-French factors are analysed using the Fama-MacBeth two-step regression.

The purpose of this chapter is to reveal whether the effect of connectedness is a significant risk factor across the sectors, so that we can confirm or reject the hypothesis that the factor of connectedness should be priced while determining the true value of risk premium for the investor. Furthermore, by analyzing the effect of connectedness at different sectors, we answer the question, whether the investors at different sectors should require different risk premium for bearing connectedness risk. Finally, based on our data and our previously conducted sector analysis that serves as robustness check, we conclude whether the connectedness is a factor that approximates risk in financial markets well.

5.1 Connectedness Analysis

The companies in the market are thought to be directly connected through the counterparty linkages related to the positions in various assets, contractual obligations associated with providing services to the customers and other institutions, and in other various ways. As noted by Diebold and Yilmaz (2012), it is possible to use the stock market returns and the return volatilities for measuring the connectedness and its evolution, because they provide the needed information. Studying the connectedness volatility is therefore useful for two main reasons. Firstly, it reflects the connectedness of investor fear which is expressed by market participants while trading. For this reason, economists are particularly interested in the level, variation, patterns and clustering of this fear connectedness. Secondly, volatility connectedness is crisis-sensitive. Since the volatility is latent, it must be estimated.

In this section, we present the results of the connectedness measures estimation based on the realized volatilities of the assets and the asset returns. These measures are based on the methodology introduced by Diebold and Yilmaz (2012), which were already described in the methodology section of this diploma thesis. To study the connectedness between the assets' realized volatilities and the asset returns within each sector, we use the connectedness measures using the VAR model, more specifically the variance decomposition approach, which allows us to examine the transmission mechanism measures. These measures work with the whole datasets of the sectors and produce the estimations of the overall connectedness and the directional connectedness measures *FROM* and *TO*.

One of the VAR model assumptions is the stationarity process in time series data. Since our estimations of connectedness are based on variance decompositions, we would like to test the stationarity of our datasets. The frequently used methods for testing the stationarity of realized volatilities of time series are Dickey-Fuller or Augmented Dickey-Fuller (ADF) test. The null hypothesis is the presence of unit root in the realized volatilities, hence non-stationarity, and the alternative hypothesis is the stationarity. If these tests reject the null hypothesis, we can assume that the time serie has a stationary process. Other type of unit root test is Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. In comparison with other tests, presence of unit root is an alternative hypothesis in this test. The testing of stationarity of time-series data on such extended datasets like our datasets is very complex, and hence, it is out of the scope of this diploma thesis. Nonetheless, we need to be aware of the possibility of the non-stationarity nature of the realized volatilities, and mainly the asset returns, since the measured volatilities and returns are usually strongly serially correlated and non-stationary. Fortunately, the recent literature argues that the violation of the assumption of the global stationarity is possible. Instead of concentrating on the global stationarity, we can focus on the locally stationary structure of the data by using an approximation of locally non-stationary data by stationary models (Baruník and Křehlík, 2018, Starica and Granger, 2005). Moreover, to approximate normality of our data for further analysis, we take the natural logarithms of the realized volatilities as proposed by Baruník et al. (2018).

To determine the lag order for the VAR model, the information criteria such as Akeike Information Criterion (AIC), Bayesian Information Criterion (BIC) or Schwarz Criterion (SC) can be used. As suggested by Diebold and Yilmaz (2012), who provided a sensitivity analysis of Diebold-Yilmaz index to the length of VAR lag, the results do not significantly change for lags 2 to 6. They showed that the results are almost similar if we apply 2, 3 or 4 lags. Due to extensiveness of our data sample, we follow the suggestion of Diebold and Yilmaz (2012), and we choose the VAR with 2 lags. This decision is consistent with the other existing academic works (Baruník et al., 2016; Baruník and Křehlík, 2018). In addition, Baruník et al. (2016) suggests running the usual diagnostics to control for possible deviations from the VAR assumptions. These checks are crucial for checking that there is no dependence left in the residuals, so that our estimates are consistent.

5.1.1 Connectedness Tables

Let us now briefly summarize the main types of connectedness measures for better understanding of each of them. Table 5.1 provides the overview of the types of connectedness measures together with a simple explanation.

Table 5.1: Overview of Connectedness Measures

Type	*Explanation*
Overall Connectedness	Connectedness of all assets in the system
Pairwise Connectedness	Connectedness from j^{th} asset to the i^{th} asset
TO Connectedness	Connectedness from i^{th} asset *to* all assets in the system
FROM Connectedness	Connectedness to i^{th} asset *from* all assets in the system
NET Connectedness	Difference between *TO* and *FROM* connectedness of asset i

For each studied sector, the connectedness table was estimated based on the methodology of Diebold and Yilmaz (2012) using the variance decompositions from a vector autoregression model. From the connectedness tables, one can see the *pairwise*, *TO* and *FROM connectedness* and easily compute *NET connectedness*. In comparison with the overall connectedness measure, which is represented by one single number for each sector (or generally for one system or one portfolio), the directional connectedness measures such as *TO connectedness*, *FROM connectedness*, *NET connectedness* and *pairwise connectedness* can not be that easily presented in the text, especially for the sectors with large number of companies. The connectedness tables for large sectors are unfortunately very extensive, and hence, it is not possible to fit them to the standardized A4 pages. For this reason, we show only the connectedness table for the Telecommunication sector (Table 5.2) that includes only six companies and serves as an illustrative example of given connectedness measures for the readers. The other sectors' connectedness tables are constructed in the analogical way.

To illustrate the connectedness linkages between the individual assets' realized volatilities and asset returns in each of the sectors, we provide two heat maps for each sector that display the intensity of the linkages based on the calculated connectedness tables. A heat map serves as a graphical representation of data in which the individual values included in the matrix are represented by certain shadow of colour. In our heat maps, the darker is the colour, the higher is the factor of connectedness between the individual assets in the sector.

Table 5.2: Illustrative Connectedness Table, Telecommunication Sector

	X.cien.	X.ctl.	X.ftr.	X.s.	X.t.	X.vz.	FROM
X.cien.	0.993	0.003	0.000	0.002	0.001	0.001	0.124
X.ctl.	0.002	0.992	0.003	0.001	0.001	0.000	0.133
X.ftr.	0.001	0.005	0.992	0.001	0.000	0.001	0.141
X.s.	0.002	0.003	0.000	0.987	0.005	0.004	0.212
X.t.	0.001	0.003	0.000	0.005	0.989	0.002	0.183
X.vz.	0.001	0.002	0.001	0.005	0.003	0.989	0.179
TO	0.107	0.257	0.064	0.256	0.159	0.128	

Therefore, the dark shadows of grey colour represent higher exposure to the risk associated with the connectedness of the given asset i and other assets j in the particular sector/portfolio.

When we compare the heat maps based on the calculated connectedness tables of returns and connectedness tables of realized volatilities (Appendix A), we can notice obvious differences between these two measures of asset performance. In all sectors, we can spot the same pattern. The heat maps of volatility connectedness are significantly darker than the heat maps of returns connectedness in all sectors. This means that the volatilities of assets are more connected to other volatilities of assets than the asset returns. This fact confirms the assumption that the connectedness of returns is lower than the connectedness of volatilities, since the returns are generally not that much persistent. We can therefore conclude that if we consider the asset volatilities, the factor of connectedness plays a larger role than in case of asset returns. In other words, the volatilities of assets in the sector are generally more affected by the shocks coming from the other assets in the sector than the asset returns.

Comparing the sectors, we can see that the telecommunication sector exhibits weaker connectedness linkages between the assets than for example the financial or the real estate sector. This can be seen from the shadows of grey colour in each sector. Therefore, we argue that the factor of connectedness plays different role at different sectors i.e. there is a different level of risk associated with the connectedness of assets in different sectors. Considering these results, the risk premium for the investors should reflect the risk associated with the connectedness linkages especially in the financial, real estate, health care and consumer sectors, in which the heat maps as well as original connectedness tables signify stronger connectedness linkages between assets, and hence, higher risk for investors.

Figure 5.1: Heatmap of Financial Sector, Volatility Connectedness

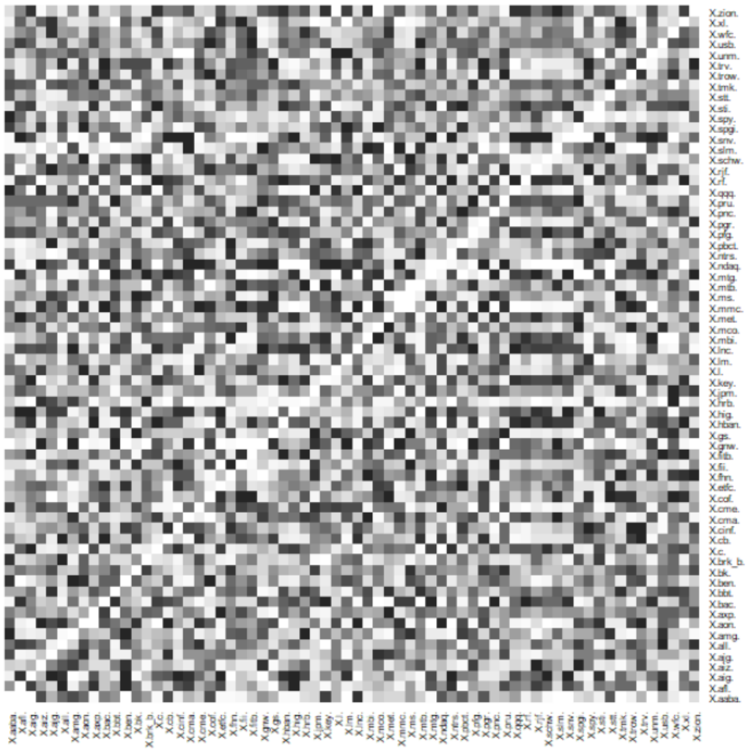
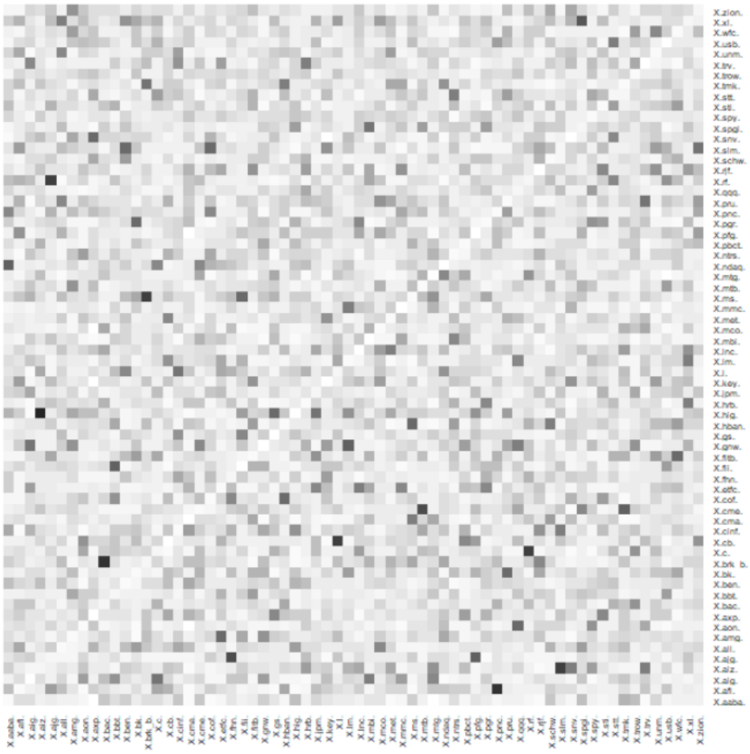


Figure 5.1 and Figure 5.2 show a simple representation of the connectedness tables in the financial sector by using the heat maps. Figure 5.1 contains volatility connectedness table of 66 companies representing the connectedness linkages within the financial sector, Figure 5.2 displays the connectedness linkages in the same sector based on the return connectedness table. In both heat maps, the strength of the connectedness linkages is expressed by the scale from 0 (white colour) to 100 (black colour). This means that the darkest shadows of black colour in the heat maps represent the strongest linkages between the assets. We present here the connectedness tables of the financial sector, because the connectedness linkages reach the highest and most significant values among the examined sectors. The heat maps of other sectors are provided at Appendix A of this diploma thesis. For the clarity, the diagonal of the connectedness tables was in all cases set to zero, otherwise the own spillovers, spillovers originating shock to/from asset i from/to asset i, would be represented by the darkest colour, because these spillovers reach from their design always the highest values.

Figure 5.2: Heatmap of Financial Sector, Return Connectedness



5.1.2 Overall Connectedness

The *overall connectedness* is the aggregated measure of the *system-wide connectedness*. It is calculated as a sum of the *total directional TO* and *FROM connectedness*. Thus this measure determines the overall level of the connectedness in the studied system during the particular period of time. The interpretation is intuitive, the larger is the value of the *overall connectedness*, the higher is the volatility/ return connectedness in the system. The overview of the size of the *overall connectedness* in each sector is shown in Table 5.3.

From Table 5.3, we can conclude that the overall volatility connectedness of each of the sectors are significantly higher than the overall return connectedness, and therefore, we can state that the realized volatilities of the assets are more connected than the asset returns. The highest overall connectedness of the returns as well as of the realized volatilities can be found in the financial sector, 37.9 and 63.71 respectively. We can see that the difference between these two values is significantly different. The other sectors marked with high overall volatility and return connectedness are the real estate sector and the industry sector. On the other hand, the lowest overall connectedness of the returns and volatilities is in the telecommunication sector. However, these results can be caused by the small sample of the telecommunication companies. Using another sample of telecommunication sector, we could come to different conclusions. From the results, it can be also seen that the difference between the sector with highest and lowest connectedness measure is significantly large, using both returns and realized volatilities.

From the results in Table 5.3, we can see that if we order each column based on the values of the overall connectedness in ascending order, the ordering of the sectors would not be the same for the overall connectedness of returns and volatilities. We can notice especially high value difference between the overall volatility connectedness and the overall return connectedness in the consumer discretionary sector.

Although the analysis of system-wide connectedness in the sectors provides a valuable information, it does not reveal the time-frequency dynamics of connectedness, and hence the structure of systemic risk. For such analysis we would have to study the distinct time-persistence in which the shocks impact the sectors and we would have to decompose the connectedness measures into frequency bands such as high frequency, medium-term and low-term frequency. However, this analysis is out of the scope of this diploma thesis.

Table 5.3: Overall Volatility and Return Connectedness

Sector	Overall Volatility Connectedness	Overall Return Connectedness
Consumer Discretionary	47.332	7.568
Consumer Staples	24.918	5.666
Health Care	48.494	9.602
Industry	50.438	18.788
Information Technology	42.759	12.749
Materials	37.635	7.932
Real Estate	49.747	29.474
Financials	63.720	37.923
Energy	47.472	11.227
Telecommunication	16.377	0.973
Utility	37.024	11.230

The above described overall connectedness analysis shows only the overall level of connectedness present in the sectors for the whole studied period from July 1, 2005 to December 31, 2018. We will concentrate more on the dynamics of the overall connectedness in the following sections, in which we will use the time-series of the overall connectedness, determined by using the connectedness rolling window, as one of the risk factors in the risk premium analysis.

5.1.3 Directional Connectedness

The *total directional connectedness* linkages between the studied assets can be more precisely analysed by using the *TO* and *FROM connectedness*. These two measures tell us to what extent is the particular asset affected by the changes/shocks in the other assets in the system (*FROM*) and how much it transmits its changes to the others in the system (*TO*). In order to distinguish between net receivers and net transmitters of volatility/return connectedness among the assets, we use the *total directional NET connectedness* measure, which expresses the difference between *TO* and *FROM connectedness*. The positive difference (*net connectedness* > 0) signifies that the asset is considered as net transmitter, the negative difference (*net connectedness* < 0) indicates the net receiver.

To construct the directional connectedness measures, we need to measure first the *pairwise directional connectedness*. This measure provides us the information about the sources of volatility/return connectedness and it is crucial for creating the networks. Through aggregation of the pairwise connectedness of one given asset in one direction, we obtain *TO* and *FROM connectedness*. All of these measures are displayed in the previously mentioned connectedness tables. From *TO* and *FROM connectedness*, we can then calculate the *NET connectedness* as well.

From the obtained results of *FROM connectedness* of asset i, we can then see the share of forecast error variation that is explained by the shocks originating from the other assets j in the particular sector. The results of *TO* connectedness of asset i shows the volatility/return transmission towards assets j in the analysed sector or portfolio (Diebold and Yilmaz, 2012).

To sum up, the directional connectedness implies the exposure to the risk of the particular asset that is associated with the connectedness linkages with the other assets in the system. From the perspective of the investor, the *FROM connectedness* of the given asset should be considered as a risk that is caused by the other assets in the system. The higher is the effect of the shocks coming from the other assets on the investor's asset, the higher is the risk of given asset as well as the risk of the overall portfolio. Contrariwise, the regulator should focus also on the *TO connectedness* to see which assets are probable to transmit their shocks to the other assets in the market.

To illustrate these three measures of connectedness, we provide Table 5.4 and Table 5.5 that describe the connectedness situation of the individual assets in the telecommunication sector based on the returns (Table 5.4) and realized volatilities (Table 5.5) of the assets. As previously mentioned, we have to take the results of the telecommunication sector with caution due to the size of this sector. Other sample of companies in telecommunication sector could result in different conclusions. Nonetheless, these tables confirm our previous assumptions and conclusions that the volatility connectedness is higher than the return connectedness.

Table 5.4: Return Connectedness, Telecommunication Sector

	X.cien.	X.ctl.	X.ftr.	X.s.	X.t.	X.vz.
TO	0.107	0.257	0.064	0.256	0.159	0.128
FROM	0.124	0.133	0.141	0.212	0.183	0.179
NET	-0.017	0.124	-0.077	0.044	-0.024	-0.051

Table 5.5: Volatility Connectedness, Telecommunication Sector

	X.cien.	X.ctl.	X.ftr.	X.s.	X.t.	X.vz.
TO	2.974	0.935	2.925	2.528	4.853	2.162
FROM	2.581	2.972	1.791	1.091	3.051	4.891
NET	0.393	-2.037	1.134	1.437	1.802	-2.729

From the results of the connectedness table using the dataset of realized volatilities (Table 5.5), we can see that in our telecommunication sector we have 2 net receivers, i.e. 2 companies (marked as X.ctl. and X.vz.) in which the *FROM connectedness* is higher than *TO connectedness*, and 4 net transmitters, i.e. 4 companies (marked as X.cien, X.ftr, X.s. and X.t) in which *FROM connectedness* is lower than *TO connectedness*. We can see that the company marked as X.ctl. has the lowest *TO connectedness* from the whole sample with the above-average *FROM connectedness*. This means that shocks received from the other companies in the sector affect significantly this company, however shock to company X.ctl. has only a small effect on the other companies in the sector. On the other hand, the opposite situation is true for company marked as X.t., which has the highest *TO connectedness*. When we look at Table 5.4, we can see that the number of net receivers and net transmitters in the telecommunication sector changes if we use the returns of assets. In the same way as we analyse the telecommunication sector, we can analyse all sectors, however due to extensiveness of the tables, it was not possible to include the conducted sector analyses in the text.

Table 5.6: Net Transmitters and Net Receivers

	Volatility Transmitters	Volatility Receivers	Return Transmitters	Return Receivers
Consumer Discretionary	23	50	28	45
Consumer Staples	8	26	14	20
Health Care	14	39	20	33
Industry	22	51	23	50
Information Technology	23	44	24	43
Materials	12	21	12	21
Real Estate	10	19	7	22
Financials	18	48	22	44
Energy	12	24	16	20
Telecommunication	4	2	2	4
Utility	11	15	8	18

In addition, Table 5.6 provides the number of the net transmitters and net receivers in each sector. It can be seen that the net receivers dominate by significant number in all sectors, except the telecommunication sector. This fact can correspond to some extent with the lowest overall connectedness factor of the telecommunication sector. However, this specific result can be also biased due to the small sample of firms in the telecommunication sector. From Table 5.6, we can also notice that in most of the sectors, we have more net transmitters than net receivers when we use realized volatilities than if we apply the returns. From the results of the previously conducted analysis concerning the magnitudes of the sector overall connectedness (Table 5.3), we can hence assume that high sector overall connectedness corresponds with high number of net receivers. We can see that high sector overall connectedness is present in the sectors, in which the net receivers significantly dominate to the net transmitters.

5.2 Asset Pricing Analysis

As noted by Cochrane (2005), the risk premium represents more than 80% of the asset prices. The main goal of this thesis is therefore to contribute to the main question of the asset pricing concerning the pricing of the uncertainty of the future cash flow. We aim to find out whether the factor of connectedness should be considered by asset pricing model as one of the risk factors affecting the price.

In this section, we present the results concerning the asset pricing model extended by the factor of the connectedness linkages, which were estimated in the previous section 5.1 and now they will serve as a one of the risk factor. This analysis aims to show how the connectedness measures can contribute to pricing of the risk premium while using the robust methodology. Each of the presented analysis of the risk premium factors is conducted separately for each sector in order to determine the differences in exposure to the risk resulting from the connectedness linkages between the assets at different sectors. This chapter intends to answer the question whether the connectedness factor has a significant effect on the risk premium pricing, and therefore, should be included in the asset pricing model and taken into the account by the investors. Moreover, we attempt to examine whether the connectedness between the assets plays the same role in all sectors, and can be priced similarly, or whether there exists some sectors in which the connectedness affects the risk premium more significantly than in other sectors.

Our asset pricing model uses the dataset consisting of three Fama-French factors provided on the webpage of Professor Kenneth R. French, daily asset returns, and our daily estimated connectedness measures based on the returns and realized volatilities. All of these data span from 22.11.2005 to 31.8.2018 and include 3181 trading days. The time series of the connectedness measures for all the assets are obtained by a connectedness rolling window over 100 days. Therefore, the first date to which we estimate the connectedness factor is 22.11.2005 (1.7.2005 + (100-1) trading days = 22.11.2005). Due to the method of connectedness rolling window estimation, we have to drop almost 5 months of observations from the initial dataset of the asset returns that includes the period from 1.7.2005 to 31.8.2018 (3 280 trading days). Connectedness rolling window estimation provides us the connectedness tables for each of the day for the examined period. Baruník et al. (2016) created the spillover index based on the 200-day, 150-day and 100-day window and tested the robustness of the results based on the estimates of different lengths of rolling window. They came to conclusion that the results do not change materially, and hence, they are robust to the selection of the rolling window and the horizon. Based on these results, we choose the 100-day rolling window to maintain highest possible length of observations in time series.

Using the ideas of Fama-MacBeth regression model (1973), we first regress the returns of each company on four risk factors in order to determine the asset's betas for each risk factor. Secondly, we regress all average asset returns on the estimated betas from the first step in order to determine which of the risk factors have a significant effect on the risk premium. The aim of this analysis is to confirm or reject the hypothesis, whether the connectedness factor should be priced in the risk premium, i.e. whether the effect of connectedness linkages represent a significant risk factor. The Fama-MacBeth regression is conducted for each sector.

Our main analysis is based on the equation using four main risk factors - the connectedness factor and three Fama-French factors. The equation for the first step is defined as follows:

$$R_{it} = \beta_{0,i} + \beta_{1,i}C_{it} + \beta_{2,i}MKT_t + \beta_{3,i}SMB_t + \beta_{4,i}HML_t + u_{it} \tag{5.1}$$

where R_{it} is the total return of a stock i at time t, C_{it} stands for the connectedness factor of a stock i at time t, MKT_t represents the excess return on the market portfolio (index) at time t, SMB_t stands for the size premium (small minus big) at time t, HML_t stands for the value premium (high minus low) at time t and $\beta_{1,2,3,4}$ are the risk factors coefficients.

The estimated equation for the second step is defined as follows:

$$\overline{R}_i = \alpha_0 + \alpha_1\hat{\beta}_{1,i} + \alpha_2\hat{\beta}_{2,i} + \alpha_3\hat{\beta}_{3,i} + \alpha_4\hat{\beta}_{4,i} + \epsilon_i \tag{5.2}$$

where $\hat{\beta}_{1,2,3,4}$ are the estimated coefficients from the first step, $\overline{R}_i$ is the average return over time of asset i, and $\alpha_{1,2,3,4}$ are the risk premiums for the factors of connectedness, excess return on market portfolio, size and value respectively.

Both of the equations (5.1, 5.2) stated above are estimated using the Ordinary Least Squares (OLS) method with the HAC standard errors, which are recommended by the existing literature to use in case of the potential threat of heteroscedasticity and the autocorrelation. Since the error term u_{it} in the given model may be serially correlated due to correlation of R_{it} determinants not explicitly stated in the specified model, it is useful to apply heteroskedasticity- and autocorrelation-consistent estimators of the variance-covariance matrix that solve the problem of both, autocorrelation and heteroscedasticity. In case that error term u_{it} is serially correlated, and the HAC standard errors are not used, the statistical inference that is derived from the standard errors may be invalid, and therefore strongly misleading while making the conclusions. However, if we use the HAC standard errors even though there is no serial correlation, the assumptions are not violated, and the OLS estimators remain consistent and unbiased, the only drawback of this approach is the reduction of the efficiency.

To properly analyse the effect of connectedness on the overall risk of portfolio in given sector, we performed series of the Fama-MacBeth regressions, using three different measures of connectedness. Firstly, we use the rolling window estimates of the *overall connectedness* factor as one of the four factors determining the risk premium. In this case, we are interested whether the connectedness linkages between the assets in the sector on the whole have a significant effect on the level of risk. Secondly, we apply the *FROM connectedness* as a risk factor in our equation. In comparison with the overall connectedness factor that is same for all the assets in given sector, *FROM connectedness* is related to the particular asset, and hence, it differs for each of the assets. This factor determines the risk of connectedness that is related to the shocks that originate in the other assets in the sector and are received by our particularly chosen asset i. In these regressions, we match the individual *FROM connectedness* factor with the given asset. On the analogical basis, for a third type of analysis, we apply the *TO connectedness* factor to our asset pricing equation. This factor provides information about the risk connected with the shocks that are caused by the examined asset i and transmitted to the other assets in the system. In all of these analyses, we firstly apply the connectedness factor based on the realized volatilities, and secondly based on the returns.

Each section in this chapter provides a summary of the results of the sectors using different connectedness measures as risk factors. The tables displayed in the following sections present only the results of the sectors, in which the factor of particular connectedness measure is significant. The tables of each of the estimated models for each sector can be then found in the Appendix B, which is attached at the end of this diploma thesis.

5.2.1 Overall Connectedness as Risk Factor

With the purpose to analyse whether the connectedness linkages between assets represent a significant risk factor that should be included while determining the risk premium, we use firstly the *overall connectedness* measure. We know that the overall connectedness, known also as system-wide connectedness, is the most aggregate measure that equals the overall level of connectedness between all the assets in the system, in our case in one sector. This means that there is only one system-wide connectedness measure for one studied sector, which is obtained from generalized variance decomposition.

Using the rolling window of 100 trading days (100 observations in our dataset), we estimate the time series of the overall connectedness for each sector, so that we can run the model using the multiple time-series of each variable. Following the Fama-MacBeth regression, we estimate the following equation in the first step:

$$R_{it} = \beta_{0,i} + \beta_{1,i}C_t^{Overall} + \beta_{2,i}MKT_t + \beta_{3,i}SMB_t + \beta_{4,i}HML_t + u_{it} \tag{5.3}$$

where $C_t^{Overall}$ stands for the overall connectedness of the given sector at time t.

In the first step, we regress the daily returns of each asset in the sector on the daily overall connectedness of the given sector, and on the three Fama-French factors. We obtain the coefficients of betas for each asset in the sector. In the second step, we regress the average return on the estimated betas from the first step, and we obtain the coefficients gammas, which tell us whether the exposure to the risk caused by the sector overall connectedness is significant for determining the risk premium. The second step follows the Equation 5.2.

Table 5.7, 5.8 and 5.9 provide the estimates of the risk factors from OLS regression (second step of Fama-MacBeth two-step regression).The standard errors are displayed in the parantheses. The risk factors are *MKT*, the excess return on the value-weighted equity market portfolio, *SMB*, the Small minus Big portfolio, and *HML*, High minus Low value premium, all obtained from Kenneth French's website, and *C_Overall*, representing the overall connectedness of the given sector. The *Constant* tells us the estimated constant in the affine price of risk specification for each pricing factor.

Firstly, we focus on the volatility connectedness results (Table 5.7 and 5.8). When we use the overall connectedness factor estimated from the realized volatilities, the connectedness factor is significant in many sectors, namely financial sector, consumer discretionary, consumer staples, health care, materials, real estate and utility sector. We can see that the beta coefficients of the sector overall connectedness is not only statistically, but also economically significant in many cases.

From the results, we can therefore conclude that the value of the sector overall connectedness is a significant risk factor, and should be therefore taken into account while determining the risk premium. This information can be especially important for the investors, whose portfolio comprises of the assets just from one sector or primarily from one sector. In that case, the information of overall connectedness in given sector can be valuable for estimating the potential risk of the portfolio and determining the size of the requested risk premium.

These results can be further generalize for the randomly chosen system of assets, portfolio or market as a whole. With the purpose to request the true risk premium, it is useful to find out whether the overall connectedness of the system/portfolio is low or high. If the overall connectedness of the system/portfolio is high, then it can be expected that the system/portfolio suffers from higher risk associated with shocks coming from/to one asset to/from other assets. Hence, we argue that the overall connectedness should be priced in the risk premium because it represents a significant exposure to the risk.

Let us now focus on the results obtain by using the dataset of returns (Table 5.9). In comparison with the overall connectedness based on the realized volatilities, the overall connectedness factor estimated from the returns is highly significant in only two systems - sector of materials and real estate sector. It is also significant in utility and consumer staples sector, but only on 10% significance level. In all of these sectors the overall volatility connectedness was significant on 5% significance level. We can therefore conclude, that the sector overall connectedness is generally lower and less significant, when it is determined from returns, however, there exists some sectors in which the overall return connectedness is significant, not only statistically, but also economically. These results are in accordance with the results of Diebold and Yilmaz (2009), who claimed that the results of the connectedness measures calculated from the returns provide less information of connectedness dynamics in comparison with the volatility connectedness.

Table 5.7: Results - Overall Volatility Connectedness, Part A

	Dependent variable:			
	Average return			
	Financial	Health	Consumer Discretionary	Consumer Staples
	(1)	(2)	(3)	(4)
C_Overall	4.799***	7.529***	1.722*	0.918**
	(0.540)	(2.279)	(0.932)	(0.442)
MKT	-0.039	-0.049	0.031	0.087
	(0.026)	(0.066)	(0.045)	(0.052)
SMB	-0.049***	0.0003	-0.045*	-0.011
	(0.016)	(0.032)	(0.023)	(0.030)
HML	-0.016*	-0.106***	-0.080***	-0.075*
	(0.009)	(0.038)	(0.027)	(0.038)
Constant	0.0004**	0.0004	0.0003	-0.0003
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
Observations	66	53	73	34
R^2	0.740	0.347	0.473	0.457
Adjusted R^2	0.723	0.293	0.442	0.382
F Statistic	43.414***	6.384***	15.272***	6.100***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.8: Results - Overall Volatility Connectedness, Part B

	Dependent variable:		
	Average return		
	Materials	Real Estate	Utility
	(5)	(6)	(7)
C_Overall	1.649^{**}	1.335^{**}	1.935^{***}
	(0.606)	(0.523)	(0.672)
MKT	-0.176^{***}	0.035	-0.041
	(0.038)	(0.065)	(0.039)
SMB	0.006	-0.070^{**}	0.040
	(0.035)	(0.027)	(0.064)
HML	-0.132^{***}	-0.002	-0.096
	(0.045)	(0.024)	(0.085)
Constant	0.001^{***}	0.0001	0.0003
	(0.0003)	(0.0005)	(0.0002)
Observations	33	29	26
R^2	0.616	0.476	0.481
Adjusted R^2	0.561	0.388	0.382
F Statistic	11.222^{***}	5.442^{***}	4.868^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 5.9: Results - Overall Return Connectedness

	Dependent variable:			
	Average return			
	Real Estate	Utility	Materials	Consumer Staples
	(1)	(2)	(3)	(4)
C_Overall	1.335***	5.385***	1.380*	0.733*
	(0.357)	(0.496)	(0.733)	(0.418)
MKT	0.023	-0.502	-0.048	-0.073
	(0.055)	(0.816)	(0.056)	(0.056)
SMB	-0.060**	-0.466	-0.045	-0.045
	(0.024)	(0.455)	(0.054)	(0.042)
HML	0.005	-0.166	0.081	-0.021
	(0.021)	(0.514)	(0.054)	(0.062)
Constant	0.0002	0.00001	0.0003	0.001**
	(0.0004)	(0.00001)	(0.0004)	(0.0003)
Observations	29	26	33	34
R^2	0.579	0.944	0.192	0.324
Adjusted R^2	0.509	0.934	0.077	0.231
F Statistic	8.254***	89.342***	1.668	3.478**
Note:				*p<0.1; **p<0.05; ***p<0.01

5.2.2 FROM Connectedness as Risk Factor

As suggested by Branger et al. (2019), directed links in cash flow networks have an effect on the cross-section of risk premia through three main channels- spreading channel, receiving channel and hedging channel. The spreading channel includes the shocks that propagate through the economy a higher market price of risk, and should therefore increase the risk premium. Receiving channel lays in the fact that the shock-receiving assets earn an extra premium for spillover risk because their valuation ratios drop upon shocks in connected assets, and hence, should increase the risk premium. The hedging channel comprises of the hedge effect that pushes risk premia down, because when a shock propagates through the economy, an asset that is unconnected to this propagated shock becomes more attractive and the valuation ratio increases. Moreover, the direct connectedness linkages from and to a particular asset determined the spreading and the receiving channel. However, the hedging channel is determined by all linkages in the network. This fact implies that the risk premium of an asset is affected as well by the cash flow linkages in unconnected or very remote parts of the economy (Branger et al., 2019).

Our connectedness analysis focuses on the receiving channel i.e. on the shock-receiving system. The main intuition behind the receiving channel, which is represented by the connectedness factor in our analysis, is easily explained by a stylized example. Let assume a market with three assets. Shocks can be transmitted from asset 1 to asset 2, but there exists no other linkages between assets. Therefore, asset 3 is unconnected to the rest of the market (in our case to asset 1 and asset 2). The spreading channel works in the way that the shocks to the cash flow of asset 1 increases cash flow risk in the market, in our example in the asset 2. These shocks are hence more systematic and bring a higher market price of risk than the cash flow shocks of assets 2 or asset 3. Therefore, the more connected are the assets to the cash flow risk of other assets, the higher should be the risk premium. The receiving channel is usually determined by the direct linkages from and to a particular asset (Branger et al., 2019). In our analysis, the receiving channel is represented by the *FROM connectedness* that captures the shocks coming to asset i from the other assets j in the sector.

From the construction and the information that are provided by different connectedness measures, it is expected that we need to employ the *total directional FROM connectedness*, if we want to capture a significant risk factor determining the risk premium. We claim that this factor is related to the risk of the assets, because it provides the information to which extent is the asset affected by the volatility transmissions from the other assets in the system. In other words, this measure shows the shares of the forecast error variance of asset i that originates from the shocks coming to assets j in the sector, and signifies an exposure to the risk .

Hence, as a second type of analysis, we apply the *FROM connectedness* as risk factor in our asset pricing model. In comparison with the overall connectedness measure which is same for all assets in one sector, the *FROM connectedness* is unique for each of the assets in the sector. For this reason, we match each asset with the individual time series of *FROM connectedness* derived by using the connectedness rolling window. To analyse the connectedness linkages, we employ again the Fama- MacBeth regression.

The estimated equation in the first step of this regression is defined as follows:

$$R_{it} = \beta_{0,i} + \beta_{1,i} C_{it}^{FROM} + \beta_{2,i} MKT_t + \beta_{3,i} SMB_t + \beta_{4,i} HML_t + u_{it} \qquad (5.4)$$

where C_{it}^{FROM} represents the *FROM connectedness* of the given asset i at time t. By regressing these daily frequency factors, we want to test whether the *FROM connectedness* factor affects the risk premium differently in different sectors, and whether this effect is significant or not.

Let us first focus on the connectedness results based on the realized volatilities of the assets (Table 5.9). From the results, it can be seen that the variable *Connectedness*, representing the *FROM connectedness*, is either highly significant or insignificant among the sectors. The overview of sectors in which this connectedness measure is significant can be found in Table 5.10, the rest of the results for the remaining sectors is displayed in Appendix B. We can conclude that the connectedness among the assets plays an important role in financial, real estate, health care, materials and consumer staples sectors. In all of these sectors, the *FROM connectedness* factor is significant on 5% significance level. These results correspond with the values of the overall connectedness which were generated based on the whole datasets of the sectors (Table 5.3). We can see that in those sectors, in which the sector overall connectedness is generally high such as financial, real estate, materials and health care sectors (Table 5.3), the time-series sector overall connectedness factor is significant (Table 5.7 and

5.8), and the *FROM connectedness* is also significant (Table 5.10).

These results can serve as a valuable information for the investors. If the *FROM connectedness* is high for asset i, the shocks coming to the other assets in the system transmit in large extent to asset i. By conducting the Fama-MacBeth regression, we showed that this connectedness measure is a significant risk factor in determination of the risk premium. This confirms our hypothesis, that the more is the asset i affected by the shocks originating in the assets j in the sector, the more risky is the asset i, and this risk should be priced in the risk premium. This corresponds with the ideas of Branger et al. (2019).

However, we can notice that *FROM connectedness* factor is insignificant in some sectors, especially in telecommunication sector, in which all the connectedness measures are estimated to be rather small and insignificant. These results can signify that the connectedness of linkages between the assets in the telecommunication sector is insignificant, and that there is no need to price the connectedness while determining the risk premium in telecommunication sector. On the other hand, we should consider that there are only six assets in our telecommunication sector, and that using different assets or larger dataset we may come to different patterns in the results. The connectedness factor is also estimated to be insignificant factor for determining the risk premium in the sector of information technology and industry sector. In comparison with the telecommunication sector, the samples of these two sectors are larger, they comprise of 67 and 73 companies respectively, and hence, they could be considered as more representative samples providing more informative and valid results. Moreover, all measures of connectedness used in our analyses are estimated to be insignificant for determination of the risk premium in these three sectors (information technology, industry and telecommunication sector), which suggests that the connectedness linkages between the assets do not represent a significant risk factor in these sectors.

Table 5.10: Results - FROM Volatility Connectedness

	Dependent variable:				
	Average return				
	Financial	Health	Materials	Real Estate	Consumer Staples
	(1)	(2)	(3)	(4)	(5)
Connectedness	0.060***	0.133**	0.063**	0.055***	0.061**
	(0.017)	(0.052)	(0.029)	(0.015)	(0.024)
MKT	-0.061*	-0.032	-0.188***	0.063	0.076
	(0.036)	(0.068)	(0.039)	(0.060)	(0.050)
SMB	-0.050**	-0.018	0.019	-0.065**	-0.023
	(0.022)	(0.032)	(0.035)	(0.025)	(0.029)
HML	-0.031**	-0.144***	-0.127**	-0.017	-0.069*
	(0.013)	(0.040)	(0.047)	(0.023)	(0.037)
Constant	0.001**	0.0003	0.002***	0.00002	-0.0002
	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Observations	66	53	33	29	34
R^2	0.503	0.297	0.586	0.565	0.492
Adjusted R^2	0.470	0.238	0.526	0.492	0.422
F Statistic	15.412***	5.060***	9.892***	7.791***	7.014***
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 5.11: Results - FROM Return Connectedness

	Dependent variable:		
	Average return		
	Health	Real Estate	Materials
	(1)	(2)	(3)
Connectedness	0.032***	0.045***	0.063**
	(0.008)	(0.011)	(0.027)
MKT	-0.042	0.003	-0.033
	(0.068)	(0.051)	(0.055)
SMB	-0.026	-0.065***	-0.065
	(0.032)	(0.023)	(0.054)
HML	-0.082**	-0.007	0.096*
	(0.039)	(0.021)	(0.054)
Constant	0.0004	0.0005	0.0003
	(0.0004)	(0.0003)	(0.0004)
Observations	53	29	33
R^2	0.429	0.615	0.238
Adjusted R^2	0.375	0.551	0.129
F Statistic	7.897***	9.584***	2.184*
Note:			*p<0.1; **p<0.05; ***p<0.01

5.2.3 TO Connectedness as Risk Factor

In the third analysis, we run the Fama-MacBeth regression using the *TO connectedness* and apply the same method as in the previous subsection 5.2.2. We estimate the following regression:

$$R_{it} = \beta_{0i} + \beta_{1i}C_{it}^{TO} + \beta_{2i}MKT_t + \beta_{3i}SMB_t + \beta_{4i}HML_t + u_{it} \quad (5.5)$$

where C_{it}^{TO} is the *TO connectedness* of the given asset i at time t.

We provide the results of the second step of Fama-MacBeth regression in Table 5.12 and 5.13. The standard errors are in both tables displayed in the parantheses. The variable *TO_Connectedness* represents the linkages that captures the connectedness between the assets and the shocks that originate at given asset i and are transmitted to the other assets j in the sector. This factor of connectedness shows therefore the risk that given asset i brings to the other assets j in the sector or generally in the system or portfolio.

Table 5.12 and Table 5.13 display the sectors in which the *TO connectedness* factor is significant. In comparison with the *FROM connectedness*, there are only few sectors, in which the *TO volatility connectedness* and *TO return connectedness* are significant. Moreover, we can spot negative correlation between the risk premium and *TO connectedness* in most of the cases. *TO connectedness* factor is negative and significant in the health care and consumer discretionary sector and positive in the sectors of energy and consumer staples. Unfortunately the current literature does not have yet the explanation for the signs of this connectedness measure. However, as in the previous analyses, we can assume that the significance of this measure of connectedness signifies a presence of potential risk, and hence, we argue that the connectedness between the assets should be taken into account by the investors while considering the risk factors of the assets in the consumer, health care and energy sectors.

Finally, we can conclude that by performing the series of sector analyses using different connectedness measures, we tested how the connectedness is priced in different market sectors. Based on the results from all performed sector regressions serving as a robustness check, we argue that the connectedness is a factor that approximates the risk on the financial market well. Unfortunately, the currently available methodology does not allow to perform the market connectedness analysis using the dataset of all 496 asset in the same way as we conducted the individual sector analyses due to the extensiveness of the sample.

Table 5.12: Results - TO Volatility Connectedness

	Dependent variable:		
	Average return		
	Health	Energy	Consumer Discretionary
	(1)	(2)	(3)
TO_Connectedness	-0.418***	0.403**	-0.108*
	(0.125)	(0.162)	(0.058)
MKT	0.006	-0.055	0.011
	(0.065)	(0.067)	(0.045)
SMB	-0.028	-0.141***	-0.030
	(0.030)	(0.045)	(0.024)
HML	-0.147***	-0.030	-0.107***
	(0.038)	(0.063)	(0.026)
Constant	0.00005	0.0004	0.0004
	(0.0003)	(0.001)	(0.0003)
Observations	53	36	73
R^2	0.354	0.577	0.474
Adjusted R^2	0.300	0.522	0.443
F Statistic	6.562***	10.568***	15.307***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 5.13: Results - TO Return Connectedness

	Dependent variable:	
	Average return	
	Health	Consumer Staples
	(1)	(2)
TO_Connectedness	-1.524***	0.265**
	(0.350)	(0.097)
MKT	-0.032	-0.055
	(0.066)	(0.053)
SMB	-0.019	-0.051
	(0.031)	(0.040)
HML	-0.079**	-0.059
	(0.038)	(0.061)
Constant	0.0003	0.0005*
	(0.0003)	(0.0002)
Observations	53	34
R^2	0.460	0.405
Adjusted R^2	0.408	0.323
F Statistic	8.939***	4.929***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Chapter 6

Conclusion

The central contribution of this diploma thesis is the analysis of connectedness characteristics of assets at 11 different market sectors and the analysis of the significance of factor of connectedness for determination of the risk premium on the sector and subsequently on the market level. The currently existing literature has studied market risk using the variance decompositions (Diebold and Yilmaz, 2014; Demirer et al., 2018) or the network measures (Ahern, 2013; Herskovic, 2018). However, none of these studies examined the connectedness measures as one of the risk factor while determining the risk premium at different sectors. Based on the performed analyses and the results in this diploma thesis, we confirmed the hypotheses that the connectedness is a factor that should be priced in the risk premium and that the investors at different sectors require different risk premium for bearing connectedness risk. Moreover, we showed that the connectedness serves as a good factor for approximation of the market risk.

The graphical analysis using the heat maps of each sectors, which are based on the realized volatilities and asset returns, provides an efficient visual tool for identification of the connectedness that represents a potential source of the systemic risk. The heat maps reflect the connectedness linkages in each sector, which are determined by using the variance decomposition framework of Diebold and Yilmaz (2014). Comparing the heat maps based on the calculated return connectedness and volatility connectedness, we can notice obvious differences between these two measures. In all sectors, we find the same pattern. The heat maps of volatility connectedness are significantly darker than the heat maps of returns connectedness in all sectors. Since darker colours represent stronger linkages between the individual assets, we can conclude that the volatilities of assets are more connected to other volatilities of assets than the asset returns. This fact confirms the assumption that the connectedness of returns is lower than the connectedness of volatilities, because the returns are generally not that much persistent. These conclusions are also in accordance to Diebold and Yilmaz (2014) who claimed that the volatility connectedness is more appropriate for connectedness analyses, because it provides more information in terms of dynamics.

Our analysis focused mainly on two measures of connectedness, sector overall (system-wide) connectedness and the total directional FROM connectedness. We obtained both of the measures, firstly from the data of asset realized volatilities, and then from the data of asset returns. Calculated connectedness tables, graphical visualizations, and the asset pricing model confirmed our assumption that the volatility connectedness provides more information about the connectedness dynamics than the return connectedness. In all of these analyses, the volatility connectedness showed to be more significant.

Using the Fama-MacBeth two-step regression, we showed that the sector overall connectedness is a significant risk factor in consumer, financial, health care, materials, utility and real estate sector. Based on the results, we argue that the sector overall connectedness plays a significant role in the determination of the risk premium, and should be taken into account while considering the risks in all sectors. This information can be especially important for the investors, whose portfolio comprises of the assets just from one sector or primarily from one sector. In that case, the information of overall connectedness in given sector can be valuable for estimating the potential risk of the portfolio and determining the size of the requested risk premium. These results can be further generalize for the randomly chosen system of assets, portfolio or market as a whole.

Apart from analyzing the sector overall connectedness, we concentrated also on the total directional connectedness, namely total directional FROM connectedness that provides the information to which extent is the asset affected by the volatility transmissions from the other assets in the system, and hence, it captures the shares of the forecast error variance of asset i that originates from the shocks coming to assets j in the sector. As the results suggest, connectedness linkages among the assets represent a significant risk factor especially in financial, real estate, health care, materials and consumer staples sectors. These results correspond with the sector overall connectedness results, and can serve as a valuable information for the investors. If the FROM connectedness is high for an asset i, the shocks coming to the other assets in the system transmit in large extent to the asset i, and hence, it makes the asset i more risky. This confirms our hypothesis, that the more is the asset i affected by the shocks originating in the assets j in the sector, the more risky is the asset i, and this risk should be priced in the risk premium.

By performing the series of sector analyses, we tested robustly how the connectedness is priced in different sectors of the market. Based on the results from all the sector regression analyses using various measures of connectedness, we conclude that the connectedness is a factor that approximates the risk on the financial market well. Future works might extend this market analysis by calculating the connectedness measures from the whole dataset of 496 assets (data of all 11 sectors together). Such analysis could serve as check for our sector analyses and could bring new information about the market risk associated with the connectedness of the market. Unfortunately, the currently available methodology does not allow such analysis on such an extended dataset. Furthermore, it would be also interesting to test the riskiness of individual assets in the asset pricing model based on its individual connectedness factors on the market.

Bibliography

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, & A. Tahbaz-Salehi (2012): "The network origins of aggregate fluctuations." *Econometrica* **80(5)**: pp. 1977–2016.

Ahern, K. R. (2013): "Network centrality and the cross section of stock returns." *Available at SSRN 2197370* .

Ahern, K. R. & J. Harford (2014): "The importance of industry links in merger waves." *The Journal of Finance* **69(2)**: pp. 527–576.

Allen, F. & A. Babus (2009): "Networks in finance." *The network challenge: strategy, profit, and risk in an interlinked world* **367**.

Aruoba, S. B., F. X. Diebold, & C. Scotti (2009): "Real-time measurement of business conditions." *Journal of Business & Economic Statistics* **27(4)**: pp. 417–427.

Baker, S. R., N. Bloom, & S. J. Davis (2016): "Measuring economic policy uncertainty." *The quarterly journal of economics* **131(4)**: pp. 1593–1636.

Bala, V. & S. Goyal (2000): "A strategic analysis of network reliability." *Review of Economic Design* **5(3)**: pp. 205–228.

Banz, R. W. (1981): "The relationship between return and market value of common stocks." *Journal of financial economics* **9(1)**: pp. 3–18.

Barndorff-Nielsen, O. E. & N. Shephard (2002): "Econometric analysis of realized volatility and its use in estimating stochastic volatility models." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **64(2)**: pp. 253–280.

Baruník, J., M. Bevilacqua, & R. Tunaru (2018): "Asymmetric connectedness of fears in the us financial sector." *Available at SSRN 3274538* .

Baruník, J., E. Kočenda, & L. Vácha (2016): "Asymmetric connectedness on the us stock market: Bad and good volatility spillovers." *Journal of Financial Markets* **27**: pp. 55–78.

Baruník, J. & T. Křehlík (2018): "Measuring the frequency dynamics of financial connectedness and systemic risk." *Journal of Financial Econometrics* **16(2)**: pp. 271–296.

Bekaert, G. & G. Wu (2000): "Asymmetric volatility and risk in equity markets." *The review of financial studies* **13(1)**: pp. 1–42.

Bhandari, L. C. (1988): "Debt/equity ratio and expected common stock returns: Empirical evidence." *The journal of finance* **43(2)**: pp. 507–528.

Bilgin, M. & K. Yilmaz (2018): "Producer price inflation connectedness and input-output networks." *Available at SSRN 3244645* .

Billio, M., M. Caporin, R. Panzica, & L. Pelizzon (2016): "The impact of network connectivity on factor exposures, asset pricing and portfolio diversification." .

Black, F., M. C. Jensen, M. Scholes *et al.* (1972): "The capital asset pricing model: Some empirical tests." *Studies in the theory of capital markets* **81(3)**: pp. 79–121.

Bloch, F. & M. Jackson (2006): "Equilibrium definitions in network formation games." *International Journal of Game Theory* **34**: pp. 305–318.

Bloch, F. & M. O. Jackson (2007): "The formation of networks with transfers among players." *Journal of Economic Theory* **133(1)**: pp. 83–110.

Bostanci, G. & K. Yilmaz (2020): "How connected is the global sovereign credit risk network?" *Journal of Banking & Finance* p. 105761.

Bramoullé, Y., R. Kranton *et al.* (2007): "Public goods in networks." *Journal of Economic Theory* **135(1)**: pp. 478–494.

Branger, N., C. Meinerding, P. Konermann, & C. Schlag (2018): "Equilibrium asset pricing in directed networks." .

Buraschi, A. & C. Tebaldi (2017): "Asset pricing implications of systemic risk in network economies." *Available at SSRN 3074012* .

Carhart, M. M. (1997): "On persistence in mutual fund performance." *The Journal of finance* **52(1)**: pp. 57–82.

Cochrane, J. H. (2005): *Asset pricing: Revised edition.* Princeton university press.

Cohen, L., A. Frazzini, & C. Malloy (2008): "The small world of investing: Board connections and mutual fund returns." *Journal of Political Economy* **116(5)**: pp. 951–979.

Corominas Bosch, M. *et al.* (1999): *On Two Sided Network Markets.* Universitat Pompeu Fabra.

Cotter, J., M. Hallam, & K. Yilmaz (2017): "Mixed-frequency macro-financial spillovers." *Available at SSRN 2904536* .

Demirer, M., F. X. Diebold, L. Liu, & K. Yilmaz (2018): "Estimating global bank network connectedness." *Journal of Applied Econometrics* **33(1)**: pp. 1–15.

Demirer, M., U. Gokcen, & K. Yilmaz (2019): "Financial sector volatility connectedness and equity returns." *Available at SSRN 3099738* .

Diebold, F. X. & K. Yilmaz (2009): "Measuring financial asset return and volatility spillovers, with application to global equity markets." *The Economic Journal* **119(534)**: pp. 158–171.

Diebold, F. X. & K. Yilmaz (2012): "Better to give than to receive: Predictive directional measurement of volatility spillovers." *International Journal of Forecasting* **28(1)**: pp. 57–66.

Diebold, F. X. & K. Yilmaz (2013): "Measuring the dynamics of global business cycle connectedness." .

Diebold, F. X. & K. Yilmaz (2014): "On the network topology of variance decompositions: Measuring the connectedness of financial firms." *Journal of Econometrics* **182(1)**: pp. 119–134.

Diebold, F. X. & K. Yilmaz (2015): *Financial and macroeconomic connectedness: A network approach to measurement and monitoring.* Oxford University Press, USA.

DURLAUF, S. N. (1996): "A theory of persistent income inequality." *Journal of Economic growth* **1(1)**: pp. 75–93.

EASLEY, D., J. KLEINBERG *et al.* (2010): *Networks, crowds, and markets*, volume 8. Cambridge university press Cambridge.

EDWARDS, S. & R. SUSMEL (2001): "Volatility dependence and contagion in emerging equity markets." *Journal of Development Economics* **66(2)**: pp. 505–532.

ELLISON, G. (1993): "Learning, local interaction, and coordination." *Econometrica: Journal of the Econometric Society* pp. 1047–1071.

ENGLE, R. F., V. K. NG, & M. ROTHSCHILD (1990): "Asset pricing with a factor-arch covariance structure: Empirical estimates for treasury bills." *Journal of econometrics* **45(1-2)**: pp. 213–237.

FAMA, E. F. & K. R. FRENCH (1992): "The cross-section of expected stock returns." *the Journal of Finance* **47(2)**: pp. 427–465.

FAMA, E. F. & J. D. MACBETH (1973): "Risk, return, and equilibrium: Empirical tests." *Journal of political economy* **81(3)**: pp. 607–636.

FRENCH, K. (2020): "Finance data library website."

GALE, D. & S. KARIV (2003): "Bayesian learning in social networks." *Games and Economic Behavior* **45(2)**: pp. 329–346.

GALEOTTI, A. & S. GOYAL (2007): "A theory of strategic diffusion." .

GARCIA, R. & G. TSAFACK (2011): "Dependence structure and extreme comovements in international equity and bond markets." *Journal of Banking & Finance* **35(8)**: pp. 1954–1970.

HERSKOVIC, B., B. KELLY, H. LUSTIG, & S. VAN NIEUWERBURGH (2016): "The common factor in idiosyncratic volatility: Quantitative asset pricing implications." *Journal of Financial Economics* **119(2)**: pp. 249–283.

HERSKOVIC, B., B. T. KELLY, H. N. LUSTIG, & S. VAN NIEUWERBURGH (2018): "Firm volatility in granular networks." *Chicago Booth Research Paper* **(12-56)**.

HOECHLE, D. (2011): "Xtfmb: Stata module to execute fama-macbeth two-step panel regression." .

HONG, H., J. D. KUBIK, & J. C. STEIN (2004): "Social interaction and stock-market participation." *The journal of finance* **59(1)**: pp. 137–163.

JACKSON, M. O. (2005): "A survey of network formation models: stability and efficiency." *Group formation in economics: Networks, clubs, and coalitions* **664**: pp. 11–49.

JACKSON, M. O. & A. WATTS (2002): "On the formation of interaction networks in social coordination games." *Games and Economic Behavior* **41(2)**: pp. 265–291.

JACKSON, M. O. & A. WOLINSKY (1996): "A strategic model of social and economic networks." *Journal of economic theory* **71(1)**: pp. 44–74.

KLÖSSNER, S. & R. SEKKEL (2014): "International spillovers of policy uncertainty." *Economics Letters* **124(3)**: pp. 508–512.

KLÖSSNER, S. & S. WAGNER (2014): "Exploring all var orderings for calculating spillovers? yes, we can!-a note on diebold and yilmaz (2009)." *Journal of Applied Econometrics* **29(1)**: pp. 172–179.

LINTNER, J. (1965): "Security prices, risk, and maximal gains from diversification." *The journal of finance* **20(4)**: pp. 587–615.

OZSOYLEV, H. N. & J. WALDEN (2011): "Asset pricing in large information networks." *Journal of Economic Theory* **146(6)**: pp. 2252–2280.

PAGE JR, F. H., M. H. WOODERS, & S. KAMAT (2005): "Networks and farsighted stability." *Journal of Economic Theory* **120(2)**: pp. 257–269.

ROSS, S. A. (1977): "The capital asset pricing model (capm), short-sale restrictions and related issues." *The Journal of Finance* **32(1)**: pp. 177–183.

SEGAL, G., I. SHALIASTOVICH, & A. YARON (2015): "Good and bad uncertainty: Macroeconomic and financial market implications." *Journal of Financial Economics* **117(2)**: pp. 369–397.

STĂRICĂ, C. & C. GRANGER (2005): "Nonstationarities in stock returns." *Review of economics and statistics* **87(3)**: pp. 503–522.

TIBSHIRANI, R. (1996): "Regression shrinkage and selection via the lasso." *Journal of the Royal Statistical Society: Series B (Methodological)* **58(1)**: pp. 267–288.

ULUCEVIZ, E. & K. YILMAZ (2018): "Measuring real-financial connectedness in the us economy." *Technical report*, Working Paper.

WU, G. (2001): "The determinants of asymmetric volatility." *The review of financial studies* **14(3)**: pp. 837–859.

YILMAZ, K. (2010): "Return and volatility spillovers among the east asian equity markets." *Journal of Asian Economics* **21(3)**: pp. 304–313.

Appendix A

Heatmaps of Sectors

Figure A.1: Heatmap of Telecommunication Sector, Volatility Connectedness

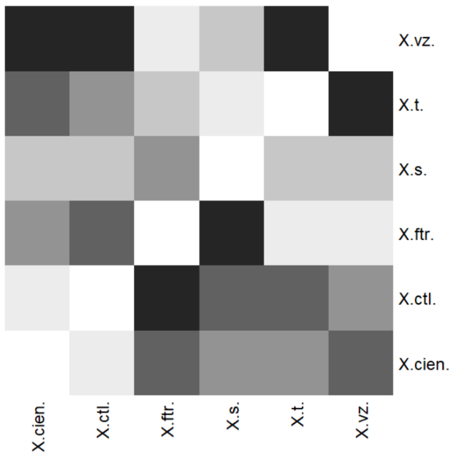


Figure A.2: Heatmap of Telecommunication Sector, Return Connectedness

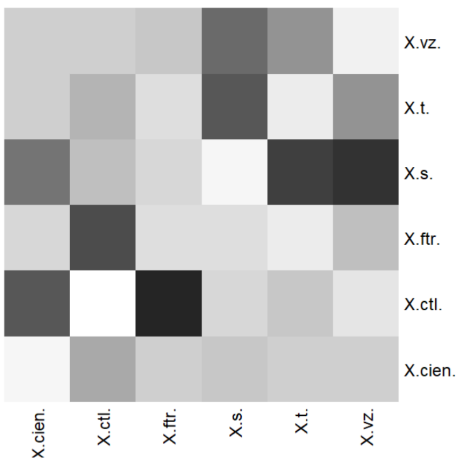


Figure A.3: Heatmap of Consumer Discretionary Sector, Volatility Connectedness

Figure A.4: Heatmap of Consumer Discretionary Sector, Return Connectedness

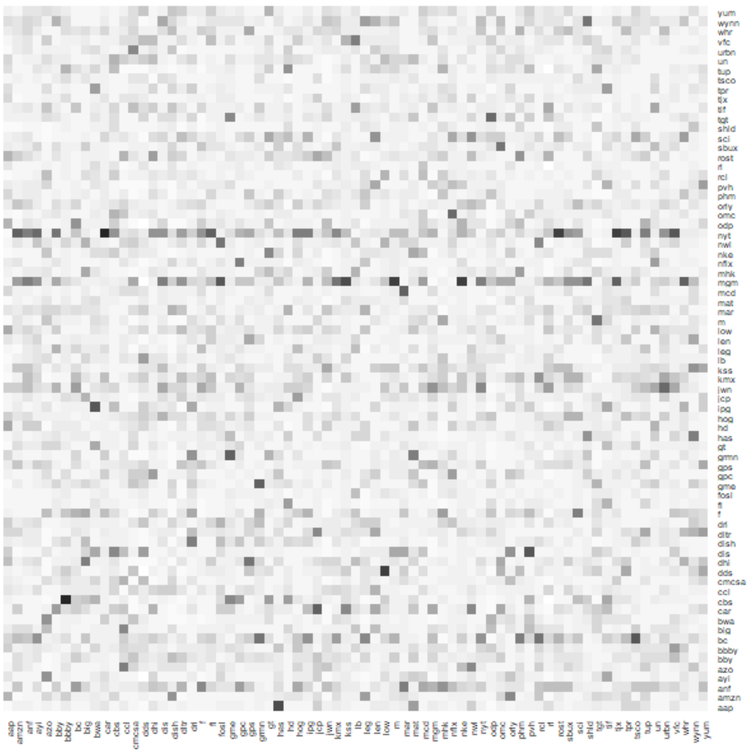


Figure A.5: Heatmap of Consumer Staples Sector, Volatility Connectedness

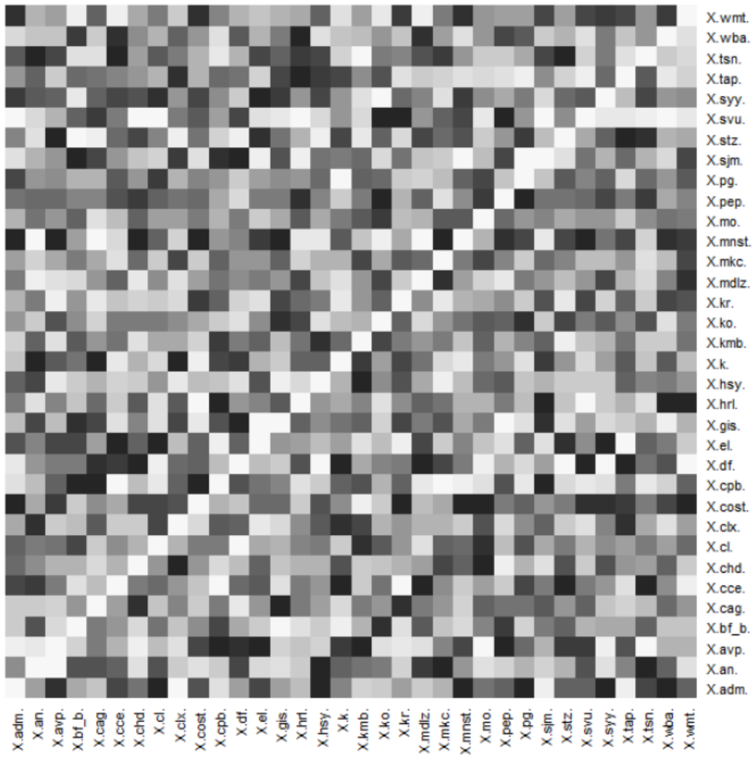


Figure A.6: Heatmap of Consumer Staples Sector, Return Connectedness

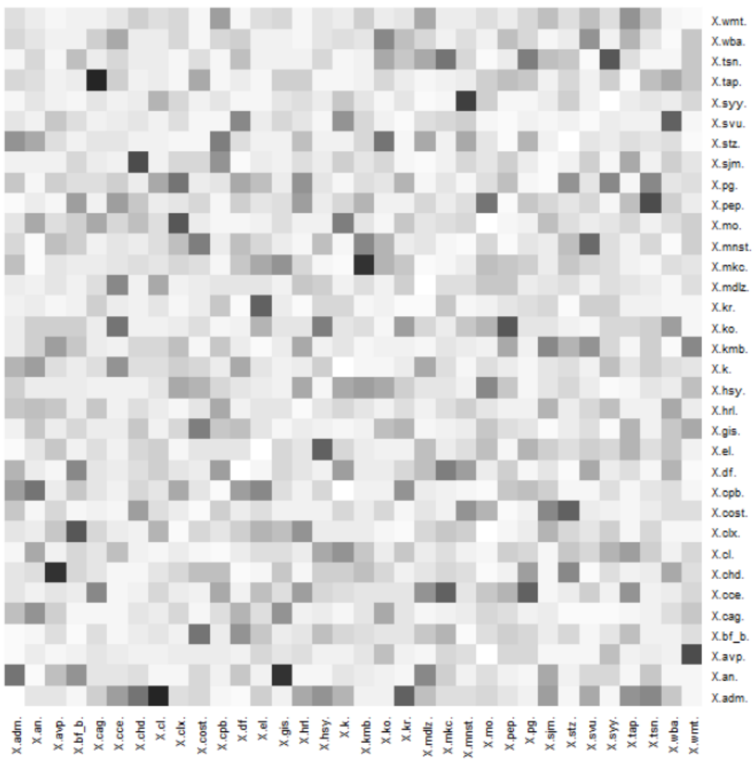


Figure A.7: Heatmap of Health Care Sector, Volatility Connectedness

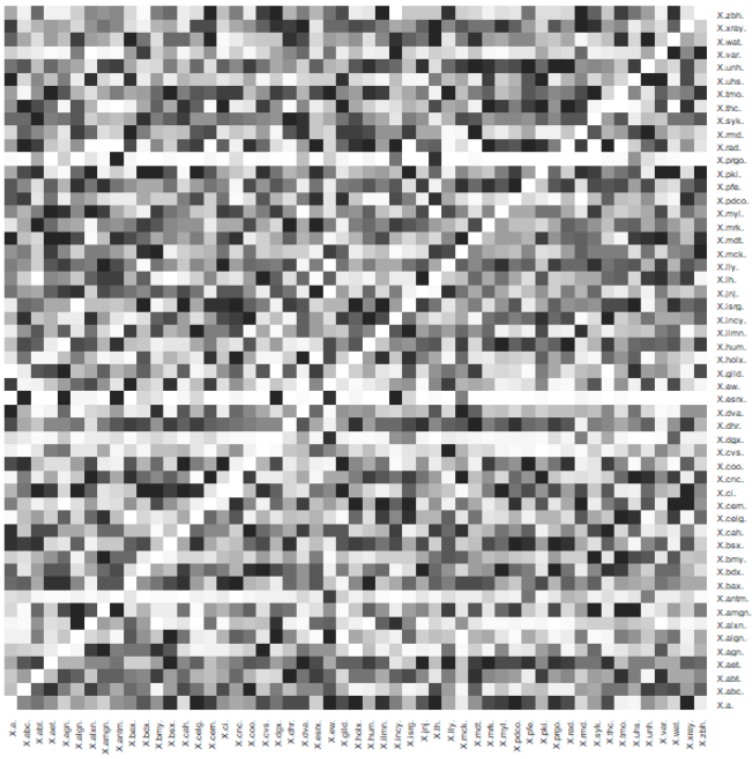


Figure A.8: Heatmap of Health Care Sector, Return Connectedness

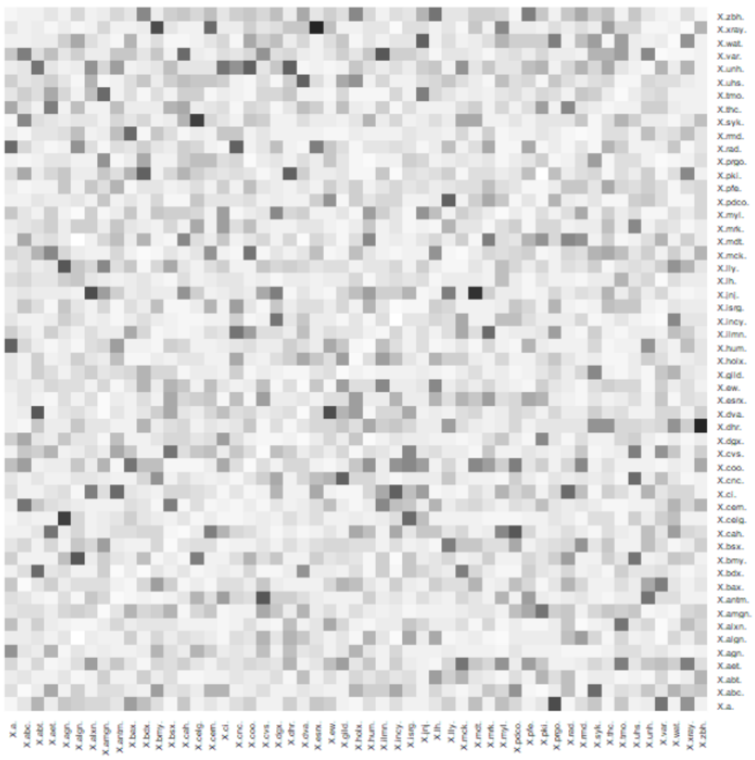


Figure A.9: Heatmap of Industry Sector, Volatility Connectedness

Figure A.10: Heatmap of Industry Sector, Return Connectedness

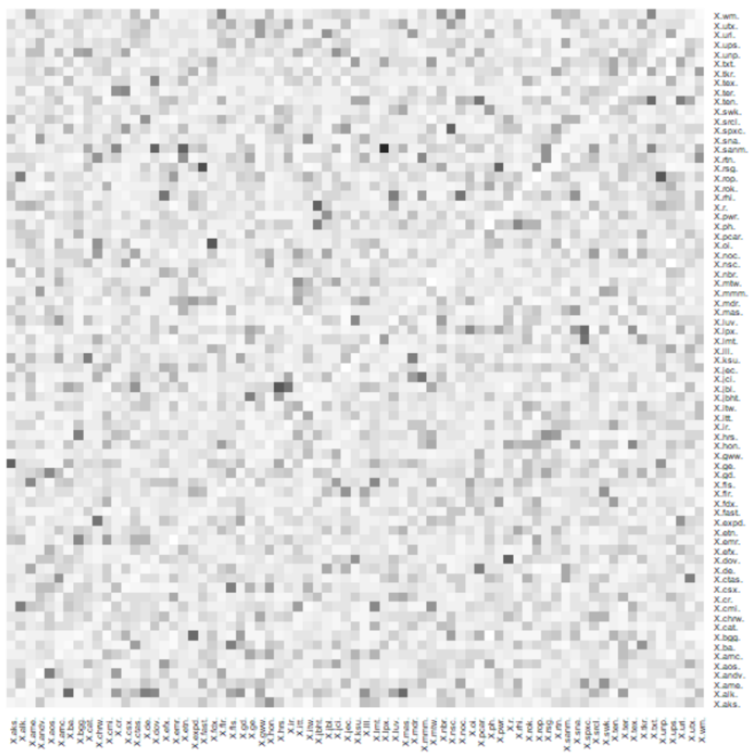


Figure A.11: Heatmap of Information Technology Sector, Volatility Connectedness

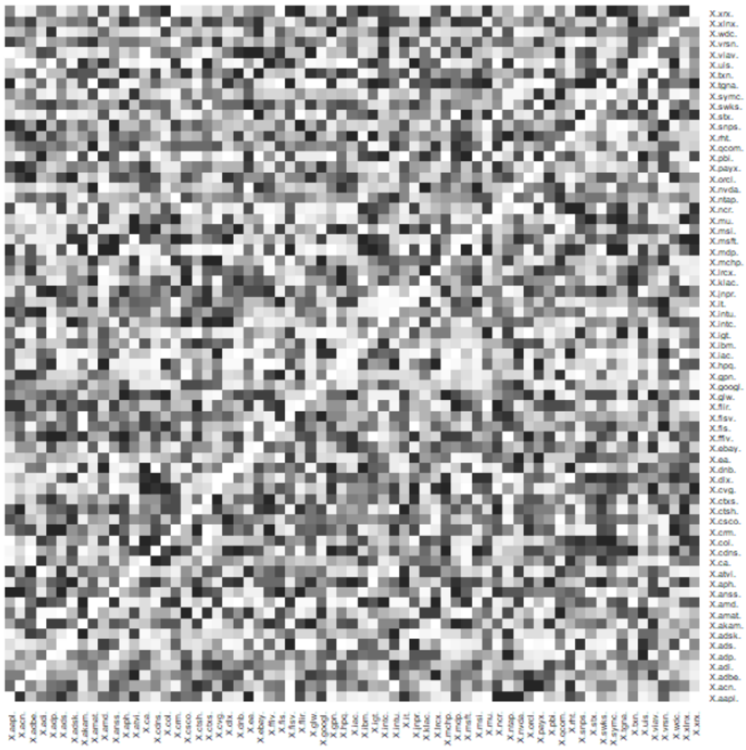


Figure A.12: Heatmap of Information Technology Sector, Return Connectedness

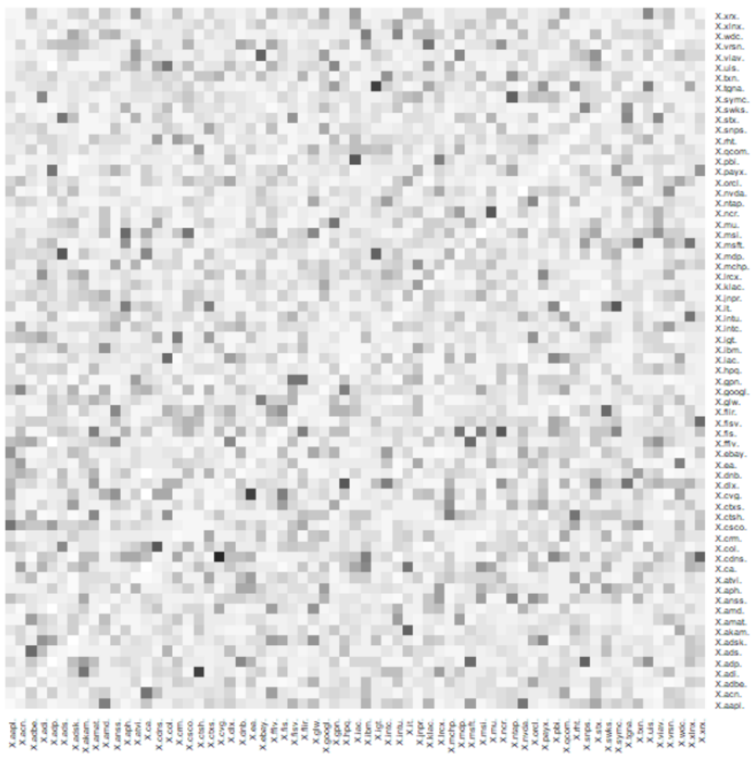


Figure A.13: Heatmap of Materials Sector, Volatility Connectedness

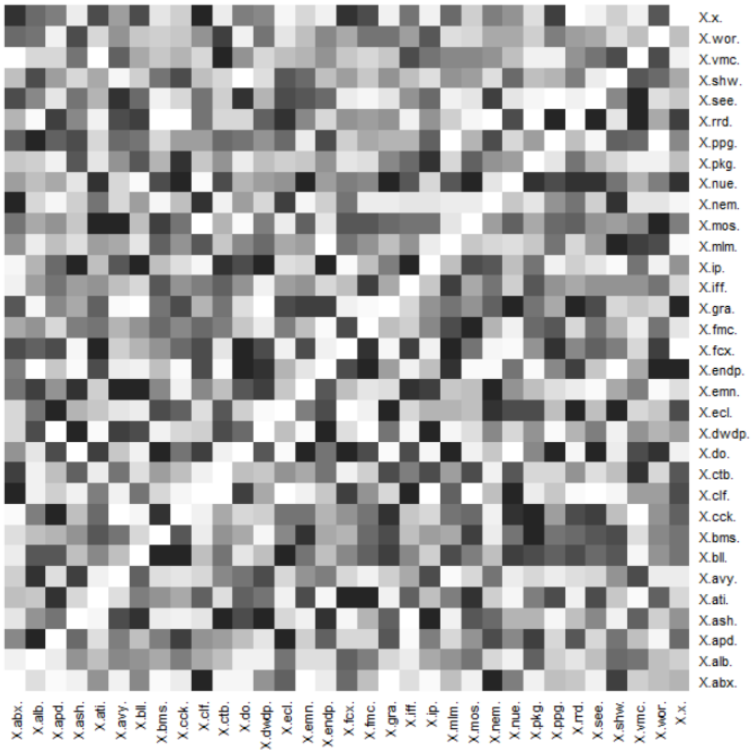


Figure A.14: Heatmap of Materials Sector, Return Connectedness

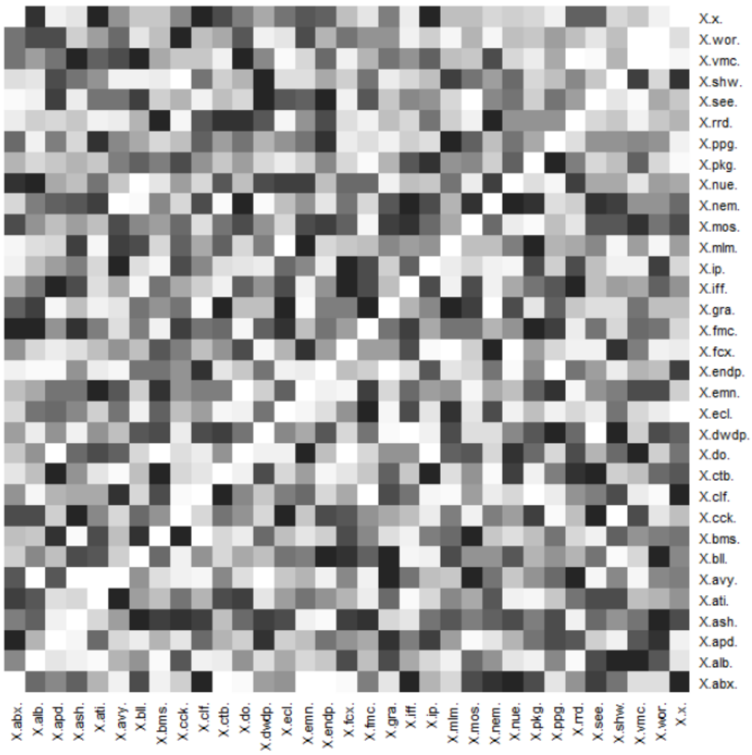


Figure A.15: Heatmap of Real Estate Sector, Volatility Connectedness

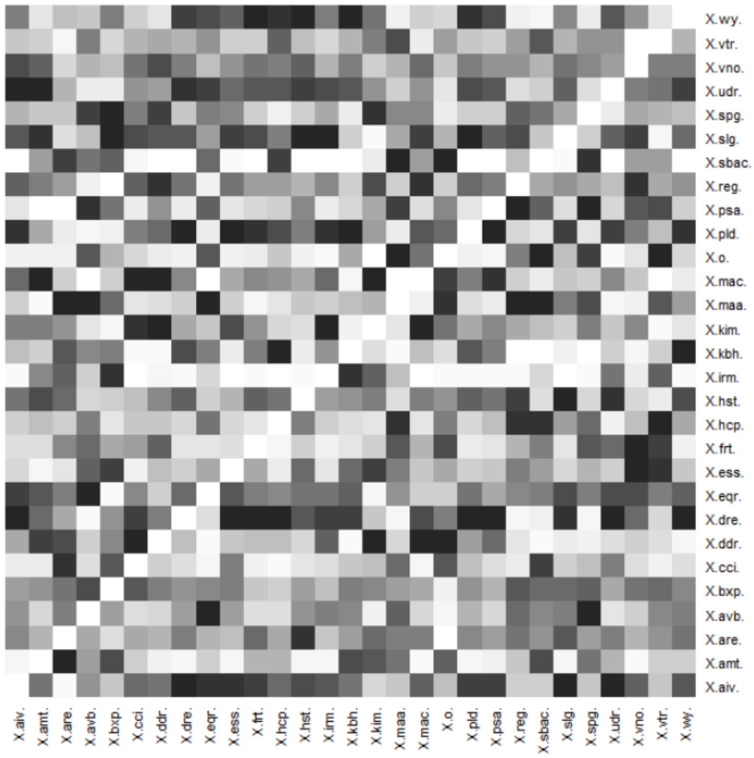


Figure A.16: Heatmap of Real Estate Sector, Return Connectedness

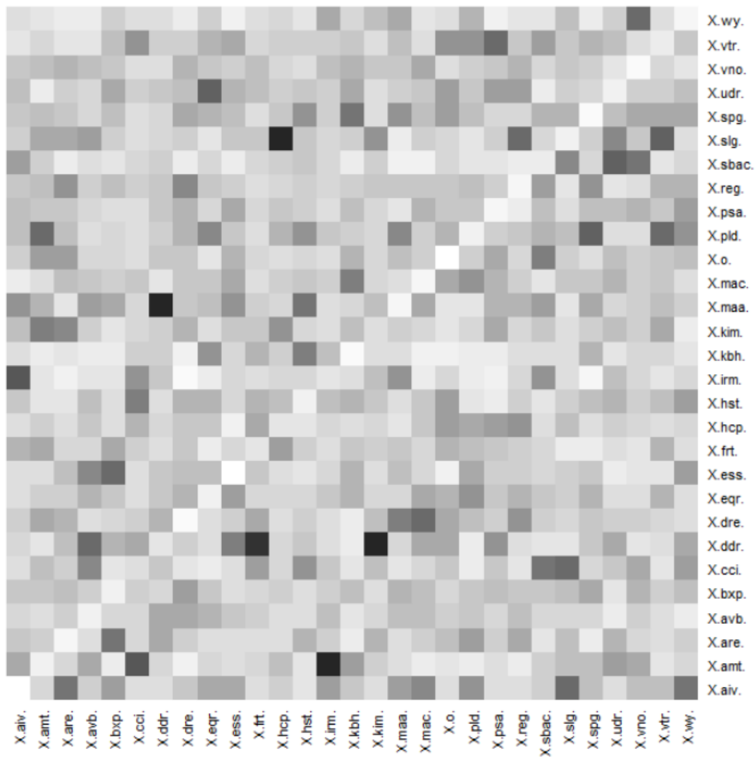


Figure A.17: Heatmap of Energy Sector, Volatility Connectedness

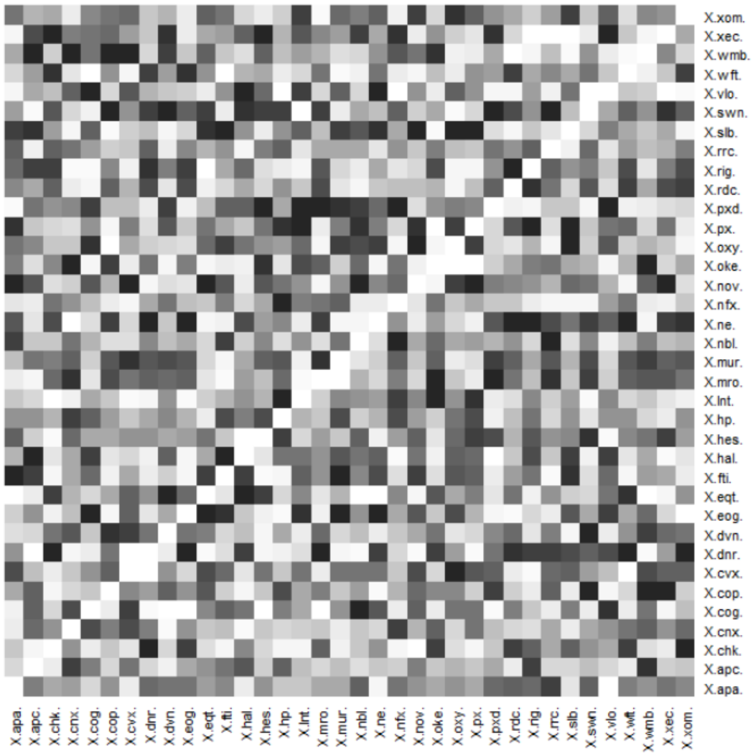


Figure A.18: Heatmap of Energy Sector, Return Connectedness

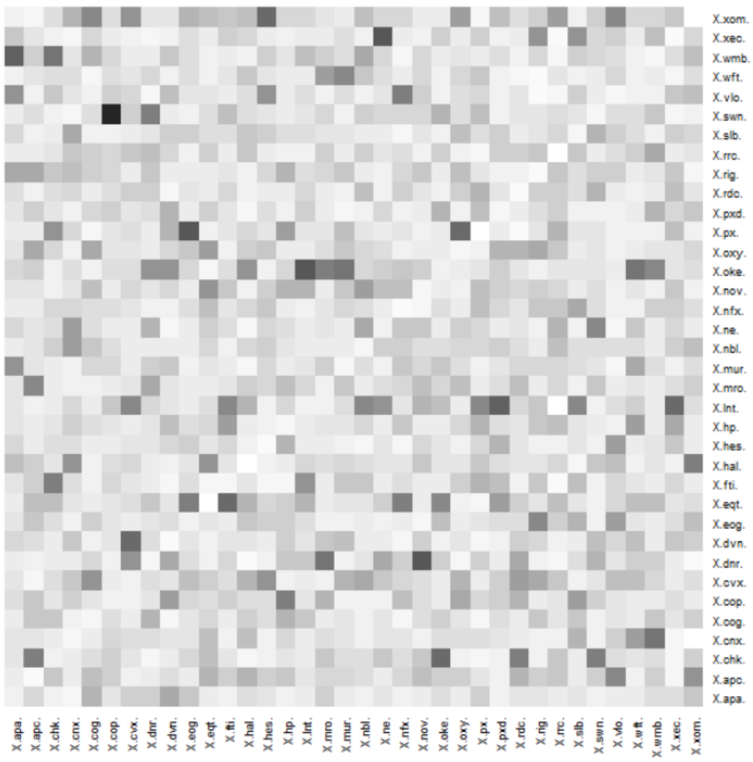


Figure A.19: Heatmap of Utility Sector, Volatility Connectedness

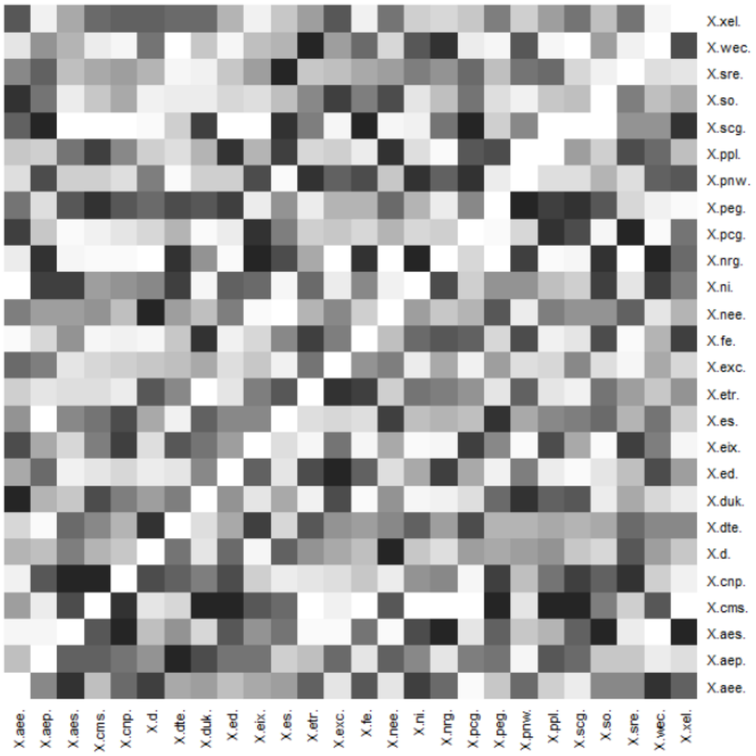
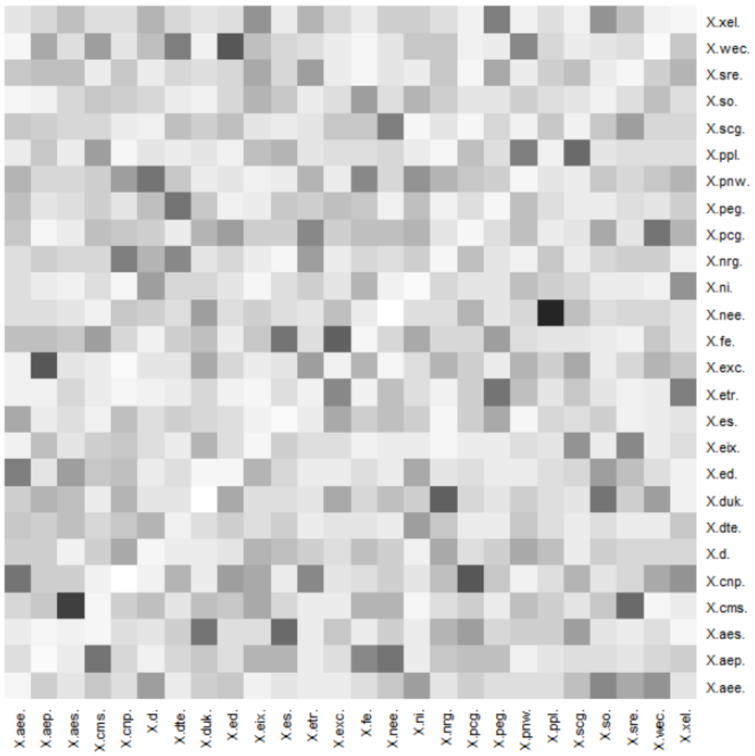


Figure A.20: Heatmap of Utility Sector, Return Connectedness



Appendix B

Fama-MacBeth Regressions

Table B.1: Volatility Connectedness, Consumer Discretionary Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.722*	0.011	-0.108*
	(0.932)	(0.016)	(0.058)
MKT	0.031	0.023	0.011
	(0.045)	(0.046)	(0.045)
SMB	-0.045*	-0.043*	-0.030
	(0.023)	(0.024)	(0.024)
HML	-0.080***	-0.089***	-0.107***
	(0.027)	(0.028)	(0.026)
Constant	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)
Observations	73	73	73
R^2	0.473	0.450	0.474
Adjusted R^2	0.442	0.418	0.443
F Statistic (df = 4; 68)	15.272***	13.929***	15.307***

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.2: Return Connectedness, Consumer Discretionary Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	-0.011	0.0004	0.029
	(0.022)	(0.006)	(0.239)
MKT	-0.033	0.065	0.064
	(0.067)	(0.051)	(0.051)
SMB	0.039	-0.009	-0.009
	(0.038)	(0.028)	(0.028)
HML	-0.002	-0.113***	-0.112***
	(0.042)	(0.030)	(0.030)
Constant	0.0001	-0.00000	-0.00000
	(0.0004)	(0.0003)	(0.0003)
Observations	73	73	73
R^2	0.060	0.423	0.423
Adjusted R^2	-0.031	0.368	0.368
F Statistic (df = 4; 68)	0.657	7.684***	7.683***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.3: Volatility Connectedness, Consumer Staples Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.918**	0.061**	0.142
	(0.442)	(0.024)	(0.143)
MKT	0.087	0.076	0.092
	(0.052)	(0.050)	(0.055)
SMB	-0.011	-0.023	0.003
	(0.030)	(0.029)	(0.033)
HML	-0.075*	-0.069*	-0.105***
	(0.038)	(0.037)	(0.038)
Constant	-0.0003	-0.0002	-0.0003
	(0.0004)	(0.0003)	(0.0004)
Observations	34	34	34
R^2	0.457	0.492	0.400
Adjusted R^2	0.382	0.422	0.317
F Statistic (df = 4; 29)	6.100***	7.014***	4.824***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.4: Return Connectedness, Consumer Staples Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.733*	-0.030	0.265**
	(0.418)	(0.029)	(0.097)
MKT	-0.073	-0.062	-0.055
	(0.056)	(0.061)	(0.053)
SMB	-0.045	-0.052	-0.051
	(0.042)	(0.044)	(0.040)
HML	-0.021	0.006	-0.059
	(0.062)	(0.065)	(0.061)
Constant	0.001**	0.0005*	0.0005*
	(0.0003)	(0.0003)	(0.0002)
Observations	34	34	34
R^2	0.324	0.278	0.405
Adjusted R^2	0.231	0.178	0.323
F Statistic (df = 4; 29)	3.478**	2.792**	4.929***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.5: Volatility Connectedness, Health Care Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	7.529***	0.133**	-0.418***
	(2.279)	(0.052)	(0.125)
MKT	-0.049	-0.032	0.006
	(0.066)	(0.068)	(0.065)
SMB	0.0003	-0.018	-0.028
	(0.032)	(0.032)	(0.030)
HML	-0.106***	-0.144***	-0.147***
	(0.038)	(0.040)	(0.038)
Constant	0.0004	0.0003	0.00005
	(0.0003)	(0.0004)	(0.0003)
Observations	53	53	53
R^2	0.347	0.297	0.354
Adjusted R^2	0.293	0.238	0.300
F Statistic (df = 4; 48)	6.384***	5.060***	6.562***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.6: Return Connectedness, Health Care Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	-0.033	0.032***	-1.524***
	(0.022)	(0.008)	(0.350)
MKT	-0.010	-0.042	-0.032
	(0.078)	(0.068)	(0.066)
SMB	-0.047	-0.026	-0.019
	(0.037)	(0.032)	(0.031)
HML	-0.123***	-0.082**	-0.079**
	(0.043)	(0.039)	(0.038)
Constant	0.00004	0.0004	0.0003
	(0.0004)	(0.0004)	(0.0003)
Observations	53	53	53
R^2	0.250	0.429	0.460
Adjusted R^2	0.179	0.375	0.408
F Statistic (df = 4; 48)	3.506**	7.897***	8.939***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.7: Volatility Connectedness, Industry Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.655	0.014	0.031
	(0.763)	(0.010)	(0.047)
MKT	-0.111***	-0.083***	-0.114***
	(0.029)	(0.026)	(0.028)
SMB	0.026	0.025	0.030
	(0.024)	(0.022)	(0.024)
HML	-0.081**	-0.081***	-0.091***
	(0.031)	(0.029)	(0.031)
Constant	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
Observations	73	73	73
R^2	0.425	0.405	0.422
Adjusted R^2	0.391	0.369	0.388
F Statistic (df = 4; 68)	12.568***	11.386***	12.428***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.8: Return Connectedness, Industry Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	-0.002	0.004	-0.155
	(0.010)	(0.005)	(0.242)
MKT	-0.184***	-0.187***	-0.186***
	(0.032)	(0.032)	(0.032)
SMB	0.060**	0.059**	0.059**
	(0.029)	(0.029)	(0.029)
HML	-0.135***	-0.133***	-0.134***
	(0.037)	(0.036)	(0.037)
Constant	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
Observations	73	73	73
R^2	0.583	0.587	0.586
Adjusted R^2	0.543	0.548	0.547
F Statistic (df = 4; 68)	14.677***	14.939***	14.876***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.9: Volatility Connectedness, Information Technology Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	2.935**	0.024	-0.039
	(1.190)	(0.027)	(0.083)
MKT	-0.076	-0.081	-0.075
	(0.065)	(0.067)	(0.068)
SMB	-0.040	-0.042	-0.045
	(0.032)	(0.033)	(0.033)
HML	-0.059*	-0.078**	-0.079**
	(0.031)	(0.031)	(0.032)
Constant	0.001**	0.001**	0.001**
	(0.0004)	(0.0004)	(0.0004)
Observations	67	67	67
R^2	0.332	0.276	0.269
Adjusted R^2	0.289	0.229	0.222
F Statistic (df = 4; 62)	7.694***	5.909***	5.709***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.10: Return Connectedness, Information Technology Sector

	Dependent variable:		
	Average Return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.002	0.003	-0.062
	(0.019)	(0.009)	(0.417)
MKT	-0.057	-0.051	-0.055
	(0.086)	(0.087)	(0.087)
SMB	-0.026	-0.027	-0.026
	(0.044)	(0.043)	(0.043)
HML	-0.055	-0.052	-0.054
	(0.049)	(0.050)	(0.050)
Constant	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Observations	67	67	67
R^2	0.091	0.093	0.091
Adjusted R^2	0.004	0.007	0.004
F Statistic (df = 4; 62)	1.050	1.076	1.050
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.11: Volatility Connectedness, Materials Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.649**	0.063**	0.047
	(0.606)	(0.029)	(0.187)
MKT	-0.176***	-0.188***	-0.200***
	(0.038)	(0.039)	(0.042)
SMB	0.006	0.019	0.053
	(0.035)	(0.035)	(0.035)
HML	-0.132***	-0.127**	-0.157***
	(0.045)	(0.047)	(0.056)
Constant	0.001***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)
Observations	33	33	33
R^2	0.616	0.586	0.516
Adjusted R^2	0.561	0.526	0.447
F Statistic (df = 4; 28)	11.222***	9.892***	7.459***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.12: Return Connectedness,Materials Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.380*	0.063**	0.052
	(0.733)	(0.027)	(0.127)
MKT	-0.048	-0.033	-0.054
	(0.056)	(0.055)	(0.059)
SMB	-0.045	-0.065	-0.033
	(0.054)	(0.054)	(0.057)
HML	0.081	0.096*	0.053
	(0.054)	(0.054)	(0.058)
Constant	0.0003	0.0003	0.0004
	(0.0004)	(0.0004)	(0.0004)
Observations	33	33	33
R^2	0.192	0.238	0.091
Adjusted R^2	0.077	0.129	-0.039
F Statistic (df = 4; 28)	1.668	2.184*	0.700
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.13: Volatility Connectedness, Real Estate Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.335**	0.055***	-0.161
	(0.523)	(0.015)	(0.173)
MKT	0.035	0.063	-0.037
	(0.065)	(0.060)	(0.065)
SMB	-0.070**	-0.065**	-0.073**
	(0.027)	(0.025)	(0.032)
HML	-0.002	-0.017	0.016
	(0.024)	(0.023)	(0.026)
Constant	0.0001	0.00002	0.001*
	(0.0005)	(0.0004)	(0.0004)
Observations	29	29	29
R^2	0.476	0.565	0.356
Adjusted R^2	0.388	0.492	0.249
F Statistic (df = 4; 24)	5.442***	7.791***	3.320**
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.14: Return Connectedness, Real Estate Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.335***	0.045***	0.004
	(0.357)	(0.011)	(0.035)
MKT	0.023	0.003	-0.037
	(0.055)	(0.051)	(0.067)
SMB	-0.060**	-0.065***	-0.084**
	(0.024)	(0.023)	(0.032)
HML	0.005	-0.007	0.020
	(0.021)	(0.021)	(0.027)
Constant	0.0002	0.0005	0.001*
	(0.0004)	(0.0003)	(0.0004)
Observations	29	29	29
R^2	0.579	0.615	0.326
Adjusted R^2	0.509	0.551	0.214
F Statistic (df = 4; 24)	8.254***	9.584***	2.900**
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.15: Volatility Connectedness, Financial Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	4.799***	0.060***	-0.063
	(0.540)	(0.017)	(0.065)
MKT	-0.039	-0.061*	-0.069*
	(0.026)	(0.036)	(0.039)
SMB	-0.049***	-0.050**	-0.054**
	(0.016)	(0.022)	(0.025)
HML	-0.016*	-0.031**	-0.052***
	(0.009)	(0.013)	(0.012)
Constant	0.0004**	0.001**	0.001***
	(0.0002)	(0.0003)	(0.0003)
Observations	66	66	66
R^2	0.740	0.503	0.413
Adjusted R^2	0.723	0.470	0.375
F Statistic (df = 4; 61)	43.414***	15.412***	10.739***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.16: Return Connectedness, Financial Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.012	-0.010	0.507
	(0.014)	(0.007)	(0.308)
MKT	-0.081	-0.048	-0.050
	(0.051)	(0.054)	(0.052)
SMB	-0.042	-0.039	-0.038
	(0.029)	(0.028)	(0.028)
HML	-0.063***	-0.058***	-0.057***
	(0.017)	(0.016)	(0.016)
Constant	0.001***	0.001**	0.001**
	(0.0004)	(0.0004)	(0.0004)
Observations	66	66	66
R^2	0.437	0.455	0.462
Adjusted R^2	0.383	0.403	0.410
F Statistic (df = 4; 61)	8.144***	8.777***	9.007***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.17: Volatility Connectedness, Energy Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.521	-0.006	0.403**
	(0.436)	(0.015)	(0.162)
MKT	-0.075	-0.051	-0.055
	(0.073)	(0.075)	(0.067)
SMB	-0.123**	-0.137**	-0.141***
	(0.048)	(0.051)	(0.045)
HML	-0.072	-0.062	-0.030
	(0.065)	(0.070)	(0.063)
Constant	0.001	0.0004	0.0004
	(0.001)	(0.001)	(0.001)
Observations	36	36	36
R^2	0.514	0.494	0.577
Adjusted R^2	0.452	0.429	0.522
F Statistic (df = 4; 31)	8.210***	7.568***	10.568***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.18: Return Connectedness, Energy Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.119	0.007	-0.028
	(0.279)	(0.012)	(0.068)
MKT	-0.061	-0.067	-0.059
	(0.073)	(0.074)	(0.073)
SMB	-0.134**	-0.128**	-0.129**
	(0.049)	(0.049)	(0.049)
HML	-0.069	-0.057	-0.065
	(0.067)	(0.069)	(0.069)
Constant	0.0004	0.0005	0.0004
	(0.001)	(0.001)	(0.001)
Observations	36	36	36
R^2	0.495	0.498	0.496
Adjusted R^2	0.430	0.433	0.431
F Statistic (df = 4; 31)	7.594***	7.683***	7.620***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.19: Volatility Connectedness, Telecommunication Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	-2.889	0.732	-2.700
	(10.971)	(4.560)	(11.168)
MKT	0.080	0.279	-0.111
	(0.337)	(0.737)	(1.154)
SMB	0.002	-0.102	0.084
	(0.182)	(0.352)	(0.547)
HML	-0.623	-0.495	-0.477
	(0.287)	(0.326)	(0.277)
Constant	-0.0001	-0.001	0.001
	(0.002)	(0.004)	(0.006)
Observations	6	6	6
R^2	0.979	0.977	0.978
Adjusted R^2	0.893	0.885	0.889
F Statistic (df = 4; 1)	11.397	10.573	11.038
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.20: Return Connectedness, Telecommunication Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	0.524	-1.583	-0.875
	(6.886)	(6.577)	(1.758)
MKT	0.192	-0.049	0.117
	(0.382)	(0.908)	(0.160)
SMB	-0.060	0.048	-0.032
	(0.176)	(0.403)	(0.055)
HML	-0.531	-0.667	-0.510
	(0.236)	(0.516)	(0.106)
Constant	-0.001	0.001	-0.001
	(0.002)	(0.005)	(0.001)
Observations	6	6	6
R^2	0.977	0.979	0.983
Adjusted R^2	0.883	0.894	0.913
F Statistic (df = 4; 1)	10.442	11.504	14.194
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table B.21: Volatility Connectedness, Utility Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.935***	0.029	-0.077
	(0.672)	(0.042)	(0.275)
MKT	-0.041	-0.080*	-0.093**
	(0.039)	(0.046)	(0.041)
SMB	0.040	0.009	-0.002
	(0.064)	(0.073)	(0.076)
HML	-0.096	-0.059	-0.042
	(0.085)	(0.099)	(0.101)
Constant	0.0003	0.0005*	0.001**
	(0.0002)	(0.0003)	(0.0002)
Observations	26	26	26
R^2	0.481	0.293	0.280
Adjusted R^2	0.382	0.158	0.142
F Statistic (df = 4; 21)	4.868***	2.174	2.038
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table B.22: Return Connectedness, Utility Sector

	Dependent variable:		
	Average return		
	Overall	FROM	TO
	(1)	(2)	(3)
Connectedness	1.298*	0.010	-0.005
	(0.652)	(0.031)	(0.102)
MKT	-0.054	-0.091**	-0.096**
	(0.043)	(0.042)	(0.046)
SMB	0.042	0.005	0.002
	(0.070)	(0.074)	(0.079)
HML	-0.099	-0.051	-0.045
	(0.094)	(0.098)	(0.108)
Constant	0.0004*	0.001**	0.001**
	(0.0002)	(0.0002)	(0.0003)
Observations	26	26	26
R^2	0.391	0.280	0.275
Adjusted R^2	0.275	0.143	0.137
F Statistic (df = 4; 21)	3.375**	2.041	1.994
Note:	*p<0.1; **p<0.05; ***p<0.01		