Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Measurement of volatility spillovers and asymmetric connectedness on commodity and equity markets

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Academic Year: **2016/2017**

Declaration of Authorship

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

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Prague, July 31, 2017

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Acknowledgments

I would like to express my gratitude to my supervisor, doc. PhDr. Jozef Baruník, Ph.D., for his advice, comments and guidance, and Mgr. Tomáš Křehlík, M.A., for providing the software package for R and technical help. I also thank Miroslav Palanský for our many discussions that have encouraged me throughout the writing of this thesis. A special word of thanks goes to my family who have supported me greatly during my studies.

The research leading to these results was supported by the European Union's Horizon 2020 Research and Innovation Staff Exchange programme under the Marie Sklodowska-Curie grant agreement No 681228.

Abstract

We study volatility spillovers among commodity and equity markets by employing a recently developed approach based on realized measures and forecast error variance decomposition invariant to the variable ordering from vector-autoregressions. This enables us to measure total, directional and net volatility spillovers as well as the asymmetry of responses to positive and negative shocks. We exploit high-frequency data on the prices of Crude oil, Corn, Cotton and Gold futures, and the S&P 500 Index and use a sample which spans from January 2002 to December 2015 to cover the entire period around the global financial crisis of 2008. Our empirical analysis reveals that on average, the volatility shocks related to other markets account for around one fifth of the volatility forecast error variance. We find that shocks to the stock markets play the most important role as the S&P 500 Index dominates all commodities in terms of general volatility spillover transmission. Our results further suggest that volatility spillovers across the analyzed assets were rather limited before the global financial crisis, which then boosted the connectedness between commodity and stock markets. Furthermore, the volatility due to positive and negative shocks is transmitted between markets at different magnitudes and the prevailing effect has varied. In the pre-crisis period, the positive spillovers dominated the negative ones, however, in several years following the crisis, the negative shocks have had a significantly higher impact on the volatility spillovers across the markets, pointing to an overall increase in uncertainty in the commodity and equity markets following a major crisis. In recent years, the asymmetric measures seem to have returned to their pre-crises directions and magnitudes.

JEL Classification	C18, C58, G01, G15, Q02
Keywords	Volatility, Spillovers, Relized Semivariance, Asymmetric effects, Commodity markets, Equity markets

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Abstrakt

V této práci zkoumáme přelévání volatility mezi komoditními a akciovými trhy metodou založenou na realizovaných měrách volatility a rozkladu prognózy chybových odchylek invariantních vůči pořadí proměnných při vektorových autoregresích. To nám umožňuje měřit nejen celkové, směrové a čisté přelévání volatility, ale i asymetrii reakcí na pozitivní a negativní šoky. V analýze využíváme vysokofrekvenční data o cenách termínových kontraktů na trzích s ropou, kukuřicí, bavlnou a zlatem a hodnotách indexu S&P 500. Data pokrývají období od ledna 2002 do prosince 2015 tak, aby zahrnula globální finanční krizi v roce 2008. Naše empirická analýza ukazuje, že v průměru je volatilita na ostatních trzích zodpovědná za přibližně jednu pětinu chybové odchylky prognózy volatility. V souladu s předchozí literaturou zjišťujeme, že nejdůležitější úlohu hrají šoky na akciových trzích, neboť Index S&P 500 dominuje všem komoditám z hlediska přelévání volatility. Naše výsledky naznačují, že před vypuknutím globální finanční krize v roce 2008 bylo přelévání volatility napříč analyzovanými trhy poměrně omezené, nicméně krize výrazně posílila propojenost mezi komoditními a akciovými trhy. Dále zjišťujeme, že volatilita vyvolaná pozitivními a negativními šoky je přenášena mezi trhy v různých velikostech a převažující efekt se v předkrizovém období lišil, avšak v několika letech po skončení krize měly negativní šoky výrazně větší dopad na přelévání volatility mezi jednotlivými trhy, což poukazuje na celkový nárůst nejistoty na komoditních a akciových trzích po velké krizi. V posledních letech se zdá, že čisté směrové efekty přelévání volatility se vrátily do svých předkrizových směrů a objemů.

Klasifikace JEL	C18, C58, G01, G15, Q02
Klíčová slova	volatilita, přelévání volatility, realizované odchylky, asymetrické efekty, komoditní trhy, kapitálové trhy

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Acronyms

ADF Augmented Dickey-Fuller

AIC Akaike Information Criterion

ARMA Autoregressive Moving Average

BIC Bayesian information criterion

CL Oil Crude

CN Corn

CT Cotton

CRB Commodity Research Bureau

GARCH Generalized Autoregressive Conditional Heteroscedasticity Model

GC Gold

KPSS Kwiatkowski-Phillips-Schmidt-Schin

MCMC Markov Chain Monte Carlo methods

PP Phillips-Perron

RS Realized Semivariances

RV Realized Variance

SAM Spillover Asymmetry Measure

SP Standard & Poor's 500 Index

U.S. United States

VAR Vector autoregression

Master's Thesis Proposal

Author	Bc. Tereza Malířová
Supervisor	PhDr. Jozef Baruník, Ph.D.
Proposed topic	Measurement of volatility spillovers and asymmetric connectedness on commodity and equity markets

Motivation In the last decades, individual markets have become interconnected in an unprecedented manner, which led to increased interest in the study of interaction of different markets. Literature analyzing this interdependence has focused mainly on returns and their volatility. Since volatility is considered to be an alternative measure of risk, the motivation to analyze its behavior is straightforward. Monitoring such spillovers should be in the interest of investors and other financial market participants as it can provide useful signals about the future development of the market.

In this thesis, we will try to model volatility spillovers across the most developed commodity – oil crude, stocks and exchanged rate among the United States, Germany and the Czech Republic. We will cover the period from January 2005 to January 2015 which will enable us to examine volatility spillovers before, during, and after the financial crisis.

Following the approach of Diebold and Yilmaz (2009), we base our methodology on the construction of a simple quantitative measure of such interdependence, the so-called spillover index. Specifically, we examine the volatility spillovers based directly on the decomposition of the forecast error variance of a vector auto-regressive model. This allows to distinguish the forecast error variance in one market from the shocks in other markets and thus to estimate the spillover effect.

We employ the extension to this approach pioneered by Barunik, Kocenda and Vacha (2013), who build not only upon the work on spillover indices by Diebold and Yilmaz (2009), but also on the updated methodology introduced in (Diebold and Yilmaz, 2012), which introduces measures of both total and directional volatility spillovers. The empirical fact that negative shocks are more pronounced in terms of volatility has been formalized by a number of extensions to the ARCH model family. However, the limitations of these approaches led to the development of two methodologies of measuring volatility, which were combined by Barunik, Kocenda and Vacha (2013). The resulting modified indices allow for modeling asymmetric responses to positive and negative shocks.

Hypotheses

Hypothesis #1: Volatility spillovers between two assets within one country vary across different countries.

Hypothesis #2: Volatility spillovers are asymmetric in response to negative or positive shocks. In particular, negative shocks have greater impact on volatility spillovers than positive ones.

Hypothesis #3: The volatility of oil prices, stocks and exchanged rates in the U.S. and German market affect the volatility in the Czech market.

Hypothesis #4: Volatility spillovers among countries vary for different frequencies.

Hypothesis #5: The size of volatility spillovers varies over time.

Methodology To test our hypotheses, we will employ the connectedness measurement methodology which was originally developed by Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012), using a generalized vector autoregressive framework. Specifically, we will apply the variance decomposition which helps to demonstrate the amount of information each variable contributes to the other variables in the regression and it will show how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables (Diebold and Yilmaz, 2013). Such method will allow us to measure both the total and directional volatility spillovers and will reveal the level of cross-country spillovers.

To study the volatility-spillover asymmetries, we will employ the volatility spillover index devised in Diebold and Yilmaz (2009) as modified by Barunik, Kocenda and Vacha (2013). Based on the concept of realized semi- variances presented by Barndorff-Nielsen et al. (2010), the model allows us to decompose the realized variance into parts corresponding to positive and negative shocks in the market. Focusing on both intra-market and cross-market volatility, we estimate the size of the spillovers using these asymmetric spillover indices.

Expected Contribution The expected contribution is to show the inter-market connectedness, how the negative and positive shocks influence the volatility spillovers and how the level of spillovers is changing in response to character of the observed period – before crises, during crises and recovery phases. While most of the studies on this topic focus only on data on U.S. firms, we compare several Central European markets with the U.S. market. Furthermore, we reveal the intra-market characteristics such as for example the spillover effect of exchange rate on oil prices in each market. We thus provide further evidence for the effects found by Barunik, Kocenda and Vacha (2015) for the U.S. market during the 2008 financial crisis.

Outline

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5. Empirical Analysis, results and discussion
6. Conclusion

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Author Supervisor

Chapter 1

Introduction

In the last decades, individual markets have become interconnected in an unprecedented manner, which led to an increased interest in the study of the interaction of different markets. Additionally, financial liberalization and internationalization of trade have induced a significant increase in volatility in the markets. With both higher integration and increased volatility of major financial markets, the commodity market as well as the equity market have become more sensitive to innovations, changing political and economic situation, positive and negative shocks or changes in the investors' expectations. Moreover, quite recently the commodity markets have gone through considerable financialization and the fast growth in the liquidity of commodity futures has generated an increasing inflow of investors interested in commodities exclusively as investments. Volatility is considered to be an alternative measure of risk, therefore the motivation to analyze its behavior is straightforward as it can provide useful signals about the future development of the markets. Monitoring, analyzing and understanding time-varying volatility and the transmission mechanism across different asset classes have become a fundamental issue for researchers, investors as well as for policy makers. The global financial crisis of 2008 has further strengthened the notion of increasing integration between seemingly uncorrelated markets and has underlined the importance of diversification of the investment portfolio. It is thus of an especially high interest to study the patterns of volatility transmission and the evolution of intra-market connectedness in the light of the worldwide crash of financial markets.

Most previous studies have focused on volatility spillovers among major stock markets, across one specific industry or between the crude oil market and financial markets. The aim of this thesis is to model volatility spillovers across widely traded commodities, specifically among Crude oil, Gold, Corn and Cotton futures, and one of the main U.S. stock market indices, the S&P 500 Index, to represent the equity market. Each of the included commodities represents a specific branch of the commodity market - energy, precious metal, grain and fiber markets, respectively. The importance of each of these commodities within their markets is sufficient to consider them as a proxy for each sector. Our sample covers the period from January 2002 to December 2015 which enables us to examine volatility spillovers before, during, and after the global financial crisis. Thanks to the sample's 14-year span we can observe the development long before the financial market crash as well as quite long after the turbulent period fades away which allows us to clearly assess the impact of the global crisis on the markets under research.

Following the approach of Diebold & Yilmaz (2009), we base our methodology on the construction of a simple quantitative measure of interdependence, the so-called spillover index. Specifically, we examine the volatility spillovers based directly on the decomposition of the forecast error variance of a vector auto-regressive model. This allows us to distinguish the forecast error variance in one market from the shocks in other markets and thus to estimate the spillover effect. We employ an extension to this approach pioneered by Baruník *et al.* (2016), who build not only upon the work on spillover indices by Diebold & Yilmaz (2009), but also on the updated methodology introduced by Diebold & Yilmaz (2012), which introduces measures of both total and directional volatility spillovers. The empirical fact that negative shocks are more pronounced in terms of volatility has been formalized by a number of extensions to the ARCH model family. However, the limitations of these approaches led to the development of two methodologies of measuring volatility, which were combined by Baruník *et al.* (2016). The resulting modified indices allow for modeling asymmetric responses to positive and negative shocks.

In our research, we contribute to the discussion of intra-market connectedness regarding commodity and equity markets. The present analysis of the connectedness between seemingly unrelated widely traded commodities and an American stock index reveals many interesting findings. We find that the volatility spillovers across the analyzed assets were rather limited before the 2008 financial crisis, which then deepened the connectedness between commodity and stock markets and emphasized further financialization of commodities. The shocks to the stock markets play the most important role regarding the transmission of volatility as the S&P 500 Index dominates all commodities in terms of general volatility spillover transmission measures. Moreover, we provide an analysis of asymmetric responses to positive and negative shocks. To our best knowledge, no research has dealt with asymmetric connectedness within a sample similar to that used in our analysis. The results contradict the common perception that the negative shocks impact the volatility spillovers more heavily than the positive ones and suggest that except for the times of crises, the attitude of market participants is not as pessimistic as generally assumed. In the pre-crisis period, the positive spillovers dominated the negative ones, however, after the Lehman Brothers crash in September 2008, the negative shocks have had a significantly higher impact on the volatility spillovers across the analyzed markets. Nevertheless, in recent years, we can observe that the asymmetric measures seem to have gradually returned to their pre-crises directions and magnitudes.

The remainder of the thesis is structured as follows. Chapter 2 provides an overview of the existing literature focusing on inter-market connectedness, transmission of volatility between different markets, measuring the volatility spillovers as well as the asymmetric response to positive and negative shocks. In Chapter 3 we describe the theoretical background behind the construction of realized measures and the methodology used to estimate the effects of volatility in commodity and equity markets. A detailed description of the selected commodities and stock index is provided in Chapter 4 along with the construction, adjustments and descriptive statistics of the data. In Chapter 5 we evaluate a static and dynamic analysis of volatility spillovers between two asset classes—stocks and commodities—as well as volatility spillovers across different commodities and we further investigate potential asymmetries in the transmission mechanism due to negative and positive shocks. Finally, Chapter 6 concludes and discusses the possible extensions of our analysis.

Chapter 2

Literature review

In the last decades, individual asset markets have become interconnected in an unprecedented manner, which led to an increased interest in the study of the interaction between different markets. This chapter is devoted to an overview of the existing literature focusing on the inter-market connectedness especially between assets included in our analysis in general, transmission of volatility between different sectors, measuring of the volatility spillovers as well as the asymmetric response to positive and negative shocks. In our analysis we are mostly interested in commodity markets and its intra-connectedness between different asset classes as well as the link between commodity market and stock market which is represented by the S&P 500 Index.

Most studies focus on the volatility transmission among different key stock markets or between the crude oil market and financial markets. Arouri *et al.* (2012) investigate the volatility transmission between oil and stock markets in Europe using the VAR–GARCH model enabling the analysis of spillover effects in both returns and conditional volatility. By analyzing the European global market index and seven stock sector indices over the period from 1998 to 2009, the authors unveil the existence of significant volatility spillovers between oil and stock markets in Europe with various intensity of volatility interactions in different sectors. Moreover, the transmission effect from oil to stock markets shows to be more evident. In order to extract the nature of relationship between the volatility of stock market and the volatility of oil futures market, Vo (2011) employ the bivariate VAR(1)-SV model for the joint processes governing the S&P 500 Index and the oil futures returns during the 1999–2009 period. The author finds that there is time-varying correlation between the stock and oil futures markets which tends to grow with increasing volatility in the market. The daily volatility in both markets shows to be very persistent and hence quite predictable. Moreover, the inter-dependence between the two markets is revealed, i.e. innovations that hit either market can have impact on the volatility in the other market. Further, Degiannakis *et al.* (2013) examine the relationship between the returns of oil prices and industrial sector indices in a time-varying heteroskedastic environment, taking into consideration the origin of the oil prices shocks. The results show that the correlation between industrial sectors' returns and oil price returns is influenced by the origin of the oil price shock as well as by the type of industry. Degiannakis *et al.* (2014) follow up with a study showing that oil price changes due to aggregate demand shocks lead to a reduction in stock market volatility in Europe, and that supply-side shocks and oil specific demand shocks do not affect volatility.

In recent years, significant volatility in the U.S. stock market and dramatic fluctuations in the global price of crude oil have been observed. Using a structural VAR model, Kang *et al.* (2015) study the impact of global oil price shocks on the covariance of U.S. stock market returns and the stock market volatility. The results reveal that after the financial crisis, oil-market specific demand shocks predicted a much larger fraction of implied-covariance of stock returns and volatility than in the period before the global financial crisis. Moreover, the authors find that positive shocks to aggregate demand and to oil-market specific demand are associated with negative effects on the covariance of return and volatility, while oil supply disruptions are associated with positive effects. The spillover index measuring the degree of connectedness for the oil market and the stock market showed to be quite large and highly statistically significant proving the oil price shocks and the connection between stock market return and volatility to be correlated. Malik & Hammoudeh (2007) study the volatility and its transmission mechanism among equity markets of the U.S., Saudi Arabia, Kuwait, and Bahrain and the global crude oil market and they reach results seminal for accurate asset pricing models, hedging strategies and forecasting future equity and oil price return volatility.

Literature focusing on the relationship between the stock market and the foreign exchange market is quite voluminous as both markets play an indisputably important role in portfolio diversification and economic development in general. Different theoretical models have implied that stock price changes in two countries may have an impact on the exchange rate between the two respective currencies. Kanas *et al.* (2000) studied the interaction between stock returns and exchange rate changes within the same economy in six different developed countries, specifically Japan, Germany, Canada, France, the UK and the US. A significant contemporaneous relationship between the two markets has been found. Examining the interdependence in terms of the conditional second moments of the distribution of stock returns and exchange rate changes, the volatility spillovers from stock returns to exchange rate changes appeared in all countries except for Germany during the 1986–1998 time period. In addition, the spillovers increased after the October 1987 crash. On the other hand, the volatility spillovers from exchange rate changes to stock returns show to be insignificant for all countries. Finally, spillovers from stock returns seem to be symmetric which means that the negative and the positive stock market shocks of equal magnitude have the same impact on the exchange rate.

Yang & Doong (2004) also confirm the evidence of information transmission between the two markets suggesting their integration. Using a multivariate extension of the EGARCH model, they test for the mean and volatility transmission mechanism between the stock market and the foreign exchange market for the G-7 countries including weekly observations from 1979 to 1999. As the model allows to capture potential asymmetries in the volatility spillovers, the authors find evidence for the asymmetric volatility from the stock market to the foreign exchange which is in contrast with the findings of Kanas *et al.* (2000). Furthermore, the results show that the movements in stock prices have a relatively large impact on the future changes in exchange rates while the other way around the influence is less clear. The significant volatility spillovers and asymmetric effects from the stock market to the foreign exchange market appear in four countries, i.e. the US, Japan, France and Italy.

Lizardo & Mollick (2010) examine how oil price shocks affect the value of the U.S. dollar (USD) in the long–run as well as in the short–run by adding oil prices to the monetary model of exchange rates. The results show that oil price shocks significantly explain movements in the value of the USD against major currencies during the whole examined 1975-2008 period. Changes in real oil price lead to a significant movement of the USD against net importer currencies such as Canada, Mexico and Russia. Variation in the currencies of oil importers, such as Japan, relative to the USD with increasing or decreasing oil price, is also revealed. The results thus suggest that the variation in US dollar exchange rate can influence the volatility of crude oil price and thus its forecasting accuracy. This result is important for this thesis as we are interested in the connectedness of the financial and equity markets and the commodity markets. In particular, we focus on volatility spillovers between the two types of markets.

Employing various econometric methods such as cointegration, VAR model and ARCH type models, Zhang *et al.* (2008) explore three spillover effects, specifically mean spillover, volatility spillover and risk spillover. A significant long-term equilibrium interacting relationship between the two markets is revealed implying that the US dollar depreciation during the 2000-2005 examined period was an crucial factor in driving up the international crude oil price. Further, Zhang *et al.* (2008) find evidence for volatility and clustering in both market prices with insignificant spillover effects suggesting that the immediate fluctuations in the US dollar exchange rate do not influence substantially the oil crude market. Additionally, the risk spillover between the two markets appears to be negligible concluding that the impact of the US dollar exchange rate on the oil market is only fractional. Employing several different measures of oil prices, Chen & Chen (2007) test the interaction between exchange rates and the real oil prices for G7 countries—Canada, France, Germany, Italy, Japan, the UK, and the US—by using monthly panel data from 1972 to 2005. The cointegration between the two markets has been confirmed showing that the real oil prices may have been the fundamental cause of real exchange rate movements. Moreover, using panel predictive regression estimates, Chen & Chen (2007) study the ability of real oil prices to predict future real exchange returns concluding that real oil prices have relevant forecasting power in terms of exchange returns. The out-of-sample prediction performances show major foreseeability over longer horizons.

The interest in commodity prices is not a new phenomenon, however, the recent global financial crisis as well as substantial fluctuations in commodity prices have further increased the interest on the connection between them as well as their dynamic relationship to other markets such as the equity market. An increasing volatility in commodity prices and its causes and impacts is a fundamental topic in many studies. Cashin & McDermott (2002) analyze the behavior of real commodity prices using the Economist's index of industrial commodity prices. They find that there is a downward trend in real commodity prices of about 1% per year over the observed period from 1862 to 1999 and more importantly, a substantial increase in volatility is observed. They conclude that a downward trend in real commodity prices is of little importance as it is utterly dominated by the fluctuations of prices which have a significant impact on the terms of trade. Tang & Xiong (2012) aim to explain the extensive increase in the price volatility of non-energy commodities around 2008 as a result of the financialization[1] process accelerated by the fast growth of commodity index investment and causing increased commodity price correlations. The authors find intensified price co-movements between non-energy commodity futures and oil prices since 2000, contemporaneously with the rapidly increasing index investment in commodity markets. The expanding financialization of commodities in general is documented by other studies as well (Dwyer *et al.* 2011; Vivian & Wohar 2012; Mensi *et al.* 2013; Creti *et al.* 2013; Basak & Pavlova 2016).

Increased correlation between commodity prices has induced further research. Nazlioglu *et al.* (2013) study the volatility transmission between oil and selected agricultural commodity prices, namely sugar, wheat, soybeans and corn, i.e. key agricultural products for biofuels and for food. The time period under research is divided into two, the period before the food price crisis (1986-2005) and post-crisis period (2006-2011). By employing a recently developed variance causality test, they show that the risk spills over between oil and agriculture commodity markets (except for sugar) in the post-crisis period while there is no such evidence in the period before the food crisis. Furthermore, they analyze the transmission of shocks from the oil price to agricultural markets using impulse response functions and their findings underline the previous results that the transmission of risk between energy and agriculture markets reaches substantially higher levels after the crisis. Du *et al.* (2011) also study the relationship between crude oil prices and agricultural markets and the potential transmission of their volatility over the time period from November 1998 to January 2009. They apply stochastic volatility models with parameters estimated by Bayesian Markov Chain Monte Carlo (MCMC) methods to weekly average settlement prices of crude oil, corn and wheat futures and find that the recent oil price shocks appear to have a substantial impact on agricultural commodity

[1] A situation when a substantial increase in the popularity of commodity investing triggers unusually high inflow of institutional funds into commodity futures markets is referred to as the financialization of commodities (Basak & Pavlova 2016).

markets. These results confirm their assumption about the volatility spillovers among crude oil, corn, and wheat markets after the fall of 2006 potentially caused by the increasing presence of commodity investments. In addition, various economic factors such as scalping, speculation, and petroleum inventories, are found to have a significant influence on the crude oil price volatility.

A distinct body of literature also studies the links between the commodity markets and the stock markets and the transmission of volatility between them. Creti *et al.* (2013) study the connectedness between price returns for 25 commodities and stocks. In particular, they cover various sectors such as energy, precious metals, agricultural, non-ferrous metals, food, oleaginous, exotic and livestock, including also an aggregate commodity price index, the Commodity Research Bureau (CRB) index, as well as the S&P 500 Index representing the U.S. equity market. To investigate the time evolution of correlations between the various markets during 11 years spanning from 2001 to 2011, they proxy the volatility by the daily squared returns of prices and employ the dynamic conditional correlation GARCH methodology. Creti *et al.* (2013) show that the correlations between commodity and stock markets evolve over time and fluctuate substantially. High volatility is particularly observable in the post-crisis period, the recent global financial crisis has thus played an important role, emphasizing the connectedness between commodity and stock markets and inducing further financialization of commodity markets. Furthermore, their results suggest that some commodities such as oil, coffee, and cocoa possess speculation phenomenon, their correlations with the S&P 500 Index increase when stock prices increases and decline in times of bearish equity market.

On the other hand, the safe-haven role of gold is revealed as the correlation with the stock market is mainly negative and in times of declining stock prices is less considerable. Despite the fact that there are some common features for the commodities included in the analysis, Creti *et al.* (2013) conclude that they cannot be regarded as a homogeneous asset class which is in line with empirical results provided by Vivian & Wohar (2012), who argue that commodities are too diverse to be considered as an asset class. Mensi *et al.* (2013) examine possible correlations and potential volatility spillovers across commodity and stock markets, specifically using the VAR-GARCH model they analyze the transmission between the S&P 500 Index returns and BRENT, WTI, WHEAT, GOLD, and BEVERAGE spot prices over the period from 2000 to 2011. Their results suggest a substantial correlation and volatility spillovers across commodity and stock markets revealing that the highest conditional correlations are exhibited between the S&P 500 Index and Gold and the S&P 500 Index and the WTI index. Further emerging empirical literature studying the links between the commodity and equity markets also underlines the usefulness of the analysis of volatility transmission between the two types of markets as volatility plays a crucial role in determining substitution strategies and hedging possibilities (Choi & Hammoudeh 2010; Dwyer *et al.* 2011; Silvennoinen & Thorp 2013).

A wide range of literature studying the volatility transmission among markets and across assets has used multivariate GARCH models, cointegration, structural VAR models or ARCH type models. However, these models have their limitations as they are not able to quantify spillovers in sufficient detail (Baruník *et al.* 2015). In order to better measure and capture volatility spillovers, Diebold & Yilmaz (2009) introduce a simple and intuitive measure of connectedness between assets based on forecast error variance decompositions from vector autoregressions. Several drawbacks of this approach were solved by Diebold & Yilmaz (2012) who provide an improved volatility spillover measure in which forecast-error variance decompositions are invariant to the variable ordering. This updated methodology allows us to measure both the total and directional volatility spillovers and reveals the level of intra-market spillovers. Klößner & Wagner (2014) further enhance the volatility spillover index by developing a new algorithm for the swiftly calculation of the minimum and maximum of the index over all renumerations. In this thesis, we use the extended approach proposed by Baruník *et al.* (2016). Combining the volatility spillover index methodology and the concept of positive and negative realized semivariances proposed by Barndorff-Nielsen *et al.* (2010) allows us to analyze the asymmetric spillovers using high-frequency measures.

Regarding directional spillovers, Diebold & Yilmaz (2009) analyze nineteen global equity markets from the early 1990s and find a strong evidence of divergence in the dynamics of return spillovers and volatility spillovers. Diebold & Yilmaz (2012) measure both the total and directional daily volatility spillovers among four U.S. asset classes—stocks, bonds, foreign exchange rates and commodities—from January 1999 to January 2010. The authors show that the cross-market volatility spillovers proved to have an increasing importance during the global financial crisis of 2008. Until then, the volatility transmissions across assets were quite limited. Specifically, the spillovers from the stock market to the other markets have shown to be significant after the collapse of the Lehman Brothers in September 2008.

Diebold *et al.* (2017) study the connectedness among 19 key commodities over 2011-2016 time period and their results show a clear clustering of commodities into groups that match traditional industry groupings with some exceptions. The energy sector turns out to be most important in terms of transmitting shocks to others. Baruník *et al.* (2016) employ their approach on data covering most liquid U.S. stocks in several sectors between 2004 and 2011 (thus including the period of the financial crisis as well as the pre-crisis and post-crisis periods). The results suggest there is asymmetric connectedness in the U.S. stock market. Furthermore, the positive and negative volatility transmissions show to have a different volume which changes over time in different sectors. The authors conclude that the overall intra-market connectedness of the U.S. stocks rose significantly during the recent financial crisis. Baruník *et al.* (2015) study spillovers from volatility among petroleum commodities during the 1987-2014 period and find evidence for increasing volatility spillovers that substantially change after the 2008 financial crisis. They argue that the observed higher volumes of volatility spillovers are related to the progressive financialization of commodities. Regarding the asymmetric spillovers, the prevalence of spillovers due to negative shocks corresponds to periods of increasing crude oil prices and the asymmetries in spillovers markedly declined after the financial crisis. Baruník *et al.* (2017) analyze the asymmetric response to shocks in the foreign exchange market using high-frequency data of widely traded currencies between 2007 and 2015 and find that the spillovers from bad volatility dominate. The complete framework for defining, measuring, and monitoring connectedness of markets has been summarized in (Diebold & Yilmaz 2015).

Our hypothesis that volatility spillovers are likely to exhibit different magnitude based on whether the shock originates from negative or positive returns has its roots in a broad area of research. As an example, Barberis (2013) argue that market agents possess asymmetric attitudes toward good and bad news and related outcomes and that on average, people are more sensitive to losses than to gains of the same volume. Regarding good and bad volatility, by which we understand volatility stemming from positive and negative returns, respectively, the literature has mainly focused on return-based measures which we also employ in our analysis. Patton & Sheppard (2015) and Feunou *et al.* (2013) use realized semivariance measures of returns to study the differences between the two volatilities and focus on their impact on the equity returns' dynamics. According to Feunou *et al.* (2013), the decomposition of volatility caused by positive and negative news can be perceived as a level of downside and upside risk. Segal *et al.* (2015) decompose aggregate uncertainty into good and bad volatility components, associated with positive and negative innovations to macroeconomic growth to study whether and how the uncertainty increases or decreases aggregate growth and asset prices. Apart from variable supply and demand on the market, there are various reasons for bad and good volatility. Bad volatility may result from a single highly important negative news, increased political risk, slowdown and worsening of economic conditions, and so on. On the other hand, good volatility may be caused by positive macroeconomic, sectoral, or firm-specific announcements (Baruník *et al.* 2016).

Chapter 3

Methodology

In this section, we describe the theoretical background behind the specific hypotheses and methodology used to estimate the effects of volatility in commodity markets. First, we discuss the realized measures—realized variance and its decomposition into positive and negative semi-variances. Then, we present the methodology behind the construction of the spillover index and the measures of spillover asymmetry. We employ the connectedness measurement methodology which was originally developed by Diebold & Yilmaz (2009) and Diebold & Yilmaz (2012), using a generalized vector autoregressive framework. Specifically, we use variance decomposition which helps to demonstrate the amount of information each variable contributes to the other variables in the regression and it shows how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables Diebold & Yilmaz (2013). Such method allows us to measure both the total and directional volatility spillovers and will reveal the level of intra-market spillovers.

To study the volatility-spillover asymmetries, we will employ the volatility spillover index devised in Diebold & Yilmaz (2009) as modified by Baruník *et al.* (2016). Based on the concept of realized semi-variances presented by Barndorff-Nielsen *et al.* (2010), the model allows us to decompose the realized variance into parts corresponding to positive and negative shocks in the market. Focusing on the intra–market spillovers, we estimate the size of the spillovers using these asymmetric spillover indices.

3.1 Realized measures

Following Baruník *et al.* (2016), we first sum up the construction of the measures of volatility. Let us consider a continuous-time stochastic process for logarithmic prices of an asset, p_t. This price evolves over a given time period $t \in \langle 0, T \rangle$. The price process consists of two components—a continuous component and a pure jump component—and takes the following form:

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t, \tag{3.1}$$

where μ represents a predictable drift process, σ_s a strictly positive volatility process, W a standard Brownian motion and J the pure jump. All variables used in this equation are adapted to a common filtration F. The quadratic variation of the process is then defined as:

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0<s\leq t} \triangle p_s^2, \tag{3.2}$$

where $\triangle p_s = p_s - p_{s-}$ represent possible present jumps. The first term on the right-hand side of this equation denotes the integrated variance of the process, which is observed to be equal to zero Andersen *et al.* (2001).

As proposed by Andersen *et al.* (2001) and Barndorff-Nielsen (2002), the sum of squared returns, $\sum_{i=1}^{n} r_i^2$, can be used as a natural estimator of the quadratic variation. If we suppose that the intraday logarithmic returns $r_i = p_i - p_{i-1}$ are equally spaced on the interval $[0, t]$, then the sum, denoted RV, converges in probability to the quadratic variation of the underlying price process, or $[p_t, p_t]$, as $n \to \infty$. If we use a small-enough interval between observations, we can approximate the quadratic variation using this concept. This simple approach, however, does not differentiate between positive and negative returns. Therefore, we cannot focus individually on positive and negative shocks to prices and the volatility these shocks induce. In reality, the reactions of markets to positive and negative shocks differ, which is why Barndorff-Nielsen *et al.* (2010) derived the concept of dividing the realized variances into positive and negative realized semi-variances.

3.1.1 Realized semi-variances

Since markets may differ in ways they cope with volatility due to general increase and decrease of prices, Barndorff-Nielsen *et al.* (2010) define signed returns as follows:

$$RS^{-} = \sum_{i=1}^{n} r_i^2 I_{[r_i<0]} \tag{3.3}$$

$$RS^{+} = \sum_{i=1}^{n} r_i^2 I_{[r_i>0]} \tag{3.4}$$

By definition, $RV = RS^{-} + RS^{+}$. RS^{-} represents a measure of downside risk and captures the variation determined only by falls of the underlying prices; RS^{+}, on the other hand, captures the variation determined by increases in the price of the asset. The limiting behavior of RV is transferred to RS^{-} and RS^{+}, with both being equal to exactly one half of the integrated variance and the sum of squared jumps due to negative and positive jumps, respectively.

Moreover, the positive and negative realized semi-variances correspond to the good and bad states of the underlying variable and serve as a proxy for good and bad volatility, respectively. Consequently, we may observe asymmetries in the volatility spillovers due to these different states as they may spread differently across markets (Baruník *et al.* 2016).

3.2 Spillover index

In this section, we introduce a measure of volatility spillovers which will allow for the distinction between negative and positive jumps. Based on the approach of Diebold & Yilmaz (2012), Baruník *et al.* (2016) propose an extension in the form of including the above-defined concept of realized semi-variances.

The initial uniform spillover index introduced by Diebold & Yilmaz (2009) was built on the variance decomposition of the forecast errors in a vector autoregressive model (VAR). These measures record how much of the H-step-ahead forecast error variance of some variable i is due to innovations in another variable j and hence provide a simple way of measuring volatility spillovers (Baruník *et al.* 2016). However, this methodology has several limitations. A substantial drawback of the original Diebold and Yilmaz framework is that the variance decompositions employ the Cholesky factorization of the covariance matrix of the VAR residuals, which may lead to the dependence of the variance decomposition results on the ordering of variables in the underlying VAR process. Moreover, the initial spillover index allows to measure only the total spillovers (the transmission *from* (*to*) one market *to* (*from*) all other markets) while one may be interested also in the directional spillovers, i.e. how the volatility *from* one particular market i is spilled over *to* another specific market j and vice versa. Further limitations concern the application of the methodology only on spillovers across identical asset in different countries whereas many other types of spillovers, such as spillovers across asset classes within one country, may be of interest. These methodological shortcomings were overcome by Diebold & Yilmaz (2012), who develop a generalized vector autoregressive framework which makes forecast error variance decomposition invariant to the variable ordering and enables to measure not only total but also directional volatility spillovers.

3.2.1 Total spillover index

In this section, we shed light on the construction of the extended spillover index as developed by Diebold & Yilmaz (2012), which follows directly from the variance decomposition in a generalized VAR framework instead of employing the Cholesky factor orthogonalization. Simply put, the forecast error variance decomposition indicates what percent of the k-step ahead forecast error variance is due to which variable (Cochrane 2005). First, consider a covariance stationary N-variable VAR (p):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \epsilon_t, \tag{3.5}$$

where $x_t = (x_{1t}, x_{2t}, ..., x_{nt})$ is an N-dimensional vector, Φ_i, with $i = 1, ..., p$, stands for coefficient matrices and $\epsilon_t \sim N(0, \Sigma_\epsilon)$ is a vector of independently and identically distributed disturbances. In our subsequent empirical work, a vector x will represent realized variances of N assets, more precisely positive or negative realized semivariances. Assuming covariance stationarity, the moving average (MA) representation of the VAR exists and is given by

$$x_t = \sum_{i=0}^{\infty} \Psi_i \epsilon_{t-1}, \tag{3.6}$$

where the $N \times N$ coefficient matrices Ψ_i obey the following recursive definition:

$$\Psi_i = \Phi_1 \Psi_{i-1} + \Phi_2 \Psi_{i-2} + ... + \Phi_1 \Psi_{i-1} = \sum_{j=1}^{p} \Phi_j \Psi_{i-j}, \tag{3.7}$$

with Ψ_0 being an $N \times N$ identity matrix I_N and with $\Psi_i = 0$ for $i < 0$.

The total spillover index developed by Diebold & Yilmaz (2012) is composed of two parts—own variance shares and cross variance shares. Own variance shares are defined as fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1, 2, ..., N$. Cross variance shares, or spillovers, are defined 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 $i \neq j$. Following the notation used by Baruník *et al.* (2016), the H-step-ahead generalized forecast error variance decomposition matrix then looks as follows:

$$\omega_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{\Psi}_h \mathbf{\Sigma}_\epsilon \mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i' \mathbf{\Psi}_h \mathbf{\Sigma}_\epsilon \mathbf{\Psi}_h' \mathbf{e}_i)}, \tag{3.8}$$

where $\mathbf{\Sigma}_\epsilon$ is the variance matrix for the error vector, ϵ_t, σ_{jj} is the standard deviation of the error term for the j^{th} equation, $\mathbf{e}_i$ is the selection vector, with one as the i^{th} element and zeros otherwise, and $\mathbf{\Psi}_h$ are moving average coefficients from the forecast at time t. Because the shocks to each variable are not necessarily orthogonalized, the sum of contributions to the variance of forecast error (i.e. the row sum of the elements of the variance decomposition table) is not necessarily equal to one:

$$\sum_{j=1}^{N} \omega_{ij}^{H} \neq 1 \tag{3.9}$$

Therefore, to be able to use the information available in the variance decomposition matrix in the calculation of the spillover index, we normalize each entry of the variance decomposition matrix by the row sum:

$$\tilde{\omega}_{ij}^{H} = \frac{\omega_{ij}^{H}}{\sum_{j=1}^{N} \omega_{ij}^{H}} \tag{3.10}$$

This step ensures that $\sum_{j=1}^{N} \tilde{\omega}_{ij}^{H} = 1$ and $\sum_{i.j=1}^{N} \tilde{\omega}_{ij}^{H} = N$ (i.e. the contributions of spillovers from volatility shocks are normalized by the total forecast error variance (Baruník *et al.* 2016)). Diebold & Yilmaz (2012) then define the spillover index, a measure of the contribution of spillovers from volatility shocks across the variables in the system to the total forecast error variance, as:

$$\mathcal{S}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^{H} \tag{3.11}$$

3.2.2 Directional spillovers

The crucial improvement achieved by using the generalized VAR framework lies in the fact that we are now able to identify the directional spillovers, i.e. we can decompose the total spillover to those coming *from* and *to* each observed asset (Diebold & Yilmaz 2012). The directional spillovers received by asset i from all other assets j are defined as follows:

$$\mathcal{S}_{i \leftarrow \bullet}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ij}^{H} \tag{3.12}$$

Similarly, the directional spillovers transmitted by asset i to all other assets j can be measured as:

$$\mathcal{S}_{i \rightarrow \bullet}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\omega}_{ji}^{H} \tag{3.13}$$

3.2.3 Net spillovers and net pairwise spillovers

Once we have obtained the directional spillovers, following Diebold & Yilmaz (2012), it is then straightforward to derive a simple measure of net spillovers as the difference between gross volatility shocks transmitted to and received from all other assets:

$$\mathcal{S}_{i}^{H} = \mathcal{S}_{i \rightarrow \bullet} - \mathcal{S}_{i \leftarrow \bullet}^{H} \tag{3.14}$$

As explained by Baruník *et al.* (2016), the above measure tells us how much each asset contributes to the volatility in other assets in net terms. The net pairwise spillovers between two assets, i and j, can then be simply computed as the difference between the gross shocks transmitted from asset i to asset j and those transmitted from asset j to asset i:

$$\mathcal{S}_{ij}^{H} = 100 \times \frac{1}{N}\left(\tilde{\omega}_{ji}^{H} - \tilde{\omega}_{ij}^{H}\right) \tag{3.15}$$

3.3 Bad and good volatility

The innovation brought by Baruník *et al.* (2016) lies mainly in fitting the N-variable vector auto regression model to semivariances defined above instead of volatility itself. This combined methodology allows for focusing individually on effects that one asset's volatility has on the other, while also differentiating between negative and positive shocks to the asset price. In particular, using this method, we are able to account for spillovers due to negative returns ($\mathcal{S}^{-}$) and positive returns ($\mathcal{S}^{+}$) and also directional spillovers from volatility due to negative returns ($\mathcal{S}^{-}_{i\leftarrow\bullet}, \mathcal{S}^{-}_{i\rightarrow\bullet}$) and positive returns ($\mathcal{S}^{+}_{i\leftarrow\bullet}, \mathcal{S}^{+}_{i\rightarrow\bullet}$).

Using the extension developed by Baruník *et al.* (2016), we are able to isolate asymmetric volatility spillovers by replacing the vector of volatilities $\boldsymbol{RV_t} = (RV_{1t}, ..., RV_{nt})'$ defined above with the vector of negative semivariances, $\boldsymbol{RS_t^-} = (RS_{1t}^-, ..., RS_{nt}^-)'$, or the vector of positive semivariances, $\boldsymbol{RS_t^+} = (RS_{1t}^+, ..., RS_{nt}^+)'$[1]. This approach allows to distinguish between the effects of positive and negative shocks on volatility spillovers. We are thus able to test which volatility (good or bad) matters more for volatility spillover transmission or whether their effects are similar in magnitude.

3.3.1 Spillover asymmetry measure

Following Baruník *et al.* (2016), we define the spillover asymmetry measure $\mathcal{SAM}$ as the difference between positive and negative spillovers:

$$\mathcal{SAM} = \mathcal{S}^{+} - \mathcal{S}^{-} \tag{3.16}$$

where $\mathcal{S}^{+}$ and $\mathcal{S}^{-}$ are volatility spillover indices due to positive and negative semivariances ($\mathcal{RS}^{+}$ and $\mathcal{RS}^{-}$), respectively, with an H-step-ahead forecast

[1] This notation excludes the H index for ease of display, however, it remains a valid parameter for the estimation of spillover indices

at time t. Defining the measure in this way allows for a straightforward interpretation of the results. In the case when $\mathcal{SAM} \geq 0$, the spillovers from positive realized semivariances are larger in magnitude than those coming from negative realized semivariances and vice versa in the case when $\mathcal{SAM} \leq 0$. When $\mathcal{SAM} = 0$, the spillovers coming from $\mathcal{RS}^{+}$ and $\mathcal{RS}^{-}$ are of the same magnitude.

Chapter 4

Data

In our analysis, we use five-minute high-frequency data to study volatility spillovers and their asymmetries on the commodity market and how the commodity market's volatility is transmitted to the stock market and the other way around. From four different commodity classes—energy, precious metal, grain and fiber futures—we select four widely traded commodities (one from each) to represent each sector, namely Crude oil, Gold, Corn and Cotton. As we are also interested in the connectedness between the commodity market and the stock market, we use data for the S&P 500 Index to represent the stock market. The data spans from January 2, 2002 to December 31, 2015, which means that the data set includes the global financial crisis of 2008 as well as the pre-crisis period and the recovery phase. The selected time period thus enables the study of an interesting development in the financial markets during the disturbance period. The data were obtained from Tick Data, Inc., one of the leading providers of historical data from stock, futures, options and forex markets.

In this chapter, we first analyze in Section 4.1 each of the selected commodities with a particular focus on the features these commodities that may have an effect on the interplay with other markets. In Section 4.2, we explain what adjustments of these data were necessary for the purposes of our analysis. Section 4.3 provides some descriptive statistics of the data and finally, in Section 4.4, we discuss the computation of realized variances and semivariances as accurate measures of volatility.

4.1 Selected commodities

The commodities selected for this analysis can be divided into two subgroups. Firstly, soft commodities, represented by Cotton and Corn, include primarily agricultural products such as grains, food, fiber or livestock. Secondly, hard commodities, represented by Gold and Crude Oil, are commodities that are mined, such as metals and energy products. We select these four major commodities because they are among the most traded commodities in their specific branches and thus enable us to cover a wide spectrum of the commodity markets.

This section provides a brief description of the particularities of markets for each of the commodity covered in our analysis. The reason why we analyze these features is to understand the forces that may govern the transmission of volatility across markets. The nature of the relationships between the selected commodities is a crucial determinant of the behavior of agents in the markets and thus of the reasons why volatility may spill over to other markets and how. We include also a brief description of the Standard and Poor's 500 Index and its relationship with our selected commodities.

Crude oil

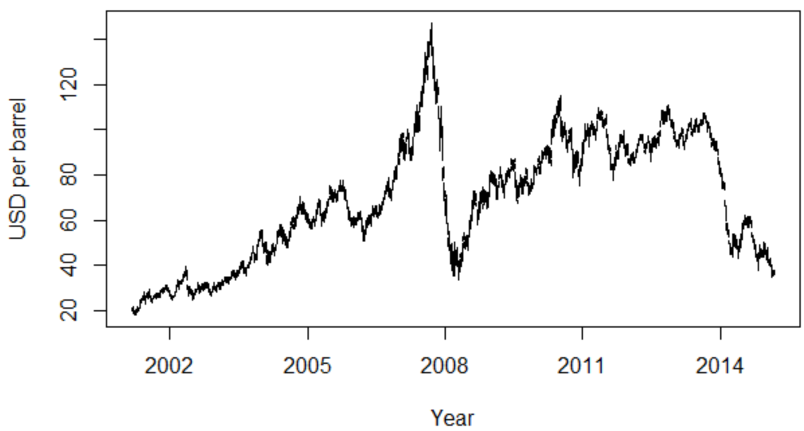
Crude oil (CL) represents the most important natural resource of the industrialized nations. Due to the fact that it cannot be replaced naturally at the rate at which it is consumed, it is considered a non-renewable resource and scarcity is thus one of its defining features. It is typically recovered from the ground by oil drilling following extensive geological research and is thus costly to obtain, however, its wide and intensive use in most major industries makes it well worth it. The Oil Market Report of the International Energy Agency (IEA 2017) estimates that nearly 96 million barrels of oil per day, or more than 35 billion barrels per year, have been used globally in 2016. The world's economy is largely dependent on fossil fuels such as crude oil, which makes it possible for its exporters to extract significant profits from its sale. It is thus not surprising that a large body of literature has dealt with the study of its impact on the economy.[1] Recent literature also recognizes the growing interaction between

[1] See Vo (2011) for a concise review of the literature dealing with the impact of fluctuations in the price of Crude oil on the economy

oil markets and financial markets (Zhang *et al.* 2008).

The prices in the oil market are set primarily by futures contracts traders and speculators. The presence of speculators in these markets largely underlies the motivation of this thesis and will be a recurring source of motivation of the present analysis. In particular, we are interested in how the volatility present in the markets for our selected commodities transfers into other observed markets. Figure 4.1 shows the development of the price of crude oil futures between 2002 and 2015.

Figure 4.1: Price of Crude oil futures over time



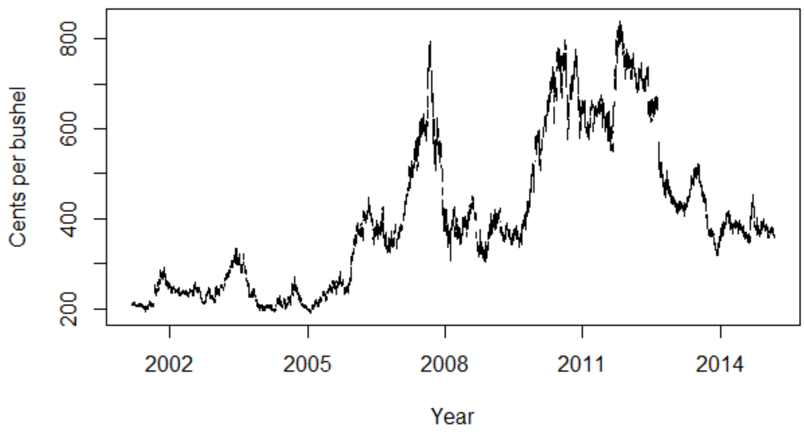
Source: Author based on data from Tick Data, Inc.

Corn

Corn (CN) is among the most important grain crops on Earth, being widely used not only directly as food for humans, but also for the production of animal feed or corn ethanol used as a biomass. According to estimates by the United States Department of Agriculture USDA (2016), around 970 million metric tons of corn has been produced globally in the 2015/2016 season, with the U.S. being responsible for about one third of this amount. Its importance and widespread supply and demand make it extremely price-sensitive, with natural and other conditions in different parts of the world influencing the production (and thus price) levels significantly. Notably, in the recent years, China has been a significant source of uncertainty in world corn trade because of changing government subsidies of the Chinese Communist Party, making China's corn trade difficult to predict (USDA 2016).

All grains, including corn, are usually quoted in cents per bushel. Trading corn futures can be a fairly seasonal matter, because corn is planted in the spring and harvested in the fall. Therefore, trading in the winter months is guided primarily by demand and is relatively calm, while the summer months are the ones that usually see the most volatility due to new weather reports coming in. On the demand side, since a substantial part of the world's supply of corn is used to produce ethanol, there is a clear link between corn and other commodities used to produce ethanol, such as crude oil and gasoline. Figure 4.2 shows the development of the price of Corn futures between 2002 and 2015.

Figure 4.2: Price of Corn futures over time

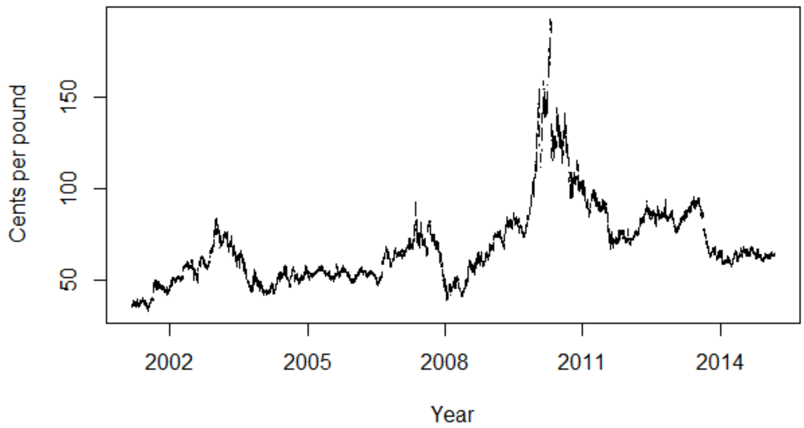


Source: Author based on data from Tick Data, Inc.

Cotton

Cotton (CN) is the most classical commodity in our sample. It has been extensively cultivated in India for thousands of years before being hugely popularized by the British colonial power in the 18th century. In the 2015/2016 season, nearly 97 million 480-pound bales of cotton have been produced globally (USDA 2016). Figure 4.3 shows the development of the price of Cotton futures between 2002 and 2015.

Figure 4.3: Price of Cotton futures over time

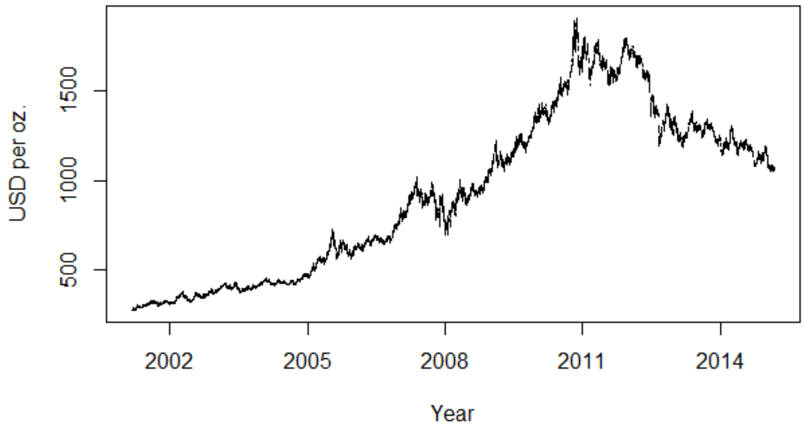


Source: Author based on data from Tick Data, Inc.

Gold

Gold (GC) has historically been the most prominent precious metal. It is widely used as an investment commodity due to its scarcity and character of a luxury good that has a low number of substitutes. At the same time, gold is used in the production of electronics (due to the fact that it is a highly efficient conductor that is able to carry tiny electrical charges) and other fields, such as the aerospace industry or dentistry and medicine. Gold is generally believed to be a relatively safe investment over the long term, even though the price can be volatile in the short term. Many investors use gold as a hedge against adverse events since its value typically increases in response to events that decrease the value of paper investments such as stocks and bonds. Figure 4.4 shows the development of the price of Gold futures between 2002 and 2015.

Figure 4.4: Price of Gold futures over time



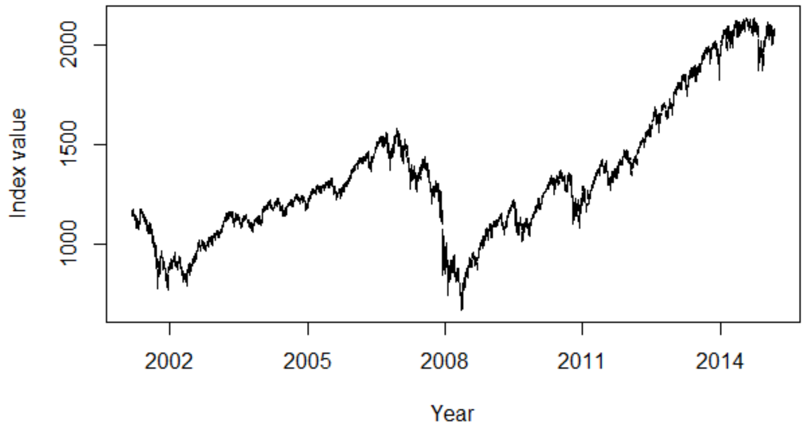
Source: Author based on data from Tick Data, Inc.

Standard and Poor's 500 Index

Standard and Poor's 500 Index is a capitalization-weighted index of 500 stocks. The index is designed to measure the performance of the broad domestic economy through changes in the aggregate market value of 500 stocks representing all major industries.[2] Figure 4.5 shows the development of the value of the S&P 500 Index between 2002 and 2015.

[2]Source: https://www.bloomberg.com/quote/SPX:IND

Figure 4.5: Value of the S&P 500 Index over time



Source: Author based on data from Tick Data, Inc.

4.2 Data construction

In order to prevent estimation bias that may be caused by low trading activity on the market, we exclude weekends, U.S. federal holidays and some state holidays such as the Black Friday. As all five selected futures are traded on different Exchanges, the number of observations per trading day as well as the number of days when the exchange was open varies among the analyzed commodities, as seen in Table 4.1 which shows a summary of the original data set before adjustments.

For the purposes of our analysis, we exclude all days on which at least one of the Exchanges was closed. Figure 4.6 depicts the variation in the number of observations per day for each observed market. We discard days on which, for at least one variable, more than 20% observations is missing as compared to the average trading day. An exception to this rule is Cotton whose numbers of observations per day are, somewhat surprisingly, extremely unstable and their exclusion would lead to the loss of a significant amount of observations. Therefore, we will treat Cotton futures with care and use a sample that excludes Cotton entirely as a robustness check. Nevertheless, this harmonization of data across markets enables us to eliminate days when there are some missing observations due to special opening hours of the Exchanges (e.g.

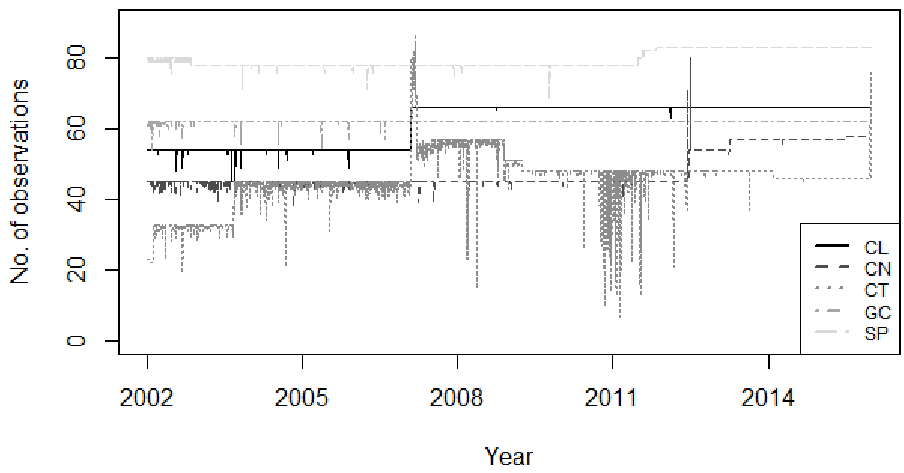
Table 4.1: Original data set - summary of observations

Variable	Exchange	No. of days	Total no. of observations	Average no. of observations per day
Light Crude (CL)	New York Mercantile Exchange (NYMEX)	3 576	219 138	61.28
Corn (CN)	Chicago Board Of Trade (CBOT)	3 526	167 758	47.58
Cotton (CT)	Intercontinental Exchange	3 514	160 086	45.56
Gold (GC)	Commodity Exchange Inc. (COMEX)	3 573	220 618	61.75
S&P 500 Cash Index	CME Group	3 524	279 567	79.33

Source: Author based on data from Tick Data, Inc.

the day before Independence Day) which could lead to a bias in our estimation.

Figure 4.6: Observations per day over the observed time period



Source: Author based on data from Tick Data, Inc.

These adjustments lead to the final sample which consists of 3,437 trading days. The average number of observations per day differs across commodities (from 46 to 80) since we include trading days even if the opening hours on these days are not common for all Exchanges. As described in more detail in Section 4.4, we use the 5-minute data only to compute daily realized measures, therefore, using different trading hours is not an issue.

4.3 Descriptive statistics

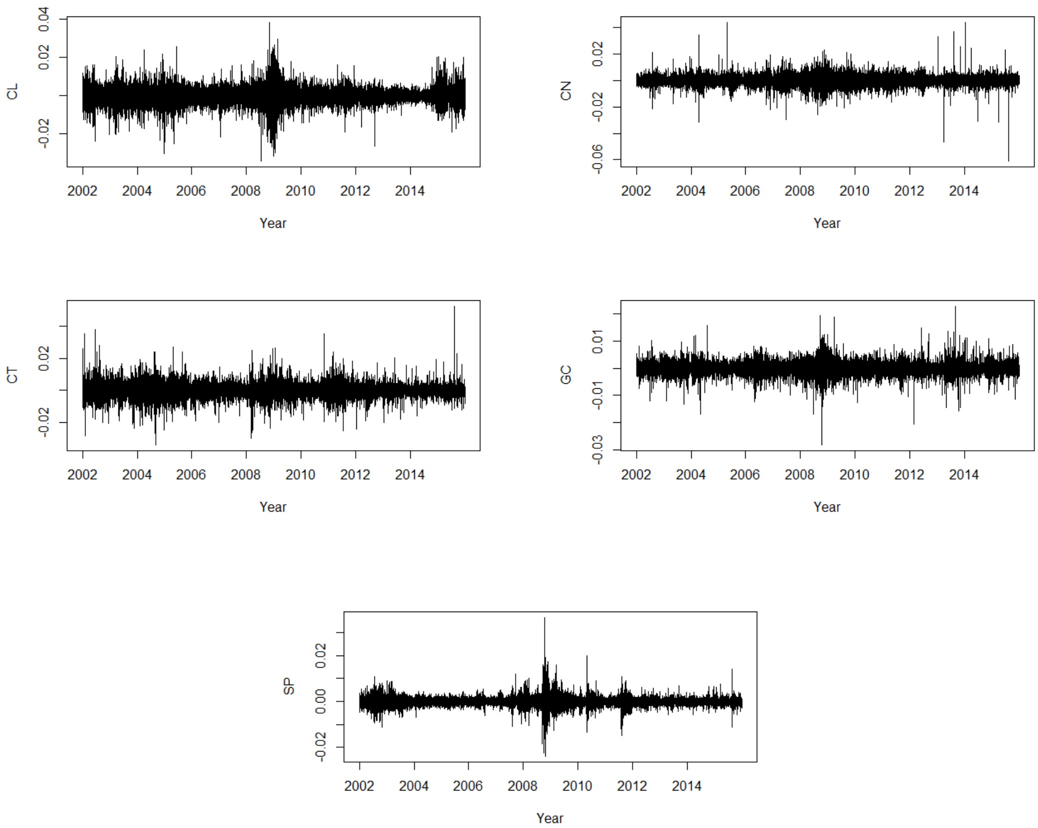
In this section, we explore the final adjusted data set. We calculate the 5-minute return at time t as the change in log price between times $t-1$ and t. Overnight returns are not computed in order to avoid possible distortion. We provide some descriptive statistics of the calculated returns in Table 4.2. Summary statistics are relatively similar for all observed variables. The mean return is close to zero for all series—small and positive for Crude oil, Corn and Gold, and small and negative for Cotton and the S&P 500 Index. The returns for Crude oil and Cotton are spread out over a wider range of values as their standard deviations are the highest, while the S&P 500 Index and Gold exhibit the lowest variation. The volatilities of high-frequency returns are well documented by Figure 4.7. We observe that the volatility varies substantially over the observed time period. During the unstable periods in 2008 and 2009 that were caused by the global financial crisis, the data shows a significant increase in the volatility of returns, a pattern that is observable for all time series except for Cotton, which exhibits relatively high volatility during the whole analyzed time period. The negativity of skewness for the series of Crude oil, Corn and Gold indicates that their distributions of returns are skewed left and points to frequent small gains which are underlined by the slightly positive mean of the series. The returns on the Corn futures and the S&P 500 Index exhibit positive skewness (the right tails of the distribution of returns are larger relative to the left ones). The S&P 500 Index reached the highest value not only for skewness but also for kurtosis. This means that the distribution of its returns tends to have more outliers than our selected commodity markets, which have lighter tails, however, inspecting the plots of 5-minute returns in Figure 4.7, we can conclude that outliers are to some extent present in all series.

Table 4.2: Descriptive statistics of 5-minute returns

Variable	Mean	Min	Max	SD	Skewness	Kurtosis	Observations
Light Crude (CL)	0.0000089	-0.0341775	0.0384028	0.0022465	-0.1286002	11.5111832	208 705
Corn (CN)	0.0000016	-0.0609825	0.0439631	0.0019734	-0.1057595	24.3690218	161 029
Cotton (CT)	-0.0000091	-0.0338341	0.0523929	0.0020779	0.1040618	20.5265105	153 669
Gold (GC)	0.0000029	-0.0280942	0.0227638	0.0011010	-0.2001009	19.0230779	209 576
S&P 500	-0.00000032	-0.02389203	0.03666528	0.00106975	0.27506588	30.44928775	270 363

Source: Author based on data from Tick Data, Inc.

Figure 4.7: 5-minute returns



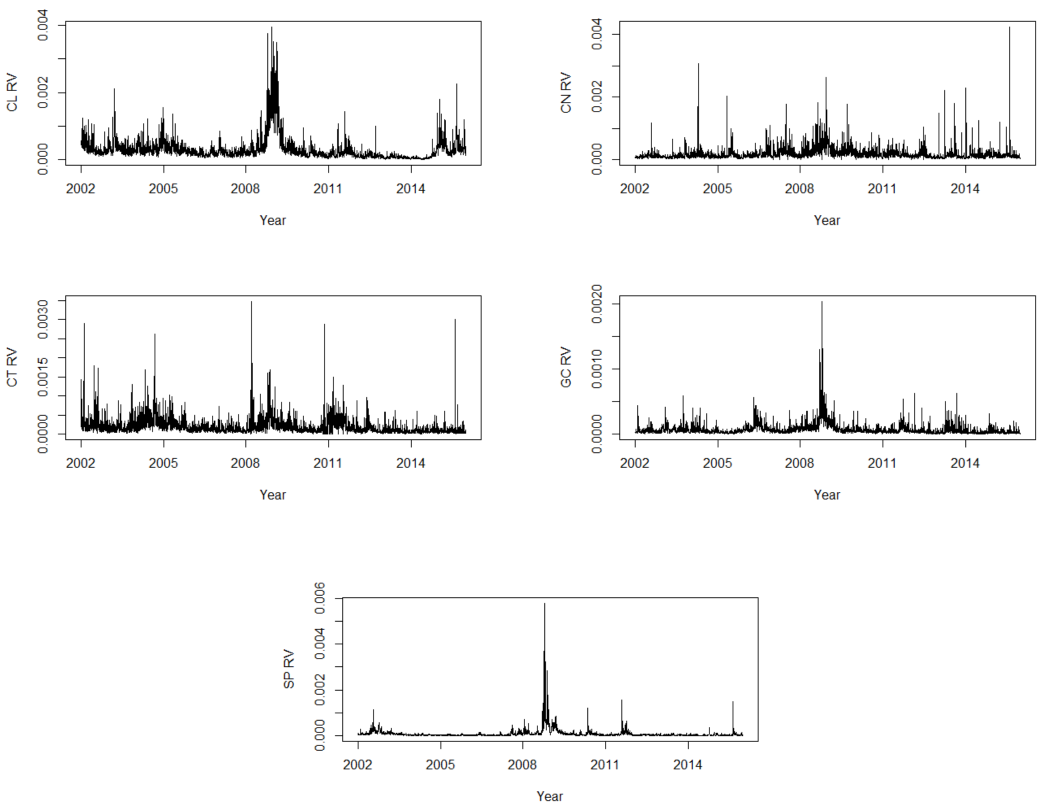
Source: Author based on data from Tick Data, Inc.

4.4 Realized variance and semivariance

In order to construct an accurate measure of volatility, we compute the realized variance as a sum of squared intraday logarithmic 5-minute returns for each trading day in our sample. Moreover, as we are also interested in whether the volatility is asymmetric, we further compute positive and negative semivariances as sums of positive and negative intraday returns, respectively. The methodology for the computation of realized measures is described in more detail in Section 3.1. In Figures 4.8 – 4.10, the plots of daily realized variances and semivariances for each observed variable are presented. We can observe that the highest realized variances (both positive and negative) are reached during the mid-2008 and 2009 which corresponds to the turbulent periods during the global financial crisis. This pattern is particularly substantial for the S&P 500

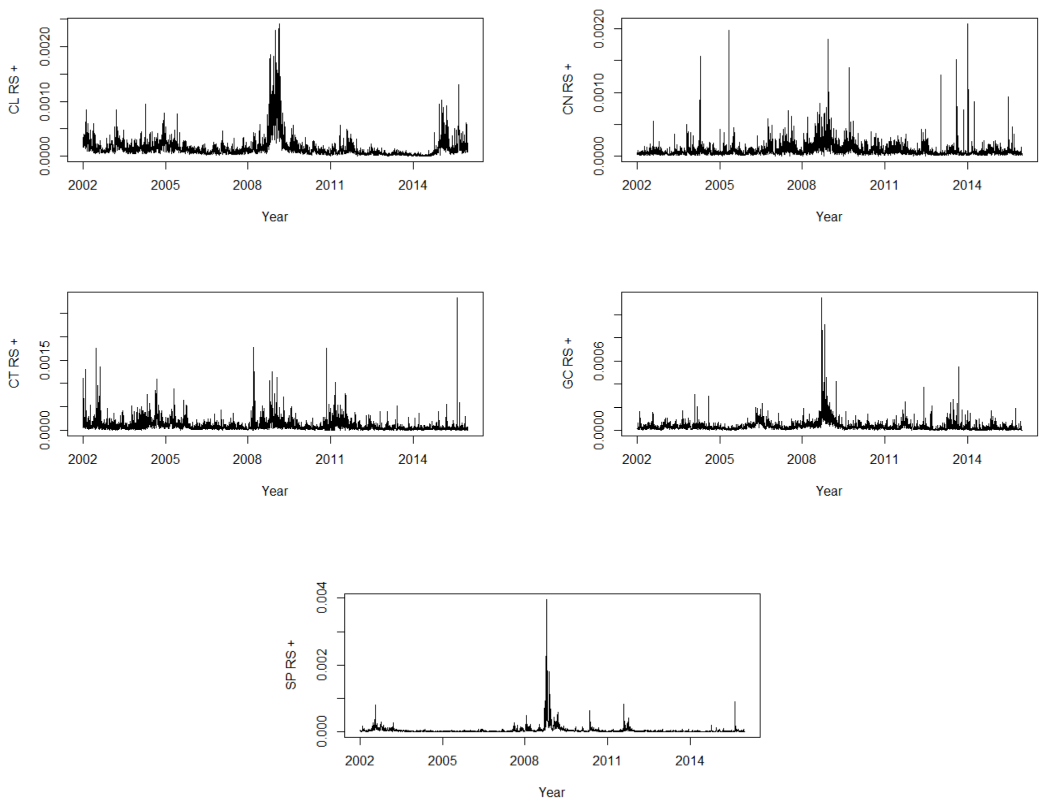
Index which is not surprising as the index is based on the market capitalizations of 500 largest companies listed on the U.S. exchange stocks. Prices in markets that are tied more firmly to the financial markets tend to be affected the most by financial crises. Accordingly, the Crude oil and Gold markets were influenced by the financial crisis more as compared to the Cotton and Corn markets.

Figure 4.8: Daily realized variances



Source: Author's computations.

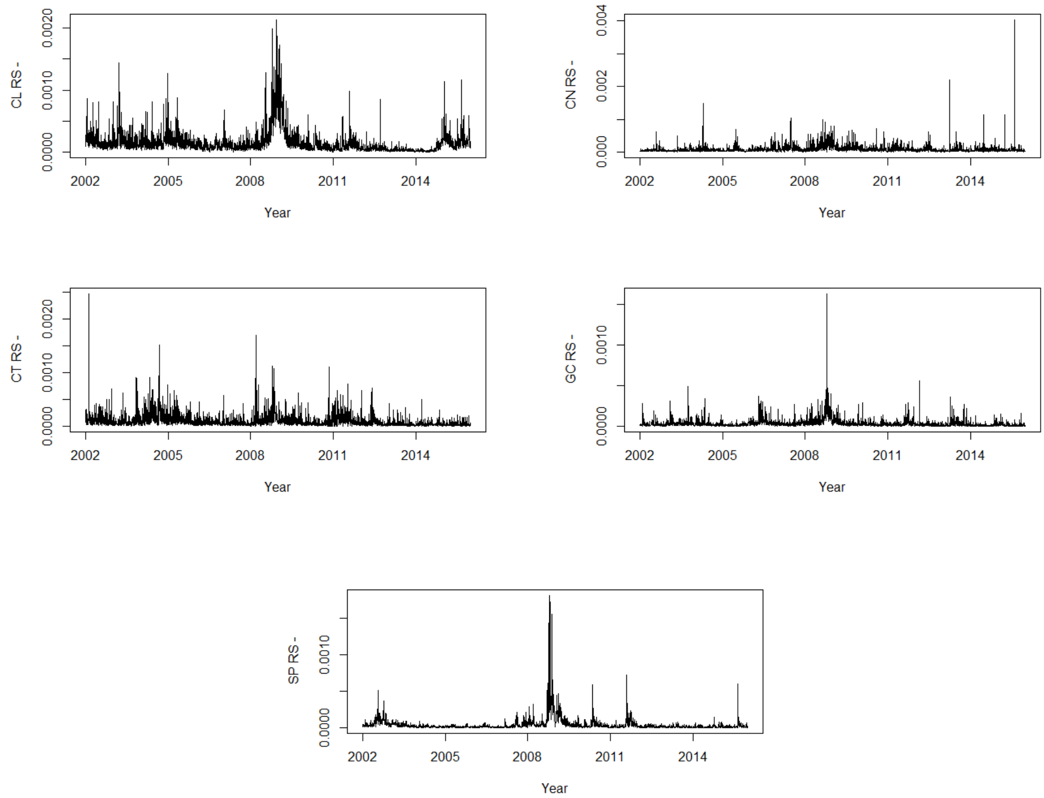
Figure 4.9: Daily positive realized semivariances



Source: Author's computations.

Tables 4.3 – 4.5 reveal some interesting descriptive statistics regarding the daily realized measures. The highest mean, as well as the highest standard deviation of realized variance, is reported for Crude oil. The distributions of realized measures for all analyzed commodities exhibit positive skewness, which means that the majority of the values are smaller than the mean. For all distributions of realized measures the kurtosis has shown to be substantially different from 3, which is the kurtosis of a univariate normal distribution. Therefore, based on these two statistical measures we can conclude that none of the distributions of realized measures is normally distributed.

Figure 4.10: Daily negative realized semivariances



Source: Author's computations.

Comparing the statistics of positive realized semivariances (RS) with those of negative RS, we can conclude that there is the only a negligible difference in the mean and thus we may say that both semivariances contribute to the realized variance with more or less similar magnitude. While the values for standard deviation are slightly higher for negative RS in the cases of Crude oil, Corn, and Gold, this does not apply to Cotton and the S&P 500 Index. For the latter two variables, the positive RS are more volatile than the negative ones. Therefore, we cannot infer based on these observations that the negative shocks in our sample imply higher volatility. Furthermore, we can observe some significant differences in the values of skewness and kurtosis. In particular, the kurtosis of the Corn distribution is more than three times higher for the negative realized semivariances than for the positive ones. On the contrary, inspecting the S&P 500 Index the values of both skewness and kurtosis are considerably higher for positive semivariances. This suggests that the high level of kurtosis of the distribution of realized daily variances for the S&P 500 Index comes from the positive semivariances. Examining the statistics of all distributions with an emphasis on the kurtosis, we can deduce that their shape is leptokurtic which is characterized by thick tails and a very tall and thin peak (Davidson & MacKinnon 1993).

Table 4.3: Descriptive statistics of daily realized variances

Variable	Mean	Min	Max	SD	Skewness	Kurtosis	Observations
Light Crude (CL)	0.0003065	0.0000093	0.0039532	0.000343	4.0789507	27.2559129	3437
Corn (CN)	0.00018	0.00000	0.00425	0.00020	6.71499	89.18923	3437
Cotton (CT)	0.00019	0.00000	0.00348	0.00022	4.93142	48.00934	3437
Gold (GC)	0.0000739	0.0000039	0.0020434	0.0000931	6.9574072	95.6782445	3437
S&P 500	0.0000900	0.0000025	0.0057833	0.0002180	10.9549756	193.8430740	3437

Source: Author's computations.

Table 4.4: Descriptive statistics of daily realized positive semivariances

Variable	Mean	Min	Max	SD	Skewness	Kurtosis	Observations
Light Crude (CL)	0.0001509	0.0000056	0.0024102	0.0001825	4.8824188	39.6556808	3437
Corn (CN)	0.000091	0.000000	0.002084	0.000113	7.460891	97.780711	3437
Cotton (CT)	0.000096	0.000000	0.002833	0.000133	6.904429	90.979120	3437
Gold (GC)	0.0000362	0.0000014	0.0011482	0.0000485	8.4376699	135.7749452	3437
S&P 500	0.0000453	0.0000014	0.0039692	0.0001240	14.6075444	351.1167638	3437

Source: Author's computations.

Table 4.5: Descriptive statistics of daily negative realized semivariances

Variable	Mean	Min	Max	SD	Skewness	Kurtosis	Observations
Light Crude (CL)	0.0001556	0.0000036	0.0021295	0.0001877	4.0006299	25.8312976	3437
Corn (CN)	0.000091	0.000000	0.004041	0.000124	13.022621	337.589790	3437
Cotton (CT)	0.000097	0.000000	0.002475	0.000125	5.405588	63.384144	3437
Gold (GC)	0.0000377	0.0000021	0.0016285	0.0000563	9.7747490	209.6757499	3437
S&P 500	0.00004471	0.00000088	0.00181411	0.00010216	8.55460505	104.03274277	3437

Source: Author's computations.

Chapter 5

Results

In this chapter, we provide a full-sample analysis of volatility spillovers between two asset classes—stocks and commodities—as well as volatility spillovers between different commodity markets. As detailed above, this approach can help us detect to what extent expectations in the markets change in reaction to events in other markets and how the connectedness between different class assets evolves. Since volatility is regarded as a proxy for market risk, the direction and intensity of its spillovers, which will be the central theme of the analysis presented in this chapter, are of high interest especially because of their major importance in times of financial crises. The covered sample, which includes sufficient amounts of observations before, during and after the global financial crisis of 2008, enables a thorough study of the effects that a major crisis may have on volatility spillovers across different markets. For all estimations and computations presented in this chapter, we use the common, freeware statistical software R studio.

The remainder of this chapter proceeds as follows. First, in Section 5.1, we briefly summarize the selection of our model. In Section 5.2, we inspect the level of overall volatility spillovers. For further details, we decompose the Spillover Index into all of the forecast error variance components for variable i coming from shocks to variable j, for all i and j, and analyze the average gross directional spillovers as well as net and pairwise spillovers. In Section 5.3, we track the time variation of the volatility spillovers using 200-day rolling samples and we assess the extent and nature of the development of the total volatility spillover index over time. Furthermore, we focus on the development over the observed time period also for the gross directional and net spillovers. Finally, in Section 5.4, we employ the Spillover Asymmetry Measure (SAM) framework, as described above, to study the differences in the spillovers from bad and good volatility and we quantify the spillover dynamics via rolling window estimation.

5.1 Model selection

First, in order to check whether the time series under research is stationary, we run three common tests. We employ an augmented Dickey–Fuller test (ADF; due to Dickey & Fuller (1979)) and Phillips-Perron (PP; due to Phillips & Perron (1988)) tests with the null hypothesis that a unit root is present in our time series sample and with the alternative hypothesis that the time series is stationary. The augmented Dickey–Fuller (ADF) statistic is a negative number—the more negative it is, the stronger the rejection of the null hypothesis of the presence of a unit root. The PP test statistics can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using the heteroskedasticity- and autocorrelation-consistent covariance matrix estimator (Phillips & Perron 1988). The results of these two unit root tests are provided in Tables A.1 and A.2 in the Appendix. Based on the p-values obtained for the two tests, we can reject the null hypothesis of the presence of a unit root even at the 1% level of significance.

Nonetheless, both the ADF and the PP unit root tests have as the null hypothesis that a time series is integrated of order 1. For stationarity tests, on the other hand, the presence of a unit root is not the null hypothesis but the alternative. The most commonly used stationarity test is the Kwiatkowski, Phillips, Schmidt and Shin (KPSS; due to Kwiatkowski *et al.* (1992)) test. The results of the KPSS test are provided in Table A.3 in the Appendix and suggest that we can reject the null hypothesis of stationarity at the 1% significance level. Similar results from unit root and stationarity tests are quite common for financial data as they often exhibit long-memory behavior. These results may imply that our data series are maybe not stationary, but mean-reverting. This notion is supported by Fouque *et al.* (2000) who provide an empirical analysis of high-frequency S&P 500 Index data and confirm that volatility reverts to its mean.

In order to determine the lag length of the VAR model, we calculate two information criteria, the Akaike information criterion (AIC) and the Bayesian information criterion (BIC; also called the Schwarz criterion). For the purposes of comparability of the results, we will use the same number of lags for the VAR model for realized variances and for realized positive and negative semivariances. Similarly, we will not use different specifications for the full sample and for samples excluding some assets. Table A.4 in the Appendix reports the AIC and BIC values for a different number of lags—2, 4 and 10—and reveals that there is no significant difference between the values obtained for each number of lags. Therefore, we choose the number of lags to be 2 as it balances the relative simplicity of the model with its good performance. Moreover, using 2 lags is in line with the related literature that has a similar scope of study. The VAR lag of length 2 was chosen (based on the AIC) by Baruník *et al.* (2016) when studying asymmetric connectedness on the U.S. stock market as well as by Baruník *et al.* (2015) when studying volatility spillovers in petroleum markets. In addition, Diebold & Yilmaz (2012) provide a sensitivity analysis of their volatility spillover index employed in this analysis to the VAR lag structure and show that results do not differ substantially for lags of 2 to 6. Baruník *et al.* (2016) obtained analogous results for lags of 2 to 4. All their results are in support of the assumption that the spillovers are not sensitive to the choice of the order of the VAR model. Furthermore, Baruník *et al.* (2016) run the residual diagnostics to check whether there is deflection from assumptions on VAR concluding that there is no dependence in the residuals and their estimates are consistent. We also perform this robustness check and in Figure A.1 in the Appendix we present the spillover plots produced by employing the VAR model with different lags from 2, which we use in our analysis, to 4. Comparing the dynamic behavior of the volatility spillover indices obtained from the VAR(3) and VAR(4) models with our VAR(2) we can conclude that there are no significant differences and the volatility spillover indices are robust to the choice of the VAR model specification.

For the purposes of the dynamic analysis, we have to specify the length of the rolling window. We set the window length to 200 days which is consistent with the approach employed by Baruník *et al.* (2016) and Diebold & Yilmaz (2012). Furthermore, we check the robustness of our model with respect to the length of the rolling window and also with respect to the forecasting horizon. Regarding the rolling window width, we construct the Spillover Index with rolling windows of 150, 200, and 250. Regarding the forecasting horizon, we select 5 and 15 days as the appropriate alternatives to our selection of the forecasting horizon of 10 days. Figure A.2 in the Appendix presents the spillover volatility plots employing different lengths of the rolling window and forecasting horizon for the full sample. We observe that the development of all analyzed specifications of the volatility spillover indices do not vary significantly. To sum up, we find that the results do not substantially change and are robust with respect to the window length and horizon selection as well as with respect to the choice of the model specification.

5.2 Unconditional patterns - volatility spillover tables

In this section, we analyze volatility spillovers between four selected commodities traded on U.S. Exchanges and the S&P 500, an American stock market index. The calculations of the total volatility spillover indices are based on variance decompositions of 10-days-ahead forecast errors employing VAR models, as specified in the previous section. Tables below are called volatility spillover tables and provide an approximate "input–output" decomposition of the total volatility spillover index. The i^{th} entry represents the estimated contribution to the forecast error variance of market j coming from shocks to market i. Numbers on the diagonal account for the share of own variance and the off-diagonal values represent the cross-variance, i.e. the volatility spillovers between markets. The sum of the off-diagonal columns stands for the contribution *to* others while the sum of rows stands for the contribution *from* others. Furthermore, by subtracting the contributions *to* others from the contributions *from* others, we obtain the net volatility spillovers. In the lower right corners of Tables 5.1 – 5.6, we report the results for the Volatility Spillover Indices for three samples—the full sample, a sample that includes the four selected commodities only and at last for a sample that excludes Cotton.[1]

[1] As explained in more detail above, the data for the Cotton futures were inconsistent in the number of observations per day, which is why we explore the effects of its exclusion from the analysis as a type of a robustness check.

5.2.1 Static analysis for the full sample

Table 5.1 reports the average volatility spillovers for the full sample over the time period spanning from January 2, 2002, to December 31, 2015. The directional spillovers are shown as the off-diagonal values of the matrix represented by Table 5.1. We may conclude that the share of volatility shocks that are spilled over from one market to another substantially differs across the analyzed markets and ranges from 0.6% to 26%. The Cotton futures exhibit the lowest values of volatility transmission among our sample, followed by Corn. On the other hand, the highest spillovers are reported from the S&P 500 Index to Crude Oil and Gold futures—the share of volatility transmitted from the S&P 500 Index to these two markets has been 26.4% and 17.8%, respectively. Regarding the contribution *to* others, we can see that gross directional volatility spillovers to others from each of the five assets span from 6.4% for Cotton to 51.7% for the S&P 500 Index. This means that the shocks related to Cotton are reflected only slightly in other analyzed markets while more than half of the variance in the S&P 500 Index is transmitted to other markets considered in our analysis. Furthermore, more than 20% of realized variance in the prices of Gold and Crude Oil futures are transmitted to other assets in our sample.

Table 5.1: Volatility spillover table - full sample

		From					
		CL	**CN**	**CT**	**GC**	**SP**	**Directional from others**
	CL	73.675	2.135	1.183	5.217	17.790	26.325
	CN	2.748	85.679	3.501	4.019	4.053	14.321
	CT	2.749	3.786	88.674	1.297	3.493	11.326
To	**GC**	6.341	2.299	0.583	64.399	26.377	35.601
	SP	8.684	1.450	1.147	13.353	75.366	24.634
	Directional to others	20.523	9.670	6.414	23.888	51.714	112.208
	Directional including own	94.198	95.348	95.088	88.286	127.079	**Total Spillover Index 22.44%**

Source: Author's computations.

Looking at the directional volatility spillovers from all markets to one specific market (i.e. contributions *from* others in the last column of Table 5.1), we observe that the range of results is narrower as compared to contributions *to* others, reaching values from 11.3% to 35.6%, for Cotton and Gold, respectively. While significant differences between the results for different markets persist, we may conclude that volatility in all observed assets is at least from one tenth caused by the events taking place in other markets. Gold, as a representant of precious metals, is the one most affected by the shocks in other markets, which is also reflected in the diagonal values in Table 5.1, which shows that the share of the effects of own shocks is by far the lowest one for Gold. These results are in line with the economic intuition, since precious metals are often used as a hedge against adverse events in other markets. As explained in Section 4.1, the price of Gold futures tends to increase in response to events that decrease the value of paper investments, such as stocks and bonds, and vice versa.

Finally, let us consider the total volatility spillovers, which are essentially extracted from the separated directional spillovers to form one complex index. On average, the volatility shocks related to other markets account for 22.44% of the volatility forecast error variance in our sample. The rest of the volatility can be attributed to the idiosyncratic shocks or to innovations that have taken place in other markets which are not included in our analysis.

To obtain more detailed information about the direction and magnitude of volatility spillovers, we calculate the net spillovers and the net pairwise spillovers. The results are presented in Tables 5.2 and 5.3, respectively. As described above, the net volatility spillovers are calculated simply the difference between the contribution *to* others and the contribution *from* all others. Subsequently, when we subtract the gross volatility spillovers from asset j to asset i from the volatility transmitted from asset i to asset j, we obtain the net pairwise spillovers. Therefore, as an example, the notation "CL-CN" stands for the contribution from CL to CN minus the contribution from CN to CL.

Table 5.2 shows whether the asset acts as a net "receiver" or "giver", i.e. whether the contribution (in terms of volatility that is spilled over to other markets) from all other markets is greater than the transmission of its own shocks to other markets. We find that the only net giver in our sample is the S&P 500 Index as it transmits more than twice as much volatility than it receives. The results thus suggest that all our selected commodities are more affected by the volatility in the other assets than what they transfer to others. Gold shows to be the biggest receiver of volatility spillovers among the markets in our sample.

Table 5.2: Net volatility spillovers - full sample

CL	**CN**	**CT**	**GC**	**SP**
-5.80242	-4.652	-4.912	-11.714	27.079

Source: Author's computations.

Table 5.3 provides an overview of net pairwise spillovers. The S&P 500 Index acts as a net giver of volatility with respect to all commodities which should not be surprising as the index reflects the performance of the stocks of the 500 U.S. leading companies on the two largest[2] exchanges in the world representing all major industries. Its development is thus largely representative of the overall situation on the market, including the commodity markets. As expected, Crude Oil and Gold are the largest receivers of volatility from the S&P 500 Index. Crude Oil is widely used in nearly all industries, making it largely dependent on the performance of the business sector, while Gold, as explained above, is often used as a hedge against adverse events on the financial and equity markets. Cotton, on the other hand, acts as a net pairwise receiver of volatility with respect to all other examined assets.

Table 5.3: Net pairwise spillovers - full sample

CL - CN	**CL - CT**	**CL - GC**	**CL - SP**
0.613	1.566	1.124	-9.106
	CN - CT	**CN - GC**	**CN - SP**
	0.285	-1.720	-2.603
		CT - GC	**CT - SP**
		-0.714	-2.347
			GC - SP
			-13.024

Source: Author's computations.

5.2.2 Static analysis for adjusted samples

In this section, we conduct a similar static analysis as above but for samples modified by excluding one of the assets. First, we eliminate the S&P 500 Index from our sample as we are interested in the interconnectedness exclusively among the commodity markets. Table 5.4 reveals unconditional patterns of

[2] In terms of total market capitalization of its listed companies.

volatility transmission among the examined commodities. The total volatility spillover index is substantially lower than the one we obtained for the full sample—the overall transmission of volatility within this sample only slightly exceeds 12%. Thus almost 88% of the total variance of forecast errors can be attributed to the idiosyncratic volatility shocks and to events that have taken place in other markets not included in our sample.

Table 5.4: Volatility spillover table - sample excluding the S&P 500 Index

		From				
		CL	**CN**	**CT**	**GC**	**Directional from others**
To	**CL**	86.718	2.864	1.738	8.679	13.282
	CN	3.431	87.729	3.796	5.044	12.271
	CT	3.565	4.069	90.242	2.123	9.758
	GC	10.616	3.471	1.149	84.764	15.236
	Directional to others	17.612	10.405	6.683	15.846	50.547
	Directional including own	104.330	98.134	96.926	100.610	**Total Spillover Index 12.64%**

Source: Author's computations.

Comparing the gross directional spillovers with the results from the volatility spillover table for the full sample, we may conclude that while the values for Cotton and Corn do not exhibit significant changes neither regarding the directional transmission to others nor the contribution from others, the figures for Crude oil and Gold vary rather extensively. The gross directional spillovers to Gold are twice as small as for the full sample which includes the S&P 500 Index, and for Crude oil, the difference is even more substantial, decreasing from 35% to 15%. The same applies for the directional effects to others, although the difference is less significant. It follows from the above that the U.S. stock market represented by the S&P 500 Index plays an eminent role in the transfer of volatility to hard commodities, represented by Gold and Crude Oil, but does not play such an important role for soft commodities, represented by Corn and Cotton. These results are in line with the notion that while the production process in many industries relies heavily on hard commodities, soft commodities are more often consumed directly (Creti *et al.* 2013). Taking into account the results from Table 5.5 which summarizes the net spillovers, we can conclude that the volatility shocks to Crude Oil and Gold spill over to other commodities the most. On the other hand, the shocks related to volatility in the Cotton futures are the least influential in both samples. To summarize the results shown in Table 5.4, we can say that both the total as well as the directional spillovers over the studied period were rather low among the commodity markets themselves.

Table 5.5: Net spillovers - sample excluding the S&P 500 Index

CL	CN	CT	GC
4.330	-1.866	-3.074	0.610

Source: Author's computations.

As the number of observations per trading day for Cotton futures was relatively unstable over time, we did not harmonize the data for CT as we did for all other assets to prevent unnecessary loss of too many observations (see Section 4.2 for more details). For this reason, we perform the same analysis as above but for a sample excluding Cotton in order to reveal some possible hidden patterns due to its inconsistency in observations. Table 5.6 reports the volatility spillovers for the sample that excludes Cotton. The total volatility spillover index is slightly higher than the one obtained for the full sample, at 23.9%.

Table 5.6: Volatility spillover table - sample excluding Cotton

		From				
		CL	**CN**	**GC**	**SP**	**Directional from others**
To	**CL**	74.536	2.146	5.258	18.059	25.464
	CN	2.853	88.768	4.158	4.220	11.231
	GC	6.383	2.307	64.792	26.518	35.208
	SP	8.829	1.451	13.423	76.296	23.704
	Directional to others	18.065	5.905	22.839	48.798	95.607
	Directional including own	92.601	94.674	87.631	125.094	**Total Spillover Index 23.90%**

Source: Author's computations.

Concerning the off-diagonal figures representing directional spillovers as well as the diagonal figures standing for idiosyncratic volatility shocks, the results do not exhibit significant differences as compared to the volatility spillover table for the full sample. Inspecting the cumulative contribution to and from other markets, the figures do not change excessively compared to the results from the full sample (Table 5.1). An exception to this is Corn, the results for which change relatively significantly after the exclusion of Cotton from the sample—contribution to other markets as well as the transmission from other markets declines markedly in absolute numbers, from 9.7% to 5.9% and from 14.3% to 11.2%, respectively. Table 5.7 reports the net volatility spillovers and underlines our conclusion that by the exclusion of the Cotton market from our sample, we do not observe significant variation from results obtained from the full sample analysis. The impact of the change of the sample affects almost exclusively the Corn market results and we may conclude that the connectedness between the two markets (Corn and Cotton) is more intense than the connection between the Cotton market and other assets included in our sample. These results suggest that regarding volatility spillovers, the connectedness is higher among soft commodities than between soft and hard commodities.

Table 5.7: Net spillovers - sample excluding CT

CL	**CN**	**GC**	**SP**
-7.399	-5.326	-12.369	25.094

Source: Author's computations.

5.3 Conditioning and dynamics

The data used in our analysis spans over 14 years from the beginning of 2002 until the end of 2015. During such a long time period, many changes have occurred in the financial markets due to rapidly increasing globalization, expanded mobility of capital and crucial changes in the trading system such as the launch of the electronic online platforms that enable almost continuous trading, but also due to the business cycles and fluctuations in economic activity over time, which result in expansions and contractions of the markets (Barunik *et al.* 2016). By far the most important event that occurred during the observed time period was the global financial crisis of 2008. While the previous static analysis provides a useful overview of the average volatility spillovers over the period under research, it would be inadequate to assume that the spillover index obtained from matrices above would be appropriately informative for the whole time period. To be able to examine the development of the volatility spillovers over time, as explained above, we estimate our preferred model using

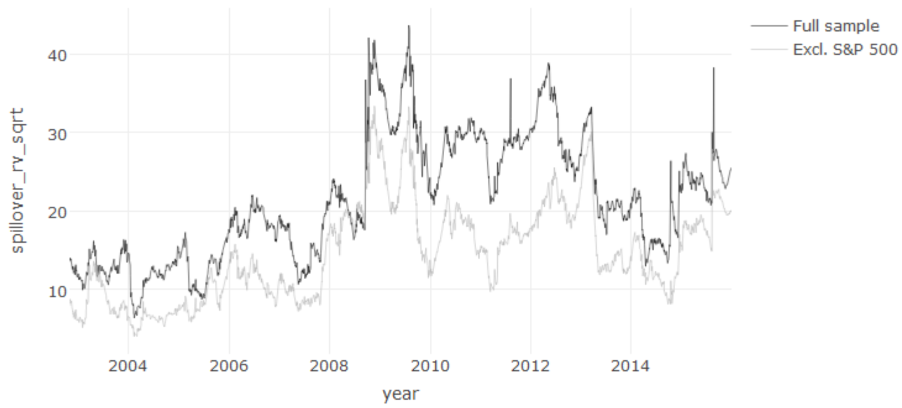
200-day rolling windows, horizon h = 10, and VAR lag length of 2, and we also let these parameters vary to provide a robustness check for our results. Firstly, we examine the dynamics of total spillovers for three samples defined in the previous section. Secondly, we capture the time variation employing the rolling window estimation on the contribution to other markets, from other markets, and net and pairwise volatility spillovers. The changing dynamics of volatility transmission over time are depicted in spillover plots[3] in Figures 5.3 – 5.7.

5.3.1 Total spillover index's development

Figure 5.1 presents the moving-window estimation of total spillovers for the full sample and for the sample including only commodities. We can easily observe the rich dynamics of volatility spillovers between the commodities and the S&P 500 Index over the studied period. The volatility spillover indices for both samples evolve relatively similarly over the studied time period, however, some marked differences can be isolated. The spillovers based on the full sample reach larger magnitudes during the whole time period under research which is in accordance with our findings from the static analysis. Figure 5.2 depicts the dynamics of the differences between volatility spillover index for the full sample and for the sample that contains only the four selected commodity markets. We can observe that in the years following the crisis the difference between indices is greater than before 2008 which suggests that the impact of the crisis on the commodity market (or at least regarding the commodities included in our sample) was not as extensive as that on the U.S. stock market (represented by the S&P 500 Index). Table 5.8 provides some basic summary statistics regarding the differences in the two measures.

[3] As is common in the related literature, all presented spillover plots in this section are presented in squared root terms.

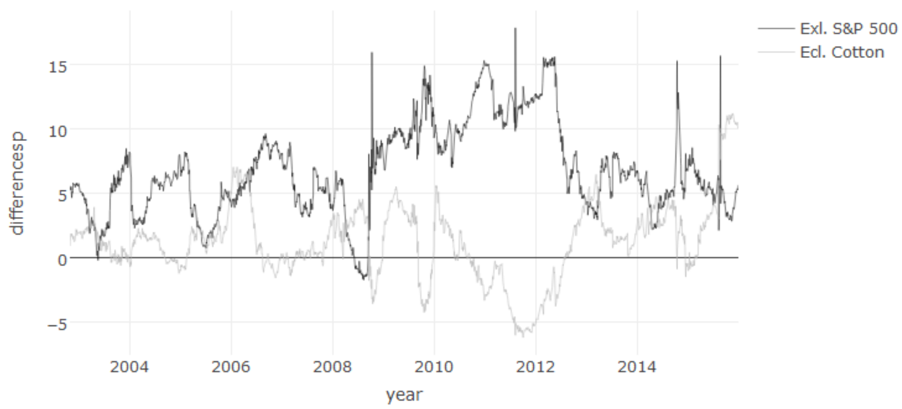
Figure 5.1: Total volatility spillovers - full sample and sample excluding the S&P 500 Index



Source: Author's computations.

Note: The black line represents the total volatility spillover index for the full sample, the gray line for the sample excluding the S&P 500 Index.

Figure 5.2: Differences in spillover indices with respect to the full sample



Source: Author's computations.

The level of volatility spillovers in both samples is rather low at the beginning of the observed period and fluctuates between 5% to 15% for the first four years. The volatility spillovers index for the full sample hits 20% in the middle of 2006 and then slightly declines during the first half of the year 2007. The same pattern seems to repeat during the following year. The first substantial

Table 5.8: Summary statistics - Differences in spillover indices with respect to the full sample

	Mean	**Min**	**Median**	**Max**	**St. Dev.**
Excluding S&P 500	6.831	-1.722	6.267	17.877	3.556
Excluding CT	1.292	-6.196	1.381	11.234	2.980

Source: Author's computations.

increase in inter-market connectedness can be detected in September 2008 following the collapse of Lehman Brothers, an investment bank, and the burst of the U.S. sub-prime mortgage crisis which turned into a global recession and affected the world's economy in a major way over several years that followed.[4] During the fall of 2008, the index for the full sample more than doubled and exceeded the 40% level of volatility spillovers. Concerning only the commodity markets sample, the values of the index increased from 18% before the Lehman Brothers collapse by 15 percentage points, reaching their maximum of 33.37% during November 2008. The high level of volatility spillovers has lasted also throughout the first half of 2009 due to the increased level of uncertainty and instability of the financial markets. At the end of July, the spillover indices hit their second peak and the full-sample index reached its maximum over the studied period, at 43.7%. The probable cause of this peak is the development of the financial crisis which around this time started to impact the economy around the world to its full extent. From mid-2009, the volatility transmissions between markets gradually declined with some minor fluctuations until late 2014 when both indices reached their pre-crisis levels. However, after this point, we can observe again an increase in the transmission of volatility in both samples in the last observed year. To analyze the largest jumps in the volatility spillovers, we calculated their intra-day returns and found that the highest returns correspond to adverse events on the financial market. Table 5.9 provides an overview of the important events and explains most of the major spikes observable in Figure 5.1.

[4]Source: https://www.theguardian.com/commentisfree/cifamerica/2011/dec/12/lehman-brothers-bankrupt

Table 5.9: Event study

Date	Volatility Spillover Index	Return	Event
9/17/2008	28.892	10.714	Bankruptcy of Lehman Brothers
9/18/2008	51.234	22.342	Bankruptcy of Lehman Brothers
10/10/2008	64.454	38.617	The great crash of 2008[5]
8/5/2011	64.519	36.548	Asian markets plunge on back of euro fears and U.S. losses, oil and gold both decline as investors race for U.S. Treasuries[6]
10/15/2014	34.569	14.621	U.S. stock market decline[7]
12/17/2014	39.400	15.377	Sharp decline in world stock markets, the tumbling price of oil, and the prospect of another eurozone crisis prompted by political uncertainty in Greece.[8]
8/12/2015	38.351	18.225	Global stock markets plunge on China currency rapid decline [9]
8/24/2015	79.994	49.438	China's Black Monday flash crash[10]

Source: Author.

To sum up, the overall connectedness of the markets included in our analysis increased substantially following the global financial crisis of 2008. We can distinguish two main periods regarding the behavior of the volatility spillovers over the 14 years under research—before 2008 and after 2008. During the pre-crisis period, the average value of the volatility spillover index was about 15% for the full sample and 10% for the sample including commodities only, whereas in the post-crisis period, the average values of the index for the full and the restricted sample reached 25% and 17%, respectively. Furthermore, regarding the full sample, the highest spikes of spillovers before 2008 do not reach the average level of the index after the global financial crisis. As the period under study covers 7 years after the crisis, we may conclude that the uncertainty and skepticism of stock market participants persist in the market long after the crisis and the traders may change their behavior by diversifying the portfolio more extensively which may lead to higher intra-market connectedness. Our

[5]Source: https://www.theguardian.com/business/2008/oct/10/marketturmoil-credit crunch

[6]Source: https://www.theguardian.com/business/2011/aug/04/stock-markets-exchange-plunge-business

[7]Source: http://money.cnn.com/2014/10/15/investing/stocks-markets-wall-street-correction /index.html

[8]Source: https://www.theguardian.com/business/2014/dec/12/world-stock-markets-tum ble-and-ftse-suffers-worst-fall-since-2011

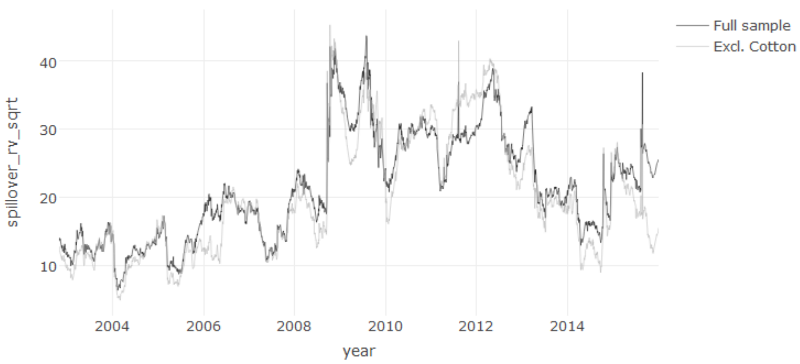
[9]Source: http://money.cnn.com/2015/08/12/investing/china-yuan-stock-markets-sell-off /index.html

[10]Source: https://www.theguardian.com/business/live/2015/aug/24/global-stocks-sell-off -deepens-as-panic-grips-markets-live

findings reflect the financial situation on the market and are in line with those reached by Baruník *et al.* (2016), Baruník *et al.* (2015) and Diebold & Yilmaz (2012).

We also analyze the development of the total volatility index when excluding Cotton from our sample as a type of a robustness check since, as explained above, the observations for Cotton are somewhat inconsistent in the number of observations per day. In Figure 5.3, we present the development of two total volatility indices—for the full sample and for the sample excluding Cotton. A visual inspection of the figure reveals that both spillovers indices share a largely common path. Somewhat surprisingly, the level of spillovers is even greater at some points of the observed period for the sample that excludes Cotton. These findings indicate that Cotton does not play an important role in the volatility spillovers within our sample and that there is not significant connectedness between Cotton and other commodities included in our analysis. Furthermore, these results suggest that our previous estimates are robust with respect to the selection of assets.

Figure 5.3: Total volatility spillovers - full sample and sample excluding Cotton



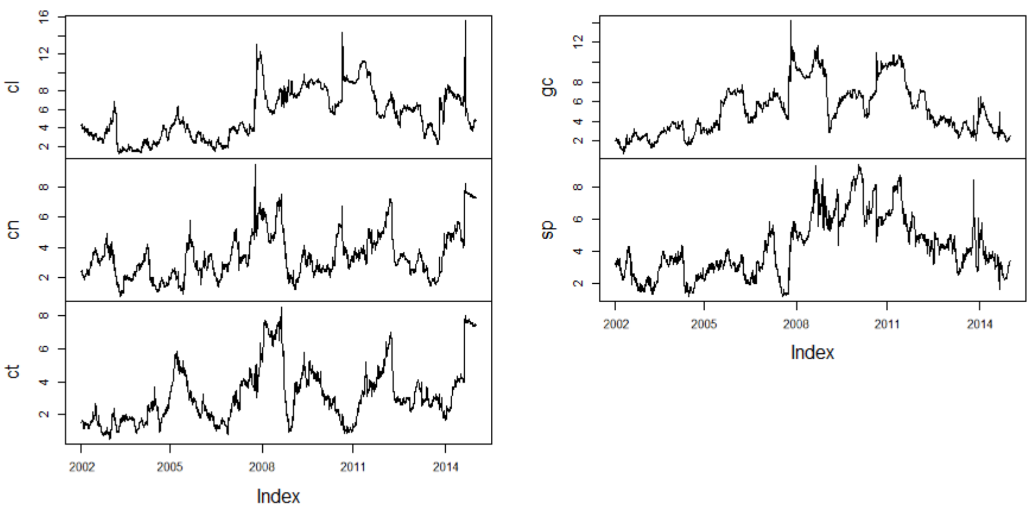
Source: Author's computations.

Note: The black line represents the total volatility spillover index for the full sample, the gray line for the sample excluding Cotton.

5.3.2 Gross directional spillover plots

In the previous section, we interpreted the total spillover plots which revealed interesting patterns and allowed us to further understand the intra-market transmission of volatility. However, it concealed information about directional spillovers from one particular asset to others and vice versa. This section provides a dynamic estimation of the contribution to and from other assets separately for each asset covered in our analysis. The development of directional spillovers over the 14-year period is depicted in Figures 5.4 and 5.5.

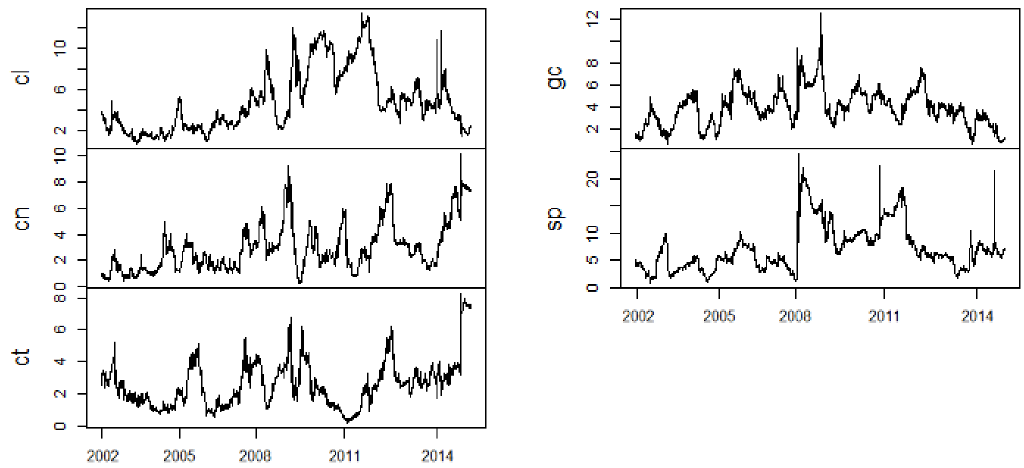
Figure 5.4: Directional spillovers from other assets



Source: Author's computations.

Figure 5.4 presents the directional volatility spillovers from others to each of the five assets over time (corresponding to the "directional from others" column in Table 5.1). For the full sample, we can observe higher values of gross directional spillovers during the turbulent period of the end of 2008 and the first months of 2009 as compared to those before the crisis. Nevertheless, while the level of volatility transmission from others to Crude oil, the S&P 500, and Gold remains relatively high for a long period after the crisis, the directional contributions from others to Cotton and Corn return relatively fast to their pre-crisis levels. During the whole period under research, the directional transmissions from others to the last two mentioned are lower than for the first three assets. We can observe a spike in the market for Cotton and Corn in 2013 when, at the same time, the gross directional spillovers to Crude oil, Gold and the S&P 500 have a decreasing trend. These findings further support our previous results that the soft commodities, represented by Cotton and Corn, are the least connected to the rest of the sample.

Figure 5.5: Directional spillovers to others



Source: Author's computations.

Figure 5.5 depicts the evolution of the gross directional spillovers to others from each of the five observed assets. The directional contributions to others vary greatly over time, however, they seem to reach lower overall volume than the gross directional spillovers from others for all assets except for the S&P 500 Index which exhibits significantly higher transmission to others than any other commodity. This is in line with the results obtained in the "directional to others" row compared to the "directional from others" column in Table 5.1. An interesting pattern can be observed for Crude oil. While all other assets hit their maximum of gross spillovers to others during the turbulent period corresponding to the global financial crisis, the spillovers from Crude oil to others reach their highest values relatively long after the crisis. This may be the impact of the unstable situation in the oil markets caused by the political problems and rising tensions in the Middle East and North Africa in 2011 when Crude oil prices reached their highest levels since 2008[11].

[11] Source: https://www.eia.gov/todayinenergy/detail.php?id=4550

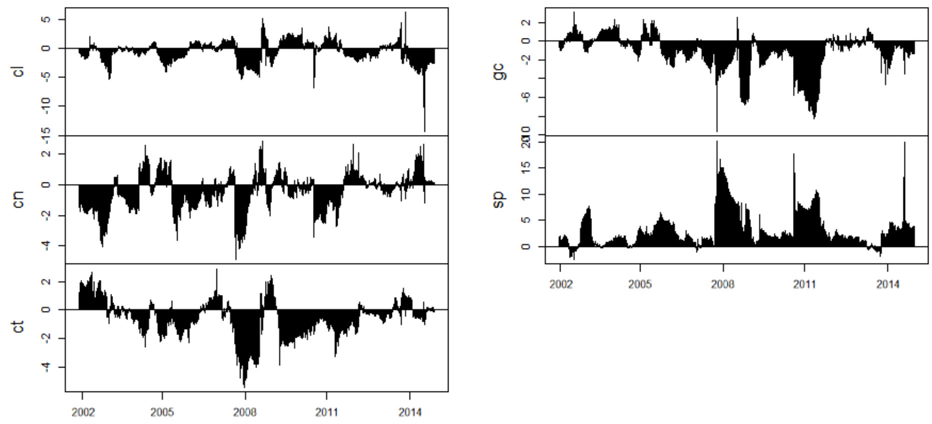
5.3.3 Net directional volatility spillover plots

Above, we inspected the gross directional spillovers within our sample. In what follows, we analyze the net spillovers and the net pairwise spillovers. The former is defined simply as the difference between contribution from others and contribution to others. Therefore, when the values for a specific asset are above zero, the commodity was transmitting more volatility to others than it was receiving from others. In that case, we call that commodity a net spillover giver. The negative domain corresponds to the net spillovers that a commodity receives from the others and therefore the asset acts as a net spillover receiver. Figure 5.6 shows that the net effects alternate over the sample period as the net spillovers for all assets take both positive and negative values at some point. The net spillovers of all assets except for Crude oil reached their maximum (in absolute value) during the global financial crisis of 2008.

Moreover, the impact of financial instability reflected in the net spillovers is more evident for Cotton, Gold and the S&P 500 Index as their absolute values in the post-crisis period are substantially higher and the increased level of net spillovers is also noticeable in the years following the crisis. Furthermore, the net spillovers of Gold and Cotton take almost exclusively negative values and thus make these two commodities appear as net spillover receivers while the opposite is true for the S&P 500 Index whose net spillovers reach significantly higher volumes compared to the rest of the sample and do not take almost any negative values over the 14-year observed period. These emerged patterns are in accordance with the static analysis and the results obtained in Table 5.2. Cotton and Crude oil seem to be more balanced in terms of transmitting and receiving net spillovers from other assets, however, it appears that the negative values prevail for both commodities. Furthermore, regarding Crude oil and the S&P 500 Index, we can observe extensive spikes taking the opposite values at the end of the analyzed time period. These correspond to August 2015, the time of the so-called Black Monday in China, which caused the U.S. stock market to suffer its biggest sell-off in four years and commodity prices have also been hit by worries over China, especially oil which tumbled by 6%.[12]

[12] Source: https://www.theguardian.com/business/live/2015/aug/24/global-stocks-sell-off-deepens-as-panic-grips-markets-live.

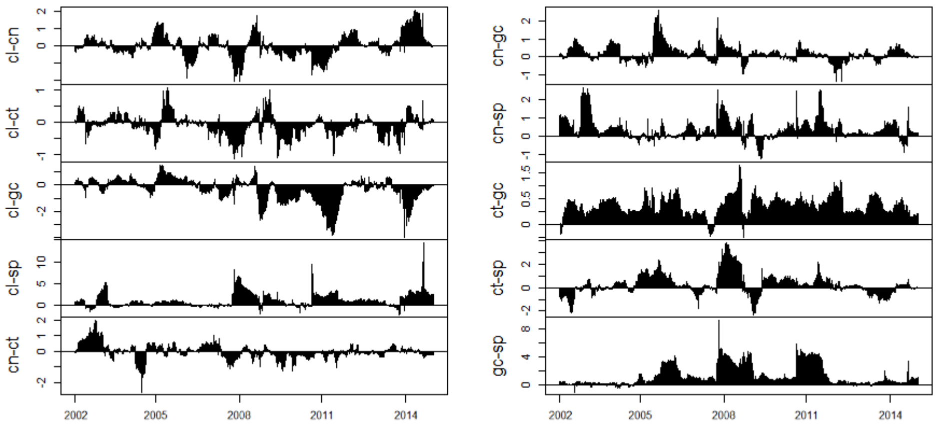
Figure 5.6: Net spillovers



Source: Author's computations.

Figure 5.7 depicts the net pairwise spillovers that show the dynamics and dominance of the net spillovers between two specific commodities. For example, in the plot labeled $cl - cn$, when the values are above zero, the spillovers from cn to cl exceed those from cl to cn. Based on visual inspection, we can determine the dominant position of an asset in almost each pair. The S&P 500 Index appears to be dominant in all pairs. The volatility in Crude oil spills over to Gold more extensively than the other way around, particularly in the post-crisis period. For most of the observed time period, Crude oil also seems to dominate Cotton in terms of spillover transmission. The volatility of Gold impacts considerably more the fluctuation of Cotton than vice versa. The shocks to Gold are also transmitted more heavily to Cotton than in the opposite direction. The transmission of pairwise net spillovers appears quite balanced in $cl - cn$ and $cn - ct$ pairs.

Figure 5.7: Pairwise spillovers



Source: Author's computations.

5.4 Asymmetric volatility spillovers

In the previous static and dynamic analysis the presence of volatility spillovers among the selected commodities and the S&P 500 Index has been confirmed. We have also examined the evolution of the volatility transmission over time and the amount of volatility spilled over from each of the studied assets. In this section, we investigate potential asymmetries in the transmission mechanism due to negative and positive shocks.

Based on the methodology proposed by Barndorff-Nielsen *et al.* (2010) we decompose the realized variance to positive and negative semivariances and use them to derive negative and positive volatility spillovers. Furthermore, in order to quantify the extent of the asymmetric transmission of the volatility within our sample, we calculate the spillover asymmetric measures (SAM) proposed by Baruník *et al.* (2016).

5.4.1 Asymmetric volatility spillovers – static and dynamic analysis

First, we analyze the results summarized in the spillover volatility tables based on negative and positive semivariances which provide a useful overview of the average volatility spillovers due to negative and positive shocks. In the low right corners of Tables 5.10 and 5.11, we present the total spillover indices for negative and positive returns, respectively. The overall average contribution of positive shocks to volatility spillovers in our sample is only slightly higher compared to the negative ones (17.72% compared to 16.46%). This finding is not in support of our hypothesis that on average, volatility spillovers resulting from negative realized semivariances are of higher magnitude than the ones stemming from the positive ones. For all commodities, the gross directional spillovers to others reach greater values when taking into account good news. However, the S&P 500 Index exhibits higher transmission of bad volatility to others and lower from others as compared to good volatility spillovers. The differences are particularly significant for Gold, Cotton, and Corn, where the transmission of good volatility to others reaches almost twice the volume of spillovers due to bad volatility. These results indicate that the stock market represented by the S&P 500 Index is more sensitive to bad news corresponding to negative returns than the commodity market. The directional spillovers of good and bad volatilities from others do not vary as considerably, however, the most distinct output is observed again for the S&P 500 Index. When employing the positive realized semivariances in the estimation, the volatility in all commodities included in our analysis is responsible for almost 22% of the fluctuations observed in the S&P 500 Index compared to 15.9% of bad volatility transmitted from others.

Table 5.10: Volatility spillover table - Negative realized semivariances

		From					
		CL	**CN**	**CT**	**GC**	**SP**	**Directional from others**
To	**CL**	77.698	1.147	0.938	3.863	16.354	22.302
	CN	1.476	93.034	0.917	1.515	3.059	6.966
	CT	2.162	0.859	92.175	1.464	3.339	7.825
	GC	5.872	1.263	0.407	70.643	21.815	29.357
	SP	7.425	0.803	0.734	6.908	84.130	15.869
	Directional to others	16.935	4.072	2.996	13.750	44.568	82.320
	Directional including own	94.633	97.105	95.171	84.393	128.698	**Total Spillover Index 16.46%**

Source: Author's computations.

Table 5.11: Volatility spillover table - Positive realized semivariances

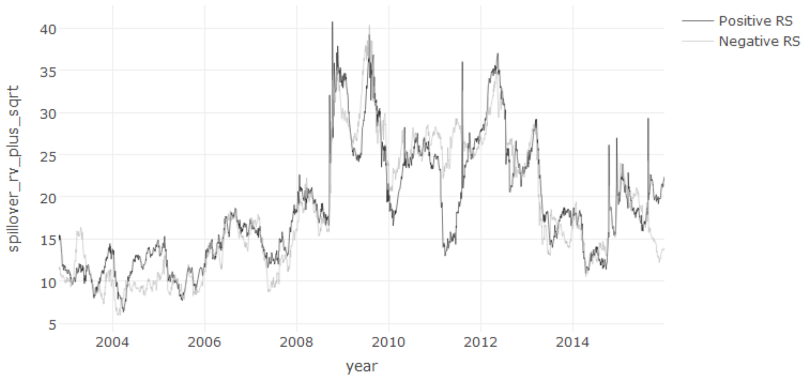
		From					
		CL	**CN**	**CT**	**GC**	**SP**	**Directional from others**
To	**CL**	77.249	2.486	1.527	5.068	13.670	22.750
	CN	2.951	89.585	1.308	3.308	2.847	10.415
	CT	2.272	1.502	93.262	0.545	2.418	6.738
	GC	4.539	2.554	0.608	73.260	19.038	26.739
	SP	7.605	1.582	1.499	11.291	78.023	21.977
	Directional to others	17.368	8.125	4.942	20.212	37.973	88.619
	Directional including own	94.617	97.710	98.204	93.472	115.996	**Total Spillover Index 17.72%**

Source: Author's computations.

Figure 5.8 depicts the development of two spillover indices based on negative and positive realized semivariances which allows us to observe the differences in volatility transmission that emerge due to negative and positive returns. The black line represents the spillover index from positive RS whereas the gray line depicts the spillover index from negative RS. There are some observable differences in the development of the two measures, especially in the post-crisis period. The volatility spillover index from positive RS dominates the one from negative RS almost throughout the whole first part of the studied time period, between 2002 and 2005. For years 2005 to 2008, the good and bad volatilities exhibit a more or less common path and reach similar levels. The dominance of volatility transmission due to positive news remains also at the beginning of the crisis in 2008. However, from March 2009 until mid-2011, the volatility index based on negative RS prevails and the differences between the two indices are more excessive. In the period that follows, we can again observe a rather interchangeable development of both indices. At the end of the studied period the impact of positive shocks on the volatility spillover re-dominates.

In Figure 5.9 we can observe the development of the spillover indices based on negative and positive RS for the sample that includes commodities only. Both indices evolve very similarly to the corresponding ones in Figure 5.8 which study the whole sample, however, they both reach lower volumes. This is in line with our findings above that the level of volatility transmission is higher for the full sample than for the sample excluding the S&P 500 Index. A closer inspection of different asymmetries in the two samples is provided in Section 5.4.2 as the differences are better visible using the asymmetry measure. To conclude, we can confirm the presence of certain asymmetries in the impact of positive and negative shocks on the volatility and its transmission. Furthermore, our findings in this section are not in line with the hypothesis that the bad news resulting in negative returns affect the volatility more intensively than good news and related positive shocks. In the following section, we inspect the asymmetries further by employing the Spillover Asymmetry Measure.

Figure 5.8: Asymmetric volatility spillovers - full sample



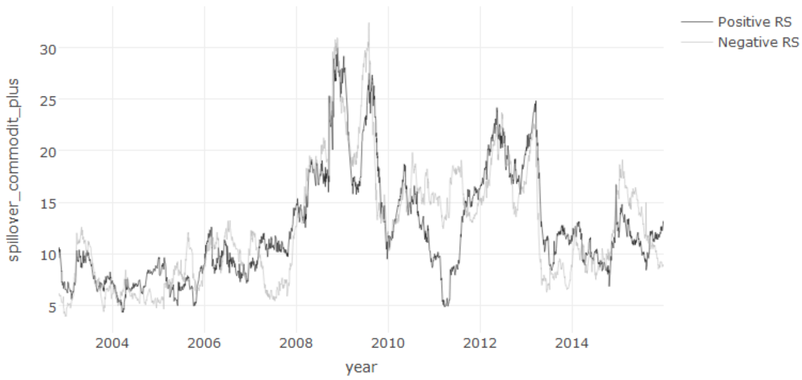
Source: Author's computations.

Note: The black line represents the spillover index from positive realized semivariances (RS^+), the gray line from negative realized semivariances (RS^-).

5.4.2 Spillover asymmetry measure (SAM)

Finally, we use the Spillover Asymmetry Measure ($\mathcal{SAM}$) proposed by Baruník *et al.* (2016) and defined in Section 3.3 to quantify the differences in the volatility spillovers due to negative and positive shocks. This approach allows us to study the extent of the asymmetry in the volatility transmission independently of the level of spillovers. Positive values of $\mathcal{SAM}$ indicate the dominance of the volatility spillover index based on positive RS while negative values of $\mathcal{SAM}$ imply that the transmission of volatility due to negative returns reaches higher volume than that due to positive returns. When $\mathcal{SAM} = 0$, the effects of both negative and positive spillovers offset each other, however, as we will see, this situation is very rare on the markets.

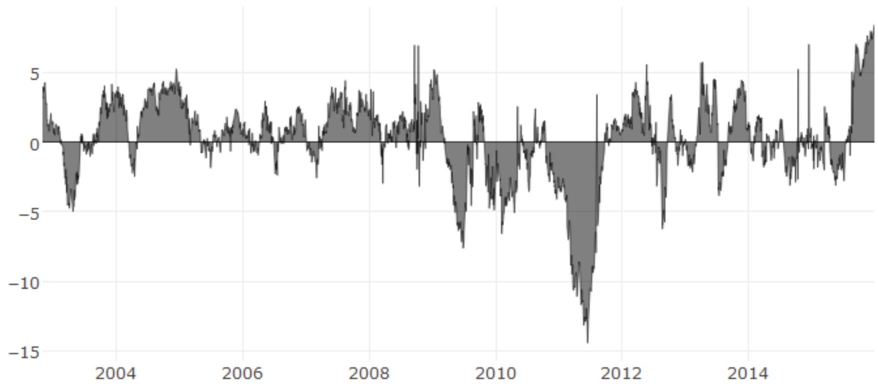
Figure 5.9: Asymmetric volatility spillovers - sample excluding the S&P 500 Index



Source: Author's computations.

Note: The black line represents the spillover index from positive realized semivariances (RS^{+}), the gray line from negative realized semivariances (RS^{-}).

Figure 5.10: Spillover ssymmetry measure (SAM) - full sample



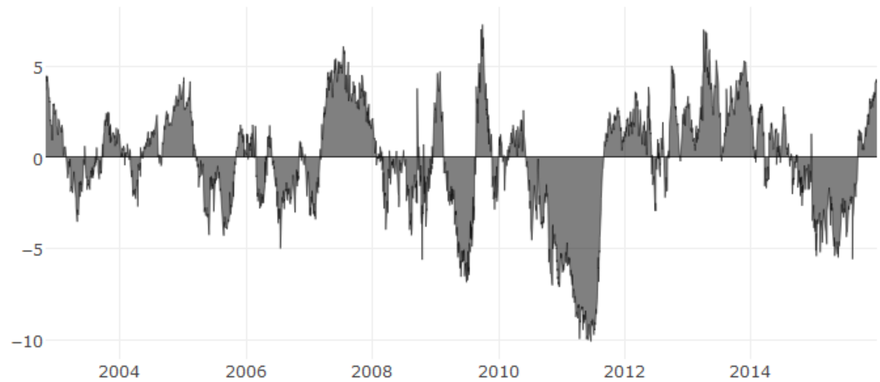
Source: Author's computations.

Figure 5.10 presents the $\mathcal{SAM}$ for our full sample. Significant fluctuations of the measure are evident over the whole time period under study. We can observe that the extent of asymmetric behavior reflects not only the magnitude but also the duration. Considering the pre-crisis period, we find that the $\mathcal{SAM}$ takes predominantly positive values except for several months at the beginning of 2003 which may be associated with the perturbed situation in the oil markets caused by the second Gulf War and unrest in Venezuela (Baruník *et al.* 2015). The overall dominance of the positive values in this period means that the transmission of volatility due to positive shocks is higher than the bad volatility spillovers which may be related to the optimistic sentiment persisting from the prosperous period before the global financial crisis. Moreover, the asymmetries in spillovers from negative and positive shocks in the pre-crisis period do not take very high values—they range from approximately -5% to +5%.

The most significant asymmetric effect is visible after the crisis starting in March 2009 until September 2011 when we observe a prevalence of negative asymmetries. The clusters of negative spillovers during the years that followed the crisis document the pessimistic mood on the markets, when the negative shocks had a higher impact than the positive ones as the investors were more cautious and more sensitive to bad news. Furthermore, during this period, the extent of negative asymmetries is much higher compared to the pre-crisis period, falling to -14.4% in June 2011, which may point to concerns about uncertainty and stability of the financial markets following the crisis. In the subsequent period, we can observe much less excessive fluctuations of volatility spillovers with a varying dominant position of spillovers based on positive and negative returns. The lower fluctuation with similar range as in the pre-crisis period and the variability of the prevalence of good and bad volatility may be to some extent caused by increasing financialization (Baruník *et al.* 2015). Similarly, Tang & Xiong (2012) find support for the notion of increasing financialization of commodities by showing that synchronized price movements of major commodities markets in the U.S. are a consequence of such financialization. Moreover, Baruník *et al.* (2015) argue that as a further consequence, higher volatility transmission occurs simultaneously with a lower level of asymmetries between volatility spillovers due to positive and negative shocks. At the end of the observed period, good news had a substantially larger influence on the markets than bad news.

Figure 5.11 depicts the asymmetries induced by positive or negative shocks for the sample that excludes the S&P 500 Index. We notice several differences as compared to the asymmetries presented for the full sample. First, the impact of negative shocks is stronger during the period between 2005 and 2006. This may be caused by uncertainty on the commodity markets associated with the food price crisis which is in line with the findings of Nazlioglu *et al.* (2013), who examine volatility transmission between oil and selected agricultural commodity prices. They find that oil market volatility spills on the agricultural markets in the post-crisis era while there is no risk transmission between oil and agricultural commodity markets before the food price crisis. Regarding the immediate post-crisis period, the dominance of volatility spillovers based on negative semivariances is also observable for the sample that includes only commodities, however, it does not reach such a high volume as in the case of the full sample.

Figure 5.11: Spillover asymmetry measure (SAM) - sample excluding the S&P 500 Index



Source: Author's computations.

From mid-2011 till mid-2014, the good volatility transmission prevails. However, in the late 2014 and for several first months of 2015, negative shocks to commodity markets had a substantially larger impact as compared to positive shocks. This negative cluster may be associated with the global commodity price crash when the global commodity prices fell by almost 40% and large drops across many different commodity classes were observable (Saggu & Anukoonwattaka 2015). Table 5.12 provides summary statistics for the SAM for both samples. The asymmetries for the full sample reach higher extremes especially regarding the transmission of volatility induced by the negative shocks. However, the mean for the full sample is slightly above zero while for the sample including only commodities, the mean is -0.215 which means that on average, volatility stemming from the negative semivariances spilled over to the commodity markets fractionally more than the good volatility.

Table 5.12: SAM - Summary statistics

	Mean	**Min**	**Median**	**Max**	**St. Dev.**
Full sample	0.156	-14.438	0.550	8.462	3.132
Commodities only	-0.215	-10.102	0.091	7.278	3.074

Source: Author's computations.

Overall we find some asymmetric behavior in volatility transmission for both samples. In particular, in the years following the crisis, the negative shocks have had a higher impact on the volatility spillovers across the markets included in our analysis. Nevertheless, the level of the asymmetry measure does not take very high values compared to the results obtained by Baruník *et al.* (2015) who find the asymmetric effects in spillovers on the petroleum market rather substantial. Similarly, Dovhunová (2014) finds stronger evidence of asymmetric volatility transmission also for the stock markets in Central and Eastern Europe. Despite the fact that the asymmetric connectedness of markets included in our analysis is not as substantial, the good and bad volatility is transmitted at different magnitudes and the dominant position changes over the studied time period. While negative spillovers reach higher extremes, they do not strictly dominate the transmission of volatility based on positive returns. These findings are in line with those of Baruník *et al.* (2016) and suggest that risk transmission is not driven by pessimism as much as generally assumed.

Chapter 6

Conclusion

In this thesis, we study volatility spillovers using a recently developed approach based on the volatility spillover index, as introduced by Diebold & Yilmaz (2009) and further developed by Diebold & Yilmaz (2012). The approach uses a generalized vector autoregressive framework in which forecast-error variance decompositions are invariant to the variable ordering which enables us to measure total, directional and net volatility spillovers. We employ an extension to this approach introduced by Baruník *et al.* (2016) who build upon the volatility spillover index proposed by Diebold & Yilmaz (2012) and combine it with the concept of positive and negative realized semivariances developed by Barndorff-Nielsen *et al.* (2010). The realized measures allow not only to better estimate the total volatility but most importantly, the resulting modified indices allow for modeling asymmetric responses to positive and negative shocks.

We apply the methodology proposed by Baruník *et al.* (2016) to quantify the volatility spillovers and the asymmetric response to positive and negative shocks in high-frequency data within two datasets. First, we model the volatility transmission between four selected widely traded commodities and one of the main U.S. stock market indices, the S&P 500 Index, as a representative of the equity market. The second dataset includes commodities only, specifically Crude oil, Gold, Corn and Cotton futures. Each of the included commodities represents a specific branch of the commodity market—energy, precious metals, grains and fiber markets, respectively. The importance of each of these commodities within their markets is sufficient to consider them as a proxy for each sector. In order to provide accurate estimates, five-minute returns are used for the construction of realized measures. Our sample covers a 14-year period from January 2002 to December 2015, which allows us to analyze the development long before the global financial crisis of 2008 as well as quite long after the turbulent period fades away and we can thus evaluate the impact of the global crisis on the commodity and equity markets.

The results are divided into several categories. First, we provide a static analysis of three different samples—the full sample, a sample including only commodities and a sample excluding Cotton futures (as a type of robustness check). The decomposition of the total volatility spillover index allows us to estimate the directional spillovers, i.e. how much the shocks to one asset are transmitted to another asset, as well as the net and the pairwise spillovers. Second, in order to capture the development of spillovers over time, we employ the rolling window estimation. Third and last, we investigate potential asymmetries in the transmission mechanism due to negative and positive shocks.

The static analysis reveals that the volatility transmission within the sample including the S&P 500 Index is substantially higher than the volatility spillovers only between commodities. On average, the volatility shocks related to other markets account for 22.44% of the volatility forecast error variance in our full sample while only for 12.64% in the sample that includes commodities only. The S&P 500 Index turns out to be a net giver of volatility when compared to all commodities under research, i.e. the transmission of shocks from the stock index to others exceeds the volatility spillovers from others to the stock index. Our findings thus show that the shocks to stock markets play a rather important role in the volatility in commodities while commodities do not influence each others' volatility to such an extent. Especially, the soft commodities such as Cotton and Corn exhibit the lowest contribution of spillovers to other markets.

The dynamic analysis shows the development of volatility spillovers between markets over time and provides strong evidence that the connectedness between markets has become much more significant after the global financial crisis of 2008 for all three samples. The uncertainty and skepticism of market participants persist in the markets long after the crisis as the volatility spillovers reach higher volumes than in the pre-crisis period. The recent global financial crisis has thus played an important role for volatility spillovers, emphasizing the connectedness between commodity and stock markets and inducing further financialization of commodities. Furthermore, by applying the rolling window estimation also on the net, pairwise and directional spillovers, we reveal that the S&P 500 Index exhibits significantly higher volatility transmission to commodities than any other commodity and also the S&P 500 appears to be dominant in all pairs over the whole period. The stock markets turn out to play a crucial role in the volatility transmission on the commodity market.

Finally, we investigate asymmetries in the response to negative and positive shocks. Despite the fact that the level of the asymmetry measure is not very substantial, the good and bad volatility is transmitted at different magnitudes and the dominant position changes over the studied time period. We find that in the years following the crisis, the negative shocks have had a higher impact on the volatility spillovers across the markets included in our analysis. However, while negative spillovers reach higher extremes, they do not strictly dominate the transmission of volatility based on positive returns. Moreover, an inspection of volatility spillover tables reveals that for all the observed commodities, the gross directional spillovers to others based on positive semivariances reach greater values than the directional spillovers due to negative shocks. Nevertheless, the S&P 500 Index exhibits a higher transmission of bad volatility to others and lower from others compared to good volatility spillovers which indicates that the stock market is more sensitive to bad news than the commodity market.

This thesis provides further corroboration of the increased importance of intra-market connectedness following the global financial crisis of 2008. While most previous studies focus on the volatility transmission among different stock markets or between the crude oil market and financial markets, we provide a complex analysis of the connectedness between seemingly unrelated widely traded commodities, representing different sectors, and the S&P 500 Index. The increasing financialization on the commodity market and the fast growth in the liquidity of commodity futures are of particularly high interest. Moreover, our results from the analysis of the asymmetric responses to positive and negative shocks defy the common notion that the negative shocks impact the volatility spillovers more heavily than the positive ones and indicate that the attitude of market participants has not been as pessimistic as generally assumed, except for the period of a few years following the global financial crisis. We thus provide a fresh look at the speed of the healing process of the markets following a major financial crisis.

We see several possible extensions of the present research. First, the inclusion of more commodities representing each sector would enable a more precise analysis of how the individual markets are related and one might want to inspect also the connectedness at the disaggregate sectoral level. Similarly, the connectedness between our selected commodities and the bond market could lead to interesting findings. Furthermore, a more detailed event analysis would further clarify the volatility transmission mechanism following major events in the commodity and equity markets. Last but not least, a directional spillover asymmetry measure would allow to study the source of asymmetry among assets and to identify the extent to which volatility from one specific asset transmits to other assets asymmetrically.

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Appendix A

Appendix

Complementary results to model specification

This appendix reports complementary tables and plots supporting the results from Chapter 5. We employed statistical software R to run the stationarity tests and calculate other statistics below. The R code employed in this thesis can be provided upon request.

Table A.1: ADF unit root test

	ADF Statistic for lag 2 and 4					
	RV		**Negative RS**		**Positive RS**	
CL	-10.641	-7.2925	-12.817	-8.8728	-12.86	-8.8002
CN	-22.479	-16.578	-25.62	-19.081	-24.273	-17.746
CT	-22.768	-15.955	-24.316	-17.267	-25.975	-18.388
GC	-16.916	-10.88	-18.728	-11.866	-19.33	-13.38
SP	-13.828	-9.1947	-13.011	-8.7874	-15.781	-10.443

Source: Author's computations.

Table A.1 provides the ADF statistic for our time series, in the first row for each of the series (RV, RS^-, RS^+) the ADF statistic for lag 2 is proveded and in the second row the results for lag 4. As the critical value for ADF for $T > 500$ and rejection at 1% is -3.96[1] and all the values in the Table A.1 are well below this limit, the p-value for all test has shown to be < 0.01.

[1]Source: `http://home.cerge-ei.cz/petrz/GDN/crit_values_ADF_KPSS_Perron.pdf`

Table A.2: PP unit root test

	p-value		
	RV	RS^-	RS^+
CL	<0.01	<0.01	<0.01
CN	<0.01	<0.01	<0.01
CT	<0.01	<0.01	<0.01
GC	<0.01	<0.01	<0.01
SP	<0.01	<0.01	<0.01

Source: Author's computations.

Note: Truncation lag parameter = 9

Table A.3: KPSS stationarity test

	p-value		
	RV	RS^-	RS^+
CL	<0.01	<0.01	<0.01
CN	<0.01	<0.01	<0.01
CT	<0.01	<0.01	<0.01
GC	<0.01	<0.01	<0.01
SP	<0.01	<0.01	<0.01

Source: Author's computations.

Note: Truncation lag parameter = 13

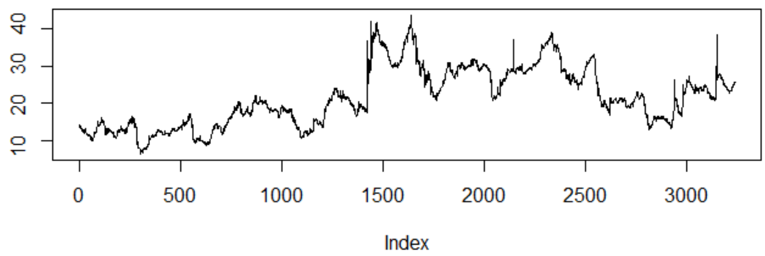
Table A.4: AIC, BIC

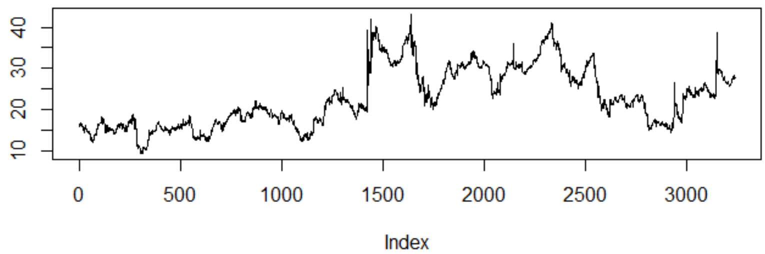
No. of lags	AIC	BIC
2	-254 379.6	-254 041.8
4	-255 370.2	**-254 725.4**
10	**-255 878.4**	-254 312.8

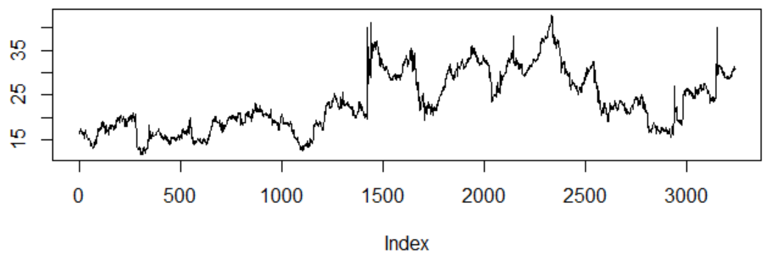
Source: Author's computations.

Robustness Check

Figure A.1: Robustness of volatility spillovers to VAR model specification



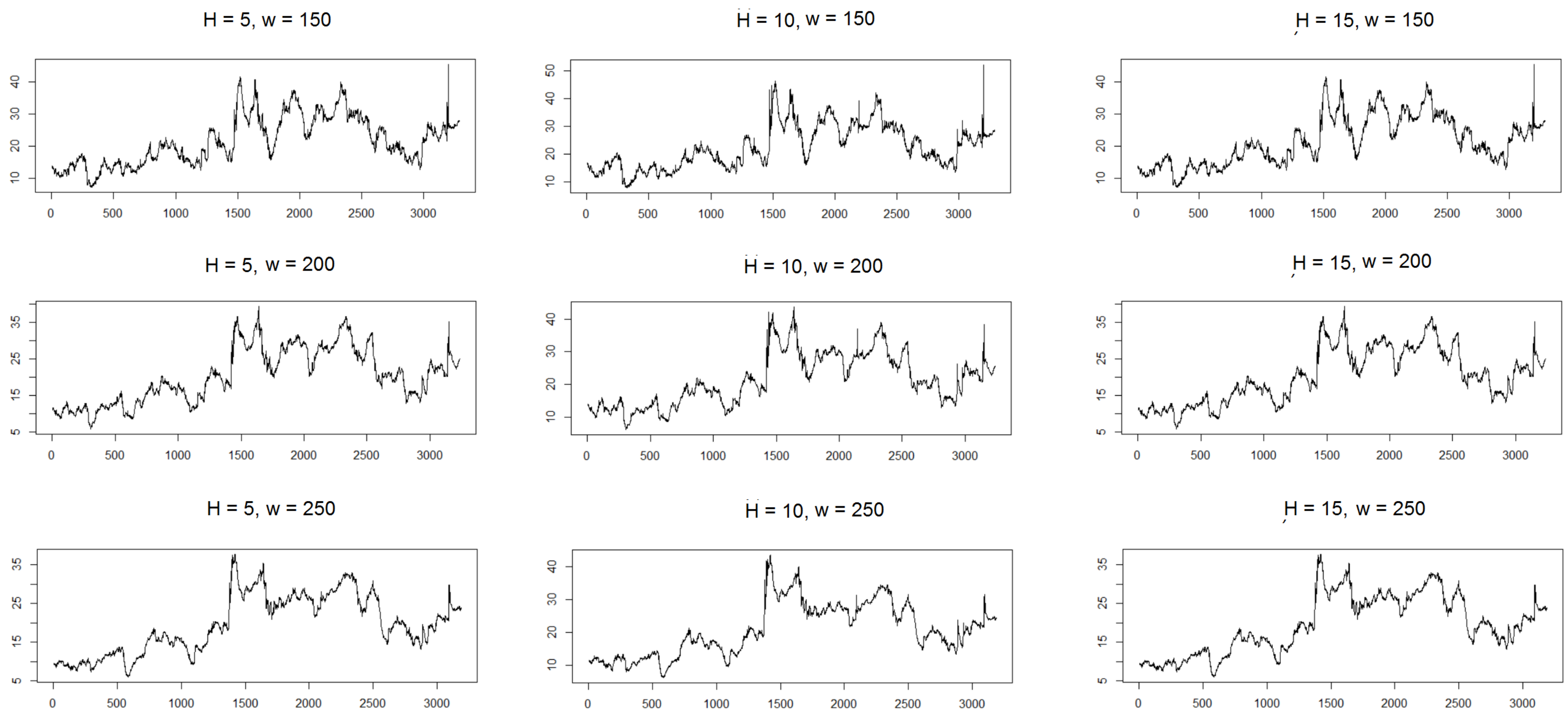




Source: Author's computations.

Note: The first plot represents the VAR(2)-based spillover index, second depicts the VAR(5)-based index and the third the VAR(4)-based index.

Figure A.2: Robustness check with respect to the window width, w, and forecasting horizon H = 5, H = 10 and H = 15



Source: Author's computations.