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Measurement of Volatility Spillovers and Asymmetric Connectedness on Commodity and Equity Markets*

Tereza PALANSKA - Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic (tereza.palanska@gmail.com)

Abstract

We study total, directional, and asymmetric connectedness between four commodity futures and S&P 500 Index over the 2002-2015 period by employing a recently developed approach based on realized measures and variance decomposition. We estimate that, on average, volatility transmission accounts for around one-fifth of the volatility forecast error variance. The shocks to the stock markets play the most crucial role. Volatility spillovers were limited before the 2008 financial crisis, and then sharply increased during the crisis. The directional spillovers detect quite low connectedness between soft agricultural commodities and the rest of the assets that we study, which may improve portfolio investors' trading strategies. Finally, we analyze asymmetric connectedness. Our results defy the common perception that adverse shocks impact volatility spillovers more heavily than the positive ones. Overall, we provide new insights into volatility transmission between analyzed markets, which may inform investment decisions and hedging strategies.

1. Introduction

In the last decades, individual markets have become interconnected in an unprecedented manner. Financial liberalization and the escalation of international trade have induced a significant increase in volatility in these markets. With higher integration, commodity and equity markets have become more sensitive to innovations, changing political and economic situations, positive and negative shocks, and changes in investor expectations. Moreover, as commodity markets become more financialized, and the liquidity of commodity futures increases, a growing number of investors are interested in commodities exclusively as investments. Monitoring, analyzing, and understanding time-varying volatility and the transmission mechanism across different asset classes has thus become of fundamental concern for researchers, investors as well as for policymakers. In this paper, we focus on widely traded commodities from different sectors and analyze volatility spillovers between commodity and stock markets.

Why do we study volatility spillovers on these markets, and what may be the implications for portfolio investors' trading strategies and regulators? Investors and other market players consider volatility as a good measure of risk. Significant changes

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in volatility and its transmission to different markets can have a substantial impact on portfolio diversification and insurance against risk. It is thus of especially high interest to study the patterns of volatility transmission and the evolution of intra-market connectedness. This paper aims to provide new insights into channels of volatility transmission, which may affect investment decisions and reduce uncertainty when taking into account volatility spillovers in the hedging strategy.

Most previous studies have focused mainly on volatility spillovers among major stock markets, across one specific industry or between the crude oil market and financial markets. However, several studies highlight the utility of analyzing the volatility spillovers between agriculture and financial markets as the financialization has generated a link between these two markets. In this paper, we contribute to this less bulky literature that analyzes volatility transmission on the commodity markets and its integration with the financial market. We model volatility spillovers across widely traded commodity markets, specifically among Crude oil, Gold, Corn, and Cotton futures, and one of the leading U.S. stock market indices, the S&P 500 Index, to represent the equity market. Each of the included commodities represents an essential asset in its class - energy, precious metal, grain, and fiber, respectively. On purpose, we have selected four commodities from four different industry sectors and a representative of the equity market to study how much are these seemingly unrelated markets interconnected. Understanding the volatility transmission mechanism between the commodity markets and the stock exchanges can be crucial for many, including governments, traders, portfolio managers, consumers, and producers. We employ high-frequency data for the 2002 - 2015 period, which enables us to examine volatility spillovers before, during, and after the global financial crisis of 2008.

Following the approach of Diebold and Yilmaz (2009), we base our methodology on the construction of a simple quantitative measure of interdependence, the so-called spillover index. Specifically, our approach is based directly on the decomposition of the forecast error variance of a vector autoregressive model, which 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 upon the work on spillover indices by Diebold and Yilmaz (2012, 2009), and combine it with the concept of positive and negative realized semivariances developed by Barndorff-Nielsen et al. (2010) The resulting modified indices allow for the modeling of asymmetric responses to positive and negative shocks. Furthermore, Baruník et al. (2016) define a new spillover asymmetry measure $\mathcal{SAM}$, as the difference between positive and negative spillovers. Such a measure allows us to document whether volatility is transmitted more due to positive or negative shocks and reveal possible asymmetry of these responses.

We find that volatility spillovers across the analyzed assets were limited before the 2008 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 crucial role regarding the transmission of volatility as the S&P 500 Index dominates all commodities in terms of general volatility spillover transmission measures. Analyzing asymmetric responses to positive and negative shocks, we contradict the common perception that the adverse shocks impact volatility spillovers more heavily than the positive ones. The results suggest that except for the times of crises, the attitude of market participants is not as pessimistic as generally assumed. Moreover, for all the observed commodities, the positive directional spillovers to other markets based on positive semivariances reach higher values than the negative directional spillovers. Nevertheless, the S&P 500 Index exhibits a higher transmission of negative volatility to others and lower from others compared to positive volatility spillovers. These findings indicate that the good news on the commodity markets translates to volatility on selected markets to a greater extent than the bad news. However, the opposite applies for the stock market.

We consider the contribution of this paper to be twofold. First, we provide a thorough analysis of how the selected commodity markets and the stock market are interconnected, revealing not only the extent of volatility transmissions between the markets but also the development of spillovers over 14 years, including the 2008 financial crisis. We thus contribute to a growing literature that draws attention to the importance of increasing integration between commodity and equity markets. Second, by employing recently developed methodology, we document the asymmetric responses to positive and negative shocks on these markets, defying the common notion that the negative shocks impact the volatility spillovers more heavily than the positive ones.

The remainder of this paper is structured as follows. Section 0 provides an overview of the existing literature focusing on inter-market connectedness and transmission of volatility between different markets. In Section 0, we describe the theoretical background behind the construction of realized measures and introduce the methodological approach. We describe the data in Section 0. In Section 0, we evaluate the results of total and directional connectedness and investigate potential asymmetries in the volatility transmission. Section 0 concludes and discusses the contribution of our analysis.

2. Literature

The majority of the existing studies that analyze volatility transmission focus on the relationships 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 showing the transmission effect from oil to stock markets to be more evident. Vo (2011) extract the nature of the relationship between the volatility of stock and oil futures markets by finding that there is time-varying correlation between the stock and oil futures markets which tends to grow with increasing volatility in the market. 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. Kang et al. (2015) reveal that after the 2008 crisis, oil-market specific demand shocks predicted a much larger fraction of implied-covariance of U.S. stock returns and volatility than in the pre-crisis period. Furthermore, authors show that the spillover index measuring the degree of connectedness for the oil market and the stock market shows to be relatively large and highly statistically significant, suggesting a strong connection between the volatility of oil prices and stock market returns.

Other commodity markets and their inter-connectedness have received relatively less attention, however, there are reasons to think that it plays an important role. First, there has been an extensive increase in the price volatility of non-energy commodities, argued by Tang and Xiong (2012) to be a result of financialization of the markets (Basak and Pavlova, 2016), a process accelerated by the fast growth of commodity index investment and causing increased commodity price correlations. Tang and Xiong (2012) 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 and Wohar, 2012; Mensi et al., 2013; Creti et al., 2013; Basak and Pavlova, 2016). Nazlioglu et al. (2013) study volatility transmission between oil and selected agricultural commodity prices - sugar, wheat, soybeans and corn before and after the food price crisis. Authors 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. Du et al. (2011) find that the oil price shocks between 1998 and 2009 appear to have a substantial impact on volatility in agricultural commodity markets. Kang et al. (2017) estimate a positive equicorrelation between six commodity futures market returns with increased volume during the crises.

A distinct body of literature 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. The results suggest that the correlations between commodity and stock markets evolve over time and fluctuate substantially, with high volatility being particularly observable in the post-crisis period. Mensi et al. (2013) also show 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 and Hammoudeh, 2010; Dwyer et al., 2011; Silvennoinen and Thorp, 2013; Baldi et al., 2016).

The vast majority of this research has used multivariate GARCH models, cointegration, structural VAR models or ARCH type models to study volatility spillovers. These models are, however, very limited in the detail in which they are able to quantify spillovers Baruník et al. (2015). In order to better measure and capture volatility spillovers, Diebold and 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 and Yilmaz (2012) who provide an improved volatility spillover measure in which forecast-error variance decompositions are invariant to variable ordering. Klößner and 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. Diebold and 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 and Yilmaz (2012) show that the volatility spillovers among four U.S. asset classes - stocks, bonds, foreign exchange rates and commodities - proved to have an increasing importance during the global financial crisis of 2008. Until then, the volatility transmissions across assets were quite limited. Diebold et al. (2017) study the connectedness among 19 key commodities between and find a clear clustering of commodities into groups that match traditional industry groupings, with the energy sector being the most important in terms of transmitting shocks to other markets.

The volatility spillover measure developed by Diebold and Yilmaz (2012) does not distinguish between the spillovers that originate due to bad and good uncertainty and thus does not allow for measuring the potential asymmetric effect. According to Feunou et al. (2013), we can perceive the decomposition of volatility caused by positive and negative news as a level of the downside and upside risk. Segal et al. (2015) decompose aggregate uncertainty into positive and negative 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 positive and negative volatility. Negative 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, positive volatility may be caused by optimistic macroeconomic, sectoral, or firm-specific announcements Baruník et al. (2015).

As the use of high-frequency data has increased substantially, Andersen et al. (2001) and Barndorff-Nielsen (2002) developed an estimator of the realized variance by estimating quadratic variation as the sum of the squared returns. Barndorff-Nielsen et al. (2010) further proposed a new measure - positive and negative realized semivariance, which captures volatility coming from positive and negative returns, respectively. Patton and Sheppard (2015) implemented this methodology to reveal new findings on the predictability of equity price volatility, Bollerslev et al. (2017) use this decomposition to study the cross-section of stock returns, and Feunou and Okou (2019) evaluate the economic significance of that decomposition by evaluating the mispricing of S&P 500 derivatives. Feunou et al. (2017) rely on similar techniques decomposing not only the realized volatility but also the implied volatility into up and downside components. Guo et al. (2019) employ analogous decomposition to predict a rising (falling) near-term equity premium. Feunou et al. (2018) propose a new decomposition of the variance risk premium in terms of upside and downside constituents.

In this paper, we use an approach that builds on these developments. To document asymmetries in volatility spillovers among the most liquid U.S. stocks., Baruník et al. (2016) combine the volatility spillover index methodology and the concept of positive and negative realized semivariances proposed by Barndorff-Nielsen et al. (2010). Such approach allows us to analyze the asymmetric spillovers using high-frequency measures. Using the methodology, Baruník et al. (2015) find evidence for increasing volatility spillovers among petroleum commodities that substantially change after the 2008 financial crisis. The authors argue that the observed higher volumes of volatility spillovers are related to the progressive financialization of commodities. Furthermore, Baruník et al. (2015) suggest that 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, and Baruník and Kočenda (2019) show that divergence in monetary policy regimes affects forex volatility spillovers but including oil to a forex portfolio decreases the total connectedness of the mixed portfolio.

In this paper we hypothesize that volatility spillovers exhibit different magnitudes based on whether the shock originates from negative or positive returns. This notion has roots in a broad body of research, represented for example by (Barberis, 2013), who 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. To test for these effects, we use return-based measures which has been the standard approach in the literature (Feunou et al., 2013; Patton and Sheppard, 2015).

Baldi et al. (2016) and Silvennoinen and Thorp (2013) highlight the motivation and the utility of analyzing the volatility spillovers between agriculture and financial markets as the financialization has generated a link between these two markets. This paper follows up on this conception and aims to bring new insights about integration between commodity and stock markets by not only investigating to what extent shocks in stock markets impact commodity price volatility but also by studying the asymmetric connectedness. Thus, the primary innovation presented by this paper is that we estimate directional spillover indices and document asymmetries in volatility spillovers among commodities representing very different commodity markets and equity markets. The knowledge of whether good news in the commodity market also translates to the stock market and vice versa can be beneficial for many portfolio managers and investors.

3. Methodology

In this section, we describe the theoretical background behind our hypotheses and the methodology that we use to estimate the effects of volatility and their spillovers in commodity markets. First, we discuss the realized measures - realized variance and its decomposition into positive and negative semivariances. 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 and Yilmaz (2009, 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 and Yilmaz, 2013). This method allows us to measure both the total and directional volatility spillovers and reveals the level of intra-market spillovers.

To study the volatility-spillover asymmetries, we employ the volatility spillover index devised in Diebold and Yilmaz (2009) as modified by Baruník et al. (2016). Based on the concept of realized semivariances 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

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:

$$p_t = \int_0^t \mu_s \, ds + \int_0^t \sigma_s \, dW_s + J_t, \tag{1}$$

where μ represents a predictable drift process, σ_s a strictly positive volatility process, W a standard Brownian motion and J the pure jump. The quadratic variation of the process is then defined as:

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

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 $n \rightarrow \infty$. 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 semivariances.

3.2 Realized Semivariances

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:

$$RS^- = \sum_{i=1}^{n} r_i^2 \, I_{[r_i<0]} \tag{3}$$

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 semivariances correspond to the good and bad states of the underlying variable and serve as a proxy for positive and negative 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).

3.3 Spillover Index

Next, we introduce a measure of volatility spillovers which allows for the distinction between negative and positive jumps. Based on the approach of Diebold and Yilmaz (2012), Baruník et al. (2016) propose an extension in the form of including the above-defined concept of realized semivariances.

The initial uniform spillover index introduced by Diebold and 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 and 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.

3.4 Total Spillover Index

We further describe the construction of the extended spillover index as developed by Diebold and 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):

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \epsilon_t, \tag{4}$$

where $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})$ is an N-dimensional vector, Φ_i, with $i = 1, \dots, p$, 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, the vector x represents 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

$$x_t = \sum_{i=0}^{\infty} \Psi_i \, \epsilon_{t-1}, \tag{5}$$

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

$$\Psi_i = \Phi_1 \Psi_{i-1} + \Phi_2 \Psi_{i-2} + \dots + \Phi_1 \Psi_{i-1} = \sum_{j=1}^{p} \Phi_j \, \Psi_{i-j}, \tag{6}$$

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 and 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 $i = 1,2, \dots, N$. Cross variance shares, or spillovers, are defined as fractions of the H-step-ahead error variances in forecasting to x_i, due to shocks to x_j, for $i, j = 1,2, \dots, N$ 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:

$$\omega_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Psi_{\boldsymbol{h}} \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}} \boldsymbol{e}_{\boldsymbol{j}} \right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Psi_{\boldsymbol{h}} \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}} \Psi'_{\boldsymbol{h}} \boldsymbol{e}_{\boldsymbol{i}} \right)}, \tag{7}$$

where Σ_ϵ 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, e_i is the selection vector, with one as the i^{th} element and zeros otherwise, and Ψ_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:

$$\sum_{j=1}^{N} \omega_{ij}^{H} \neq 1 \tag{8}$$

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:

$$\widetilde{\omega_{ij}^{H}} = \frac{\omega_{ij}^{H}}{\sum_{j=1}^{N} \omega_{ij}^{H}} . \tag{9}$$

This step ensures that $\sum_{j=1}^{N} \widetilde{\omega_{ij}^{H}} = 1$ and $\sum_{i.j=1}^{N} \widetilde{\omega_{ij}^{H}} = N$ (i.e. the contributions of spillovers from volatility shocks are normalized by the total forecast error variance (Baruník et al., 2016)). Diebold and 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:

$$\mathcal{S}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\omega_{ij}^{H}} . \tag{10}$$

3.5 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 and Yilmaz, 2012). The directional spillovers received by asset i from all other assets j are defined as follows:

$$\mathcal{S}_{i\leftarrow\cdot}^{H} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\omega_{ij}^{H}} . \tag{11}$$

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

$$\mathcal{S}_{\mathrm{i}\rightarrow\cdot}^{\mathrm{H}} = 100 \times \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\omega_{ji}^{H}} . \tag{12}$$

3.6 Net Spillovers and Net Pairwise Spillovers

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

$$\mathcal{S}_{\mathrm{i}}^{\mathrm{H}} = \mathcal{S}_{\mathrm{i}\rightarrow\cdot} - \mathcal{S}_{\mathrm{i}\leftarrow\cdot}^{\mathrm{H}} . \tag{13}$$

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:

$$\mathcal{S}_{ij}^{H} = 100 \times \frac{1}{N}\left(\widetilde{\omega}_{ji}^{H} - \widetilde{\omega}_{ij}^{H}\right). \tag{14}$$

3.7 Positive and Negative Volatility

The innovation brought about 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 ($\mathcal{S}_{i\leftarrow\cdot}^-, \mathcal{S}_{i\rightarrow\cdot}^-$) and positive returns ($\mathcal{S}_{i\leftarrow\cdot}^+, \mathcal{S}_{i\rightarrow\cdot}^+$).

We are thus able to isolate asymmetric volatility spillovers by replacing the vector of volatilities $RV_t = (RV_{1t}, \dots, RV_{nt})'$ defined above with the vector of negative semivariances, $RS_t^- = (RS_{1t}^-, \dots, RS_{nt}^-)'$, or the vector of positive semivariances, $RS_t^+ = (RS_{1t}^+, \dots, RS_{nt}^+)'$[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 (positive or negative) matters more for volatility spillover transmission or whether their effects are similar in magnitude.

3.8 Spillover Asymmetry Measure

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

$$\mathcal{SAM} = \mathcal{S}^+ - \mathcal{S}^- \tag{15}$$

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 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.

4. Data

In this paper, we use five-minute high-frequency data to study volatility spillovers and their asymmetries on the commodity market and stock market. 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: Crude

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

oil (CL), Gold (GC), Corn (CN) and Cotton (CT).[2] All commodity futures included in the analysis are traded on the U.S. commodities exchanges, specifically in New York, Chicago, and Atlanta. Therefore, the possibility of lagged effects due to time zone differences is minimized. NYMEX WTI Light Sweet Crude Oil futures represent the world's most liquid and actively traded crude oil contracts. Gold is the leading precious metal utilized by speculators as an investment vehicle, and COMEX Gold futures included in the analysis represent one of the world's major benchmark futures contract for gold prices. Corn 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 biomass. CBOT Corn futures serve as a liquid tool to profit from or hedge against price movements in grain market. At the center of the global textiles industry, Cotton No. 2 Futures traded on the Intercontinental Exchange are preferred contracts among commodity trading advisors and hedge funds. All these commodity futures are quoted against the U.S. dollar; specifically, cents per barrel, cents per troy ounce, cents per bushel, and cents per pound for crude oil, gold, corn and cotton futures, respectively. Each of these commodity futures serves as a proxy for specific markets in which they play the leading role, i.e. oil market, precious metal market, grain market and fiber market. As we are also interested in the connectedness between these commodity markets and the stock market, we use data for the S&P 500 Index (S.P.) to represent the stock market. The data spans from January 2, 2002, to December 31, 2015, and comes from Tick Data, Inc., one of the major providers of historical data from stock, futures, options, and forex markets.

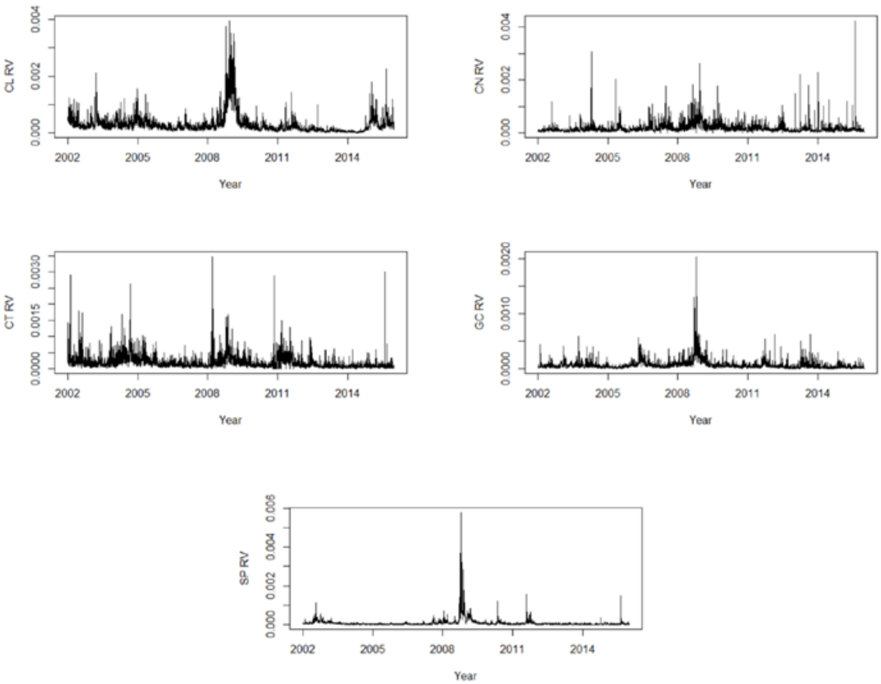
In order to prevent estimation bias that may be caused by low trading activity on the market, we exclude weekends, U.S. federal holidays, and some state holidays. As the selected futures are traded on different Exchanges, the number of observations per trading day, as well as the number of days when the exchange was open, varies among the analysed commodities. For the analysis's purposes, we exclude all days on which at least one of the Exchanges was closed. Furthermore, we discard days on which, for at least one variable, more than 20% observations is missing as compared to the average trading day.[3] Such 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., the day before Independence Day) which could lead to a bias in our estimation. These adjustments lead to the final sample, which consists of 3,437 trading days.

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 included in order to avoid possible distortion. 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 correlation matrix and

[2] The abbreviations represent the ticker symbol for these futures.
[3] 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 treat Cotton futures with care and use a sample that excludes Cotton entirely as a robustness check.

descriptive statistics tables are provided in the Appendix (available on the website of this journal). Tables A3 – A5 provides some interesting descriptive statistics regarding the daily realized measures showing that that based on the statistics for kurtosis and skewness none of the distributions of realized measures is normally distributed. The highest mean, as well as the highest standard deviation of realized variance, is reported for Crude oil.

Figure 1 Daily Realized Variances



Notes: The daily realized variance are defined as a sum of squared intraday logarithmic 5-minute returns for each trading day. Notation: RV= Realize variances, CL = Crude oil, CN = Corn, CT = cotton, GC = Gold, SP = S&P 500 Index.
Source: Author's computations.

Figure 1 presents the plots of daily realized variances (R.V.) for each observed variable. The realized variances reached the highest values 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.

5. Results

This section summarizes the empirical results and is divided into three parts. First, we carry out the static and dynamic analysis providing evidence of the total connectedness of the selected markets. The second part shows which assets under study are the most influential and the ones most influenced in terms of volatility spillovers. Lastly, we study possible asymmetries in the transmission mechanism.

5.1 Total Connectedness

As an initial observation of overall connectedness on the analyzed markets, we report the so-called volatility spillover table which provide an approximate ``input–output" decomposition of the total volatility spillover index. Table 1 aggregates the estimated average contribution to the volatility of market j coming from shocks to market i over the studied period. 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 individual 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. The off-diagonal values of the matrix represent the directional spillovers between commodity pairs. 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. An interesting observation is that on average shocks to S&P 500 Index impact the studied commodities the most.

Table A7 in the *Appendix* (on the website of this journal) provides the average estimated volatility spillovers within markets including only the four studied commodities. The volatility spillover index is 12.64% when including only commodity futures. This result reveals that the connectedness increases when both commodity and stock markets are assessed jointly.

Chyba! Nenalezen zdroj odkazů. provides more complex observations as it captures the dynamics of the volatility spillovers among the four commodities and S&P 500 Index over the examined time period. To study the development over time we estimate our preferred model using 200-day rolling windows, horizon h = 10, and VAR lag length of 2.[4] As the data in the analysis spans over 14 years from the beginning of 2002 until the end of 2015, we can observe rich dynamics and important patterns. By

[4] Robustness check with respect to the window width, w = 150, w = 200 and w = 250, and forecasting horizon H = 5, H = 10 and H = 15 is provided in the *Appendix* (on the website of this journal). The results do not substantially change and are robust with respect to the window length and horizon selection. We determined the lag length of the VAR model based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The results (available upon request) reveal 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. The specification of the model is consistent with the approach employed by Baruník et al. (2016) and Diebold and Yilmaz (2012). In addition, Diebold and Yilmaz (2012) provide a sensitivity analysis of their volatility spillover index to the VAR lag structure and show that results do not differ substantially for lags of 2 to 6. Baruník et al. (2015) obtained analogous results for lags of 2 to 4. We also perform this robustness check provided in the *Appendix* (on the website of this journal) and conclude that there are no significant differences and the volatility spillover indices are robust to the choice of the VAR model specification.

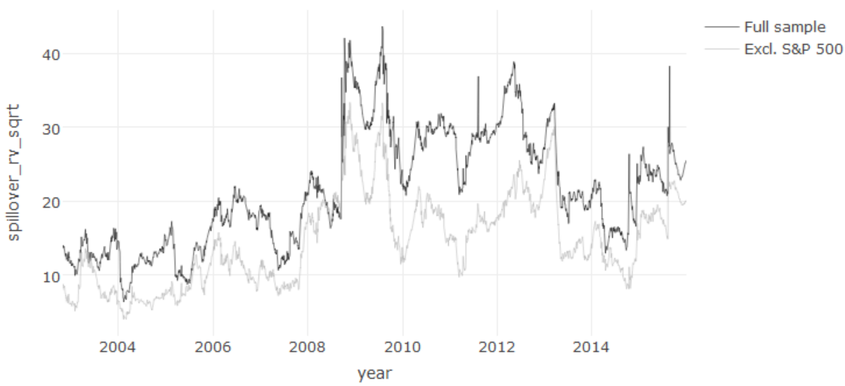
far the most important event that occurred during the observed time-period was the global financial crisis of 2008.

Table 1 Volatility Spillover Table - Full Sample

		From					
		Crude oil	*Corn*	*Cotton*	*Gold*	*S&P*	*Directional from others*
To	*Crude oil*	73.675	2.135	1.183	5.217	17.790	26.325
	Corn	2.748	85.679	3.501	4.019	4.053	14.321
	Cotton	2.749	3.786	88.674	1.297	3.493	11.326
	Gold	6.341	2.299	0.583	64.399	26.377	35.601
	S&P	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	*Total Spillover Index* 22.44%

Notes: The underlying variance decomposition is based upon a daily VAR of order 2. The (i, j)-th value is the estimated contribution to the variance of the return volatility forecast error of asset i coming from innovations to the return volatility of asset j.
Source: Author's computations

Figure 2 Total Volatility Spillovers - Full Sample and Sample Excluding The S&P 500 Index



Notes: We plot moving volatility spillover indexes, defined as the sum of all variance decomposition from volatility spillovers tables, estimated using 200-week rolling windows. The black line represents the total volatility spillover index for the full sample, the grey line for the sample excluding the S&P 500 Index.
Source: Author's computations.

Chyba! Nenalezen zdroj odkazů. presents the moving-window estimation of total spillovers for the full sample and for the sample including only commodities. The volatility spillover indices for both samples evolve relatively similarly over the studied time period, however, the spillovers based on the full sample reach larger magnitudes during the whole time period. 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 in our sample was not as extensive as that on the U.S. stock market (represented by the S&P 500 Index).[5]

The first notable observation is the strong dynamics of the spillovers among the four commodities and S&P 500 Index. The time-varying spillover index exhibits a great degree of fluctuation, ranging from about 7% to almost 45%. This suggest that the volatility of one commodity does not necessarily excessively impact the volatility of other commodities or stock index under study. As the commodities belong to different classes, such result seems anticipated and provides evidence that may be used to increase the benefits from portfolio diversification during periods of low spillovers.

Table 2 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
08/05/2011	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
10/15/2014	34.569	14.621	U.S. stock market decline
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.
08/12/2015	38.351	18.225	Global stock markets plunge on China currency rapid decline
8/24/2015	79.994	49.438	China's Black Monday flash crash

Notes: The spillover index in the table represents a measure of the contribution of spillovers from volatility shocks across the variables in the system to the total forecast error variance in the selected sample. To see the exact formula for calculating the index see Section 0.
Source: Author.

Second, we can evidently 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. The first substantial increase in inter-market connectedness can be detected in September 2008 following the collapse of Lehman Brothers 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. During the fall of 2008, the index for the full sample more than doubled and exceeded the 40% level of volatility

[5] We have also analyzed the development of the total volatility index when excluding Cotton from our sample as a type of a robustness check since the observations for Cotton are somewhat inconsistent. The results suggest that our previous estimates are robust with respect to the selection of assets and are available upon request.

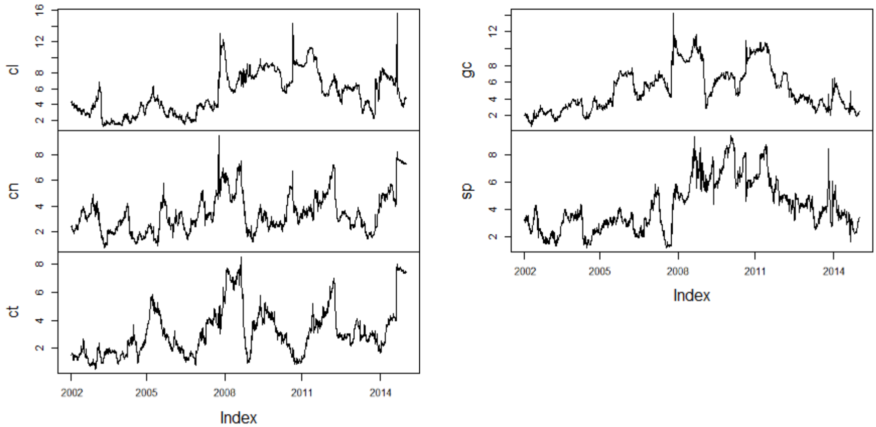
spillovers. Concerning only the commodity markets sample, the values of the index increased from 18% before the Lehman Brothers collapse by 15 percentage points, reaching their maximum of 33.37% during November 2008. The high level of volatility spillovers has lasted also throughout the first half of 2009 which can be explained by 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 2 provides an overview of the important events and explains most of the major spikes observable in **Chyba! Nenalezen zdroj odkazů.**.

To sum up, the overall connectedness of the markets included in the analysis increased substantially following the global financial crisis of 2008. 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 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 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 and Yilmaz (2012).

5.2 Directional and Net Spillovers

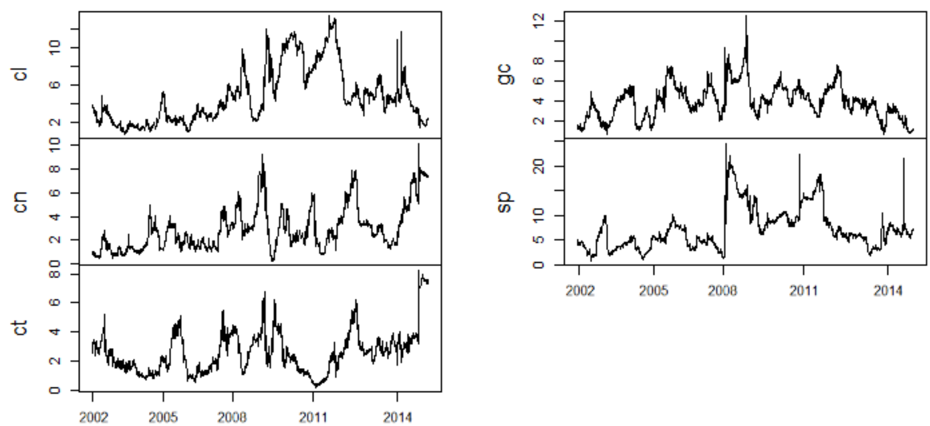
To identify which assets under study are the most influential and the ones most influenced in terms of volatility transmission, we analyze the directional and net spillovers. Figure 3 presents directional volatility spillovers from others to each of the five assets over time. For the full sample, we 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 (cl), the S&P 500 (sp), and Gold (gc) remains relatively high for a long period after the crisis, the directional contributions from others to Cotton (ct) and Corn (cn) return relatively fast to their pre-crisis levels. During the whole analyzed period, the directional transmissions from others to Cotton and Corn are lower than for the other 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 agriculture commodities, represented by Cotton and Corn, are the least connected to the rest of the sample and thus may present good options for diversifying the portfolio.

Figure 3 Directional Spillovers from Other Assets



Notes: We plot moving volatility Spillover Indexes for each asset, defined as the sum of all variance decomposition in a column for each asset except its own, i.e. the values for each assets presented in the row "Directional from others" in Table 1, estimated using 200-week rolling windows. Notation: cl = Crude oil, cn = Corn, ct = cotton, gc = Gold, sp = S&P 500 Index.
Source: Author's computations.

Figure 4 Directional Spillovers to Others



Notes: We plot moving volatility Spillover Indexes for each asset, defined as the sum of all variance decomposition in a row for each asset except its own, i.e. the values for each assets presented in the row "Directional to others" in Table 1, estimated using 200-week rolling windows. Notation: cl = Crude oil, cn = Corn, ct = cotton, gc = Gold, sp = S&P 500 Index.
Source: Author's computations.

Figure 4 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, especially during the period corresponding to financial crisis. 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 of 2008-2009, 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.

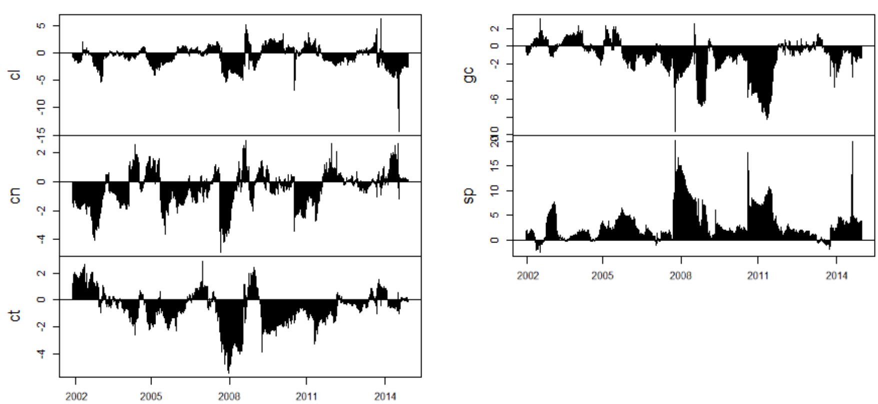
To obtain more detailed information about the direction and magnitude of volatility spillovers, we calculate net spillovers, i.e. the difference between contribution from others and contribution to others. Table 3 shows the static analysis of net volatility measures and reveals whether the asset acts 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. 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 3 Net Volatility Spillovers - Full Sample

Crude oil	*Corn*	*Cotton*	*Gold*	*S&P*
-5.80242	-4.652	-4.912	-11.714	27.079

Notes: Net spillovers are calculated the difference between "Directional from others" and "Directional to others" from Table 1.
Source: Author's computations.

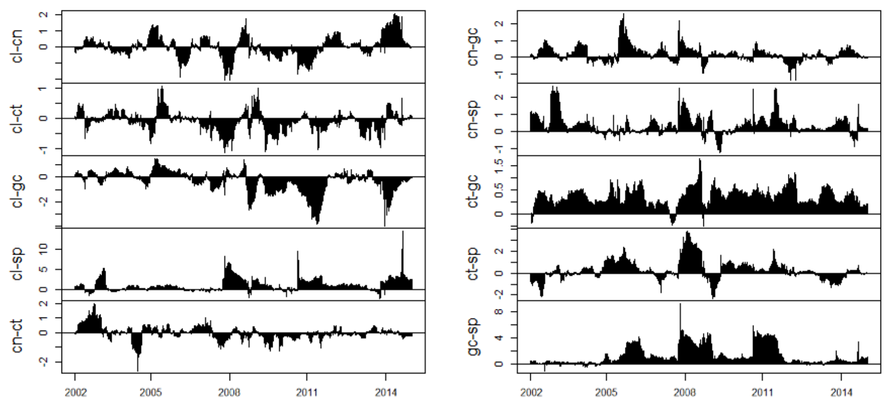
Figure 5 Net Spillovers



Notes: We plot moving net volatility spillover indexes for each asset calculated the difference between "Directional from others" and "Directional to others" from Table 1, estimated using 200-week rolling windows. Notation: cl = Crude oil, cn = Corn, ct = cotton, gc = Gold, sp = S&P 500 Index
Source: Author's computations.

Figure 5 shows that net spillovers alternate over the sample period as the net spillovers for all assets take both positive and negative values at some point. The impact of financial instability reflected in the net spillovers is relatively 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. On the contrary, S&P 500 Index does not take almost any negative values over the 14-year observed period and reach significantly higher volumes compared to the rest of the sample. Cotton and Crude oil seem to be more balanced in terms of transmitting and receiving net spillovers from other assets. 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% (Denyer, 2015).

Figure 6 Pairwise Spillovers



Notes: We plot moving pairwise volatility spillovers, 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 crude-oil to CN minus the contribution from CN to CL. Notation: cl = Crude oil, cn = Corn, ct = cotton, gc = Gold, sp = S&P 500 Index.
Source: Author's computations.

For a more detailed analysis, Figure 6 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 Corn (cn) to Crude oil (cl) exceed those from cl to cn Based on these plots, we can determine the dominant position of an asset in almost all pairs - the S&P 500 Index (sp) appears to have principal influence in all pairs. The volatility in Crude oil spills over to Gold (gc) 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 (ct) in terms of spillover transmission. The volatility of Gold impacts considerably more the fluctuation of Cotton than vice versa. The transmission of pairwise net spillovers appears quite balanced in $cl - cn$ and $cn - ct$ pairs.

To conclude, the directional and the net pairwise spillover analysis underlines the dominant role of the S&P 500 Index and reveals that the volatility on the stock market has substantial influence specifically on the volatility in Gold and Crude oil future markets. We can infer that the financial crisis has induced an increased volatility transmission for all analyzed assets. However, the volatility in Corn and Cotton futures proved not to be so much significantly influenced by the shocks in Gold and Crude oil future markets and the stock market even during the turbulent period. This result adverts to quite low connectedness between the two soft agriculture commodities and the rest of the assets under review which may improve portfolio investors' trading strategies.

5.3 Asymmetric Volatility Spillovers

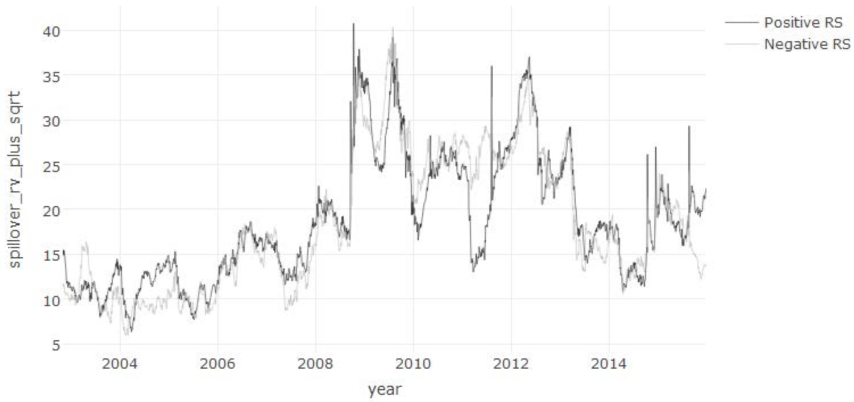
In this section, we investigate potential asymmetries in the transmission mechanism due to negative and positive shocks. Based on the methodology proposed by Barndorff-Nielsen et al. (2010) we decompose the realized variance to positive and negative semivariances and use them to derive negative and positive volatility spillovers. This enables us to quantify to what extent the analyzed markets process information asymmetrically.

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%). However, this finding does not support our conjecture 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. Gold, Cotton, and Corn exhibit particularly significant differences as the transmission of positive volatility to others reaches almost twice the volume of spillovers due to negative volatility. However, the S&P 500 Index exhibits higher transmission of negative volatility to others and lower from others as compared to positive volatility spillovers. 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. We provide the so-called volatility spillover table based on negative and positive realized semivariances in Tables A8 and A9 in the *Appendix* (on the website of this journal).

Furthermore, in Table A10 in the *Appendix* (on the website of this journal), we also provide the net spillovers, which allow us to compare the results better and link them to previous findings. Examining the negative and positive net spillovers, we can observe that the magnitude for the Gold and S&P 500 Index differs substantially. For Gold, the reason is that the positive volatility transmission from the Gold market to other markets reaches a higher volume. Regarding the S&P 500 Index, the change is mainly caused by the higher transmission of positive volatility from others and lower positive volatility spillovers to others comparing to the negative ones. Nevertheless, all selected assets remain to have the same role in terms of 'net giver' and 'net receiver'.

As in the case of net spillovers based on realized variances presented in Table 3, the only 'net giver' is the representative of the equity market while all selected commodities remain to be receivers. This further highlights the importance of equity market's development to analyzed commodities.

Figure 7 Asymmetric Volatility Spillovers - Full Sample



Notes: We plot moving volatility spillover indexes, defined as the sum of all variance decomposition from volatility spillovers tables for relized semivariances, estimated using 200-week rolling windows. The black line represents the spillover index from positive realized semivariances (RS^{+}), the gray line from negative realized semivariances (RS^{-}).
Source: Author's computations.

Figure 7 allows us to observe the differences in volatility transmission that emerge due to negative and positive returns over time.[6] The black line represents the spillover index from positive RS whereas the gray line depicts the spillover index from negative RS. Both spillovers share a common path. However, we can identify some differences in the development of the two measures during the time, especially in the post-crisis period. A closer inspection of different asymmetries is provided in Figure 8 as the differences are better visible using the Spillover Asymmetry Measure ($\mathcal{SAM}$).

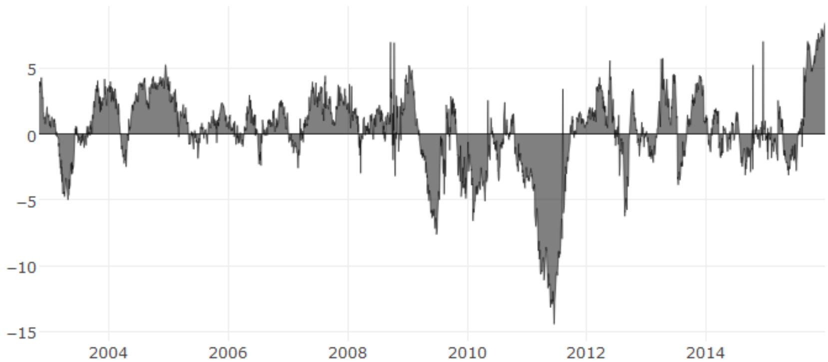
$\mathcal{SAM}$ allows us to study the extent of the asymmetry in the volatility transmission independently of the level of spillovers. Positive values of $\mathcal{SAM}$ indicate the dominance of the volatility spillover index based on positive RS while negative values of $\mathcal{SAM}$ imply that 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 8 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

[6] In the *Appendix* (on the website of this journal), we provide Figure A1, which depicts the positive and negative spillovers for the sample including only commodities.

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 negative 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%.

Figure 8 Spillover Asymmetry Measure (SAM) - Full Sample

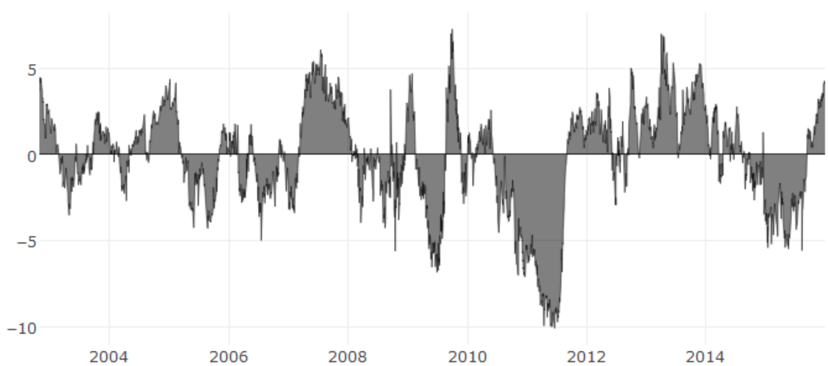


Notes: We plot moving spillover asymmetry measures, defined as $\mathcal{SAM} = \mathcal{S}^{+} - \mathcal{S}^{-}$, estimated using 200-week rolling windows. When the line is above zero, the transmission of volatility due to positive returns is higher than that due to negative returns. The opposite applies for values below zero.
Source: Author's computations.

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 positive and negative volatility may be to some extent caused by increasing financialization (Baruník et al., 2015). Similarly, Tang and 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 9 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 period after the financial crisis, the dominance of volatility spillovers based on negative semivariances is also observable for this sample however, it does not reach such a high volume as in the case of the previous sample including S&P 500 Index.

Figure 9 Spillover Asymmetry Measure (SAM) - Sample Excluding The S&P 500 Index



Notes: We plot moving spillover asymmetry measures, defined as $\mathcal{SAM} = \mathcal{S}^{+} - \mathcal{S}^{-}$, estimated using 200-week rolling windows. When the line is above zero, the transmission of volatility due to positive returns is higher than that due to negative returns. The opposite applies for values below zero.
Source: Author's computations.

From mid-2011 till mid-2014, the positive volatility transmission prevails. However, in late 2014 and for several first months of 2015, adverse shocks to commodity markets had a substantially more significant 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 and Anukoonwattaka, 2015). Moreover, one may also associate the dominance of negative volatility spillovers in this period to a negative bubble in oil prices in 2014/15, which decreased oil prices beyond the level justified by economic fundamentals (Fantazzini, 2016). Khan (2017) analyzes possible factors explaining this plunge in oil prices, such as the domestic oil boom in the United States and Iraq, or the November 2014 meeting of OPEC, when they did not cut production despite the steady increase in non-OPEC oil production. Another explanation why we observe a more substantial negative asymmetry in the pre- and post-financial crisis, when excluding S&P 500, is because these events might have a relatively more significant impact on the volatility transmission when taking into account only the commodity futures than when also considering the S&P 500. The previous results have shown that the S&P 500 Index is the most influential asset in our sample in terms of volatility spillovers. And thus, the development on the stock market may overshadow adverse shocks on the selected commodity markets.

Overall, we find some asymmetric behavior in volatility transmission for both samples. In particular, in the years following the crisis, the adverse shocks have had a higher impact on the volatility spillovers across the markets included in our analysis. The level of the asymmetry measure does not take very high values during the whole period. Baruník et al. (2015) obtained a similar result finding that after 2004 the magnitude of the asymmetries on the petroleum market decisively declined, and the measure is rather small and less volatile than in the previous 20 years. When studying connectedness between oil and forex markets, Baruník and Kočenda (2019) find that asymmetries in volatility transmission are also relatively small. In both cases, authors conjecture that lower asymmetries may be partly caused by increasing commodity financialization and argue that as a further consequence, higher volatility transmission coincides with a lower level of asymmetries between volatility spillovers due to positive and negative shocks. Although the asymmetric connectedness of markets included in our analysis is not as substantial, the positive and negative volatility is transmitted at different magnitudes, and the dominant position changes over the studied 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 Apergis et al. (2017), and suggest that risk transmission is not driven by pessimism as much as generally assumed.

6. Conclusion

In this paper, we employ an approach introduced by Diebold and Yilmaz (2009, 2012) and its extension developed by Baruník et al. (2016) based on realized volatility measures. We quantify the volatility spillovers using data on Crude oil, Gold, Corn, and Cotton futures, and the S&P 500 Index representing the equity market.

We find that the connectedness increases when both commodity and stock markets are assessed jointly reaching 22.44%. The dynamic analysis provides strong evidence that the connectedness between markets has become much more significant after the global financial crisis of 2008 and shows that the uncertainty and skepticism of market participants persist in the markets quite long after the crisis.

The directional and the net pairwise spillover analysis reveal that the S&P 500 Index exhibits significantly higher volatility transmission to commodities than any other asset. The volatility on the stock market has substantial influence, specifically on the volatility in Gold and Crude oil future markets. Our findings show that the shocks to stock markets play a rather important role in the volatility in commodity futures, while commodities do not influence each other's volatility to such an extent.

Finally, the analysis of asymmetric connectedness reveals that the level of the asymmetry measure in our sample is not very substantial. We find that in the years following the crisis, the adverse 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, the positive directional spillovers to other markets based on positive semivariances reach greater values than the negative directional spillovers. These findings 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. Nevertheless, the S&P 500 Index exhibits a higher transmission of negative volatility to others and lower from others compared to positive volatility spillovers, which indicates that the stock market is more sensitive to bad news than the commodity market.

This paper provides further corroboration of the increased importance of intra-market connectedness following the global financial crisis of 2008 and a fresh look at the speed of the healing process of the markets following the crisis. We show that in the post-crisis period, higher volatility transmission coincides with a lower level of asymmetries between volatility spillovers due to positive and negative shocks. Such a pattern may be partly caused by increasing commodity financialization and fast growth in the liquidity of commodity futures.

REFERENCES

Andersen TG, Bollerslev T, Diebold FX, Labys P (2001): The Distribution of Realized Exchange Rate Volatility. *Journal of the American Statistical Association*, 96:42–55.

Apergis N, Baruník J, Lau MCK (2017): Good Volatility, Bad Volatility: What Drives The Asymmetric Connectedness of Australian Electricity Markets? *Energy Economics*, 66:108–115.

Arouri MEH, Jouini J, Nguyen DK (2012): On the Impacts of Oil Price Fluctuations on European Equity Markets: Volatility Spillover and Hedging Effectiveness. *Energy Economics*, 34:611–617.

Baldi L, Peri M, Vandone D (2016): Stock Markets' Bubbles Burst and Volatility Spillovers in Agricultural Commodity Markets. *Research in International Business and Finance*, 38:277–285.

Barberis NC (2013): Thirty Years of Prospect Theory in Economics: A Review and Assessment. *Journal of Economic Perspectives*, 27:173–195.

Barndorff-Nielsen O, Kinnebrock S, Shephard N (2010): *Volatility and Time Series Econometrics: Essays In Honor Of Robert F. Engle, Chapter Measuring Downside Risk-Realised Semivariance*. Oxford University Press.

Barndorff-Nielsen, O.E., 2002. Econometric Analysis of Realized Volatility and its Use in Estimating Stochastic Volatility Models. J. R. Stat. Soc. Ser. B Stat. Methodol. 64, 253–280.

Baruník J, Kočenda E (2019): Total, Asymmetric and Frequency Connectedness Between Oil and Forex Markets. *The Energy Journal,* Forthcoming.

Baruník J, Kočenda E, Vácha L (2017): Asymmetric Volatility Connectedness on the Forex Market. *Journal of International Money and Finance*, 77(C):39–56.

Baruník J, Kočenda E, Vácha L (2016): Asymmetric Connectedness on the US Stock Market: Bad and Good Volatility Spillovers. *Journal of Financial Markets*, 27:55–78.

Baruník J, Kočenda E, Vácha L (2015): Volatility Spillovers Across Petroleum Markets. *The Energy Journal*, 36(3):309-329.

Basak S, Pavlova A (2016): A Model Of Financialization of Commodities. *The Journal of Finance,* 71(4):1511-1556.

Bollerslev T, Li SZ, Zhao B (2017): Good Volatility, Bad Volatility, and the Cross Section of Stock Returns. *Journal of Financial and Quantitative Analysis*, 1–31.

Choi K, Hammoudeh S (2010): Volatility Behavior of Oil, Industrial Commodity and Stock Markets in a Regime-Switching Environment. *Energy Policy*, 38:4388–4399.

Cochrane JH (2005): Time Series for Macroeconomics and Finance. *Manuscript.* University of Chicago.

Creti A, Joëts M, Mignon V (2013): On the Links Between Stock and Commodity Markets' Volatility. *Energy Economics*, 37(C):16-28

Degiannakis S, Filis G, Floros C (2013): Oil and Stock Returns: Evidence from European Industrial Sector Indices in a Time-Varying Environment. *Journal of International Financial Markets, Institutions and Money*, 26:175–191.

Degiannakis S, Filis G, Kizys R (2014): The Effects of Oil Price Shocks on Stock Market Volatility: Evidence from European Data. *The Energy Journal*, 35:35–56.

Denyer S (2015): China's 'Black Monday' spreads Stock Market Fears Worldwide. Washington Post Available Online: https://www.washingtonpost.com/world/world-markets-lose-ground-amid-black-monday-for-shanghai-index/2015/08/24/a1c88a48-0161-404c-a48b-6cee7d04f864_story.html

Diebold FX, Liu L, Yilmaz K (2017): Commodity Connectedness. *Unpublished Manuscript.*

Diebold FX, Yilmaz K (2013): Measuring the Dynamics of Global Business Cycle Connectedness. *PIER Working Paper*.

Diebold FX, Yilmaz K (2012): Better to Give Than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting*, 28(1):57-66.

Diebold FX, Yilmaz K (2009): Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets*. *The Economic Journal*, 119(January):158–171.

Du X, Cindy LY, Hayes DJ (2011): Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis. *Energy Economics*, 33:497–503.

Dwyer A, Gardner G, Williams T (2011): Global Commodity Markets–Price Volatility and Financialization. *RBA Bulletin*, June:49–57.

Fantazzini D (2016): The Oil Price Crash in 2014/15: Was There a (Negative) Financial Bubble? *Energy Policy*, 96:383–396.

Feunou B, Aliouchkin RL, Tédongap R, Xu L (2017): Variance Premium, Downside Risk and Expected Stock Returns. *Bank of Canada Staff Working Paper*.

Feunou B, Jahan-Parvar M, Tédongap R (2013): Modeling Market Downside Volatility. *Review of Finance*, 17:443–481.

Feunou B, Jahan-Parvar MR, Okou C (2018): Downside Variance Risk Premium. *Journal of Financial Econometrics*, 16:341–383.

Feunou B, Okou C (2019): Good Volatility, Bad Volatility, and Option Pricing. *Journal of Financial and Quantitative Analysis*, 54:695–727.

Guo, H., Wang, K., Zhou, H., 2019. Good Jumps, Bad Jumps, and Conditional Equity Premium. In: *Asian Finance Association (Asianfa) 2014*. Conference Paper. pp. 14–05.

Kang SH, McIver R, Yoon SM (2017): Dynamic Spillover Effects Among Crude Oil, Precious Metal, and Agricultural Commodity Futures Markets. *Energy Economics*, 62:19–32.

Kang W, Ratti RA, Yoon KH (2015): The Impact of Oil Price Shocks on the Stock Market Return and Volatility Relationship. *Journal of International Financial Markets, Institutions and Money*, 34:41–54.

Khan MI (2017): Falling Oil Prices: Causes, Consequences and Policy Implications. *Journal of Petroleum Science and Engineering*, 149:409–427.

Klößner S, Wagner S (2014): Exploring All VAR Orderings for Calculating Spillovers? Yes, We Can! - A Note on Diebold And Yilmaz (2009). *Journal of Applied Econometrics*, 29:172–179.

Mensi W, Beljid M, Boubaker A, Managi S (2013): Correlations and Volatility Spillovers Across Commodity and Stock Markets: Linking Energies, Food, and Gold. *Economic Modelling*, 32(C):15-22.

Nazlioglu S, Erdem C, Soytas U (2013): Volatility Spillover Between Oil and Agricultural Commodity Markets. *Energy Economics*, 36:658–665.

Patton AJ, Sheppard K (2015): Good Volatility, Bad Volatility: Signed Jumps and the Persistence of Volatility. *The Review of Economics and Statistics*, 97:683–697.

Saggu A, Anukoonwattaka W (2015): Commodity Price Crash: Risks to Exports and Economic Growth in Asia-Pacific LDCs and LLDCs. *Trade Insights U. N. Econ. Soc. Comm. Asia Pac.*

Segal G, Shaliastovich I, Yaron A (2015): Good and Bad Uncertainty: Macroeconomic and Financial Market Implications. *Journal of Financial Economics*, 117:369–397.

Silvennoinen A, Thorp S (2013): Financialization, Crisis and Commodity Correlation Dynamics. *Journal of International Financial Markets, Institutions and Money*, 24:42–65.

Tang K, Xiong W (2012): Index Investment and the Financialization of Commodities. *Financial Analyst Journal*, 68(6):54–74.

Vivian A, Wohar ME (2012): Commodity Volatility Breaks. *Journal of International Financial Markets, Institutions and Money*, 22:395–422.

Vo M (2011): Oil and Stock Market Volatility: A Multivariate Stochastic Volatility Perspective. *Energy Economics*, 33:956–965.