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Directional Volatility Spillovers between Agricultural, Crude Oil, Real Estate and other Financial Markets

Stephanie-Carolin Grosche

Thomas Heckelei

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Editor: Thomas Heckelei

Institute for Food and Resource Economics

University of Bonn

Nußallee 21

53115 Bonn, Germany

Phone: +49-228-732332

Fax: +49-228-734693

E-mail: thomas.heckelei@ilr.uni-bonn.de

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The research that led to this paper was mainly conducted over the period 2012-2013. The research idea and preliminary results were first presented at the IATRC Annual General Meeting in San Diego, California, Dec 9-11, 2012 as well as at the ZEF Workshop on Food Price Volatility Jan 31 - Feb 01, 2013. The article Chevallier, J. and F. Ielpo (2013): “Volatility spillovers in commodity markets”, Applied Economics Letters, Vol. 20 (13): 1211-1227, first published online on 14 June 2013 shows similarities both in results and motivation of the paper, which came as a surprise to us. We were not aware of this parallel development of ideas.

Abstract

The addition of commodities to financial portfolios and resulting weight adjustments may create volatility linkages between commodity and financial markets, especially during financial crises. Also, biofuel mandates are suspected to integrate agricultural and energy markets. We calculate directional pairwise range volatility spillover indices (Diebold and Yilmaz, 2012) for corn, wheat, soybeans, crude oil, equity, real estate, U.S. Treasury notes and a U.S. dollar index between 06/1998 and 12/2013. During the recent financial crisis, volatility spillovers from equity and real estate to commodities, particularly crude oil, rise to unprecedented levels. Yet, we find no indication of a parallel increase of volatility linkages between agricultural and crude oil markets.

Keywords: Volatility spillovers, financialization, generalized forecast error variance decomposition, VAR

JEL classification: Q13, C32, G11, G01

1 Introduction

Portfolio diversification is a principal motive for financial commodity trading (Fortenbery and Hauser, 1990). The fundamentals that drive their supply and demand largely differ from those of other financial assets, suggesting low or negative return correlations. And, like real estate, commodities can serve as an inflation hedge as their prices drive inflation but their holding is not directly associated with inflation-threatened cash flows (Ankrum and Hensel, 1993; Huang and Zhong, 2013; Bodie and Rosansky, 1980; Satyanarayan and Varangis, 1996; Anson, 1999; Gorton and Rouwenhorst, 2006; Daskalaki and Skiadopoulos, 2011).

The spread of electronic trading and the creation of commodity index-linked exchange-traded products (ETPs) or mutual funds have made commodities more accessible to financial portfolio managers (Conover et al., 2010; Daskalaki and Skiadopoulos, 2011). Between 2002 and 2010, assets under management of commodity ETPs grew from 0.1 billion (bn) to 45.7 bn U.S. dollars (BlackRock, 2011). Simultaneously, combined open interest for the Chicago Board of Trade (CBOT) corn, soybean and wheat futures climbed from 0.7 million (m) to 2.7 m contracts (CFTC 2013).

Attractive diversification benefits and a facilitated portfolio inclusion stimulate the use of agricultural commodities in strategic or tactical portfolio management. While the former may maintain a fixed commodity share (e.g. 4-7% according to Greer, 2007) the latter continuously resets portfolio asset weights due to cross-market arbitrage (Büyükhahin et al., 2010) or as a response to shocks or extreme regimes in selected markets (cf. Conover et al., 2010; Jensen et al., 2002). Particularly during financial crises, portfolio managers may shift weights to comparatively less risky and more liquid refuge assets, a phenomenon known as “flight-to-quality” or “flight-to-liquidity” (Beber et al., 2008). Such use of commodities is suggested e.g. by Silvennoinen and Thorp (2013) and Chong and Miffre (2010) who propose a shift out of equity and bond markets and into commodities during crisis periods. Finally, the need to meet margin calls in

distressed markets may affect weights of all other portfolio assets, if the latter are sold to obtain liquidity (Büyükşahin et al., 2010).

By any of these channels, tactical portfolio allocation may create or intensify commodity and financial market linkages, especially during crises. It may also affect agricultural and energy linkages as both commodity groups are included in indices such as the Standard and Poor's (S&P) GSCI or the Dow Jones UBS (DJ UBS) Commodity index, which are replicated by index-linked products and funds. In any case, volatility rather than returns is the more interesting linkage due to its closer relation to information flows (Chiang and Wang, 2011; Cheung and Ng, 1996). Also, the development of ETP assets suggests a steadily emerging financial interest and motivates the search for a gradual change rather than a sudden structural break in market linkages.

In this paper we analyse time-varying short-term volatility spillovers between (1) commodity and financial markets and (2) agricultural and energy markets with rolling volatility spillover indices as introduced in Diebold and Yilmaz (2012) over the period June 1998 to December 2013. These are based on rolling generalized forecast error variance (FEV) decompositions in a Vector Autoregressive (VAR) model and allow us to calculate gradually changing directional volatility spillovers between any pair of included assets over the entire observation period. Volatility is measured as the daily range, based on the difference between high and low prices (Parkinson, 1980).

Our analysis contributes to existing research in several aspects. First, we investigate volatility linkages between agricultural commodities and financial assets, which remain scarcely researched. Second, we include a broad market network rather than conduct a bivariate analysis, thereby specifically taking into account potential substitution between commodity and real estate as a result of the subprime crisis and the aforementioned parallel characteristics between the two asset classes. This also aids the investigation of agricultural-energy linkages as commodity markets are part of a global financial market network and any bivariate relation may thus be affected by the state of third markets. Finally, we do not

impose any structural breakpoint and reach beyond the comparison of selected periods (e.g. before and after the financial crisis or before and after the introduction of biofuel mandates) towards the analysis of gradual structural change.

The remainder of the paper is structured as follows. The next section focuses on existing empirical evidence on commodity-financial and agricultural-energy linkages, which is followed by a brief description of the methodology. Subsequently, we present and discuss our model results and compare them to previous research. The final section concludes the analysis.

2 Previous empirical results on market linkages

Agricultural-energy market linkages via the use of crops in biofuel production or the use of energy as an agricultural production input are frequently researched. In comparison, research on commodity-financial market linkages is scarce and only recently gaining momentum (Chan et al. 2011).

2.1 Agricultural-energy market linkages

We review recent empirical studies that focus on volatility linkages and cover at least part of the time period after the subprime crisis.¹ The studies typically split their data sample either around 2006, due a hypothesized structural change in market linkages after the introduction of biofuel mandates or around 2008, reflecting the potential effect of the financial and food price crises. Most studies use daily data, Gardebroek and Hernandez (2012) and Du et al. (2011) use weekly data.

To investigate volatility dependencies, Nazlioglu et al. (2013) and Harri and Hudson (2009) conduct Granger Causality in variance tests (cf. Cheung and Ng, 1996). Nazlioglu et al. (2013) find no volatility linkages between daily energy and

¹ This remains a vibrant field of research and any potential omission is not deliberate.

agricultural spot prices before 2005. The exception is wheat, which Granger causes the variance of crude oil in that period. Likewise, Harri and Hudson (2009) do not detect volatility linkages between daily corn and crude oil futures prices in the period before 2006. After 2006, Nazlioglu et al. (2013) find volatility spillovers from crude oil to corn and bidirectional spillovers between crude oil and soybeans and crude oil and wheat. Harri and Hudson (2009) only discover Granger Causality in mean, but not in variance, from crude oil to corn.

Du et al. (2011) use bivariate weekly stochastic volatility models for corn, wheat and crude oil futures returns over the period 1998-2009. They detect increasing volatility transmission from crude oil to both corn and wheat as well as within the corn-wheat couple in the later subsample 2006-2009.

Several studies employ multivariate GARCH models. Gardebroek and Hernandez (2012) estimate both BEKK and DCC trivariate GARCH models for weekly US corn, crude oil and ethanol spot prices over the period 1997-2011. There are some short-run volatility spillovers from corn to ethanol but no significant volatility spillovers in the other direction. Structural break tests and subsequent sample splits show that after 2008 volatility persistence is stronger in all markets. Trujillo-Barrera et al. (2011) estimate BECKK GARCH models with daily futures returns for U.S. crude oil, ethanol and corn for the period 2006-2011. Similar to Gardebroek and Hernandez (2012) they find that volatility linkages between corn and ethanol increase after 2007 with significant volatility spillovers from corn to ethanol but only modest spillovers from ethanol to corn. But they do find strong volatility spillovers from crude oil to both corn and ethanol markets. Ji and Fan (2012) and Chang and Su (2010) employ bivariate E-GARCH models. Chang and Su (2010) use daily returns for crude oil, corn and soybean futures over the period 2000-08. Before 2004, there are no significant volatility spillovers from crude oil to either corn or soybeans, which changes in the 2004-2008 period. Ji and Fan (2012) use daily returns of crude oil futures and several Commodity Research Bureau (CRB) indices over the period from 2006 until 2010 and introduce the U.S.

Dollar exchange rate as an exogenous shock. They find that volatility spillovers from crude oil to the CRB crop index decrease after the subprime crisis.

2.2 *(Agricultural) commodity-financial market linkages*

We review recent empirical studies that cover at least part of the time period of the subprime crisis and also consider corn, soybeans, wheat or a relevant commodity index in their sample. Most studies centre on relations between selected U.S. commodities and equity markets. Other financial asset classes, especially real estate, are underrepresented. In the past, the emphasis was on return linkages but volatility dependencies are moving into focus.

Volatility relations are again mostly examined with help of multivariate GARCH models. Gao and Liu (2014) use bivariate regime switching GARCH models for pairings between the S&P 500 and selected commodity indices over the weeks 1979-2010. Volatility linkages between the S&P 500 and both the grains and energy indices only slightly increase in the few short periods when the assets share a high volatility regime. But, regime switches for the energy index appear more closely related to equity volatility than those of the grains index. Mensi et al. (2013) estimate bivariate VAR-GARCH models for pairings of the S&P 500 with daily wheat, beverage, gold, crude oil, and Brent oil price indices over the period 2000-2011. Past volatility and unexpected volatility shocks to the S&P 500 have significant effects on oil, gold and beverage markets but not on wheat. For commodity-foreign exchange relations, Ji and Fan (2012) find that volatility spillovers from the U.S. Dollar index to the CRB crop index were weaker after than before the subprime crisis while Harri and Hudson (2009) observe Granger Causality in mean but not in variance from the U.S. Dollar exchange rate to corn futures prices in the period before and after 2006.

Diebold and Yilmaz (2012) use their volatility spillover indices to investigate volatility linkages between the DJ UBS Commodity index and the S&P 500, U.S. Treasuries and a U.S. Dollar index over the period 1999-2010. They find a significant increase in linkages between the DJ UBS Commodity index and the

other markets after the beginning of the subprime crisis. Volatility spillovers from the S&P 500 to the commodity index occur throughout the crisis while the commodity index spills volatility to U.S. Treasury and the U.S. Dollar index during the middle and end of the last decade.

Multivariate GARCH models are also used to investigate commodity-financial return linkages. Using a bivariate DCC GARCH model for the period 1991-2008, Büyükşahin et al. (2010) find negative weekly conditional return correlations between the S&P GSCI, its energy sub-index or the DJ UBS Commodity index and equities to peak during 2003-04 and to a lesser extent also at the beginning of the subprime crisis. Correlations between the S&P 500 and the S&P GSCI agricultural index returns appear unaffected by the crisis. Créti et al. (2013) use bivariate DCC GARCH models for pairings between the daily S&P 500 returns and a sample of 25 commodity spot returns and the CRB index over the period 2001-2011. While they find that dynamic correlations decrease during the subprime crisis for most of the sampled commodities, return correlations between crude oil and the S&P 500 increase in times of increasing and decrease in times of decreasing stock prices. In contrast, Silvennoinen and Thorp (2013), who use a bivariate DSTCC GARCH² model with weekly data between 1990-2009, show that conditional weekly return correlations between both corn and soybeans and equities increased in 2002-03 while correlations between wheat and crude oil and equities peaked in mid 2008. Commodity-bond relations remain relatively constant. Similarly, results from the DCC GARCH model in Huang and Zhong (2013) for the days between 1999-2010 and the months between 1979-2010 show that conditional correlations of the S&P GSCI with U.S. bonds do not considerably increase in the subprime crisis period. Yet, conditional rolling return correlations between the S&P GSCI and equities increase from negative to strongly positive. In addition, mean-variance spanning

² Dynamic Smooth Transitional Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity model.

tests reveal that the S&P GSCI, REITs and U.S. inflation-linked securities each offer unique portfolio diversification benefits, suggesting relatively weak market linkages. Finally, Bicchetti and Maystre (2012) examine rolling window bivariate intraday return correlations over the period 1996-2011 between corn, wheat, soybeans and crude oil and equities. The authors find an increase in correlations between all sampled commodity and equity returns after September 2008, which only in the case of crude oil decline again in 2011.

Thus, there is some indication of increased agricultural-energy and commodity-financial volatility or return linkages around 2006-2008. But in the former case, results are rather mixed. In the latter case, the strongest effects appear to exist between U.S. equities and crude oil. In both cases the time-dependent dynamics and the direction of influence remain unclear. The wide majority of studies focus on multivariate GARCH models and therefore have to restrict the investigation to a bivariate or at maximum trivariate model.

3 Description of the methodology and data

Volatility spillover indices as introduced by Diebold and Yilmaz (2009; 2012) allow us to include a larger sample of asset markets while permitting a time-dependent analysis of gradually changing volatility relations. Their computation requires externally calculating a volatility proxy variable, which is then used in the rolling VAR model estimation.³

Given that there is no universally accepted best volatility measure (Engle and Gallo, 2006), a choice has to be made based on informational content, interpretability and statistical properties. We expect financial linkages between markets to mostly affect short-term volatility relations. Therefore, we use the range

³ The full model documentation including the MATLAB code is available from the corresponding author on request.

volatility proxy that is illustrated in Parkinson (1980), which has also been shown to have superior statistical properties over the classical volatility proxy, calculated as the variance of daily returns, which may be associated with large, non-Gaussian measurement errors (cf. Parkinson, 1980; Alizadeh et al., 2002; Chiang and Wang, 2011). The range is calculated as:

$$(1) \quad Range_{it} = 0.361 \left[\ln \left(\frac{high_{it}}{low_{it}} \right) \right]^2,$$

where *high* is the highest and *low* the lowest price observed on a trading day *t*.

3.1 Data

We use a sample of CBOT corn, soybeans and (soft red winter) wheat futures, New York Metal Exchange (NYMEX) WTI crude oil futures, the S&P 500 U.S. equity index, the Dow Jones Equity all REIT index, CBOT 10-year U.S. Treasury Note futures, and the Intercontinental Exchange (ICE) Futures U.S. Dollar index. The REITs index consists of all U.S. publicly traded companies within the Dow Jones stocks indices that are classified and taxed as equity REITs. The U.S. Dollar Index is a geometrically-averaged index of exchange rates of the Euro, Japanese Yen, British Pound, Canadian Dollar, Swedish Krona and Swiss Franc against the U.S. Dollar.⁴ Price and volume data is obtained from Bloomberg for trading days between 3 June 1998 and 31 December 2013.⁵ Missing observations are linearly interpolated.⁶ All futures prices are historical first generic price series and expiring

⁴ Weights are as follows: Euro: 57.7%, Yen: 13.6%, British Pound: 11.9%, Canadian Dollar: 9.1%, Swedish Krona: 4.2%, Swiss Franc: 3.6%.

⁵ Data for the REIT index is not available prior to that period.

⁶ Interpolation implemented with the MATLAB linear interpolation function.

active futures contracts are rolled to the next deferred contract after the last trading day of front month.⁷

3.2 Generalized forecast error variance decompositions

The FEV decompositions split the FEV of the range of each asset i included in a VAR model into shares stemming from own shocks and shares stemming from shocks to the range of another asset j . A VAR model with lag length p (VAR(p)) that consists of range observations for all assets is written as $y_t = A_0 + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t$, where y_t is a $N \times 1$ vector of range volatilities and N corresponds to the number of assets in the system. A_i is a fixed coefficient $N \times N$ matrix (including intercept terms), and u_t is a $N \times 1$ vector of white noise innovations, such that $E(u_t) = 0$, $E(u_t u_t') = \Sigma$ and $E(u_t u_{t-s}) = 0$. The equivalent VAR(1) in matrix notation is given as $Y_t = c + A Y_{t-1} + U_t$, where

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix}; c = \begin{bmatrix} c \\ 0 \\ \vdots \\ 0 \end{bmatrix}; A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ I_N & 0 & \dots & 0 & 0 \\ 0 & I_N & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_N & 0 \end{bmatrix}; U_t = \begin{bmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

$N \cdot p \times 1$ $N \cdot p \times 1$ $N \cdot p \times N \cdot p$ $N \cdot p \times 1$

The Moving Average (MA) representation of this process is

$$y_t = \mu + \sum_{h=0}^{\infty} \Phi_h u_{t-h} \quad \text{with} \quad \Phi_h = J A^h J' \quad \text{and} \quad J = [I_N \ : \ 0 \ : \ \dots \ : \ 0],$$

which is a $N \times N \cdot p$ selection matrix (Lütkepohl 2007, pp. 15 ff.). The coefficient matrices Φ_h contain the impact multipliers of the system. Their element $\phi_{ij,h}$ describes the response of the i^{th} asset range volatility to a shock in the j^{th} asset

⁷ This corresponds to Bloomberg's "relative to expiration" rolling procedure.

range volatility, h periods ago. $\Phi_j(h)$ is the corresponding impulse response function.

The elements in u_t are correlated and estimation of the coefficient matrix Φ_h requires external coefficient restrictions. One possibility is to orthogonalize the shocks, e.g. via a Cholesky decomposition of the covariance matrix (Σ) such that the orthogonalized impulse response function traces the system's response to a *specific ceteris paribus shock* in the range of asset j over time. But this makes impulse responses sensitive to VAR model variable ordering (Enders 2010, p. 309). As we investigate volatility interactions within a system of different asset markets such an order is difficult to impose and inhibits the danger of adding an unwanted subjective element to the estimation.

Generalized impulse responses are an alternative restriction method developed in Koop et al. (1996) and extended in Pesaran and Shin (1998). The generalized impulse response function is computed as $\Phi_j^g(h) = \sigma_{jj}^{-\frac{1}{2}} \Phi_h \Sigma e_j$, where σ_{jj} is the variance of the error term in the equation for the j^{th} range volatility and e_j is a $N \times 1$ selection vector containing 1 as its j^{th} element and 0 otherwise (Pesaran and Shin 1998). These impulse responses are responses of the range of asset i to a shock in the range of asset j , taking into account the contemporaneous correlations contained in Σ (Pesaran and Pesaran, 1997, p. 428). The impulse response function thus traces the system's response to a *typical composite shock* emanating from the range in asset j (Pesaran and Shin, 1998). The responses are independent of variable ordering and therefore more suitable for the analysis of our asset market system. Pesaran and Shin (1998) calculate generalized FEVs (θ_{ij}^g) as:

$$(2) \quad \theta_{ij}^g(h) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{h-1} (e_i' \Phi_l \Sigma e_j)^2}{\sum_{l=0}^{h-1} (e_i' \Phi_l \Sigma \Phi_l' e_i)} \quad , i, j = 1, 2, \dots, N,$$

where the subscript l denotes the respective forecast period.⁸ The correlated shocks lead to a non-diagonal Σ and elements in the rows of the θ_{ij}^g matrix will not sum up to 1.

3.3 Volatility spillover indices

Time-varying volatility spillover indices require rolling estimation of the VAR(p) model. A regression window of size w and T observations for the range volatilities will give a total of $T-w+1$ estimates for the θ_{ij}^g matrices. For a system of N assets, the elements off the main diagonal in the θ_{ij}^g matrices show the contributions of shocks to the range of assets $j = 1, \dots, N$ to the h -step ahead FEV for the range of assets $i=1, \dots, N$ with $i \neq j$ and the diagonal elements denote the contributions of own shocks. Analogously to the definitions provided by Diebold and Yilmaz (2012), a spillover is defined as the share of the contributions of shocks to the range of assets $j = 1, \dots, N$ in relation to the total FEV of the range of assets i with $i \neq j$. This constitutes the basis for the spillover index calculations.

⁸ The typing error in Pesaran and Shin (1998, pp. 20 ff.) where σ_{ii} is used instead of σ_{jj} as pointed out in Diebold and Yilmaz (2011, p. 6) has been corrected.

Table 1. Volatility Spillover Indices

Total spillover index (TOTAL)	
Sum of spillovers to the range across all asset classes in relation to the total FEV in the system.	$TOTAL(h) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^N \theta_{ij}^s(h)}{N} \cdot 100$
Directional spillover index from all other assets (FROM)	
Spillovers received by the range of asset i from the range of all other assets $j = 1, \dots, N, j \neq i$, in relation to the total FEV in the system.	$FROM_i(h) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \theta_{ij}^s(h)}{N} \cdot 100$
Directional spillover index to all other assets (TO)	
Spillovers transmitted by the range of asset i to all other assets $j = 1, \dots, N, j \neq i$, in relation to the total FEV in the system.	$TO_i(h) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \theta_{ji}^s(h)}{N} \cdot 100$
Net spillover index (NET)	
Spillovers transmitted by the range of asset i to the range of all other assets $j = 1, \dots, N, j \neq i$ less spillovers received from the range of all other assets $j = 1, \dots, N, j \neq i$, in relation to the total FEV in the system.	$NET_i(h) = TO_i(h) - FROM_i(h)$
Net pairwise spillover index (PAIR)	
Spillovers transmitted by the range of asset i to the range of one specific asset $j, j \neq i$, less spillovers received from the range of this asset j , in relation to the total FEV.	$PAIR_{ij}(h) = \left(\frac{\theta_{ji}^s(h) - \theta_{ij}^s(h)}{N} \right) \cdot 100$

First, the θ_{ij}^s matrices are normalized with the respective row sums such that the entries in each row sum up to 1.⁹ Consequently, the total FEV across the range for all assets in the system is equal to N . The definitions and formulas to calculate the individual spillover indices according to Diebold and Yilmaz (2012) are presented in Table 1.

4 Empirical results

First, we calculate the assets' range volatilities and use them in the rolling VAR estimation from which we compute the volatility spillover indices. Finally, we discuss the results and relate the findings to the current literature.

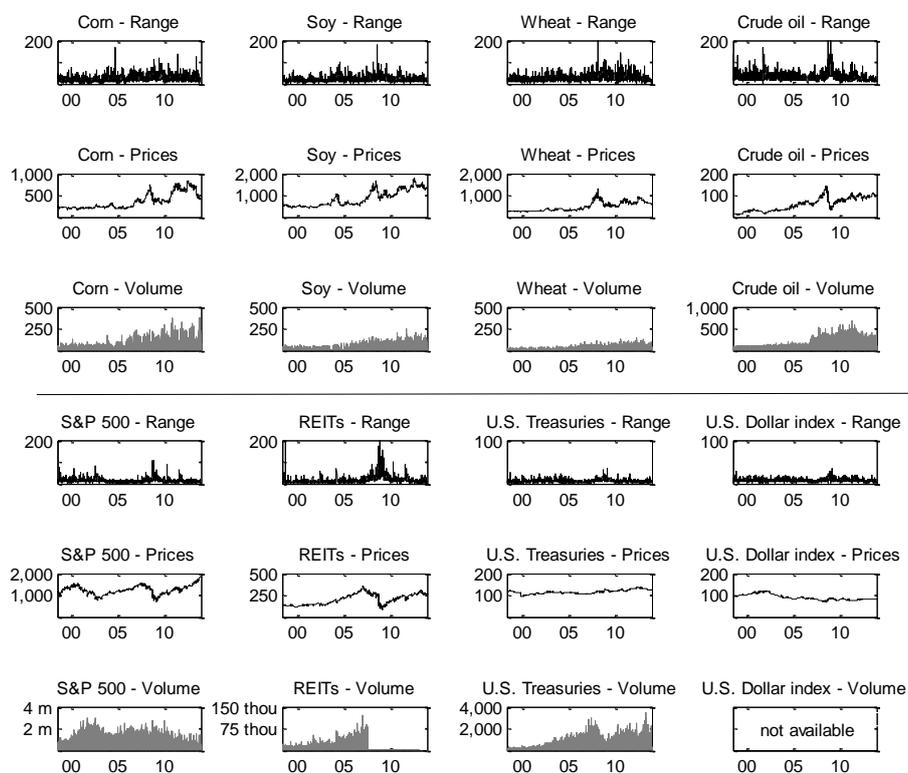
4.1 *Development of volatilities, prices and trading volumes*

Figure 1 shows annualized range volatilities as well as daily closing prices and trading volume for all assets. Starting in 2005, commodity market volume gradually increased. Crude oil volume almost tripled from an average of 80 thousand contracts between June 1998 and October 2006 to an average of 270 thousand contracts between October 2006 and December 2012. Over the period 2007/08 price levels and range volatilities soared in all commodity markets. Before that, oil prices were high in August 2004 and smaller price spikes for corn, soybeans and wheat occurred in March and April 2004. Range volatility for corn and soybeans was highest in September 2004, wheat volatility in March 2002 and crude oil volatility in September 2001 during the wars in Afghanistan and Iraq.

S&P 500 trading volume was highest between 2000–02 after the index price had peaked in March 2000. Prices dropped with the burst of the U.S. dot.com bubble and by October 2002 the index level had almost halved. The subprime crisis

⁹ As suggested in Diebold and Yilmaz (2012), it would also be possible to normalize with the column sums.

Figure 1. Annualized range volatilities, closing prices and trading volume



Notes: Upper graphs show annualized range volatilities, calculated as $(Range_{it} * 252)^{1/2} * 100$, middle graphs closing prices in U.S. Dollars and lower graphs trading volume in thousand contracts.

resulted in a second price floor in March 2009 but trading volume moved horizontally. Range volatility was high during and after the dot.com bubble and peaked in November 2008. In contrast, REIT index volume crashed during the subprime crisis and decreased from 32.2 million contracts to a mere 32.1 thousand contracts in August 2008. Prices reached bottom in March 2009 after a peak in February 2007. Range volatility soared to an all time high in December 2008. Compared to equity and real estate, U.S. Treasuries and the U.S. Dollar index exhibit little price fluctuations and only few peaks. range volatilities are on average less than half of those of the other assets. Yet, volatilities in both markets sharply increase in March 2009. U.S. Treasuries volume peaked in July 2007 before plummeting in 2008.

4.2 *Rolling VAR estimation and spillover index calculation*

Lütkepohl and Xu (2012) show that taking logs can in many cases substantially improve forecast precision. We thus estimate the rolling VAR model with logged range volatilities (summary statistics are provided in Annex 1) and include a total of 3,930 observations for each of the 8 assets and a window length of 252 trading days. Augmented Dickey Fuller (ADF) tests show the logged ranges to be stationary. Details are shown in Annex 2.

To obtain a parsimonious model, the lag lengths are selected with the Schwartz Bayesian Criterion (SBC), which is a consistent criterion with good large sample properties (Lütkepohl, 2007). For the full sample, the SBC selects a VAR(5), which is also used in each of the 252-day regression windows. The generalized FEV matrices are calculated for a forecast horizon of 10 days. The choice depends on the underlying assumption regarding the time horizon of asset market linkages and 10 days is a common horizon used in financial Value at Risk calculations (Diebold and Yilmaz, 2011). A total of 3,679 observations are obtained for each index and the first observation corresponds to the end of the first regression window (2 June 1999).

We perform a range of robustness checks, such as using a different futures rolling procedure (on first notice day), including the CBOT S&P 500 futures instead of index prices, using a window size of 126 instead of 252 days, using different lag lengths and forecast horizons. None of the changes significantly affected the patterns of volatility spillovers. The biggest effect came from a change in window size. Results from the robustness checks are presented in Annex 3.

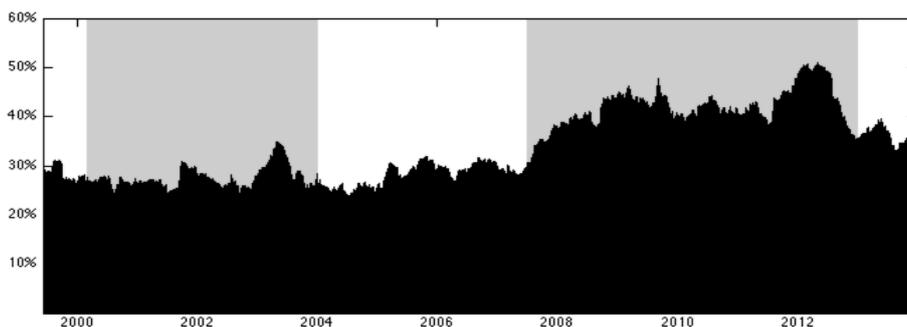
4.3 *Volatility spillover indices*

Figure 2 shows the total volatility spillover index between 2 June 1999 and 31 December 2013. The grey-shaded areas mark the two main crisis periods of the last decade. The “first/ early crisis period” between March 2000 and December 2003 is characterized by the burst of the dot.com bubble, the NASDAQ crash and the

overall downturn in equity markets. The real economy in the U.S. and the EU experienced low GDP growth rates and the events of September 11 and the wars in Afghanistan and Iraq led to political unrest. Agricultural commodity markets were influenced by the continued EU effort to reduce buffer stocks as well as China’s WTO accession in December 2001 with growing U.S. soybean exports.

The “second/ later crisis period” between July 2007 and December 2012 started with the early events of the subprime crisis and transformed into a global liquidity crisis and later sovereign bond and state debt crisis. The U.S. Federal Reserve Bank decreased interest rates 12 times successively during the period between August 2007 and December 2008 and the real economy in the U.S. and EU was hit with low or negative GDP growth rates. Agricultural commodity markets experienced further growing soybean imports from China and the introduction of biofuel mandates in the EU and U.S. At the beginning of the period, stock-to-use ratios for corn and wheat were at low levels of around 13% and 18%, respectively, while the ratio for soybeans was at a peak of 21% (USDA ERS, 2012). Commodity ETP assets under management strongly increased from 6.3 bn U.S. dollars in 2007 to 45.7 bn U.S. dollars in 2010 (BlackRock, 2011).

Figure 2. Total volatility spillover index

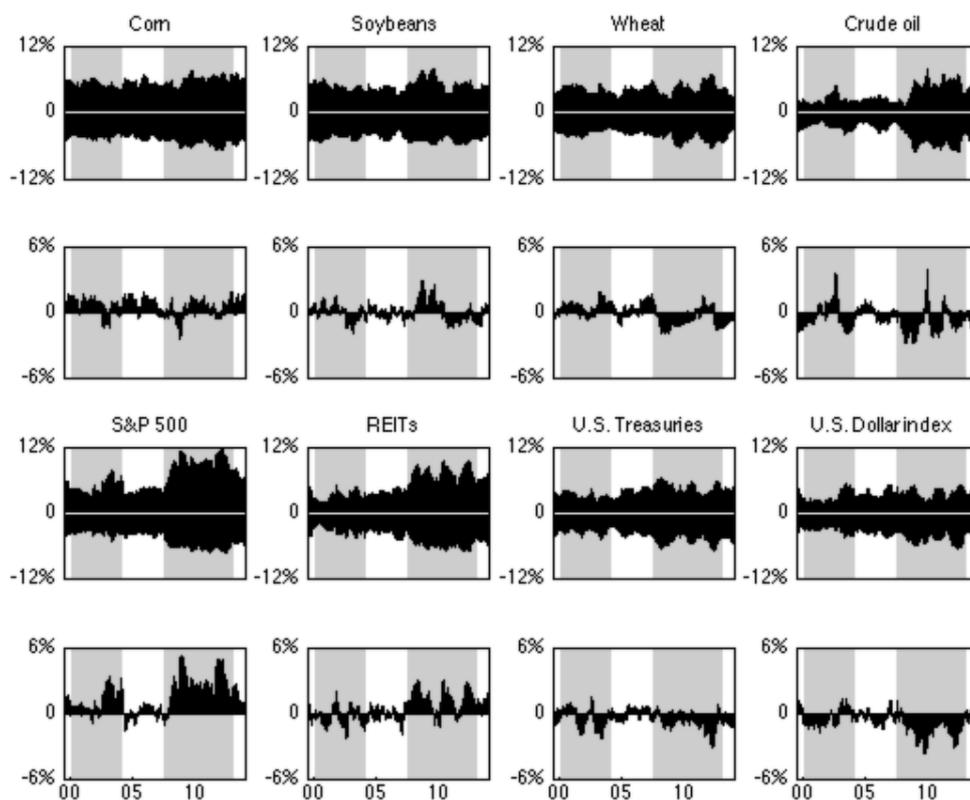


The level of volatility spillovers is much higher in the later compared to the early crisis period. While there are two spikes of 31% in September 2001 and 35% in April 2003, the average total spillover between 1 March 2000 and 31 December

2003 was 26% compared to an average of 42% between 1 July 2007 and 31 December 2012. The peak of the index is at 51% on 3 May 2012.

In the following, positive values for the spillover indices indicate spillovers *from* the asset and negative values spillovers *to* the asset. Directional spillovers and the resulting net spillover indices are depicted in Figure 3. The upper graphs in each pair show the spillovers from and to this asset compared to all other assets in the system. The lower graph is the resulting net volatility spillover index where a positive (negative) value indicates that the asset is a net volatility transmitter (receiver).

Figure 3. Directional and net spillover indices



During the first crisis neither of the commodity markets shows a distinct pattern and the indices move almost horizontally into the tranquil interim period.

Only crude oil and to some extent wheat futures have spiking directional volatility spillovers. Net spillovers from crude oil peak at 3.4% in August 2002 and net spillovers from wheat at 1.8% in May 2003. In contrast, during the second crisis, volatility spillovers to and from the commodity markets are on a higher level and the net spillover patterns differ from the previous periods. The most pronounced effects are again observable for crude oil, which is a net volatility receiver during most of the crisis period. Notable spillovers also occur in wheat and soybean markets. Soybean net volatility transmission to other assets reaches up to 2.9% in September 2008. Wheat markets are net volatility receivers with a peak of 1.9% in June 2008. Only corn market volatility spillovers appear relatively unaffected by the crisis and only show a slight increase in level.

Among the financial asset markets, the S&P 500 is the largest net volatility transmitter in the system with visible increases in the first (up to 3.4% in February 2003) and very pronounced peaks in the second crisis period (up to 5.3% in November 2008). In difference, both U.S. Treasuries and the U.S. Dollar index are volatility receivers during both crisis periods. Again, the effect is more pronounced in the second crisis where net spillovers to the U.S. Treasuries reach up to 3.2% in March 2012 and spillovers to the U.S. Dollar index up to 3.7% in October 2009. The REITs market shows the biggest change in volatility interaction between the two crisis periods. While during the early crisis the market is alternating between the position of net volatility transmitter and receiver, it almost unexceptionally transmits volatility to of up to 3% during the later crisis.

The pairwise spillover indices allow the most detailed investigation of structural changes in volatility interaction between agricultural and energy commodities as well as between commodity and financial asset markets.¹⁰ Figure 4

¹⁰ Pairwise indices for financial asset markets cannot be discussed in detail in the scope of this paper but are available from the authors upon request.

first shows the pairwise indices for the agricultural commodities. Over most of the observation period, corn is transmitting volatility to the soybean market at a general magnitude of between 3 and 6%. There is no marked difference between the early crisis and the interim tranquil period. But during the second crisis, the volatility spillover relation is reversed. Between 2008 and 2010 soybean markets are transmitting volatility to corn markets of up to 7.5% in September 2008. Paralleling this development, the volatility spillover relation between soybeans and wheat also changes. Starting in 2008, soybeans are net transmitters of volatility to wheat with a peak of 6% in June 2009. Wheat is mostly a net volatility receiver from corn at a magnitude of up to 4.7% in September 2002 and 6.5% in January 2010. There are exceptions towards the end of the first crisis, before the beginning of the later crisis and, most importantly, between 2010 and 2012 where wheat spillovers to corn reach up to 5.3% in February 2011.

Figure 4. Pairwise spillover indices: agricultural commodities

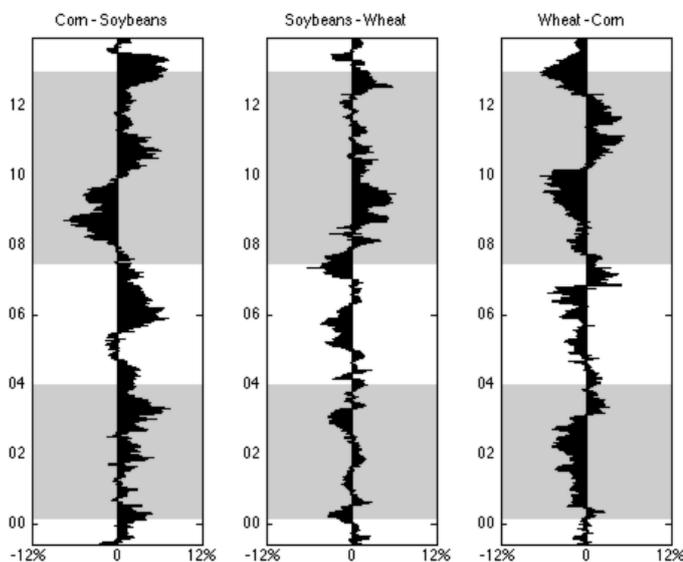


Figure 5 shows the indices for the agricultural-crude oil pairings. Corn is transmitting volatility to crude oil during most of the tranquil period, before the early crisis and during the later crisis of up to 5% in March 2000 and 5.3% in July 2009 respectively. Between November 2001 and January 2003, during the first

crisis, and after February 2011, during the second crisis, this relation is reversed and crude oil transmits volatility to corn with spillovers reaching up to 6.1% in September 2002 (first crisis) and 2.6% in May 2011 (second crisis). The soybean-crude oil volatility linkages almost perfectly mirror this development. Soybeans mostly transmit volatility to crude oil and receive volatility of up to 5.2% in July 2002 during the early crisis and up to 4.5% in May 2011 during the later crisis period. While wheat is also mostly transmitting volatility to rather than receiving volatility from crude oil, the magnitude of interaction between the markets' volatility is generally lower than in the case of corn and soybeans. But there is one notable spillover spike of up to 12% in June 2003. And during the tranquil period we observe some stronger spillovers from wheat to crude oil of up to 5.4% in June 2006.

Figure 5. Pairwise spillover indices: agricultural – crude oil

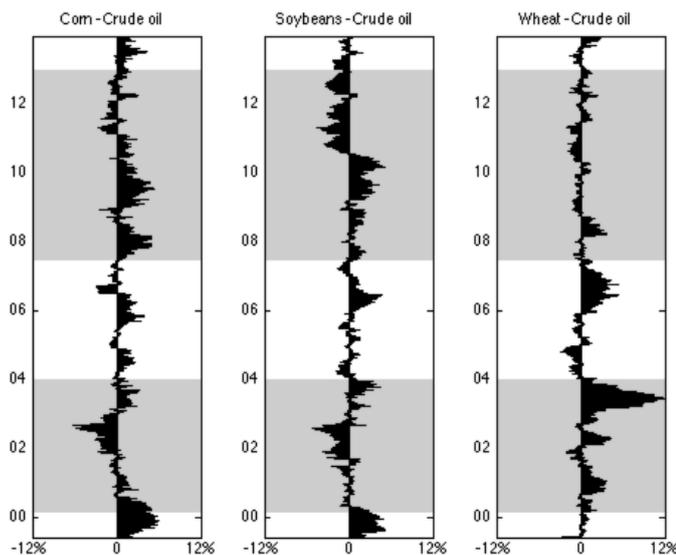


Figure 6 shows the pairwise indices for the commodities and the financial asset markets. During the early crisis, spillovers from the S&P 500 reach predominantly corn and wheat markets, with a high of 6.4% in February 2003 for corn and 4.3% in November 2002 for wheat. Soybeans, in contrast, are mostly net transmitters of volatility to the S&P 500 during that period. While crude oil

receives some spillovers, the market also transmits volatility to the S&P 500 during November 2001 and October 2002 with a strong magnitude of up to 10.6% in August 2002. But during and after the later crisis, there is a notable change in this volatility spillover relation, both in direction and in magnitude. Crude oil almost unexceptionally receives volatility from the S&P 500 with a peak at 10.8% in December 2010. A less pronounced but nevertheless visible change occurs in corn and wheat markets where net S&P 500 spillovers increase in frequency around the time of the subprime crisis with peaks of 5.3% in October 2008 for corn and of 6.7% in April 2008 for wheat. Soybeans show no change in the magnitude of spillover relations but in difference to the early 2000s crisis are mostly net volatility receivers from the S&P 500.

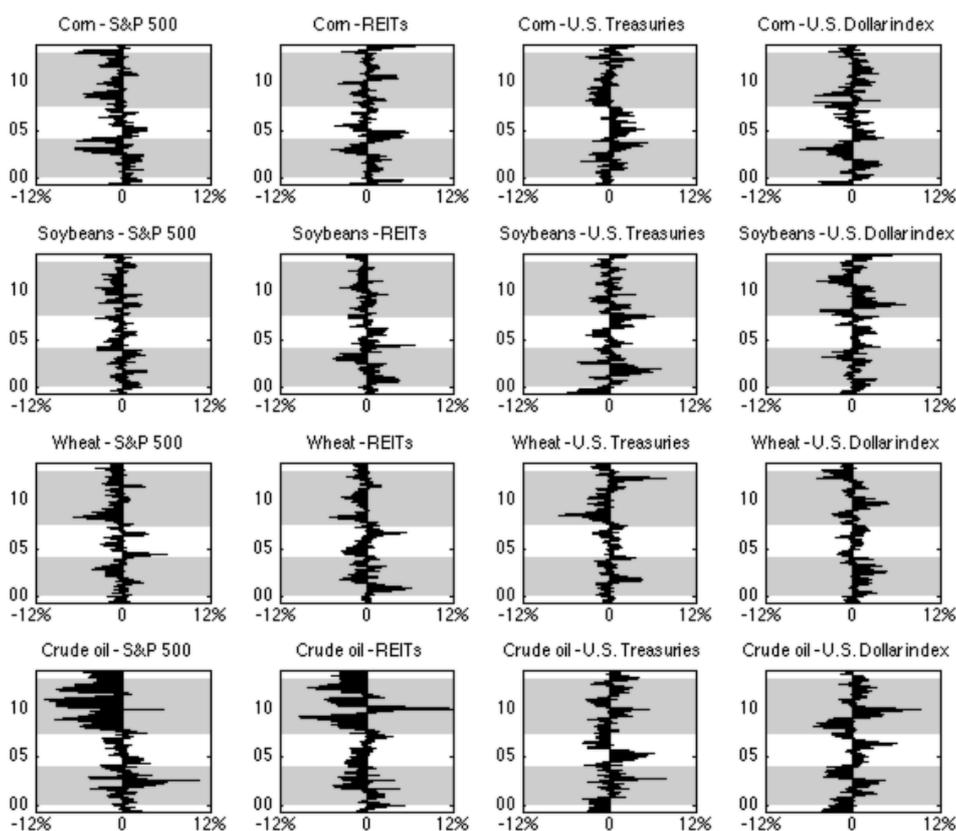
While the REITs market is a net volatility transmitter to all commodities during some periods of the early crisis, this tendency continues for most commodities (except soybeans) into the tranquil interim period. During the crisis, spillovers rise to 4.7% in January 2003 for corn, to 3.8% in October 2001 for wheat, to 4.7% in January 2003 for soybeans and to 4.5% in January 2002 for crude oil. For the agricultural commodities, there is no marked difference in spillover patterns during the later crisis. But, paralleling the developments in the volatility relation with the S&P 500, crude oil starts to receive markedly higher REITs net spillovers of up to 9.3% in February 2009. There is only a short period of reversed transmission between July 2009 and April 2010.

Net spillover between commodities and U.S. Treasuries occur bidirectionally both during the early crisis and during the tranquil period. But there are some exceptions. Around December 2001, there is a period of spillovers of up to 7.2% from soybeans to Treasuries. In the later crisis, corn and wheat markets are almost exclusively net U.S. Treasury volatility receivers of up to 3.2% in March 2008 (corn) and 7% in July 2008 (wheat) while for soybeans and crude oil the patterns are less distinct.

Towards the end of the first crisis, the U.S. Dollar index transmits volatility to the corn, soybean and crude oil markets of up to 7.1% in February 2003 (corn),

4.3% in March 2003 (soybeans) and 4% in December 2002 (crude oil) respectively, while during almost the entire crisis period wheat is a net volatility transmitter to the index with a peak of 4.6% in August 2002. During the second crisis, in contrast, soybeans and crude oil markets along with wheat transmit net volatility of up to 7.2% in August 2008 (soybeans), 4.9% in September 2009 (wheat), and 9.4% in December 2009 (crude oil) to the U.S. Dollar index while for corn net volatility transmission is lower and directionally less clear.

Figure 6. Pairwise spillover indices: commodity – financial



4.4 Discussion of results

The analysis of the above volatility spillover indices does not permit any direct causal attribution of single spillovers. Nevertheless, it is interesting to examine the

results in light of the political and economic developments on the markets and in relation to existing empirical findings on volatility linkages.

The total volatility spillover index shows a distinct increase in range volatility interdependence between the markets during the later crisis period. While at the height of the subprime crisis the level of individual range volatilities was also high, the total spillover index peak was only in May 2012 when individual markets' volatility levels had decreased again. In contrast, during the early crisis, there were only two smaller volatility spillover spikes despite high volatility levels in some markets. Thus, during the subprime crisis individual volatilities moved increasingly in sync with significant parallel jumps. On the other hand, the period of increased volatility interdependence stretched beyond the period of individual volatility jumps, pointing to a generally higher degree of market interaction.

Directional and net volatility spillover indices show the S&P 500 to be the strongest volatility transmitter among the assets during the times of financial crises. Thus, the drivers behind the S&P 500 range volatility will likely influence range volatility in other markets. The magnitude of spillovers to and from the other financial asset markets is much lower. While there is also a REITs component within the S&P 500, the stand-alone REITs spillover indices better illustrate the volatility linkages during the subprime crisis where REITs are strong net volatility transmitters and maintain this position until the end of the observation period. U.S. Treasuries, in contrast, are classical refuge assets, towards which liquidity is shifted in times of general economic recessions and individual market crises (e.g. equity or real estate). This effect is visible from the spillover indices where U.S. Treasuries are net volatility receivers during both crisis periods. Unsurprisingly net spillovers are especially high during the sovereign bond crisis at the end of the late crisis period. The U.S. economy experienced an economic recession during both crisis periods, which affects demand for U.S. Dollars. But the U.S. Dollar is also the most important currency for international monetary reserves. While the U.S. Dollar index is a net volatility receiver during both crisis periods, the level of spillovers

increases in the second period, at a time when both the need to adjust monetary reserves and to allocate liquidity to comparably “save” U.S. Treasuries was high.

4.4.1 Agricultural – energy linkages

Corn appears to be the strongest volatility transmitter among the agricultural commodities with significant spillovers to both wheat and soybeans. This is plausible as on the one hand the U.S. are the world’s largest producer of corn and a significant acreage area is allocated to the crop, and on the other hand, corn futures have much higher trading volumes on the CBOT than soybean or wheat futures. Thereby, information could rather disseminate from corn markets to other affected futures markets than in the opposite direction. While seemingly unaffected by the early crisis, the corn-soybean relation reverses between 2008 and 2010. At that time, soybeans also transmit volatility to wheat. This effect could be related to the surging Chinese soybean demand, which shocked the soybean market and through substitution effects also affected corn and wheat.

The pairwise agricultural-energy spillover indices show that the magnitude of spillovers between both corn and soybeans and crude oil is higher than for wheat. The fact that the level of spillovers does not considerably change after 2006 would speak against a clear attribution of this effect to the biofuel production. In fact, the spillover indices do not yield any convincing evidence of an increase in spillovers from the energy to relevant commodity markets as a consequence of biofuel mandates. While there were some spillovers from crude oil to both corn and soybeans in the early crisis, between 2006 and 2010 both markets transmit volatility to crude oil rather than receive it. Only soybeans experience a clear reversal in that relation after 2010.

These results are most in line with the findings from Gardebroek and Hernandez (2012) who, based on weekly conditional volatility over the period 1997-2011 do not discover evidence of energy volatility spilling over to corn price volatility. And while Ji and Fan (2012) do find significant linkages in the conditional daily volatility between crude oil and the crop index (includes corn,

wheat, soybeans, soft commodities, livestock, cotton), they also found a decrease in spillovers during the time of the subprime crisis. On the other hand, the results contradict the findings from e.g. Nazlioglu et al. (2013), Du et al. (2011), Chang and Su (2010) who, based on their respective models and volatility measures all show volatility spillovers between crude oil and corn, wheat or soybeans to increase after 2006. But Nazlioglu et al. (2013) also find bidirectional spillovers between crude oil and soybeans and crude oil and wheat after 2006, which is again closer to the results obtained from the spillover indices.

The extraordinary volatility spillover spike from wheat to crude oil of up to 12% in June 2003 would merit closer (causal) investigation. There could be some connection to the end of the UN Iraq oil-for-food program in 2003, which was used by the Iraqi government to secure wheat supplies in exchange for crude oil. It is interesting that Nazlioglu et al. (2013) also find Granger Causality in variance from wheat to crude oil before 2005, which in later periods disappears.

Thus, there is little indication for short-term daily range volatility linkages in the corn, soybean and wheat markets to be affected by biofuel policies. The contradictions with some findings from the GARCH-type models could stem from their sample splits and the restricted sample of two or three markets. The volatility spillovers are calculated for a more comprehensive system of asset markets where some of the apparent bivariate volatility spillovers may be absorbed by other markets. Also, structural breaks are not exogenously imposed. Instead, more gradual structural changes are permitted.

4.4.2 *Commodity – financial linkages*

The linkages between commodity and financial markets vary strongly depending on the commodity and financial asset class involved. In the early crisis, S&P 500 volatility spillovers to commodities were few and of low magnitude. There were in contrast some spillovers from crude oil to the S&P 500, which could from a fundamental side be explained with the wars in Afghanistan and Iraq. We thus confirm and strengthen the results from Diebold and Yilmaz (2012) on a DJ UBS

Commodity index-S&P 500 range volatility spillover during that time, which the authors also assume to be linked to the Iraqi war. During and after the later crisis, however, all commodity markets are net S&P 500 spillover receivers. This again parallels and extends the findings in Diebold and Yilmaz (2012) for the DJ UBS Commodity index. Our individual commodity market results allow to further disaggregate the spillovers and to show that most reach the crude oil market. Yet, corn and wheat also receive some transitory spiking net spillovers. All commodities, but especially crude oil have strong fundamental and financial linkages with U.S. equities as inputs in production and as components of all important commodity indices, where crude oil has generally higher weights than corn, soybeans or wheat. The observed increase in short-term range volatility linkages during a time where both commodity index-linked products spread and commodity trading volume increased, provide evidence in favour of the hypothesis that the financial linkage factor became more important in the second crisis period.

Our results strengthen the existing results on volatility linkages between the S&P 500 and commodities. The results from Mensi et al. (2013) who showed that volatility shocks to the S&P 500 can significantly affect the oil market are confirmed also for range volatility spillovers. Gao and Liu (2014) find that correlations between energy and grains indices and the S&P 500 increase in volatile periods, which is also in line with the above results. But, in their model neither U.S. energy nor grains indices appear to frequently share common volatility regimes with the S&P 500 from which the authors conclude that commodities remain attractive portfolio diversifiers. Yet, the spillover indices show stronger volatility relations, especially between the S&P 500 and crude oil, which may in fact decrease diversification benefits. In addition, our spillover results complement the evidence on increased dynamic conditional return correlations between commodities and the S&P 500 during and after 2008 (e.g. Huang and Zhong, 2013; Bicchetti and Maystre, 2012; Büyükşahin et al., 2010). The observed increase in oil-S&P 500 return correlations in times of increasing stock prices in Créti et al.

(2013) cannot be confirmed for daily range volatility spillovers, which rather increase in times of decreasing stock prices.

The fundamental connection between REITs and commodity markets is much weaker than between commodities and the S&P 500. Nevertheless, spillovers from REITs to crude oil are high in the early 2000s and surge in the late 2000s crisis, which provides additional evidence in favour of the financial linkage hypothesis. But the agricultural commodities appear less affected. Volatility spillovers between commodities and U.S. REITs are barely analysed in the literature. Somewhat related to our results, Huang and Zhong (2013) show that commodities and REITs (along with inflation-protected securities) each offer unique diversification benefits that tend to disappear in times of financial crisis.

In difference to the S&P 500 and REITs, the magnitude of range volatility spillovers between commodities and U.S. Treasuries generally appears unaffected by either of the crisis periods. This confirms results from Huang and Zhong (2013) who also find that conditional correlations between the S&P GSCI and U.S. Treasuries did not significantly increase during the subprime crisis. The identified net spillovers from the DJ UBS Commodity index to U.S. Treasuries in Diebold and Yilmaz (2012) can again be disaggregated in our model and appear to mostly stem from crude oil and soybeans as both wheat and corn markets are net receivers of U.S. Treasury volatility during that period.

The U.S. Dollar index receives net volatility spillovers from wheat, soybeans and crude oil during both crisis periods. But spillovers during the late 2000s crisis increase in magnitude. There could be a relation to the increase in Chinese imports of soybeans and crude oil and the associated U.S. dollar demand. Another explanation is foreign activity on U.S. commodity futures markets. The corn-U.S. Dollar index relation is less clear and during the second crisis period corn transmits less volatility to the U.S. Dollar index than the other commodities. Linkages could have decreased following the drop in U.S. corn exports as corn was increasingly used for domestic biofuel production. The results in Diebold and Yilmaz (2012) on the DJ UBS Commodity index-U.S. dollar index spillovers are substantiated for

most individual commodities and do not appear to be driven mainly by crude oil. The results in Ji and Fan (2012) on weaker volatility spillovers from a U.S. Dollar index to the CRB crop index after the subprime crisis only match the respective volatility spillover index for corn but not that for soybeans or wheat.

5 Conclusions

This paper has investigated directional time-varying range volatility spillovers using a new method developed in Diebold and Yilmaz (2009; 2012). The focus was on short-term volatility interaction effects within a system composed of agricultural, crude oil and selected financial asset markets over the period 3 June 1998 – 31 December 2013. We have put special emphasis on comparing the two periods of financial and economic crises whereby the later crisis period is also characterized by an increased use of commodities in financial investment.

During and after the subprime crisis, individual range volatilities moved increasingly in sync with significant parallel jumps. Also, the total volatility spillover index shows stronger volatility interdependence. This suggests an overall higher degree of market interaction. The S&P 500 is the strongest net volatility transmitter in the system and spillovers peak during crisis periods. REITs net volatility transmission starts to rise only with the beginning of the subprime crisis.

The pairwise agricultural-energy volatility spillover indices do not provide significant evidence for an increase in spillovers from the energy to relevant commodity markets as a consequence of biofuel mandates. While this confirms some of the findings of e.g. Gardebroek and Hernandez (2012) it stands in contrast to results of other related studies. This could result from the full sample rolling approach of the index as opposed to exogenously introduced structural breaks and the extension of the system to financial assets that can absorb some of the volatility spillovers. Yet, our results do not permit the conclusion that biofuel mandates did not have any effect on the volatility (or return) relation between crude oil and biofuel crops. Due to the focus on short-term range volatility we do not capture any

longer-term structural changes arising from e.g. a reallocation of land towards biofuel crops as a consequence of a high or volatile oil price.

The pairwise commodity-financial volatility spillover indices show that commodity-U.S. Treasury volatility interaction appears relatively unaffected by the crisis periods but spillovers from commodities to the U.S. Dollar index increase (except in the case of corn). Yet, the most profound shift in volatility interaction occurs between the S&P 500, U.S. REITs and commodity markets. Crude oil receives high net spillovers from both financial asset markets during and after the later crisis period. Agricultural commodities are less affected although there are some spillover spikes in corn and wheat markets during the later crisis.

The volatility spillover patterns to and from commodities observed in the later crisis period are not to the same extent visible during the early crisis. While direct causal attribution is not possible, these results do provide evidence in favour of the hypothesis of increased financial linkages between the markets. There are two important implications. First, short-term commodity market volatility may increasingly be affected by shocks to financial asset markets that have no direct fundamental connection to commodity markets. Second, if commodities find an increased use as portfolio diversifiers and refuge assets, their diversification benefits may be impeded, especially in times of crisis.

Thus, future research should be directed towards investigating the underlying structural relations behind the volatility linkages. And, as also suggested by Diebold and Yilmaz (2012), a theoretical and empirical comparison of the spillover indices with multivariate GARCH models would be useful. We feel that focus should be put on the relation between short-term conditional volatility and range volatility. A starting point could be the range volatility based GARCH models such as the E-GARCH model in Brandt and Jones (2006) and the conditional autoregressive range model in Chiang and Wang (2011). In any case, the volatility spillover indices are a useful addition to the thitherto GARCH-centred analysis on volatility relations. They should be further exploited to investigate alternative asset systems

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Annex

Annex 1. Summary statistics for logged range volatilities

	Corn	Soybeans	Wheat	Crude oil
Mean	-8,7	-8,9	-8,4	-8,0
Median	-8,7	-9,0	-8,4	-8,1
Minimum	-13,1	-12,3	-12,2	-13,4
Maximum	-4,5	-4,4	-4,0	-4,0
Std. deviation	1,1	1,0	1,0	0,9
Skewness	0,0	0,4	0,2	0,4
Kurtosis	2,9	3,3	3,4	4,0

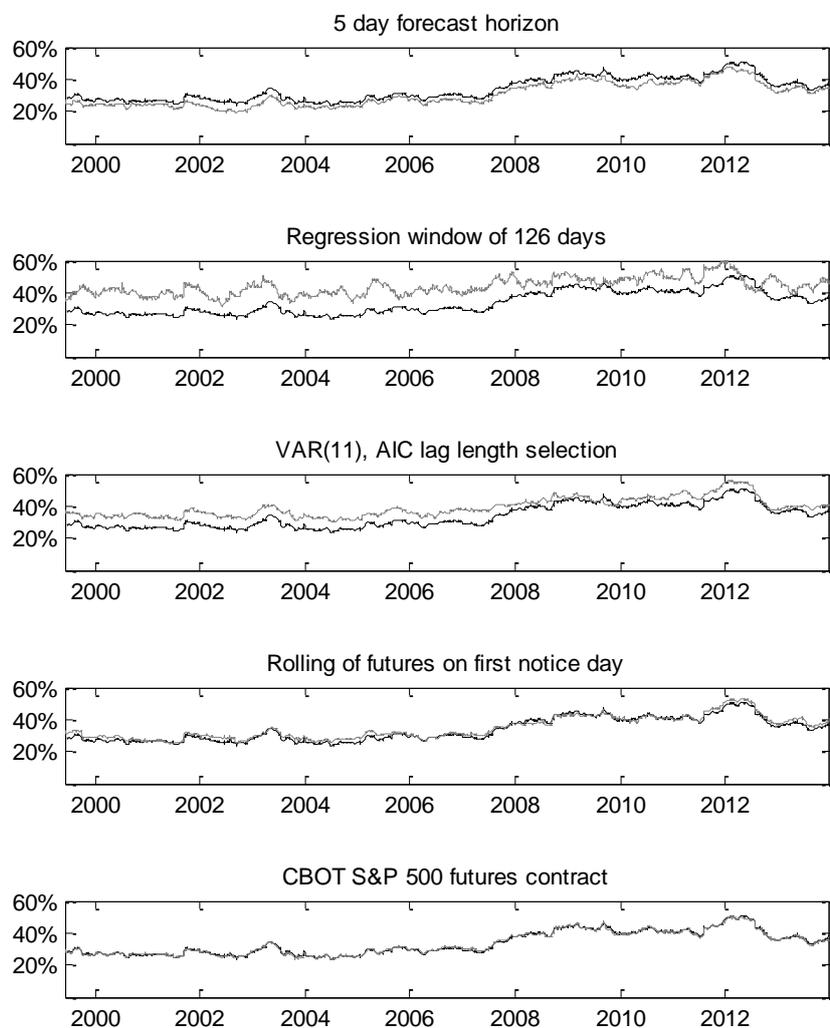
	S&P 500	REITs	Treasuries	Dollar index
Mean	-9,7	-9,8	-11,5	-10,8
Median	-9,8	-9,9	-11,5	-10,8
Minimum	-13,0	-13,5	-15,1	-17,6
Maximum	-5,5	-4,0	-7,6	-7,6
Std. deviation	1,2	1,6	1,0	0,9
Skewness	0,2	0,5	0,1	-0,5
Kurtosis	3,1	3,2	3,1	6,3

Annex 2. Results from ADF tests for stationarity

Model: $\Delta y_t = a_0 + g y_{t-1} + \sum b \Delta y_{t-i} + e_t$, $H_0: \gamma=0$, lag length selected with SBC

y	i	p-value
Corn	8	0.00
Soybeans	10	0.00
Wheat	11	0.00
Crude oil	13	0.00
S&P 500	9	0.00
REITs	10	0.00
U.S. Treasuries	9	0.00
U.S. Dollar index	12	0.00

Annex 3. Results from robustness checks



Notes: The grey lines mark the adjusted spillover indices according to the specifications given above the figure which deviate from the standard specification (black line). The Akaike Information Criterion (AIC) selects a lag length of 11.