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Price Transmissions During Financialization and Turmoil: New Evidence from North American and European Agricultural Futures

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38/2015

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January 23, 2015

Abstract

Empirical studies on price transmissions between North American and European agricultural futures neglect the period of financialization in the US commodity market, the increase of futures trading in Europe and the recent price turmoils. We fill this gap by analyzing the price dynamics of canola, wheat and corn futures between 2000 and 2013. Our empirical results show that US and European prices have become strongly intertwined in recent years and that the US market leads in terms of price transmissions. The latter results are especially apparent between 2007 and 2013, the period where prices and financialization in the US reached their peak.

JEL Classification: G10, Q11, G10

Keywords: Price Transmission, Volatility Spillovers, VECM, VAR, GARCH, Dynamic Conditional Correlations

*The study was financially supported by the German Ministry of Food and Agriculture (BMEL) through the Federal Office for Agriculture and Food (BLE). We thank the AGRAVIS AG, Thomas A. Doan, Christian Groß and Philipp Kaufmann for helpful comments.

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1. Introduction

Agricultural futures trading in the US faced significant changes in recent years due to the process of financialization and the switch to electronic trading (Irwin and Sanders, 2012). In Europe, high guaranteed fixed prices for producers have been abolished since they led to overproduction and isolation from international price signals (European Commission, 2011). This lead to new hedging needs resulting in an increase of futures trading at European exchanges. As a result, European producers today dependent more on price signals originating in futures markets than several years ago. Another development which impacted international commodity markets were the price spikes and crashes between the years 2007 and 2013. Previous literature investigating price transmissions between North American and European agricultural futures neither accounts for the institutional changes in those markets nor for the possible impact of the price turmoils after the year 2007. To fill this gap, we investigate the dynamics of futures prices between the storable commodities corn, wheat and canola, which are traded at US (CBoT and ICE) and European (NYSE Liffe) exchanges.

Empirical studies on international agricultural price dynamics predominantly focus on the North American market. Those studies either investigate volatility spillovers (e.g. Yang et al., 2003; Hernandez et al., 2013) or price transmissions. The latter are divided into studies that use spot prices (Mohanty et al., 1995, 1999; Thompson et al., 2002; Bessler et al., 2003) or futures prices (e.g. Booth and Ciner, 1997; Booth et al, 1998). However, since derivative exchanges are more liquid and thus incorporate information faster than spot markets (Protopapadakis and Stoll, 1983; Yang et al., 2001), our analysis is based on futures prices.

Studies that include European agricultural futures contracts in their samples are scarce.[1] Yang et al. (2003) investigate price transmissions between the biggest wheat producers, USA, Canada and Europe. The authors use daily prices and a sample running from May 1, 1996 to April 30, 2002. They apply generalized forecast error variance decomposition and

[1] Recent research concerning price transmissions investigates dynamics between Chinese and US commodity markets (e.g. Han et al., 2013; Liu and An, 2011).

generalized impulse response analysis (Koop et al., 1996; Pesaran und Shin, 1998). Their results indicate that US wheat prices influence Canadian prices, while European prices tend to be autonomous in their price discovery process. In addition, their findings suggest that European prices slightly influence US-prices. However, since their sample ends in 2002 the study neither covers the recent period of price turmoils nor the recent structural shifts in international commodity markets.

Fung et al. (2013) investigate price transmissions between 16 commodity futures which are traded in China, USA, Japan, Malaysia, and Great Britain. Depending on data availability, the earliest sample starts on December 2003, while all samples end on October 31, 2011. For Europe, the authors include industrial metals traded at the London Metal Exchange (LME), and white sugar traded at the NYSE Liffe in London. The findings of their causality analysis are not unanimous, but rather hint towards a dominance of European prices in the discovery of international prices. The paper covers the period of recent price turmoils in commodity markets. However, it investigates white sugar which is considered as a soft rather than an agricultural commodity.

The main contribution of this paper to the literature is the analysis of price transmissions between North American and European agricultural futures during the recent period of financialization and price turmoils. To account for possible changes in price dynamics before and after the year 2007, we use two subsamples, namely from 2000 to 2006 and from 2007 to 2013. In addition, the analysis of international canola prices has been neglected in previous studies, despite the fact that canola serves broadly for the production of biofuel today, especially in Europe. The econometric approach is based on cointegration techniques as well as bivariate VECM- and VAR-TDCC-GARCH models which allow the estimation of conditional correlations between futures returns.[2] Another feature of the econometric approach is the fact that we can account for volatility spillovers.

The empirical results show that the US exchanges are dominant concerning short-run

[2]Tersvirta (2006) provides a broad overview of univariate GARCH models, and Bauwens et al. (2006) for multivariate ones.

price dynamics. Information flows from Europe to the US are indirect, since the US market predominantly reacts to deviations from the long-run equilibrium. The empirical results concerning volatility spillovers of corn and canola predominantly verify the price transmission results. For wheat, however, we find robust univariate spillovers, running from the European to the US wheat market during the recent price turmoils. Time-varying conditional correlations indicate that European and US futures returns started to increase substantially after mid-2006, especially those of corn and wheat.

The empirical results are of interest to agricultural producers who cross-hedge their harvests in international markets. In addition, financial investors can benefit, considering the fact that commodity investments have become a main pillar of financial portfolio management in recent years (Silvennoinen and Thorp, 2013).

The remainder of the paper is structured as follows. Section 2 explains our econometric approach. Section 3 describes the data along with the attached issue of different trading hours and time zones. Section 4 presents and discusses the empirical results. Section 5 finally concludes.

2. Econometric model

To investigate long- and short-run dynamics between international agricultural futures prices, we check in the first step whether US/Canadian and European futures prices are cointegrated. To verify that logarithmic futures prices are integrated of order one we apply the ADF (Dickey and Fuller, 1979, 1981) and the KPSS (Kwiatkowski et al., 1992) test. These tests are chosen due to their different null hypotheses. While the ADF test assumes a unit root in the null, the KPSS test assumes a unit root in the alternative. Thus, if the null hypothesis for the data in levels cannot (can) be rejected for the ADF (KPSS) test, but can (cannot) be rejected in first differences, we have solid proof that the time series contain a unit-root. This joint use of stationary and unit-root tests is known as confirmatory data analysis (Brooks, 2008). The ADF equation includes a constant and a linear time trend if the latter t-statistic is significant at the 10%, 5% or 1% statistical level. In first differences, the ADF equation only includes a constant. The KPSS test includes a linear time trend and a constant for level data, and a constant in first differences.

If all time series are integrated of order one, we follow Engle and Granger (1987) and estimate the equation:

$$f_{e,t} = \beta_0 + \beta_1 f_{us,t} + \epsilon_t, \tag{1}$$

where $f_{e,t}$ and $f_{us,t}$ denote European and US logarithmic commodity prices, respectively. To check for cointegration, we test whether the estimated residuals, ϵ_t, are stationary. Since the distribution is nonstandard, we obtain critical values from MacKinnon (1996).

If the chosen times series have a common stochastic trend, we estimate the following bivariate vector error correction model with heteroscedastic error terms (VECM-TDCC-GARCH) to investigate long- and short-term adjustment patterns:

$$\Delta f_{e,t} = \beta_{e,0} + \gamma_e(f_{e,t-1} - \beta_0 - \beta_1 f_{us,t-1}) + \sum_{k=1}^{K} \beta_{ee,k}\Delta f_{e,t-k} + \sum_{k=1}^{K} \beta_{eus,k}\Delta f_{us,t-k} + \varepsilon_{e,t} \tag{2}$$

$$\Delta f_{us,t} = \beta_{us,0} + \gamma_{us}(f_{e,t-1} - \beta_0 - \beta_1 f_{us,t-1}) + \sum_{k=1}^{K} \beta_{use,k}\Delta f_{e,t-k} + \sum_{k=1}^{K} \beta_{usus,k}\Delta f_{us,t-k} + \varepsilon_{us,t}. \tag{3}$$

Δ denotes the difference operator which transforms the logarithmic prices into returns, $\Delta f_{e,t} = f_{e,t} - f_{e,t-1}$ and $\Delta f_{us,t} = f_{us,t} - f_{us,t-1}$. The error-correction coefficients γ_e and γ_{us} measure the degree of adjustment in case of deviations from the long-run equilibrium. The parameters $\beta_{ee,k}$ and $\beta_{usus,k}$ measure the returns' reaction towards own lagged returns. They indicate the degree of mean-reverting behavior. The coefficients $\beta_{eus,k}$ and $\beta_{use,k}$ indicate the short-term predictive power of one futures return on the other and thus capture return spillovers. The lag length of each model is based on the Schwartz (1978) criterion. To check for model adequacy, the Ljung-Box (1978) test is applied to standardized residuals.

To investigate long-term relationships and possible information flows, we postulate the following null hypotheses: $H_0 : \gamma_e = 0$ and $H_0 : \gamma_{us} = 0$. If, for example, the t-statistic of γ_{us} is statistically significant but not γ_e, the price adjustment towards the long-run equilibrium occurs in the US market. This would indicate information flows from the European to the US market. Adjustments to long-run deviations in just one market can be caused by the higher liquidity in the market that reacts (Liu and An, 2011). To obtain insight into short-term lead-lag relationships we investigate the parameters $\beta_{eus,k}$ and $\beta_{use,k}$. Granger causality exists if either $H_0 : \beta_{eus,1} = ... = \beta_{eus,k} = 0$ or $H_0 : \beta_{use,1} = ... = \beta_{use,k} = 0$ can be rejected. The first null hypothesis is denoted by $\hat{H}_0^{us}$, stating that US prices do not influence European prices. $\hat{H}_0^{e}$ denotes the null hypothesis that European prices do not influence US prices. To check for statistical significance, we apply the Likelihood-Ratio test as outlined in Guajarati (2003). If the chosen lag length equals one, we use the corresponding t-statistics of the parameters. In case of no cointegration, the error correction terms of equations (2) and (3) are deleted and a VAR-TDCC-GARCH model estimated instead.

Since we analyze daily returns, the error terms contain heteroscedasticity. Suppose that Ψ_t denotes the information set at day t, we define the conditional variance-covariance matrix by:

$$Var(\varepsilon_{e,t}, \varepsilon_{us,t}|\Psi_{t-1}) \equiv H_t = \begin{bmatrix} h_{e,t} & h_{eus,t} \\ h_{use,t} & h_{us,t} \end{bmatrix}. \tag{4}$$

The off-diagonals of matrix H_t denote the conditional covariances. The diagonals contain conditional variances which are assumed to follow univariate GARCH process given by

$$h_{e,t} = \omega_e + \delta_{1e}\varepsilon^2_{e,t-1} + \delta_{2e}h_{e,t-1} + \delta_{3e}\varepsilon^2_{us,t-1} \tag{5a}$$

$$h_{us,t} = \omega_{us} + \delta_{1us}\varepsilon^2_{us,t-1} + \delta_{2us}h_{us,t-1} + \delta_{3us}\varepsilon^2_{e,t-1}. \tag{5b}$$

The parameters ω_e and ω_{us} denote each equation's constant. δ_{1i} and δ_{2i} denote the reaction to past squared shocks (ARCH) and the persistence of the lagged conditional variance

(GARCH), respectively. The parameters δ_{3i} account for the possibility of volatility spillovers between both markets. If, for example, the parameter δ_{3e} is statistically significant and positive, the hypothesis of no volatility spillovers from the US to the European market can be rejected.

We follow Engle (2002) and apply his dynamic conditional correlations (DCC) approach. In this case the conditional variance-covariance matrix corresponds to:

$$H_t = \begin{bmatrix} h_{e,t} & \rho_{eus,t}\sqrt{h_{e,t}h_{us,t}} \\ \rho_{use,t}\sqrt{h_{us,t}h_{e,t}} & h_{us,t} \end{bmatrix}, \tag{6}$$

where $\rho_{eus,t}$ and $\rho_{use,t}$ denote the time-varying conditional correlation coefficients. To guarantee that H_t is positive definite, the matrix is decomposed into $H_t = D_t R_t D_t$, where:

$$D_t = diag(h_{11,t}^{1/2}, ..., h_{22,t}^{1/2}), \tag{7}$$

and the correlation matrix:

$$R_t = diag(q_{11,t}^{-1/2}, ..., q_{22,t}^{-1/2})Q_t diag(q_{11,t}^{-1/2}, ..., q_{22,t}^{-1/2}). \tag{8}$$

Note that the diagonals of matrix R_t equal one and the off-diagonals are given by $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$, with i, j = 1,2. Q_t in equation(8) is a symmetric positive definite matrix which follows an autoregressive moving average process given by:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 u_{t-1}u_{t-1}^{'} + \theta_2 Q_{t-1}. \tag{9}$$

Here, u_t is a 2x1 matrix with standardized residuals. θ_1 and θ_2 are non-negative parameters satisfying $\theta_1 + \theta_2 < 1$. The parameter θ_1 measures the impact of past shocks/news on conditional correlations. The parameter θ_2 accounts for the impact of past correlations. If θ_2 equals one and θ_1 zero, the model collapses to the constant conditional correlation (CCC) model, proposed by Bollerslev (1990). The "dynamic" part is thus captured by the coefficient θ_1, since it measures the impact of past shocks/news on current conditional correlations. Furthermore, both parameters – θ_1 and θ_2 – have to be statistically significant in order to be a DCC model (Hammoudeh et al., 2010).

3. Data description and the matter of asynchronous trading hours

Our data consist of daily European and US/Canadian closing prices. US wheat and US corn are traded at the CBoT (CME group). Until September 2007 Canadian canola has been traded at the Winnipeg Commodity Exchange (WCE), whereas today the WCE is a subsidiary of the Intercontinental Exchange (ICE). Its futures are traded at the New York Stock Exchange besides exchanges in Singapore and London. European canola, wheat and corn are traded at the NYSE Liffe exchange in Paris. All prices are taken from Thomson Reuters Datastream. Although data is available for wheat and canola since January 1999 and for corn since October 1999, our samples start on January 1, 2000 to have common starting dates. All samples end on April 1, 2013, since the CBoT changed its electronic trading hours after this day. To analyze whether dependencies and interlinkages changed before and during the recent price turmoils, the sample is split into two subsamples of seven years each, i.e., from January 2000 to December 2006 and from January 2007 to April 2013. Since futures contracts loose liquidity towards maturity, we use observations from the first-nearby contract until the first day of the last trading month. The samples thus only include observations for the most immediate contract except for the expiry month. Observations on holidays are deleted since Datastream does not account for the fact that no trading occurs during these days.

The contract size at the CBoT is 5000 bushels for corn ($\sim$ 127 metric tons) and 5000 bushels for wheat ($\sim$ 136 metric tons). The pricing units are US cents per bushel. ICE canola contracts refer to 20 metric tons and are priced in Canadian dollar per tonne. In Europe, the contract size is 50 metric tons and the pricing units are Euro per tonne. FIGURE 1 depicts the European and US/Canadian futures prices, all converted into Euro per metric ton. For conversion we use daily US/Euro and Canadian/Euro exchange rates. We convert all prices into Euros since it is rather unlikely that an American producer hedges or invests in the European market, since the US has the world's most liquid financial markets. It thus seems more appealing for a European producer to cross-hedge its harvest in the US than vice versa.

[Figure 1 about here]

The graphs visualize that futures prices of canola and wheat co-move before and after the price spikes and crashes from 2007 to 2009 and from 2010 to 2011. Corn prices, however, do not show this co-movement pattern until mid 2008.

International futures contracts are traded at different hours and in different time zones. After requesting, Datastream reported to us that they determine European settlement prices at 15:00 h and US settlement prices at 14:00 h, each local time. European trading, however, is only conducted electronically with trading hours running from 10:45 - 18:30 Central European Time (CET). Canadian canola also solely trades electronically between 20:00-14.15 Central Time (CT). The CBoT still trades in both manners, electronically and pit, although electronic trading accounts for the highest share of trading volume since 2006/2007 (Irwin and Sanders, 2012). Until April 2013, electronic trading was conducted between 17:00-2:00, while pit trading occurred between 9:30-14:00 CT. Figure 2 depicts the trading hours and the time of the determined settlement prices of Thomson Reuters Datastream, all expressed in CET. It is apparent that European prices can have an immediate impact on North American prices on day t but not vice versa.

[Figure 2 about here]

The fact that the European and US market trade asynchronously impacts the long-run relation in equation (1), since the equation assumes information of US on European prices which are not yet available.

To account for this "daylight" issue, we follow the approach by Liu and An (2011) and reestimate the long-run equation which considers lagged US prices:[3]

$$f_{e,t} = \beta_0 + \beta_1 f_{us,t-1} + \epsilon_t. \tag{10}$$

The corresponding bivariate VECM-TDCC-GARCH model is:

$$\Delta f_{e,t} = \beta_{e,0} + \gamma_e(f_{e,t-1} - \beta_0 - \beta_1 f_{us,t-2}) + \sum_{k=1}^{K} \beta_{ee,k}\Delta f_{e,t-k} + \sum_{k=1}^{K} \beta_{eus,k}\Delta f_{us,t-k} + \varepsilon_{e,t} \tag{11}$$

$$\Delta f_{us,t} = \beta_{us,0} + \gamma_{us}(f_{e,t-1} - \beta_0 - \beta_1 f_{us,t-2}) + \sum_{k=1}^{K} \beta_{use,k}\Delta f_{e,t-k} + \sum_{k=1}^{K} \beta_{usus,k}\Delta f_{us,t-k} + \varepsilon_{us,t}. \tag{12}$$

We choose this approach for our analysis since it only uses information of the US market that could have had an impact on European prices. For robustness reasons we also estimate equations (2), (3), (5a), and (5b). Empirical results, however, remain qualitatively the same.[4] In case of no cointegration, the error correction term is deleted and a VAR-TDCC-GARCH model estimated instead.

To estimate the DCC model, Engle (2002) suggests a two step procedure. The first step consists of estimating univariate GARCH equations for each time series. The second step consists of standardizing the residuals with their conditional standard deviations. Standardized residuals are then used to estimate equation (8). Although the two-step procedure gives consistent estimators, they are not statistically efficient.[5] To circumvent this problem, we jointly estimate equations (5a), (5b), (8), (11) and (12) via Maximum Likelihood. We assume a t-student distribution of conditional residuals to account for heavy tails. To obtain

[3]Herndanez et al. (2013) synchronize their data before estimating their multivariate GARCH models. For this purpose, they use a first-order moving average, VMA(1), process. However, they do not account for the electronic trading hours at the CBoT. In addition, they obtain their data from the Commodity Research Bureau while our data is taken from Thomson Reuters Datastream where prices are determined at different hours.

[4]Results are avaiable upon request

[5]We thank Thomas A. Doan for pointing this out to us.

feasible starting values, we estimate the mean equations (11) and (12) via OLS and use the estimated parameters. For the GARCH equations we estimate univariate models and use their estimated parameters.

The European exchange had a low trading volume in earlier years. The first row of Panel A in Table 1 shows the daily average trading volume of each exchange for all periods and subperiods.

[Table 1 about here]

In Europe, wheat has the highest average trading volume during the entire sample, and corn the lowest. It is apparent, however, that the high trading volume of wheat is based on the strong increase of trading activity during the second subperiod (2007 to 2013). In the US, corn has the highest average trading volume during all periods, while canola has the lowest. The US market exceeds the European market in terms of traded contracts at all time. Figure 3 visualizes the volume of daily traded contracts at the European and US exchanges.

[Figure 3 about here]

Another stylized fact of our data is the large share of zero returns of European futures, especially in the wheat and corn market during the first subsample. The last row of Panel B in Table 1 shows the share of zero returns in each sample. Note that during the main sample almost 1/5 and during the first subsample almost 1/3 of European wheat and corn returns are zero. This large amount of zero returns may bias our empirical results. To verify the empirical results we therefore estimate the econometric models with three types of European data: (i) All zero returns included, (ii) all zero returns deleted and (iii) only those prices considered for which the trading volume equals or surpasses one hundred trades per day.

4. Empirical findings

4.1 Stylized facts of commodity returns

Before turning to the analysis of cointegration, price transmissions and volatility spillovers, we focus on some noteworthy characteristics of the commodity returns, where results are presented in Panel B of Table 1. Average returns ($\hat{\mu}$) are predominantly centered around zero, but increased from the first (2000-2006) to the second sample (2007-2013). In addition, higher average returns are accompanied by higher unconditional volatility, as seen by the increase of $\hat{\sigma}$. Another interesting fact is that European futures returns are strongly skewed to the left before 2007, but centered around zero in the second subperiod (depicted by $\hat{s}$). North American returns, by contrast, indicate no skewness in neither subperiod. The estimated kurtosis coefficients ($\hat{\kappa}$) are very high in the first subperiod for European returns but lowered during the second one. Nevertheless, all coefficients are above three which infer leptokurtic distributions. In addition, Jarque Bera test statistics (JB) reject the assumption of normal distributions in all cases. This further supports our econometric approach of using a t-density distribution for the likelihood function. It should be noted, however, that the European sample includes a high share of zero returns, which is partly responsible for the high kurtosis coefficients and the high Jarque Bera test statistics. Nevertheless, returns remain skewed and highly leptokurtic when deleting the zero returns (unreported results).

Pearsons's unconditional correlation coefficients ($\hat{\rho}$) show that canola returns have the highest correlation during all periods, and corn the lowest. In addition, all correlation coefficients increased from the first subperiod to the second, indicating a stronger co-movement between returns. Futures prices thus seem to have become inter- rather than untwined during the recent price spikes and crashes.

4.2 Cointegration analysis

In the following, all empirical results refer to the data which include all zero returns. The results of the two robustness checks are shown further below.

To check whether US/Canadian and European futures prices are cointegrated, we first investigate whether all time series are integrated of order one. For this purpose, the ADF test and the KPSS test are applied. TABLE 2 shows empirical results. With one exception only, the results indicate that the time series are integrated of order one during all samples and subsamples.

[TABLE 2 about here]

The next step consists of checking whether the chosen time series are cointegrated. For this purpose equation (10) is estimated. Based on Engle-Granger (1987) we test whether the residuals of the equations are stationary. TABLE 3 shows empirical results.

[TABLE 3 about here]

It is apparent that all international prices are found to be cointegrated during the main sample. Comparing the long-term slope parameters ($\hat{\beta}_1$), however, corn has the lowest value. The parameter of canola and wheat parameters are almost one, indicating a strong co-movement between futures prices.

During the first subsample (2000-2006) each of the long-term slope parameters decreases considerably compared to the parameters for the whole sample. These results indicate lower co-movements between futures prices. In the case of canola, the Engle-Granger test rejects the null hypothesis of no cointegration. In the case of wheat and corn, however, the null hypothesis of no cointegration can not be rejected.

In the second subperiod, all long-term slope parameters ($\hat{\beta}_1$) increase substantially compared to the first subsample. Nevertheless, test results indicate cointegration only in the cases of canola and wheat but not for corn.

The results of the cointegration analysis coincide with the visual impression of the price movements in FIGURE 1. The divergence of European and US corn prices is predominantly based on the fact that the United States had strong export surplusses before the financial crisis while the European Union majorly imported corn due to the lower prices in the US.[6] Another aspect for price divergences during the second subsample are based on the the Energy Policy Act of 2005, after which the US used a large amount of its corn production for biofuel (Westcott, 2007). This can explain the increase of US corn prices between 2008 and 2009, a period when European prices were already declining.

4.3 Price transmissions and volatility spillovers between exchanges

Based on the cointegration results, we either estimate a VECM-TDCC-GARCH or a VAR-TDCC-GARCH model. Tables 4 show empirical results for canola, wheat and corn. Each table is split into Panel A, B, and C, showing results for the main sample and two subsamples. $\hat{H}_0^e$ is the null hypothesis stating that European prices do not influence US prices while $\hat{H}_0^{us}$ states that US prices do not influence European prices.

[Table 4 about here]

4.3.1 Main Sample: 2000-2013

For canola the BIC criterion suggests a lag length of two, while in the other cases a lag length of one is favored. In the case of canola and corn, the null hypothesis $\hat{H}_0^{us}$ is rejected at 1% significance levels and $\hat{H}_0^e$ at 10% significance level. This hints towards bidirectional price transmissions between US and European futures returns. By contrast, the empirical results for wheat indicate a univariate causal relationship, running from the US to the European market.

The statistical significance of γ_{us} in the wheat and corn market shows that the US market adjusts after deviations from the long-run equilibrium. These results infer that, relative to the European markets, the CBoT assesses long-run deviations between futures prices as an important information that has to be priced in (Liu and An, 2011). The reason for this one sided adjustment might be the fact that the trading volume of the US corn and wheat

[6] We thank the AGRAVIS AG for pointing this out to us.

market exceeds the European volume by far, enabling a quicker reaction to price deviations in the US market. Surprisingly, none of the adjustment parameters in the canola market is statistically significant.

Volatility spillovers are identified by the significance of the parameters $\hat{\delta}_3$ in equations (5a) and (5b). For canola and wheat, the empirical results indicate unidirectional volatility spillovers, running from the US to the European market. For wheat, both parameters are highly significant, suggesting bivariate volatility spillovers. Interestingly, the spillovers from the European to the US market are larger in magnitude (0.05) than vice versa (0.002).

Further noteworthy results are given by the the ARCH (δ_1) and GARCH (δ_2) parameters. In all cases, the parameters are significant at the 1% level, indicating to the existence of conditional volatility. In addition, all GARCH parameters are larger than the ARCH parameters, indicating that own volatility persistence is stronger than the effect of short-term shocks. Comparing the European and the US parameters, however, it becomes apparent that the European market reacts much stronger towards own past shocks than the North American market. This is especially true for the European corn market, where the ARCH parameter (0.23) exceeds the corresponding US parameter (0.07) by far. As shown below, this pattern is probably caused by the low European trading volume in the first subsample. The characteristic of a larger impact of short-term shocks (ARCH) has been confirmed for less liquid and less developed markets (e.g. Aggarwal et al. 1999; Korkmaz et al. 2012).

4.3.2 Subsample: 2000 - 2006

Since our cointegration analysis indicates that corn and wheat prices do not share a common stochastic trend, we estimate a bivariate VAR-TDCC-GARCH model for these commodities. For canola, we estimate a VECM-TDCC-GARCH model. Based on the BIC criterion each model includes one lag.

All results indicate that European and US prices influence themselves in a bidirectional manner since the null hypotheses $\hat{H}_0^e$ and $\hat{H}_0^{us}$ are either rejected to the 1% or 5% significance level. The adjustment towards the long-run equilibrium in the canola market occurs in

Europe. Concerning volatility spillovers, our empirical results indicate univariate spillovers, running from the US to the European markets in the case of corn and canola and no spillovers in the case of wheat.

As in the main sample, European commodities' ARCH parameters are apparently higher than the corresponding North American ones. This indicates a stronger reaction to own market shocks in the European market. Again, this pattern is apparent for the corn market where the European ARCH parameter (0.42) exceeds the US parameter (0.09) by far.

4.3.3 Subsample: 2007 - 2013

As in the first subsample, European and US corn prices are not cointegrated. We therefore estimate a VAR-TDCC-GARCH model for corn. The BIC criterion favors a lag length of one for all models. In the case of wheat, standardized residuals appear to be serially correlated. The empirical results do not change when increasing the lag length to two.[7]

For all markets, the null hypotheses $\hat{H}_0^{us}$ can be rejected at 1% significance levels but none of the null hypotheses $\hat{H}_0^{e}$. These results indicate univariate transmissions of US on European returns during the recent period of price turmoils.

Concerning volatility spillovers, we find no significant spillovers between European and North American corn returns. For canola, the parameter δ_{3e} can be rejected at the 1% significance level, indicating univariate volatility spillovers from the US to the European market. Empirical results for wheat are most surprising since they indicate univariate volatility spillovers from the European to the US market. The latter results contradict the findings of Hernandez et al. (2013) who find that the CBOT predominantly dominates the European market in terms of volatility spillovers. Their results might differ due to their shorter sample (2005 to 2009) which does not cover the recent period of price spikes and crashes in the wheat market between 2010 and 2013. In addition, the sample does not cover the sharp increase of European's trading volume (see FIGURE 3) which might be responsible for the univariate spillovers.

[7] For the sake of brevity, empirical results are not shown, but are available upon request.

Concerning the adjustment to the long-run equilibrium, empirical results indicate that the US market adjusts in the case of canola, while both exchanges adjust to the long-run equilibrium in the wheat market. The fact that both markets react to deviations between wheat prices might as well be caused by the substantial increase of daily trading volume in European's wheat contracts. All adjustment parameters increased in magnitude compared to the first subsample, indicating a quicker convergence in case of deviations from the long-run equilibrium.

Comparing the European ARCH/GARCH parameter constellations with the first subsample it becomes apparent that the ARCH parameters lowered substantially which hints towards a more liquid and developed European market since the year 2007.

4.4. Robustness checks

As explained above, the European samples have a large share of zero returns in the first subsample, especially corn and wheat. To obtain robust empirical results, we reestimate all models by (i) deleting the European zero returns and by (ii) using only those prices on days where the traded contracts equal or exceed 100. Table 5 summarizes empirical results with all three types of data. The arrows indicate the direction of causality concerning price transmission (third column) and volatility spillovers (fourth column). All depicted results refer to the mean equations (11) and (12). Empirical results, however, remain similar when estimating equations (2) and (3).[8]

[Table 5 about here.]

It is apparent that the US market obtains the dominant role regarding price transmissions and volatility spillovers. For wheat, however, we find robust univariate volatility spillovers, running from the European to the US market. The latter results might be caused by the sharp increase of European's trading volume in wheat contracts.

[8] Empirical results are not shown but available upon request.

European influence on North American prices is rather indirect since the long-term adjustment occurs predominantly in the US market. The fact that the US exchanges have a higher trading volume than the European exchanges might be responsible for these results (Liu and An, 2011).

4.5. Time-varying correlations

The analysis of the time-varying conditional correlations deepens the insight into the linkages and dependencies between the futures returns. FIGURE 4 depicts estimated conditional correlations. It is apparent that canola's conditional correlations are highest from the beginning, but fluctuate around a mean of approximately 0.5. Conditional correlations of corn and wheat, on the other hand, are much lower in earlier years but increase substantially after mid 2006 and reach maximum values in mid 2011.

[FIGURE 4 about here]

The reasons for the different movement patterns of conditional correlations are twofold. First, canolas' "dynamic" coefficent - $\hat{\theta}_1$ - is much higher than the corresponding parameters of corn and wheat, which are closer to zero (see Panel A of table 4). Second, next to the higher "dynamic" parameter, canola's persistence of past correlation (denoted by $\hat{\theta}_2$) is much lower than the other ones. An increase of canola's conditional correlation in $t-1$ has a much lower impact on day t than in the corn or wheat market.

In sum, our results hint to an increase of linkages between North American and European returns during the recent price turmoils. The increase of correlations lead to better cross-hedging opportunities, especially for European agricultural producers. For financial investors, however, diversification benefits have substantially lowered. The drop of diversification benefits in commodity markets has so far been confirmed for the US market (Silvennoinen and Thorp, 2013).

5. Conclusion

Current literature on dynamics between North American and European agricultural prices focuses primarily on volatility spillovers. Studies on price transmissions neglect the period of financialization in the US market, the increase of futures trading in Europe and the recent price turmoils in commodity markets. Canola has been neglected in recent studies as well, despite the fact that it serves broadly for the production of biofuel today, especially in Europe. We fill this gap by analyzing the transmissions of futures prices between the storable commodities corn, wheat and canola. We cover the period from 2000 to 2013. Based on cointegration results we either estimate bivariate VECM- or VAR-TDCC-GARCH models to analyze short-term and long-term price dynamics. Our econometric approach also allows to account for volatility spillovers. To obtain robust empirical results, we account for the issue of different time zones and for thinly traded European markets until mid-2000.

Concerning price transmissions, we predominantly find unidirectional causalities running from the US to the European exchange. This pattern is especially apparent during the second subsample, which covers the period of price turmoils in commodity markets. European prices influence US prices rather indirectly since adjustments towards the long-run equilibrium occur more often in the US market than vice versa. The higher US trading volume might be responsible for these patterns.

The empirical results furthermore indicate that volatility spillovers run predominantly from the US to the European markets. For wheat, however, we find robust univariate volatility spillovers from the European to the US market during the second sample – namely from 2007 to 2013. Time-varying conditional correlations indicate that canola has been the the most intertwined market during the entire sample. In addition, shocks in the canola market have a stronger impact on conditional correlations than in the other two markets. Conditional correlations between wheat and corn returns, however, increased substantially in recent years, indicating a rise of cross-hedging opportunities for agricultural producers. For financial investors, on the contrary, diversification benefits have diminished.

To deepen the insight into price dynamics, future research could focus on the impact of Europe's increased trading volume, both on international returns and volatilities. In addition, empirical studies could investigate the price dynamics and correlations among the various agricultural returns themselves.

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Figure 1: Futures Prices

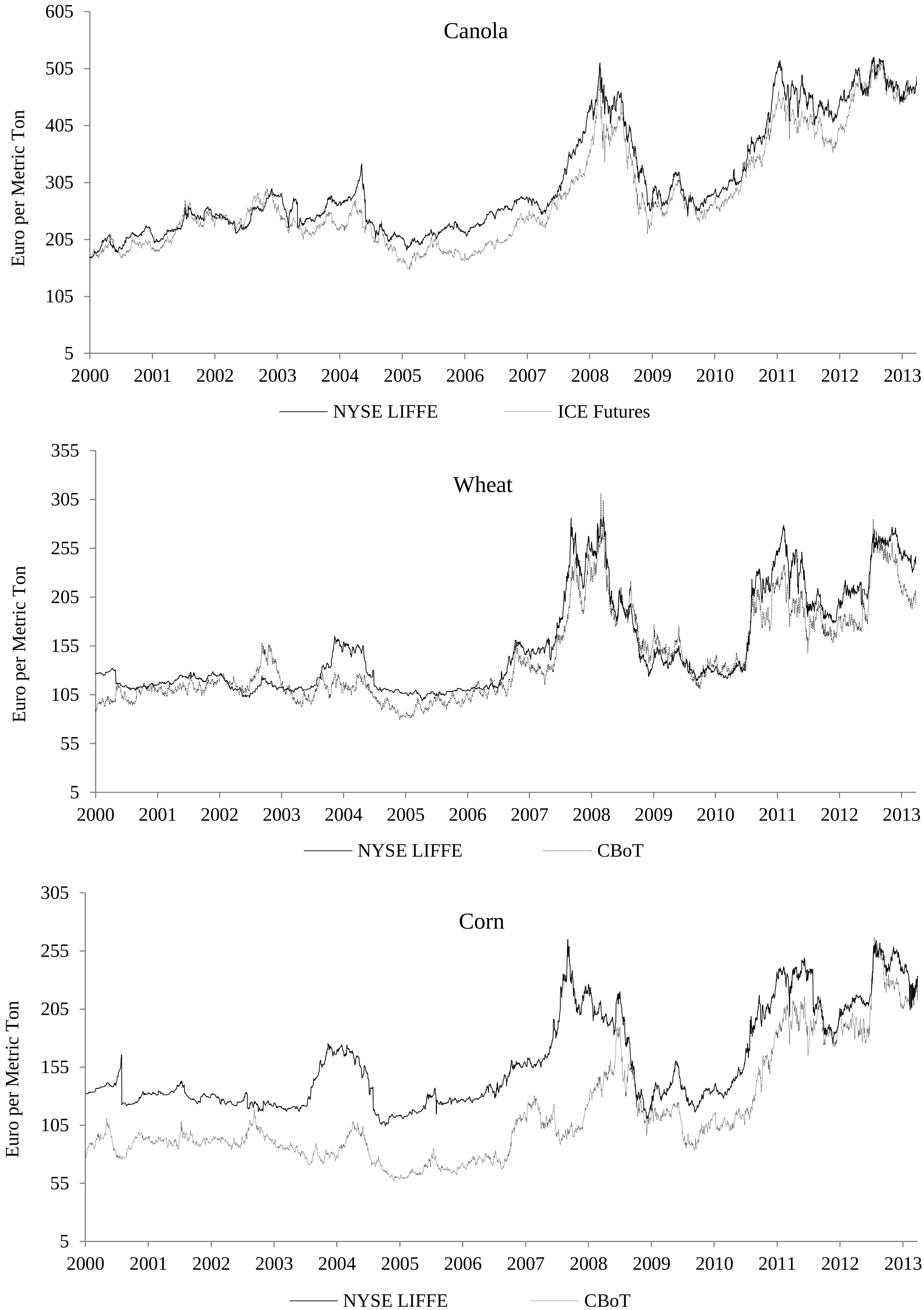

Figure 2: Settlement Prices and Trading Hours in CET at Paris, Chicago and New York

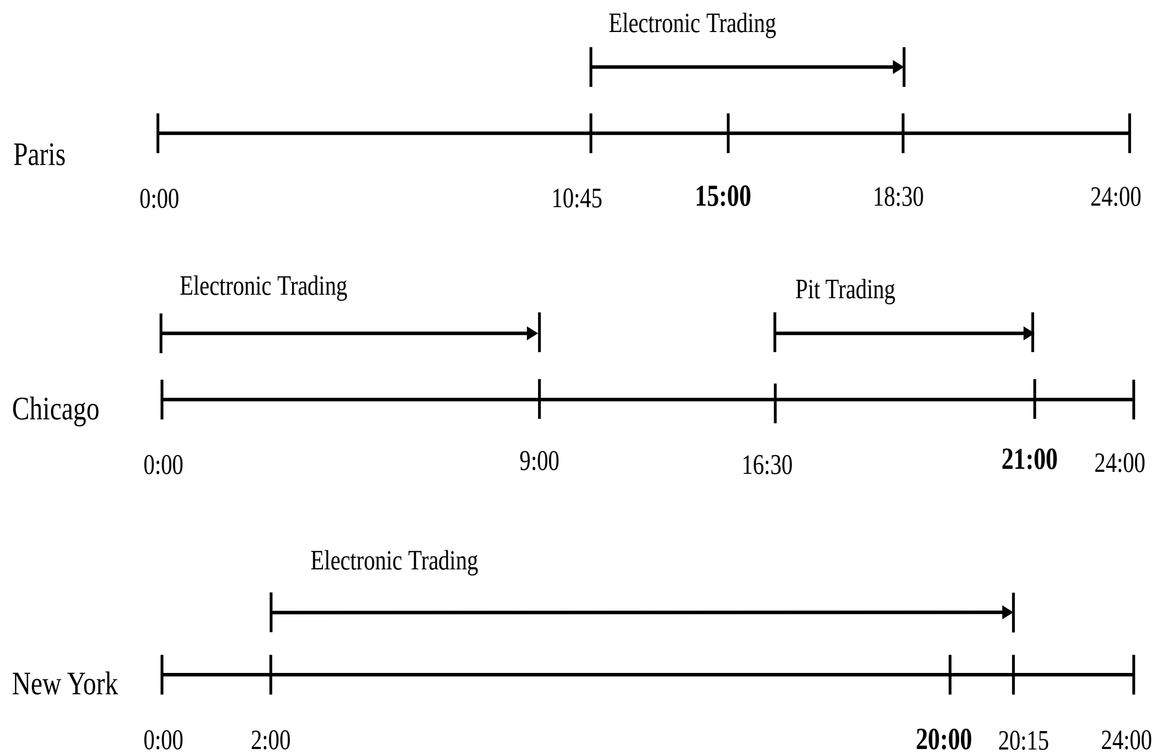

Figure 3: Volume of Daily Traded Contracts

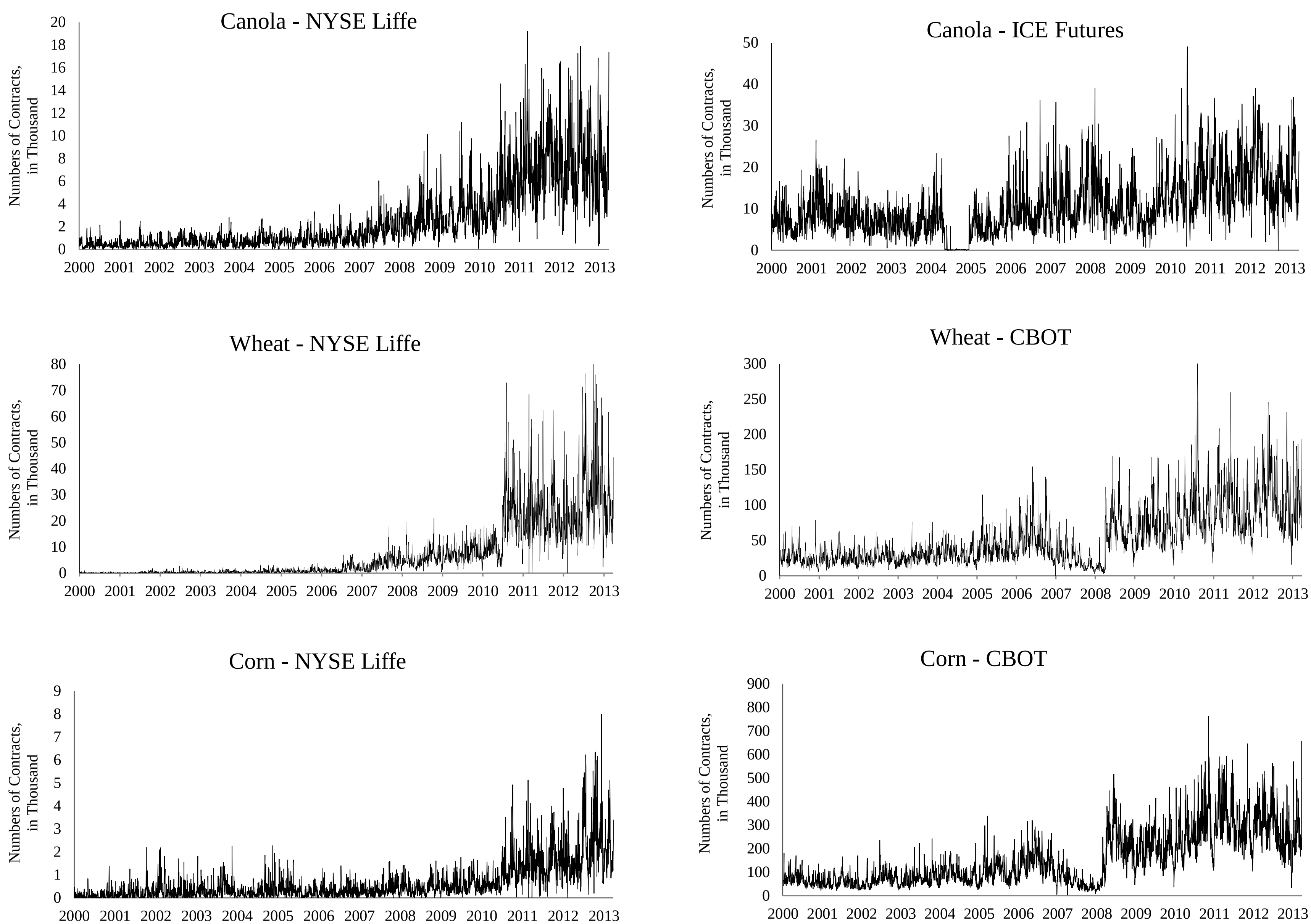

Figure 4: Dynamic Conditional Correlations

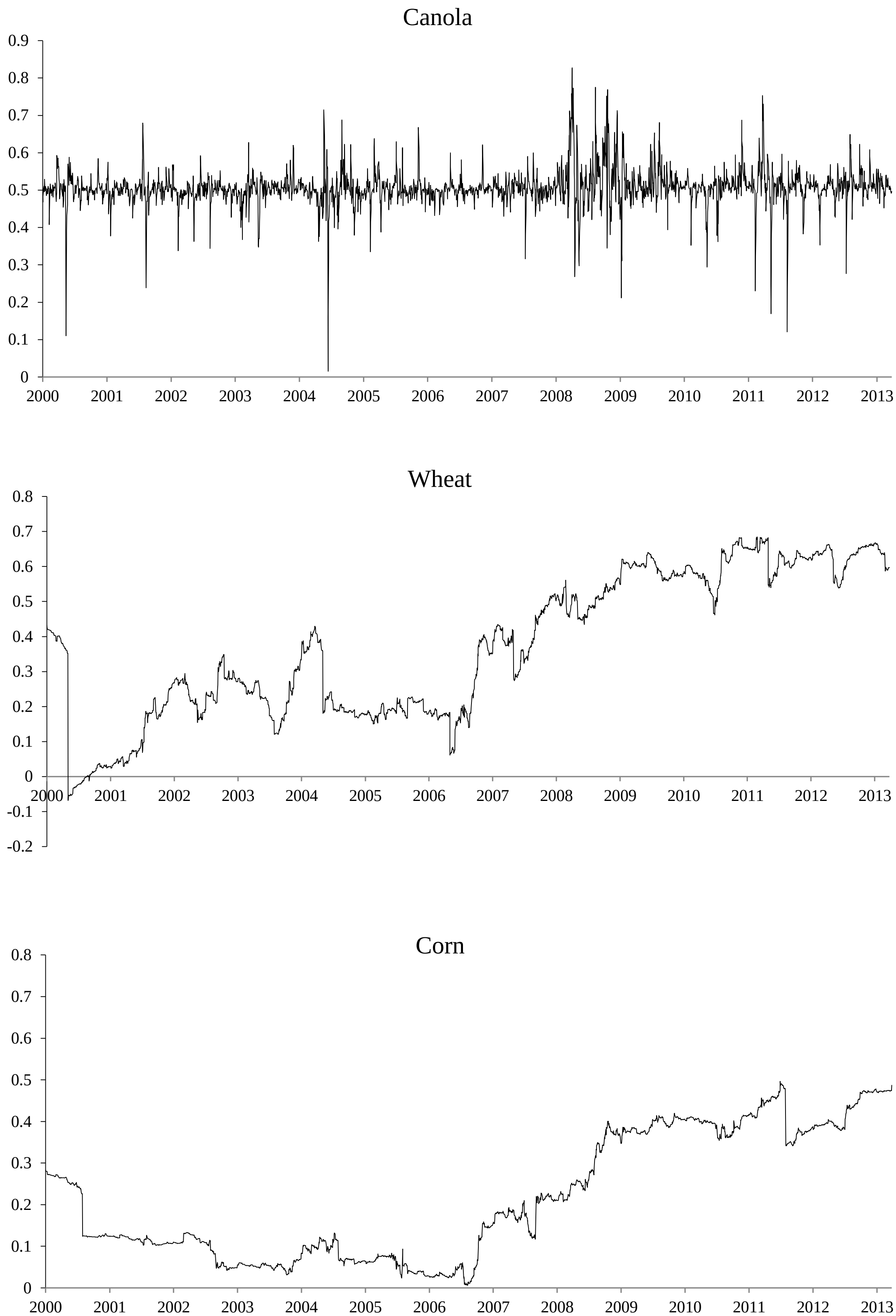

Table 1: Descriptive Statistics

		2000-2013			2000-2006			2007-2013		
		Canola	Wheat	Corn	Canola	Wheat	Corn	Canola	Wheat	Corn
Panel A: Trading Volume and Zero Returns										
Trading Volume	NYSE Liffe	2,588	7,293	644	708	621	269	4,691	14,731	1,061
	CBoT/ICE	10,475	52,951	152,259	7,144	37,807	86,175	14,203	32,591	226,015
Zero Returns	NYSE Liffe	6.57%	20.65%	18.98%	9.66%	32.09%	30.07%	3.11%	7.89%	6.61%
	CBoT/ICE	3.24%	1.64%	0.00%	4.57%	2.42%	0.00%	1.75%	0.77%	0.0%
Panel B: Return Characteristics										
$\hat{\mu}$	NYSE Liffe	0.031%	0.019%	0.017%	0.027%	0.008%	0.010%	0.035%	0.031%	0.024%
	CBoT, ICE	0.031%	0.024%	0.029%	0.020%	0.022%	0.016%	0.043%	0.025%	0.042%
$\hat{\sigma}$	NYSE Liffe	1.16%	1.36%	1.31%	1.05%	0.83%	1.16%	1.27%	1.77%	1.46%
	CBoT, ICE	1.50%	2.13%	1.92%	1.35%	1.84%	1.69%	1.65%	2.42%	2.16%
$\hat{s}$	NYSE Liffe	-1.71	-0.35	-4.76	-3.44	-2.15	-11.61	-0.59	-0.10	-0.74
	CBoT, ICE	-0.26	0.16	0.14	0.11	0.52	0.58	-0.48	-0.03	-0.09
$\hat{\kappa}$	NYSE Liffe	24.10	15.80	106.12	56.51	39.62	288.87	6.12	9.43	16.15
	CBoT, ICE	7.84	4.88	5.11	5.49	4.73	5.78	8.58	4.48	4.44
$\hat{\rho}$	NYSE Liffe									
	CBoT,ICE	0.51	0.44	0.28	0.37	0.14	0.06	0.61	0.57	0.42
JB	NYSE Liffe	$62,336^{***}$	$22,572^{***}$	$1,473,664^{***}$	$209,791^{***}$	$98,629^{***}$	$5,967,267^{***}$	715^{***}	$2,685^{***}$	$11,371^{***}$
	CBoT, ICE	$3,231^{***}$	501^{***}	627^{***}	452^{***}	297^{***}	659^{***}	$2,064^{***}$	143^{***}	136^{***}

The table shows descriptive statistics of all samples and subsamples. $\hat{\mu}$, $\hat{\sigma}$, $\hat{s}$ and $\hat{\kappa}$ denote the estimated mean, unconditional variance, skewness and kurtosis coefficient, respectively. $\hat{\rho}$ denotes Pearson's unconditional correlation coefficient between commodity returns. JB denotes the Jarque Bera test statistics. *,** and *** denote statistical significance at the 1%, 5%, and 10% significance levels, respectively. Trading Volume denotes daily average trading volume of each exchange. Zero Returns denotes the share of zero returns for each corresponding sample period.

Table 2: Unit Root Tests

	ADF-Test				KPSS-Test			
	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$
Panel A: 2000-2013								
Canola	-2.23	-51.74***	-2.03	-42.22***	0.45***	0.05	0.75***	0.07
Wheat	-2.16	-53.36***	-3.08	-58.45***	0.31***	0.10	0.40***	0.03
Corn	-2.16	-55.56***	-2.23	-56.41***	0.35***	0.08	1.06***	0.09
	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$
Panel B: 2000-2006								
Canola	-2.48	-38.70***	-2.04	-41.74***	0.59***	0.09	0.72***	0.11
Wheat	-1.40	-36.11***	-3.04**	-41.98***	0.18**	0.10	0.39***	0.05
Corn	-1.93	-41.76***	-1.91	-40.91***	0.18**	0.10	0.28***	0.12
	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$	$f_{e,t}$	$\Delta f_{e,t}$	$f_{us,t}$	$\Delta f_{us,t}$
Panel C: 2007-2013								
Canola	-1.34	-34.75***	-1.22	-22.88***	0.45***	0.11	0.46***	0.07
Wheat	-1.36	-37.31***	-2.36	-40.47***	0.58***	0.11	0.44***	0.06
Corn	-1.16	-37.26***	-1.25	-38.84***	0.67***	0.11	0.56***	0.06

The table shows empirical results for the stationary and unit root tests. The ADF equation includes a constant. It additionally includes a linear time trend if the corresponding t-statistic is statistically significant. In first differences, the ADF equation only includes a constant. Critical values are taken from MacKinnon (1996). The KPSS equation includes a linear time trend and a constant for level data, and a constant in first differences. Critical values are taken from Kwiatkowski et al. (1992). *,** and *** denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 3: Cointegration Results

	$\hat{\beta}_0$	$\hat{\beta}_1$	EG
Panel A: 2000-2013			
Canola	0.52	0.92	-4.84***
Wheat	0.37	0.94	-4.72***
Corn	2.41	0.56	-3.14*

	$\hat{\beta}_0$	$\hat{\beta}_1$	EG
Panel B: 2000-2006			
Canola	1.97	0.65	-3.23*
Wheat	2.65	0.45	-2.43
Corn	3.64	0.27	-2.51

	$\hat{\beta}_0$	$\hat{\beta}_1$	EG
Panel C: 2007-2013			
Canola	0.47	0.93	-4.54***
Wheat	-0.50	1.11	-4.14***
Corn	2.38	0.57	-1.91

The table shows empirical results of equation (10). EG denotes the ADF test statistic of the residuals from the long-run equations. Critical values are taken from MacKinnon (1996). *,** and *** denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 4: VECM/VAR-TDCC-GARCH Results

	Canola		Wheat		Corn	
	$\Delta f_{e,t}$	$\Delta f_{us,t}$	$\Delta f_{e,t}$	$\Delta f_{us,t}$	$\Delta f_{e,t}$	$\Delta f_{us,t}$
Panel A: 2000-2013	VECM-TDCC-GARCH		VECM-TDCC-GARCH		VECM-TDCC-GARCH	
$\hat{\gamma}_e$	-0.002		-0.00		0.00	
$\hat{\gamma}_{us}$		0.003		0.01***		0.007***
$\hat{H}_0^e$		5.16*		1.00		-1.66*
$\hat{H}_0^{us}$	71.49***		6.69***		5.96***	
$\hat{\omega}$	0.00***	0.00***	0.00	0.00***	0.00	0.00***
$\hat{\delta}_1$	0.12***	0.08***	0.10***	0.04***	0.23***	0.07***
$\hat{\delta}_2$	0.79***	0.84***	0.89***	0.90***	0.77***	0.93***
$\hat{\delta}_3$	0.01***	0.01	0.002***	0.05**	0.01***	0.00
$\hat{\theta}_1$	0.05***		0.007**		0.003***	
$\hat{\theta}_2$	0.57***		0.991***		0.996***	
$\hat{\nu}$	4.73***		4.36***		3.86***	
Panel B: 2000-2006	VECM-TDCC-GARCH		VAR-TDCC-GARCH		VAR-TDCC-GARCH	
$\hat{\gamma}_e$	-0.003**		-		-	
$\hat{\gamma}_{us}$		-0.00		-		-
$\hat{H}_0^e$		-1.81*		-2.15**		-2.22**
$\hat{H}_0^{us}$	7.24***		4.73***		3.46***	
$\hat{\omega}$	0.00	0.00	0.00***	0.00	0.00**	0.00**
$\hat{\delta}_1$	0.18***	0.04*	0.16***	0.01***	0.42***	0.09***
$\hat{\delta}_2$	0.51***	0.93***	0.78***	0.95***	0.50***	0.89***
$\hat{\delta}_3$	0.12***	0.01	0.003	0.03	0.007***	0.00
$\hat{\theta}_1$	0.00**		0.003**		0.004**	
$\hat{\theta}_2$	0.95***		0.996***		0.995***	
$\hat{\nu}$	4.57***		3.87***		2.95***	
Panel C: 2007-2013	VECM-TDCC-GARCH		VECM-TDCC-GARCH		VAR-TDCC-GARCH	
$\hat{\gamma}_e$	0.00		0.008***		-	
$\hat{\gamma}_{us}$		0.02***		0.02***		-
$\hat{H}_0^e$		1.19		0.80		-0.75
$\hat{H}_0^{us}$	5.52***		5.40***		6.30***	
$\hat{\omega}$	0.00	0.00***	0.00	0.00*	0.00**	0.00*
$\hat{\delta}_1$	0.11***	0.06***	0.10***	0.05***	0.09***	0.06***
$\hat{\delta}_2$	0.69***	0.90***	0.84***	0.90***	0.87***	0.92***
$\hat{\delta}_3$	0.09**	0.00	0.02	0.04**	0.00	0.00
$\hat{\theta}_1$	0.07***		0.007***		0.005***	
$\hat{\theta}_2$	0.61***		0.99***		0.994***	
$\hat{\nu}$	5.24***		5.24***		5.42***	

The table shows empirical results for the VECM and VAR-TDCC-GARCH models of equations (11), (12), (5a) and (5b). $\hat{H}_0^e$ is the null hypothesis stating that European prices do not influence US prices. $\hat{H}_0^{us}$ states that US prices do not influence European prices. Panel A for canola shows Likelihood-Ratio test statistics when the chosen lag length equals two. In the other cases, t-statistics are shown. *,** and *** denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 5: Overview - Empirical Results

	Long-Run Adjustment	Price Transmission	Volatility Spillover
Panel A: Canola, 2000 - 2013			
All Prices	Not significant	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
No Zero Returns	Not significant	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Trading Volume >= 100	Not significant	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Panel B: Canola, 2000 - 2006			
All Prices	Europe	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
No zero returns	Europe	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Trading Volume >= 100	Europe	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
Panel C: Canola, 2007 - 2013			
All Prices	US	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
No Zero Returns	US	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Trading Volume >= 100	US	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Panel D: Wheat, 2000 - 2013			
All Prices	US	US $\longrightarrow$ Europe	US $\longleftrightarrow$ Europe
No Zero Returns	US	US $\longleftrightarrow$ Europe	US $\longleftrightarrow$ Europe
Trading Volume >= 100	US	US $\longrightarrow$ Europe	US $\longleftrightarrow$ Europe
Panel E: Wheat, 2000 - 2006			
All Prices	-	US $\longleftrightarrow$ Europe	No spillover
No Zero Returns	-	US $\longrightarrow$ Europe	No spillover
Trading Volume >= 100	-	US $\longrightarrow$ Europe	US $\longleftarrow$ Europe
Panel F: Wheat, 2007 - 2013			
All Prices	US and Europe	US $\longrightarrow$ Europe	US $\longleftarrow$ Europe
No Zero Returns	US and Europe	US $\longrightarrow$ Europe	US $\longleftarrow$ Europe
Trading Volume >= 100	US and Europe	US $\longrightarrow$ Europe	US $\longleftarrow$ Europe
Panel G: Corn, 2000 - 2013			
All Prices	US	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
No Zero Returns	US	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Trading Volume >= 100	US	US $\longrightarrow$ Europe	US $\longrightarrow$ Europe
Panel H: Corn, 2000 - 2006			
All Prices	-	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
No Zero Returns	-	US $\longleftrightarrow$ Europe	US $\longrightarrow$ Europe
Trading Volume >= 100	-	US $\longrightarrow$ Europe	No spillover
Panel I: Corn, 2007 - 2013			
All Prices	-	US $\longrightarrow$ Europe	No spillover
No Zero Returns	-	US $\longrightarrow$ Europe	No spillover
Trading Volume >= 100	-	US $\longrightarrow$ Europe	No spillover

The table summarizes the empirical results of equations (5a), (5b), (11) and (12) for three types of data: The first row of each panel represents the empirical results which include all observations. The second row of each panel shows empirical results where observations are deleted when European returns are zero. The third row of each Panel shows empirical results for the model in which only those observations are considered when the European trading volume equals or is higher than 100. The arrows indicate the direction of causality.