

Price Discovery in European Agricultural Markets: When Do Futures Contracts Matter?

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Abstract

The literature on price discovery in agricultural markets is predominantly devoted to North America. This paper extends the analysis to Europe to investigate the influence of futures markets on the pricing process during periods of price turmoil and rising trading activity. By quantifying the contribution of the futures market to price discovery over time, we show that its impact was high during the first period of price spikes (2007 to 2009) but lower during the second one (2010 to 2013). These results are noteworthy as trading volume in futures markets was low during the first period but high during the latter. More liquidity did thus not lead to a higher influence on spot prices. We argue that futures markets especially mattered for price discovery during the period of unanticipated price shocks, namely between 2007 and 2009.

JEL Classification: G10, G12, G13, Q10

Keywords: Price Discovery, European Agricultural Markets, Common Factor Weights, Time-Varying VECM

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1. Introduction

Despite being praised during calm economic periods for facilitating reliable price information and serving as hedging instruments, futures markets are quickly blamed when commodity prices spike on allegedly unwarranted grounds. Since the early 2000s, commodity markets faced significant changes in terms of the investor structure, trading volume, open interest and electronic trading. The so called financialization has been a phenomenon predominantly connoted to US markets. These institutional changes in combination with the recent turmoil in commodity prices have renewed the interest in the pricing process in agricultural markets (Irwin and Sanders, 2012).

It has been early hypothesized that futures markets react quicker to new information than spot markets due to higher liquidity, more transparency and lower transaction costs (Working 1962; Black 1976). The empirical investigation of price discovery in agricultural markets has been predominantly devoted to the US, most likely because of the global relevance and long history of US futures exchanges. The empirical findings underscore the dominant role of futures markets in the price discovery process and they are qualitatively similar for samples before and during the years of price turmoil. The results suggest that the financialization did not significantly disrupt commodity pricing in agricultural futures markets (e.g., Brorsen et al. 1984; Covey and Bessler 1992; Brockman and Tse 1995; Hernandez and Torero, 2010; Baldi et al., 2011; Dwyer et al., 2012).

Studies which focus on European markets are scarce, despite the fact that Europe obtains a large share of global agricultural production today (USDA, 2015). Similar to the US, European spot markets faced significant institutional changes in recent years such as the abolition of high guaranteed fixed prices (European Commission, 2011). This abolition led to international competition and higher hedging needs for European producers. Hence, European futures exchanges have become more relevant in recent years for the agricultural business. Institutional differences between North America and Europe impede the use of US findings to derive implications about the pricing mechanisms in Europe. For example, US

markets have already been very liquid before the recent period of price spikes. The average monthly trading volume of US corn contracts traded at the Chicago Board of Trade between 2000 and 2006 was about 1.8 million. This exceeded three hundred times the volume of the corresponding European contract. The trading volume of the US wheat contract exceeded Europe's by fifty and in the case of canola by ten. In addition, the largest commodity index traders (CITs) such as Goldman Sachs and AIG traditionally invested in US (agricultural) commodity markets (IATP, 2008). However, CITs have recently started to invest in certain European commodity markets as well (Reuters Online, 2013).

To the best of our knowledge, no study has investigated in depth the price discovery process in European agricultural markets since the year 2000. Although Kuiper et al. (2002) analyze potato futures contracts that are traded at the Amsterdam Exchange, their sample spans from 1989 to 1992. Figuerola-Feretti and Gonzalo (2010) analyze price discovery in European commodity markets but they investigate non-ferrous metals traded at the London Metal Exchange. Adämmer et al. (2015) look at price discovery in European hog and piglet markets but their sample spans from 2009 to 2014, which does not include the price spikes between 2007 and 2009. In addition, their focus is on price discovery in thinly traded futures markets and they exclude important grain commodities.

We extend the literature to European markets by using a unique and hand collected data set of German spot prices for canola, wheat and corn. As Germany is one of the biggest agricultural producers in the European Union, the data is well suited for this analysis. In addition, we apply a time-varying vector error correction model with heteroscedastic disturbances to overcome previous drawbacks of econometric models applied to US data. By quantifying the relative contribution of the futures market to price discovery over time we are able to analyze in depth the price discovery process during the recent periods of price turmoil. Our findings concern futures markets in general and European agricultural markets in particular as we shed new light on the importance of futures contracts for price discovery during times of crises and rising trading activity.

The empirical results show that the impact of the futures markets was stronger during the first period of price turmoil (from 2007 to 2009) than during the second one (from 2010 to 2013). However, trading activity in the futures markets was much higher during the second period than during the first. Our results thus contradict previous findings that more liquidity (trading volume) automatically leads to a stronger impact on pricing (e.g., Garbade and Silber, 1983). We argue that commodity markets were hit by surprise during the first period but anticipated the latter due to policy reactions, academic research and media coverage. Our results imply that European agricultural futures markets especially mattered for price discovery when markets faced unanticipated price shocks, namely between 2007 and 2009.

The remainder of the paper is structured as follows: Section 2 outlines the econometric approach and Section 3 describes the data. Section 4 shows and discusses empirical results while Section 5 concludes.

2. Econometric model

The cost-of-carry model implies that the natural logarithms of spot and futures prices for the same commodity are cointegrated.¹ This relation can be written as:

$$f_t = \beta_0 + \beta_1 s_t + ec_t, \quad (1)$$

where f_t and s_t denote the logarithms of spot and futures prices, respectively. The parameter β_0 denotes the equation's constant and β_1 its slope parameter. To verify that the logarithmic futures prices are integrated of order one we apply the test by Dickey and Fuller (1979, 1981), hereafter ADF test, and the test by Kwiatkowski et al. (1992), hereafter KPSS test. To test for cointegration we apply the methodology by Engle and Granger (1987) and the trace statistic by Johansen (1988, 1991). If both time series are found to be cointegrated, long- and short-run dynamics can be analyzed by a bivariate vector error correction model (VECM).

¹Our econometric approach abstracts from time-varying interest rates, dividends and the time to maturity of the futures contract.

These econometric approaches have been broadly applied to US data but without accounting for time-variation in the parameters.

As our focus is on the evolution of price discovery during the recent periods of price turmoil, such time-invariant approaches are unsuitable for our analysis. We therefore apply a model that allows the parameters to change over time. This can be written as:

$$\Delta s_t = \beta_t^{s0} + \gamma_t^s ec_{t-1} + \sum_{k=1}^K \beta_{t,k}^{ss} \Delta s_{t-k} + \sum_{k=1}^K \beta_{t,k}^{sf} \Delta f_{t-k} + \varepsilon_{s,t} \quad (2a)$$

$$\Delta f_t = \beta_t^{f0} + \gamma_t^f ec_{t-1} + \sum_{k=1}^K \beta_{t,k}^{ff} \Delta s_{t-k} + \sum_{k=1}^K \beta_{t,k}^{fs} \Delta f_{t-k} + \varepsilon_{f,t}, \quad (2b)$$

where Δ denotes the difference operator which transforms the logarithmic prices into returns. The time-varying error-correction terms γ_t^s and γ_t^f measure the speed of adjustment after deviations from the long-run equilibrium at each observation t . The parameters $\beta_{t,k}^{ss}$ and $\beta_{t,k}^{ff}$ measure the commodity returns' reaction towards own lagged returns. $\beta_{t,k}^{sf}$ and $\beta_{t,k}^{fs}$ indicate the short-term predictive power of one futures' return on the other at each t .

To obtain time-varying parameters, we apply the Kalman filter. For this, we rewrite the outlined model in state-space form. The Kalman filter is a recursive algorithm which computes the optimal estimates of the state variables for each t , conditional on the information set available up to time t (Durbin and Koopman, 2001; Kim and Nelson, 1999). The dynamic VECM then reads:

$$\mathbf{y}_t = \mathbf{Z}_t \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t | \boldsymbol{\Psi}_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t) \quad (3a)$$

$$\boldsymbol{\xi}_t = \mathbf{F} \boldsymbol{\xi}_{t-1} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t | \boldsymbol{\Psi}_{t-1} \sim N(\mathbf{0}, \mathbf{Q}_t^*), \quad (3b)$$

where Eq. (3a) represents the measurement equation and Eq. (3b) the transition equation. Time-varying coefficients are represented by the vector $\boldsymbol{\xi}_t$ which is evolving according to a random walk. We also account for heteroscedasticity in the error terms by assuming a

Diagonal-VECH-GARCH (1,1) structure for the error terms of the mean equation $(\epsilon_t | \Psi_{t-1})$.² So far, this approach has only been used within a homoscedastic framework to analyze price discovery in the oil market (Silvério and Szklo, 2012; Caporale et al., 2014) and to analyze the behavior of price discovery in thinly traded futures markets (Adämmer et al., 2015). The merit of our approach is that it enables the calculation of time-varying correlations between spot and futures returns. In addition, the state-space model should account for volatility clustering when analyzing financial time series with sufficient frequency (Durbin and Koopman, 2001).

To quantify the contribution of each market to the price discovery process, we extend the approach by Schwarz and Szakmary (1994). The time-varying common factor weights, hereafter CFW, are calculated for each market as:

$$\theta_t^f = \frac{|\gamma_t^s|}{|\gamma_t^s| + |\gamma_t^f|} \quad \text{and} \quad \theta_t^s = 1 - \theta_t^f = \frac{|\gamma_t^f|}{|\gamma_t^s| + |\gamma_t^f|}, \quad (4)$$

where θ_t^f and θ_t^s correspond to the CFW of the futures and spot market, respectively. Each value is by definition bounded to the interval between 0 and 1. The intuition is straightforward: the market with the larger error correction coefficient mostly adjusts to deviations from the long-run equilibrium. Therefore, $\theta_t^f > 0.5$ implies that $|\gamma_t^s| > |\gamma_t^f|$, which means that price discovery primarily occurs in the futures market. The lower the CFW of the futures market, the higher is the impact of the spot market on the price discovery process.

3. Data

Our spot prices consist of a unique and hand-collected data set from the largest and most important grain exchange in Germany (Hamburg), whose prices are determined every Tuesday. The samples start on January 2000 and end on December 2013. Since the year 2004 the exchange publishes spot prices on its website in pdf form. For data before the year 2004 the exchange provided us with prices from its archive. According to Eurostat,

²The state-space model is explained in detail in the Appendix.

Germany is one of the biggest grain, wheat and oilseed producer in the European Union. It thus represents an important agricultural market within the economic union.

The corresponding futures contracts are traded at the NYSE Liffe exchange in Paris. Closing prices are taken from Thomson Reuters Datastream. Since trading volume decreases towards maturity, we switch to the second-nearby contract on the first day of the last trading month. Our samples thus only include observations for the most immediate contract except for the expiry month. As the contracts expire on the 10th of each calendar month, our rolling criterion assures that we do not miss important trading information by rolling over too early.

To be tenderable, the futures contracts for wheat and corn require that the underlyings are of European origin. The rapeseed contracts do not require any origin. All three commodities have to comply to certain standards. An important difference between the contracts are the locations for physical delivery. Figure 1 shows a map of Germany, Belgium and France for possible delivery points. Silos for canola are in Germany, Belgium and northern parts of France. Wheat can only be delivered to certain cities in northern France and corn to cities located in southern France. The decision as to where the commodity will be delivered to after the expiration of a futures contract is typically given to the seller. Silos which are farther away from the seller increase price risk due to higher transaction costs (Lien and Tse, 2006). It is thus likely that correlations between spot and futures prices of canola and wheat are higher than between those of corn due to the proximity of silos for German producers.

[FIGURE 1 about here]

Figure 2 shows the spot and futures prices of canola, wheat and corn. Prices of the same commodity appear to follow a common trend. This co-movement between spot and futures prices is strongest in the canola and wheat market but weaker in the market for corn. The wheat and corn crop failure caused by the hot summer in 2003 and the following price increases are apparent as well. All three commodities share the price spikes and crashes between 2007 and 2009 as well as between 2010 and 2013, which are the focus of our analysis.

[FIGURE 2 about here]

Figure 3 depicts the daily trading volume and open interest of all markets. Since the year 2007 all futures markets faced a notable increase of trading activity which reached its heights between 2010 and 2013. In 2011, the NYSE Liffe exchange in London started publishing trading positions for selected commodities to promote transparency. No corresponding reports are published for the NYSE Liffe in Paris, which prohibits a distinction between different types of traders in these markets at the moment.

[FIGURE 3 about here]

Table 1 displays descriptive statistics. ZR denotes the relative amount of zero returns for each market. In the case of canola, 10% of spot returns are zero while for wheat and corn the share is 24% and 32%, respectively. The largest share of zero returns occurs before 2007 which mirrors the lower trading volume during those years. To overcome a possible bias of our empirical results, we estimate for robustness the econometric model with a sample of observations where all zero returns are deleted. During the entire sample, canola prices have the highest weekly average returns ($\hat{\mu}$) and corn the lowest. Standard deviations ($\hat{\sigma}$) are highest in the corn market. Pearson's correlation coefficients ($\hat{\rho}$) imply that canola is the most intertwined market and corn the least, most likely explained by the proximity of silos for physical delivery (see above). The empirical results of the ARCH-LM test in Table 1 indicate heteroscedasticity in the returns. This supports our approach to account for conditional volatility in the mean equation of the state-space model.

[TABLE 1 about here]

4. Empirical results

a.) Unit-root and cointegration tests

Panel A of Table 2 shows empirical results for the unit root tests. The equations for both

tests either include a constant (denoted by C) or a constant and a linear time trend (denoted by CT). Irrespective of the chosen test equation, the empirical results show that all log-prices are $I(1)$ in levels but stationary in first differences. The empirical results of the Engle and Granger (1987) methodology and the trace statistic by Johansen (1988,1991) are displayed in Panel B of Table 2. Both test statistics reject the null hypothesis of no cointegration at the 1% significance level.

[TABLE 2 about here.]

b.) Price discovery and correlations

The common stochastic trend in spot and futures prices allows the estimation of the time-varying VECM and the corresponding time-varying CFW. The left column of Figure 4 depicts the CFW for canola, wheat and corn. The dotted lines correspond to the four week moving average of the trading volume in the respective futures market. The right column depicts the corresponding time-varying conditional correlations. The shaded areas highlight the recent periods of price turmoil, namely from 2007 to 2009 and from 2010 to 2013.

All three CFW are constantly above 0.5, implying that the futures markets dominate the price discovery process over time. The CFW of wheat and corn increase until around 2005 while the CFW of the canola market constantly fluctuate around 0.8. The finding of a dominant futures market *on average* is supported by empirical results from time-invariant VECMs with Diagonal VECM-GARCH (1,1) structure.³

The shaded areas reveal that the CFW of all three markets decrease during the second period of price turmoil compared to the first. The decrease of the CFW implies an increase of the spot market in the price discovery process. The trading volume in all futures markets, however, increased substantially between 2010 and 2013. These results contradict the argument that increasing financial activity raises the influence of the futures market on spot prices.

³The empirical results are available upon request.

[FIGURE 4 about here.]

As outlined above, the share of zero returns in spot prices is quite high until the year 2007. To confirm our empirical results we estimate the model with observations where the zero returns are deleted. Figure 5 shows the results. The most notable differences to our previous estimates appear in the years between 2000 and 2004, especially in the wheat and corn market. Now, both CFW fluctuate constantly around 0.95 and do not rise compared to previous results in Figure 4. The differences are most likely explained by the fact that the largest share of zero returns occurs before 2007. Looking at the periods of price turmoil, the results strongly support our findings, namely that the impact of the futures market on pricing was stronger during the first period of price turmoil than during the second one. This is reflected in the decline of the CFW during the years 2010 and 2013.

[FIGURE 5 about here.]

Garbade and Silber (1983) were among the first to argue that there exists a positive relationship between trading volume and price discovery. We refine their argument. It is quite certain that trading activity is an important aspect for efficient price discovery. However, our results imply that the relationship between trading volume and price discovery is not linear. Once a certain level of trading volume is reached, other factors become more relevant. This argument is supported by the findings of Adämmer et al. (2015). The markets analyzed in our paper were facing sharp increases of trading volume since 2007, but its heights were reached after the year 2010. The futures markets did not increase their impact on price discovery during these years. Yet, the spot market did.

What can explain these surprising results? As outlined by Headey and Fan (2008), Piesse and Thirtle (2009), Headey et al. (2010) and Timmer (2010), international commodity markets were hit by surprise during the first period of price turmoil. For example, Piesse and Thirtle (2009) write that “*the suddenness and extent of the increases in world commodity*

prices in 2007-2008 took the world by surprise, even the institutions that monitor the world food situation.” Another common line of argument was that (agricultural) commodity markets will have to accustom to periods of higher prices and volatilities in upcoming years. This argument was supported by the FAO (2008) and The Economist, which wrote about “The end of cheap food” in December 2007. In response to the first food price spikes, the European Commission set up a task force to examine the functioning of the food supply chain on which Eurostat developed the so called Prices Monitoring Tool for food products (European Parliament, 2012). We argue that these articles and political responses raised the level of information and transparency in agricultural markets. It is thus valid to assume that spot market participants were better informed during the second period of price turmoil which led to an anticipation of these price spikes.

Whether information that originated in futures markets was fundamentally justified or merely reflected speculative behavior still remains a controversial question (e.g., Timmer, 2010; Irwin and Sanders, 2011; Aulerich et al. 2014). Our results, however, show that the period with the highest level of trading activity in futures markets did not correspond to the period with the highest impact on agricultural commodity pricing.

For both data sets (all observations and no zero returns) the time-varying conditional correlations indicate that correlations have remained rather constant over time (see Figures 4 and 5). Differences appear in their magnitudes: spot and futures markets of canola and wheat share higher correlations than those of the corn market. Similar to the results of price discovery, correlations did not increase when trading volume rose. This implies that other factors are more important for the linkage between spot and futures prices than merely the level of trading activity. The proximity of silos for German producers most likely explains the differences in magnitude of the correlations (see above).

5. Conclusion

The empirical analysis of price discovery in agricultural markets has been predominantly devoted to North America, most likely because of the global relevance of US futures exchanges, their long history and the process of financialization which originated in US markets. Although neglected in the literature, Europe obtains a large share of global agricultural production and it recently faced significant institutional changes, e.g., the abolition of high guaranteed fixed prices. We extend the literature on price discovery to European agricultural markets to shed new light on the importance of futures markets for price discovery during times of crises and rising trading activity.

The results are based on a unique and hand collected data set of German spot prices for canola, wheat and corn. The corresponding futures contracts are traded at the NYSE Liffe exchange in Paris. By applying a time-varying VECM with heteroscedastic disturbances we overcome drawbacks of econometric techniques applied to US data. Our approach enables to quantify the future's market relative contribution to price discovery over time.

The impact of the futures market on pricing during the periods of price turmoil was stronger between 2007 and 2009 than between 2010 and 2013. This is noteworthy as the trading volume in the futures markets was much higher during the second period than during the first. These findings contradict the argument that more activity in futures markets leads to a stronger impact on commodity pricing. We argue that agricultural markets were hit by surprise between 2007 and 2009 but anticipated the second period, probably due to scientific research and media coverage. Futures markets thus mattered during those years when agricultural markets were hit by unanticipated price shocks.

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Table 1: Descriptive Statistics

		ZR	$\hat{\mu}$	$\hat{\sigma}$	$\hat{\rho}$	ARCH_LM
Canola	<i>Spot</i>	10%	0.107%	2.753%		463.54***
	<i>Futures</i>	2%	0.109%	2.894%	0.71	466.79***
Wheat	<i>Spot</i>	24%	0.068%	2.671%		462.65***
	<i>Futures</i>	7%	0.072%	3.250%	0.66	484.37***
Corn	<i>Spot</i>	32%	0.043%	3.264%		380.99***
	<i>Futures</i>	8%	0.043%	3.730%	0.35	372.58***

The table shows descriptive statistics of spot and futures returns. ZR denotes the share of zero returns, $\hat{\mu}$ the estimated mean, $\hat{\sigma}$ the unconditional variance and $\hat{\rho}$ the unconditional correlation coefficient. ARCH_LM refers to the test statistic of the ARCH_LM test which is conducted with a lag length of five. *, ** and *** denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Table 2: Unit-Root and Cointegration Results

Panel A: Unit-Root Tests					
		ADF _C	ADF _{CT}	KPSS _C	KPSS _{CT}
Canola	<i>Spot</i>	-1.71	-1.96	2.24***	0.17**
	Δ	-24.73***	-24.77***	0.08	0.06
	<i>Futures</i>	-1.84	-2.20	2.27***	0.16**
	Δ	-25.49***	-25.49***	0.08	0.06
Wheat	<i>Spot</i>	-1.73	-2.67	1.80***	0.18**
	Δ	-11.43***	-11.42***	0.06	0.05
	<i>Futures</i>	-1.25	-2.25	1.96***	0.13*
	Δ	-24.34***	-24.33***	0.04	0.04
Corn	<i>Spot</i>	-1.72	-2.40	1.69***	0.18**
	Δ	-25.05***	-25.03***	0.04	0.04
	<i>Futures</i>	-1.80	-2.46	1.74***	0.14*
	Δ	-29.72***	-29.69***	0.05	0.05
Panel B: Cointegration Tests					
		$\hat{\beta}_0$	$\hat{\beta}_1$	<i>EG</i>	<i>J_T</i>
Canola		0.19	0.97	-8.82***	77.62***
Wheat		0.05	0.98	-5.42***	25.21***
Corn		0.17	0.95	-7.15***	77.41***

The table shows empirical results of the unit-root (Panel A) and cointegration (Panel B) tests. In Panel A, each test equation includes a constant (C) or a constant and a linear time trend (CT). In Panel B, $\hat{\beta}_0$ denotes the estimated constant and $\hat{\beta}_1$ the estimated slope parameter of Eq. (1). EG denotes the ADF test statistic of the corresponding residuals. Critical values are taken from MacKinnon (1996). J_T denotes Johansen's trace statistic. The lag length of the test equation is based on the BIC. Critical values are taken from MacKinnon et al. (1999). *, ** and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1: Delivery Points in Europe for Canola, Wheat and Corn



Figure 2: Spot and Futures Prices

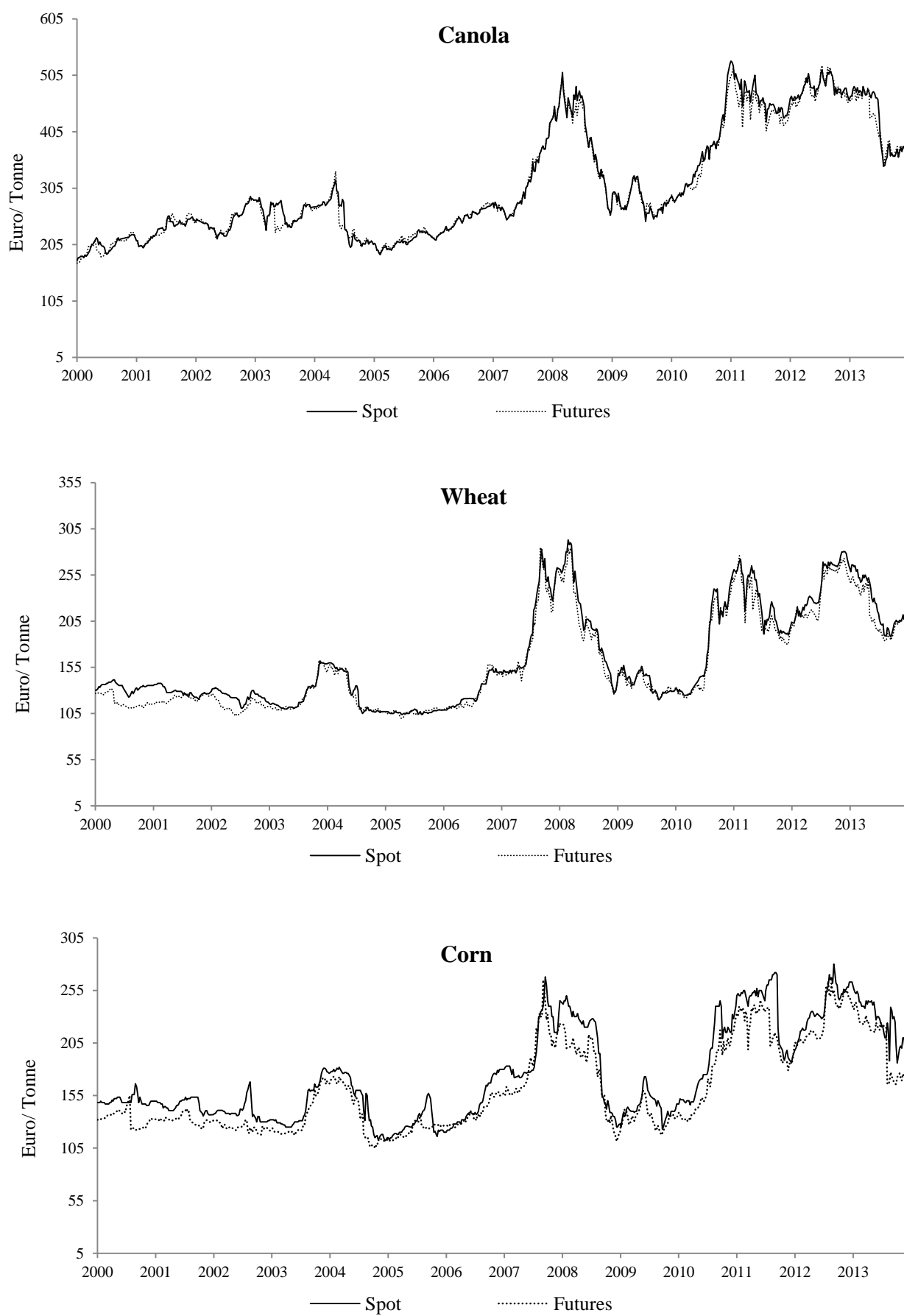


Figure 3: Volume of Weekly Traded Contracts and Open Interest

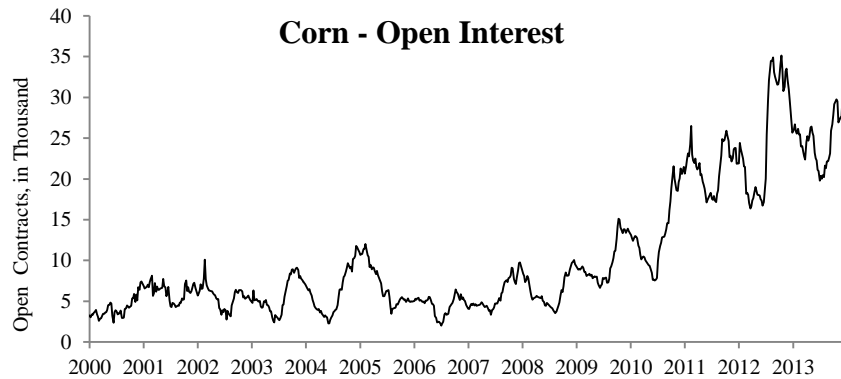
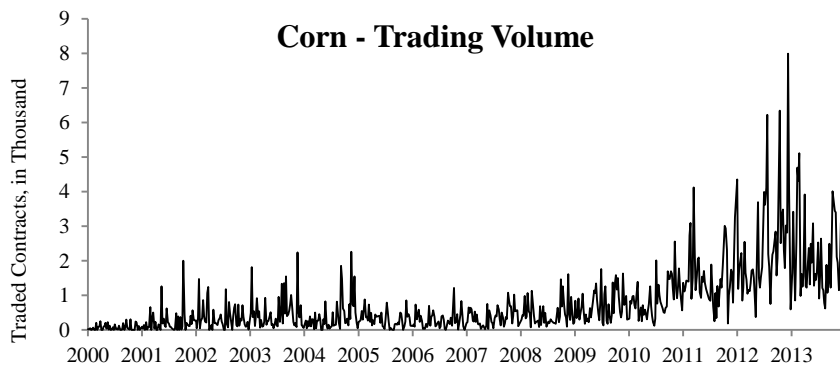
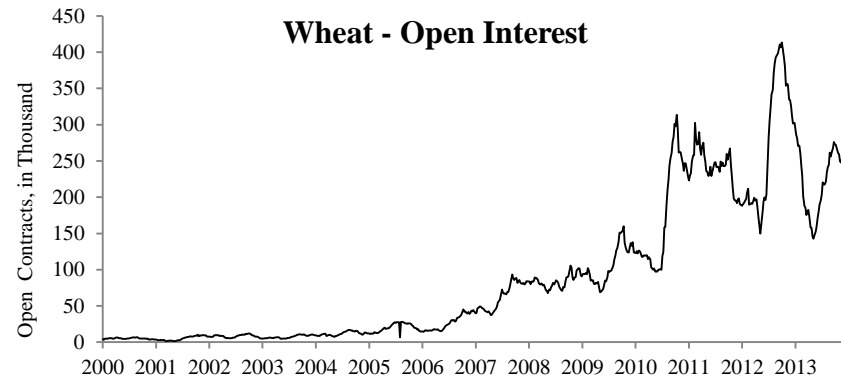
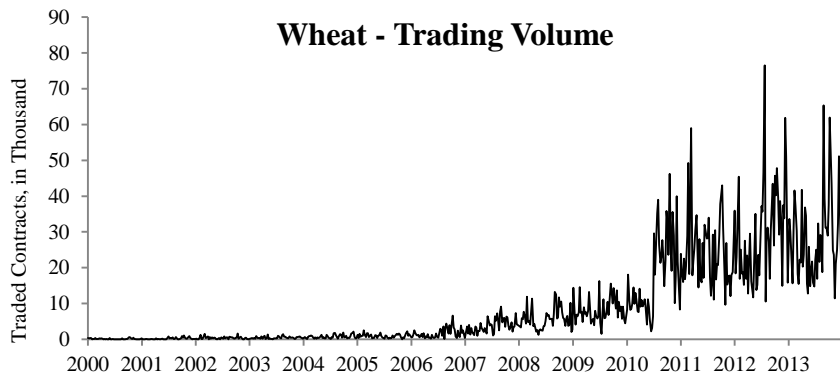
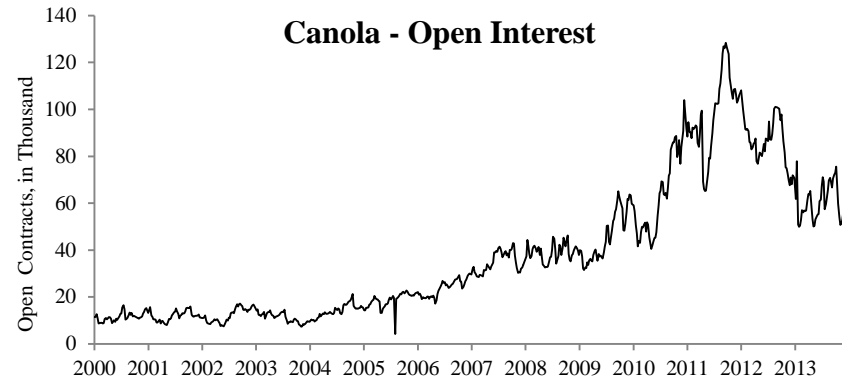
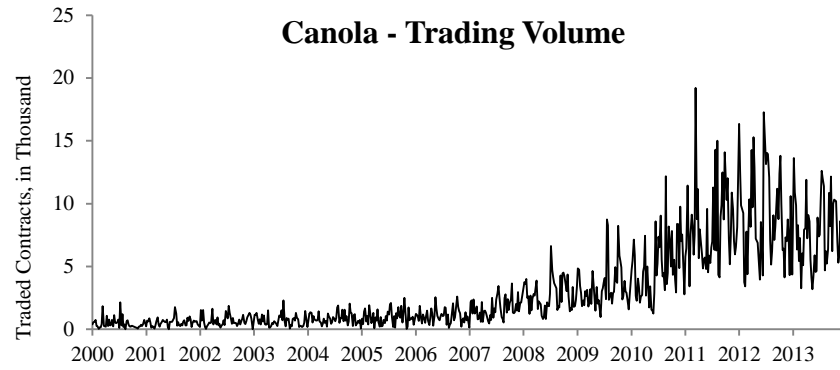
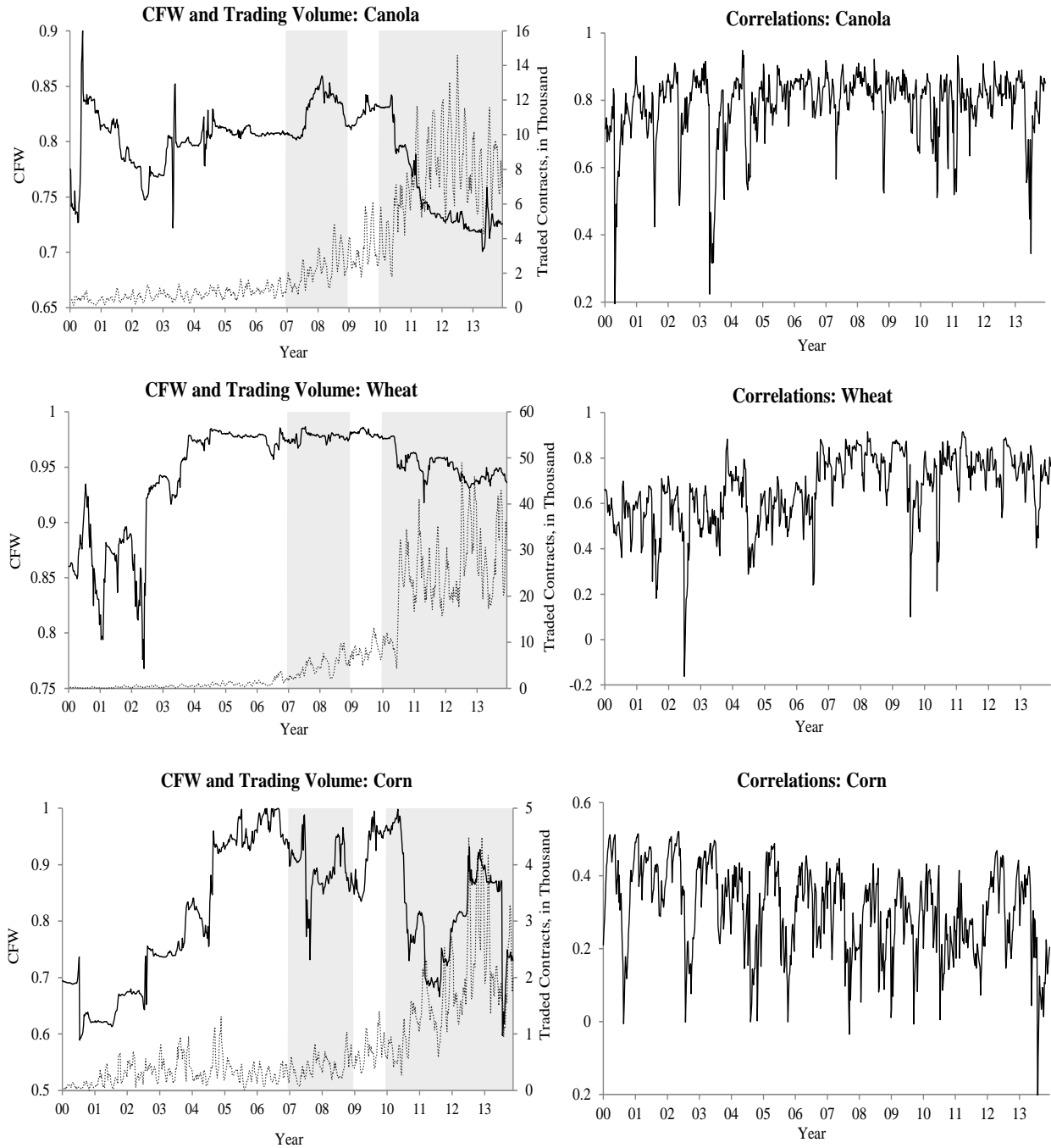
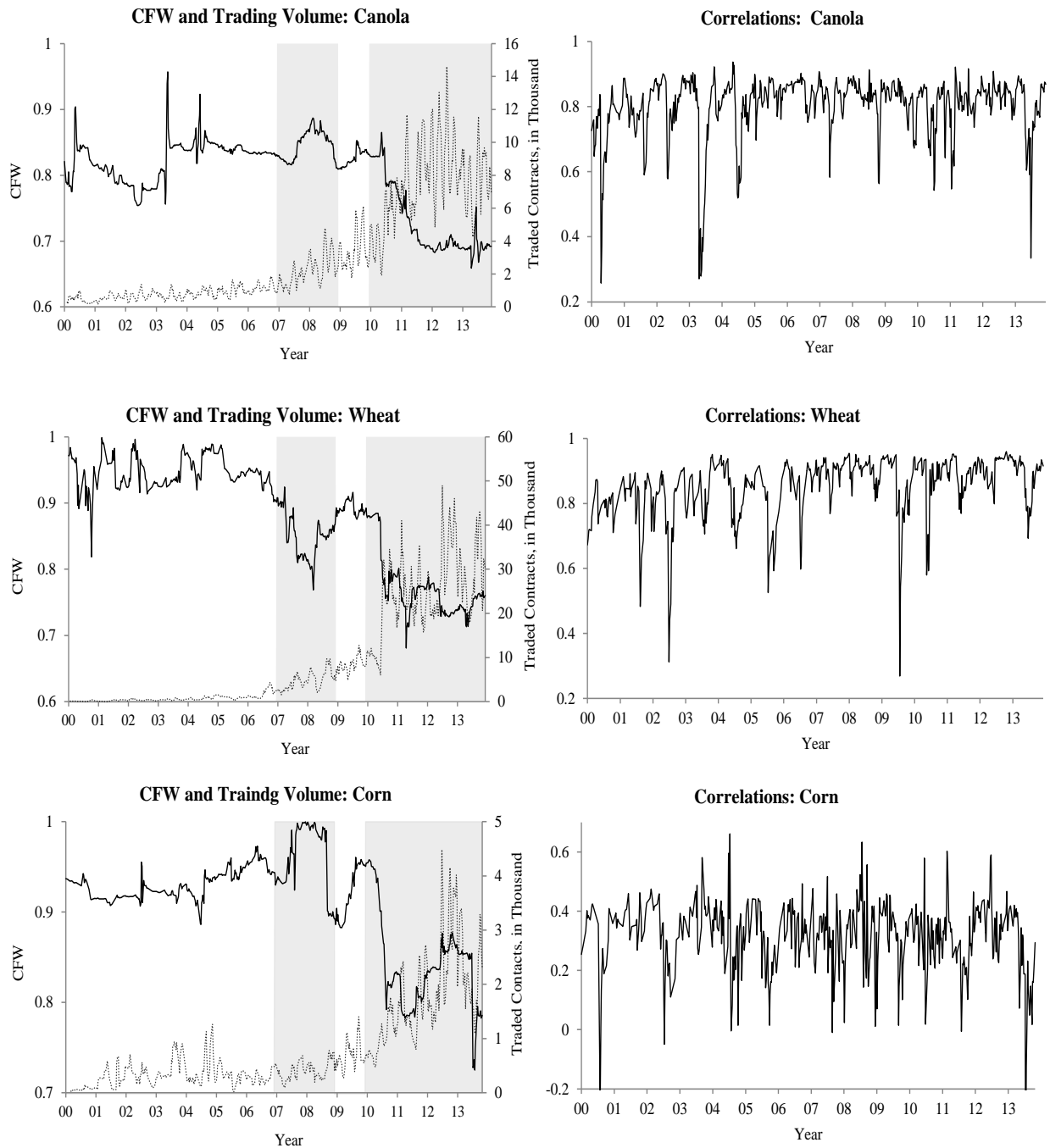


Figure 4: Time-Varying CFW and Correlations, All Observations



The left column shows the time-varying CFW (black line) and the four week moving average of the trading volume (dotted line). The right column depicts the time-varying correlations. The shaded areas highlight the periods of price turmoil, namely from 2007 to 2009, and from 2010 to 2013.

Figure 5: Time-Varying CFW and Correlations, No Zero Returns



The left column shows the time-varying CFW (black line) and the four week moving average of the trading volume (dotted line). The right column depicts the time-varying correlations. The shaded areas highlight the periods of price turmoil, namely from 2007 to 2009, and from 2010 to 2013.

Appendix A: State-Space Model

Our econometric approach is based on the assumption that the conditional variances of the disturbances in the measurement equation are heteroscedastic. We assume a Diagonal-VECH-GARCH (1,1) structure for the conditional residuals. Our model extents the univariate approach by Harvey et al. (1992) which is outlined in Kim and Nelson (1999). To filter the conditional variances and covariances, we need the squared shocks of the disturbances $(\epsilon_{s,t-1}^2, \epsilon_{f,t-1}^2)$. To obtain these in the filtering process, we have to augment the disturbances into the state vector by plugging them into the measurement equation:

Measurement Equation:

$$\begin{bmatrix} \Delta s_t \\ \Delta f_t \end{bmatrix} = \begin{bmatrix} 1 & ec_{t-1} & \Delta s_{t-1} & \Delta f_{t-1} & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & ec_{t-1} & \Delta s_{t-1} & \Delta f_{t-1} & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_{s0,t} \\ \gamma_{s,t} \\ \beta_{ss,t} \\ \beta_{sf,t} \\ \beta_{f0,t} \\ \gamma_{f,t} \\ \beta_{fs,t} \\ \beta_{ff,t} \\ \epsilon_{s,t} \\ \epsilon_{f,t} \end{bmatrix},$$

$$\begin{aligned} \mathbf{y}_t &= \mathbf{Z}_t \boldsymbol{\xi}_t + \boldsymbol{\epsilon}_t, \\ \boldsymbol{\epsilon}_t &\sim N(\mathbf{0}, \mathbf{R}), \\ \boldsymbol{\epsilon}_t | \boldsymbol{\Psi}_{t-1} &\sim N(\mathbf{0}, \mathbf{H}_t). \end{aligned} \tag{5}$$

Note that the unconditional variances are time-invariant while the conditional variances $(\boldsymbol{\epsilon}_t | \boldsymbol{\Psi}_{t-1})$ behave heteroscedastic. The transition equation of the state space model reads:

Transition Equation:

$$\begin{bmatrix} \beta_{s0,t} \\ \gamma_{s,t} \\ \beta_{ss,t} \\ \beta_{sf,t} \\ \beta_{f0,t} \\ \gamma_{f,t} \\ \beta_{fs,t} \\ \beta_{ff,t} \\ \epsilon_{s,t} \\ \epsilon_{f,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_{s0,t-1} \\ \gamma_{s,t-1} \\ \beta_{ss,t-1} \\ \beta_{sf,t-1} \\ \beta_{f0,t-1} \\ \gamma_{f,t-1} \\ \beta_{fs,t-1} \\ \beta_{ff,t-1} \\ \epsilon_{s,t-1} \\ \epsilon_{f,t-1} \end{bmatrix} + \begin{bmatrix} \nu_{s0,t} \\ \nu_{s,t} \\ \nu_{ss,t} \\ \nu_{sf,t} \\ \nu_{f0,t} \\ \nu_{f,t} \\ \nu_{fs,t} \\ \nu_{ff,t} \\ \epsilon_{s,t} \\ \epsilon_{f,t} \end{bmatrix},$$

$$\boldsymbol{\xi}_t = \mathbf{F}\boldsymbol{\xi}_{t-1} + \boldsymbol{\nu}_t, \quad \boldsymbol{\nu}_t | \boldsymbol{\Psi}_{t-1} \sim N(\mathbf{0}, \mathbf{Q}_t^*), \quad (6)$$

$$\mathbf{Q}_t^* = \begin{bmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{H}_t \end{bmatrix} = \begin{bmatrix} \sigma_{\nu_{s0}}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\nu_s}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{\nu_{ss}}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\nu_{sf}}^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{\nu_{f0}}^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\nu_f}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\nu_{fs}}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \sigma_{\nu_{ff}}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & h_{ss,t} & h_{sf,t} & h_{ff,t} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & h_{fs,t} & h_{ff,t} & h_{ff,t} \end{bmatrix}. \quad (7)$$

For \mathbf{H}_t we assume a Diagonal-VECH-GARCH (1,1) representation:

$$h_{ss,t} = a_{s0} + a_{s1}\epsilon_{s,t-1}^2 + a_{s2}h_{ss,t-1} \quad (8)$$

$$h_{ff,t} = a_{f0} + a_{f1}\epsilon_{f,t-1}^2 + a_{f2}h_{ff,t-1} \quad (9)$$

$$h_{sf,t} = a_{sf0} + a_{sf1}\epsilon_{s,t-1}\epsilon_{f,t-1} + a_{sf2}h_{sf,t-1}, \quad (10)$$

where $h_{ss,t}$ and $h_{ff,t}$ denote the conditional variances of the spot and futures market, respectively, and $h_{sf,t}$ the conditional covariances. Time-varying correlations are calculated

as $\rho_t = h_{sf,t}/\sqrt{h_{ss,t}h_{ff,t}}$. To ensure that the covariance matrix is positive definite we follow Lediot et al. (2003) and impose the following restrictions during the optimization: $|\alpha_{sf0}| \leq \sqrt{\alpha_{f0}\alpha_{s0}}$; $|\alpha_{sf1}| \leq \sqrt{\alpha_{f1}\alpha_{s1}}$; $|\alpha_{sf2}| \leq \sqrt{\alpha_{f2}\alpha_{s2}}$.

Appendix B: Kalman Filter

The Kalman filter is a recursive procedure which computes optimal estimates of the unobserved-state vector $\boldsymbol{\xi}_t$, where $t = 1, 2, \dots, T$. In the following, $\mathbf{P}_{t|t-1}$ denotes the covariance matrix of the unobserved state vector ($\boldsymbol{\xi}_t$) conditional on information up to $t - 1$. $\boldsymbol{\eta}_{t|t-1}$ denotes the prediction error, and $\mathbf{f}_{t|t-1}$ the corresponding conditional variance. The Kalman filter consists of six equations, grouped into a so called prediction and updating step:

Prediction:

$$\boldsymbol{\xi}_{t|t-1} = \mathbf{F}\boldsymbol{\xi}_{t-1|t-1} \quad (11)$$

$$\mathbf{P}_{t|t-1} = \mathbf{F}\boldsymbol{\xi}_{t-1|t-1}\mathbf{F}' + \mathbf{Q}_t^* \quad (12)$$

$$\boldsymbol{\eta}_{t|t-1} = \mathbf{y}_t - \mathbf{Z}_t\boldsymbol{\xi}_{t|t-1} \quad (13)$$

$$\mathbf{f}_{t|t-1} = \mathbf{Z}_t\mathbf{P}_{t|t-1}\mathbf{Z}_t' + \mathbf{R} \quad (14)$$

Updating:

$$\boldsymbol{\xi}_{t|t} = \boldsymbol{\xi}_{t|t-1} + \mathbf{P}_{t|t-1}\mathbf{Z}_t'\mathbf{f}_{t|t-1}^{-1}\boldsymbol{\eta}_{t|t-1} \quad (15)$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \mathbf{P}_{t|t-1}\mathbf{Z}_t'\mathbf{f}_{t|t-1}^{-1}\mathbf{Z}_t\mathbf{P}_{t|t-1} \quad (16)$$

By applying the Kalman filter, we obtain the prediction error ($\boldsymbol{\eta}_{t|t-1}$) and its variance ($\mathbf{f}_{t|t-1}$) as a by-product. Those are needed to calculate the log likelihood function:

$$\ln L = -\frac{1}{2} \sum_{t=1}^T \ln((2\pi)^2 |\mathbf{f}_{t|t-1}|) - \frac{1}{2} \sum_{t=1}^T \boldsymbol{\eta}_{t|t-1}' \mathbf{f}_{t|t-1}^{-1} \boldsymbol{\eta}_{t|t-1}. \quad (17)$$

We maximize the log-likelihood with respect to the unknown parameters in \mathbf{R} and \mathbf{Q}_t^* . After having estimated the parameters we apply the Kalman Filter a second time as outlined above to filter the optimal states.