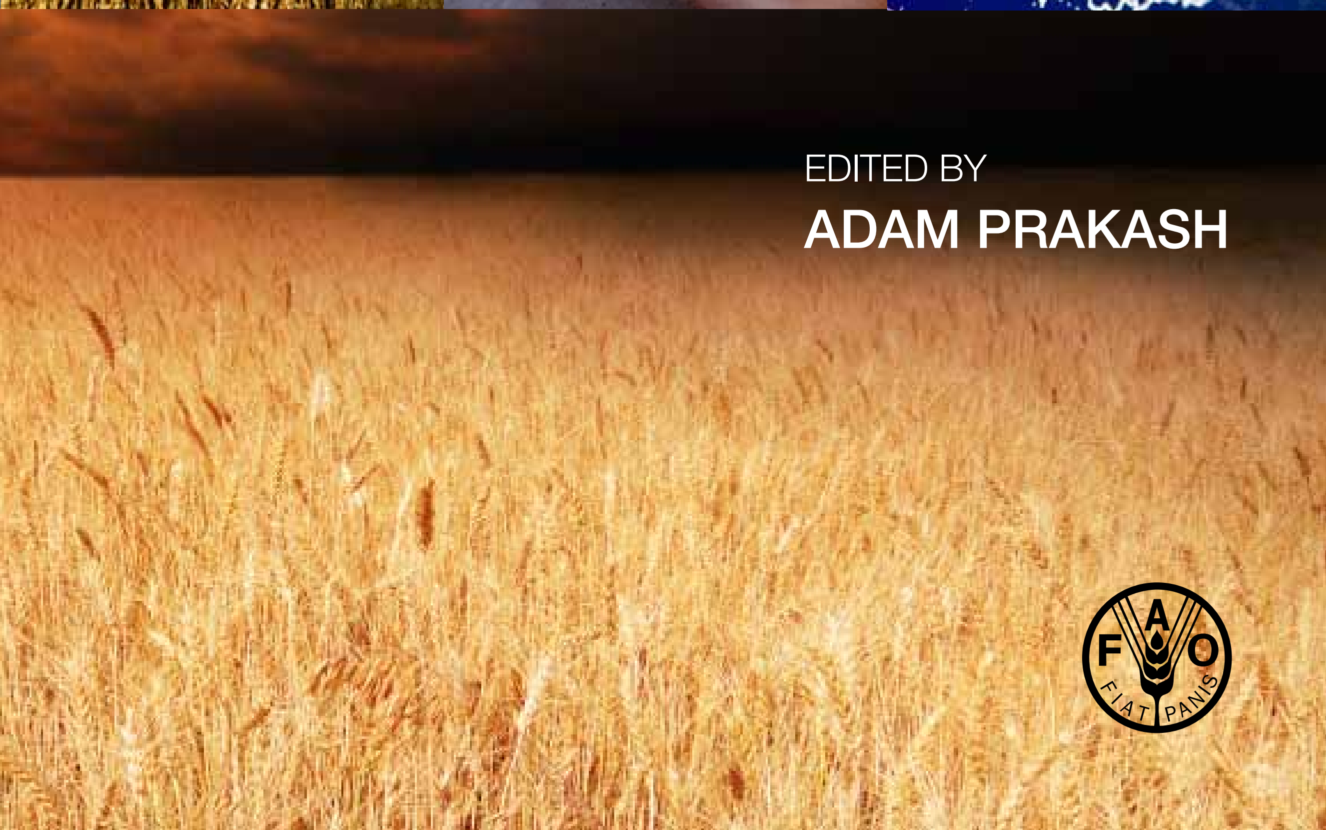
SAFEGUARDING FOOD SECURITY IN VOLATILE GLOBAL MARKETS



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Safeguarding food security in volatile global markets

Edited by Adam Prakash

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Chapter 6

Emerging linkages between price volatilities in energy and agricultural markets

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This chapter investigates the development of volatilities in agricultural commodity prices during and after the 2006-08 high price episode by focusing on rapeseed future prices at the Marché à Terme International de France (MATIF). We study the behaviour of daily returns of rapeseed, crude oil and related agricultural commodity prices using the method pf dynamic conditional correlation belonging to the class of multivariate General Autoregressive Conditional Heteroskedasticity Models (GARCH) models.

By looking at daily volatility developments between 1999 and 2009, particularly in the 2006-08 period, we found an increasing correlation between the returns in rapeseed and crude oil price. This correlation not only increased during the high price episode but it continued to rise afterwards. This implies that rapeseed prices react in an increasing manner to the same information as crude oil prices. Furthermore, rapeseed prices show high sensitivity to shocks and low persistency in volatilities and thus bear the risk of overreactions in volatility phases.

This increased correlation raises the prospect of even more pronounced volatilities in agricultural commodity prices during future periods of turbulence, as crude oil prices have exhibited a higher volatility level *vis-à-vis* agricultural commodity prices in the past. Because of the difficulty of distinguishing commodity price trends caused by changes in supply and demand from volatilities stemming from expectations and speculation, optimal production schemes are difficult to establish. Therefore, farmers as well as consumers will face an additional source of uncertainty owing to more prominent price changes over the long-run.

Background

Both during and after the high price episode in 2006-08, the level of agricultural product prices and their increasing volatility raised concerns among policy-makers and interest groups. The World Bank (World Bank, 2009) declared that "high volatility in food prices, combined with the impact of the financial crisis, threatens to further increase food insecurity." Episodes

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of increased volatilities imply higher uncertainty and therefore influence production and consumption decisions. Price changes should usually reflect supply or demand shifts to which markets adjust. In regimes of high and persistent volatility, however, it is difficult to distinguish between market instability and higher price levels (FAO, 2009).

Discussions about the integration of agricultural markets with energy markets took place well before the 2006-08 event, and can be exposed for several commodity markets using different econometric techniques (e.g. Balcombe & Rapsomanikis, 2008; Serra et al., 2008; De Gorter & Just, 2008). The topic of volatility in agricultural markets is, by contrast, rather new. A number of recent studies have examined price volatility linkages between agricultural and energy markets. For instance, Meyers & Meyer (2008) investigated the causes and implications of price increases between 2005 and 2008 by focusing on the impact of biofuels. While conclusions can be drawn about biofuel impact on agricultural price levels, no clear conclusions can be provided about their effects on price volatility. However, Du et al. (2009) were able to show volatility spillovers from crude oil to maize prices in the United States using a stochastic volatility model. Multivariate GARCH (MGARCH) models were used by Bekkerman & Pelletier (2009) who studied the effect of ethanol demand on maize and soybean in the US using a dynamic conditional correlation model (DCC). Tejda & Goodwin (2009) employed similar data in applying a regime switching dynamic correlation model. They found positive dynamic correlation between maize and soybeans, and provided a discussion on the impact of ethanol demand. Kananmura (2008) used a DCC model to find changing correlation between petroleum and agricultural commodity prices.

The methods commonly used to analyse volatilities in time series are GARCH- Models. They allow for rich insights into the volatility structure of time series. In addition, the multivariate versions provide information about the conditional correlation between the volatilities of different price series (for a survey on this model class see Bauwens et al., 2006). The main drawback of MGARCH models is their data and computational requirements, which demand a number of observations that are usually hard to obtain for agricultural commodities.

The current study contributes to this literature with an analysis of volatility developments in the European market. We use rapeseed prices quoted at the MATIF in Paris, which is today the most important exchange for rapeseed. Our analysis compares the volatility structure of rapeseed prices to commodity spot market prices of vegetable oil traded at Rotterdam along with Brent crude oil prices. The behaviour of volatility during and after the 2006-08 event has up to now not been analysed in detail. We aim to fill this gap and provide some insights into volatility behaviour. This should help elucidate price developments, especially volatility developments. Furthermore, we investigate the correlation in price volatility of different commodities and their evolution over time. This allows conclusions to be drawn about how closely different price pairs follow the same market information and, hence, how closely volatilities in different markets are related. The DCC model is chosen because it allows the estimation of time-varying correlations between a set of commodity returns series and thus provides insight into the temporal changes in the correlation matrix. The DCC belongs to the class of nonlinear combinations of univariate GARCH models and is particularly suitable for analysing a high series dimension, while the "Baba, Engle, Kraft and Kroner" (BEKK) model of Engle & Kroner (1995) is a multivariate extension of the univariate GARCH model suitable for up to four series only because of its exceptional computational demands (Bauwens et al., 2006; Huang & Chang, 2005).

Figure 6.1: Rapeseed price quotations at the MATIF (EUR per tonne), 2006-08 high price period (shaded area)

Source: MATIF

Market overview

Although the cultivation of rapeseed has a long tradition in Europe, the crop gained particular importance with the rise of the biofuel industry in the last decade. Biodiesel developed during this time and was transformed from being a niche product into an important driver of demand in the rapeseed oil market. Overall rapeseed area as well as production within the European Union (EU) increased strongly from 4.03 million ha (1998) to 6.49 million ha (2007), raising production from 11.65 to 21.42 million tonnes. On the global scale, the rapeseed production area increased from 25.8 million ha to 31.0 million ha over the same period, and production rose from 35.7 to 50.6 million tonnes. While rapeseed is the most important oilseed in the EU, it plays a much smaller role on the world market. Globally, soybeans (90 million ha/221 million tonnes) stand as the most important oilseed, but they have recently been outperformed by palm oil in terms of vegetable oil production (FAOstat).

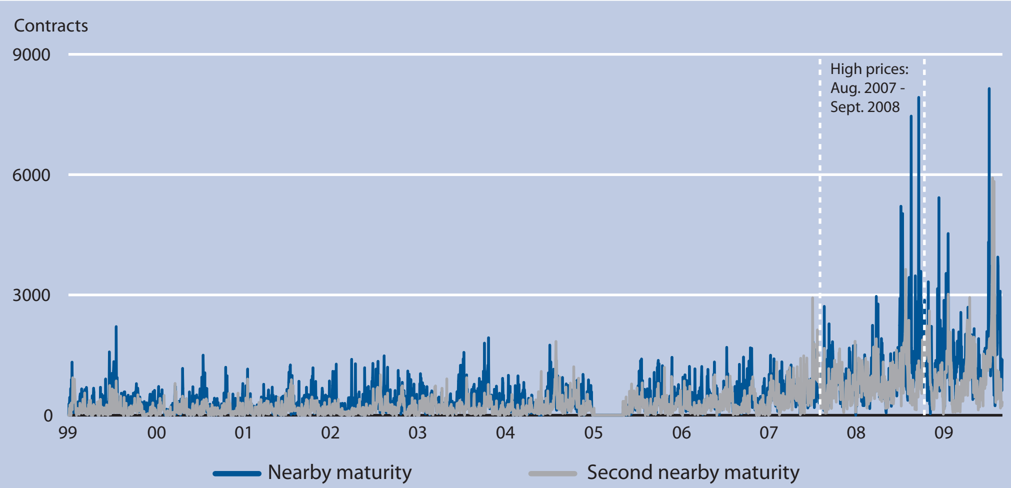
Figure 6.1 shows rapeseed price developments over the past decade. In the episode of 2006-08, rapeseed prices, as well as most other agricultural commodity prices, increased strongly and peaked in early 2008. The peak of EUR 500 per tonne reflects a doubling of prices within one year. The data shown here were obtained from the MATIF.[2]

Figure 6.2 shows the increase in traded volumes at the MATIF during the past ten years. The MATIF offers different contracts with the expiration dates of February, May, August and November for six consecutive contract months. The most important, and hence those with the highest volume, are the nearest (first) and the second-nearest front months (plotted in Figure 6.2). The series are constructed in such a way that with the expiration of one contract, the data structure is shifted towards the next date. The same principle will be used later for constructing the (synthetic) price series.

The rising importance of MATIF is illustrated by volumes reaching a level of up to 8 000 daily contracts, representing almost 1 percent of annual world rapeseed production traded

2 For details see: www.euronext.com.

Figure 6.2: Volume of contracts traded during one day at the MATIF nearest (first) and second-nearest expiration



Source: MATIF.

on a single day. The average daily volume of trade in the nearest contract was 1 562 contracts in 2008-09 compared with 945 during 2007-08 and 536 in the period 2006-07. The average daily volume in 2008-09 was almost six times higher than in 1999-2000.

This rise in volume is not solely a phenomenon of rapeseed at the MATIF but was observed also for other agricultural commodities at commodity exchanges around the world (Robles et al., 2009). The importance of rapeseed price quotations at the MATIF grew not only for global traders but also for wholesalers and farmers. These agents do not necessarily participate at the MATIF but use these price trends for their own production and trading decisions.

The price increase in 2006-08 was accompanied by strong price fluctuations in many markets. Daily returns in rapeseed prices, calculated as $\ln(p_{t+1}/p_t)$, are shown in Figure 6.3a. Figure 6.3b shows squared returns in order to give a clearer picture of the evolution of volatility over time.[3]

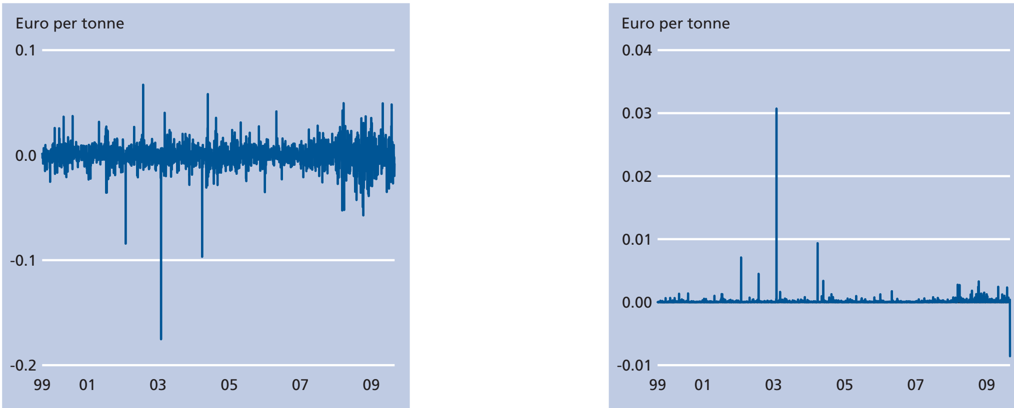
A change in volatility over time, where volatility is defined as the conditional standard deviation of the returns series, can be observed here. More important than the amplitude of price changes is the persistency in volatility. The right panel shows clearly a much higher persistency of price fluctuations in 2008 than, for example, in 2006. The price increase in 2007 was not accompanied by increased volatility but rather took place steadily. Volatility rose as late as December 2007 and became particularly high in the summer of 2008. A most interesting point is that volatility in rapeseed prices did not decrease substantially during the months after the 2006-08 event.[4]

3 We prefer using squared returns as they facilitate the distinction between phases of small and large volatility, that is, they magnify the differences between phases of clustered small and large returns.

4 A more detailed analysis of price behaviour will be provided after the results from model estimation have been obtained.

Figure 6.3: Returns and squared returns of rapeseed prices

(a) Returns (b) Squared returns



Source: MATIF.

Theoretical framework

The method used to analyse rapeseed price behaviour belongs to the class of multivariate GARCH models. MGARCH models allow for investigation of volatilities in markets as well as the correlation of volatilities between markets. These correlations can occur because the arrival of news can affect not only the price volatility on a specific market but also the volatility of different commodity prices simultaneously. The model used in this analysis is the DCC in the Engle (2002) specification that Bauwens et al. (2006) categorized as a nonlinear combination of univariate GARCH models. It can be regarded as a generalization of the Constant Conditional Correlation (CCC) model proposed by Bollerslev (1990).

The quantity of interest is a $I \times 1$ dimensional vector of returns $R_t = \{r_{i,t}\}_{i=1,...,I}$ where $r_{it} = ln(p_{i,t+1}/p_{i,t})$ and $p_{i,t}$ is the price of commodity i at time t. For the sake of simplicity, let us first consider the returns of only one commodity i. The conditional mean μ_t and conditional variance σ_t^2 of the series $r_t = r_{i,t}$ given the information set available in the previous period denoted by F_{t-1} are:

$$\mu_t = E(r_t|F_{t-1}) \quad (1)$$

$$\sigma_t^2 = Var(r_t|F_{t-1}) = E\left[(r_t - \mu_t)^2|F_{t-1}\right] \quad (2)$$

It is assumed that r_t follows an Autoregressive Moving Average (ARMA) process of orders p and q so that:

$$r_t = \mu_t + a_t \quad (3)$$

$$\mu_t = \phi_0 + \sum_{j=1}^{p} \phi r_{t-j} - \sum_{j=1}^{q} \theta_j a_{t-j} \quad (4)$$

The constants p and q are non-negative integers. The parameters ϕ_i and $\theta_i$are called the autoregressive (AR) and moving average (MA) parameters, respectively. a_t is the innovation of the commodity returns at time t. In the context of GARCH models, this equation is often referred to as the *mean equation* for r_t.[5] Combining (2) and (3) yields the *volatility equation* for r_t:

$$\sigma_t^2 = Var(r_t|F_{t-1}) = Var(a_t|F_{t-1}) \tag{5}$$

The analysis focuses on the evolution of the conditional standard deviation σ_t of the returns r_t, that is, the *conditional volatility* of the series.

In this univariate context, a GARCH(1,1) process can be described as:

$$a_t = \sigma_t \varepsilon_t \tag{6}$$

and

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{7}$$

where ε_t is a standardized i.i.d. random variable. Equation (7) has to satisfy the nonnegativity constraints $0 \leq \alpha_1$ and $0 \leq \beta_1$and the stationarity condition $\alpha_1 + \beta < 1$ which ensures that the process has finite variance (Hamilton, 1994, chap. 21).

As we are interested in the multivariate analysis of five commodities, we use the DCC model (Engle, 2002) that allows the estimation of time-varying covariances and time-varying correlations. Because this model is not so computationally demanding, it is suitable for high-dimensional analysis. In the first step, univariate GARCH models are estimated for each series and, in the second step, the dynamic correlation parameters are estimated. We follow Engle & Sheppard (2001) and assume the vector of returns follows a conditional multivariate normal distribution:

$$R_t|F_{t-1} \sim N(0,\Omega_t). \tag{8}$$

The $I \times I$ covariance matrix Ω_t of the vector of returns is allowed to be time-varying and is assumed to have the structure:

$$\Omega_t = D_t C_t D_t \tag{9}$$

where D_t is a $I \times I$ diagonal matrix, that is, $D_t = \text{diag}\left\{\sqrt{\sigma_{i,t}^2}\right\}$, $i = 1,\ldots,I$. The typical elements $\sigma_{i,t}$of this matrix can follow a number of functional forms. We adopt the usual approach in the literature and model the elements as the time-varying standard deviations of the univariate GARCH(1,1) model of each series, similarly as in (7):

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 a_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2 \tag{10}$$

where $(a_{1,t},\ldots,a_{I,t})' = \Omega_t^{1/2}\mathrm{E}_t$ and E_t is a $I \times 1$ random vector with properties corresponding to those of ε_t.

C_t is a $I \times I$ matrix containing the time-varying conditional correlations characterized by the following dynamic correlation structure:

$$C_t = \text{diag}\left(q_{11,t}^{-1/2},\ldots,q_{II,t}^{-1/2}\right) Q_t \ \text{diag}\left(q_{11,t}^{-1/2},\ldots,q_{II,t}^{-1/2}\right) \tag{11}$$

5 Note that this equation can be augmented by a set of explanatory variables.

where

$$Q_t = \left\{q_{ij,t}\right\} = (1-\alpha-\beta)S + \alpha(u_{t-1}u_{t-1}^{'}) + \beta Q_{t-1} \tag{12}$$

and $i,j = 1,\ldots,I$, $u_t = D_t^{-1}a_t$ are the standardized residuals and S is the $I \times I$ unconditional variance of u_t. As above, the parameters α and β have to be non-negative and to satisfy the condition that $\alpha+\beta<1$, which ensures a mean-reverting, i.e. stationary process (Engle, 2002). The typical element of the correlation matrix C_t is thus of the form $c_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$ (Engle & Sheppard, 2001). The coefficient α represents here the influence of the lagged error term, and hence, the role of shocks to the market in the previous period (the ARCH parameter). The coefficient β indicates the impact of the volatility of previous periods and therefore the persistency of volatility in the market[6] (the GARCH parameter). Of particular interest is the evolution of the conditional correlation estimates $c_{ij,t}$ that can take values between plus and minus unity.

Data

The data used in this analysis are daily observations (5 obs./week) of commodity prices over the period 1999 to 2009 (2537 obs.). Rapeseed prices were obtained from the MATIF in Paris. Prices of the second-nearest contract are used because nearest contract prices tend to fluctuate heavily when the contract expires. Later contracts show a substantially lower level of activity. The other commodity prices were obtained from the Public Ledger. Soybean oil and rapeseed oil prices are collected in Rotterdam (Netherlands) as FOB (free on board) prices for crude vegetable oil. The soybean prices are import prices CIF (cost, insurance and freight) in Rotterdam for beans imported from Brazil.[7] All agricultural prices presented in Figure 6.4 are in EUR per tonne without value-added tax (VAT) or other duties. The crude oil prices are Brent prices one month forward for crude oil FOB (in EUR per barrel).

The dataset has been chosen in order to obtain comparability. Rotterdam is currently the most important trading point for agricultural commodities in Europe. Vegetable oil prices from Rotterdam are assumed to represent EU prices. Import prices for soybeans are chosen as almost no soybeans are grown within the EU. Rapeseeds as well as soybeans are crushed within the EU and very little extra-European trade of soybean oil and rapeseed oil takes place. Palm oil and sunflower oil prices are not used for this analysis because the latter have a small market share and serve a specific segment of the food-oil market. Palm oil is usually crushed in the exporting countries and imported as oil. While competition for rapeseed oil appears on the food-oil market, the competition there is much lower and no competition for rapeseed appears in the processing industry. In favour of a more parsimonious model setup, we focus on the most important commodities in relation to rapeseed.

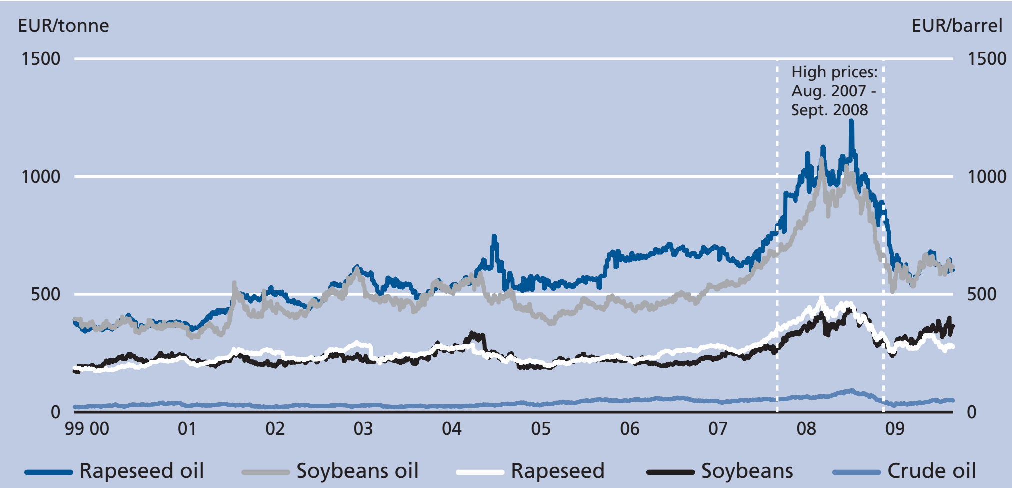
Empirical results

Prices are used in our empirical analysis as daily returns to ensure stationarity. The Augmented Dickey Fuller (ADF) test reveals non-stationarity in levels where the null

6 This characteristic of scalar coefficients instead of matrix parameters is sometimes criticized in the literature as it implies that the estimated conditional correlations are subject to constant dynamics; see Bauwens et al (2006) for extensions.

7 The usage of CIF and FOB prices in one model has the disadvantage that developments of e.g. transportation costs are not taken into account. However, we argue that these prices best reflect the market prices and determine the crushers and buyers choice in the EU market.

Figure 6.4: Price developments: 1999-2009, EUR per tonne (crude oil EUR per barrel)



Source: MATIF.

Table 6.1: ADF test for unit roots in levels and returns

	Levels		Returns	
	Test statistic	Lags	Test statistic	Lags
Rapeseed	-1.62	1	-47.55***	0
Soybeans	-1.98	1	-52.60***	0
Rapeseed oil	-1.64	5	-42.17***	1
Soybean oil	-1.54	8	-42.17***	1
Crude oil	-1.63	0	-21.13***	5

Note: One, two and three asterisks indicate significance at the 10, 5 and 1 percent level, respectively. Lags are chosen according to the Akaike information criterion (AIC).

hypothesis of the existence of a unit root cannot be rejected for any series (Table 6.1). However, the returns series show stationarity. From Table 6.2 it can be seen that all series show excess kurtosis in levels as well as in returns. The standard deviation of crude oil price returns is much higher than for the agricultural commodities, illustrating the substantial return fluctuations on the crude oil market.

Next, the DCC model (Engle, 2002) is estimated in two steps. The univariate part is defined as an ARMA(p,q)-GARCH(1,1) process including a constant in the mean and variance equations. The underlying ARMA(p,q) process captures serial correlation in the residuals, while the GARCH(1,1) process accounts for serial correlation in squared residuals. The second step consists of a maximum likelihood estimate based on the assumption of a student t-distribution.

The lagged parameters of the ARMA model in (4) are chosen according to the AIC and also residual behaviour, i.e. correlation in residuals and squared residuals. The results of the univariate models are displayed in Table 6.3. The rapeseed as well as the crude oil models

Table 6.2: Distribution characteristics of the returns series

	Mean	Standard deviation	Skewness	Kurtosis	ARCH test
Rapeseed	0.00015	0.0107	-2.19	37.66	0.264
Soybeans	0.00029	0.0188	-0.29	14.06	<0.001
Rapeseed oil	0.00017	0.0159	0.51	30.52	<0.001
Soybean oil	0.00018	0.0177	0.44	15.88	<0.001
Crude oil	0.00031	0.0226	-0.12	5.31	<0.001

Note: The last column contains the p-values of an ARCH test of order five.

seem over-specified, as none shows significant autoregressive or moving average behaviour in the returns series. However, both show a significant positive drift indicated by the constant in the mean equation. As the other three models show significant autoregressive and moving average behaviour, the ARMA specification is maintained for all models in order to keep the residuals free from serial correlation.

The GARCH estimates α and β appear to be significant at the 1 percent level in nearly all equations. The required conditions on the α and β parameters hold for all commodities, and hence all GARCH processes are mean reverting. However, the sums of α and β are close to unity, a phenomenon commonly observed when using high frequency data. This implies a high volatility persistency (compounded shocks to the prices) as the sum of α and β defines the decay factor of the exponentially declining autocorrelation function. High β coefficients indicate a strong impact of the own-variance on volatility development. This can be interpreted as the general volatility development in the market. Rapeseed prices show a comparatively low own-variance impact (low β) and a high sensitivity to external shocks to the market (large α). A large α combined with a low β as observed here for rapeseed prices indicates a pronounced susceptibility to external shocks in volatility phases.

Table 6.4 displays the estimated conditional correlations of the DCC model. Furthermore, α and β parameters of 0.0025 (0.0004) and 0.9973 (0.0005) are estimated, respectively. The high β coefficient indicates that the conditional correlation between the residuals is highly persistent. Although the conditional correlation is time-varying, the coefficients presented in Table 6.4 are often interpreted as their average.

At first glance, soybeans show a comparatively high correlation with rapeseed, rapeseed oil and soybean oil while all commodities show a low correlation with crude oil. Our focus will lie on rapeseed price volatilities that show, as expected, highest correlation with soybeans and rapeseed oil. The correlation between rapeseed and crude oil is not significant. This is owing to the dynamics in correlation, which will later be discussed when analysing the development over time.

Discussion

We will now discuss the empirical results in detail with a focus on rapeseed price volatilities. Figure 6.5 shows the development of the conditional variances over time. The figure had to be truncated as the variance of rapeseed price returns peaked at 0.012 in January 2003. Rapeseed prices exhibited a lower conditional variance during most of the period studied

Table 6.3: Estimation results for the univariate part of the MGARCH model					
Parameter	Rapeseed	Soybeans	Rapeseed oil	Soybean oil	Crude oil
φ_0	0.0007 (0.0002)***	0.0003 (0.0002)	0.0003 (0.0003)	0.0005 (0.0002)**	0.0007 (0.0004)*
φ_1	0.161 (0.316)	0.773 (0.102)***	-0.846 (0.044)***	0.371 (0.078)***	0.110 (0.178)
θ_1	-0.014 (0.324)	-0.838 (0.089)***	0.828 (0.039)***	-0.495 (0.073)***	-0.149 (0.143)
α_0	0.000019 (0.000007)***	0.000001 (0.000004)	0.000002 (0.000001)*	0.000001 (0.000002)	0.000007 (0.000003)**
α_1	0.368 (0.147)***	0.018 (0.024)	0.022 (0.009)***	0.028 (0.011)***	0.041 (0.011)***
β_1	0.551 (0.082)***	0.978 (0.036)***	0.972 (0.010)***	0.968 (0.016)***	0.944 (0.016)***
$\alpha_1 + \beta_1$	0.918	0.996	0.994	0.997	0.986
LL	8 143	6 581	7 136	6 842	6 144

Note: One, two and three asterisks indicate significance at the 10, 5 and 1 percent level respectively. The standard deviations are given in parentheses. For the ARMA model, $p = q = 1$ in all cases. *LL* denotes the log-likelihood of the model.

Table 6.4: Estimated conditional correlations				
	Rapeseed	Soybeans	Rapeseed oil	Soybean oil
Soybeans	0.386 (0.098)***			
Rapeseed oil	0.255 (0.087)***	0.400 (0.092)***		
Soybean oil	0.141 (0.070)***	0.371 (0.085)***	0.107 (0.068)***	
Crude oil	0.095 (0.065)	0.152 (0.069)***	0.097 (0.049)***	0.005 (0.080)

Note: One, two and three asterisks indicate significance at the 10, 5 and 1 percent level, respectively.

in comparison with the other series; and all series besides rapeseed show a relatively high persistency in their conditional variance.

The variance in soybean oil was higher than that of other agricultural commodities during most of the first half of the sample period, but was in line with the others thereafter. All series show a comparatively low conditional variance between mid-2005 and mid-2007. Periods of high volatility tend to cluster. Agricultural raw materials show similar patterns; except for the soybean price, variance is at a higher level. This might be owing to the fact that soybeans are imported from more unregulated countries. While the vegetable oil prices show comparable variances in levels, the frequency of increased variances appears to be more pronounced for soybean oil in the first half of the sample period. Until 2008, rapeseed prices exhibited a very low level of variance. The variance of the crude oil price also increased the most in 2008. Both were at far lower levels throughout 2007, while soybean and rapeseed oil prices had already begun displaying increased variance. During this period, agricultural prices started increasing sharply.

Conditional covariances should show a similar pattern if constant ratios to the variances are assumed. Instead of discussing the issue of covariances, we proceed directly the topic of conditional correlation estimates. These indicate the ratio between the covariances and the variances of price pairs. Most of the conditional correlations presented in Figure 6.6 show significant time-varying behaviour. While the correlation of rapeseed with rapeseed oil was decreasing, the correlation with crude oil reached a level that had not been observed before the period under investigation. This appears to indicate strong structural changes in pricing behaviour as both prices tend to increasingly react to the same market signals and their volatility develops concurrently. The model neither allows for conclusions about causal mechanisms of volatility spillovers nor is it able to capture the magnitude of influence of one market on the other. Correlations in volatility can occur from similar impacts of market signals but also from direct transmission. As the role of crude oil in the world economy is disproportionally higher than that of any agricultural commodity and has gained importance for many agricultural commodities, it can be assumed that part of this correlation is owing to reactions in rapeseed prices to volatilities in crude oil prices.

Crude oil prices exhibited higher volatility during most of the sample period compared with rapeseed. Furthermore, rapeseed prices at the MATIF are shown to be very sensitive to external shocks and tended to overreact if shocks occurred in volatility phases. The conditional correlation is higher with crude oil prices than with the corresponding spot market prices. This shows that rapeseed price volatilities do not follow the same market signals as those of the commodities on the spot markets, but rather follow the same market signals as crude oil.

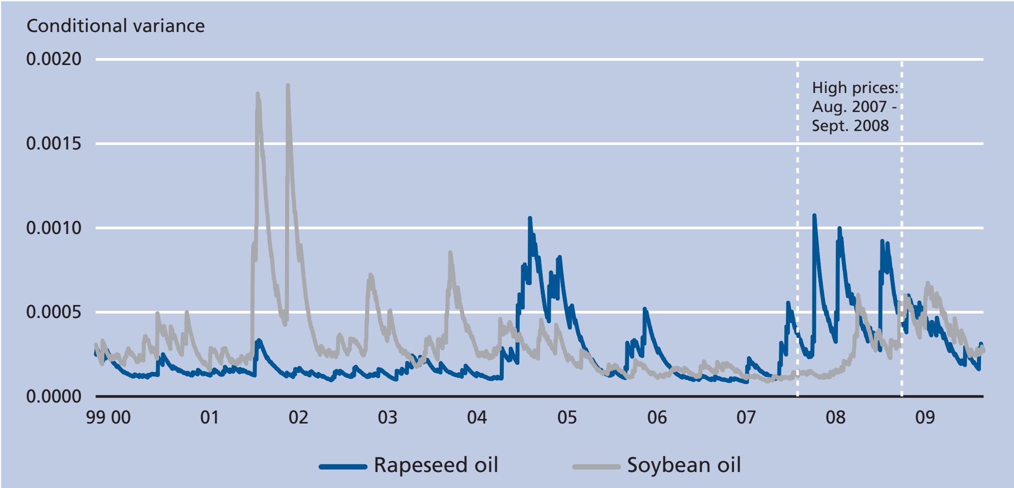
Figure 6.7 shows this development over time separately and also highlights the dynamics of the conditional correlation. The dotted line represents the average correlation where the shaded area indicates the 95 percent confidence interval. The conditional correlation estimate was not significantly different from zero for most of the period between 2001 and 2005. Furthermore, it moved around the average until the end of 2007. In 2006 and 2007 the correlation reached the level of the pre-2001 period. What stands out, however, is the strong increase in correlation after the turmoil hit its peak in midway in 2008. A conditional correlation between 0.35 and 0.40 was observed in 2008/09 that is considerably higher than during the event and significantly different from the estimated average correlation. The high persistency that was estimated for the conditional correlations can be observed here. This further indicates that such correlation will not dissipate quickly in the future.

Price fluctuations alone are not problematic as they reflect market adjustments to changes in supply and demand. However, overreaction and high volatility in the short-run might represent not only market adjustment, but speculation as well. If market signals are blurred by those effects, it becomes difficult to extract price signals from fundamentals. It therefore becomes difficult to enact production and processing decisions in an efficient manner. Furthermore, market actors have to adjust their behaviour in order to cope with increased price risk. The observation that rapeseed prices react increasingly to the same signals as crude oil prices, but react little to the same developments as commodities on spot markets, may be indicative of spillovers from investor behaviour on oil markets.

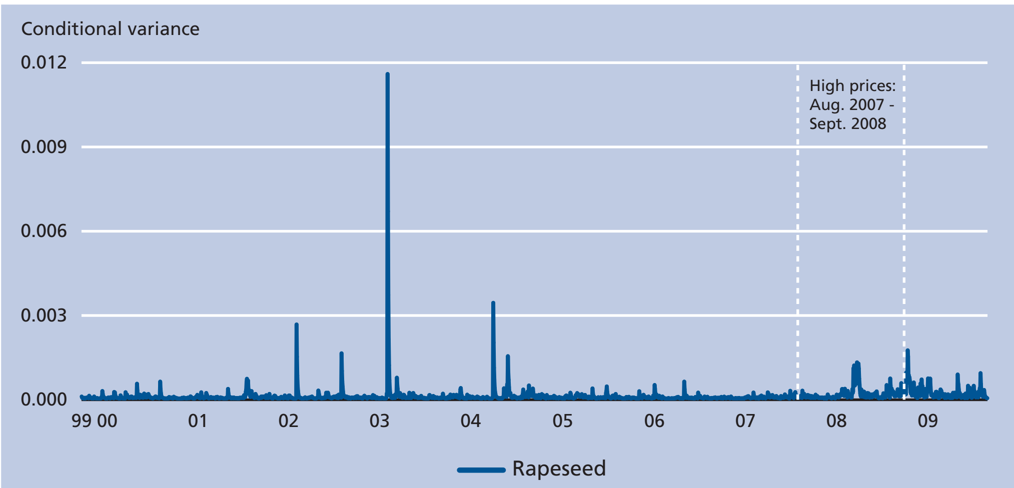
It is possible that such behaviour is mainly influenced by expectations about biodiesel production and policy. Crude oil prices determine the profitability of biofuels and any increase (or decrease) in crude oil prices improves (worsens) the competitiveness of biofuels and leads to increasing (decreasing) demand for rapeseed as the main biofuel feedstock. Hence, volatility in crude oil prices might increasingly lead to volatility in rapeseed prices as prices are adjusted towards changing expectations caused by crude oil price shifts. The

Figure 6.5: Conditional variance of different commodity price returns

(a) Rapeseed oil and soybean oil



(b) Rapeseed



reactions, hence, do not reflect actual changes in the markets but rather expectations towards changes in the medium-term. Whether, and to what extent, volatilities originate from changes in crude oil prices or from other market signals is difficult to determine. Vegetable oil prices on the spot market seem to be less affected by these market signals.

The MATIF has gained importance during the past years not only for traders but also as a centre for price discovery for farmers and wholesalers. Ambiguous price signals owing to volatility make it more difficult not only for traders to define their business strategies but also for farmers to make production decisions. Our empirical findings raise suspicion about how strongly returns of rapeseed prices at the MATIF reflect changes in agricultural

Figure 6.5: Conditional variance of different commodity price returns (continued)

(c) Crude oil and soybeans

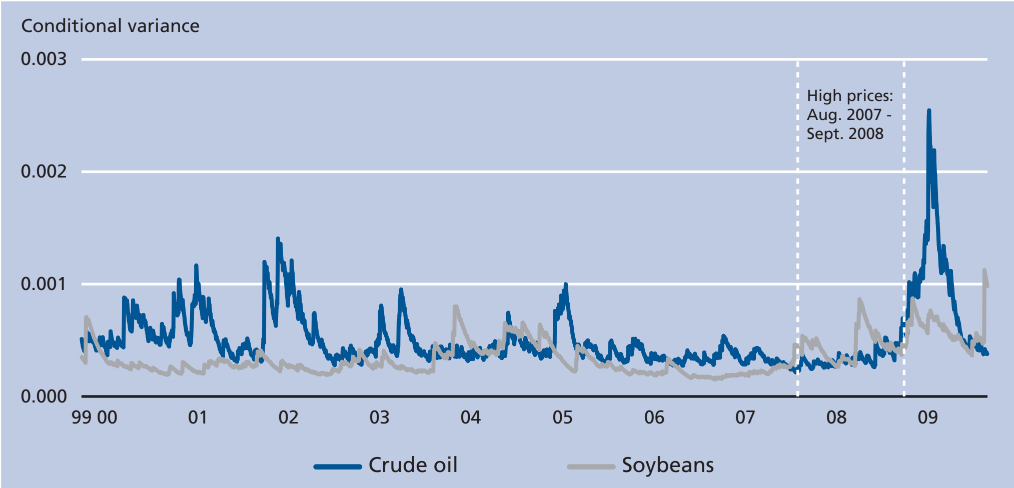
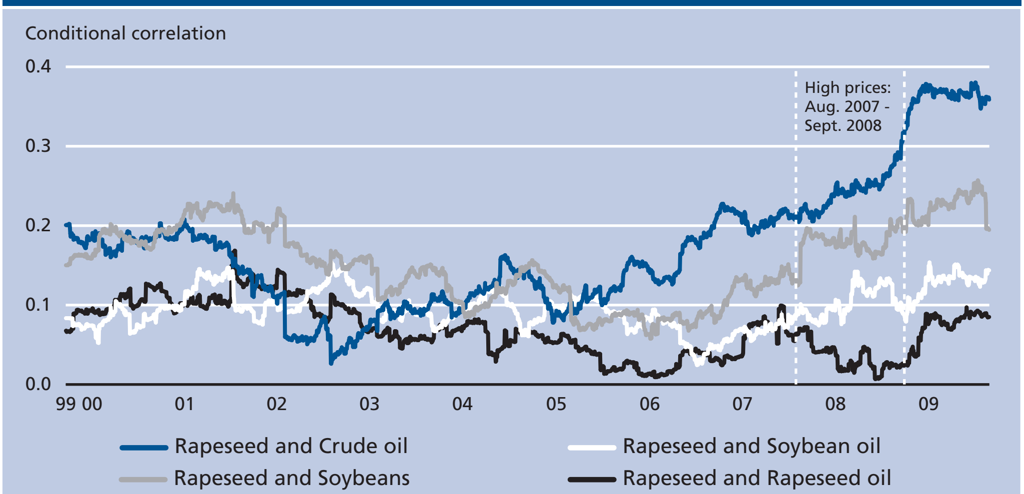


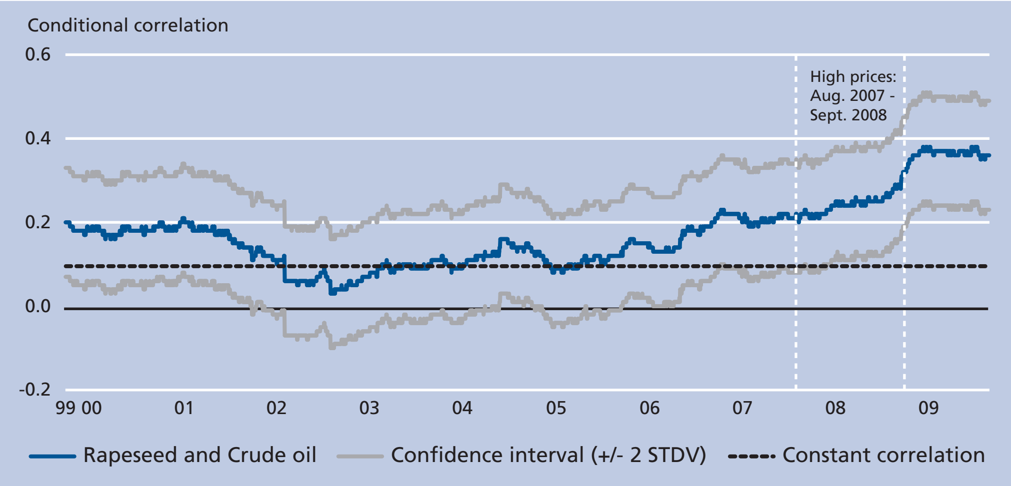
Figure 6.6: Dynamic conditional correlation of rapeseed price returns and other commodities



market fundamentals. The sensitivity of rapeseed prices to shocks and the increased volatility correlation with crude oil prices points to other factors. However, it should be noted that we do not question whether rapeseed price levels are determined by crude oil prices. Market interdependencies seem to be restricted to volatility spillovers.

The variance of both rapeseed price returns as well as that of crude oil price returns increased substantially in 2008 and 2009 compared with previous years (+59 percent for crude oil, +179 percent for rapeseed). Furthermore, the variance in crude oil price returns

Figure 6.7: Dynamic conditional correlation of rapeseed and crude oil: straight line indicates constant correlation, shaded area +/- 2 standard deviations



was higher than that of many other agricultural commodities, and in the case of rapeseed more than five times higher. Based on the increase and persistence in conditional correlation with crude oil price returns, a higher volatility in rapeseed prices can be expected to continue into the future. As our analysis was conducted on price returns, and price levels are currently considerably lower than in 2008, the effects will become more apparent if prices start to increase again.

Conclusions

In our study of the volatility behaviour of MATIF rapeseed prices we found a non-stable and increasing correlation between the returns of rapeseed and crude oil prices. Furthermore, rapeseed prices are found to be relatively sensitive to market shocks. The correlations of rapeseed price returns with vegetable oil and soybean price returns on the spot market are much lower than that with crude oil. The former only moderately increased since 2006 in contrast to the correlation between rapeseed and energy markets. This indicates that rapeseed price returns react increasingly to the same market signals as crude oil price returns, if not even directly to them. Hence, if high volatilities in one market are observed, volatilities in the other will be of a similar magnitude. In view of the differences between markets in terms of traded quantity and economic importance, it seems likely that causality extends from the crude oil to the much smaller market of the agricultural feedstock. Because the MATIF has gained such importance for the rapeseed market during the past years, our findings concern not only participants at the commodity exchange but also traders and farmers who follow these price signals. Excessive volatility blurs the signals of supply and demand, making the optimization of production and processing decisions at each stage of the value chain more difficult.

We suspect that the increase in rapeseed price volatility is influenced by speculation. Additionally, its increasing correlation with crude oil indicates that rapeseed prices are not based on market fundamentals. Thus the potential for a further increase in volatilities in the future is high. Concerns about high price levels in agricultural prices and the influence of crude oil prices on them were much larger than concerns regarding their short-term fluctuation. The impact of the latter on the former should, however, not be underestimated. Our findings further imply that in the discussions of how to deal with increased volatility, the role of commodity exchanges should not be neglected. The increase in the volume of futures contracts traded at the MATIF shows its rising importance in global agricultural markets.

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