Volatility linkages between German biofuel prices and agricultural commodity prices

Master Thesis Submitted to

Prof. Dr. Brenda López Cabrera

Prof. Dr. Ostap Okhrin

Ladislaus von Bortkiewicz Chair of Statistics

C.A.S.E.- Centre for Applied Statistics and Economics

Humboldt-Universität zu Berlin

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Franziska Schulz

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Abstract

In this thesis we study linkages between the volatilities of energy prices and agricultural commodity prices in Germany. We investigate whether linkages exist and how they behave over time. To achieve this, weekly prices of biodiesel, crude oil and rapeseed are analyzed over a period from 2002 to 2012. Crude oil and rapeseed prices are first generic future prices traded at ICE futures Europe and LIFFE-Paris respectively. Biodiesel prices are German consumer prices at the pump. We apply a vector error correction model (VECM) in order to filter the data from long run comovement in the level of prices. Volatility and volatility linkages are analyzed using a dynamic conditional correlation (DCC) GARCH model as well as a multiplicative volatility model. We find that in the long run biodiesel prices adjust to crude oil and rapeseed prices. Furthermore, our analysis reveals that the volatility of biodiesel is only weakly linked to the volatility of crude oil and rapeseed. The linkage between the volatility of rapeseed and crude oil is increasing in recent years.

Keywords: Biofuel, Volatility transmission, VECM, MGARCH, Multiplicative volatility model

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1 Introduction

Energy is an essential input in the agricultural sector since it is needed e.g. for transportation and processing of food. This creates a linkage between the two sectors. Due to the emergence of large-scale biofuel production in the last years, further linkages between the two sectors arise, since e.g. agricultural products are now used as input for energy production. The increasing integration between the markets of energy and agricultural commodities raises the question about the effect on the prices in the two markets. Especially in view of the extremely high food prices in recent time and the global food crisis in 2008 the effect of biofuel production is controversially discussed. In public opinion it is often blamed for rising food prices and increasing volatility. The Guardian (2011) for example posted "Biofuels are driving food prices higher" and BBC (2012) stated "Nestle blames biofuels for high food prices".

Biodiesel is one of the most common biofuels. It is mainly produced in Europe, where Germany is the largest producer. Today, biodiesel production in Germany is more than twelve times as high as it was in 2002 (LEL, LfL, 2012). The rising production level was mainly fostered by government policies. The introduction of biodiesel was supposed to reduce the dependency on fossil fuel, which is considered desirable since on the one hand its sources are limited and on the the other hand its use has negative impacts on the environment, e.g. due to the high emission of green house gas. In 2007 a sequentially rising and binding minimum quota was introduced to further promote the use of biodiesel.

In this thesis we study linkages between the volatilities of energy prices and agricultural commodity prices in Germany. We aim at answering the question whether linkages exist and how they behave over time. To achieve this, weekly prices of biodiesel, crude oil and rapeseed are analyzed over a period from 2002 to 2012. Crude oil and rapeseed prices are first generic future prices traded at ICE futures Europe and LIFFE-Paris respectively. Biodiesel prices are German consumer prices at the pump. We apply a vector error correction model (VECM) in order to filter the data from long run comovement in the level of prices. The VECM yields estimates of the long run and short run relations between the price levels. Volatility and volatility linkages are analyzed using a dynamic conditional correlation (DCC) GARCH model as well as a multiplicative volatility model. The DCC-GARCH model allows to model dynamics in the conditional volatilities and their correlations over time. However, it is based on the assumption of a constant unconditional covariance matrix. In order to relax this assumption we apply the multiplicative volatility model. It yields estimates of the long run unconditional variances and correlations.

The link between prices of biofuel and agricultural commodities has been addressed by an increasing number of researches. Most of them focus on dependencies between the level of prices. To the best of our knowledge, volatility linkages between agricultural commodity prices and biofuel in Germany have not been studied so far. Our analysis reveals that in the long run German biodiesel prices adjust to crude oil and rapeseed prices. Furthermore, we find that the volatility of biodiesel is only weakly linked to the volatility of crude oil and rapeseed. The linkage between the volatility of rapeseed and crude oil is increasing in recent years

The remainder of this paper is structured as follows. The next section gives an overview about the German biodiesel market and policies. Section 3 presents recent literature on price transmissions and spillover effects between energy and agricultural markets. Section 4 provides a description of the methodology applied in our empirical analysis. In section 5, we conduct an empirical analysis on real data and present the results. Section 6 concludes.

2 German biodiesel market and policies

Biofuel first gained importance after the oil crisis in the 1970's. Due to extremely high prices for fossil fuel in the subsequent years, the demand for alternative fuels arose. The desire to become less dependent on fossil fuel and to obtain a renewable alternative led many governments to introduce programs that supported national production of biofuel.

Biofuels cover a wide range of fuels. The two most common ones are ethanol and biodiesel. Since according to the European Biodiesel Board (EBB, 2008) in the EU diesel was the mostly used transportation fuel during the last decade, the production of biofuel in the EU mainly concentrated on biodiesel, with Germany being the largest producer (30% of EU production). The production of biodiesel is mainly based on vegetable oil. The most common vegetables used as biodiesel feedstock are soybeans and rapeseed, but also sunflower and soybean oil are used (OECD-FAO, 2009). In Germany, about 87% of biodiesel is produced of rapeseed oil (LEL, LfL, 2012).

Worldwide biodiesel production shows an exponential growth in the last decade. While in 2000 worldwide production was about 0.72 million tons, it increased to 23.6 million tons in 2011. In Germany biodiesel production strongly increased until 2007, when it amounted to 2,89 million tons compared to 0.22 million tons in 2002. Since 2007 German biodiesel production remained relatively constant and is projected at 2.78 million tons in 2011 (LEL, LfL, 2012).

The large increase in biodiesel production in Germany was mainly encouraged by tax exemptions. In 2006 the Biokraftstoffquotengesetz (Biofuel Quota Act) was passed. It replaced the prevailing tax incentives by a gradually increasing and binding minimum quota of renewable energy in the transport sector. In 2009 minimum quotas were revised and set to 5.25% in 2009 and to 6.25 % from 2010 onwards (Lamers, 2011). Additionally, since 2009 the minimum content of biodiesel in transport diesel is set to 4.4% (Sorda et al., 2010).

While the production of biofuel is on the one hand promoted by many governments around the world, the increasing production level is on the other hand subject to critical observation. Many critics raise the question about the sustainability of biofuel and its effect on agricultural commodity prices.

3 Literature Review

The link between biofuel and agricultural commodity prices has been addressed by an increasing number of researches. Most part of the literature has concentrated on price interdependencies. So far, only few have analyzed volatilities and their transmission between markets. Since Brazil and the U.S. are the leading producers of biofuel, most studies on linkages between biofuel and agricultural commodity prices analyze data from these countries. The amount of studies on European data is limited. Results differ depending on location and period regarded.

Balcombe and Rapsomanikis (2008) use Bayesian techniques to analyze price transmissions between crude oil, ethanol and sugar in Brazil. They find a long run equilibrium between each price pair and apply a vector error correction model (VECM) where dynamic adjustments towards the long-run equilibrium are potentially non-linear. Crude oil prices are found to be the main drivers of sugar as well as ethanol prices. Further, their analysis reveals a causal hierarchy from oil to sugar to ethanol.

Nonlinear adjustment dynamics towards a long run equilibrium in the Spanish market are analyzed by Hassouneh et al. (2012). They apply a parametric VECM as well as a nonparametric multivariate local polynomial regression (MLPR) to sunflower oil, biodiesel and crude oil price data. The results of the VECM suggest that only biodiesel reacts to deviations from the long run equilibrium. However, sunflower oil reacts to short-run price changes of biodiesel. Furthermore, the results of the MLPR reveal that biodiesel adjusts faster to the long-run equilibrium when its price is below the equilibrium price than when it is above the equilibrium price.

Busse et al. (2010b) apply a VECM to investigate the relationships between weekly crude oil, rapeseed oil, soy oil and biodiesel prices in Germany. In order to allow for changes in the price adjustment behavior due to changing economic and political influences, they additionally estimate a regime-dependent Markov-switching vector error correction model, which allows the parameters of the model to differ between regimes. They find that in the long run crude oil is the driving force of biodiesel prices and that in turn, biodiesel prices drive vegetable oil prices.

Additional to price transmissions Zhang et al. (2009) study volatility spillovers between weekly U.S. ethanol, corn, soybean, gasoline and oil prices using a multivariate BEKK-GARCH model. They find no spillovers from ethanol price volatility to corn and soybean price volatility, but instead discover volatility transmissions from agricultural commodity prices to energy prices.

Volatility spillover effects between the U.S. energy and agricultural market in a more recent time period are analyzed by Trujillo-Barrera et al. (2011). They adopt a trivariate model in which exogenous shocks from the oil market are transmitted to the corn and ethanol market and corn and ethanol markets interact. Estimation is conducted in a two-stage procedure. First, a VECM of the cointegrated corn and ethanol prices is estimated. Second, the VECM residuals from the first stage are used to model the conditional volatility of corn and ethanol in a bivariate BEKK-GARCH model jointly with exogenous shocks from the crude oil market. Results show strong evidence for the existence of linkages from crude oil to corn and ethanol. This differs from the findings of Zhang et al. (2009) and therefore indicates that there is an amplified connection between these markets in recent years. Furthermore, Trujillo-Barrera et al. (2011) find spillovers between corn and ethanol, but the direction goes mainly from corn to ethanol.

A similar approach is applied by Serra et al. (2011). They use a VECM together with a multivariate BEKK-GARCH model in order to analyze price transmissions and volatility spillovers between Brazilian weekly ethanol, crude oil and sugar prices. For estimation they use a new method from Seo (2007) which jointly estimates the VECM and the GARCH model parameters. They find a long run equilibrium between the prices. While ethanol is adjusting to deviations from the long-run equilibrium, crude oil and sugar are exogenous for long-run parameters. This is compatible with the result of Hassouneh et al. (2012). The estimation of the multivariate GARCH model reveals that volatility in oil prices is affected by its own lagged volatility as well as by past volatility of sugar and ethanol. This corresponds to the findings of Zhang et al. (2009). However, Serra et al. (2011) find that ethanol price volatility is affected by shocks in the oil and sugar market, which is a different result than Zhang et al. (2009) found in the U.S. market.

In a further study on Brazilian data Serra (2011) apply a semiparametric multivariate GARCH model proposed by Long et al. (2011), which is robust to potential misspecifications of the error density and of the functional form of the conditional covariance matrix. The estimation of a VECM shows that in the long run ethanol adjusts to sugar and crude oil prices. Sugar and crude oil are weakly exogenous. This is very much in line with the findings of Serra et al. (2011) and Hassouneh et al. (2012). Correspondingly, the estimates of the multivariate GARCH model indicate that ethanol markets only have a reduced capacity to influence sugar and crude oil price volatility.

A drawback of the BEKK specification is that the parameters cannot be easily interpreted and net effects on variances and covariances cannot be seen immediately (Tse and Tsui, 2002). Therefore, another class of multivariate GARCH models, which is based on the decomposition of the conditional covariance matrix into conditional variances and conditional correlations, is very popular. A model that falls into this class is the dynamic conditional correlation (DCC) GARCH model. It models the conditional variances as univariate GARCH processes and the conditional correlations as functions of past market shocks, both varying over time (Engle and Sheppard, 2001). The advantage of the model is the intuitive interpretation of parameters (Silvennoinen and Teräsvirta, 2009).

A DCC-GARCH model is applied by Busse et al. (2010a), who analyze linkages between price volatilities in German agricultural and energy markets. They use daily returns of rapeseed, rapeseed oil, soybean, soybean oil and crude oil prices. The results of the univariate estimation process indicate that the conditional volatility of all return series is affected by own past volatility as well as by own market shocks. The results of the conditional correlations show an increasing correlation between rapeseed and crude oil volatility during the sample period. Hence, volatility in the energy market and in the agricultural market develops concurrently, which supports the ideas of an increasing integration between energy and agricultural markets.

Du and McPhail (2012) investigate dynamic evolutions of ethanol, gasoline and corn prices in the United States. Estimation of a DCC-GARCH models reveals that conditional correlations are largely varying. A structural change test gives evidence for a structural break in March 2008. In order to account for this break a structural VAR model is estimated for each period. The results reveal no significant effects of one price on the other in the first period. In the second period relationships seem to be strengthened, as there are significant effects between the prices. Variance decomposition shows that in the second period variances of the prices can largely be explained by price changes in the other markets. These results are compatible with earlier studies. Zhang et al. (2009) do not find significant integration between the U.S. agricultural and energy markets in the early 2000s. For more recent data however, Trujillo-Barrera et al. (2011) do find an increased strength in the relationship between these markets.

The studies described above each focus only on a small selection of commodities and a single region. Kristoufek et al. (2012) in contrast use a method of taxonomy which enables them to simultaneously analyze price transmissions and correlations of different biofuels and related commodities from different locations. The idea is to create networks by translating correlations of commodities into distances. Minimal spanning trees are used do identify the most important connections between the commodities. Hierarchical trees are used to identify correlation clusters. They divide their sample into subperiods, one before and one during and after the food crisis in 2008/2009. The results show that before the food crisis the commodity prices under consideration were only weakly connected. During and after the food crisis the connections strengthened. However, the directions of the connections cannot be determined using the taxonomy approach.

All studies considered find evidence for a strong level of integration between the markets of oil, biofuel and related agricultural commodities, which is increasing in recent years. However, the evidence for an effect of biofuel prices on the level and volatility of agricultural commodity prices is limited. Especially for the German market, to the best of our knowledge, there exists no study on volatility linkages between agricultural commodity prices and biofuel.

4 Methodology

As mentioned above, the aim of this thesis is to model the volatility behavior of price series. Myers (1994) points out that commodity price series share some characteristic time series properties that have to be considered in a sound statistical analysis. These properties are (i) high volatility, (ii) stochastic trends, (iii) comovement in commodity price series and (iv) time-varying volatility. Considering these properties, one has to be careful when specifying the mean and the variance of the price series. To specify the mean, we apply a vector error correction model (VECM). Thereby, we filter the price series from comovements in their conditional mean. Volatilities and volatility transmissions are modeled by a multivariate GARCH model as well as by a more general multivariate multiplicative volatility model.

4.1 Vector error correction model

The characteristic comovement of commodity price series is addressed by the concept of cointegration, which was introduced by Granger (1981). The idea behind cointegration is that though individual price series are non-stationary, a linear combination of price series might be stationary.

Engle and Granger (1987) formalized the idea of cointegration for vectors with components that are all integrated of the same order. Campbell and Perron (1991) generalized the definition to vectors with components that are allowed to be integrated of different orders:

Definition 1. *(Campbell and Perron, 1991) An $(n \times 1)$ vector of variables p_t is said to be cointegrated if at least one nonzero n-element vector β_i exists such that $\beta_i^\top p_t$ is trend stationary. β_i is called a cointegrating vector. If r such linearly independent vectors β_i $(i = 1, \dots, r)$ exist, we say that $\{p_t\}$ is cointegrated with cointegration rank r. We define the $(n \times r)$-matrix of cointegrating vectors $\beta = (\beta_1, \dots, \beta_r)$. The r elements of the vector $\beta^\top y_t$ are trend-stationary and β is called the cointegrating matrix.*

A linear combination $\beta_i^\top p_t$ can be interpreted as an equilibrium relationship between the components of p_t and is called cointegration relation. If at least one of the components is integrated of order one, there can exist at most $n-1$ such cointegrating vectors β_i and hence, at most $n-1$ independent cointegration relations (Campbell and Perron, 1991).

In the vector error correction model (VECM) changes in the vector p_t depend on deviations from such a long run equilibrium relationship as well as on short term dynamics. The VECM of order 2 is defined by

$$\begin{aligned}\Delta p_t &= c + \Pi p_{t-1} + \Gamma \Delta p_{t-1} + u_t \\ &= c + \alpha\beta^\top p_{t-1} + \Gamma \Delta p_{t-1} + u_t\end{aligned}$$

where Δ is a first difference operator, such that $\Delta p_t = p_t - p_{t-1}$ denotes the change in the vector p from time $t-1$ to time t. c and is a constant and $\beta^\top p_{t-1}$ is the cointegration relation. $\beta^\top p_{t-1}$ describes a long run equilibrium, whereas Δp_{t-1} corresponds to short term price changes. α is the speed of adjustment with which prices return to the long run equilibrium, Γ measures reactions to short term price changes. u_t is an error term which captures potential GARCH effects.

The parameters of the VECM are estimated by quasi maximum likelihood (QML) under the assumption of homoscedastic errors. This enables us to estimate VECM parameters and GARCH parameters separately. Under the presence of heteroscedasticity estimation results are still consistent (Bauwens et al., 2012). The normal density based QMLE is defined as maximizing

$$
\begin{aligned}
\mathscr{L}(\theta) &= -\frac{Tn}{2}\log(2\pi) - \frac{T}{2}\log|\Sigma| - \frac{1}{2}\sum_{t=1}^{T} u_t^\top \Sigma^{-1} u_t \\
\text{with } u_t &= \Delta p_t - c - \alpha\beta^\top p_{t-1} - \Gamma \Delta p_{t-1}
\end{aligned}
$$

where θ denotes the parameters of the model and Σ is the unconditional covariance matrix of u_t (Hamilton, 1994).

4.2 Multivariate GARCH model

Let u_t be a $d-$variate vector of T observations with $\mathrm{E}(u_t|\mathscr{F}_{t-1}) = 0$, where $\mathscr{F}_{t-1}$ is a sigma field generated by the past information until time $t-1$. In the following we will assume that u_t is a vector of residuals, in our case, u_t denotes the vector of VECM residuals. The multivariate GARCH (MGARCH) model describes the dynamics of the conditional covariance matrix of u_t. The MGARCH model is defined by

$$
u_t = H_t^{1/2} z_t, \quad z_t \sim iid(0, \mathrm{I}_n), \quad t = 1, 2, \ldots, T \tag{4.1}
$$

where $H_t^{1/2}$ is a $n \times n$ positive definite matrix such that $H_t^{1/2}(H_t^{1/2})^\top = H_t$ and $H_t = \mathrm{Var}(u_t|\mathscr{F}_{t-1})$ is the covariance matrix of u_t conditional on the sigma field $\mathscr{F}_{t-1}$. Several specifications for H_t are proposed in the literature. An overview is given e.g. by Bauwens et al. (2006) or Silvennoinen and Teräsvirta (2009).

In our analysis, we will focus on the dynamic conditional correlation (DCC) model proposed by Engle and Sheppard (2001), which can be viewed as a nonlinear combination of univariate GARCH models. The conditional covariance matrix is decomposed into conditional variances and a conditional correlation matrix, which can be specified separately. The DCC model is defined by

$$
\begin{aligned}
H_t &= D_t R_t D_t \\
D_t &= diag(h_{11t}^{1/2}, \ldots, h_{nnt}^{1/2}) \\
R_t &= (\mathrm{I}_n \odot Q_t)^{-1/2} Q_t (\mathrm{I}_n \odot Q_t)^{-1/2} \\
Q_t &= (1-a-b)\bar{Q} + a\,\xi_{t-1}\xi_{t-1}^\top + bQ_{t-1}
\end{aligned}
$$

where $\odot$ denotes the Hadamard product, $\xi_{it} \stackrel{def}{=} u_{it}/\sqrt{h_{iit}}$ $(i = 1, \ldots, n)$ are the residuals u_t standardized by their conditional standard deviations, $\bar{Q}$ is the unconditional covariance matrix of ξ_t and a and b are non-negative scalar parameters satisfying $a+b<1$. D_t is the diagonal matrix of time varying standard deviations from univariate GARCH processes and R_t is the time varying conditional correlation matrix.

The DCC model was designed to allow for a two stage estimation procedure. In the first stage, the conditional variances are estimated using a univariate GARCH specification. In the second stage residuals standardized by the standard deviations obtained in the first stage are used to estimate the parameters of the dynamic correlations. By assuming z_t in (4.1) to be normally distributed, consistent estimates can be obtained by a two stage quasi-maximum likelihood (QML) procedure. The log likelihood function of the model is given by

$$\mathscr{L}(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left\{n \ \log(2\pi) + \log(|D_t R_t D_t|) + u_t^{\top} D_t^{-1} R_t^{-1} D_t^{-1} u_t\right\} \tag{4.2}$$

where θ denotes the parameters of the model. The parameters θ can be divided into parameters of the univariate variances ψ and parameters of the conditional correlations ϕ. In the first step R_t is replaced by an identity matrix of size n. This yields the first step log likelihood function

$$\begin{aligned}
\mathscr{L}_1(\psi) &= -\frac{1}{2}\sum_{t=1}^{T}\left\{n \ \log(2\pi) + 2 \ \log(|D_t|) + \log(|\,\mathrm{I}_n\,|) + u_t^{\top} D_t^{-1}\,\mathrm{I}_k\, D_t^{-1} u_t\right\} \\
&= -\frac{1}{2}\sum_{t=1}^{T}\left\{n \ \log(2\pi) + 2\log(|D_t|) + u_t^{\top} D_t^{-2} u_t\right\} \\
&= -\frac{1}{2}\sum_{i=1}^{n}\left\{T \ \log(2\pi) + \sum_{t=1}^{T}\left\{\log(h_{it}) + \frac{u_{it}^2}{h_{it}}\right\}\right\}
\end{aligned}$$

which is the sum of log-likelihoods of univariate GARCH equations (Engle and Sheppard, 2001). The univariate GARCH equations can be specified in various ways. In our analysis we apply an exponential GARCH (EGARCH) model introduced by Nelson (1991). The EGARCH model allows for asymmetric responses to shocks and does not require any parameter restrictions. It is given by

$$\log(h_{iit}) = \omega_i + \alpha_i\{|\frac{u_{it-1}}{h_{iit-1}}| - \mathrm{E}(|\frac{u_{it-1}}{h_{iit-1}}|)\} + \gamma_i \frac{u_{it-1}}{h_{iit-1}} + \beta_i \log(h_{iit-1})$$

where $i = 1, \ldots, n$. α_i, β_i, γ_i and ω_i are scalar parameters to be estimated. The parameter α_i is a symmetric measure of the GARCH effect, that is it indicates how much the conditional volatility is affected by the magnitude of past shocks. γ_i measures the asymmetry of the model. If $\gamma_i < 0$, positive shocks generate less volatility than negative shocks. If $\gamma_i > 0$ it is the other way around. β_i measures the persistence of past conditional volatility and ω_i is a constant.

In the second step, (4.2) is estimated conditional on the parameter estimates obtained in the first step. The QMLE is given by maximizing

$$\begin{aligned}\mathscr{L}_2(\phi|\psi) &= -\frac{1}{2}\sum_{t=1}^{T}\left\{n\ \log(2\pi)+\log(|D_tR_tD_t|)+u_t^\top D_t^{-1}R_t^{-1}D_t^{-1}u_t\right\}\\ &= -\frac{1}{2}\sum_{t=1}^{T}\left\{n\ \log(2\pi)+2\ \log(|D_t|)+\log(|R_t|)+\xi_t^\top R_t^{-1}\xi_t\right\}\\ &= \text{constant}-\frac{1}{2}\sum_{t=1}^{T}\left\{\log(|R_t|)+\xi_t^\top R_t^{-1}\xi_t\right\}\end{aligned}$$

4.3 Multivariate multiplicative volatility model

A core assumption of MGARCH models is that the unconditional covariance matrix is constant over time. In order to relax this assumption Bauwens et al. (2012) developed a multiplicative volatility model which allows for smooth changes in the unconditional covariance matrix through a multiplicative component. The idea is to decompose the unconditional covariance matrix of u_t into a long run component and a short run component. The long run component is a smooth function of time and corresponds to the unconditional covariance. The short run component captures potential dynamics of multivariate GARCH processes. The model is defined by

$$\begin{aligned}H_t &= \Sigma(\tau)^{1/2}G_t^{1/2}(G_t^{1/2})^\top\{\Sigma(\tau)^{1/2}\}^\top\\ &= \Sigma(\tau)^{1/2}G_t\{\Sigma(\tau)^{1/2}\}^\top\end{aligned}$$

where $\tau = \frac{t}{T}$. By assuming $\mathrm{E}(G_t) = \mathrm{I}_n$ for identification it follows that

$$\mathrm{Var}(u_t) = \Sigma(\tau)^{1/2}\,\mathrm{E}(G_t)\{\Sigma(\tau)^{1/2}\}^\top = \Sigma(\tau)$$

Hence, $\Sigma(\tau)$ is the unconditional covariance matrix of u_t. It captures the long run dynamics and is a deterministic and smooth function of time.

Let $\varepsilon_t \stackrel{def}{=} \Sigma(\tau)^{-1/2}u_t$ be the vector of residuals standardized by its unconditional covariance. It follows that $\mathrm{Var}(\varepsilon_t) = \mathrm{I}_n$ and $\mathrm{Var}(\varepsilon_t|\mathscr{F}_{t-1}) = G_t$. Hence, ε_t is a vector with a constant unconditional covariance matrix and with G_t as its conditional covariance matrix. In case the standardized residuals ε_t show ARCH effects, they can be modeled using a multivariate GARCH model as described in the previous section. Due to the standardization, they fulfill the assumption of a constant unconditional covariance matrix.

Hafner and Linton (2010) show that the unconditional covariance matrix $\Sigma(\tau)$ can estimated efficiently by the nonparametric Nadaraya-Watson estimator:

$$\Sigma(\tau) = \frac{\sum_{t=1}^{T} K_h(\tau-\frac{t}{T})u_tu_t^\top}{\sum_{t=1}^{T} K_h(\tau-\frac{t}{T})} \tag{4.3}$$

where $\tau = \frac{1}{T}, \frac{2}{T}, \ldots, 1$, $K_h(.)$ is a kernel function and h is a positive bandwidth parameter. The bandwidth parameter is selected using a likelihood cross-validation criterion as proposed by Yin et al. (2010). It is given by

$$CV(h) = \frac{1}{n} \sum_{t=1}^{T} \left\{ u_t^\top \Sigma_{(-t)}^{-1}(\frac{t}{T}) u_t + \log(|\Sigma_{(-t)}(\frac{t}{T})|) \right\} \tag{4.4}$$

where $\Sigma_{(-t)}$ is the leave-one-out estimator of the unconditional covariance matrix. That is, it is estimated as (4.3), but with the t-th observation left out. The optimal bandwidth is determined by minimizing (4.4).

5 Empirical analysis

5.1 Data

The empirical analysis utilizes weekly prices of biodiesel (p_b), crude oil (p_c) and rapeseed (p_r) from July 19, 2002 to April 24, 2012. This amounts to a total of 511 observations. All prices are expressed in Euros per cubic meter. The Data was taken from the database Bloomberg, the corresponding tickers and contract specifications are given in Table 5.1. Biodiesel prices are German consumer prices at the pump. Crude Oil prices are first generic future prices of brent crude oil traded at ICE Futures Europe. Rapeseed prices are first generic future prices traded at LIFFE-Paris, which operates the MATIF (Marché à Terme International de France) and which is the most important stock exchange for rapeseed worldwide (Busse et al., 2010a).

Commodity	Ticker	Contract type
Cude oil	CO1 Comdty	1^{st} generic future, ICE futures Europe
Rapeseed	IJ1 Comdty	1^{st} generic future, LIFFE Paris
Biodiesel	BIOCEUGE Index	Spot, Germany

Table 5.1: Analyzed Bloomberg Commodities

	Crude Oil p_c	Rapeseed p_r	Biodiesel p_b
Mean	320.80	515.43	1044.55
Standard Deviation	120.09	145.62	203.54
		Correlation	
Crude Oil p_c	1	0.814	0.925
Rapeseed p_r		1	0.819
Biodiesel p_b			1

Table 5.2: Descriptive Statistics (prices in Euro/m^3)

Figure 5.1 shows the price series of the analyzed commodities. Descriptive statistics are given in Table 5.2. The plot shows that prices peaked during the global food crisis in 2007/2008. Afterwards prices decreased, but went up again in 2011. The decrease in prices corresponds to the late-2000s recession, where the overall level of commodity prices decreased. The increase in food prices in 2009/2010 with its peak in 2011 is mainly attributed to production shortfalls due to bad weather. However, also structural problems that already triggered the global food crisis in 2007/2008 persist. Some of these are an increasing demand due to a steadily increasing world population and an increasing demand for meat products. Additionally, the need of feedstock for the production of biofuel causes a decline in food supply and an increased competition for agricultural land (Asian Development Bank, 2011).

Another, though ambiguous explanation often given for the sharp increase in prices is speculative activity in commodity price markets. Ghosh (2010) argues that price movements of the size as realized during the food crisis could not have been created solely by real supply and demand changes. The actual function of speculators in the market is to predict price patterns and thereby stabilize the market, reduce price volatility and ensure liquidity. Therefore, the presence of speculators in the market does not harm the market per se. However, excessive speculation and a lack of regulations can lead to prices that do not reflect demand and supply anymore. Headey and Fan (2008) though point out that higher prices induce speculation and therefore, it is hard to determine causality.

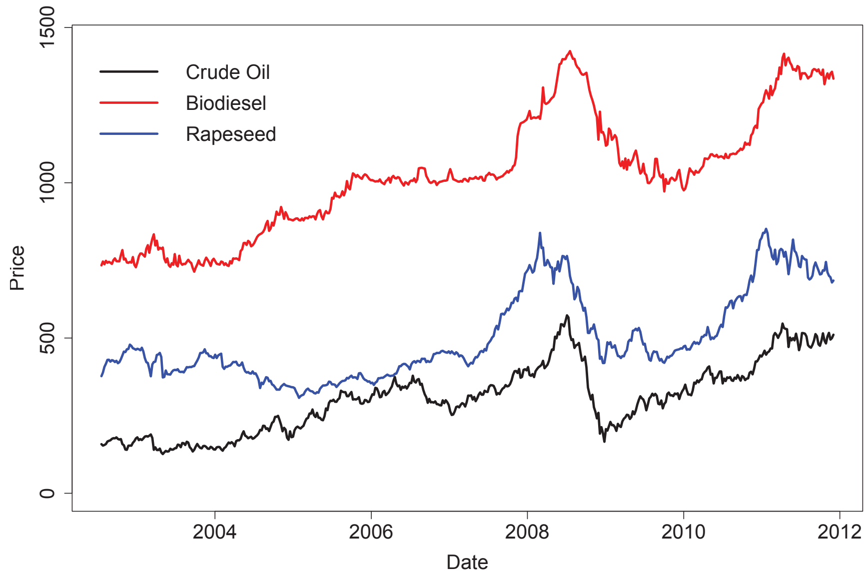

Figure 5.1: Weekly prices in €/m^3

For the statistical analysis of the data logarithmic transformations are taken in order to obtain well-behaved errors. Additionally, using logarithmic prices facilitates interpretation of results, since coefficients correspond to percentage changes and therefore, can be interpreted as price elasticities (Serra et al., 2011). Missing data points are interpolated using cubic splines. Seasonal effects in the data are removed using a local linear regression function (LLR) as suggested by Härdle et al. (2011). The seasonal effect of week t $(t = 1, \dots, 52)$ is defined as

$$\Lambda_t = \arg\min_{a,b} \sum_{i=1}^{52} \{\bar{p}_t - a - b(i-t)\}^2 K_h(i-t)$$

where $\bar{p}_t$ is the mean over years of weekly prices, $K_h(.)$ is a kernel function and h a positive bandwidth parameter. We use a Gaussian kernel and choose the bandwidth as proposed by Bowman and Azzalini (1997). The following analysis is based on deseasonalized data. Results obtained using the original data without seasonal adjustment can be found in the appendix. All estimates are in-sample estimates.

5.2 Results

5.2.1 Unit root and cointegration tests

In order to test for the presence of a unit root in the price series of crude oil, biodiesel and rapeseed the Augmented Dickey Fuller (ADF) test as well as the KPSS test proposed by Kwiatkowski et al. (1992) were conducted.

The ADF test tests the null hypothesis of a unit root process against the alternative of a stationary process. The process may contain a deterministic trend, a drift or none of both. The lag order of the ADF test is determined by a general-to-specific approach, where the number of lags is decreased until the smallest number of lags is obtained that still has uncorrelated errors. The test gives evidence for the presence of a unit root in all three price series. The existence of a trend or a drift is rejected for all series. Test statistics are given in Table 5.3.

	Test Statistic	5% Critical Value	Lags
Crude Oil	-1.1634	-1.95	9
Biodiesel	0.9899	-1.95	9
Rapeseed	-0.5339	-1.95	8

Table 5.3: Results of the Augmented Dickey Fuller Test

In contrast to the ADF test, the KPSS test tests the null hypothesis of a stationary process against the alternative of a unit root process and therefore is the more conservative test. The test statistic of the KPSS test are given in Table 5.4. The null of a stationary process is rejected in all three price series. Hence, the results of the KPSS test are in line with the results of the ADF test.

	Test Statistic	5% Critical Value
Crude Oil	2.0353	0.463
Biodiesel	2.2059	0.463
Rapeseed	1.7084	0.463

Table 5.4: Results of the KPSS Test

The cointegration rank r is determined using the Johansen trace test described by Johansen (1995). In order to apply the test, it is useful to know the lag length of the VECM. A lag-structure analysis based on the Hannan Quinn information criterion (HQ) is conducted, which yields a consistent estimate of the lag length (Lütkepohl, 2005). The result suggests an optimal lag order of 1. The results of the Johansen trace test suggest the existence of a single cointegration relation. The corresponding test statistics as well as the cointegration relationship are given in Table 5.5.

The results suggest that there exists a long run relationship between crude oil, biodiesel and rapeseed. The parameters indicate that biodiesel is positively related with crude oil and rapeseed in the long run. When biodiesel or rapeseed prices change by 10%, biodiesel prices change by 4.43% and 1.36% respectively. The positive long run link between biodiesel and rapeseed is not

H_0	H_a	Test Statistic	5% Critical Value
r=0	r > 0	49.37	31.52
r ≤ 1	r > 1	5.71	17.95
r ≤ 2	r > 2	1.14	8.18
Cointegration relation $\beta^\top p_t$: $p_{bt} = 0.443 p_{ct} + 0.136 p_{rt}$			

Table 5.5: Johansen trace test for cointegration

surprising, since biodiesel production costs largely depend on the price of its feedstock. The positive link between biodiesel and crude oil may on the one hand arise due to the fact that biodiesel serves as a substitute for petroleum diesel that comes from refined crude oil. Hence, if crude oil prices rise and as a result also petroleum diesel prices, the demand for biodiesel increases which causes an increase in biodiesel prices. On the other hand, the long run link in prices is further strenghtened through blending obligations, which demand that at least 6.25% of transportation fuel sold comes from biofuel. The results are compatible with the findings of Balcombe and Rapsomanikis (2008), Serra et al. (2011) and Hassouneh et al. (2012).

5.2.2 VECM estimation

Deviations from the long run equilibrium as well as short run dynamics are captured in the VECM. The estimation results of the VECM are shown in Table 5.6. Since we have weekly data, the estimates correspond to percentage changes from one week to the next. The estimates indicate that at a 5% significanve level only biodiesel reacts to deviations from the cointegration relation, while crude oil and rapeseed are exogenous with respect to the long run relationship. The adjustment coefficient of rapeseed is significant only at a 10% significance level and is about half the size of the adjustment coefficient of biodiesel. Hence, if at all, rapeseed adjusts much slower to deviations from the long run equilibrium than biodiesel. This can be explained by the fact that crude oil and rapeseed are traded on the world market, while biodiesel is traded mainly domestically. Crude oil is also exogenous to short term price changes and is only affected by market shocks, which indicates that the crude oil market is efficient. Rapeseed prices, when regarding significance at a 10% level, are affected by own lagged prices, but not by crude oil or biodiesel prices. Biodiesel in contrast, in the short run reacts to changes in crude oil as well as to own lagged prices. Hence, although there exists a long run link between the prices of biodiesel, crude oil and rapeseed, biodiesel does not influence rapeseed and crude oil prices in the short run and only has a limited capacity to influence rapeseed in the long run. Biodiesel prices rather react to price changes in the other two markets. This is compatible with the findings of Hassouneh et al. (2012) in the Spanish market. However, they find that rapeseed reacts to biodiesel price changes in the short run.

	c	$\beta^\top p_{t-1}$	Δp_{ct-1}	Δp_{rt-1}	Δp_{bt-1}
Δp_{ct}	0.0027	0.0020	-0.0587	-0.0832	-0.0840
	(0.0020)	(0.0135)	(0.0486)	(0.0801)	(0.1236)
Δp_{rt}	0.0012	0.0141*	-0.0167	0.0832*	0.0395
	(0.0012)	(0.0080)	(0.0287)	(0.0473)	(0.0730)
Δp_{bt}	0.0011*	0.0296***	0.0694***	0.0328	-0.1566***
	(0.0007)	(0.0045)	(0.0160)	(0.0265)	(0.0408)

Table 5.6: Estimates of the VECM. *, **, *** Statistically significant at the 10%, 5% and 1% significance level.

5.2.3 Multivariate GARCH model estimation

Figure 5.2 shows the residuals of the VECM. The visual impression suggests the presence of volatility clustering. In order to confirm this impression the residuals of the VECM are tested for autocorrelation and GARCH effects. The autocorrelation function (ACF) and partial autocorrelation function (PACF) suggest that the residuals are not autocorrelated. The ACF and PACF are depicted in Figure 5.3. This is supported by the results of the Ljung-Box test for autocorrelation. However, the ACF and PACF of squared residuals give evidence for autocorrelation as can be seen in Figure 5.4. Again, the results of the Ljung-Box test support this impression. Hence, there seem to exist GARCH effects in the residuals which is revealed in the clustered volatility.

In order to model the GARCH effects a multivariate GARCH model as described in section 4.1 is utilized. Several specifications for the univariate GARCH equations were tried, however, the exponential GARCH model fits the data best. Tests for normality reveal that the VECM residuals are not normally distributed. Though the QMLE are still consistent, non-normality of the residuals causes inefficiency. Therefore, we additionally estimate the parameters under the assumption that the residuals follow a generalized error distribution (GED). The GED contains the normal distribution as a special case, and many other distributions with thinner and thicker tails. The distribution depends on the parameter ν, which determines the thickness of tails and is estimated together with the other parameters of the MGARCH model. If $\nu = 2$ the GED equals the standard normal distribution. $\nu < 2$ implies a distribution with thicker tails than the standard normal distribution and $\nu > 2$ implies a thinner tailed distribution.

The normality based QML estimates of the MGARCH model are given in Table 5.9. Table 5.10 shows the estimates under the assumption of a GED. The results differ only slightly, regarding significance at a 5% level, both lead to the same conclusion. The tail-thickness parameter ν is significant different from 2 for all three univariate GARCH processes. This indicates that the distribution of the residuals is thicker tailed than the standard normal distribution, which is in line with the results of the Shapiro-Wilk test.

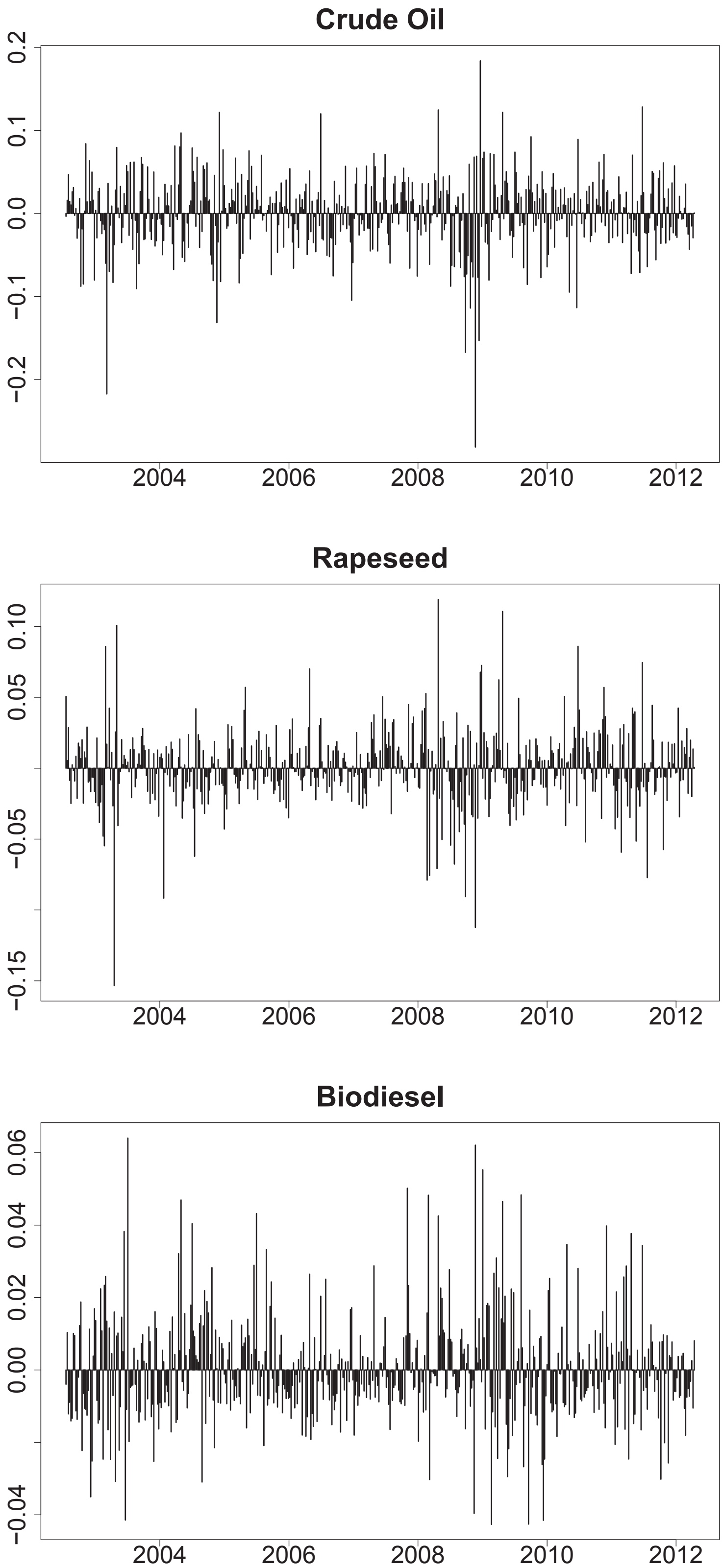

Figure 5.2: VECM residuals

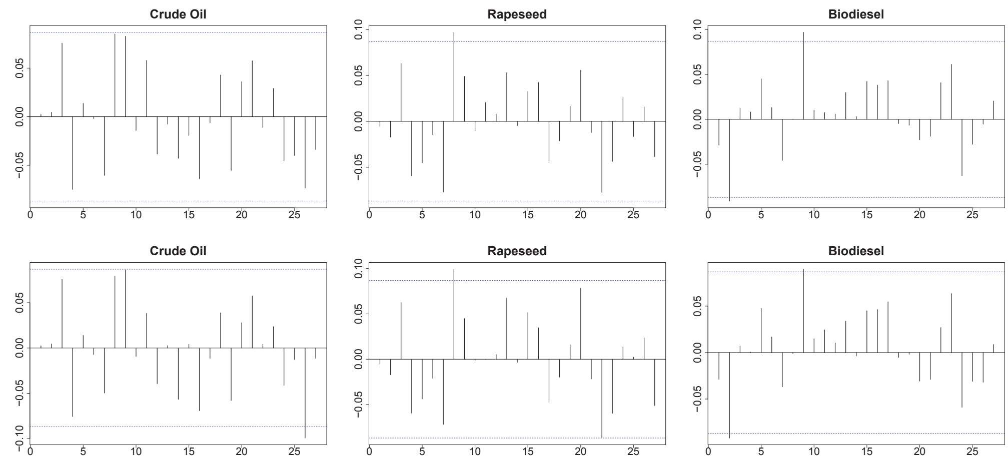

Figure 5.3: ACF (upper panel) and PACF (lower panel) of VECM residuals

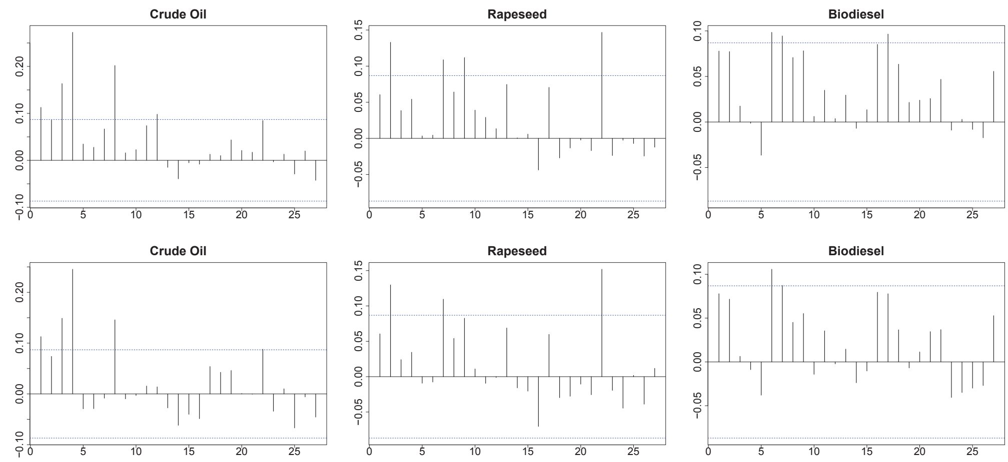

Figure 5.4: ACF (upper panel) and PACF (lower panel) of squared VECM residuals

	Residuals			Squared residuals		
	Test Statistic	p-Value	lags	Test Statistic	p-Value	lags
Crude oil	24.46	0.22	20	97.44	0.000	10
Rapeseed	20.79	0.41	20	28.81	0.001	10
Biodiesel	15.46	0.74	20	22.44	0.013	10

Table 5.7: Box-Ljung test for autocorrelation of the VECM residuals and the squared VECM residuals

For crude oil, the GARCH parameter α is significant at a 5% level and negative. This implies that market shocks have a negative impact on volatility. At the same time, the asymmetry measure γ is positive and significant at a 10% significance level. This suggests that positive shocks reduce the volatility less than negative shocks. For rapeseed and biodiesel, the GARCH

	Test Statistic	p-Value
Crude oil	0.96	4.84e-11
Rapeseed	0.94	2.33e-13
Biodiesel	0.95	1.65e-11

Table 5.8: Shapiro-Wilk test for normality of the VECM residuals

paramter α is insignificant, while the asymmetry measure γ is positive and significant at a 5% and 10% significance level, respectively. This suggests that positive shocks increase volatility, while negative shocks decrease volatility. The persistence coefficients β are significant and close to one. A persistence coefficient close to one implies a high degree of persistency in the volatility. This means that high volatility today implies high volatility in the future. The DCC model estimates indicate that shocks in the market cause correlations to increase. The persistence measure is insignificant, hence correlations seem to be independent of past correlations.

A plot of the estimated conditional variances can be found in Figure 5.5. The volatilities show strong time-varying behavior. The conditional variance of crude oil is largest in 2008. It reaches a historically high level during the sample period and returns relatively fast its initial level. Rapeseed and biodiesel prices show high volatility in phases of high price levels. Their volatility peaks during the food crisis in 2008 and remains large afterwards. This corresponds to the finding that rapeseed and biodiesel volatility increases with positive market shocks and are highly persistent. During the food crisis prices jumped to extremely high levels, causing the volatility to increase as well.

Figure 5.6 shows the estimated conditional correlations. The insignificant persistency coefficient can be recognized in the large fluctuations of the correlations. Regarding the correlation between the volatilities of crude oil and rapeseed, it can be seen that is positive during the almost whole sample period except for the end of 2011 when it shortly turns negative. The correlation shows several large peaks in 2008 and 2009. The correlations between biodiesel and crude oil and biodiesel and rapeseed are much smaller than the one between crude oil and rapeseed. Furthermore, they turn negative several times during the sample period. Since 2008 negative peaks occur more frequently. This corresponds to a time of high price levels and instability due to the global food crisis. Additionally, intensified speculative activity in the agricultural market might be responsible for negative correlations due to unpredictable volatility movements.

	Crude Oil		Rapeseed		Biodiesel	
ω_i	-0.5281	(0.1061)	-0.3117	(0.2298)	-0.6355	(0.2028)
α_i	-0.1367	(0.0025)	-0.0372	(0.3536)	-0.0352	(0.5819)
β_i	0.9159	(0.0000)	0.9556	(0.0000)	0.9236	(0.0000)
γ_i	0.0782	(0.0760)	0.2187	(0.0006)	0.2059	(0.0766)
	DCC Parameters					
a	0.0838	(0.0031)				
b	0.2183	(0.1996)				

Table 5.9: Estimates of the DCC-EGARCH(1,1). P-value in parentheses.

	Crude Oil		Rapeseed		Biodiesel	
ω_i	−0.4874	(0.1389)	−0.5149	(0.1331)	−0.4547	(0.2649)
α_i	−0.1198	(0.0036)	−0.0602	(0.1704)	−0.0203	(0.6967)
β_i	0.9228	(0.0000)	0.9303	(0.0000)	0.9465	(0.0000)
γ_i	0.0848	(0.0640)	0.1950	(0.0028)	0.1703	(0.0950)
ν_i	1.4514	(0.0000)	1.1664	(0.0000)	1.3155	(0.0000)
	DCC Parameters					
a	0.0814	(0.0043)				
b	0.2201	(0.2140)				

Table 5.10: Estimates of the DCC-EGARCH(1,1) model with generalized error distribution with shape parameter ν. P-value in parentheses.

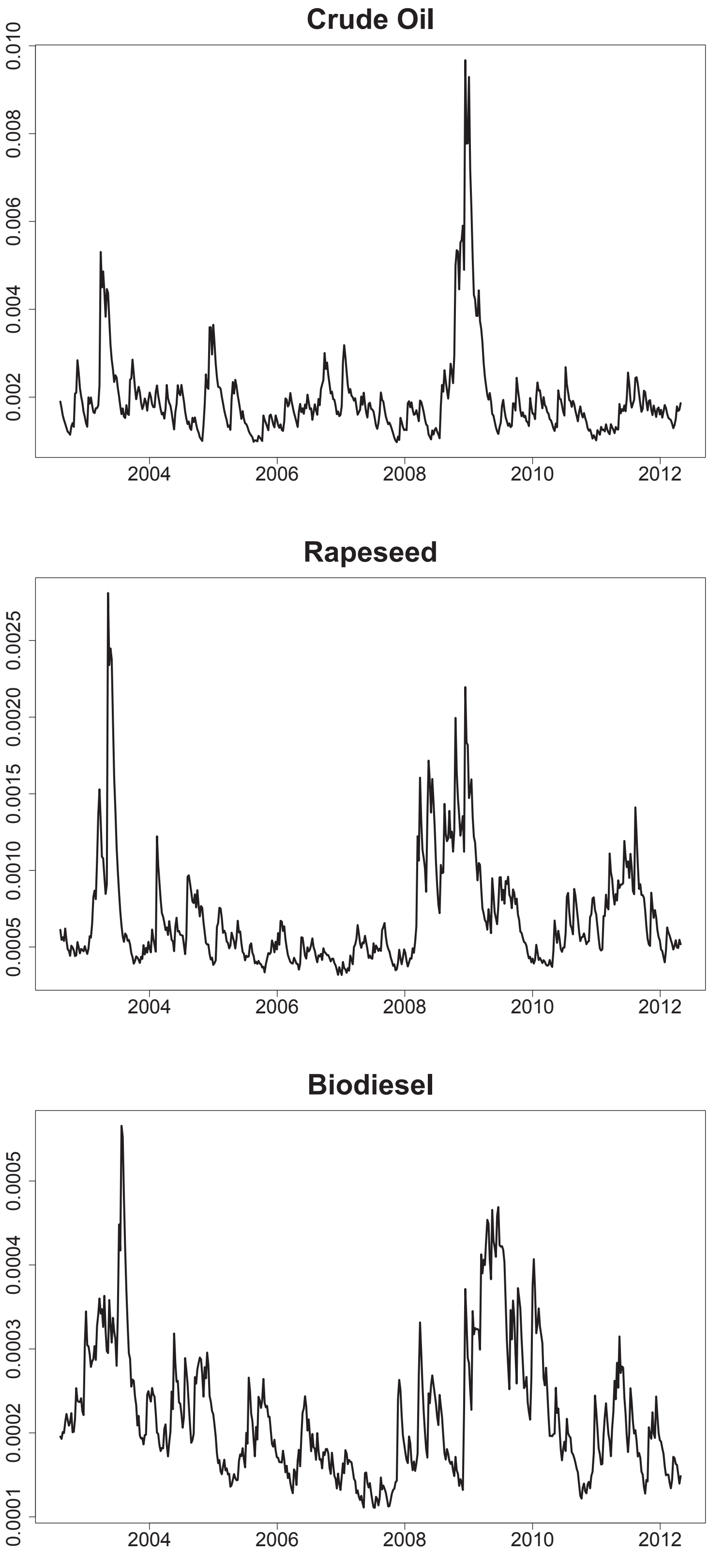

Figure 5.5: Conditional variance estimates

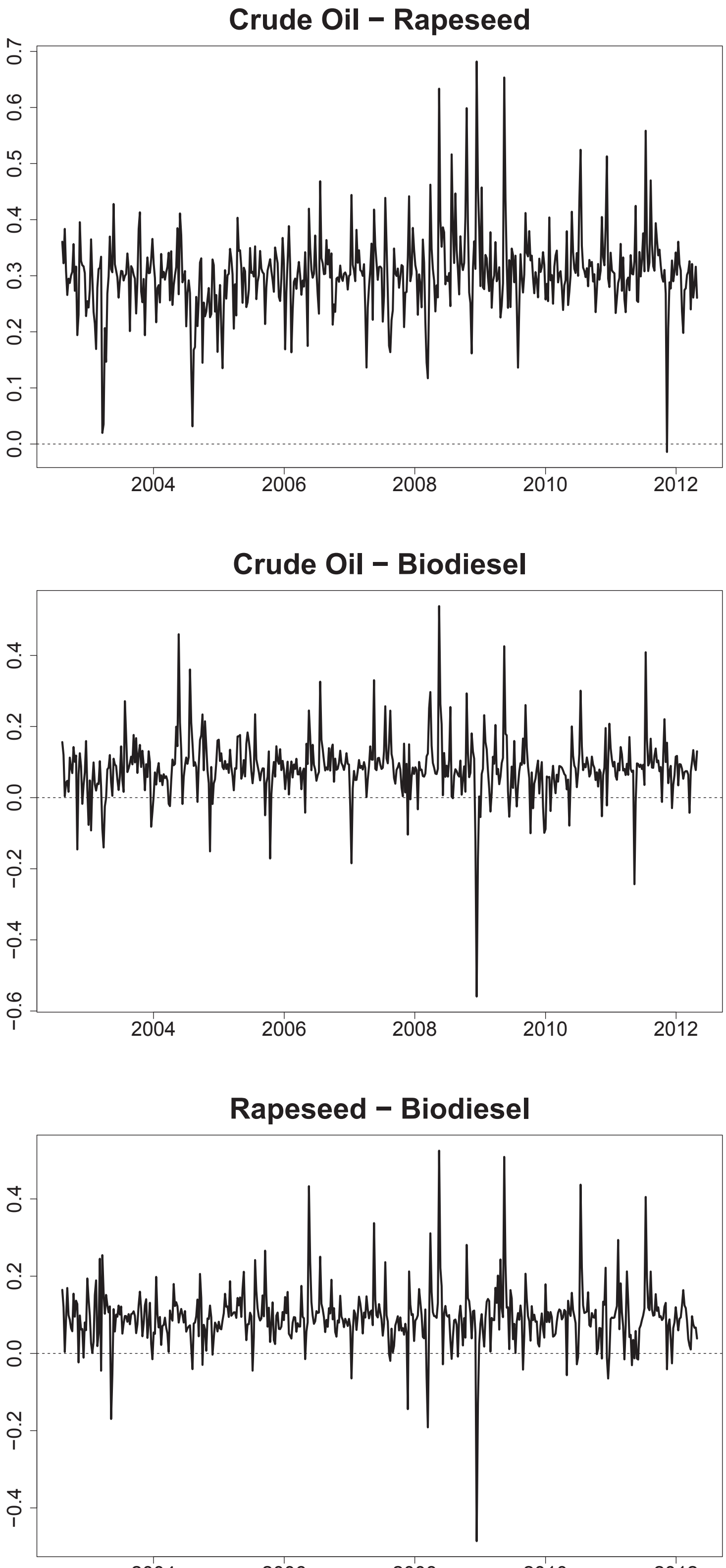

Figure 5.6: Conditional correlation estimates

5.2.4 Multivariate multiplicative volatility model estimation

In order to relax the assumption of a constant unconditional covariance matrix the multiplicative volatility model as described in section 4.3 is applied to the VECM residuals. In a first step the unconditional covariance matrix is estimated nonparametrically. The Likelihood cross-validation criterion yields a bandwidth parameter of 0.137. Figure 5.7 shows the estimated unconditional variances and correlations together with their pointwise 90% confidence interval. The confidence interval was computed using the 0.10 and 0.90 quantiles obtained based on 200 bootstrap experiments. The plots indicate that the assumption of a constant unconditional covariance matrix is unvalid.

Since the true unconditional covariance matrix cannot be observed, in order to assess the quality of the nonparametric estimates, in Figures 5.8 and 5.9 the estimated unconditional variances and correlations are shown together with the corresponding 6-month and 12-month rolling window variances and correlations. Especially with regard to the 12-month rolling covariance, the nonparametric estimates seem to fit the data quite well.

The estimated long run volatility of crude oil is relatively stable except for a large peak that reaches its maximum in the beginning of 2009. This corresponds to the phase of the food crisis, where prices reached a historically high level and markets were unstable. A similar pattern can be observed in the long run volatilities of rapeseed and biodiesel. They peak during and after the food crisis and return only slowly to the pre-crisis volatility level. Crude oil reaches its pre-crisis level of volatility much faster and shows an even lower volatility at the end of the sample period. In none of the commodities a trend for higher volatility in prices is visible.

The unconditional correlation between the volatility of crude oil and rapeseed is positive over the whole sample period. Until the end of 2005 however, it is very small and insignificant. From 2006 onwards it increases and reaches a peak at the end of 2008, where it is about 0.5. After 2009 the correlation decreases, but still remains relatively high. The high correlation between the volatility of crude oil and the volatility of rapeseed indicates that on the one hand there is an increasing tendency to react to the same market signals. On the other hand, the simultaneous development of their volatilities may also be an indicator for volatility transmission between the markets. However, the direction and magnitude of such a transmission can not be derived from the utilized model. Though, since crude oil is the much larger and more international market and therefore unlikely to be influenced by the volatility of rapeseed prices, it can be assumed that part of the correlation is due to volatility spillovers from crude oil to rapeseed prices. Phase of high correlation corresponds to phase where volatilities in the crude oil and rapeseed market were especially high. This finding suggests that the correlation is highest in volatile phases, which imposes an additional market risk. This is in line with the findings of Busse et al. (2010a), who find a historically high correlation in April 2009, where their sample however ends.

The unconditional correlation estimate for biodiesel and crude oil is increasing at the beginning of the sample period. Between 2004 and 2008 it is relatively constant at a level of about 0.3. In 2008 it starts decreasing and turns negative in 2009. Since 2010 it is increasing again, however it remains close to zero and insignificant. The sudden inversion of the correlations in 2008 corresponds to the unstable phase of the food crisis. It could be an indicator for an increasing presence of speculative activity in the market, in which many see a cause of the crisis. Speculative activity can cause high price levels and lead to unpredictable volatility behavior

(Robles et al., 2009). However, as already mentioned above, the effect of speculative activity is ambiguous.

Similar to the correlation between the volatility of crude oil and rapeseed, the one between biodiesel and rapeseed is close to zero until 2005 and then begins to increase. It peaks in 2006 and decreases afterward again. Since 2007 it stays at a low level and is insignificant during most of the remaining sample period. The peak corresponds to the time period were biofuel production in Germany boomed. From 2002 to 2007 it showed an exponential growth. Since 2007 however, biodiesel production stagnates. This is partly due to the change in the biofuel policy in Germany. Until the end of 2006 biodiesel was tax free. In 2007 tax exemptions were repealed and instead a binding minimum quote was introduced.

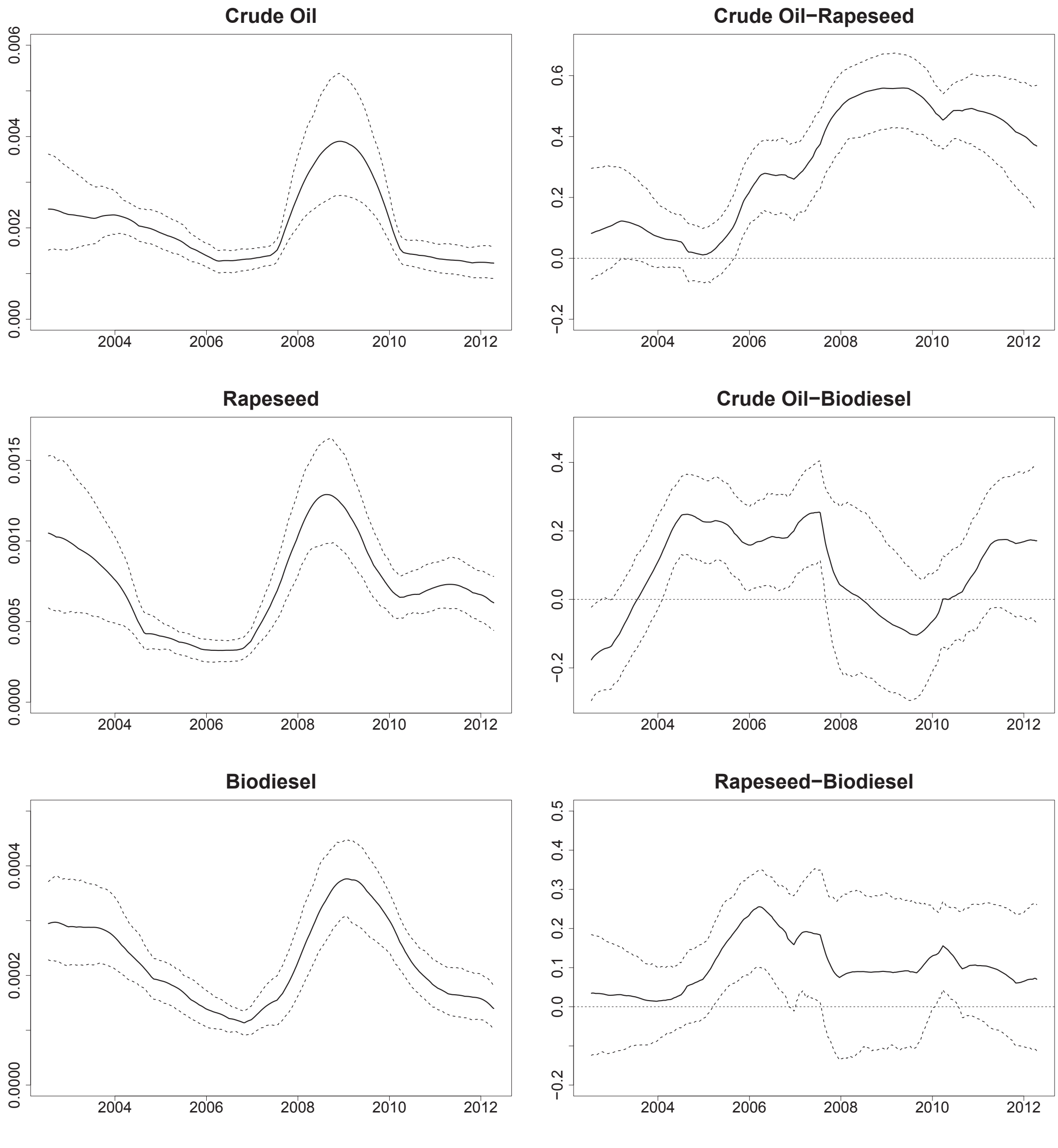

Figure 5.7: Unconditional variance and correlation estimates with 90% pointwise confidence intervals

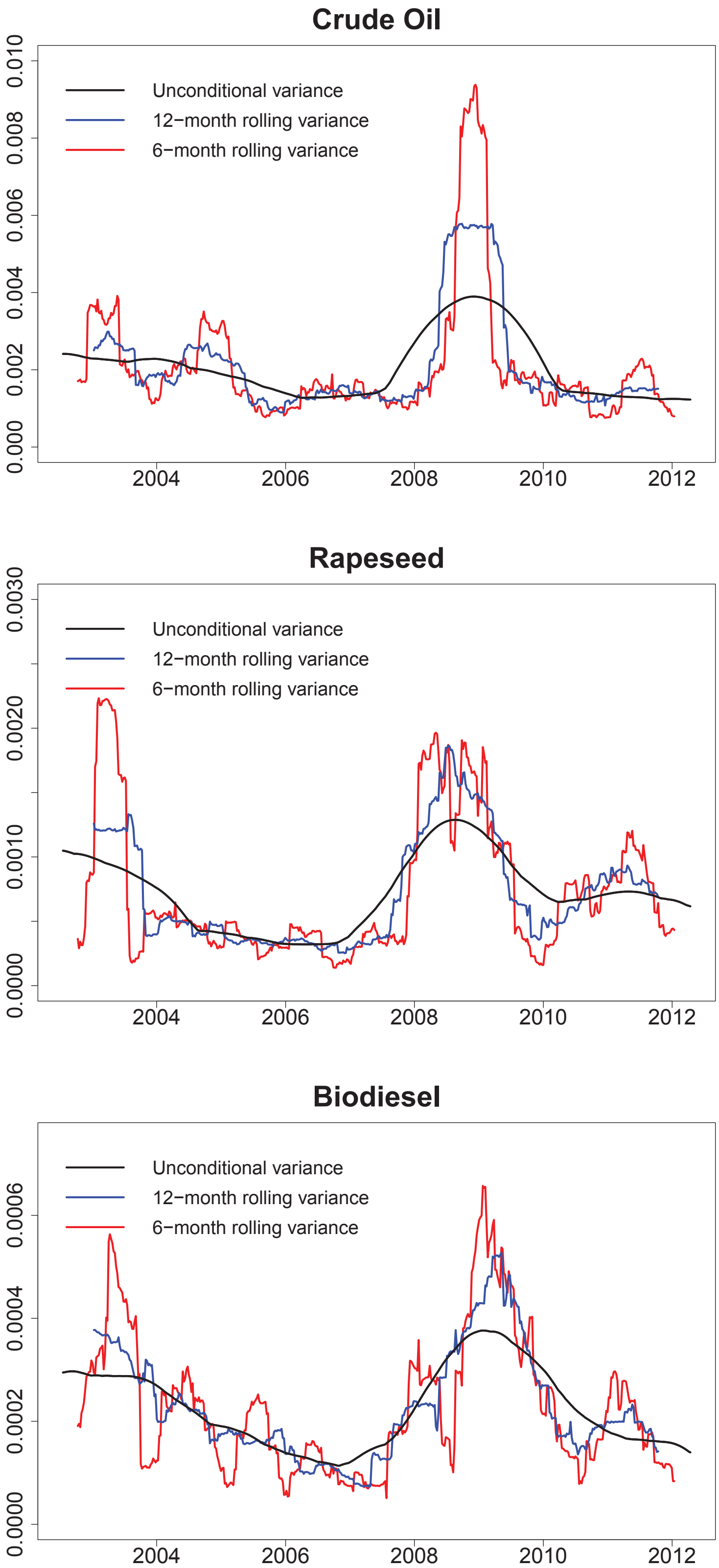

Figure 5.8: Unconditional variance estimates compared to rolling window variances

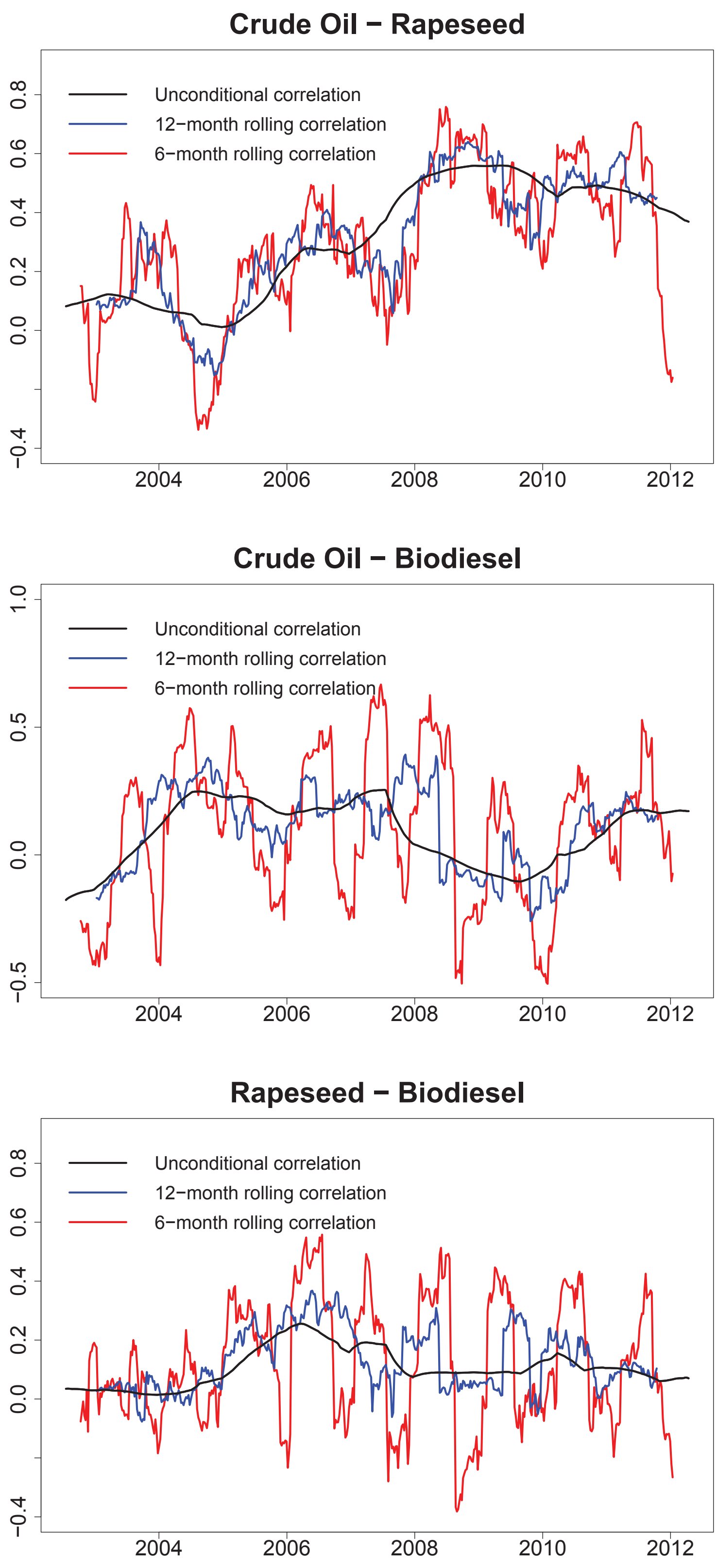

Figure 5.9: Unconditional correlation estimates compared to rolling window correlations

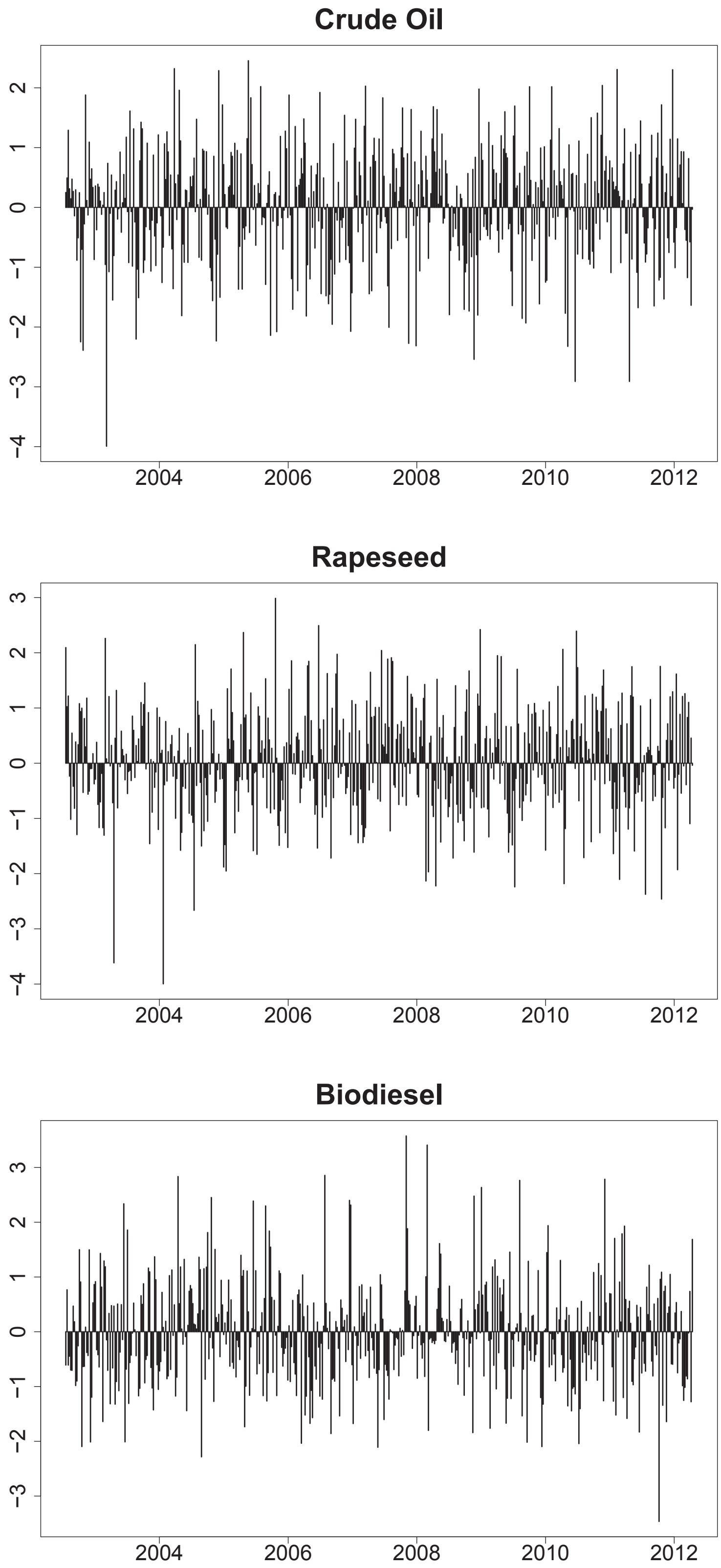

Figure 5.10: Residuals of the nonparametric covariance estimation

In a second step the residuals of the VECM are standardized by the estimated unconditional covariance matrix. Figure 5.10 shows a plot of the standardized VECM residuals. The standardized residuals are tested for autocorrelation and heteroscedasticity. Test results can be found in Table 5.11. They reveal that the standardized residuals neither contain autocorrelation nor heteroscedasticity. This is evidence against the presence of GARCH effects in the short run dynamics.

	Standardized residuals			Squared standardized residuals		
	Test Statistic	p-Value	lags	Test Statistic	p-Value	lags
Crude oil	20.9	0.40	20	19.2	0.51	20
Rapeseed	18.7	0.54	20	23.6	0.26	20
Biodiesel	18.3	0.57	20	17.9	0.59	20

Table 5.11: Box-Ljung test for autocorrelation of the standardized VECM residuals and the squared standardized VECM residuals

6 Conclusion

In this thesis linkages between the volatilities of energy prices and agricultural commodity prices in Germany are studied. Specific emphasis is given to the evolution of volatilities and their correlation over time. We analyze weekly prices of German biodiesel, crude oil and rapeseed over a period from 2002 and 2012. We find that in the long run prices move together and preserve an equilibrium relationship. A vector error correction model (VECM) is applied in order to filter the prices from the comovement. It is shown that biodiesel does not influence rapeseed and crude oil price levels in the short run and only has a limited capacity to influence rapeseed in the long run. Biodiesel prices rather react to price changes in the other two markets.

Next we apply a dynamic conditional correlation (DCC) GARCH model to the filtered prices. Results show that conditional volatilities are highly persistent and react to market shocks asymmetrically. Conditional correlations are mostly positive, but highly fluctuating, especially since the food crisis in 2008. Shocks in the markets cause an increase in the conditional correlations.

The multiplicative volatility model reveals that the unconditional covariance matrix of the filtered prices is time-varying. They exhibit a peak during and after the food crisis in 2008. A general upward trend in volatility cannot be observed. The correlation between crude oil and rapeseed volatilities is increasing in recent years, which indicates the presence of volatility spillovers. The correlations between the volatilities of biodiesel and crude oil and biodiesel and rapeseed are increasing in the beginning of the sample period, which corresponds to the boom in biofuel production. Since 2007 correlations are low and insignificant. This reveals that biodiesel only has a reduced impact on the volatilities of crude oil and rapeseed. The concern that biodiesel is the cause of high and volatile food prices seems, from the perspective of our analysis, unfounded.

So far, we analyzed linkages in volatilities and reasoned that they are an indicator for volatility spillovers. In a further study it would be interesting to investigate the direction and size of potential spill over effects. Furthermore, the DCC GARCH model does not allow for differences in the correlation structure of different commodities. Therefore, it would also be of interest to apply a generalized DCC-GARCH model, as for example proposed by Hafner and Franses (2009) , which incorporates commodity-specific correlation sensitivities.

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Appendix

A Results based on original data

The following gives the results of the analyis obtained without seasonal adjustment of the data.

	Test Statistic	5% Critical Value	Lags
Crude Oil	0.9507	-1.95	3
Biodiesel	1.8017	-1.95	1
Rapeseed	0.6075	-1.95	8

Table A.1: Results of the Augmented Dickey Fuller Test

	Test Statistic	5% Critical Value
Crude Oil	2.0285	0.463
Biodiesel	2.2205	0.463
Rapeseed	1.719	0.463

Table A.2: Results of the KPSS Test

H_0	H_a	Test Statistic	5% Critical Value
r=0	$r > 0$	53.17	31.52
$r \leq 1$	$r > 1$	5.43	17.95
$r \leq 2$	$r > 2$	0.88	8.18
Cointegration relation $\beta^\top p_t$: $p_{bt} = 0.431 p_{ct} + 0.159 p_{rt}$			

Table A.3: Johansen trace test for cointegration

	c	$\beta^\top p_{t-1}$	Δp_{ct-1}	Δp_{rt-1}	Δp_{bt-1}
Δp_{ct}	0.0782	0.0093	-0.0525	-0.1069	-0.1371
	(0.1059)	(0.0131)	(0.0481)	(0.0797)	(0.1302)
Δp_{rt}	0.0854	0.0104	-0.0023	0.0921*	0.0730
	(0.0615)	(0.0076)	(0.0279)	(0.0463)	(0.0756)
Δp_{bt}	0.2249***	0.0277***	0.0713***	0.0363	-0.1377***
	(0.0329)	(0.0041)	(0.0153)	(0.0248)	(0.0404)

Table A.4: Estimates of the VECM. *, **, *** Statistically significant at the 10%, 5% and 1% significance level.

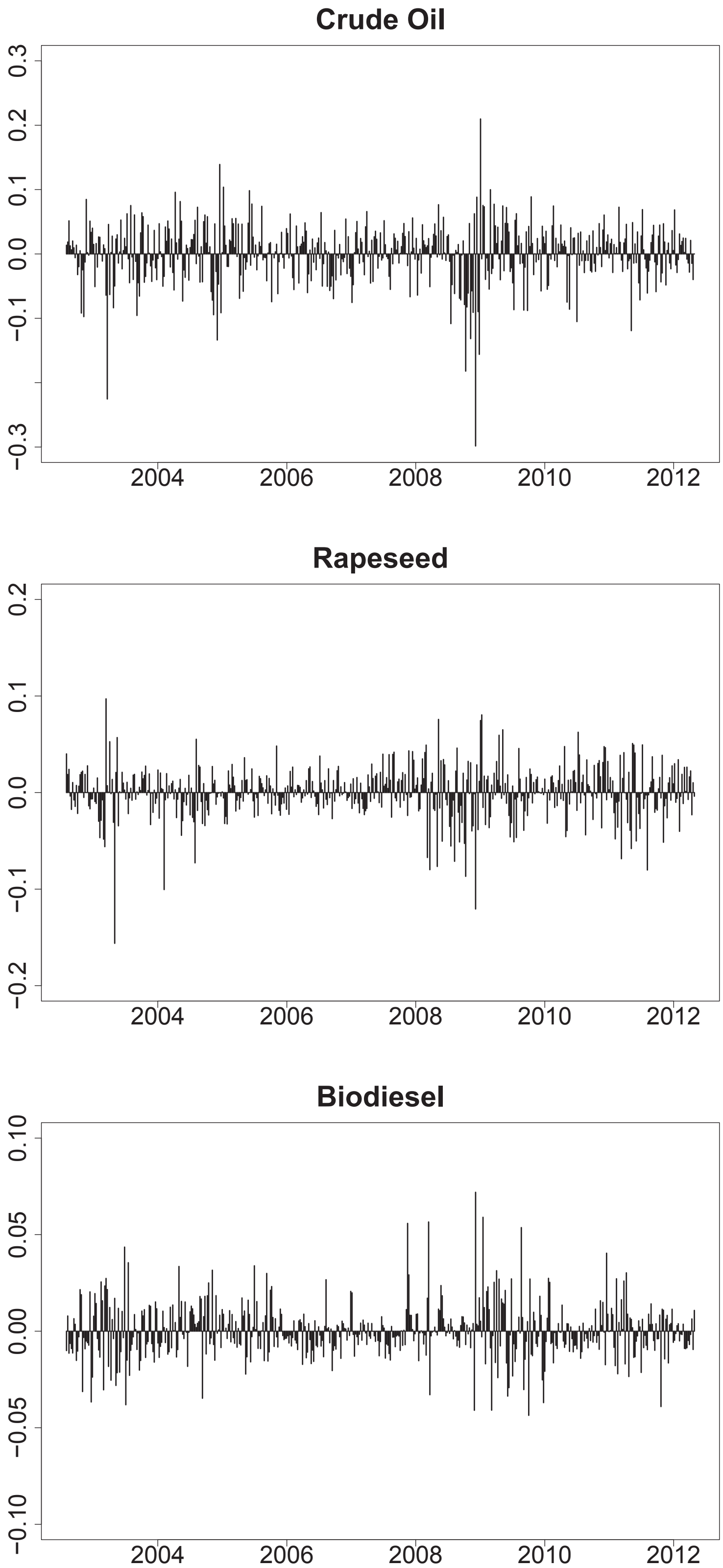

Figure A.1: VECM residuals

	Residuals			Squared residuals		
	Test Statistic	p-Value	lags	Test Statistic	p-Value	lags
Crude oil	15.07	0.12	20	9.91	0.002	1
Rapeseed	23.82	0.25	20	6.60	0.037	2
Biodiesel	14.23	0.82	20	17.33	0.000	1

Table A.5: Box-Ljung test for autocorrelation of the VECM residuals and the squared VECM residuals

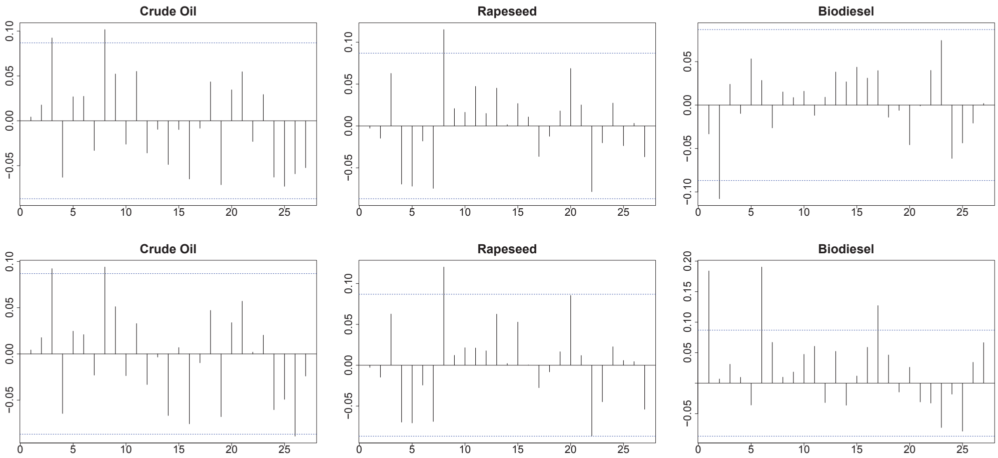

Figure A.2: ACF (upper panel) and PACF (lower panel) of the VECM residuals

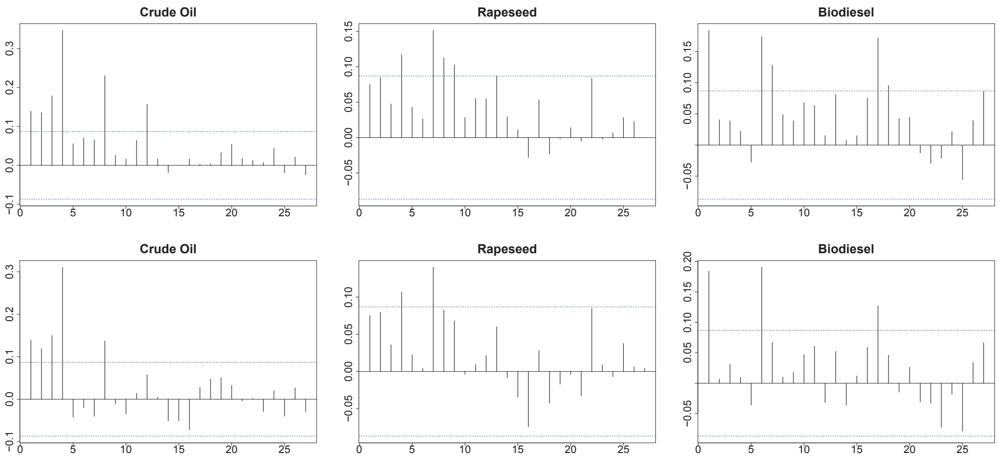

Figure A.3: ACF (upper panel) and PACF (lower panel) of the squared VECM residuals

	Test Statistic	p-Value
Crude oil	0.94	4.21e-13
Rapeseed	0.95	1.35e-11
Biodiesel	0.95	1.16e-11

Table A.6: Shapiro-Wilk test for normality of the VECM residuals

	Crude Oil		Rapeseed		Biodiesel	
ω_i	-1.0440	(0.1855)	-0.2917	(0.1389)	-1.5537	(0.4431)
α_i	-0.1877	(0.0706)	-0.0421	(0.2360)	0.0284	(0.8299)
β_i	0.8339	(0.0000)	0.9590	(0.0000)	0.8162	(0.0006)
γ_i	0.1440	(0.0132)	0.2405	(0.0000)	0.4424	(0.0360)
	DCC Parameters					
a	0.0118	(0.0837)				
b	0.9743	(0.0000)				

Table A.7: Estimates of the DCC-EGARCH(1,1). P-value in parentheses

	Crude Oil		Rapeseed		Biodiesel	
ω_i	-0.7590	(0.4215)	-0.3890	(0.0997)	-1.4830	(0.4107)
α_i	-0.1460	(0.1997)	-0.0480	(0.2510)	0.0153	(0.7699)
β_i	0.8800	(0.0000)	0.9476	(0.0000)	0.8286	(0.0000)
γ_i	0.1254	(0.0178)	0.2380	(0.0000)	0.4774	(0.0436)
ν_i	1.4313	(0.0000)	1.3018	(0.0000)	1.2339	(0.0000)
	DCC Parameters					
a	0.0124	(0.1003)				
b	0.9727	(0.0000)				

Table A.8: Estimates of the DCC-EGARCH(1,1) model with generalized error distribution with shape parameter ν. P-value in parentheses

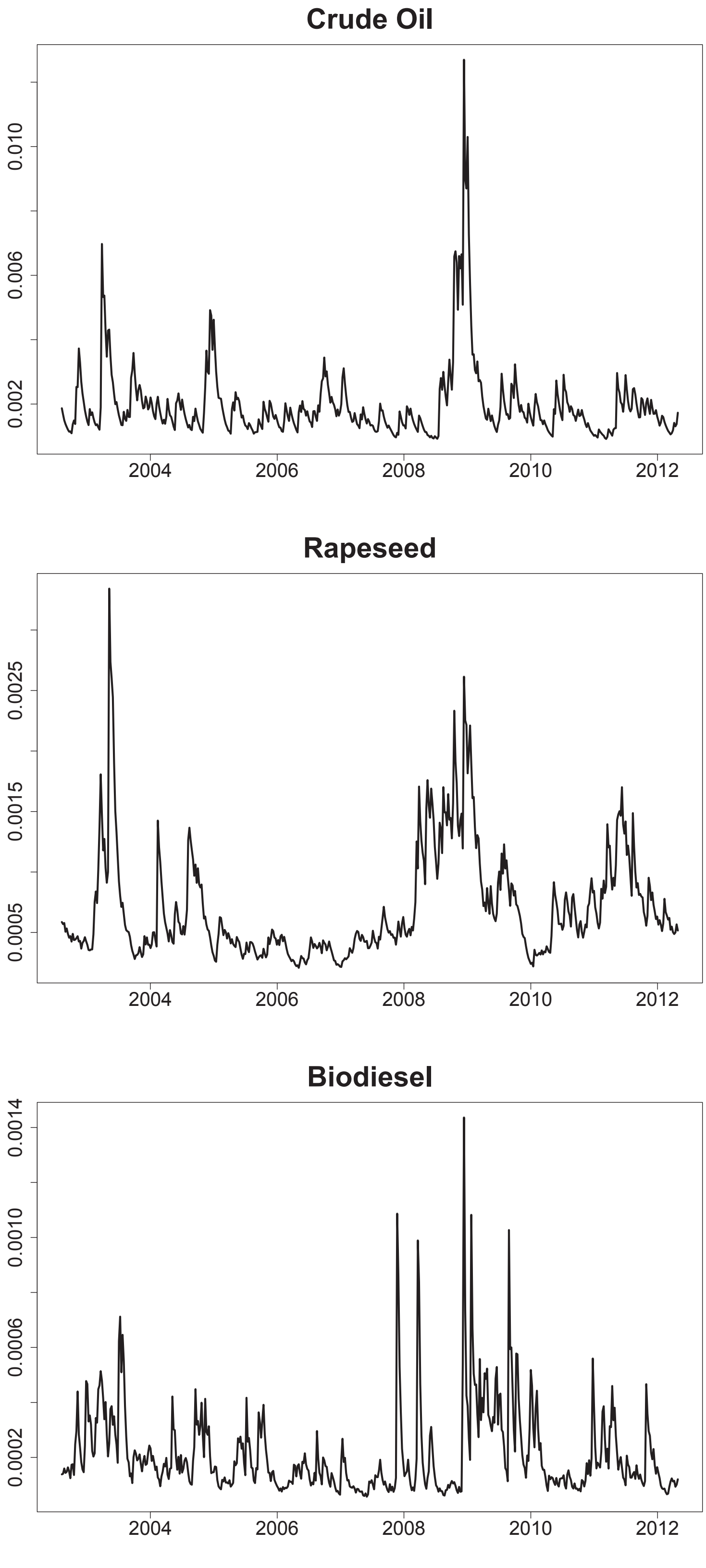

Figure A.4: Conditional variance estimates

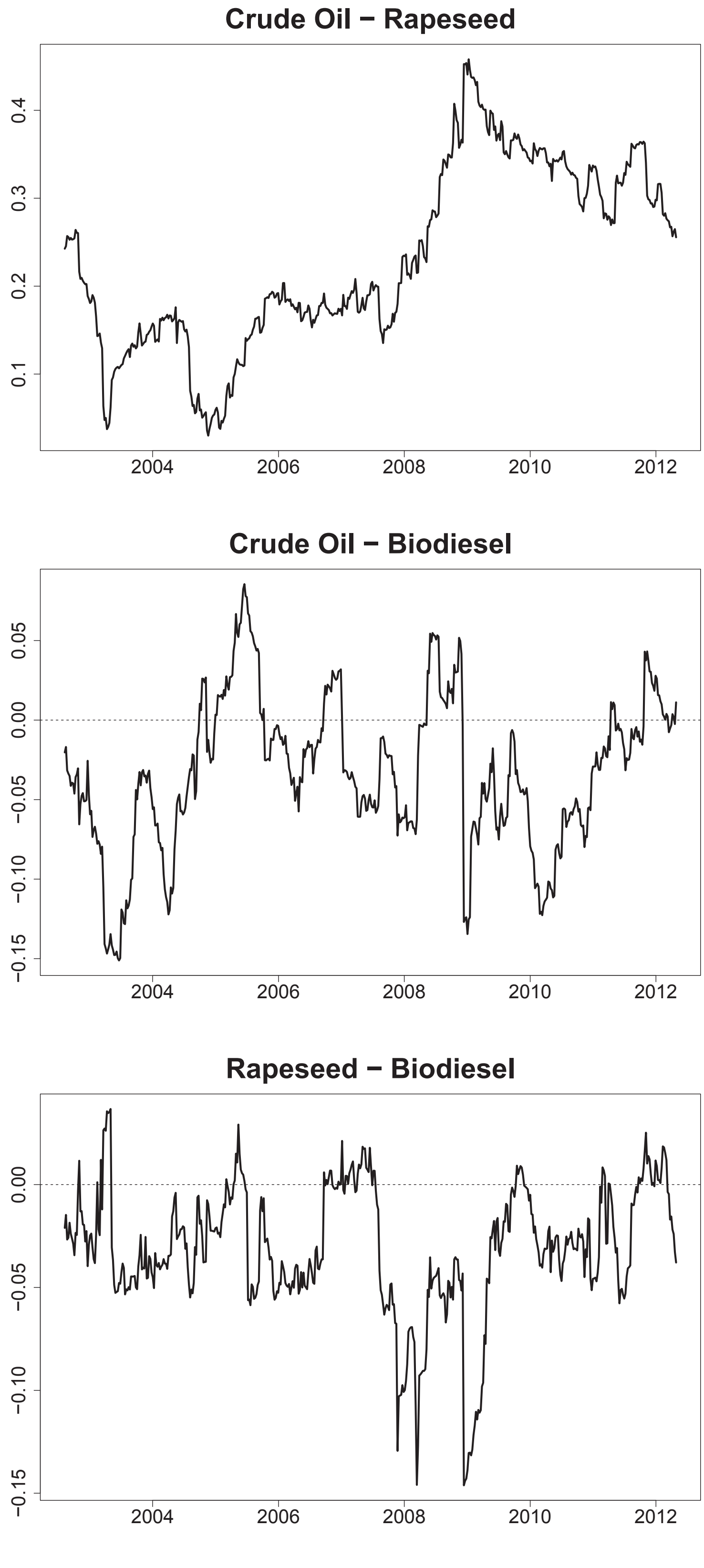

Figure A.5: Conditional correlation estimates

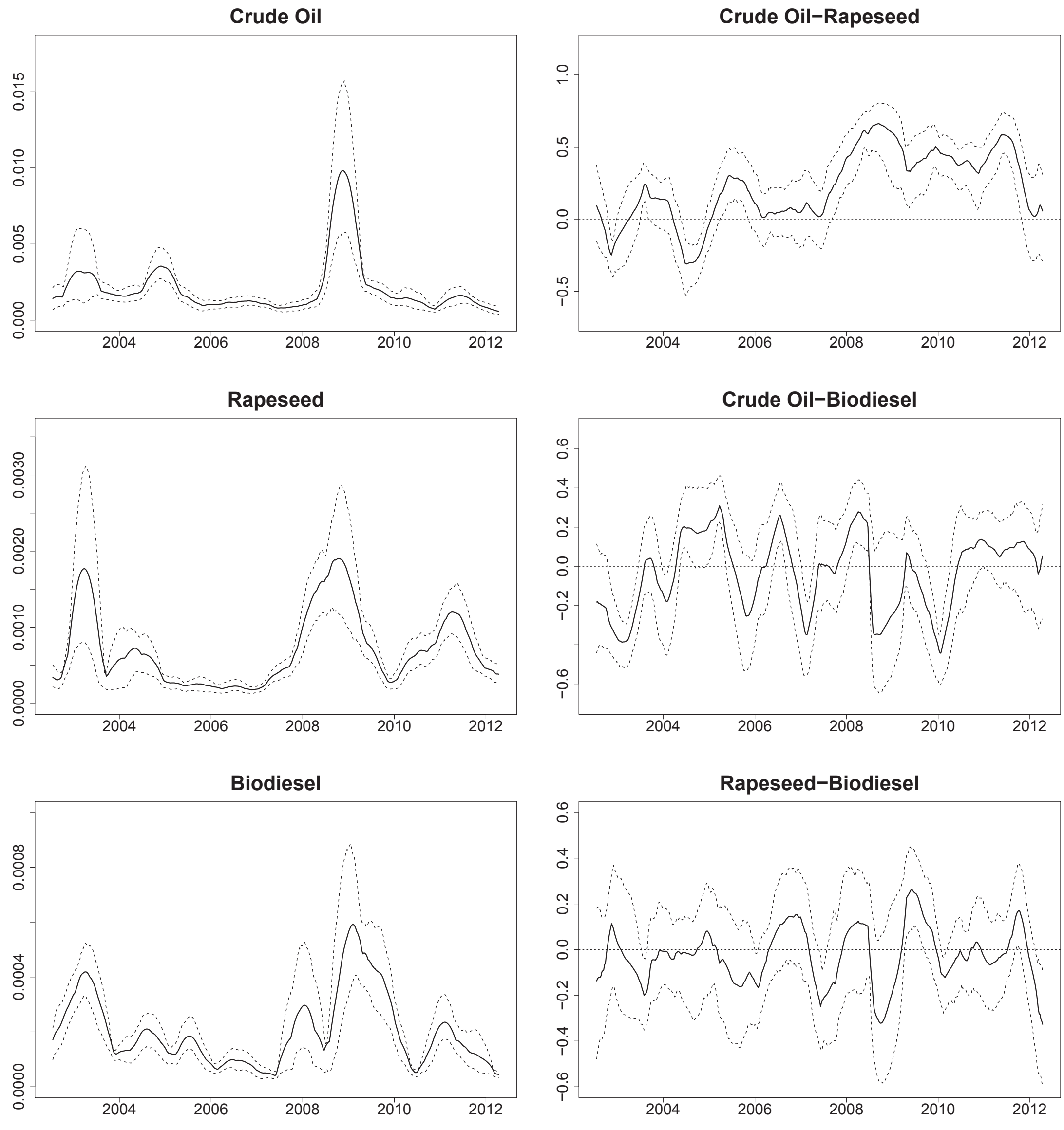

Figure A.6: Unconditional variance and correlation estimates with 90% pointwise confidence intervals

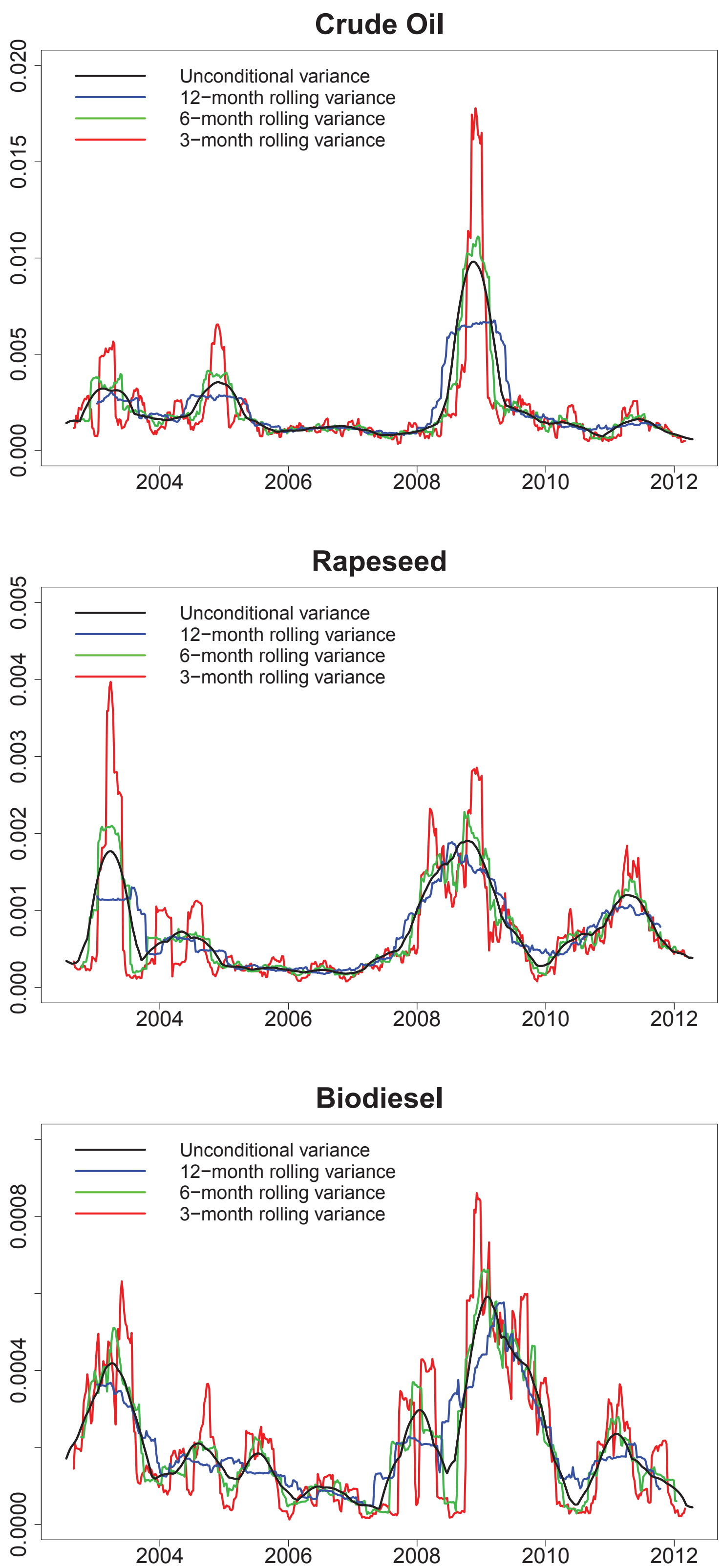

Figure A.7: Unconditional variance estimates compared to rolling window variances

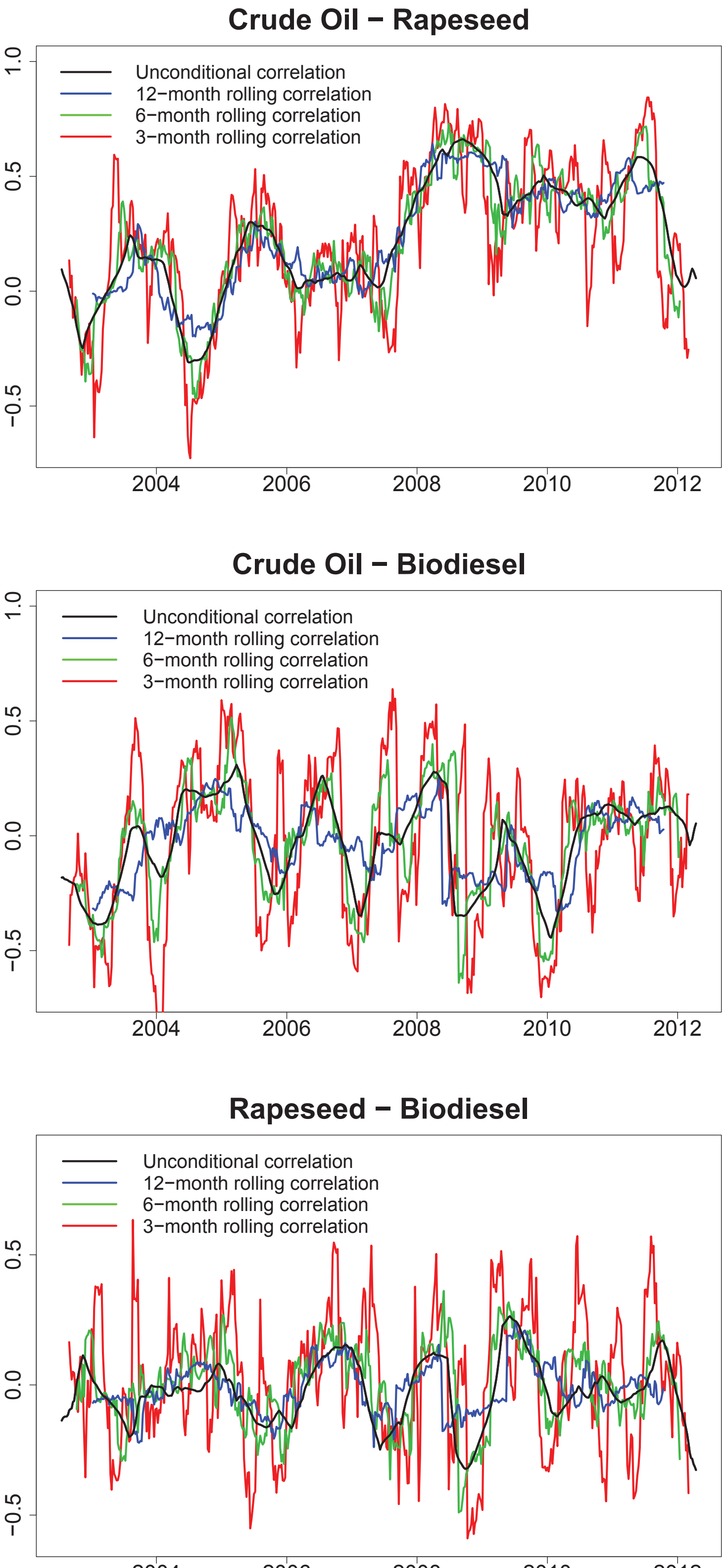

Figure A.8: Unconditional correlation estimates compared to rolling window correlations

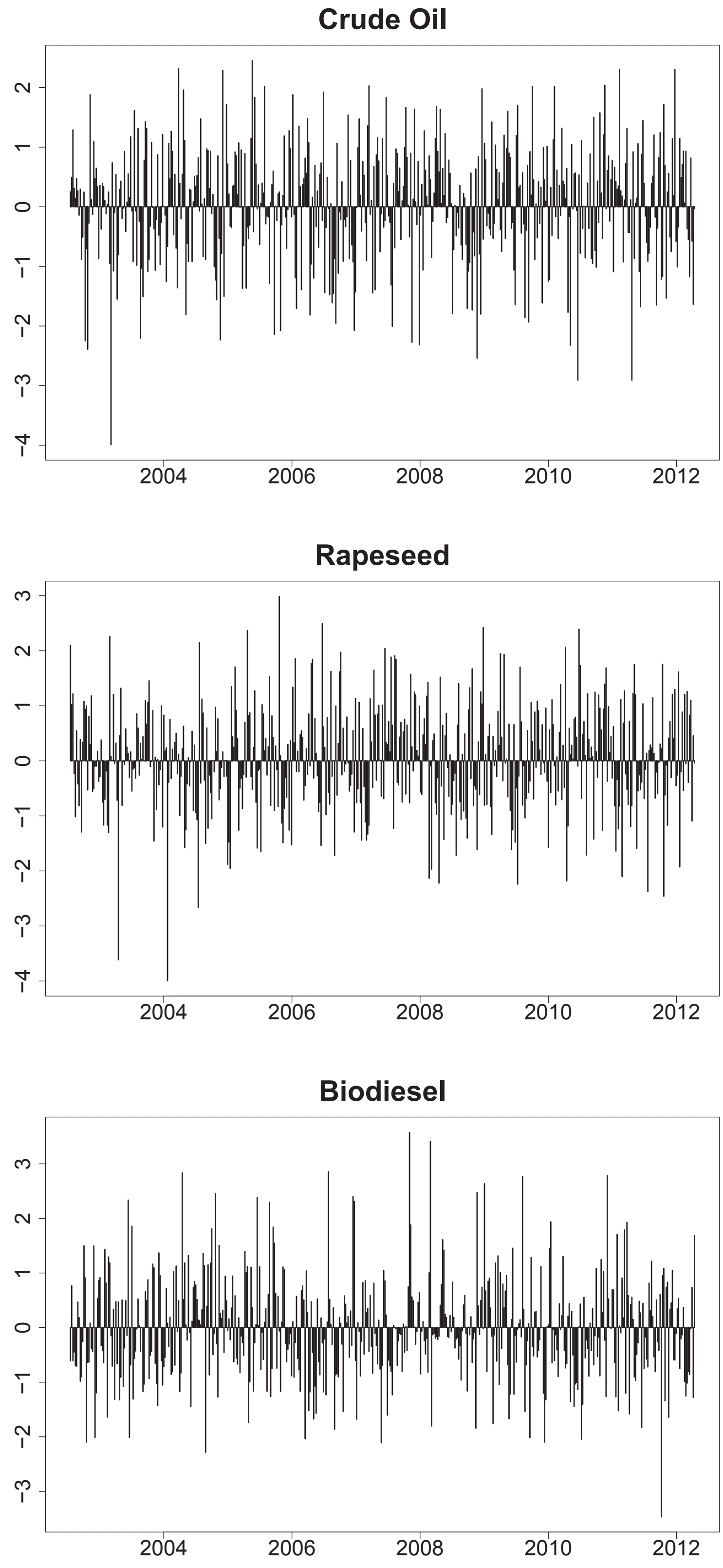

Figure A.9: Residuals of the nonparametric covariance estimation

Declaration of Authorship

I hereby confirm that I have authored this master thesis independently and without use of others than the indicated sources. Where I have consulted the published work of others, in any form (e.g. ideas, equations, figures, text, tables), this is always explicitly attributed.

Berlin, October 29th, 2012 Franziska Schulz