

The regime-dependent adjustment in energy spot and futures markets – a smooth transition approach

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Abstract

This paper analyzes the relationship between spot and futures prices for energy commodities from a new perspective. Based on data from the Dow Jones UBS Commodity Index, we first test for a long-run relationship between spot and futures prices. As a second step, smooth transition models are fitted to examine whether the adjustment of spot returns to the forward premium follows a nonlinear path. Although the findings show that the informational content of futures prices varies between different commodities, a similar pattern arises for all of them: The predictive power of futures prices can only be observed if previous volatility or basis has been low while no relationship occurs if both have been high previously.

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1. Introduction

Sharp movements and advancing volatility in energy prices have triggered concerns due to the consequent disturbing economic impacts. The question whether futures are a leading indicator of future spot price movements is an important topic in this context. If futures prices are not able to perform such a function, policymakers are in need of alternative forecasting devices or public policy actions to mitigate the effects of energy price uncertainty (Chinn et al., 2005).

In general, futures markets perform four major functions: First, they facilitate stockholding as the forward premium acts as a mechanism guide to inventory control and may be interpreted as a return on a hedged stock. Second, futures markets enable investors to hedge risk, as investors who are exposed to futures price movements are able to transfer that risk to speculators. The third function stems from the fact that futures prices act as centers for the collection and conversion of information. Finally, they perform a price discovery function which will be considered in greater detail when analyzing the relationship between spot and futures prices (Goss, 1981). Due to the engagement of speculative capital which introduces volatility and movements away from fundamentals, a critical issue arises whether these functions operate appropriately.

Since the turn of the millennium, the policy of low interest rates of many central banks in combination with a growing world economy resulted in an excess global liquidity. An increasing number of speculative funds and financial derivatives have entered the futures markets for commodities, and a new type of market participant called commodity index investor appeared in futures markets for energy commodities. Such a commodity index allows investors to trace the performance of a basket of commodities while following a long-term investment strategy of 'buy and hold.' These kinds of speculative assets could yield an excess demand for energy feedstocks which drives futures prices upwards and finally, pushes up spot prices (Fan and Xu, 2011).

A potential impact of speculative trading in futures markets for energy commodities on the intense rise in prices of the latter was subject of an extensive debate in academic literature and the media during recent years. Masters (2008) as well as Masters and White (2008) argue that considerable buy-side pressure from index funds recently created a speculative bubble in commodity prices with the consequence that prices at their highest level heavily exceeded their fundamental values. On the other hand, the US Commodity Futures Trading Commission (CFTC) argues that the level of speculation in commodity futures markets has

remained relatively constant in percentage as prices have risen (CFTC, 2008). However, Chilton (2008) states that the CFTC survey was preliminary and requires further revisions since the historical dataset on speculative trading used was potentially not sufficient due to a lack of transparency as a consequence of inadequate supervision and the complexity of such an over-the-counter market. Moreover, further studies exist that trace back the heavy increase especially in oil prices since 2000 to the ascending speculation in futures markets (Chevillon and Riffart, 2009; Cifarelli and Paladino, 2009; Kaufmann and Ullman, 2009; Fan and Xu, 2011). On the other hand, Irwin and Sanders (2012) cannot confirm this hypothesis of a speculative price bubble in commodity prices empirically and conclude that the price discovery role in commodity futures markets is not harmed by speculators.

When analyzing the relationship between spot and futures prices for commodities, early studies conducted Granger (1969) causality tests and standard cointegration techniques such as the Engle and Granger (1987) methodology or the Johansen (1988) framework (MacDonald and Taylor, 1988; Oellermann et al., 1989; Koontz et al., 1990; Serletis and Banack, 1990; Schroeder and Goodwin, 1991; Quan, 1992; Crowder and Hamid, 1993; Schwartz and Szakmary, 1994; Foster, 1996; Gülen, 1998; Peroni and McNow, 1998; McKenzie and Holt, 2002; McAleer and Sequeira, 2004). However, emphasizing financial market frictions such as high transaction costs, the role of noise traders, and the microstructure effects of commodity markets, spot and futures markets could be characterized by a nonlinear price adjustment (Silvapulle and Moosa, 1999; Chen and Lin, 2004; Bekiros and Diks, 2008; Huang et al., 2009; Lin and Liang, 2010). This nonlinear structure of the relationship between spot and futures prices could depend on the current value of the basis, the spread, and the forward premium, respectively, which should denote the difference between the current period's price of a futures contract for delivery in the next period and the current spot price in the following. Hence, if the spot price is above the futures price, what is known as backwardation, the basis is negative, and if the magnitude of the basis exceeds a certain level, investors would start selling commodities at the spot market and buying futures contracts. Conversely, if the futures price is above the spot price, what is called contango, the basis is positive, and if again the magnitude of the basis exceeds a certain threshold, investors in this case would start selling futures contracts and buying commodities at the spot market. The threshold could be characterized by 'carrying costs' which makes an investor indifferent of buying a spot commodity or a futures contract. In between these two scenarios, investors may show just a slight reaction within a certain range (Huang et al., 2009). This argument is

related to the existence of limits to speculation which states that investors only follow an investment strategy if the expected yield is higher than the one implied by other strategies (Sarno et al., 2006). In the recent literature this kind of nonlinearity has been accounted for by using methods such as the threshold autoregressive (TAR) model developed by Tong (1983), the momentum TAR (M-TAR) model suggested by Enders and Granger (1998) as well as Enders and Siklos (2001), the multivariate TAR (MVTAR) model proposed by Tsay (1998) and the threshold vector error correction (TVECM) model developed by Hansen and Seo (2002) (Ewing et al., 2006; Huang et al., 2009; Lin and Liang, 2010; Mamatzakis and Remoundos, 2011).¹

However, all those studies allow for a discrete switching from one scenario to the other. Such a pattern seems inadequate in cases where investors with different expectations and risk assessments are involved. Market participants may not all act promptly and uniformly as they are confronted with heterogeneous information and opportunity costs which implies different bands of inaction. In addition, their reaction to new information might also exhibit different delays (Teräsvirta, 1998). A more appropriate modeling strategy which corresponds to a smooth switching between two extreme regimes has been inspired by the work of Teräsvirta (1994).

In this vein, the present paper contributes to the literature by applying the corresponding smooth transition regressive (STR) models for the spot and forward relationships of energy commodities. Such models bear the main advantage of allowing for different dynamics which are determined by the choice of the transition function. The latter is either of exponential form to account for a symmetric but size increasing adjustment in both extreme regimes or logistic form to allow for a more flexible asymmetric adjustment above and below a certain threshold value. Hence, such a framework enables us to tackle the question whether futures markets exhibit speculation or incorporate new information in prices from a new perspective. Previous findings suggest that the informational content of futures prices varies between different energy commodities (Chinn et al., 2005). For this reason, we survey the overall Dow Jones UBS energy index as well as the corresponding four individual commodities.

¹ Furthermore, Cunado and Perez de Garcia (2003) as well as Maslyuk and Smyth (2009) used the Gregory and Hansen (1996) framework to account for the presence of structural breaks in the relationship between spot and futures prices. Recently, Lee and Zeng (2011) used quantile cointegration regression to describe the connection between oil spot and futures.

The remainder of the paper is organized as follows. The next section describes the general relationship between prices for spot and futures. The empirical part of the study is presented in section 3. After examining the time series properties and testing for cointegration between spot and futures prices we proceed by applying a framework which allows for a nonlinear adjustment of the spot return with respect to the forward premium. Section 4 concludes.

2. The model

As stated above, under the joint assumption of risk neutrality and rationality the current period's price of a futures contract for delivery in the next period is an unbiased estimator of the expected next period's spot price (Gülen, 1998; Kellard, 2002; Huang et al., 2009; Switzer and El-Khoury, 2007; Lin and Liang, 2010). Thus, the unbiasedness hypothesis is given below

$$E_t(s_{t+k}) = f_{t,k}, \quad (1)$$

where s_{t+k} denotes the logarithm of the spot price at time $t + k$, $f_{t,k}$ represents the logarithm of the price of a futures contract observed at time t for delivery at time $t + k$, and $E_t(\cdot)$ gives the expectations operator conditional on information available at time t . Equation (1) could be transformed as follows

$$s_{t+k} = f_{t,k} + u_{t+k}, \quad (2)$$

where u_{t+k} indicates an uncorrelated random error term with zero mean and constant variance. Moreover, subtracting s_t , the logarithm of the spot price at time t , on both sides of equation (2) yields the Fama (1984) regression

$$\Delta s_{t+k} = \alpha + \beta(f_{t,k} - s_t) + u_{t+k}, \quad (3)$$

where $\Delta s_{t+k} \equiv s_{t+k} - s_t$ denominates the spot return and the unbiasedness hypothesis given above presumes $\alpha = 0$ and $\beta = 1$.² As outlined in the introduction, equation (3) neglects the possibility of nonlinearity in the relationship between the spot return and the forward premium represented by the difference of the current futures and spot price. To allow for this kind of dynamics, we augment equation (3) as follows

² The Fama (1984) approach which is based on the theory of uncovered interest rate parity (UIP) has been used by Sarno et al. (2006), Baillie and Kilic (2006), Hochradl and Wagner (2010), Olmo and Pilbeam (2011) as well as Pilbeam and Olmo (2011) to analyze the relationship between the spot return and the forward premium for different exchange rates. The theory of UIP also implies $\alpha = 0$ and $\beta = 1$.

$$\Delta s_{t+k} = [\alpha_1 + \beta_1(f_{t,k} - s_t)] + [\alpha_2 + \beta_2(f_{t,k} - s_t)]F(z_t, \gamma, c) + u_{t+k}, \quad (4)$$

where $F(z_t, \gamma, c)$ is a transition function which ascertains the speed of adjustment and could either be a logistic or an exponential function. Moreover, equation (4) can be interpreted as a nonlinear error correction framework for the spot return with respect to a proportional long-run relationship between $f_{t,k}$ and s_t . The terms α_1 and β_1 correspond to the lower regime, while $(\alpha_1 + \alpha_2)$ and $(\beta_1 + \beta_2)$ belong to the upper regime of the adjustment process (van Dijk et al., 2002). Thus, β_1 and $(\beta_1 + \beta_2)$ can be interpreted as the error correction coefficients implying that values between 0 and 1 indicate that the spot return adjusts to the premium spread.³ While the strategy to select the adequate transition function and the technical details will be discussed and applied in the next section, it seems reasonable to point out the main differences between both formulations at this stage of the analysis. Although both configurations are close substitutes, they refer to different patterns of nonlinearities. In a nutshell, a logistic transition function allows for different adjustment above and below a threshold while the exponential transition function accounts for a distinction between small and large deviations from a threshold.

3. Data, methodology and empirical results

3.1 Data

Our analysis is based on data from the Dow Jones UBS Commodity Index (DJ-UBSCI) which is composed of commodities traded on U.S. exchanges and provided by Dow Jones Indexes (<http://www.djindexes.com/commodity/>). The DJ-UBSCI is weighted by the relative amount of trading activity of a particular commodity and has been known as the Dow Jones AIG Commodity Index until 2009. Beside the S&P Goldman Sachs Commodity Index (GSCI) the DJ-UBSCI is one of the two largest indices by market share.⁴ More precisely, we apply the subindex of prices for spot as well as for the three month futures contracts for energy products. We are also interested in the corresponding individual commodities, namely crude oil, heating oil, natural gas, and unleaded gasoline on a daily basis. Our sample period covers each working day from January 2, 1991 to October 19, 2011 and thus, exhibits the largest

³ Values above unity would indicate an overshooting of the error correction and values below zero report that the dynamic pattern is explosive.

⁴ See Tang and Xiong (2010) and Gilbert (2010) for details regarding the DJ-UBSCI and its subindices. Following Tang and Xiong (2010) the correlation between the GS and the DJ-UBS commodity indices is over 0.9. As a result, using GSCI would not significantly change our findings. Among others, Irwin and Sanders (2012) applied the DJ-UBSCI data set for a similar purpose.

available sample size which contains the low volatility period until the early 2000's as well as the high volatility period thereafter. Fan and Xu (2011) divided the price fluctuations in the oil market after 2000 into three stages in their study: the 'relatively calm market' period (from January 7, 2000, to March 12, 2004), the 'bubble accumulation' period (from March 19, 2004, to June 6, 2008), and the 'global economic crisis' period (from June 13, 2008, to September 11, 2009).

As it is common practice, we take each series as logarithm in the following. To estimate equation (4) for each spot and futures market in the context of cointegration we first have to assure that each of the current spot and futures prices is integrated of order one, e.g. $I(1)$, and both are cointegrated as well as each spot return is $I(0)$. Thus, we use the augmented Dickey-Fuller (ADF) test to check the null of a unit root in each series (Dickey and Fuller, 1979). We apply an auxiliary regression with an intercept, but without a trend regressor since a graphical inspection shows that neither series exhibits a time dependent mean. Thus, we test the null of a random walk process without drift against the alternative of a stationary process with non-zero mean for the level of each series. The results are displayed in Table 1 and indicate that the null cannot be rejected for each series. Thus, each spot and futures price can be regarded as $I(1)$ since the same null can clearly be rejected for the first difference of each series denoted by Δ . The spot return is constructed by $\Delta s_{t+k} \equiv s_{t+k} - s_t$ with $k = 66$ since we use three month futures to estimate equation (4) and 66 equals the number of working days during three months. As can be seen in Table 1, each spot return is stationary, e.g. $I(0)$.⁵

Table 1 about here

3.2 Methodology and empirical results

As a next step, we analyze whether a long-run relationship between spot and futures can be detected. After checking for cointegration we test the null of a linear specification given by equation (3) against a nonlinear specification of the form shown in equation (4) and we apply an empirical selection procedure to choose the appropriate transition function.

⁵ We have also applied the more powerful Ng and Perron (2001) MZa test to ascertain the robustness of our findings. These statistics are report in Table 1 as well. To account for the possibility of structural breaks in our series which in general reduce the power of conventional unit root tests to reject the null, we have conducted the Perron (1989) test in the fashion as described by Perron and Vogelsang (1992). The findings are not presented to save space, however these support our results given in Table 1.

3.2.1 Testing for cointegration

We start our analysis by applying the multivariate cointegration test by Johansen (1988, 1991), which draws upon the following vector autoregression representation (VAR):

$$\Delta Y_t = \Pi Y_{t-1} + \Gamma(L)\Delta Y_{t-l} + \Phi D_t + \epsilon_t, \quad t = 1, \dots, T, \quad (5)$$

where $Y_t = [f_{t,k}, s_t]'$. The non-stationary behavior of both series is accounted for by a reduced rank ($r < p$) restriction of the long-run level matrix Π , which can be fragmented into two $r \times p$ matrices α and β' ($\Pi = \alpha\beta'$). β' gives the coefficients of the variables for the r long-run relation, while α contains the adjustment coefficients describing the reaction of each variable to disequilibria from the r long-run relations given by the $r \times 1$ vector $\beta' Y_{t-1}$. The deterministic components are given by the $(p \times 1)$ vector ΦD_t , while ϵ_t describes an independent and identically distributed error term. The term $\Gamma(L)\Delta Y_{t-l}$ describes the short-run dynamics of the model using p equations between current variables, L-lagged variables and equilibrium errors (Juselius, 2006).

To identify the rank, that is, the number of cointegrating relations r , we rely on the trace test developed by Johansen (1988). The idea of the test is to separate the eigenvalues λ_i , $i = 1, \dots, r$, which correspond to stationary relations, from those eigenvalues λ_i , $i = r + 1, \dots, p$ which belong to non-stationary eigenvectors. The test statistic of the corresponding likelihood test, the so-called trace test, is given by $trace(r) = -T \sum_{i=r+1}^p \log(1 - \hat{\lambda}_i)$. Starting with the hypothesis of full rank, the rank r is determined by using a top-bottom procedure until the null cannot be rejected (Juselius, 2006). For the specification of all models, the choice of the lag length is based on tests for autocorrelation. The results of the trace tests are shown in Table 2.

Table 2 about here

According to the test statistic, the hypothesis of a rank of zero can be rejected for each spot and futures market relation at the 5% and 10% level, respectively. Moreover, the null of a rank of at most one cannot be rejected in each case.

After the determination of the rank, we followed the Johansen (1988, 1991) approach and computed the maximum likelihood estimates of the unrestricted cointegrating relations $\beta' Y_{t-1}$ for the each configuration. The corresponding results are given in column 4 of Table 2 and show that each pair of coefficients is theory-consistent in terms of sign and magnitude with

spot and futures prices always being positively related.⁶ The failure to find a strictly proportional long-run relationship between them might be attributed to nonlinear adjustment which may bias downward the speed of adjustment if a linear specification is used (Taylor, 2006). Thus, in the following we assume that each spot and futures price pair is cointegrated with a coefficient of unity and use these proportional long-run relations as transition variables for our STR models when allowing for nonlinearities in the adjustment of spot returns to the spread between both.⁷

3.2.2 Framework and tests for nonlinearity in the relationship between spot and futures prices

As outlined in section 2, two different forms of nonlinearity are considered, namely the exponential as well as the logistic case. To explain the underlying dynamics presume first that $F(z_t, \gamma, c)$ is modeled by a bounded continuous exponential transition function which lies between 0 and 1 and thus, has the following functional form:

$$F(z_t, \gamma, c) = 1 - \exp(-\gamma(z_t - c)^2 / \sigma_{z_t}) \text{ with } \gamma > 0, \quad (6)$$

where z_t indicates the transition variable, σ_{z_t} represents its standard deviation, γ denotes a slope parameter and c is a location parameter. In order to create a scale-free smoothness parameter, γ is normalized by the standard deviation of the transitional variable z_t , as suggested by Teräsvirta (1998). The transition function given by equation (6) is symmetrically U-shaped as $F(z_t, \gamma, c) \rightarrow 1$ for $z_t \rightarrow \pm\infty$ and $F(z_t, \gamma, c) \rightarrow 0$ for $z_t = c$, so that an adjustment for deviations of the transition variable z_t above and below the location parameter c , which can be interpreted as a threshold value, is symmetric as opposed to the under mentioned logistic case. The slope parameter γ determines the speed of the transition between the extreme regimes, with lower absolute values implying slower transition.

Considering the second case where $F(z_t, \gamma, c)$ in equation (4) is a bounded continuous logistic transition function which lies between 0 and 1. Therefore, it has the following form:

$$F(z_t, \gamma, c) = [1 + \exp(-\gamma(z_t - c) / \sigma_{z_t})]^{-1} \text{ with } \gamma > 0. \quad (7)$$

⁶Among others Crowder and Hamid (1993), Peroni and McNown (1998), McKenzie and Holt (2002) as well as Switzer and El-Khoury (2007) support our finding of a cointegration relationship between spot and futures prices for commodities.

⁷We have also applied the particular estimated cointegrated relationships instead of the proportional relations, however our findings stayed qualitatively unchanged. Hence, we only report the results for the latter since these are more feasible in terms of interpretability.

Thus, this implies that the lower (upper) regime is associated with negative (positive) values of the transition variable z_t relative to the location parameter c . The logistic function increases monotonically from 0 to 1 as the transition variable increases, so that $F(z_t, \gamma, c) \rightarrow 0$ as $z_t \rightarrow -\infty$ and $F(z_t, \gamma, c) \rightarrow 1$ as $z_t \rightarrow +\infty$ while it takes the value 0.5 if $z_t = c$. Hence, again the location parameter can be interpreted as a threshold value dividing equation (4) into three different extreme regimes corresponding to $\lim_{z_t \rightarrow -\infty} F(z_t, \gamma, c)$, $\lim_{z_t \rightarrow +\infty} F(z_t, \gamma, c)$ and $z_t = c$. In case of $z_t = c$ equation (4) reduces to the linear model given by equation (3) with $\alpha = \alpha_1 + 0.5\alpha_2$ and $\beta = \beta_1 + 0.5\beta_2$. Moreover, the smoothness parameter γ again gives the speed of transition between extreme regimes (Baillie and Kilic, 2006).

A natural choice for the transition variable is the basis $f_{t,k} - s_t$ with several lags j up to one week. Following Franses and van Dijk (2000), an interesting alternative is the average absolute difference between spot and futures during the last week. This measure has the advantage of approximating the overall volatility instead of focusing on a particular kind of previous prices.

In the following the use of equation (4) in combination with equation (6) and (7) is referred to as the exponential STR or ESTR and the logistic STR or LSTR, respectively. In terms of interpretation, it is worthwhile mentioning that the threshold c is unrestricted in the present study. If a strictly proportional long-run relationship between spot and futures exists, the latter might also be restricted to zero in the fashion of a smooth transition error correction model suggested by Van Dijk et al. (2002). However, although this would facilitate the interpretation of the results, an unrestricted threshold seems more appropriate as a proportional long-run relationship cannot be verified for each commodity. Owing to the fact that we also consider a volatility measure, this does not alter the interpretability of our outcomes.

The modeling cycle for smooth transition models suggested by Teräsvirta (1994) starts with a test for nonlinearity. The null hypothesis of linearity can be expressed as either $H_0: \gamma = 0$, or $H_0: \beta_1 = \beta_2$. However, both γ and β_2 are unidentified under the null hypothesis. Consequently, standard asymptotics cannot be applied due to the existence of nuisance parameters (Van Dijk et al., 2002). To overcome this caveat, Teräsvirta (1994) suggests an approximation of the transition function by a third order Taylor approximation. Thus, the

corresponding lagrange multiplier (LM) test for linearity introduced by Luukkonen et al. (1988) can be expressed as ⁸

$$\begin{aligned} \Delta s_{t+k} = & \varphi_0 + \varphi_1(f_{t,k} - s_t) + \varphi_2(f_{t,k} - s_t)z_t + \varphi_3(f_{t,k} - s_t)z_t^2 \\ & + \varphi_4(f_{t,k} - s_t)z_t^3 + \epsilon_{t+k}. \end{aligned} \quad (8)$$

The null hypothesis which refers to the linear model being adequate is tested as $H_0: \varphi_i = 0$ with $i = 2,3,4$ against the alternative H_1 that at least one $\varphi_i \neq 0$, implying that the higher order terms are significant (Teräsvirta, 1998). The test statistic has a χ^2 distribution with three degrees of freedom.⁹ This proceeding also enables the choice of an adequate transition variable. In the case of the linearity hypothesis being rejected, a method for choosing the latter lies in computing the test statistic for several transition functions, i.e. different values of the lag order j , and selecting the configuration for which its value is maximized (Taylor et al., 2001; van Dijk et al., 2002). Teräsvirta (1994, 1998) has shown that this approach works well in most cases. In the present study, delays from one to five days are considered.¹⁰ The results of the LM tests presented in Table 3 show that the hypothesis of linearity is rejected for all commodities and lag orders j .

Table 3 about here

Hence, the overall conclusion is that a nonlinear framework is adequate. An inspection of the tests statistics shows that the optimal transitions variable differs with the measure of volatility as well as different lag orders for the forward spread considered to be the most adequate choice in some cases. In order to achieve comparable and robust results, two different models will be estimated in the following: One configuration based on the volatility measure and another one on the lagged spread associated with the highest test statistic. This proceeding always includes the optimal transition variable for each commodity and enables us to draw

⁸ In the case of small samples in combination with a large number of explanatory variables, F versions of the LM test statistics are preferable, as they have better size properties (Granger and Teräsvirta, 1993; Teräsvirta, 1998; van Dijk et al., 2002).

⁹ The number of degrees of freedom $3p$ refers to the number of regressors p which in our case is one. Furthermore, the test assumes that all regressors as well as the transition variable z_t are stationary and uncorrelated with the error in equation (4) u_{t+k} (Teräsvirta, 1998). As shown in section 3.2.1 our only regressor and transition variable $(f_{t,k} - s_t)$ is a stationary linear combination of non-stationary $I(1)$ variables.

¹⁰ Longer delays have turned out to be less suitable in previous estimations carried out by the authors. The results are available upon request.

clear conclusions as the thresholds for the lagged forward premium and the volatility hold different implications.

3.2.3 Testing for the appropriate specification

Following Granger and Teräsvirta (1993), Teräsvirta (1994, 1998) as well as van Dijk et al. (2002) the above shown LM testing procedure can also be applied to distinguish between an exponential and a logistic transition function and thus, to choose the appropriate specification. If the linearity null has been rejected, equation (8) is used to test the following hypotheses successively

$$\begin{aligned} H_{04}: \varphi_4 &= 0, \\ H_{03}: \varphi_3 &= 0 \mid \varphi_4 = 0, \\ H_{02}: \varphi_2 &= 0 \mid \varphi_3 = \varphi_4 = 0, \end{aligned} \tag{9}$$

The decision rule to select the most adequate transition function introduced by Teräsvirta (1994) is as follows. If the rejection of H_{03} is the strongest one in terms of lowest p-value or largest test statistic, respectively, the ESTR model should be chosen, otherwise the LSTR model should be preferred.¹¹ Table 4 displays the empirical realizations of the test statistics and corresponding p-values for the two configurations of each commodity.

Table 4 about here

As can be seen, the ESTR specification turns out to be most adequate for crude oil while the LSTR specification is selected for heating oil, natural gas, and unleaded gasoline. In case of the whole energy index the LSTR model is preferred if using the lagged forward premium as transition variable and the ESTR seems to be appropriate if the latter is approximated by last weeks' volatility. Thus, for the energy index we estimate both specifications for both transition variables.

3.2.4 Estimation results

The results of our estimations carried out by nonlinear least squares (NLS) are presented in Table 5.

Table 5 and Figure 1 about here

¹¹ See Granger and Teräsvirta (1993) or Teräsvirta (1994) for details.

It may be worthwhile mentioning first of all that the observed insignificance of the transition parameter γ can in some cases not be interpreted as evidence against a smooth transition model, since the t-statistics need to be interpreted with caution (Taylor et al., 2001; van Dijk et al., 2002). The cause for an observed insignificance of γ is occasionally the circumstance that there are only few observations in the region of transition between two regimes as shown in Figure 1. Nevertheless, it becomes evident that the conducted smooth switching approach is more appropriate than a discrete switching framework applied in previous studies since for each spot and futures relation we have enough observations in each regime and even in the region of transition between the extreme regimes to justify our approach. Hence, a discrete function is not able to specify the dynamics adequately.

The first main result is that the adjustment of the spot return frequently differs between the two regimes, regardless if an exponential or a logistic function is chosen. This strongly supports our presumption of a nonlinear adjustment process in spot and futures markets for commodities. Starting with exponential transition frameworks, the findings for the energy index and crude oil display a positive coefficient β_1 while the sum of β_1 and β_2 turns out to be negative and close to zero for both transition variables. Hence, spot returns only adjust in case of a small forward premium or low volatility. However, if previous forward spreads and volatility, respectively, has been large, future spot returns are increasingly detached from the current spread. In that extreme regime, a positive basis may even result in a drop of future spot prices and vice versa. The other extreme can be observed if the forward premium is chosen as the transition variable for crude oil or volatility serves as a transition variable for energy. In both cases, β_1 turns out to be greater than unity, which even points to an overshooting pattern of spot returns in the first regime. Such a scenario seems plausible in times of speculation while $(\beta_1 + \beta_2) < 0$ may reflect expected market turnovers.

A similar pattern arises for heating oil based on a logistic framework: The positive sign of the coefficient β_1 is in line with theory while the sum of β_1 and β_2 turns out to be negative. Estimations for the whole energy index based on a logistic transition function display a similar pattern. Overall, these findings imply that future spot changes tend to be negatively related to the forward premium if the latter is above its threshold in the previous period while a positive coefficient can be observed if the lagged return turns out to be below the threshold. Considering that the threshold is positive for each commodity, β_1 corresponds to a falling spread which might become negative while the sum of β_1 and β_2 refers to an increasing positive spread. In terms of volatility, a value above the threshold corresponds to large

absolute spreads during the previous week while a value below the threshold corresponds to low volatility. Hence, a similar pattern as argued in case of the exponential transition function arises as an adjustment of spot returns only occurs if the spread between futures and spot prices and volatility, respectively, is low.

In case of unleaded gasoline the slope coefficient has a positive sign in both regimes. However, the predictive power of the spread is again much higher in the first regime since $\beta_2 < 0$. NLS estimations performed for natural gas did not converge, therefore these are not reported in Table 5.

Several modified estimations have been carried out to test for the robustness of the overall results. In particular, we have modified our estimations with respect to the choice of the transition variable by introducing different lags for the lagged spread. For instance, the results remain qualitatively unchanged if the lag order is chosen to be one for each commodity. Estimating all models with exponential or logistic transition functions suggests that the established results continue to hold. Overall, the outcomes suggest that our findings are robust with respect to different configurations. To save space, the corresponding results are not presented here, but are available upon request.

4. Conclusion

Examining energy commodities, this study has allowed for different nonlinear adjustment patterns when analyzing the relationship between future spot changes and the forward premium. From a general point of view, our findings suggest that a smooth switching approach should be adopted as such a framework is capable of capturing more complex dynamics of commodity spot and futures relationships compared to a discrete threshold model. Our empirical outcomes confirm the previous findings of Chinn et al. (2005) that the informational content of prices for energy futures varies between different commodities. Nevertheless, a similar pattern arises: A price discovery function of futures prices can only be observed if previous volatility or spreads have been low while no or little explanatory power is detected in the opposite case. A reasonable explanation for this pattern is that periods of high volatility or high spreads reflect market turbulences which for their turn, beside other factors, might be explained by price pressures resulting from speculation. In this case, the missing link between spot and futures stems from the engagement of investors which consider energy products as an asset class and cause price movements away from fundamental values.

The fact that futures prices lose their leading indicator function in times of turbulence implies that economic policy faces a tough task when trying to reduce energy price uncertainty. However, to clarify the role of speculation in this context, further research seems necessary. As an extension of our study, a multivariate nonlinear cointegration analysis which includes further variables such as a global liquidity measure or energy demand factors is a promising line of research.

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Tables

Table 1: Unit root tests

Commodity	Series	Level	Δ	Level	Δ
		t-stat.[Lags]	t-stat. [Lags]	MZa-stat. [Lags]	MZa-stat. [Lags]
Energy	f_t	-0.95 [1]	-72.90*** [0]	0.28 [1]	-35.59*** [7]
	s_t	-1.13 [0]	-72.19*** [0]	-2.01 [1]	-35.09*** [7]
	Δs_{t+66}	-5.35*** [0]		-41.77*** [0]	
Crude oil	f_t	-0.56 [0]	-72.11*** [0]	0.7 [1]	-32.02*** [7]
	s_t	-1.16 [0]	-70.31*** [0]	-1.05 [1]	-28.67*** [7]
	Δs_{t+66}	-5.49*** [0]		-37.13*** [0]	
Heating oil	f_t	-0.48 [1]	-73.95*** [0]	0.79 [1]	-35.61*** [7]
	s_t	-1.12 [0]	-72.26*** [0]	-2.11 [0]	-23.15*** [7]
	Δs_{t+66}	-5.81*** [0]		-55.73*** [1]	
Natural gas	f_t	-0.42 [0]	-71.30*** [0]	-1.04 [0]	-2391.84*** [0]
	s_t	1.21 [0]	-72.08*** [0]	2.93 [0]	-1901.96*** [2]
	Δs_{t+66}	-5.65*** [0]		-50.89*** [0]	
Unleaded gasoline	f_t	-0.30 [1]	-73.17*** [0]	1.12 [1]	-26.4*** [7]
	s_t	-0.97 [1]	-70.77*** [0]	-0.11 [1]	-42.87*** [7]
	Δs_{t+66}	-5.17*** [0]		-58.71*** [0]	

Note: * Statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. The ADF test equation is estimated including an intercept (c) for the levels and without deterministic regressors (n) for the first differences. For the ADF test critical values are taken from MacKinnon (1996): (c) 10% -2.57, 5% -2.86, 1% -3.43 and (n) 10% -1.62, 5% -1.94, 1% -2.57, respectively. For the MZa test critical values are taken from Ng and Perron (2001): 10% -5.7, 5% -8.1, 1% -13.8. The lag length is chosen by minimizing the Schwarz information criterion. Maximum lag length has been set to 32.

Table 2: Bi-variate Johansen cointegration rank test

Spot and futures relation	Lags	Trace stat.	Long-run relationship
Energy			$s_t - 0.254f_t - 3.185$
$H_0: r = 0$ vs. $H_1: r \geq 1$	3	40.096**	
$H_0: r \leq 1$ vs. $H_1: r \geq 2$		2.108	
Crude oil			$s_t - 0.361f_t - 2.802$
$H_0: r = 0$ vs. $H_1: r \geq 1$	3	28.467**	
$H_0: r \leq 1$ vs. $H_1: r \geq 2$		1.630	
Heating oil			$s_t - 0.556f_t - 1.765$
$H_0: r = 0$ vs. $H_1: r \geq 1$	1	18.980*	
$H_0: r \leq 1$ vs. $H_1: r \geq 2$		4.440	
Natural gas			$s_t - 3.983f_t$
$H_0: r = 0$ vs. $H_1: r \geq 1$	2	26.870**	
$H_0: r \leq 1$ vs. $H_1: r \geq 2$		5.640	
Unleaded gasoline			$s_t - 0.615f_t - 1.678$
$H_0: r = 0$ vs. $H_1: r \geq 1$	3	31.381**	
$H_0: r \leq 1$ vs. $H_1: r \geq 2$		2.738	

Note: * Statistical significance at the 10% level, ** at the 5% level. In case of significance the constant is restricted to the cointegrating space, allowing for no linear trend neither in the data nor in the cointegrating equation. Critical values for testing (i) $H_0: r = 0$ and (ii) $H_0: r \leq 1$ are taken from MacKinnon et al. (1999): 10% (i) 17.980 and (ii) 7.557, 5% (i) 20.164 and (ii) 9.142, respectively. The lag length is chosen based on tests for autocorrelation. The coefficients of each long-run relationship are highly significant.

Table 3: Teräsvirta test for nonlinearity and choice of the delay parameter

j	$t - 1$	$t - 2$	$t - 3$	$t - 4$	$t - 5$	Volatility
Energy	247.405*** (0.000)	244.641*** (0.000)	244.508*** (0.000)	244.675*** (0.000)	242.798*** (0.000)	187.750*** (0.000)
Crude oil	91.542*** (0.000)	88.162*** (0.000)	87.975*** (0.000)	85.903*** (0.000)	88.142*** (0.000)	125.809*** (0.000)
Heating oil	366.236*** (0.000)	364.418*** (0.000)	370.487*** (0.000)	374.860*** (0.000)	372.462*** (0.000)	327.674*** (0.000)
Natural gas	119.236*** (0.000)	115.999*** (0.000)	114.880*** (0.000)	113.770*** (0.000)	111.096*** (0.000)	106.280*** (0.000)
Unleaded gasoline	182.219*** (0.000)	181.048*** (0.000)	182.456*** (0.000)	182.660*** (0.000)	187.677*** (0.000)	137.922*** (0.000)

Note: The table displays the test statistic of the LM test for nonlinearity as described in Section 3.2.2 for different lag orders j and the volatility measure, with p-values in parentheses. The test is distributed as χ^2 with three degrees of freedom. For details, see Teräsvirta (1998). ***/*** implies rejection of the null hypothesis at the 10/5/1% significance level.

Table 4: Teräsvirta test for LSTR vs. ESTR

Commodity	Optimal lag (j)			Volatility			
	j	H_{04}	H_{03}	H_{02}	H_{04}	H_{03}	H_{02}
Energy	1	113.842*** (0.000)	99.164*** (0.000)	80.647*** (0.000)	43.079*** (0.000)	127.869*** (0.000)	49.851*** (0.000)
Crude oil	1	39.399*** (0.000)	42.206*** (0.000)	5.668** (0.017)	31.864*** (0.000)	74.042*** (0.000)	0.104 (0.747)
Heating oil	4	232.368*** (0.000)	18.395*** (0.000)	107.761*** (0.000)	235.200*** (0.000)	2.126 (0.145)	87.035*** (0.000)
Natural gas	1	40.395*** (0.000)	29.688*** (0.000)	78.070*** (0.000)	36.331*** (0.000)	34.731*** (0.000)	59.101*** (0.000)
Unleaded gasoline	5	139.318*** (0.000)	49.184*** (0.000)	38.597*** (0.000)	72.696*** (0.000)	53.317*** (0.000)	29.605*** (0.000)

Note: The table displays the test statistic of the LM test for the selection of the appropriate specification as described in Section 3.2.3 for the optimal lag orders j and the volatility measure, with p-values in parentheses. The test is distributed as χ^2 with one degree of freedom. For details, see Teräsvirta (1998). ***/*** implies rejection of the null hypothesis at the 10/5/1% significance level.

Table 5: Estimation results

Com.	Trans.func.	Trans.var.	α_1	β_1	α_2	β_2	γ	c
Energy	exponential	Basis (t-1)	-0.107** (0.050)	0.732*** (0.224)	0.112** (0.056)	-0.779*** (0.226)	7.641*** (2.963)	0.245*** (0.026)
		Volatility	-3.972*** (0.844)	7.751*** (1.606)	4.000*** (0.845)	-7.803*** (1.604)	142.23*** (40.720)	0.513*** (0.006)
	logistic	Basis (t-1)	-0.002 (0.007)	0.242*** (0.035)	-0.021 (0.037)	-0.263*** (0.048)	147.036 (224.965)	0.444*** (0.008)
		Volatility	-0.001 (0.007)	0.231*** (0.038)	-0.042 (0.039)	-0.236*** (0.051)	189.226 (339.253)	0.443*** (0.005)
Crude oil	exponential	Basis (t-1)	-0.484*** (0.241)	1.623*** (0.288)	0.504*** (0.125)	-1.662*** (0.285)	611.172*** (124.401)	0.419*** (0.000)
		Volatility	0.027 (0.028)	0.517*** (0.135)	-0.014 (0.031)	-0.566*** (0.138)	55.230 (34.105)	0.214*** (0.011)
Heating oil	logistic	Basis (t-4)	-0.013 (0.008)	0.101* (0.053)	0.225*** (0.033)	-0.356*** (0.070)	53.363 (46.770)	0.388*** (0.007)
		Volatility	-0.010 (0.009)	0.076 (0.059)	0.216*** (0.036)	-0.328*** (0.076)	46.808 (41.940)	0.385*** (0.008)
Unleaded gasoline	logistic	Basis (t-5)	-0.002 (0.006)	0.357*** (0.048)	-0.033 (0.040)	-0.308*** (0.076)	96.023 (147.133)	0.288 (0.005)
		Volatility	-0.001 (0.007)	0.344*** (0.043)	-0.042 (0.043)	-0.292*** (0.081)	82.275 (177.490)	0.289*** (0.005)

Note: * Statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. The coefficients are estimated by nonlinear least squares. Newey-West standard errors are given in parentheses.

Figures

Figure 1: Estimated transition functions

