http://economix.fr

Document de Travail

Working Paper

2011-25

On the link between forward energy prices: A nonlinear panel cointegration approach

Marc Joëts

Valérie Mignon

UMR 7235

Université de Paris Ouest Nanterre La Défense

(bâtiments T et G)

200, Avenue de la République

92001 NANTERRE CEDEX

Tél et Fax : 33.(0)1.40.97.59.07

Email : nasam.zaroualete@u-paris10.fr

On the link between forward energy prices: A nonlinear panel cointegration approach*

Marc Joëts† Valérie Mignon‡

May 21, 2011

Abstract

This paper investigates the relationship between forward prices of oil, gas, coal, and electricity using a nonlinear panel cointegration framework. To this end, we consider a panel of 35 maturities and control for the economic and financial environment using equity futures prices. Estimating the cointegrating relationship, we find that oil, gas and coal forward prices are positively linked, while the negative link between oil and electricity prices is consistent with a substitution effect between the two energy sources on the long run. Estimating panel smooth transition regression (PSTR) models, we show that the forward oil price adjustment process toward its equilibrium value is nonlinear and asymmetric, putting forward the key role played by self-sustaining dynamics and speculation phenomena.

JEL Classification: C33, Q40.
Keywords: forward energy prices, speculation, panel cointegration, nonlinear model, PSTR.

*Corresponding author: Valérie Mignon, EconomiX-CNRS, University of Paris Ouest, 200 avenue de la République, 92001 Nanterre Cedex, France. E-mail: valerie.mignon@u-paris10.fr. Phone: +33 (0)1 40 97 58 60. Fax: +33 (0)1 40 97 77 84. We would like to thank Joakim Westerlund for providing codes for his cointegration test.

†EconomiX-CNRS, University of Paris Ouest, France. E-mail: marc.joets@u-paris10.fr

‡EconomiX-CNRS, University of Paris Ouest and CEPII, Paris, France. E-mail: valerie.mignon@u-paris10.fr

1 Introduction

Investigating the interactions between energy markets if of crucial importance to correctly apprehend and understand their price dynamics. Indeed, energy prices are obviously connected through the production process, and economic theory suggests that a relationship should exist between input and output prices. Besides, oil—due to its physical properties and the importance of its market—is often viewed as an economic "driver" influencing the other energy prices, such as coal, gas, and electricity.

However, energy markets recently experienced significant developments that are likely to modify the potential interactions between energy prices. European gas and electricity markets have freshly known a liberalization process allowing the emergence of new contracts making prices more likely to be influenced by market participants rather than regulators (Mjelde and Bessler, 2009). While various studies[1] have investigated the links between energy prices on spot markets, they generally do not consider the long-run financial dimension of energy markets. Moreover, by relying on spot data, previous literature does not account for potential heterogeneity in the energy prices relationships across different maturities. This may be viewed as an important limitation since considering prices at various maturities allows accounting for arbitrage investors' behavior over the long run—the contracts being not only traded by agents who need physical energy delivery, but also by speculators with purely financial motivation.

In this paper, we account for the term structure of energy prices through an analysis of forward prices. More specifically, we consider forward prices of oil, coal, gas and electricity at 35 maturities, and aim at modelling the relationship between these four energy sources for all maturities in a panel data cointegration setting. This approach allows us to study the links within and between heterogeneous maturities accounting for long-term arbitrage behaviors, and to overcome the low power of traditional time series unit root and cointegration tests against the near stationary alternative.

It is worth mentioning that, given the various factors that may influence energy markets, the dynamics of energy prices is likely to be characterized by nonlinearities. Such nonlinearities may come from both fundamental factors or speculative forces. Regarding the first point, the recent huge increase in the Chinese oil demand coupled with an unexpected halt of non-OPEC production, as well as the loss of OPEC spare capacity since 2004 (Kaufmann, 2011) are examples of fundamental shocks that may generate nonlinearities and regime-switching. Turning to the speculative factors, investors may hold long-run positions to force energy prices rising, and switch between investment strategies (Ellen and Zwinkels, 2010). These elements play in favor of nonlinear, regime-switching models. To this end, we rely on panel smooth transition regression (PSTR) models, allowing us to model the nonlinear behavior of the forward energy prices adjustment process to the equilibrum value.

To sum up, and given the key role played by oil in energy markets, the aim of this paper is to investigate the nonlinear adjustment process of the forward oil price toward its equilibrium value given by the estimated long-term relationship between oil, gas, coal and electricity forward prices. To our best knowledge, our contribution is the first to account for interactions

[1]See references in Section 2.

between energy prices at various maturities in a nonlinear panel data framework.

The rest of the paper is organized as follows. Section 2 presents some stylized facts and reviews the literature on the links between energy prices. Section 3 describes the econometric methodology. Data and results of panel unit root and cointegartion tests are displayed in Section 4. Section 5 reports the PSTR estimation results, and Section 6 concludes the article.

2 Relationships between energy prices: stylized facts and literature review

The natural gas market is often considered to be potentially linked to other primary energy sources by different ways. Technically, gas is extracted from the soils either alone ("dry gas"), or associated with the oil exploration ("associated gas"). Consequently, natural gas and oil have the same extraction/exploration process, and oil producers are often gas producers too, creating an implicit link between prices. Usually, the natural gas is used for domestic needs and as an input to the electricity production process. However, it has no captive use and is in constant competition with other energy sources (with domestic and heavy fuel oil in domestic needs, and with coal in the power production). These characteristics explain the existence of (i) an input-output relationship between natural gas and electricity, and (ii) competitive relation between oil, gas, and coal. Despite the close relationship between energy markets, the entry of the gas market in the liberalization process is likely to exacerbate short-run decorrelation between oil and gas prices. Indeed, long-term gas contracts are no longer indexed to oil contracts, but to spot and futures prices, rending prices more sensitive to the behavior of market participants.

Turning to coal, due to its apparent abundance,[2] it is dominant in two specific sectors: manufacture of cement and steel, and electricity generation (IEA, 2010a and British Petroleum, 2010). It is the main input to the electricity production, making energy prices potentially connected through an input-output relationship. However, coal being extremely pollutant, it is in competition with gas and oil in the power production, likely to create substitution effects. Besides, due to its solid state and its inert nature, coal transportation is very expensive[3] because it requires seaborne trade. Then, coal prices strongly depend on the variability of the freight rates, which are significantly variable since the 1950s (Lundgren, 1996). Consequently, oil and coal prices may be indirectly related each other through the fluctuations of the transport fuel derived from oil.

Unlike oil, natural gas and coal, electricity is not a fossil energy. It can be produced either as primary energy from natural sources (like hydro, wind, solar, ...), or as secondary energy from the heat of nuclear fission, the geothermal and solar thermal heat, or by the combustion of fossil fuels (coal, natural gas, and oil) (IEA, 2010b). Accordingly, and as previously mentioned, electricity prices may be related to its products through an input-output relationship. Moreover, power energy is used for most human activities (heating, lighting, computers, powering machines, transport, ...) and in several sectors (transformation and energy sectors,

[2]The reserves/production ratio is equal to 145 years (British Petroleum, 2010), and reserves are also well distributed (no cartel exists).

[3]This is one of the reasons explaining the fact that the coal market was initially regional.

transmission and distribution of electricity sectors, and final consumption[4]). Thus, in addition to an obvious relation through the production process, electricity, gas, oil and coal prices may be interrelated by competition and substitution links.

On the whole, various factors may explain the interactions between energy prices. Turning to the empirical literature, Serletis and Rangel-Ruiz (2004) investigate the strength of shared dynamics between North American daily spot Henry Hub gas and WTI crude oil prices over the period after the deregulation, from January 1991 to April 2001. They found that while the US market deregulation has 'decoupled' the prices' relationship, North American natural gas prices are largely defined by the US Henry Hub prices trends. Focusing on the UK, Panagiotidis and Rutledge (2007) examine whether oil and gas prices 'decoupled' during the post market deregulation period (1996-2003). Using cointegration techniques, they show that a cointegrating relationship is present throughout the sample period, especially between 1999 and 2000. Relying on daily ICE futures prices of gas and Brent for five contracts, Westgaard et al. (2011) find that a long-term relationship exists between prices depending on the length of the contracts.

Considering more energy sources, Bachmeier and Griffin (2006) investigate the degree of integration between crude oil, coal, and natural gas markets. Using data from January 1990 to August 2003, and relying on the estimation of bivariate error correction models, they find a weak degree of integration between energy markets. Investigating the relationship between weekly spot prices among US electricity and its major fuel inputs (natural gas, uranium, coal and crude oil) over the period from June 6, 2001 to April 23, 2008, Mjelde and Bessler (2009) put forward that electricity prices influence natural gas prices, which in turn affect crude oil prices. Finally, one can mention the study by Ma and Oxley (2010) concerning energy prices comovements in China from January 1995 to December 2005, showing that coal and electricity prices have comoved since 1997.

To sum up, the previous literature globally puts forward some links between energy markets, depending on the market location and the type of energy considered. However, most of them deal with spot prices. Consequently, they do not investigate the potential relationships at various maturities, a fact that is of considerable importance when one wishes to account for the financial dimension of energy markets. Furthermore, relying on spot models based on long-term price relationships often require knowledge of the convenience yield for risk-neutral valuation. However, the later is not observable and difficult to deduce, whereas this is not the case for forward prices models (Eydeland and Wolyniec, 2003). For these resaons, and to account for the financial dimension of energy markets, it seems particularly relevant to focus on forward prices data, which is the aim of the present contribution.

3 Methodology

As previously mentioned, our aim is to investigate the nonlinear behavior of the forward oil price adjustment process toward its equilibrium value by estimating a panel smooth transition regression (PSTR) model. To this end, the first step consists in estimating the equilibrium value of forward oil price, given the values of the other forward energy prices and the economic

[4]The final consumption sector represents the main sector for electricity consumption.

and financial environment, the later being proxied by an European equity futures index (see below, Section 4). More specifically, we estimate the following long-term relationship:

$$p_{i,t}^{oil} = a_i + b_1 p_{i,t}^{elec} + b_2 p_{i,t}^{gas} + b_3 p_{i,t}^{coal} + b_4 p_{i,t}^{Stoxx} + \epsilon_{i,t} \tag{1}$$

where $i = 1, ..., 35$ denotes the maturity, and $t = 1, ..., T$ the time. $p_{i,t}^{oil}$, $p_{i,t}^{elec}$, $p_{i,t}^{gas}$ and $p_{i,t}^{coal}$ respectively denote the forward prices of oil, electricity, gas and coal. $p_{i,t}^{Stoxx}$ stands for the equity futures price index. All price series are expressed in logarithmic terms.

The estimation of Equation (1) using efficient panel cointegration techniques (see below, Section 5) gives the forward oil price equilibrium value, denoted as $\hat{p}_{i,t}^{oil}$. The difference between the observed and the equilibrium value of the oil price defines the misalignment for each maturity i:

$$z_{i,t} = p_{i,t}^{oil} - \hat{p}_{i,t}^{oil} \tag{2}$$

The corresponding error correction model is specified in a nonlinear form to account for the potential nonlinear adjustment of the forward oil price toward its equilibrium value. To this end, we rely on the PSTR model introduced by González et al. (2005):

$$y_{i,t} = \mu_i + \beta_1' x_{i,t} + \beta_2' x_{i,t} g\left(s_{i,t}; \gamma, c\right) + \varepsilon_{i,t} \tag{3}$$

where $g\left(s_{i,t}; \gamma, c\right)$ is the transition function, normalized and bounded between 0 and 1. $s_{i,t}$ denotes the transition variable—which may be an exogenous variable or a combination of the lagged endogenous one—, γ the speed of transition from one regime to the other and c the threshold parameter. As it is clear from Equation (3), the observations in the panel are divided into two regimes depending on whether the transition variable is lower or larger than c. The logistic specification can be used for the transition function to account for a smooth and gradual change from one regime to the other:

$$g\left(s_{i,t}; \gamma, c\right) = \left[1 + \exp\left(-\gamma \prod_{l=1}^{m} \left(s_{i,t} - c_l\right)\right)\right]^{-1} \tag{4}$$

with $\gamma > 0$ and $c_1 \leq c_2 \leq ... \leq c_m$. Turning to empirical considerations, it is sufficient to consider only the cases of $m = 1$ (logistic PSTR) or $m = 2$ (logistic quadratic PSTR) to capture the nonlinearities due to regime switching (see González et al., 2005).

Following the methodology used in the time series context, González et al. (2005) propose a three-step strategy to apply PSTR models: (i) the identification step aiming at testing for homogeneity against the PSTR alternative and selecting both the transition variable and the order m, (ii) the estimation step based on nonlinear least squares, and (iii) the evaluation step that consists in applying misspecification tests to check the validity of the estimated PSTR model.

On the whole, the model that will be estimated is given by:

$$\Delta p_{i,t}^{oil} = \mu_i + (\lambda_1 z_{i,t-1} + B_1 X_{i,t}) + (\lambda_2 z_{i,t-1} + B_2 X_{i,t}) g(s_{i,t}; \gamma, c) + \varepsilon_{i,t} \tag{5}$$

where $X_{i,t}$ represents the vector of contemporaneous and lagged first-differenced forward oil price determinants, namely $\Delta p_{i,t}^{elec}$, $\Delta p_{i,t}^{gas}$, $\Delta p_{i,t}^{coal}$, and $\Delta p_{i,t}^{Stoxx}$. Depending on the value of the transition variable, the link between $\Delta p_{i,t}^{oil}$ and its determinants evolves between B_1 and λ_1 in Regime 1 (corresponding to $g(.) = 0$) and $B_1 + B_2$ and $\lambda_1 + \lambda_2$ in Regime 2 (corresponding to $g(.) = 1$). Three transition variables will be considered: the oil price misalignment, the oil price variation, and the economic and financial environment proxied by the equity futures price returns.

4 Data, unit root and cointegration tests

We consider daily data over the January 3, 2005 to December 31, 2010 period. We rely on European forward prices of oil, gas, coal, and electricity for 35 maturities.[5] Using such a large sample of maturities allows us to account for possible heterogeneity in the relationship between energy prices,[6] as well as long-run arbitrage behavior of market participants. Energy price data are extracted from the Platt's Information Energy Agency. To control for the economic and financial environment that may impact all energy price series, we rely on a European equity futures index—which has the advantage of being available at a daily frequency. This variable also allows considering oil as a financial asset and controls for the recent financial turmoil. Our retained equity variable is the Dow Jones Euro Stoxx 50, the European leading stock index for futures contracts, extracted from Datastream. All price series are in logarithms.

Before estimating Equation (1), panel unit root and cointegration tests have to be applied. To obtain robust results, we rely on various panel unit root tests. We first consider first-generation tests that are based on the assumption of cross-sectional independence among the panel members, i.e. among the various maturities.[7] Given that cross-sectional independence may be viewed as a restrictive hypothesis,[8] we also apply second-generation panel unit root tests that relaxe this assumption.

Table 4 in Appendix B reports the results of four first-generation tests. Levin and Lin (1992, 1993)—LL—and Hadri (2000) tests are based on a common unit root process. Given that this hypothesis is a rather restrictive assumption on the dynamics of the series under the alternative hypothesis, we also consider two other tests. The IPS (Im, Pesaran and Shin, 2003) and Maddala and Wu (1999)—MW—tests allow for heterogeneity in the value of the autoregressive coefficient under the alternative hypothesis. LL, IPS and MW tests are based on the unit root null hypothesis, while the Hadri's test considers the null of no unit root. Results in Table 4 show that all series are I(1) when relaxing the common unit root hypothesis under the alternative.

These conclusions are supported by the results reported in Table 6 (Appendix B) relating to second-generation panel unit root tests. The Pesaran (2007) CIPS test is based on Dickey-Fuller-type regressions augmented with the cross-section averages of lagged levels and first

[5] As an example, Figure 1 in Appendix A depicts the one-month forward energy prices (in logs).

[6] See Joëts (2010).

[7] See Hurlin and Mignon (2006) and Hurlin (2010) for a detailed presentation of panel unit root tests.

[8] Cross-section dependence can arise for several reasons, such as spatial spillovers, financial contagion, socioeconomic interactions, and common factors (Pesaran, 2004). In the presence of cross-section correlations in the panel, first-generation tests suffer from size distortions. Regarding our panel, the application of the CD test developed by Pesaran (2004)—based on the average of pair-wise correlation coefficients of OLS residuals from the individual regressions—shows that such correlations exist in our sample (see Table 5 in Appendix B).

differences of the individual series. Regarding the Moon and Perron (2004) test, it is constructed on de-factored observations—deviations from the common components—and the factor loadings are estimated by principal component analysis. The Choi (2002) test relies on an error-components panel model and removes the cross-section dependence by eliminating (i) individual effects using the Elliott, Rothenberg and Stock (1996) methodology (ERS), and (ii) the time trend effect by centering on the individual mean. As shown in Table 6, all tests conclude in favor of the unit root hypothesis meaning that all forward energy price series entering in Equation (1) are I(1).

Turning now to the cointegration case, we first rely on first-generation tests, namely the seven tests proposed by Pedroni (1999, 2004) as well as the Kao (1999) test which are all based on the null hypothesis of no cointegration. Among the 7 Pedroni's tests, 4 are based on the within dimension (panel cointegration tests) and 3 on the between dimension (group-mean panel cointegration tests). Group-mean panel cointegration statistics are more general in the sense that they allow for heterogeneous coefficients under the alternative hypothesis. As reported in Table 1, all tests conclude that forward oil prices and the four considered fundamentals are cointegrated. As for the unit root case, we also apply second-generation cointegration tests accounting for cross-sectional dependence. The four panel error correction-based tests proposed by Westerlund (2007) rely on structural dynamics and are a panel extension of the Banerjee et al. (1998) tests developped in the time series context. Among the four Westerlund's tests, two consider an homogeneous cointegrating relation under the alternative, while the two others allow for an heterogeneous long-term relationship. Results reported in Table 2 show that our energy forward prices are cointegrated. Finally, given that our sample covers a quite turbulent period, we implement the Westerlund and Edgerton (2007) second-generation panel cointegration test that is robust to unknown heterogeneous breaks in both the intercept and slope of the cointegrating regression. Our findings reported in Table 2 confirm that energy prices are cointegrated.

Table 1: **First-generation panel cointegration tests**

Pedroni				Kao
Within dimension		Between dimension		
Panel v	12.89 (0)	Group rho	-11.85 (0)	-13.06 (0)
Panel rho	-11.59 (0)	Group PP	-9.85 (0)	
Panel PP	-9.09 (0)	Group ADF	-8.85 (0)	
Panel ADF	-8.40 (0)			

Notes: Between parentheses: p-values. For Pedroni's tests, all statistics are computed with individual effects and time trends. Kao's test statistic is computed with individual effects only. Statistics are standard Normal.

Table 2: **Second-generation panel cointegration tests**

Westerlund				Westerlund & Edgerton		
Group-mean statistics		Panel statistics		Model	τ_N	ϕ_N
G_τ	G_α	P_τ	P_α	No break	-20.85 (0)	-43.54 (0)
32.462	1.7e+03	-192.407	1.7e+03	Level break	-18.59 (0)	-40.82 (0)
(0)	(0)	(0)	(0)	Regime break	-21.28 (0)	-41.60 (0)

Notes: (1) For the Westerlund's test: (a) between parentheses: p-values with cross-section dependence based on bootstrapped distribution (100 bootstrap replications). (b) Tests are computed with individual effects and time trends. (c) The Bartlett kernel is used for the semiparametric corrections. (d) The leads and lags in the error correction test are chosen using Akaike criterion. (e) The number of common factors is determined by IC_1 criterion (see Bai and Ng, 2004) with a maximum factor number of 5. (2) For the Westerlund and Edgerton's test: (a) between parentheses: p-values. (b) All tests statistics are limiting Normal distributions free of nuisance parameters under the null hypothesis. (c) The tests are implemented using the Campbell and Perron (1991) automatic procedure to select the lag length. (d) We use three breaks, which are determined by grid search.

5 Panel smooth transition regressions: estimation results

5.1 Estimation of the cointegrating relationship

Our considered series being I(1) and cointegrated, we first proceed to the estimation of the cointegrating relationship (1). Given that the distributions of the OLS estimates corresponding to Equation (1) are biased and dependent on nuisance parameters associated with the serial correlation properties of the data, it is necessary to use an efficient estimation procedure. We rely here on the panel Dynamic OLS (DOLS) procedure developed by Kao and Chiang (2000) and Mark and Sul (2003), which consists in augmenting the cointegrating relationship with lead and lagged differences of the regressors to control for the endogenous feedback effect.[9]

The estimated cointegrating relationship is given by:

$$\hat{p}_{i,t}^{oil} = \hat{a}_i - 0.126 p_{i,t}^{elec} + 0.149 p_{i,t}^{gas} + 0.610 p_{i,t}^{coal} + 0.428 p_{i,t}^{Stoxx} \quad (6)$$

This estimated relationship between oil, gas and coal forward prices is positive, while the link between oil and electricity forward prices is negative. The relationship between gas and oil prices has the expected sign given that the gas extraction process is very similar to that of oil. As a consequence, there exists a strong link across the two energies. Turning to coal, which is mainly used for electricity production, an increase in its price leads to a rise in oil price on the long run, due to an increasing demand for electricity and heating. Regarding electricity, two facts have to be highlighted. First, there exists an input-output relationship between this energy and oil. Second, electricity is used in various activities, mainly for final consumption. In Europe, specifically, electricity is intensively used for heating purposes and is thus in competition with oil. The negative link between oil and electricity forward

[9] As a robustness check, we also estimate Equation (1) using the Fully-Modified OLS (FM-OLS) method proposed by Phillips and Hansen (1990). The results were very similar to those obtained with the DOLS procedure and are available upon request to the authors.

prices on the long run may be interpreted in terms of a substitution effect, rather than in terms of an input-output effect. Finally, given that equity prices may be viewed as a proxy for the economic and financial environment, the positive relationship between oil and equity prices may be interpreted as follows: a rise in equity futures prices refers to a period of growing economic activity, leading to an increase in oil consumption and, consequently, in oil price.

5.2 Estimation of the nonlinear oil price dynamics

Following the three-step strategy proposed by González et al. (2005), we start by applying linearity tests. We test the null hypothesis of linearity in Equation (5) using three transition variables: equity futures returns, the forward oil price misalignment, and the forward oil price variation. For all three variables, the null of linearity is strongly rejected in favor of the PSTR alternative.[10] Results corresponding to the estimation of the PSTR models are reported in Table 3.

Table 3: **Estimation of PSTR models**

$s_{i,t}$	$\Delta p_{i,t-1}^{Stoxx}$		$z_{i,t-1}$		$\Delta p_{i,t-1}^{oil}$	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
$z_{i,t-1}$	-0.0040	-0.0479	-0.0111	0.0097	-0.0074	0.0174
	(-4.80)	(-1.64)	(-2.37)	(1.67)	(-6.07)	(3.45)
$\Delta p_{i,t-1}^{oil}$	0.0060	-2.33	-0.1303	0.1639	0.0288	-0.1232
	(1.16)	(-8.63)	(-3.23)	(3.36)	(3.75)	(-6.26)
$\Delta p_{i,t-1}^{elec}$	0.0163	1.9036	0.0484	-0.0288	0.0526	-0.2360
	(5.43)	(14.43)	(1.57)	(-0.78)	(9.71)	(-8.28)
$\Delta p_{i,t-1}^{gas}$	0.0134	0.1585	0.0569	-0.0561	0.0105	0.0068
	(5.27)	(1.11)	(1.82)	(-1.51)	(2.57)	(0.33)
$\Delta p_{i,t-1}^{coal}$	0.0506	0.3725	0.5266	-0.5606	0.0174	0.3197
	(7.28)	(3.44)	(6.63)	(-5.96)	(1.89)	(8.90)
$\Delta p_{i,t-1}^{Stoxx}$	-0.0855	0.0315	-0.7727	0.8407	-0.1254	0.2058
	(-12.40)	(0.44)	(-9.84)	(9.05)	(-11.70)	(4.94)
$\hat{\gamma}$	106.8853		4.7058		60.1668	
$\hat{c}$	0.0736		-0.3623		0.0358	

Between parentheses: t-statistics.

Let us first consider the model with equity futures returns as the transition variable. In this case, forward oil price tends to reverts to its equilibrium value whatever the considered regime. This mean-reverting behavior is slower in the first state corresponding to a stock market which is decreasing or weakly increasing (until a threshold equal to 7%). Assuming that the stock market is a proxy for economic activity, this result is logical in the sense that reversion to the equilibrium is harder and takes a longer time in a depressing period than in an expansion state. Moreover, the other forward energy price returns positively affect oil price returns in

[10]Detailed results are available upon request to the authors.

both regimes, with a stronger impact in Regime 2. This result shows that when financial markets are booming, forward energy prices tend to augment. This may be explained by two reasons: (i) the need for more energy in periods of intense economic activity, and (ii) speculation purposes. Speculation on energy products goes along with speculation on financial assets. Expecting that the growing trend will continue, traders tend to take long positions on long-term contracts, selling them at higher prices before the expiry date and re-investing in new ones; a behavior that produces self-sustaining dynamics (Cifarelli and Paladino, 2010).

When the oil price misalignment acts as the transition variable, the estimated threshold is equal to -36%, corresponding to a 36% undervaluation of the forward oil price compared to its equilibrium value given by the cointegrating relationship. When oil price is strongly undervalued, a mean-reversion dynamics takes place (Regime 1). The more the reduction of the misalignment, the weaker the mean-reverting speed. In other words, corrections of disequilibria appear when oil price tends to strongly decrease, while it is not the case when oil price strongly augments compared to its fundamentals. This illustrates an asymmetric phenomenon: the adjustment process is at play only for high undervaluations, not for overvaluations. Regarding forward energy price returns, they vary in the same way as oil in case of strong undervaluations, with a decreasing influence when the magnitude of undervaluation tends to diminish. In the later case, the variable which has the strongest impact is the equity returns, again putting forward the importance of the speculation phenomenon: when oil price rises, the links across markets tend to be stronger, encouraging speculation. From a speculative viewpoint, it is reasonable to think that when oil prices are highly undervalued, the market is dominated by irrational speculators (chartists), who base their expectations on past prices fluctuations and believe trends to continue in the same direction. These speculators have a destabilizing effect, making prices deviate from their long-run fundamental equilibrium. However, when the threshold of -36% is reached, chartists no longer believe on the undervaluation and rational speculators (fundamentalists)—who base their expectations on economic fundamentals—become more prevalent. Fundamentalists believe that energy prices will revert to the intrinsic long-run equilibrium and therefore have a stabilizing effect. Consequently, chartists change their expectations and become followers of the fundamentalists. When prices tend to be overvalued, an asymmetric phenomenon occurs, that may be explained by the loss aversion behavior. Indeed, investors react differently when they are facing potential losses and profits. According to the prospect theory, agents are more hesitant to sell during overvaluation than to buy during undervaluation (Kahneman and Tversky, 1979).

Consider now the third case, with the forward oil price variations as the transition variable. The mean-reverting behavior is observed only in Regime 1, characterized by an oil price growth rate lower than 3%. This means that there exists a floor price under which oil producers decide to not produce due to profitability considerations. On the contrary, in periods of oil price boom, there is no mean-reverting behavior: the growing price tends to go away from its fundamental value, leading to self-sustaining behaviors. The other forward energy price returns are positively linked to oil price returns, except in Regime 2 for electricity. Again, this can be interpreted in terms of a substitution effect between electricity and oil when the later reaches very high values. Finally, note the positive relationship between oil and stock returns, a fact that is consistent with speculating dynamics.

6 Conclusion

This paper investigates the relationship between daily forward prices of oil, gas, coal and electricity. Relying on a panel of 35 maturities and controling for the economic and financial environment using equity futures prices, we test whether energy prices evolve toward a common long-run relationship. Using panel cointegration techniques, we show that all forward price series are cointegrated. More specifically, while oil, gas and coal forward prices are positively linked, oil and electricity display a negative relationship, consistent with a substitution effect between the two energy sources on long horizons. Paying a particular attention to the financial dimension of energy markets, we account for potential nonlinearities notably induced by market participants' behavior. To this end, we estimate panel smooth transition regression models, and show that the forward oil price adjustment process toward its equilibrium value is nonlinear and asymmetric. More precisely, our findings put forward the key role played by speculative factors and self-sustaining dynamics in phases of booming oil prices and growing economic activity.

References

Andrews, D. and Monahan, C., 1992, An improved heteroskedasticity and autocorrelation consistent covariance matrix estimator, Econometrica, 60, 953-966.

Bachmeier, L.J. and Griffin, J.M., 2006, Testing for market integration crude oil, coal, and natural gas, The Energy Journal, 27, 55-71.

Bai, J. and Ng, S., 2002, Determining the number of factors in approximate factor models, Econometrica, 70, 191-221.

Bai, J. and Ng, S., 2004, A PANIC attack on unit roots and cointegration, Econometrica, 72, 1127-1177.

Banerjee, A., Dolado, J.J. and Mestre, R., 1998, Error-correction mechanism tests for cointegration in a single-equation framework, Journal of Time Series Analysis, 19, 267-283.

British Petroleum, 2010, Statistical Review of World Energy.

Campbell, J. and Perron, P., 1991, Pitfalls and opportunities: what macroeconomists should know about unit roots, in Blanchard O. and Fisher, S. (eds), NBER Macroeconomics Annual, MIT Press, Cambridge, MA, 141-201.

Choi, I., 2002, Combination unit root tests for cross-sectionally correlated panels, Mimeo, Hong Kong University of Science and Technology.

Cifarelli, G. and Paladino, G., 2010, Oil price dynamics and speculation: A multivariate financial approach, Energy Economics, 32, 363-372.

Ellen, S. and Zwinkels, R.C.J., 2010, Oil Price Dynamics: A Behavioral Finance Approach with Heterogeneous Agents, Energy Economics, 32(6), 1427-1434.

Elliott, G., Rothenberg, T.J. and Stock, J.H., 1996, Efficient tests for an autoregressive unit root, Econometrica, 64, 813-836.

Eydeland, A. and Wolyniec, K., 2003, Energy power risk management - New developments in modeling, pricing, and hedging, Wiley Finance.

González, A., Teräsvirta, T. and van Dijk, D., 2005, Panel Smooth Transition Regression Models, Research Paper Series 165, Quantitative Finance Research Centre, University of Technology, Sydney.

Hadri, K., 2000, Testing unit roots in heterogeneous panel data, Econometrics Journal, 3, 148-161.

Hurlin, C. and Mignon, V., 2006, Second generation panel unit root tests, Working Papers, HAL.

Hurlin, C., 2010, What would Nelson and Plosser find had they used panel unit root tests?, Applied Economics, 42, 1515-1531.

Im, K.S., Pesaran, M.H. and Shin, Y., 2003, Testing for unit roots in heterogeneous panels, Journal of Econometrics, 115, 53-74.

International Energy Agency, 2010a, Coal Information.

International Energy Agency, 2010b, Electricity Information.

Joëts, M., 2010, On the relationship between forward energy prices: a panel data cointegration approach, EconomiX-CNRS Working Paper, 21.

Kahneman, D. and Tversky, A., 1979, Prospect Theory: An analysis of decision under risk, Econometrica, 47, 263-291.

Kao, C., 1999, Spurious regression and residual-based tests for cointegration in panel data, Journal of Econometrics, 90, 1-44.

Kao, C. and Chiang, M.H., 2000, On the estimation and inference of a cointegrated regression in panel data, Advances in Econometrics, 15, 179-222.

Kaufmann, R. K., 2011, The role of market fundamentals and speculation in recent price changes for crude oil, Energy Policy, 39, 105-115.

Levin, A. and Lin, C.F., 1992, Unit root test in panel data: Asymptotic and finite sample properties, University of California at San Diego, Discussion Paper, 92-93.

Levin, A. and Lin, C.F., 1993, Unit root test in panel data: New results, University of California at San Diego, Discussion Paper, 93-56.

Lundgren, N.G., 1996, Bulk trade and maritime transport costs: The evolution of global markets, Resources Policy, 22, 5-32.

Ma, H. and Oxley, L., 2010, The integration of major fuel sources markets in China: Evidence from panel cointegration tests, Energy Economics, 32, 1139-1146.

Maddala, G.S. and Wu, S., 1999, A comparative study of unit root tests with panel data and a new simple test, Oxford Bulletin of Economics Statistics, special issue, 631-652.

Mark, N.C. and Sul, D., 2003, Cointegration vector estimation by panel DOLS, and long-run money demand, Oxford Bulletin of Economics and Statistics, 65, 655-680.

Mjelde, J.W. and Bessler, D.A, 2009, Market integration among electricity markets and their major fuel source markets, Energy Economics, 31, 482-491.

Moon, H.R. and Perron, B., 2004, Testing for a unit root in panels with dynamic factors, Journal of Econometrics, 122, 81-126.

Panagiotidis, T., and Rutledge, E., 2007, Oil and gas markets in the UK: Evidence from a cointegrating approach, 29, 329-347.

Pedroni, P., 1999, Critical values for cointegration tests in heterogenous panels with multiple regressors, Oxford Bulletin of Economics and Statistics, 61, 653-670.

Pedroni, P., 2004, Panel cointegration asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis, Econometric Theory, 20, 597-625.

Pesaran, M.H., 2004, General diagnostic tests for cross-section dependence in panels, CESifo Working Paper, 1233, 255-260.

Pesaran, M.H., 2007, A simple panel unit root test in the presence of cross-section dependence, Journal of Econometrics, 22, 265-312.

Phillips, P.C.B. and Hansen, B.E., 1990, Statistical inference in instrumental variables regression with I(1) processes, Review of Economic Studies, 57, 99-125.

Serletis, A., and Rangel-Ruiz, R., 2004, Testing for common features in North American energy markets, Energy Economics, 26, 401-414.

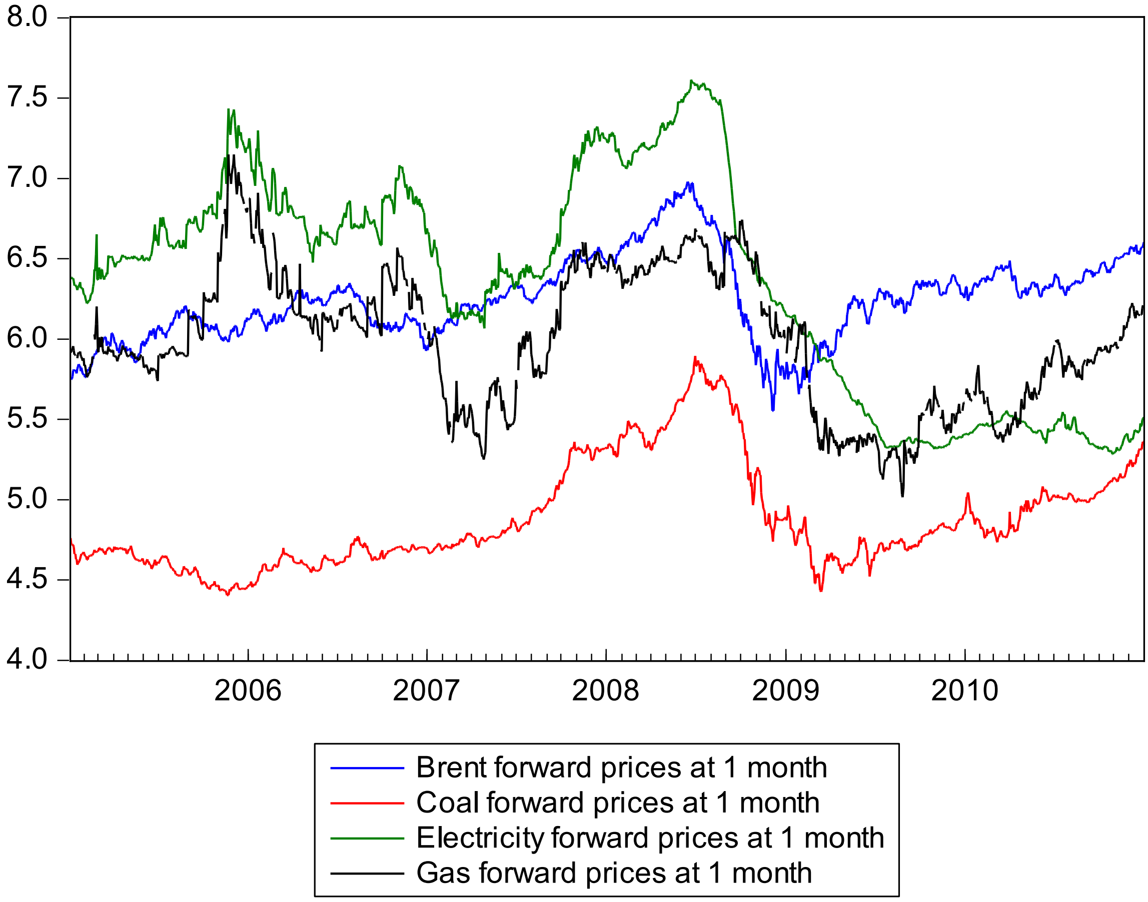
Westgaard, S., Estenstad, M., Steim, M. and Frydenberg, S., 2011, Co-integration of ICE gas oil and crude oil futures, Energy Economics, 33, 311-320.

Westerlund, J., 2007, Testing for error correction in panel data, Oxford Bulletin of Economics and Statistics, 69, 0305-9049.

Westerlund, J. and Edgerton, D., 2007, Simple tests for cointegration in dependent panels with structural breaks, Oxford Bulletin of Economics and Statistics, 70, 665-704.

Appendix A

Figure 1: **One-month forward energy prices (in logarithms)**



Appendix B: Panel unit root tests

Table 4: **First-generation panel unit root tests**

Series	k	LL	IPS	$MW(ADF)$	Hadri
$p_{i,t}^{oil}$	0	-6.01 (0.00)	1.21 (0.11)	61.81 (0.74)	43.19 (0.00)
$p_{i,t}^{coal}$	2	0.56 (0.71)	5.03 (1.00)	12.84 (1.00)	60.53 (0.00)
$p_{i,t}^{elec}$	10	-11.23 (0.00)	-1.18 (0.11)	54.35 (0.91)	95.06 (0.00)
$p_{i,t}^{gas}$	1	-6.17 (0.00)	0.97 (0.83)	39.08 (0.99)	46.96 (0.00)

Notes: Between parentheses: p-values. Tests include individual effects and linear trends; the orders k for LL, IPS, and MW tests are selected using AIC.

Table 5: **Cross-correlation of the errors and CD test**

Series	$p_{i,t}^{oil}$	$p_{i,t}^{coal}$	$p_{i,t}^{elec}$	$p_{i,t}^{gas}$
$\widehat{\rho}$	0.976	0.960	0.956	0.681
CD	925.32 (0.00)	909.73 (0.00)	906.49 (0.00)	645.51 (0.00)

Notes: Between parentheses: p-values. The CD statistics are standard Normal under the null hypothesis of cross-section independence.

Table 6: **Second-generation panel unit root tests**

	CIPS	Moon-Perron		Choi		
		t_α^*	t_β^*	P_m	Z	L^*
$p_{i,t}^{oil}$	-2.480 (0.25)	-1.805 (0.03)	-0.700 (0.24)	-3.829 (0.99)	3.393 (0.99)	3.059 (0.99)
$p_{i,t}^{coal}$	-2.078 (0.95)	0.047 (0.51)	0.016 (0.50)	-3.358 (0.99)	2.299 (0.98)	2.041 (0.97)
$p_{i,t}^{elec}$	-3.162 (0.01)	-1.287 (0.09)	-0.783 (0.21)	-5.308 (1.00)	7.894 (1.00)	7.557 (1.00)
$p_{i,t}^{gas}$	-2.707 (0.02)	1.355(0.91)	0.543 (0.70)	-2.152 (0.98)	1.090 (0.98)	0.993 (0.83)

Notes: Between parentheses: p-values. (a) For the CIPS test, all statistics are based on univariate $AR(p)$ specifications with $p \leq 8$ including individual effects and time trends; the critical values tabulated in Pesaran (2007) are -2.769, -2.653, and -2.589, at 1%, 5%, and 10% significance levels respectively. (b) For the Moon and Perron's tests, the long-run variance used in the construction of t_α^* and t_β^* is computed using the Andrews and Monahan (1992)'s estimator; the maximum number of common factors selected using AIC is 8 (see Bai and Ng, 2002); all statistics are computed with individual effects and time trends; the Moon-Perron statistics are standard Normal for large T under the unit root hypothesis. (c) For the Choi's test, the optimal lag orders in the individual ERS statistics (Elliott, Rothenberg and Stock, 1996) for each series are determined with $p_{max} = 12$; all tests are computed with individual effects and time trends specifications; under the unit root hypothesis the Choi's statistics are standard Normal when T and N converge jointly to infinity.