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## **Long Memory in German Energy Price Indices**

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# LONG MEMORY IN GERMAN ENERGY PRICE INDICES

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## Abstract

This study examines the long-memory properties of German energy price indices (specifically, import and export prices, as well as producer and consumer prices) for hard coal, lignite, mineral oil and natural gas adopting a fractional integration modelling framework. The analysis is undertaken using monthly data from January 2000 to August 2011. The results suggest nonstationary long memory in the series (with orders of integration equal to or higher than 1) when breaks are not allowed for. However, endogenous break tests indicate a single break in all series except for producer prices for lignite for which two breaks are detected. When such breaks are taken into account, and with autocorrelated disturbances, evidence of mean reversion is found in practically all cases.

**Keywords:** Energy prices, Germany, fractional integration, persistence, breaks and outliers.

**JEL classification:** C32, E30

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## 1. Introduction

Given the fact that energy price shocks have often triggered economic crises, there is considerable interest in modelling appropriately the behaviour of energy prices. These are influenced by a number of factors such as the global demand for oil, OPEC and non-OPEC oil production, market conditions and the geopolitical environment. OPEC has generally been successful in reducing price fluctuations by adjusting production. However, the emergence of the futures market has meant that the effectiveness of output adjustments in controlling prices

now depends on how they influence market participants' expectations in the futures market along with OPEC's long-term investment plans to expand production capacity (Fattouh, 2007).

Previous research on the oil industry has investigated long-memory properties in the case of oil consumption (Mohn and Osmundsen, 2008; Lean and Smyth, 2009), returns on oil investment (Boone, 2001) and oil exhaustion (Karbassi et al. 2007; Tsoskounoglou et al. 2008; Höök and Aleklett, 2008), and energy prices (Serletis, 1992; Lien and Root, 1999; Elder and Serletis, 2008; Kang et al., 2009). However, there are no existing studies on the degree of persistence of energy prices also allowing for possible breaks in the data. The present paper aims to fill this gap in the literature by adopting a fractional integration framework including breaks to examine the degree of persistence in several German energy price indices. This is an important issue, since depending on whether the effects of shocks are temporary or permanent and whether mean reversion occurs or not different policy responses are required.

The layout of the paper is the following. Section 2 briefly reviews the previous literature. Section 3 outlines the methodology. Section 4 discusses the data and the empirical findings. Section 5 provides some concluding remarks.

## **2. Literature Review**

Although there are some papers investigating the presence of unit roots in energy consumption (Chen and Lee, 2007; Narayan and Smyth, 2007; Hsu et al., 2008; Mishra et al., 2009; Lean and Smyth, 2009; Rao and Rao, 2009), only a few studies examine the behaviour of prices. Li and Thompson (2010) analyse monthly real oil prices between 1990 and 2008 using a GARCH model. Kilian (2010) examines the relationship between demand and supply shocks in the case of the price of gasoline in the US and the price of crude oil in global markets using a structural Vector AutoRegressive (VAR) model in order to assess the importance of energy price shocks in explaining the variation in US gasoline prices and consumption growth since 2002; he also identifies the origins of gasoline price shocks, and estimates the magnitude, pattern and persistence of the response of the price and consumption of gasoline to these shocks. Berument,

Ceylan and Dogan (2010) investigate how oil price shocks affect the output growth of selected countries that are either net exporters or net importers of oil and are too small to affect oil prices and conclude that oil price increases have a statistically significant and positive effect on output in Algeria, Iran, Iraq, Kuwait, Libya, Oman, Qatar, Syria, and the United Arab Emirates, but not in Bahrain, Djibouti, Egypt, Israel, Jordan, Morocco, and Tunisia. They also find that oil supply/demand shocks are associated with lower/higher output growth. Vassilopoulos (2010) analyses price signals in the French wholesale electricity market simulating an operational research model, and reports evidence of monopolistic behaviour affecting prices. Fattouh (2010) analyses crude oil price differentials using a two-regime Threshold AutoRegressive (TAR) model, and finds that the prices of different varieties of crude oil move closely. Serletis (1992) examines the random walk behaviour in energy futures prices with unit root tests, and finds evidence against unit roots if a break is taken into account. In the context of long memory, Elder and Serletis (2008) analyse long-range dependence behaviour in energy futures prices in a fractional integration dynamic model, finding evidence of anti-persistence. Other recent papers using fractional integration techniques to model oil production in the OPEC countries and US electricity consumption are Gil-Alana et al. (2010) and Barros et al. (2011) respectively.

The present paper analyses the monthly energy prices of hard coal, lignite, mineral oil and natural gas estimating a fractional integration model with structural breaks for import, export, producer and consumer price indices in Germany.

### **3. Methodology**

One characteristic of many economic time series is their nonstationary nature. There exist a variety of models to describe such nonstationarity. Until the 1980s a standard approach was to impose a deterministic (linear or quadratic) function of time assuming that the residuals from the regression model were stationary  $I(0)$ . Later on, and especially after the seminal work of Nelson and Plosser (1982), a wide consensus was reached that the nonstationary component of

most series was stochastic, and models with unit roots (or first differences, I(1)) were commonly adopted with and without deterministic trends. However, the I(1) case is only one possible specification to describe such behaviour. In fact, the degree of differentiation required to obtain I(0) stationarity is not necessarily an integer but could be any point on the real line. In such a case, the process is said to be fractionally integrated or I(d). The I(d) model can be expressed in the form

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, \dots, \quad (1)$$

where L is the lag-operator ( $Lx_t = x_{t-1}$ ) and  $u_t$  is I(0) defined, for the purpose of the present study, as a covariance stationary process with spectral density function that is positive and finite at the zero frequency.

Note that the polynomial  $(1-L)^d$  in equation (1) can be expressed in terms of its Binomial expansion, such that, for all real d,

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d L + \frac{d(d-1)}{2} L^2 - \dots,$$

and thus

$$(1 - L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \dots$$

In this context, d plays a crucial role since it indicates the degree of dependence of the time series: the higher the value of d is, the higher the level of association will be between the observations. The above process also admits an infinite Moving Average (MA) representation such that

$$x_t = \sum_{k=0}^{\infty} a_k u_{t-k},$$

where

$$a_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)},$$

and  $\Gamma(\bullet)$  representing the Gamma function. Thus, the impulse responses are also clearly affected by the magnitude of  $d$ , and the higher the value of  $d$  is, the higher the responses will be. If  $d$  is smaller than 1, the series is mean reverting, with shocks having temporary effects, and disappearing at a relatively slow rate (hyperbolically) in the long run.<sup>1</sup> On the other hand, if  $d \geq 1$ , shocks have permanent effects unless policy actions are taken. Processes with  $d > 0$  in (1) display the property of “*long memory*”, which is characterised by the spectral density function of the process being unbounded at the origin.

In this study, we estimate the fractional differencing parameter  $d$  using the Whittle function in the frequency domain (Dahlhaus, 1989) but also employ a testing procedure developed by Robinson (1994), which has been shown to be the most efficient one in the context of fractional integration against local alternatives. This method, based on the Lagrange Multiplier (LM) principle, tests the null hypothesis  $H_0: d = d_0$  in (1) for any real value  $d_0$ , where  $x_t$  in (1) can be the errors in a regression model of the form:

$$y_t = \beta^T z_t + x_t, \quad t = 1, 2, \dots, \quad (2)$$

where  $y_t$  is the observed time series,  $\beta$  is a  $(k \times 1)$  vector of unknown coefficients, and  $z_t$  is a set of deterministic terms that might include an intercept (i.e.,  $z_t = 1$ ), an intercept with a linear time trend ( $z_t = (1, t)^T$ ), or any other type of deterministic processes such as dummy variables to examine the possible presence of outliers/breaks. Other parametric methods, such as Sowell’s (1992) maximum likelihood estimator in the time domain and Beran’s (1995) least squares approach, produced essentially the same results. We also implemented a semiparametric method, introduced by Robinson (1995) and further developed by Abadir et al. (2007), where no functional form is imposed on  $u_t$  in (1). It is essentially a local ‘Whittle estimator’ in the frequency domain using a band of frequencies that degenerates to zero. The estimator is implicitly defined by:

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<sup>1</sup> The decay is hyperbolically slow as opposed to the exponentially fast decay associated with the AutoRegressive AR (I(0)) case.

$$\hat{d} = \arg \min_d \left( \log \overline{C(d)} - 2d \frac{1}{m} \sum_{s=1}^m \log \lambda_s \right), \quad (3)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^m I(\lambda_s) \lambda_s^{2d}, \quad \lambda_s = \frac{2\pi s}{T}, \quad \frac{1}{m} + \frac{m}{T} \rightarrow 0,$$

where  $m$  is the bandwidth parameter,  $I(\lambda_s)$  is the periodogram of the raw time series,  $x_t$ , given by:

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^T x_t e^{i\lambda_s t} \right|^2,$$

and  $d \in (-0.5, 0.5)$ . Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m} (\hat{d} - d_0) \rightarrow_{dtb} N(0, 1/4) \quad \text{as } T \rightarrow \infty,$$

where “ $\rightarrow_{dtb}$ ” stands for convergence in distribution, and  $d_0$  is the true value of  $d$ . This estimator is robust to a certain degree of conditional heteroscedasticity (Robinson and Henry, 1999) and is more efficient than other semi-parametric competitors. Abadir et al. (2007) extended this approach by using an extended Fourier transform in the computation of the periodogram, such that no prior differentiation is required when estimating the parameter  $d$  in nonstationary contexts.

However, it has been argued in recent years that fractional integration may be a spurious phenomenon caused by the presence of breaks in the data (see, e.g., Cheung, 1993; Diebold and Inoue, 2001; Giraitis et al., 2001; Mikosch and Starica, 2004; Granger and Hyung, 2004). Thus, we also employed a procedure that determines endogenously the number of breaks and the break dates in the series, allowing for different fractional differencing parameters in each sub-sample. This method, due to Gil-Alana (2008), is based on minimising the residual sum of the squares at different break dates and different (possibly fractional) differencing parameters. Specifically, the following model is considered:

$$y_t = \beta_i^T z_t + x_t; \quad (1-L)^{d_i} x_t = u_t, \quad t = 1, \dots, T_b^i, \quad i = 1, \dots, nb, \quad (4)$$

where nb is the number of breaks,  $y_t$  is the observed time series, the  $\beta_i$ 's are the coefficients on the deterministic terms, the  $d_i$ 's are the orders of integration for each sub-sample, and the  $T_b^i$ 's correspond to the unknown break dates. Note that given the difficulties in distinguishing between models with fractional orders of integration and those with broken deterministic trends, it is important to consider estimation procedures for fractional unit roots in the presence of broken deterministic terms.

#### 4. Data and Results

In this study, we investigate persistence in German energy prices. The data are available from *Statistisches Bundesamt*: (<http://www.destatis.de/jetspeed/portal/cms/>). Each series consists of monthly observations, ranging from January 2000 to August 2011. We first analyse the characteristics of the data by looking at their correlograms and periodograms, and then estimate a model that allows for fractional integration, initially without breaks and then allowing for structural breaks.

**[Insert Figures 1 – 3 about here]**

Figure 1 displays the time series plots of the producer prices of the four energy products: hard coal, lignite, mineral oil and natural gas. In all cases we notice a continuous increase till July 2008 followed by a sharp decrease in the period immediately after. Figure 2 displays the correlograms of the first differenced series, and shows a cyclical pattern probably reflecting the monthly frequency of the series. The corresponding periodograms, in Figure 3, indicate values close to zero at the smallest frequency, which suggests that the series may now be overdifferenced.

Tables 1 – 3 display the estimates of  $d$  (and the corresponding 95% confidence band) in the model given by equations (2) and (1) with  $z_t = (1, t)^T$ ,  $t \geq 1$ , 0 otherwise, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1-L)^{d_o} x_t = u_t, \quad t = 1, 2, \dots, \quad (5)$$



assuming that  $u_t$  in (5) is white noise (in Table 1), weakly autocorrelated as in the model of Bloomfield (1973) (in Table 2), and a seasonal (monthly) AR(1) process (in Table 3). The Bloomfield model employed in Table 2 is a non-parametric approach that approximates ARMA structures with a small number of parameters and that has been widely employed in a fractional integration framework.<sup>2</sup> All three tables report the results for the three standard cases of no regressors, an intercept and an intercept with a linear trend.

Starting with the case of white noise disturbances (in Table 1), we notice that most of the estimates of  $d$  are above 1. In fact, the unit root null hypothesis is rejected in the majority of cases and the only evidence of unit roots is found for the two lignite series and also for the consumer prices of hard coal and natural gas in the case of no regressors. As for the deterministic terms, the time trend appears not to be statistically significant in all cases, the intercept being sufficient to describe the deterministic component.

**[Insert Tables 1 - 3 about here]**

Concerning the results based on autocorrelated (Bloomfield) errors, the estimates are generally smaller than in the previous case of white noise errors. Here only one series exhibits mean reversion (i.e., with the estimated value of  $d$  being strictly below 1), namely producer prices for lignite. For the other lignite series (consumer prices) and the two prices for mineral oil, the estimates are also below 1 but the unit root null cannot be rejected at the 5% level. For the three hard coal series, the estimates are above 1 and the unit root cannot be rejected; finally, for the four natural gas series, the estimates are strictly above unity.

When assuming seasonal AR(1) disturbances, the results are completely in line with those reported in Table 1 for the white noise case: for the two lignite prices, the estimates of  $d$  are below 1 and the unit root cannot be rejected, and for the remaining series the estimates are above 1 and the unit root is rejected in favour of higher orders of integration.

**[Insert Table 4 about here]**

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<sup>2</sup> The Bloomfield (1973) model is a very suitable one in the context of the tests of Robinson (see Gil-Alana, 2004).

Given the existence of some disparities in the results presented for the cases of uncorrelated and weakly autocorrelated errors, we also estimated  $d$  using a semiparametric method, where no functional form is imposed on the error term  $u_t$ . Table 4 displays the estimates of the fractional differencing parameter  $d$  using the Whittle semiparametric method of Robinson (1995). The set of bandwidth parameters used is  $m = 5, 10, 12, 13, 15, 20$  and  $30$ . For lignite and mineral oil some of the estimates are below 1 (mean reversion) while for the remaining series (hard coal and natural gas) the estimates imply a unit root or are above 1.

The results so far provide little evidence of mean reversion in German energy prices. Next we examine the possibility of breaks in the data employing the procedure developed by Gil-Alana (2008) briefly described in the previous section. Table 5 displays the parameter estimates under the assumption of white noise errors. We find a single break in all but one series, namely lignite with producer prices, where two breaks are detected. Regarding the fractional differencing parameters, all of them are above 1, the only exception being again producer prices for lignite during the first and third subsamples, with orders of integration below 1. As for the breaks, they take place in January 2002 for lignite consumer prices; in January 2007 for hard coal consumer prices and lignite producer prices; at the end of 2008 / beginning of 2009 for the producer prices of hard coal and lignite and the two mineral oil series; finally, in April 2009 for the four natural gas series. These dates might reflect the lagged effects of the oil crisis of the second half of 2008.

**[Insert Tables 5 and 6 about here]**

Table 6 concerns the case of AR(1) error terms. Here we obtain the most interesting results since all the fractional differencing parameters are strictly below 1 implying mean reverting behaviour. Not surprisingly, the same number of breaks and the same break dates as in the previous case with white noise errors are found, and several diagnostic tests carried out on the residuals indicate that in all cases this specification is more adequate to describe the behaviour of the series than that based on uncorrelated disturbances. For many of the subsamples the estimates are strictly below the unit root, although the AR coefficients are very

large (thus indicating a high degree of persistence) in all cases. The orders of integration are strictly smaller than one in both subsamples in the case of producer and consumer prices of hard coal, consumer prices of lignite, and also consumer, producer and export prices of natural gas. For the remaining series mean reversion occurs in at least one subsample.

The above results clearly show that the presence of structural breaks is an important issue when modelling energy prices: if breaks exist but are not modelled, we find strong evidence of nonstationary behaviour with orders of integration which are equal to or higher than 1, implying lack of mean reverting behaviour. However, when the breaks are taken into account, this evidence disappears and the series appear to be mean reverting, with the effects of the shocks dying away relatively fast in all cases.

## **5. Conclusions**

In this paper, we have examined the degree of persistence in various monthly energy prices in Germany. For this purpose, we have estimated fractional integration or  $I(d)$  models, first without breaks and then allowing for structural breaks at unknown dates. In the former case, the orders of integration of the series are found to be equal to or higher than 1, thus providing strong evidence against mean reversion. However, when endogenous tests for breaks are carried out, the results indicate that there is a single break in all but one series, namely the producer prices of lignite for which two breaks are detected. If the disturbances are modelled as being autocorrelated the orders of integration are found to be smaller than 1 in practically all cases, implying that mean reversion occurs and the effects of shocks disappear in the long run.

Compared to the existing literature, the contribution of the present study is therefore threefold. First, it carries out a thorough analysis of persistence in German energy prices, whilst previous studies had not estimated long-memory models. By adopting a fractional integration framework, it allows for a more general and flexible specification than the classical models based on integer degrees of differentiation. Second, it shows that the inclusion of breaks is crucial in the present context, since it produces evidence of mean reversion not found

otherwise. Third, it examines various energy prices by source in a developed economy such as Germany, unlike most previous studies only analysing prices for one source of energy or focusing on OPEC or other groups of countries. The results are policy relevant, since a priori knowledge of the persistence behaviour of energy prices by source enables policy makers to design appropriate allocative strategies. They are also useful for German industries with a significant share of energy consumption and a consequent strong interest in long-run energy price movements.

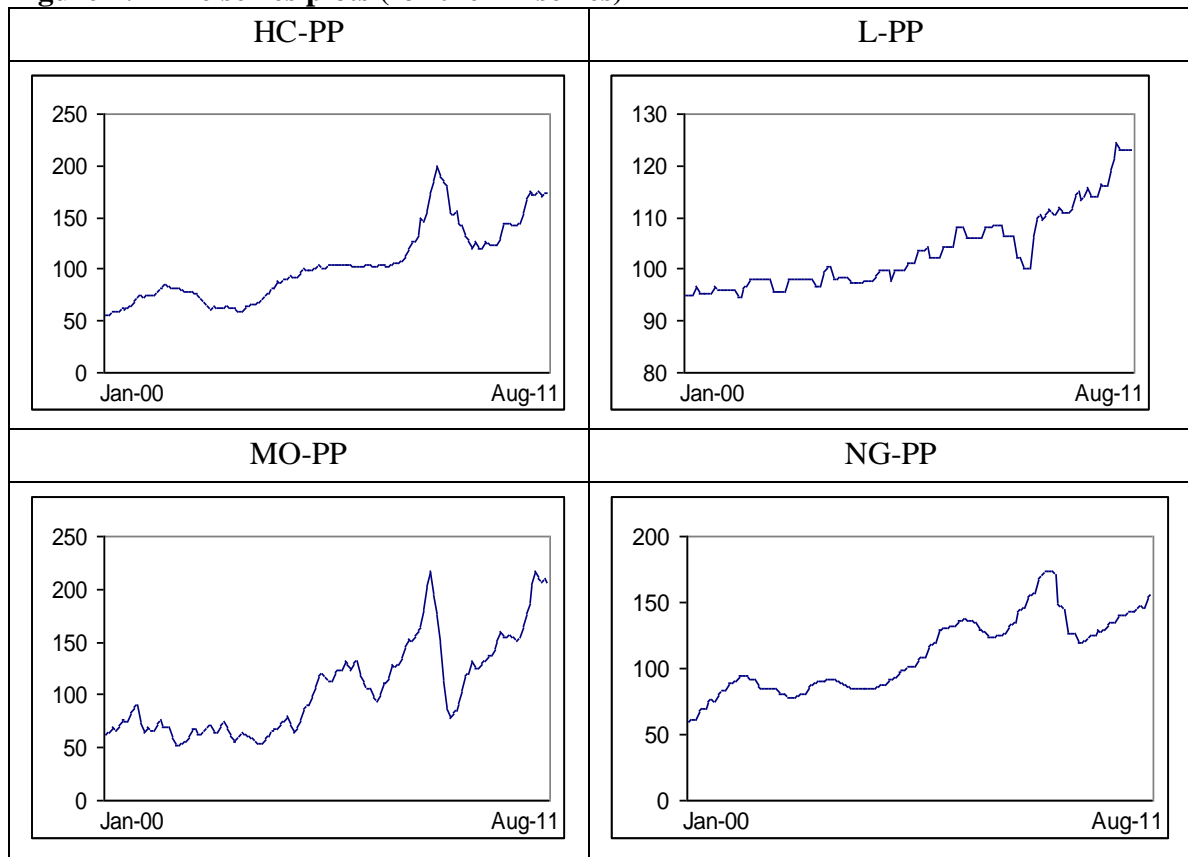
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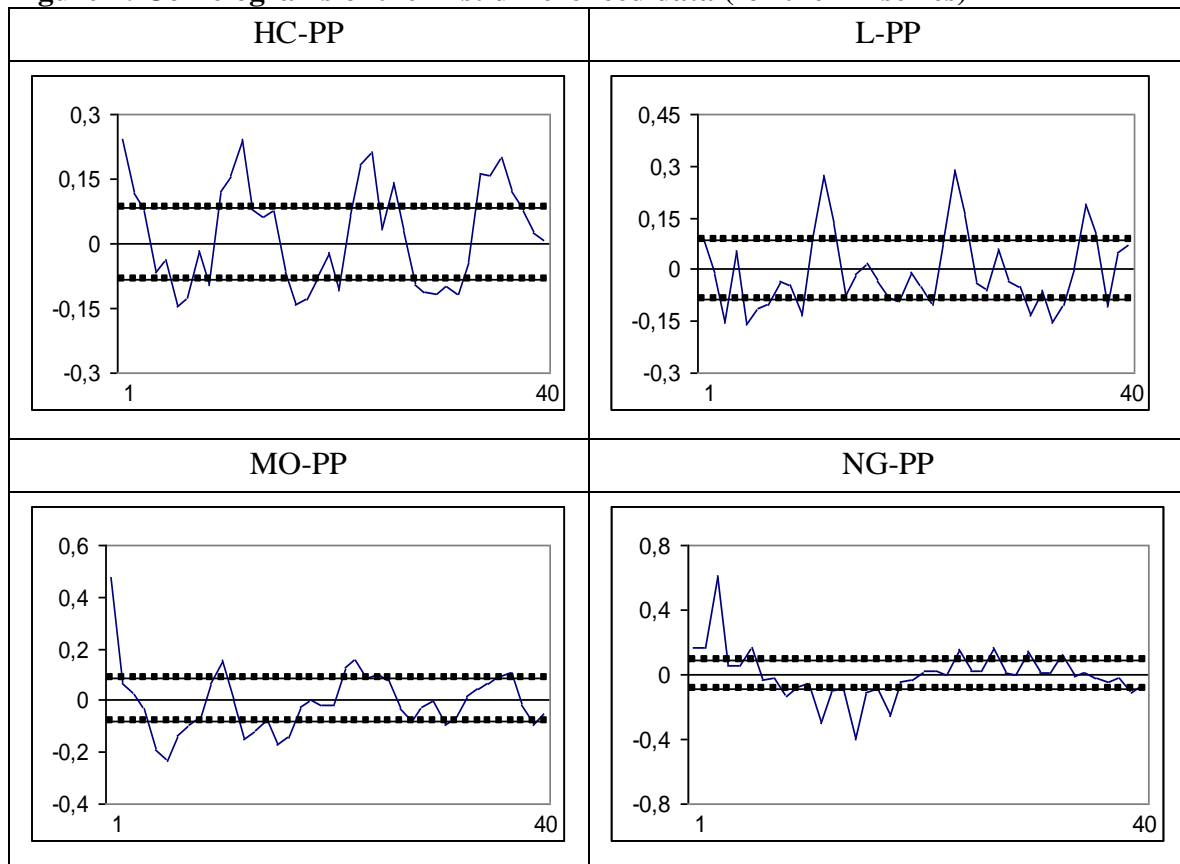
**Figure 1: Time series plots (for the PP series)**



HC stands for Hard Coal, L is lignite, MO is mineral oil, NG natural gas and PP stands for producer prices.

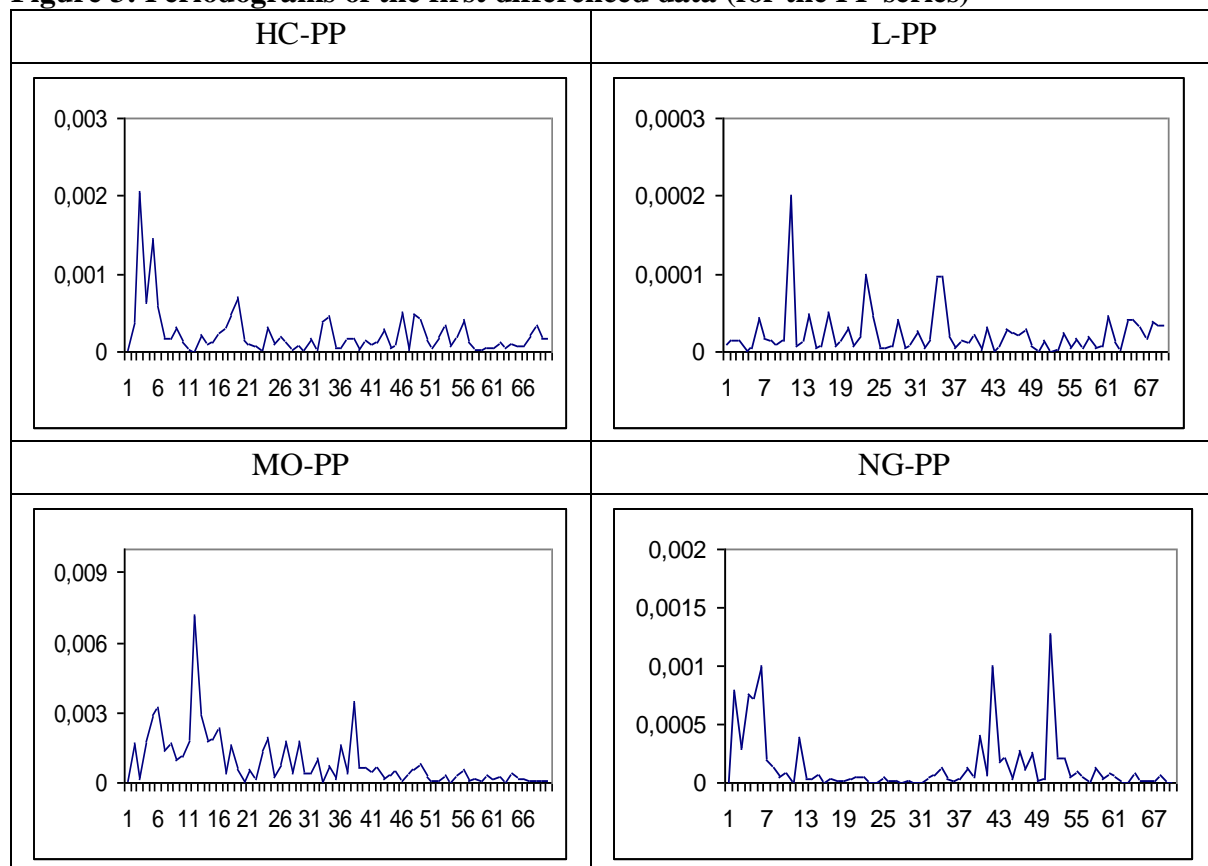


**Figure 2: Correlograms of the first differenced data (for the PP series)**



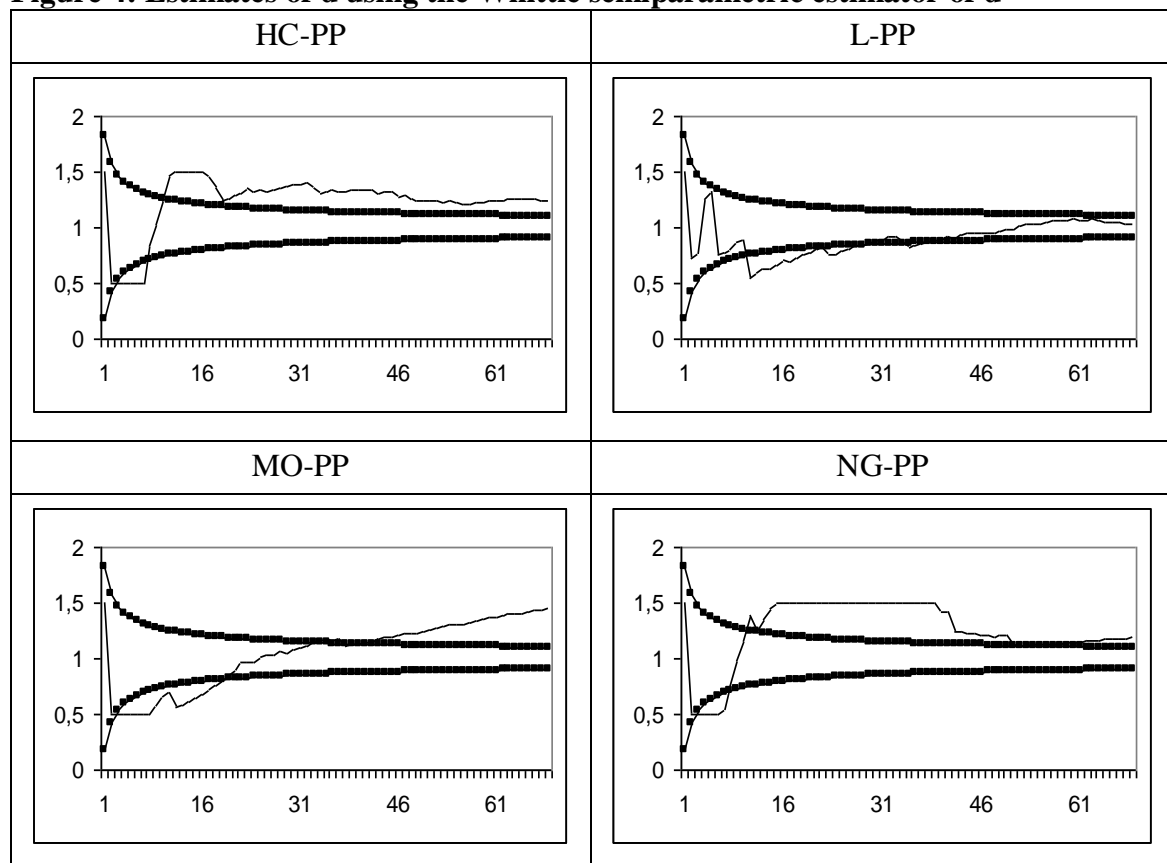
The dotted lines refer to the 95% confidence band for the null hypothesis of no autocorrelation.

**Figure 3: Periodograms of the first differenced data (for the PP series)**



The periodograms were computed based on the discrete Fourier frequencies  $\lambda_j = 2\pi j/T, j = 1, \dots, T/2$ .

**Figure 4: Estimates of  $d$  using the Whittle semiparametric estimator of  $d$**



The horizontal axis refers to the bandwidth parameter while the vertical one displays the estimates of  $d$ . The bold lines display the 95% confidence interval for the  $I(1)$  hypothesis.

**Table 1: Estimates of d based on a model with white noise disturbances**

	No regressors	An intercept	A linear time trend
HC-IP	1.139 (1.019, 1.295)	<b>1.307 (1.165, 1.502)</b>	1.308 (1.166, 1.502)
HC-PP	1.137 (1.034, 1.272)	<b>1.263 (1.149, 1.406)</b>	1.263 (1.149, 1.405)
HC-CP	0.971 (0.861, 1.123)	<b>1.168 (1.061, 1.340)</b>	1.185 (1.072, 1.352)
L-PP	0.974 (0.876, 1.109)	<b>0.999 (0.879, 1.182)</b>	0.999 (0.869, 1.186)
L-CP	0.971 (0.871, 1.126)	<b>1.105 (0.939, 1.339)</b>	1.108 (0.936, 1.337)
MO-IP	1.198 (1.061, 1.377)	<b>1.311 (1.152, 1.509)</b>	1.313 (1.154, 1.513)
MO-PP	1.297 (1.149, 1.493)	<b>1.539 (1.343, 1.789)</b>	1.542 (1.345, 1.793)
NG-IP	1.333 (1.237, 1.452)	<b>1.568 (1.464, 1.695)</b>	1.567 (1.463, 1.695)
NG-PP	1.100 (1.016, 1.230)	<b>1.202 (1.108, 1.317)</b>	1.199 (1.106, 1.313)
NG-CP	1.024 (0.927, 1.155)	<b>1.195 (1.094, 1.322)</b>	1.189 (1.092, 1.316)
NG-EP	1.169 (1.072, 1.296)	<b>1.296 (1.181, 1.443)</b>	1.293 (1.179, 1.439)

In parentheses the 95% confidence band for the values of d. In bold the best model specification for each series.

**Table 2: Estimates of d based on a model with Bloomfield disturbances**

	No regressors	An intercept	A linear time trend
HC-IP	1.027 (0.812, 1.327)	<b>1.012 (0.821, 1.299)</b>	0.808 (1.012, 1.290)
HC-PP	1.129 (0.920, 1.413)	<b>1.192 (0.903, 1.553)</b>	1.193 (0.931, 1.553)
HC-CP	0.921 (0.730, 1.178)	<b>1.049 (0.929, 1.287)</b>	1.072 (0.899, 1.319)
L-PP	0.939 (0.773, 1.168)	<b>0.801 (0.677, 0.998)</b>	0.760 (0.608, 0.998)
L-CP	0.899 (0.718, 1.180)	<b>0.834 (0.726, 1.182)</b>	0.699 (0.398, 1.172)
MO-IP	0.997 (0.760, 1.393)	<b>0.949 (0.670, 1.427)</b>	0.957 (0.660, 1.462)
MO-PP	0.998 (0.749, 1.351)	<b>0.789 (0.568, 1.159)</b>	0.809 (0.539, 1.169)
NG-IP	1.580 (1.299, 1.953)	<b>1.850 (1.413, 2.415)</b>	1.819 (1.411, 2.442)
NG-PP	1.282 (1.040, 1.604)	<b>1.678 (1.220, 2.190)</b>	1.649 (1.203, 2.181)
NG-CP	1.032 (0.839, 1.289)	<b>1.302 (1.013, 1.689)</b>	1.294 (1.013, 1.690)
NG-EP	1.267 (1.012, 1.610)	<b>1.182 (0.799, 1.558)</b>	1.172 (0.850, 1.538)

In parentheses the 95% confidence band for the values of d. In bold the best model specification for each series.

**Table 3: Estimates of d based on a model with seasonal monthly AR disturbances**

	No regressors	An intercept	A linear time trend
HC-IP	1.126 (1.008, 1.283)	<b>1.294 (1.148, 1.495)</b>	1.295 (1.149, 1.495)
HC-PP	1.121 (1.021, 1.255)	<b>1.239 (1.115, 1.396)</b>	1.239 (1.116, 1.397)
HC-CP	0.971 (0.851, 1.123)	<b>1.147 (1.039, 1.314)</b>	1.159 (1.040, 1.322)
L-PP	0.973 (0.869, 1.109)	<b>0.987 (0.873, 1.151)</b>	0.985 (0.861, 1.156)
L-CP	0.971 (0.853, 1.124)	<b>0.931 (0.806, 1.162)</b>	0.938 (0.795, 1.163)
MO-IP	1.202 (1.064, 1.382)	<b>1.314 (1.157, 1.508)</b>	1.316 (1.159, 1.511)
MO-PP	1.297 (1.149, 1.493)	<b>1.535 (1.342, 1.786)</b>	1.538 (1.345, 1.790)
NG-IP	1.332 (1.233, 1.456)	<b>1.544 (1.433, 1.687)</b>	1.545 (1.433, 1.688)
NG-PP	1.110 (1.016, 1.220)	<b>1.197 (1.103, 1.315)</b>	1.193 (1.101, 1.308)
NG-CP	1.027 (0.927, 1.160)	<b>1.193 (1.099, 1.324)</b>	1.188 (1.087, 1.318)
NG-EP	1.177 (1.075, 1.310)	<b>1.263 (1.145, 1.416)</b>	1.259 (1.142, 1.413)

In parentheses the 95% confidence band for the values of d. In bold the best model specification for each series.

**Table 4: Estimates of d based on the semiparametric Whittle estimator (Robinson, 1995)**

M	5	10	12	13	15	20	30
HC-IP	0.531*	1.397	1.500	1.328	1.203	1.149	1.257
HC-PP	0.500*	1.241	1.500	1.500	1.500	1.262	1.394
HC-CP	1.372	0.851	0.929	0.961	1.012	1.077	1.187
L-PP	1.319	0.886	0.589*	0.624*	0.666*	0.768*	0.881
L-CP	0.969	0.500*	0.500*	0.502*	0.571*	0.748*	1.023
MO-IP	0.500*	0.680*	0.575*	0.566*	0.621*	0.816*	1.002
MO-PP	0.500*	0.665*	0.561*	0.579*	0.652*	0.862	1.076
NG-IP	0.500*	1.136	1.265	1.395	1.500	1.500	1.500
NG-PP	0.500*	1.161	1.235	1.348	1.500	1.500	1.500
NG-CP	0.500*	1.206	1,117	1.207	1.344	1.487	1.469
NG-EP	0.500*	1.028	1.183	1.305	1.269	1.382	1.457
95% Lw	0.632	0.739	0.762	0.771	0.787	0.816	0.849
95% Up	1.367	1.260	1.237	1.228	1.212	1.183	1.150

M is the bandwidth parameter. \* indicates evidence of mean reversion.

**Table 5: Estimates for the different subsamples with white noise errors**

Series	Number of breaks	Estimates of d			Intercepts		
		d <sub>1</sub>	d <sub>2</sub>	d <sub>3</sub>	$\alpha_1$	$\alpha_2$	$\alpha_3$
HC-IP	1 (Dec.2008)	1.482	1.247	---	72.585 (17.315)	200.418 (28.971)	---
HC-PP	1 (Jan.2009)	1.287	1.251	---	54.767 (14.961)	155.649 (29.313)	---
HC-CP	1 (Jan.2007)	1.244	1.355	---	92.360 (265.91)	104.564 (213.79)	---
L-PP	2 (Jan.2007 /	0.787	0.954	0.781	95.367 (112.53)	107.951 (92.151)	107.994 (82.664)

	Jan.2009)						
L-CP	1 (Jan.2002)	1.482	1.196	---	94.126 (254.77)	96.515 (261.22)	---
MO-IP	1 (Oct.2008)	1.147	1.252	---	57.588 (8.940)	132.435 (15.021)	---
MO-PP	1 (Aug.2008)	1.383	1.007	---	61.302 (11.685)	194.80 (16.796)	---
NG-IP	1 (Apr.2009)	1.631	1.418	---	46.107 (17.771)	142.267 (39.607)	---
NG-PP	1 (Apr.2009)	1.237	1.205	---	58.916 (22.055)	150.169 (38.003)	---
NG-CP	1 (Apr.2009)	1.232	1.297	---	68.908 (37.716)	132.191 (111.97)	---
NG-EP	1 (Apr.2009)	1.218	1.373	---	56.149 (14.696)	15.793 (27.937)	---

In parentheses, in the second column the break date, in the third and fourth columns the estimated AR coefficients, and in the sixth and seventh columns the t-values.

**Table 6: Estimates for the different subsamples with AR(1) errors**

Series	Number of breaks	Estimates of d			Intercepts		
		d <sub>1</sub> ( AR )	d <sub>2</sub> ( AR )	d <sub>3</sub> ( AR )	α <sub>1</sub> (t-value)	α <sub>2</sub> (t-value)	α <sub>3</sub> (t-value)
HC-IP	1 (Dec.2008)	0.817 (0.720)	0.485* (0.738)	----	75.355 (12.229)	194.79 (30.256)	---
HC-PP	1 (Jan.2009)	0.367* (0.944)	0.396* (0.849)	----	86.670 (23.380)	148.18 (28.900)	---
HC-CP	1 (Jan.2007)	0.329* (0.959)	0.264* (0.977)	----	95.705 (421.01)	109.71 (319.02)	---
L-PP	2 (Jan.2007 / Jan.2009)	0.113* (0.892)	xxx	xxx	98.366 (484.54)	xxx	xxx
L-CP	1 (Jan.2002)	0.698* (0.664)	0.373* (0.937)	---	94.040 (207.01)	99.958 (446.90)	---
MO-IP	1 (Oct.2008)	0.767 (0.440)	0.479* (0.779)	---	62.731 (9.617)	126.15 (18.240)	---
MO-PP	1 (Aug.2008)	0.592* (0.788)	0.822 (0.761)	---	74.789 (11.510)	184.54 (14.072)	---



NG-IP	1 (Apr.2009)	0.751 (0.808)	0.617* (0.803)	---	54.487 (11.361)	134.98 (28.116)	----
NG-PP	1 (Apr.2009)	0.212* (0.981)	0.617* (0.599)	---	103.45 (55.949)	143.19 (33.468)	---
NG-CP	1 (Apr.2009)	0.217* (0.980)	0.318* (0.846)	---	101.70 (91.456)	123.48 (103.11)	---
NG-EP	1 (Apr.2009)	0.116* (0.981)	0.205* (0.825)	---	106.42 (52.437)	130.82 (36.325)	---

In parentheses, in the second column the break date, in the third and fourth columns the estimated AR coefficients, and in the sixth and seventh columns the t-values. xxx indicates that convergence is not achieved, and \* indicates rejections of the unit root null ( $d = 1$ ) in favour of mean reversion ( $d < 1$ ) at the 5% level.