Long Memory in Energy Prices in Gemany

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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 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, when breaks are taken into account, and permitting autocorrelated disturbances, evidence of mean reversion is found in practically all cases.

Key-Words: - Energy prices, Germany, fractional integration, persistence, breaks and outliers.

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

2 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 merely one particular model 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

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

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,

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

and thus

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

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. In this context, 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 1run. 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_o: $d = d_o$ in (1) for any real value d_o, where x_t in (1) can be the errors in a regression model of the form:

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

where y_t is the observed time series, β is a (kx1) 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.

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:

$$y_t = \beta_i{}^T z_t + x_t; \qquad (3)$$

$$(1 - L)^{d_i} x_t = u_t, \quad t = 1, \ldots, T_b^i, \quad i = 1, \ldots nb,$$

where nb is the number of breaks, y_t is the observed time series, the β_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

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those with broken deterministic trends, it is important to consider estimation procedures for fractional unit roots in the presence of broken deterministic terms.

3 Data and empirical results

In this study, we investigate persistence in German energy prices. The data are available from *Statistisches Bundesamt*:. Each series consists of monthly observations, ranging from January 2000 to August 2011.

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 ≥ 1, 0 otherwise, i.e.,

$$y_t = \beta_0 + \beta_1 t + x_t, \qquad (4)$$

$$(1 - L)^{d_o} x_t = u_t, \qquad t = 1, 2, \ldots ,$$

assuming that u_t in (4) 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 the context of fractional integration

Table 1: Estimates of d for white noise disturbances

	No regressors	An intercept	A linear time trend
HC-IP	1.139 (1.01, 1.29)	**1.307 (1.16, 1.50)**	1.308 (1.16, 1.50)
HC-PP	1.137 (1.03, 1.27)	**1.263 (1.14, 1.40)**	1.263 (1.14, 1.40)
HC-CP	0.971 (0.86, 1.12)	**1.168 (1.06, 1.34)**	1.185 (1.07, 1.35)
L-PP	0.974 (0.87, 1.10)	**0.999 (0.87, 1.18)**	0.999 (0.86, 1.18)
L-CP	0.971 (0.87, 1.12)	**1.105 (0.93, 1.33)**	1.108 (0.93, 1.33)
MO-IP	1.198 (1.06, 1.37)	**1.311 (1.15, 1.50)**	1.313 (1.15, 1.51)
MO-PP	1.297 (1.14, 1.49)	**1.539 (1.34, 1.78)**	1.542 (1.34, 1.79)
NG-IP	1.333 (1.23, 1.45)	**1.568 (1.46, 1.69)**	1.567 (1.46, 1.69)
NG-PP	1.100 (1.01, 1.23)	**1.202 (1.10, 1.31)**	1.199 (1.10, 1.31)
NG-CP	1.024 (0.92, 1.15)	**1.195 (1.09, 1.32)**	1.189 (1.09, 1.31)
NG-EP	1.169 (1.07, 1.29)	**1.296 (1.18, 1.44)**	1.293 (1.17, 1.43)

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

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 in 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 be statistically significant in any case, the intercept being sufficient to describe the deterministic component.

Table 2: Estimates of d with Bloomfield disturbances

	No regressors	An intercept	A linear time trend
HC-IP	1.027 (0.81, 1.32)	**1.012 (0.82, 1.29)**	0.808 (1.01, 1.29)
HC-PP	1.129 (0.92, 1.41)	**1.192 (0.90, 1.55)**	1.193 (0.93, 1.55)
HC-CP	0.921 (0.73, 1.17)	**1.049 (0.92, 1.28)**	1.072 (0.89, 1.31)
L-PP	0.939 (0.77, 1.16)	**0.801 (0.67, 0.99)**	0.760 (0.60, 0.99)
L-CP	0.899 (0.71, 1.18)	**0.834 (0.72, 1.18)**	0.699 (0.39, 1.17)
MO-IP	0.997 (0.76, 1.39)	**0.949 (0.67, 1.42)**	0.957 (0.66, 1.46)
MO-PP	0.998 (0.74, 1.35)	**0.789 (0.56, 1.15)**	0.809 (0.53, 1.16)
NG-IP	1.580 (1.29, 1.95)	**1.850 (1.41, 2.41)**	1.819 (1.41, 2.44)
NG-PP	1.282 (1.04, 1.60)	**1.678 (1.22, 2.19)**	1.649 (1.20, 2.18)
NG-CP	1.032 (0.83, 1.28)	**1.302 (1.01, 1.68)**	1.294 (1.01, 1.69)
NG-EP	1.267 (1.01, 1.61)	**1.182 (0.79, 1.55)**	1.172 (0.85, 1.53)

Table 3: Estimates of d with seasonal monthly AR disturbances

	No regressors	An intercept	A linear time trend
HC-IP	1.126 (1.00, 1.28)	**1.294 (1.14, 1.49)**	1.295 (1.14, 1.49)
HC-PP	1.121 (1.02, 1.25)	**1.239 (1.11, 1.39)**	1.239 (1.11, 1.39)
HC-CP	0.971 (0.85, 1.12)	**1.147 (1.03, 1.31)**	1.159 (1.04, 1.32)
L-PP	0.973 (0.86, 1.10)	**0.987 (0.87, 1.15)**	0.985 (0.86, 1.15)
L-CP	0.971 (0.85, 1.12)	**0.931 (0.80, 1.16)**	0.938 (0.79, 1.16)
MO-IP	1.202 (1.06, 1.38)	**1.314 (1.15, 1.50)**	1.316 (1.15, 1.51)
MO-PP	1.297 (1.14, 1.49)	**1.535 (1.34, 1.78)**	1.538 (1.34, 1.79)
NG-IP	1.332 (1.23, 1.45)	**1.544 (1.43, 1.68)**	1.545 (1.43, 1.68)
NG-PP	1.110 (1.01, 1.22)	**1.197 (1.10, 1.31)**	1.193 (1.10, 1.30)
NG-CP	1.027 (0.92, 1.16)	**1.193 (1.09, 1.32)**	1.188 (1.08, 1.31)
NG-EP	1.177 (1.07, 1.31)	**1.263 (1.14, 1.41)**	1.259 (1.14, 1.41)

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

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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.

The results so far provide little evidence of mean reversion in German energy prices. Next we examine the possibility of breaks in the data. Here we employ the procedure developed by Gil-Alana (2008) briefly described in the previous section. Table 4 displays the parameter estimates under the assumption of white noise errors. We find a single break in all except one series: 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 lignite with producer prices 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.

Table 5 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 of 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. We notice orders of integration strictly smaller than one in the two subsamples for the cases of producer and consumer prices of hard coal; consumer prices of lignite, and also for the consumer, producer and export prices of natural gas. For the remaining series we find at least one subsample also displaying mean reversion.

The most interesting lesson learned from the above results is 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 disappearing relatively fast in all cases.

Table 4: Estimates for the different s1ubsamples with white noise errors

Series	Number of breaks	Estimates of d			Intercepts		
		d_1	d_2	d_3	α_1	α_2	α_3
H-IP	1 (Dec.08	1.482	1.247	---	72.58 (17.31)	200.41 (28.97)	---
H-PP	1 n.09)	1.287	1.251	---	54.76 (14.96)	155.64 (29.31)	---
H-CP	1 (Jan.07)	1.244	1.355	---	92.36 (265.9)	104.56 (213.7)	---
L-PP	2 (Jan.07 / Jan.09)	0.787	0.954	0.78	95.36 (112.5)	107.91 (92.15)	107.9 (82.6)
L-CP	1 (Jan.02)	1.482	1.196	---	94.12 (254.7)	96.51 (261.2)	---
M-IP	1 (Oct.08)	1.147	1.252	---	57.58 (8.94)	132.43 (15.02)	---
M-PP	1 (Aug.08	1.383	1.007	---	61.32 (11.68)	194.80 (16.79)	---
N-IP	1 (Apr.09)	1.631	1.418	---	46.10 (17.77)	142.26 (39.60)	---
N-PP	1 (Apr.09)	1.237	1.205	---	58.91 (22.05)	150.19 (38.00)	---
N-CP	1 (Apr.09)	1.232	1.297	---	68.90 (37.716)	132.19 (111.97)	---
NG-EP	1 (Apr.09)	1.218	1.373	---	56.14 (14.696)	15.79 (27.937)	---

In parentheses, in the second column the break date; in the third and fourth

4 Conclusions

In this paper, we have examined the degree of persistence in various monthly energy prices in Germany. For this purpose, we have employed 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 autocorrelated the orders of integration are found to be smaller than 1 in practically all cases, implying that mean reversion occurs and therefore the effects of shocks disappear in the long run.

Table 5: Estimates for the different subsamples with AR(1) errors

Series	Number of breaks	Estimates of d			Intercepts		
		d_1 AR	d_2 (AR	d_3 AR	α_1 t-val	α_2 t-val	α_3 tval
H-IP	1 Dec.08	0.817 (0.72)	0.485 (0.73)	---	75.355 (12.229)	194.79 (30.256)	---
H-PP	1 Jan.09	0.367 (0.94)	0.396 (0.84)	---	86.670 (23.380)	148.18 (28.900)	---
H-CP	1 Jan.07	0.329 (0.95)	0.264 (0.97)	--	95.705 (421.01)	109.71 (319.02)	---
L-PP	2 (Jan.07 / Jan.09)	0.113 (0.89)	xxx	X	98.366 (484.5)	xxx	X
L-CP	1 Jan.02	0.698 (0.66)	0.373 (0.93)	--	94.040 (207.0)	99.958 (446.9)	---
M-IP	1 Oct.08	0.767 (0.44)	0.479 (0.77)	--	62.731 (9.61)	126.15 (18.24)	---
M-PP	1 Aug.08	0.592 (0.78)	0.822 (0.76)	--	74.789 (11.51)	184.54 (14.07)	---
N-IP	1 Apr.09	0.751 (0.80)	0.617 (0.80)	--	54.487 (11.36)	134.98 (28.11)	----
N-PP	1 Apr.09	0.212 (0.91)	0.617 (0.59)	--	103.45 (55.94)	143.19 (33.46)	---
N-CP	1 Apr.09	0.217 (0.98)	0.318 (0.84)	---	101.70 (91.45)	123.48 (103.1)	---
N-EP	1 Apr.09	0.116 (0.98)	0.205 (0.82)	--	106.42 (52.43)	130.82 (36.32)	---

In parentheses, in the second column the break date; in the third and fourth columns they are the estimated AR coefficients, and in the sixth and seventh columns the t-values. xxx indicates that convergence is not achieved.

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, we allow 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 German energy prices by source, 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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