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Carlos P. Barros, Guglielmo Maria Caporale, and Luis A. Gil-Alana

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LONG MEMORY IN GERMAN ENERGY PRICE INDICES

Carlos P. Barros
Instituto Superior de Economia e Gestao, Technical University of Lisbon, Portugal

Guglielmo Maria Caporale
Centre for Empirical Finance, Brunel University, London, United Kingdom

and

Luis A. Gil-Alana*
Faculty of Economics, University of Navarra, Pamplona, Spain

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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

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 monthlys 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 and Γ(▪) 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.[1] 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

$$\hat{d} \quad \arg\min{}_{d} \quad \log\ \overline{C(d)} \quad 2\ d\ \frac{1}{m}\ {}^{m}_{s\ \ 1} \log \quad {}_{s} \quad , \qquad (3)$$

$$y_t \quad {}_i{}^T z_t \quad x_t; \quad (1 \quad L)^{d_i} x_t \quad u_t, \quad t \quad 1,\ldots,T_b^i, \quad i \quad 1,\ldots nb,$$

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.[2] 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 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]

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

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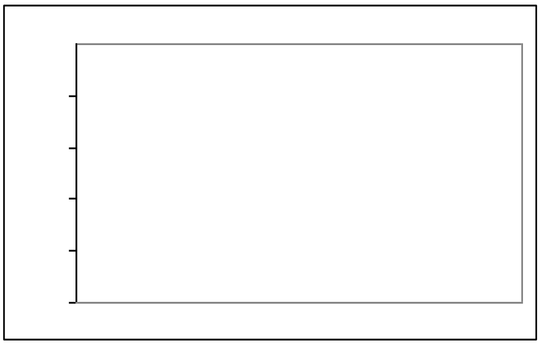
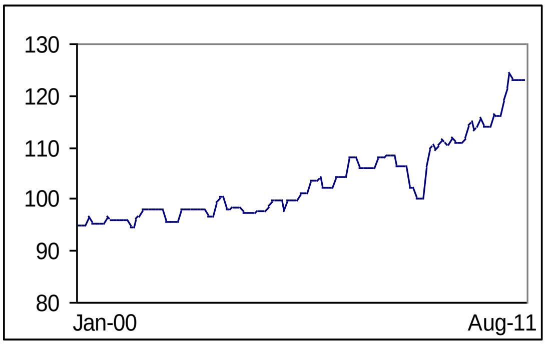
Figure 1: Time series plots (for the PP series)

<table>
<tr><td>HC-PP</td><td>L-PP</td></tr>
<tr><td></td><td>
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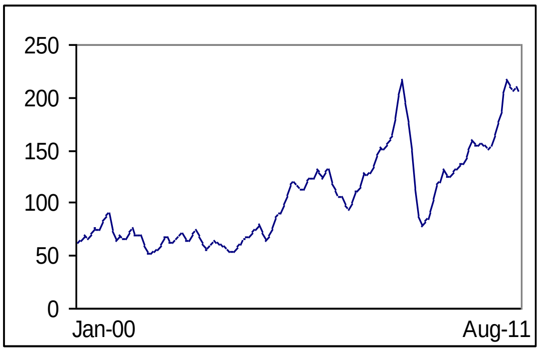
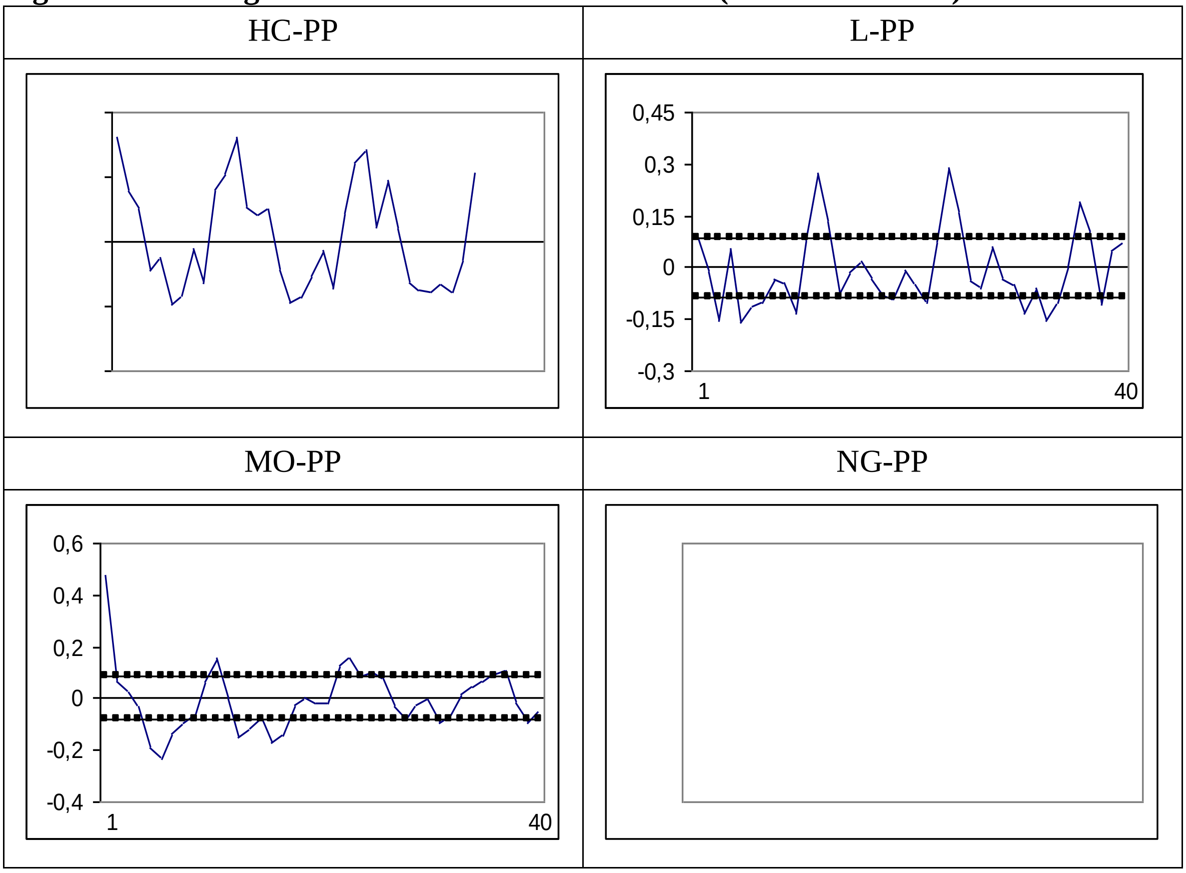
<tr><td>MO-PP</td><td>NG-PP</td></tr>
<tr><td>
</td><td></td></tr>
</table>

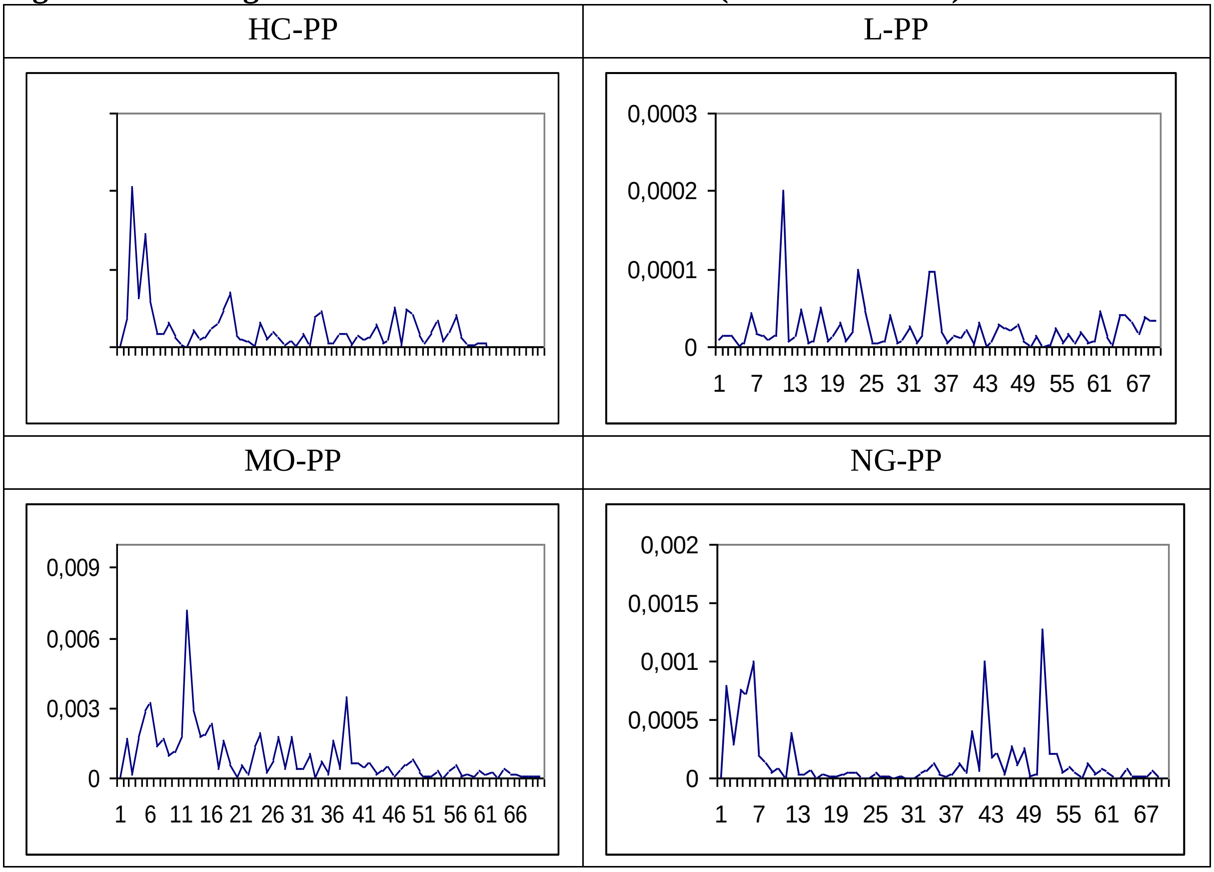
HC stands for Hard Coal, L is lignite, MO is mineral oil, NG natural gas and PP stands for producer prices.

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



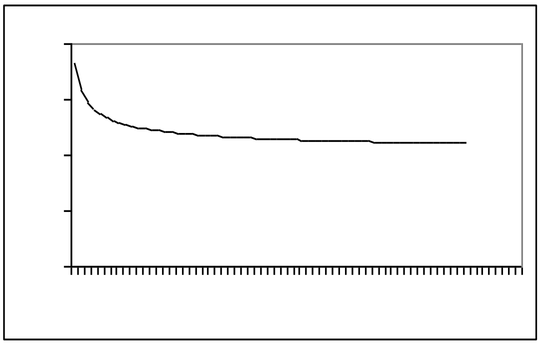
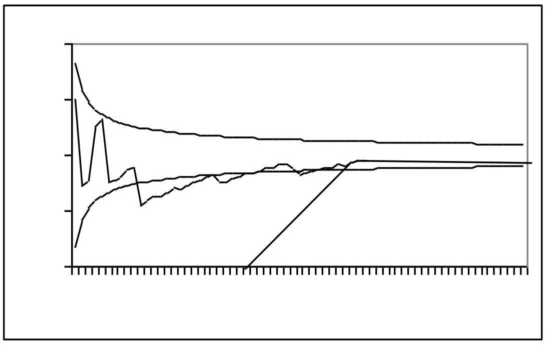
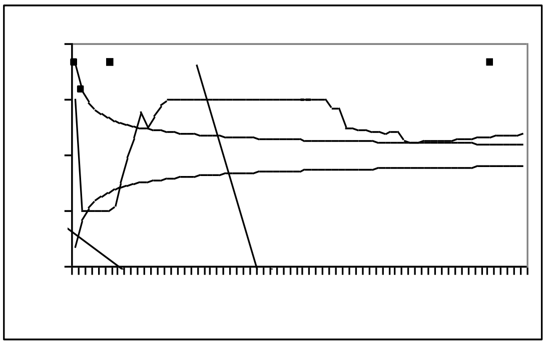
The dotted lines refer to the 95% confidence band for the null hypothesis of no autocorrelation.

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, …, T/2.

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

HC-PP	L-PP
	
MO-PP	NG-PP
	

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)	**1.307 (1.165, 1.502)**	1.308 (1.166, 1.502)
HC-PP	1.137 (1.034, 1.272)	**1.263 (1.149, 1.406)**	1.263 (1.149, 1.405)
HC-CP	0.971 (0.861, 1.123)	**1.168 (1.061, 1.340)**	1.185 (1.072, 1.352)
L-PP	0.974 (0.876, 1.109)	**0.999 (0.879, 1.182)**	0.999 (0.869, 1.186)

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)	**1.012**	**(0.821,**	**1.299)**	0.808	(1.012,	1.290)
HC-PP	1.129	(0.920,	1.413)	**1.192**	**(0.903,**	**1.553)**	1.193	(0.931,	1.553)

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)	**1.294 (1.148, 1.495)**	1.295 (1.149, 1.495)
HC-PP	1.121 (1.021, 1.255)	**1.239 (1.115, 1.396)**	1.239 (1.116, 1.397)
HC-CP	0.971 (0.851, 1.123)	**1.147 (1.039, 1.314)**	1.159 (1.040, 1.322)
L-PP	0.973 (0.869, 1.109)	**0.987 (0.873, 1.151)**	0.985 (0.861, 1.156)
L-CP	0.971 (0.853, 1.124)	**0.931 (0.806, 1.162)**	0.938 (0.795, 1.163)
MO-IP	1.202 (1.064, 1.382)	**1.314 (1.157, 1.508)**	1.316 (1.159, 1.511)
MO-PP	1.297 (1.149, 1.493)	**1.535 (1.342, 1.786)**	1.538 (1.345, 1.790)
NG-IP	1.332 (1.233, 1.456)	**1.544 (1.433, 1.687)**	1.545 (1.433, 1.688)
NG-PP	1.110 (1.016, 1.220)	**1.197 (1.103, 1.315)**	1.193 (1.101, 1.308)
NG-CP	1.027 (0.927, 1.160)	**1.193 (1.099, 1.324)**	1.188 (1.087, 1.318)
NG-EP	1.177 (1.075, 1.310)	**1.263 (1.145, 1.416)**	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.

	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	---			

(

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.