E.ON Energy Research Center
FCN | Institute for Future Energy Consumer Needs and Behavior

FCN Working Paper No. 19/2010

Short- and Long-Run Electricity Demand Elasticities at the Subsectoral Level: A Cointegration Analysis for German Manufacturing Industries

Ronald Bernstein and Reinhard Madlener

November 2010

Institute for Future Energy Consumer Needs and Behavior (FCN)

Faculty of Business and Economics / E.ON ERC

RWTH AACHEN UNIVERSITY

FCN Working Paper No. 19/2010

Short- and Long-Run Electricity Demand Elasticities at the Subsectoral Level: A Cointegration Analysis for German Manufacturing Industries

November 2010

Authors' addresses:

Ronald Bernstein, Reinhard Madlener
Institute for Future Energy Consumer Needs and Behavior (FCN)
Faculty of Business and Economics / E.ON Energy Research Center
RWTH Aachen University
Mathieustrasse 6
52074 Aachen, Germany
E-mail: rbernstein@eonerc.rwth-aachen.de, rmadlener@eonerc.rwth-aachen.de

Publisher: Prof. Dr. Reinhard Madlener
Chair of Energy Economics and Management
Director, Institute for Future Energy Consumer Needs and Behavior (FCN)
E.ON Energy Research Center (E.ON ERC)
RWTH Aachen University
Mathieustrasse 6, 52074 Aachen, Germany
Phone: +49 (0) 241-80 49820
Fax: +49 (0) 241-80 49829
Web: www.eonerc.rwth-aachen.de/fcn
E-mail: post_fcn@eonerc.rwth-aachen.de

Short- and Long-Run Electricity Demand Elasticities at the Subsectoral Level: A Cointegration Analysis for German Manufacturing Industries

by

Ronald Bernstein and Reinhard Madlener

Institute for Future Energy Consumer Needs and Behavior (FCN), Faculty of Business and Economics / E.ON Energy Research Center, RWTH Aachen University, Mathieustrasse 6, 52074 Aachen, Germany

Tel.: +49 241 80 49832; Fax: +49 241 80 49829;
Email: rbernstein@eonerc.rwth-aachen.de; rmadlener@eonerc.rwth-aachen.de

November 2010

Abstract

In this paper we use multivariate cointegration analysis to estimate electricity demand elasticities at the subsectoral industry level. This enables us to reap the benefits of lower heterogeneity within the electricity-consuming sectors investigated and of retaining additional information otherwise blurred by aggregation. The annual data set used covers eight subsectors of the German economy for the period 1970-2007. By employing a cointegrated VAR model specification and accounting for structural breaks we find cointegration relationships for five of the eight subsectors studied. The long-run elasticities range between 0.70 and 1.90 for economic activity and between –0.52 and zero for the price of electricity. The short-run elasticities are estimated by single-equation error-correction modeling and found to be between 0.17 to 1.02 for economic activity and –0.57 to zero for electricity price. Granger-causality tests indicate that in the long term causality runs from both economic activity and electricity price to electricity consumption, while Granger-causality from electricity price and electricity consumption to economic activity is detected in only two subsectors. Electricity price is found to be Granger-caused neither in the long nor the short run. Finally, an impulse response analysis yields plausible results confirming the usefulness of the approach adopted.

JEL classification: Q41; Q43

Keywords: Disaggregated data; Elasticities; Cointegration; VECM; Granger-causality; Impulse responses; Structural breaks; Germany

1. Introduction

Energy demand modeling on the basis of historical time-series data has traditionally been conducted for a specific country, at an aggregate or disaggregate level, in two dimensions. One dimension concerns the type of energy (i.e. mainly electricity, natural gas or gasoline), while the other dimension concerns different types of major end-use sectors: industry, commerce and public services, households and transportation. At one extreme, there is the analysis on the basis of data aggregated over all energy carriers and sectors (i.e. at the economy-wide level), whereas at the other extreme there is the analysis for only one energy carrier for one sector. To analyze data aggregated over widely heterogeneous sectors will most likely result in crude inference concerning economic relationships and consumer behavior. In this respect we share the view of Pesaran *et al.* (1998, p.46) that it is important for a valid econometric demand analysis to be aimed at *"…as homogenous a grouping of consumers as is feasible"*. This implies that studies on energy demand should use data at the lowest level of aggregation as possible.[1] To this end, our aim in the present study is to reap the benefits of additional information otherwise blurred through aggregation, by analyzing subsectoral demand functions for a single energy carrier (electricity). To the best of our knowledge this is the first study of its kind that makes use of disaggregated data for estimating energy demand elasticities at a subsectoral industry level. Specifically, the elasticities are estimated for each of the following eight subsectors of the German economy:[2] [1] Food & Tobacco (15-16); [2] Textile & Leather (17-19); [3] Wood & Wood Products (20); [4] Pulp, Paper & Printing (21-22); [5] Chemicals & Chemical Products (24); [6] Non-metallic Minerals (26); [7] Metal & Machinery (27-33); and [8] Transport Equipment (34-35).

Despite the crucial relevance of sound elasticity estimates in energy modeling used for policy advice, scholarly literature on the econometric estimation of energy demand elasticities in industry is surprisingly scarce, and this is even more so with regard to electricity. Table 1 summarizes recent studies in which electricity demand elasticities of economic activity and/or electricity price in industry are estimated (Beenstock *et al.*, 1999; Bose & Shukla, 1999; Kamerschen & Porter, 2004; Polemis, 2007). These studies differ with regard to the model specification, the econometric method used and time span covered, the data frequency, and

[1] Implying that aggregation in general is aimed at stepwise compiling entities with similar characteristics and, hence, also similar consumption behavior and technologies.
[2] The numbers in squared brackets are the identifiers of the corresponding subsectors used throughout this paper. The numbers in parentheses are the corresponding codes of the NACE (Rev. 1) taxonomy.

the country analyzed. Beenstock *et al.* (1999) use dynamic regression and cointegration techniques to analyze electricity demand in the household and industry sector in Israel. For the industrial sector they estimate long-run elasticities of 0.99 to 1.12 with regard to economic activity and –0.31 to –0.44 with regard to electricity price, depending on the estimation method applied. Using time series data for nine years from 19 states in India, Bose & Shukla (1999) estimate sectoral elasticities including industry (split into small/medium and large industries) by employing a pooled regression approach. The estimated elasticities of economic activity and price are 0.49 and –0.04 (the latter not significant), respectively, for the small- and medium-sized industries, and 1.06 and –0.45 for the large industries. Kamerschen & Porter (2004) employ a simultaneous equation approach for estimating price elasticities of electricity demand by U.S. industry.[3] Depending on the specification their estimates vary between –0.34 and –0.55. Polemis (2007) uses a multivariate cointegration technique (the Johansen maximum likelihood approach) to estimate aggregate oil and electricity demand functions for the Greek industry. His estimates for long-run elasticities regarding economic activity and price are 0.85 and –0.85, while in the short-run they amount to 0.61 and –0.35, respectively.

Table 1: Industrial electricity demand studies

Study	Country	Method	Data	Elasticity estimates	
				Econ. Activity	Price
Beenstock *et. al.* (1999)*	Israel	Cointegration	Time series (quarterly), 1975q2-1994q4	LR: 0.99 to 1.12	LR: –0.31 to –0.44
Bose & Shukla (1999)*	India	Pooled regression	Panel data (annual), 1985/86-1993/94	0.49 to 1.06	–0.04 to –0.45
Kamerschen & Porter (2004)*	USA	Simultaneous equations	Time series (annual), 1973-1998	–	–0.34 to–0.55
Polemis (2007)**	Greece	Cointegration	Time series (annual), 1970-2004	LR: 0.85 SR: 0.61	LR: –0.85 SR: –0.35

Notes: * also estimate demand for other sectors. ** also estimates an oil demand function separately. SR and LR denote estimates for the short- and long-run, respectively.

The only energy demand study known to us that uses disaggregated industrial data at the two-digit level of the NACE taxonomy is Agnolucci (2009). In contrast to our study however, he focuses on aggregate energy in the British and German industry. Moreover, the analysis is based on a panel approach, as the times series estimates mostly failed to show intuitive results. This presumably is due to the short time spans covered by the data. Finally, although

[3] Kamerschen & Porter (2004) also consider a partial-adjustment approach, which, however, had to be dropped due to non-sensical estimates.

information from disaggregated data is used in the estimation, the panel approach does not deliver subsector-specific estimates of energy demand elasticities.

In sum, unlike the previous econometric literature on industrial electricity demand, we aim at reducing the level of aggregation by examining data of industrial subsectors, in order to reduce the heterogeneity of the consumer groups analyzed, and thereby assess industry-specific behavioral patterns. Our approach seems preferable whenever appropriate disaggregated data on a subsectoral level is available for a sufficiently long time length.

The paper proceeds as follows. In Section 2 we provide the analytical framework for the econometric analysis. Section 3 gives a methodological overview of the applied estimation and testing procedure applied, while Section 4 discusses, the data, the application of the model and the results from the analysis. Section 5 concludes.

2. Analytical framework

A generic long-run electricity demand relationship for the industrial sectors of an economy can be characterized by the general function

$$E_t = f\left(V_t, P_t, X_t, A_t\right), \tag{1}$$

where electricity consumption (E_t) is contemporaneously dependent on the level of real economic activity (V_t), real electricity price (P_t), other endogenous or exogenous variables (X_t) (which may include, for example, the real price of an electricity substitute and/or weather variables), and exogenous factors (A_t), such as a sector-specific technical coefficient, energy-saving technological progress or shifts/changes in the structure of industrial production. The latter may comprise structural changes due to substitution of labor by electricity-using capital and the offshoring of labor-intensive production processes to other countries. In contrast to energy-saving technological progress, both changes tend to increase the electricity intensity of the respective national sectors. These factors affect the relationships between the other variables and can be indirectly accounted for by inclusion of deterministic terms.

Various econometric studies have found that other energy inputs are generally poor substitutes for electricity in industrial processes (for a survey, see Barker *et al.*, 1995). Thus, we refrain from controlling for interfuel substitution by including prices of other energy carriers. Moreover, the inclusion of heating and cooling degree day variables, which are available to us only from 1975 onwards, would have considerably reduced the number of degrees of freedom in our analysis.[4] Specifically, for the empirical analysis we chose a simple standard constant elasticity (Cobb-Douglas type) functional form

$$E_t = C_0 \exp\left(dt\right) V_t^{\beta_v} P_t^{\beta_p}, \tag{2}$$

where $A_t = C_0 \exp(dt)$ is the deterministic term. Taking the natural logarithm of (2) and adding a stochastic error term yields the linear double-log specification of our econometric model for the long-run electricity demand function

$$e_t = c_0 + dt + \beta_v v_t + \beta_p p_t + \varepsilon_t, \tag{3}$$

where $e_t = \ln(E_t)$, $v_t = \ln(V_t)$, $p_t = \ln(P_t)$, c_0 is a constant, dt is a deterministic time trend and ε_t is the error term. β_v and β_p are the constant elasticities of economic activity and price, respectively, with regard to electricity demand.

As stated by Amarawickrama & Hunt (2008), this standard log-linear specification, apart from the obvious advantages, i.e. its simplicity, its straightforward interpretation and the limited data requirements, according to Pesaran *et al.* (1998) outperforms more complex models.

This analytical framework forms the theoretical basis for the following analysis of electricity demand in Germany's industrial subsectors employing the econometric methodology described in the next section.

3. Methodology

Ever since the seminal paper by Engle & Granger (1987), cointegration analysis has increasingly become the favored methodological approach for analyzing time series data containing stochastic trends. If the data generating processes (DGPs) underlying the time series are integrated of order one, $I(1)$ (which is the case for most economic variables), or higher, usual regression analysis can lead to spurious results. Instead of taking first differences of the data, which was the common prior solution but leads to a loss of long-run

[4] Also, other studies (see Kamerschen & Porter, 2004) have found that weather variables tend to be insignificant in industrial energy demand functions, especially in electricity demand functions.

information, this problem can be tackled by identifying possibly existing stationary linear combinations of two or more non-stationary time series. Such stationary linear combinations indicate common stochastic trends (i.e. cointegration), which can be interpreted as long-run equilibrium relationships between the variables considered and, therefore, according to the Granger representation theorem, can be characterized by being generated through an error-correction mechanism.

Before turning to the analysis of the long-run relationships between the variables we check for the unit root properties of the single series, as non-stationary behavior is a prerequisite for including them in the cointegration analysis. It is well known that the standard ADF (Augmented-Dickey-Fuller) and PP (Phillips-Perron) tests suffer from a considerable loss of power in cases where the DGP underlying a series is a near-unit root (trend-)stationary process. Furthermore, the existence of structural breaks, if not accounted for, distorts unit root test results (see Perron, 1989). Therefore, we apply more recent 'efficient unit root tests', which to a certain extent overcome the deficiencies of the traditional unit root tests: the ERS (Elliott-Rothenberg-Stock, see Elliott *et al.*, 1996) test for non-breaking series and the LLS (Lanne-Lütkepohl-Saikkonen, see Saikkonen & Lütkepohl, 2002; and Lanne *et al.*, 2002) test for variables containing structural breaks, both of which have good power properties compared to alternative tests. The ERS test is a modification of the ADF test in that the series under consideration is detrended by using a GLS (Generalized-Least-Squares) regression before the actual unit root test is conducted. The LLS test works in a similar manner, but also takes into account a level shift in the deterministic term. In a Monte Carlo simulation study, Lanne & Lütkepohl (2002) show that their LLS test enables remarkable gains in size and power and performs best in comparison to a number of other unit root tests that incorporate level shifts at some known point in time.

A methodology for cointegration analysis that has received considerable attention is the maximum likelihood (ML) system estimation and testing procedure developed by Johansen (1988, 1995). In contrast to single-equation methods, the Johansen approach does not impose the assumption of a unique cointegrating vector *a priori* and efficiently estimates the short-run dynamics simultaneously along with the long-run relationship. Moreover, restrictions to the cointegration space can be applied and tested for. Furthermore, Johansen *et al.* (2000) provide an extension for incorporating structural breaks in the cointegrating vectors. In a simulation study, Gonzalo (1994) finds superior finite sample properties of the Johansen ML estimator when compared to four other commonly used estimation methods in cointegration analysis, even when the dynamics are not known and the errors are non-Gaussian. The Johansen ML system approach is briefly outlined as follows: As the basic DGP, consider the unrestricted three-variable vector autoregression model of order p, VAR(p), defined as

$$Y_t = \delta + \Phi T_t + \Xi S_t + \Theta I_t + \sum_{j=1}^{p} A_j Y_{t-j} + U_t, \tag{4}$$

where Y_t is a (3 x 1)-dimensional vector containing the endogenous $I(1)$ variables, $Y_t' = [e_t, v_t, p_t]$, the A_j are (3 x 3)-dimensional parameter matrices, and U_t is a three-dimensional Gaussian white-noise process representing the error terms. The deterministics are a constant (δ), a linear trend (T_t), a shift dummy (S_t), and impulse dummies (I_t). The vectors Φ and Ξ and the matrix Θ contain the corresponding parameters. Eq. (4) can be rewritten as a vector error-correction model of order (p – 1), VECM(p – 1), as follows

$$\Delta Y_t = \delta^{\circ} + \Pi Y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \Theta I_t + U_t, \tag{5}$$

where $\Pi = -(I - A_1 - ... - A_p)$ and $\Gamma_j = -(A_{j+1} + ... + A_p)$ for $j = 1, 2, \ldots, (p-1)$. If the variables in Y_t are indeed cointegrated, Π has reduced rank, rk(Π) = r, and can be decomposed into $\Pi = \alpha\beta'$. Here β spans the space of r cointegrating vectors, so that $\beta' Y_{t-1}$ represents up to (k – 1) cointegration relationships, whereas α contains the corresponding adjustment coefficients.[5]

Using the trace test provided by Johansen (1994, 1995) and Johansen *et al.* (2000), respectively, depending on whether structural breaks are incorporated or not, it is then possible to determine how many $r \leq (k-1)$ distinct eigenvalues (λ_i) exist that are significantly different from zero, and hence how many cointegrating relationships are present in β'. The likelihood ratio trace statistic (λ_{Trace}) is given by

$$\lambda_{Trace} = -T \sum_{i=r+1}^{k} \ln\left(1 - \hat{\lambda}_i\right), \tag{6}$$

[5] Note that in the software package JMulTi 4.24, which we use in cases where shift dummies are included in the cointegrating vector (otherwise we use EViews 6), the constant is restricted to the cointegrating vector.

where k is the number of endogenous variables and T is the number of observations. The null hypothesis is the existence of at most r cointegrating relations ($0 \leq r \leq k$) against the alternative of $(r + 1)$ cointegrating relations.

If the null hypothesis is rejected on the first level (i.e. $r = 0$), but accepted on the second level (i.e. $r \leq 1$), we can conclude that there exists only one cointegrating vector, which leads to the following most general specification of the VECM(p – 1):[6]

$$\begin{pmatrix} \Delta e_t \\ \Delta v_t \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} \alpha_{0,e} \\ \alpha_{0,v} \\ \alpha_{0,p} \end{pmatrix} + \begin{pmatrix} \alpha_{1,e} \\ \alpha_{1,v} \\ \alpha_{1.p} \end{pmatrix} \left[e_{t-1} - \beta_v v_{t-1} - \beta_p p_{t-1} - D_{t-1} \right] + \sum_{j=1}^{p-1} \Gamma_j \begin{pmatrix} \Delta e_{t-j} \\ \Delta v_{t-j} \\ \Delta p_{t-j} \end{pmatrix} + \Theta I_t + \begin{pmatrix} \varepsilon_{e,t} \\ \varepsilon_{v,t} \\ \varepsilon_{p,t} \end{pmatrix}, \tag{7}$$

where the term in squared brackets is the error-correction term ($ECT_{t\text{-}1}$). The deterministic term (D_t) in the most general case is $D_t = c + d_1 t + d_2 s$. The restricted constant (c) is always included, the linear time trend (t) is included whenever significant, and the shift dummy (s) is included only when a structural break occurs in one of the series. I_t is a vector of impulse dummies and Θ is a matrix containing the corresponding parameters. The Γ_j are the (p – 1) coefficient matrices for the lagged differences of the three endogenous variables. Following Lütkepohl & Krätzig (2004, pp.116-119), we include a shift dummy for the time of any break date (τ) and further intervention dummies for τ, $\tau + i$, …, $\tau + (m - 1)$, where m is equal to the lag length of the corresponding VAR ($m = p$).

Estimation of Eq. (7) yields the estimates of the long-run equilibrium demand relationship, i.e. the estimated cointegrating vector, which equals zero in the long-run equilibrium

$$ECT_t = e_t - \hat{\beta}_v v_t - \hat{\beta}_p p_t - \hat{D}_t, \tag{8}$$

where ECT_t stands for the error-correction term, which represents the deviation from the long-run equilibrium in any period t. In order to attain the short-run elasticities we can then proceed by estimating a standard single-equation error-correction model (ECM) based on the long-run relationship obtained from estimation of Eq. (8):

$$\Delta e_t = \gamma_0 + \alpha\, ECT_{t-1} + \sum_{i=0}^{l} \gamma_{e,i} \Delta e_{t-i-1} + \sum_{i=0}^{m} \gamma_{v,i} \Delta v_{t-i} + \sum_{i=0}^{n} \gamma_{p,i} \Delta p_{t-i} + \varepsilon_t, \tag{9}$$

[6] Note, that this specification is sufficient, since in all cases where we did find a long-run relationship, our inference has always led to a model with one cointegrating vector only.

where γ_0 is a constant, α is the loading coefficient, $\gamma_{e,i}$, $\gamma_{v,i}$ and $\gamma_{p,i}$ are the short-run parameters and ε_t is a white-noise error term. By deleting insignificant coefficients, a parsimonious specification of the short-run dynamic equation can be searched for.

An additional advantage of a cointegrated VAR setting is the possibility of further analysis on the dynamics of the examined relationship. Hence, before estimating the short-run elasticities in the single-equation ECM framework, we employ tests on Granger-causality and examine the impulse response functions. All computations in this paper were done using JMulTi 4.24 and EViews 6.

4. Empirical analysis

4.1. Data

The data required for our analysis encompasses long time series of electricity consumption, a measure for the level of economic activity, such as the real value added, and the real electricity price. The International Energy Agency (IEA) provides data for electricity consumption at a subsectoral level as well as industrial electricity prices, whereas the EU-KLEMS database (November 2009 release; www.eu-klems.org) offers subsectoral data on gross value added (VA) volume indices (1995 = 100).

Most studies on energy demand use the consumer price index (CPI) for deflating nominal energy prices. For an analysis at the aggregate (national) level, this is an appropriate approximation. However, the price underlying the decision-making process of an economic agent is the energy price relative to the prices of all other goods and services relevant to its economic activity. On a sectoral level, this is best approximated by the sector-specific value added price index. Consequently, we obtain real electricity prices through deflating the nominal industrial electricity price by using the sector-specific value added price indices from the EU-KLEMS database.[7]

Our aim to analyze industrial branches on the lowest aggregational level possible was guided by data availability. As two different databases were used as sources, matches concerning

[7] Hence, the same double deflation measure is used for both the nominal electricity price and nominal gross value added, as the value added volume indices are constructed by deflating nominal value added with the value added price index and then normalizing to 1995 = 100.

groupings had to be constructed, using NACE (Rev. 1) classifications. Table 2 provides an overview of the data availability, short descriptions of the different subsectors investigated, the aggregational groupings and the resulting matches with regard to the two databases. Due to differing aggregational groupings concerning the iron, metals and machinery subsectors (i.e. NACE codes 27-33) in the two data sets, these subsectors were aggregated to what we label as the 'Metal & Machinery' [7] sector. Moreover, it turned out to be impossible to construct a perfect data match for this sector. More specifically, and in contrast to the value added data, the aggregate electricity consumption data does not cover the 'Medical, precision & optical instruments' sector (NACE code 33).

Table 2: Data availability, aggregational groupings and matches

Sector identifier	**IEA:** Electricity consumption		**EU-KLEMS:** VA, VA price index	
	NACE	Description	NACE	Description
	Total Manufacturing Industry: 15-22, 24-37			
[1]	15-16	Food & tobacco	15-16	Food, beverages & tobacco
			15	*Food & beverages*
			16	*Tobacco*
[2]	17-19	Textile & leather	17-19	Textiles, textile, leather & footwear
			17	*Textiles*
			18	*Wearing apparel, dressing & dying of fur*
			19	*Leather, leather products & footwear*
[3]	20	Wood & wood products	20	Wood & of wood & cork
[4]	21-22	Paper, pulp & printing	21-22	Pulp, paper, printing & publishing
			21	*Pulp, paper & paper products*
			22	*Printing, publishing & reproduction*
[5]	24	Chemical & petrochemical	24	Chemicals & chemical products
[6]	26	Non-metallic minerals	26	Other non-metallic minerals
[7]	27.1-3; 27.51-52	Iron & steel	27-28	Basic metals & fabricated metal
			27	*Basic metals*
			28	*Fabricated metal*
	27.4; 27.53-54	Non-ferrous metals		
	28-32	Machinery		
			29	Machinery, NEC
			30-33	Electrical & optical equipment
			30	*Office accounting & computing machinery*
			31	*Electrical machinery & apparatus*
			32	*Radio, television & communication equipment*
	MISMATCH		*33*	*Medical, precision & optical instruments*
[8]	34-35	Transport equipment	34-35	Transport equipment

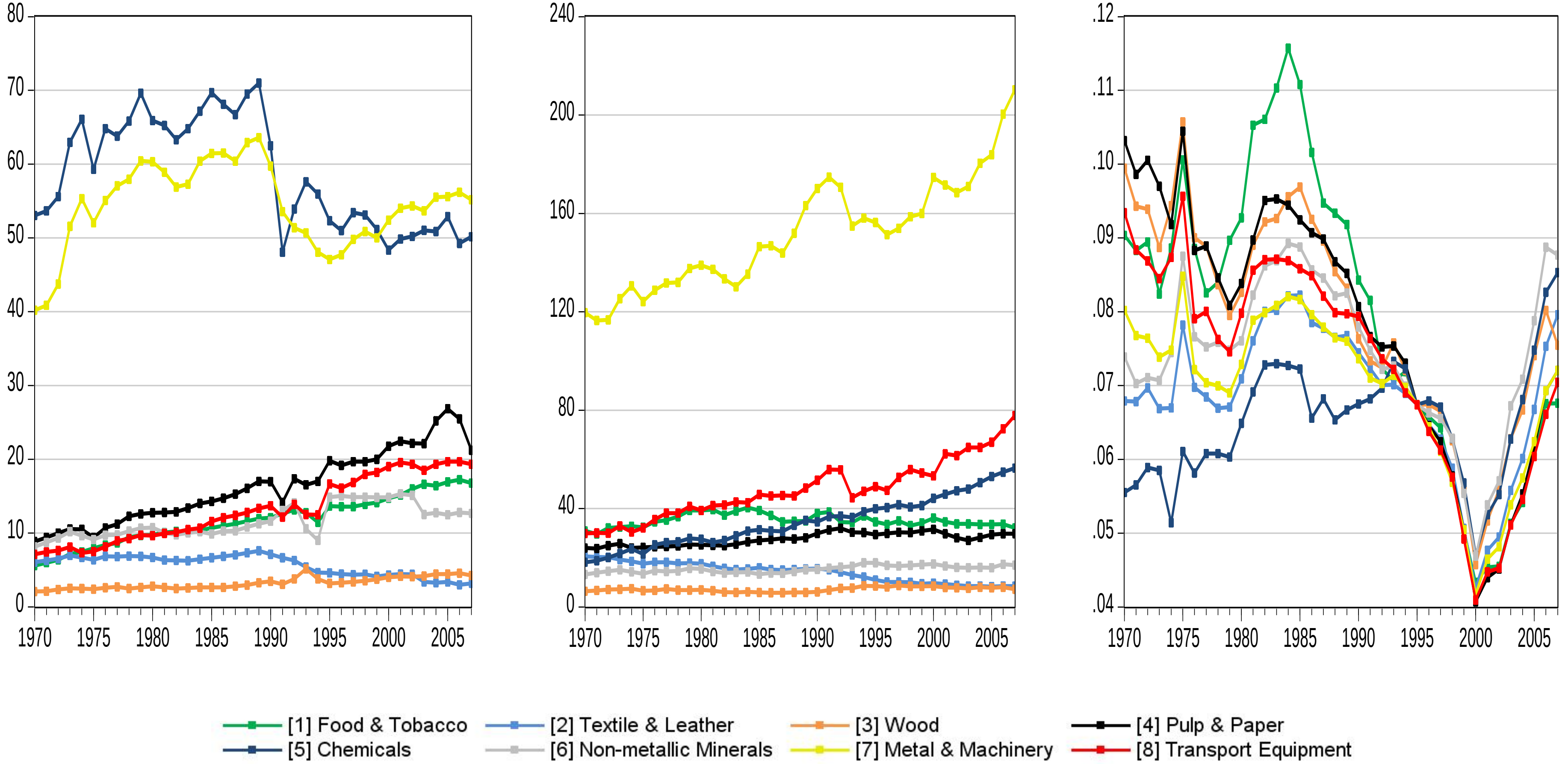
Notes: Data on sectors printed in *italics* are only available as part of a higher aggregation level.

The time series for nominal electricity price is available from 1960 onwards. The same applies to the electricity consumption variable for most of the industries. Nevertheless, data on real value added and the value added price index only start in 1970. Hence, the longest time span completely covered by the data is from 1970 until 2007. The German unification in

1991 is handled by imposing the trends for West Germany to the series of unified Germany in 1991.

Fig. 1 displays the individual time series for all the subsectors considered. Visual inspection reveals the following trends in the series: Both electricity consumption and real value added generally show an increasing trend over the time span under consideration and for nearly all the subsectors. Exceptions are the Textile & Leather [2] industry, where both variables decrease and the Food & Tobacco [1] industry, where value added more or less stagnates over the entire period. In addition, some of the series show large sudden level shifts. This is the case for electricity consumption in the Chemicals [5] sector and the Metal & Machinery [7] sector in 1991, and for real value added in the Metal & Machinery [7] sector and the Transport Equipment [8] sector in 1993. The reasons for these level shifts are not apparent, but at least the break in electricity consumption could be due to the closure of energy-intensive industries in East Germany after German reunification in 1990. These breaks will be accounted for in the unit root and cointegration analysis of the respective sectors.

From 1973 till 1975, and then again from 1979 till 1982/83, real electricity prices experienced strong increases, coinciding with the oil crises of 1973/74 and 1979/80. In April 1998 the German electricity market was liberalized, resulting in a gradual decrease of industrial electricity price of approximately 50% by the year 2000. After this initial liberalization, the power supply industry experienced a phase of market concentration, leaving the supply side with four major players (E.ON, RWE, EnBW and Vattenfall) to which approximately 80% of power generation can be attributed, and a number of minor regional utilities. On account of this oligopoly formation and hence a rise in market power, but also due to some newly introduced or increased taxes and charges, electricity prices have surged ever since.



(a) Electricity consumption

(b) Real value added

(c) Real electricity prices

Fig. 1: Visual inspection of time series used; Notes: (a) Subsectoral electricity consumption in Terawatt-hours (TWh), 1970-2007. (b) Subsectoral value added in billion Euros at constant (1995) prices, 1970-2007. (c) Industrial electricity prices in € per kilowatt-hour (kWh) at constant (1995) prices, 1970-2007. Data sources: IEA, EU-KLEMS, own calculations and illustration.

4.2. Unit root tests

To check for the non-stationary behavior of the individual time series, as a first step we apply unit root tests. Specifically, we apply the ERS test to the non-breaking series and the LLS test to the breaking series. The break dates for the LLS test are chosen according to the arguments in the last section. The results are summarized in Table 3. Based on the visual inspection of Fig. 1, we include a constant and a deterministic trend in the test regression for electricity consumption (e) and value added (v) variables in levels, and only a constant for the tests on the first differences. For the price (p) variable we include a constant in levels and no deterministic term in first differences. The lag lengths were chosen according to the conventional information criteria. For none of the series in levels the null hypothesis of a unit root can be rejected at the 10% level. For the first differences the null hypothesis is rejected on the 1% level. Thus, we conclude that all examined series are integrated of order one, $I(1)$.

Table 3: Unit root tests

Sector	*Variable*	**ERS test**		**LLS test**	
		Levels	Differences	Levels	Differences
[1]	e	–1.365 (2)	–4.094* (1)	–	–
	v	–1.310 (2)	–4.490* (1)	–	–
	p	–1.900 (1)	–4.048* (0)	–	–
[2]	e	–1.365 (0)	–4.309* (0)	–	–
	v	–2.009 (1)	–4.142* (0)	–	–
	p	–1.916 (1)	–4.161* (0)	–	–
[3]	e	–2.498 (2)	–7.385* (1)	–	–
	v	–1.548 (0)	–5.560* (0)	–	–
	p	–2.394 (1)	–4.365* (0)	–	–
[4]	e	–1.939 (3)	–4.707* (2)	–	–
	v	–2.427 (1)	–4.477* (0)	–	–
	p	–1.820 (1)	–4.432* (0)	–	–
[5]	e^{SB}	–	–	–1.271 (3)	–7.158* (1)
	v	–2.196 (2)	–7.592* (0)	–	–
	p	–2.570 (2)	–5.430* (0)	–	–
[6]	e	–2.281 (2)	–6.325* (1)	–	–
	v	–2.394 (0)	–5.176* (0)	–	–
	p	–1.934 (1)	–4.363* (0)	–	–
[7]	e^{SB}	–	–	–1.198 (0)	–4.156* (0)
	v^{SB}	–	–	–2.363 (0)	–5.316* (0)
	p	–1.286 (0)	–4.373* (0)	–	–
[8]	e	–2.833 (1)	–7.942* (0)	–	–
	v^{SB}	–	–	–2.589 (1)	–8.486* (0)
	p	–1.911 (1)	–4.200* (0)	–	–

Notes: We report t-statistics. * denotes significance at the 1% level. Lag lengths are in parentheses. ^{SB} denotes series containing structural breaks. Critical values for the LLS test are from Lanne *et al.* (2002). For the ERS test the critical values for the models in levels are taken from Elliott *et al.* (1996, Table 1), while the critical values for the models in differences are from MacKinnon (1996).

4.3. VAR specification

Having detected non-stationary behavior for all the series, we include all of them in the corresponding sector-specific cointegration models. We start by specifying a VAR model in levels for each subsector as in Eq. (4), with the aim to ensuring Gaussian residuals. For the optimal choice of lag length, the conventional information criteria were only used as a rough guideline.[8] Instead, the main focus was on ensuring that the single VAR models pass the diagnostic tests for autocorrelation. Moreover, we also conducted tests for non-normality and heteroscedasticity. To attain normality of the residuals, we accounted for outliers by using impulse dummies. Shift dummies and corresponding impulse dummies are inserted following the arguments provided in Section 3.

Table 4 shows the VAR specifications and the results of the respective diagnostic tests.[9] Most models pass the set of diagnostic tests. Exceptions are models [3] and [8], where the Jarque-Bera test indicates problems with the normality assumption. As this is due to residual kurtosis, which in contrast to residual skewness (Paruolo, 1996) does not invalidate the test results, we conclude that there is no significant deviation from the theoretical model assumptions.

Table 4: Vector autoregression (VAR) specification and diagnostic tests

Sector	VAR(p), Deterministic terms	Diagnostic tests			
		LM(2):	LM(4):	PAR(8):	JB:
[1]	VAR(1), C, T, I_{94}	0.1873	0.7334	0.3689	0.3664
[2]	VAR(3), C	0.1150	0.2905	0.2319	0.5629
[3]	VAR(1), C, I_{93}	0.8668	0.5030	0.8430	0.0347
[4]	VAR(1), C, I_{75}, I_{91}	0.1188	0.8530	0.3526	0.7432
[5]^{SB}	VAR(2), C, T, S_{91}, I_{91}, I_{92}	0.3285	0.4291	0.3261	0.3564
[6]	VAR(1), C, T, I_{93}, I_{94}, I_{00}	0.1582	0.1305	0.1856	0.1969
[7]^{SB}	VAR(2), C, T, S_{93}, I_{93}, I_{94}	0.1320	0.1245	0.6810	0.7830
[8]^{SB}	VAR(1), C, S_{93}, I_{93}, I_{00}	0.5565	0.7643	0.2388	0.0943

Notes: ^{SB} indicates models which account for structural breaks by inclusion of shift dummies. p denotes the lag length. C and T denote a constant and linear deterministic time trend, respectively. I_{YY} and S_{YY} indicate the year (YY) when an impulse dummy and shift dummy is included, respectively. The diagnostic tests are a Lagrange Multiplier test (LM) for no serial correlation at 2nd and 4th lag, a Portmanteau test (PAR) for no autocorrelation up to lag 8 and the Jarque-Bera (JB) test (orthogonalization method: Cholesky of covariance) for multivariate normally distributed residuals. For brevity we only report p-values.

[8] On account of the overparameterization problem associated with VAR models, we set the maximum lag length to three.

[9] We also run tests on heteroscedasticity. Here only model [1] shows slight signs of model defects. As the trace test is somewhat robust to heteroscedasticity we decide to ignore this deficiency.

4.4. Cointegration rank tests

In a next step we apply the trace test outlined in Section 3 to the VAR models specified in the previous section. Table 5 provides an overview of the test results. According to the trace statistics, for five of the eight models, the null hypothesis of no cointegrating vector (r = 0) can be rejected at the 5% level, while the null hypothesis of at least one cointegrating vector (r ≤ 0) cannot be rejected at the 10% level. Thus we conclude that the rank is one, i.e. a unique cointegration relationship, for five of the eight sectors, namely Food & Tobacco [1], Pulp & Paper [4], Chemicals [5], Non-metallic Minerals [6] and Transport Equipment [8]. For all other models the null of no cointegration cannot be rejected at the 10% significance level. We do not infer that the lack of significant cointegration relationships for some sectors necessarily

Table 5: Cointegration tests with and without level shifts

Panel A: Without level shift						
Sector	H_0:	H_1:	λ_{Trace}	[p-value]	Critical values: 95%	Inference
[1]	$r = 0$	$r \geq 1$	49.65*	[0.0093]	42.92	
	$r \leq 1$	$r \geq 2$	17.62	[0.3701]	25.87	Rank(Π) = 1
	$r \leq 2$	$r = 3$	3.05	[0.8700]	12.52	
[2]	$r = 0$	$r \geq 1$	26.77	[0.1073]	29.80	
	$r \leq 1$	$r \geq 2$	7.65	[0.5032]	15.49	Rank(Π) = 0
	$r \leq 2$	$r = 3$	1.41	[0.2344]	3.84	
[3]	$r = 0$	$r \geq 1$	24.54	[0.1784]	29.80	
	$r \leq 1$	$r \geq 2$	6.85	[0.5952]	15.49	Rank(Π) = 0
	$r \leq 2$	$r = 3$	1.99	[0.1578]	3.84	
[4]	$r = 0$	$r \geq 1$	45.57*	[0.0004]	29.80	
	$r \leq 1$	$r \geq 2$	10.46	[0.2471]	15.49	Rank(Π) = 1
	$r \leq 2$	$r = 3$	3.20	[0.0736]	3.84	
[6]	$r = 0$	$r \geq 1$	77.07*	[0.0000]	42.92	
	$r \leq 1$	$r \geq 2$	23.88	[0.0868]	25.87	Rank(Π) = 1
	$r \leq 2$	$r = 3$	6.35	[0.4166]	12.52	
Panel B: With level shift						
Sector	H_0:	H_1:	λ_{Trace}	[p-value]	Critical values: 95%	Inference
[5]	$r = 0$	$r \geq 1$	50.08**	[0.0208]	46.44	
	$r \leq 1$	$r \geq 2$	26.40	[0.0840]	28.30	Rank(Π) = 1
	$r \leq 2$	$r = 3$	6.39	[0.5384]	13.91	
[7]	$r = 0$	$r \geq 1$	42.82	[0.1098]	46.50	
	$r \leq 1$	$r \geq 2$	19.24	[0.4096]	28.39	Rank(Π) = 0
	$r \leq 2$	$r = 3$	6.20	[0.5742]	13.93	
[8]	$r = 0$	$r \geq 1$	41.68**	[0.0317]	40.28	
	$r \leq 1$	$r \geq 2$	22.68	[0.0935]	24.45	Rank(Π) = 1
	$r \leq 2$	$r = 3$	9.28	[0.1843]	12.79	

Notes: * and ** denote significance on the 1% and 5% level, respectively. Critical values are obtained by computing the response surfaces according to MacKinnon *et al.* (1999) in Panel A and Johansen *et al.* (2000) in Panel B.

contradicts pure economic theory. Rather, this probably reflects the missing strength of the long-run relations in some sectors. Furthermore, problems with data quality might also be an issue.

4.5. VECM estimation and Granger-causality testing

After having determined the sectors with significant cointegration relationships, the next step is to estimate the corresponding VECMs given by Eq. (7), in order to attain the long-run parameter estimates. These and the equation-specific adjustment coefficients are reported in Table 6, along with the corresponding *t*-statistics. Overall, the statistical significance and the plausibility of the cointegrating vector estimates in terms of sign and magnitude, indicate that we have attained reasonable estimates of the true equilibrium relationship.

First, for most models the elasticity estimates turn out to be economically reasonable with regard to sign and magnitude. However, for sectors [1] and [5] the price coefficient is far from significant at conventional levels. Thus, as a double check we perform tests for beta restrictions on the cointegrating vectors of these two models, in order to assess the adequacy of restricting price to zero ($\beta_p = 0$). The results indicate that these restrictions are valid and, hence, we estimate the restricted models also reported in Table 5. The elasticity estimates of economic activity are 0.70 in sector [1] (Food & Tobacco), 1.90 in sector [4] (Pulp & Paper), 1.11 in sector [5] (Chemicals), 1.01 in sector [6] (Non-metallic Minerals) and 1.00 in sector [8] (Transport Equipment). The corresponding elasticity estimates of electricity price are zero in sectors [1] (Food & Tobacco) and [5] (Chemicals), –0.52 in sector [4] (Pulp & Paper), –0.30 in sector [6] (Non-metallic Minerals) and –0.30 in sector [8] (Transport Equipment). This corroborates estimates from previous studies, where elasticities of economic activity are normally close to unity and price elasticities range between approximately zero and –0.50 (see Table 1).

Second, the time trends are retained only in the models of sectors [1] (Food & Tobacco), [5] (Chemicals) and [6] (Non-metallic Minerals) where they show significance but with differing signs. In sectors [1] (Food & Tobacco) and [6] (Non-metallic Minerals) the time trend has a positive sign, implying an increasing net effect on electricity intensity by exogenous factors, such as technical progress or changes in the structure of industry over time. In contrast, in sector [5] (Chemicals) the trend picks up a decreasing net effect on the electricity intensity of these factors.

Third, the adjustment coefficients also reveal plausible signs and magnitude whenever they are significantly different from zero, thereby establishing the error-correction mechanism, which forces the system to its long-run equilibrium. In all the VECMs, electricity consumption adjusts negatively to a deviation from long-run equilibrium, with the speed of adjustment ranging between an annual error correction of about 20% and 77% per year, depending on the sector. Hence, a near-complete adjustment (of at least 95%) to long-run equilibrium induced by electricity consumption would take approximately fourteen years in the slowest case and three in the fastest case. The level of economic activity, on the contrary, adjusts (positively) to errors from equilibrium only in the sectors [1] (Food & Tobacco) and [4] (Pulp & Paper), though with a less pronounced speed. In all other models, adjustments take place only via electricity consumption.

A cointegration relationship necessarily implies the existence of Granger-causality in at least one direction. Four hypotheses concerning the direction of causality in the energy-growth nexus have been stated in the economics literature: the growth hypothesis, the conservation hypothesis, the feedback hypothesis and the neutrality hypothesis (for a survey see Payne, 2010). While the growth hypothesis implies Granger-causality running from energy consumption to economic growth, the conservation hypothesis implies the opposite causal relationship. The feedback hypothesis claims an interdependent relationship between both variables, necessitating bidirectional Granger-causality. Finally, the neutrality hypothesis states that both variables are only of little importance in determining each other, implying the absence of Granger-causality.

Besides long-run Granger-causality, which is reflected by the adjustment coefficients, short-run Granger-causality can occur through the lagged differences of the independent variables in each equation of the system. Table 7 summarizes the results and inference on long- and short-run Granger-causality. Besides the *t*-statistics of the *ECT* for long-run Granger-causality we present Wald test statistics on the joint significance of the lagged independent variables in the respective equations. Note that this only applies to the model of sector [5], as in all other cases the VECMs have an order of zero. For all models Granger-causality from value added and electricity price to electricity consumption can be established in the long-run. Further, a Granger-causal relation in the same direction is detected by the Wald test in model [5] for the short-run as well. Conversely, value added is Granger-caused by electricity consumption and

Table 6: Estimated long-run relationships

Panel A: Without level shifts

Sector	Cointegrating vector					Adjustment coefficients		
	e_t	v_t	p_t	Constant	Trend	α_e	α_v	α_p
[1]	1.000	–0.776	0.070	–19.40	–0.024	–0.487	0.258	0.177
		(–5.815)	(1.247)		(–17.889)	(–5.959)	(1.920)	(0.747)
[1][R]	1.000	–0.703	———	–19.40	–0.025	–0.492	0.305	0.265
		(–6.610)			(–34.413)	(–5.472)	(2.187)	(1.069)
[4]	1.000	–1.899	0.516	–17.07	———	–0.201	0.085	0.239
		(–6.300)	(4.906)			(–2.839)	(2.497)	(1.052)
[6]	1.000	–1.011	0.300	–19.81	–0.007	–0.772	–0.077	0.028
		(–5.413)	(3.634)		(–5.404)	(–6.163)	(–0.602)	(0.351)

Panel B: With level shifts

Sector	Cointegrating vector						Adjustment coefficients		
	e_t	v_t	p_t	Const.	Trend	Shift	α_e	α_v	α_p
[5]	1.000	–1.045	–0.089	–20.44	0.027	0.233	–0.733	–0.450	0.090
		(–5.629)	(–1.382)	(–29.08)	(4.915)	(7.538)	(–3.709)	(–1.428)	(0.576)
[5][R]	1.000	–1.106	———	–20.56	0.028	0.242	–0.733	–0.450	0.090
		(–5.976)		(–28.75)	(5.032)	(7.782)	(–3.709)	(–1.428)	(0.576)
[8]	1.000	–0.998	0.302	–19.96	———	–0.107	–0.308	0.104	–0.200
		(–8.113)	(1.705)	(–17.89)		(–1.430)	(–2.193)	(0.937)	(–1.524)

Notes: t-statistics in parentheses. Results in Panel A are computed with Johansen's maximum likelihood estimation using EViews 6. Results in Panel B are computed with a simple two-step method (see Ahn & Reinsel, 1990) which allows to apply tests on beta restrictions using JMulTi 4.24. [R] denotes the restricted models: In sector [1] the binding restriction that $\beta_p = 0$ was tested through a LR test for beta restrictions with one degree of freedom, resulting in a test statistic of 1.290 and a corresponding p-value of 0.256. In sector [4] the binding restriction that $\beta_p = 0$ was tested through a Wald test for binding beta restrictions with one degree of freedom, resulting in a test statistic of 1.036 and a corresponding p-value of 0.309. Hence, the restricted models are not rejected.

Table 7: Granger-causality analysis

Effect variables		Long-run cause	Joint short-run cause	Inference	
		ECT	$\{\Delta v_t \,\&\, \Delta p_t\}_e$ $\{\Delta e_t \,\&\, \Delta p_t\}_v$ $\{\Delta e_t \,\&\, \Delta v_t\}_p$	Long-run causality	Short-run causality
[1]	Δe_t	–5.959*	——	v → e e → v	——
	Δv_t	1.920***	——		
	Δp_t	0.747	——		
[4]	Δe_t	–2.839*	——	v & p → e e & p → v	——
	Δv_t	2.497**	——		
	Δp_t	1.052	——		
[5]	Δe_t	–3.709*	$\{3.483^{**}\ [0.012]\}_e$	v → e	v & p → e
	Δv_t	0.576	$\{1.971\ [0.109]\}_v$		
	Δp_t	–1.428	$\{1.576\ [0.192]\}_p$		
[6]	Δe_t	–6.163*	——	v & p → e	——
	Δv_t	0.351	——		
	Δp_t	–0.602	——		
[8]	Δe_t	–2.193**	——	v & p → e	——
	Δv_t	0.937	——		
	Δp_t	–1.524	——		

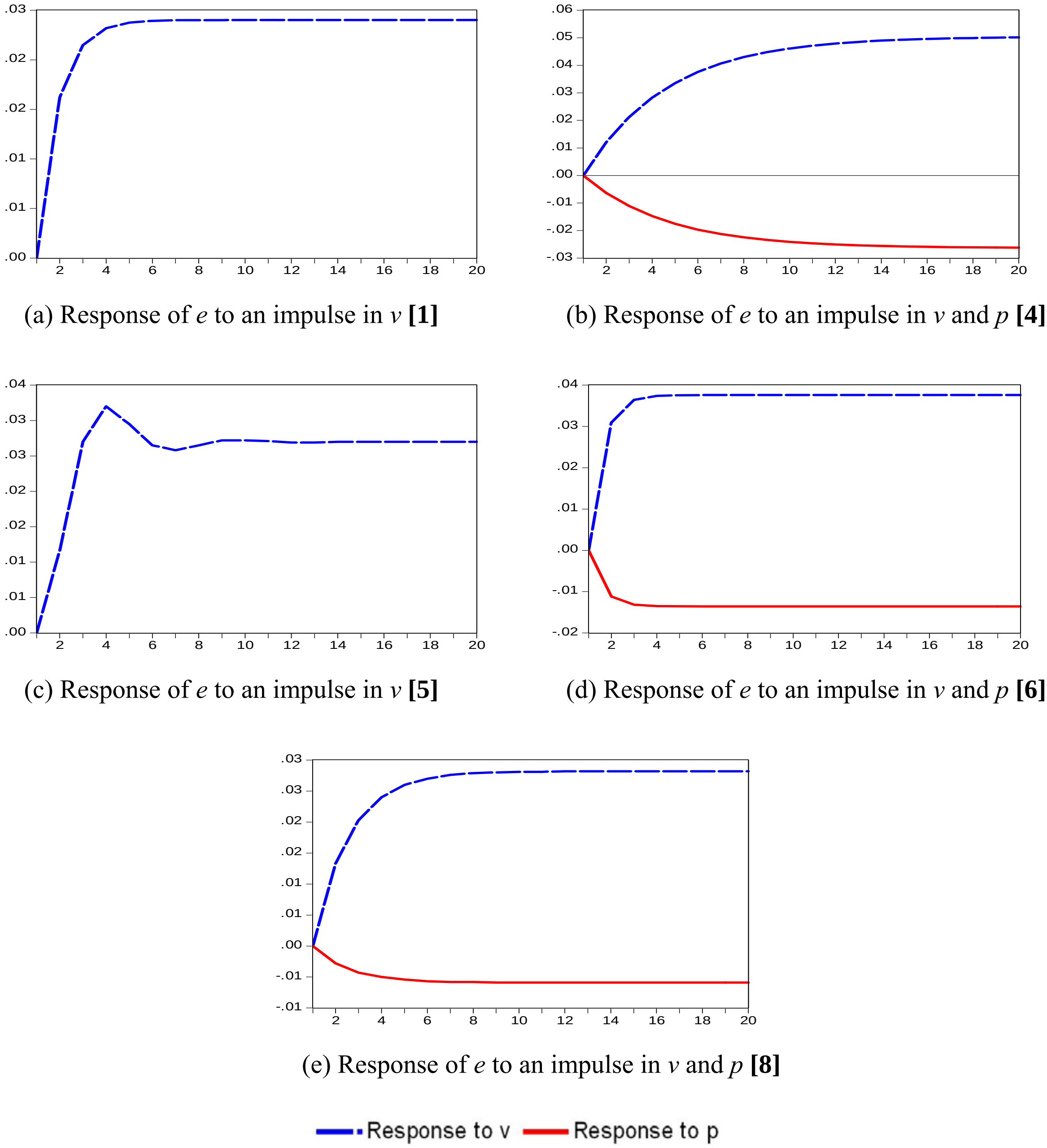
Notes: *ECT* stands for 'error-correction term'. The second column (long-run cause) presents t-statistics, while the third column (joint short-run cause) presents F-statistics with the corresponding p-values in brackets. → denotes the direction of Granger-causality. *, ** and *** denote significance on the 1%, 5% and 10% level, respectively.

electricity price in the long-run, only in models [1] (Food & Tobacco) and [4] (Pulp & Paper). The only variable which is Granger-caused neither in the short- nor in the long-run is electricity price. Thus, electricity price can be considered to be strongly exogenous in the subsectoral demand functions. This of course complies with intuition, as subsectoral demand is only a small fragment of aggregate demand and hence, is not likely to affect the process of electricity price formation.

In reference to the aforementioned hypotheses regarding the energy-growth nexus, our results indicate evidence for the feedback hypothesis in sectors [1] (Food & Tobacco) and [4] (Pulp & Paper), and the conservation hypothesis in the sectors [5] (Chemicals), [6] (Non-metallic Minerals) and [8] (Transport Equipment). This means that in the three latter sectors conservation policies would not adversely affect economic growth, whereas in the former two sectors such policies would imply a trade-off concerning growth.

4.6. Impulse response functions

In order to trace out the dynamic behavior of electricity demand in response to one-time innovations in the two other variables, we perform an impulse response analysis on the basis of the estimated VECMs. The impulse responses are displayed in Fig. 2. All of them show a plausible behavior. Electricity consumption responds positively to an impulse in value added and negatively to an impulse in electricity price. Shocks do not appear transitory but have long-term impacts, which makes sense as the variables are found to be integrated of order one, $I(1)$. Given that no further shocks hit the system, convergence to the new long-run level occurs after approximately three to fourteen periods, depending on the sector-specific speed of adjustment to long-run equilibrium, as reflected by the loading coefficients reported in Table 6.



(a) Response of e to an impulse in v **[1]**

(b) Response of e to an impulse in v and p **[4]**

(c) Response of e to an impulse in v **[5]**

(d) Response of e to an impulse in v and p **[6]**

(e) Response of e to an impulse in v and p **[8]**

Fig. 2: Orthogonalized impulse responses of electricity consumption (e) to Cholesky one standard deviation innovations in real value added (v) and real electricity price (p), based on the estimated VECMs for the subsectors [1], [4] - [6] and [8].

4.7. Short-run elasticities

Given the results of the preceding estimation and testing procedure, the estimated cointegrating vectors can be used in the estimation of the ECMs according to Eq. (9), in order to quantify the short-run elasticities. As the first differences as well as the EC terms are all $I(0)$, the equations are balanced.

We start by estimating unrestricted ECMs with a maximum lag length of three and stepwise delete insignificant covariates. Outliers are modeled using impulse dummies. The model properties are checked using a battery of diagnostic tests. More precisely, we apply a Lagrange Multiplier test for serial correlation of order one and two, a Portmanteau test for autocorrelation up to four lags, the Breusch-Pagan-Godfrey test for heteroscedasticity, the Jarque-Bera test for normality and the Ramsey RESET test for functional form misspecification. All models pass the diagnostic tests, indicating no significant deviations from the desired model properties. The estimated equations and diagnostic test results are summarized in Table 8. Further, we check for parameter instability by applying the cumulative sum of recursive residuals (CUSUM) and CUSUM of squares (CUSUMSQ) tests (see Brown *et al.*, 1975). Fig. A.1 in the appendix displays the results for the single ECMs, which overall indicate parameter stability. As can be seen only the CUSUMSQ plot for the Transport Equipment [8] model slightly crosses the lower 5% critical bound at one point.

The coefficients of the error-correction terms have the right sign and are significant in all the models. The magnitudes vary between –0.20 in the model for sector [8] (Transport Equipment) and –0.83 in the model for sector [6] (Non-metallic Minerals). The short-run demand elasticity of economic activity has the expected sign and is significant in all models. Here the magnitudes are 0.17 in sector [1] (Food & Tobacco), 1.02 in sector [4] (Pulp & Paper), 0.74 in sector [5] (Chemicals), 0.51 in sector [6] (Non-metallic Minerals) and 0.48 in sector [8] (Transport Equipment). The sizes of the short-run elasticities are in accordance with the corresponding long-run elasticities in the sense that when the long-run elasticity is relatively high in a sector, the short-run elasticity is relatively high as well. The short-run elasticity of electricity price, in contrast, is significant only in the models for sectors [6] (Non-metallic Minerals) and [8] (Transport Equipment), with magnitudes of –0.57 and –0.31, respectively. This leads to a peculiar situation in sector [6] (Non-metallic Minerals), where the price elasticity in the short-run is of a higher magnitude than in the long-run. The constant in the model of sector [8] (Transport Equipment) is only significant at the 12% level. However, we decide to keep it in the specification for technical reasons.

Table 8: Estimated ECMs and diagnostic tests

Sector	ECM
[1]	$\Delta\hat{e}_t = \underset{[0.000]}{0.031} - \underset{[0.000]}{0.404}\left(e_{t-1} - 0.776\,v_{t-1} + 0.070\,p_{t-1} - 19.40 - 0.024\,t\right) + \underset{[0.064]}{0.173}\Delta v_t - \underset{[0.000]}{0.136}\,I_{94} + \underset{[0.002]}{0.093}\,I_{95}$
[4]	$\Delta\hat{e}_t = \underset{[0.016]}{0.025} - \underset{[0.001]}{0.281}\left(e_{t-1} - 1.899\,v_{t-1} + 0.516\,p_{t-1} - 17.07\right) + \underset{[0.006]}{1.020}\Delta v_t - \underset{[0.000]}{0.260}\,I_{91}$
[5]	$\Delta\hat{e}_t = \underset{[0.009]}{-0.022} - \underset{[0.000]}{0.520}\left(e_{t-1} - 1.106\,v_{t-1} - 20.56 + 0.028\,t + 0.242\,S_{91}\right) + \underset{[0.000]}{0.740}\Delta v_t - \underset{[0.000]}{0.310}\,I_{91} + \underset{[0.007]}{0.114}\,I_{93}$
[6]	$\Delta\hat{e}_t = \underset{[0.000]}{0.036} - \underset{[0.000]}{0.832}\left(e_{t-1} - 1.011\,v_{t-1} + 0.300\,p_{t-1} - 19.81 - 0.007\,t\right) + \underset{[0.018]}{0.507}\Delta v_t - \underset{[0.000]}{0.566}\Delta p_t - \underset{[0.059]}{0.215}\Delta p_{t-1} - \underset{[0.000]}{0.232}\,I_{93} - \underset{[0.000]}{0.417}\,I_{94} - \underset{[0.002]}{0.176}\,I_{00}$
[8]	$\Delta\hat{e}_t = \underset{[0.114]}{-0.010} - \underset{[0.027]}{0.204}\left(e_{t-1} - 0.998\,v_{t-1} + 0.302\,p_{t-1} - 19.96 - 0.107\,S_{93}\right) + \underset{[0.000]}{0.480}\Delta v_t - \underset{[0.001]}{0.312}\Delta p_t - \underset{[0.000]}{0.168}\,I_{91} + \underset{[0.000]}{0.233}\,I_{95}$

Diagnostics

	Time span	Adj.R^2	LM(1)	LM(2)	PAR(4)	HET	JB	RESET
[1]	1971-2007	0.75	F = 1.58 [0.218]	F = 0.95 [0.399]	Q = 6.96 [0.138]	F = 0.40 [0.810]	χ^2 =2.89 [0.236]	F = 0.22 [0.641]
[4]	1971-2007	0.42	F = 0.24 [0.624]	F = 0.77 [0.471]	Q = 1.48 [0.831]	F = 0.35 [0.787]	χ^2= 1.72 [0.424]	F = 0.11 [0.739]
[5]	1972-2007	0.72	F = 0.58 [0.453]	F = 0.66 [0.525]	Q = 1.48 [0.831]	F = 0.52 [0.725]	χ^2= 1.16 [0.559]	F = 0.03 [0.857]
[6]	1971-2007	0.85	F = 0.46 [0.505]	F = 0.47 [0.627]	Q = 3.66 [0.454]	F = 5.96 [0.632]	χ^2= 0.65 [0.722]	F = 0.34 [0.566]
[8]	1971-2007	0.79	F = 0.35 [0.559]	F = 0.17 [0.843]	Q = 2.28 [0.685]	F = 1.36 [0.268]	χ^2= 0.57 [0.751]	F = 0.21 [0.653]

Notes: *p*-values are reported in brackets. The diagnostic tests used are a Lagrange Multiplier test (LM) for serial correlation at 1st and 2nd lag, a Portmanteau test (PAR) for autocorrelation up to lag 4, the Breusch-Pagan-Godfrey test (HET) for heteroscedasticity, the Jarque-Bera test (JB) for normality and the Ramsey RESET test for functional form misspecification.

5. Conclusions

In this article we have undertaken what, to the best of our knowledge, is the first attempt to estimate subsector-specific electricity demand elasticities with regard to economic activity and electricity price. This subsectoral approach aims at reducing the heterogeneity concerning consumption behavior of the analyzed consumer groups and thereby reaping the benefits of additional information otherwise veiled through aggregation. Making use of German annual data on a subsectoral level from 1970 to 2007, we were successful in finding statistically significant cointegration relationships in five of the eight analyzed subsectors employing a multivariate cointegrated VAR setting. We take account of structural breaks by incorporating shift dummies into the cointegrating vectors (see Johansen *et al.*, 2000). Furthermore, we check for the direction of Granger-causality and conduct an impulse response analysis. In order to attain the corresponding short-run elasticities of economic activity and price, we also estimate single-equation error-correction models in which we include the error-correction terms resulting from the VECM estimation.

Our findings for the long-run elasticity estimates are economically reasonable in terms of sign and magnitude. For three of the subsectors, long-run demand elasticities of economic activity are found to be near unity. The most extreme estimates are 0.70 in the Food & Tobacco industry and 1.90 in the Pulp & Paper industry. The estimates of price elasticities vary between zero (statistically insignificant), to which the corresponding coefficients in two of the models can be restricted, and –0.52. In the short-run, the elasticities of economic activity range between 0.17 and 1.02, whereas the price elasticities range between zero (insignificant) and –0.57. The deterministic time trends included in the long-run demand relationships pick up differing effects from exogenous factors, such as structural changes in the industry and technological progress, in three of the subsectors. In the Food & Tobacco and the Non-metallic Minerals industries the trend shows a positive sign implying an increasing net effect on electricity intensity, whereas in the Chemicals industry the sign is negative, implying the opposite net effect. Adjustments to long-run equilibrium take place with widely differing speeds in the single sectors. Hence, depending on the sector, near-complete adjustments are achieved after approximately three to fourteen years. This is also reflected by the impulse response functions. The tests on Granger-causality indicate evidence for the feedback hypothesis in the Food & Tobacco and the Pulp & Paper industry, and the conservation hypothesis in the Chemicals, the Non-metallic Minerals and the Transport Equipment sectors.

Hence, only in the two former sectors conservation policies would be confronted with a certain trade-off in terms of decreasing output growth.

References

Agnolucci, P. (2009). The energy demand in the British and German industrial sectors: Heterogeneity and common factors. *Energy Economics* **31**(1): 175–187.

Ahn, S.K., Reinsel, G.C. (1990). Estimation for partially nonstationary multivariate autoregressive models. *Journal of the American Statistical Association* **85**(411): 813–823.

Amarawickrama, H.A., Hunt, L.C. (2008). Electricity demand for Sri Lanka: A time series analysis. *Energy* **33**(5): 724–739.

Barker T., Ekins, P., Johnstone, N. (1995). *Global Warming and Energy Demand*. Routledge, Taylor & Francis Group.

Beenstock, M., Goldin, E., Nabot, D. (1999). The demand for electricity in Israel. *Energy Economics* **21**(2): 168–183.

Bose, R.K., Shukla, M. (1999). Elasticities of electricity demand in India. *Energy Policy* **27**(3): 137–146.

Brown, R. L., J. Durbin, and J. M. Evans (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society. Series B (Methodolgical)* **37**(2): 149-192.

Elliott, G., Rothenberg, T.J., Stock, J.H. (1996). Efficient tests for an autoregressive unit root. *Econometrica* **64**(4): 813–836.

Engle, R.F., Granger, C.W.J. (1987). Co-integration and error correction: representation, estimation and testing. *Econometrica* **55**(2): 251–276.

Gonzalo, J. (1994). Five alternative methods of estimating long-run equilibrium relationships. *Journal of Econometrics* **60**(1/2): 203–233.

Johansen, S. (1988). Statistical analysis of cointegrating vectors. *Journal of Economic Dynamics and Control* **12**(2/3): 231–254.

Johansen, S. (1994). The role of the constant and linear terms in cointegration analysis of nonstationary variables. *Econometric Reviews* **13**(2): 205–229.

Johansen S. (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press, Oxford.

Johansen, S., Mosconi R., Nielsen B. (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. *Econometrics Journal* **3**(2): 216–249.

Kamerschen, D.R., Porter, D.V. (2004). The demand for residential, industrial and total electricity, 1973-1998. *Energy Economics* **26**(1): 87–100.

Lanne, M., Lütkepohl, H. (2002). Unit root tests for time series with level shifts: a comparison of different proposals. *Economics Letters* **75**(1): 109–114.

Lanne, M., Lütkepohl, H., Saikkonen, P. (2002). Comparison of unit root tests for time series with level shifts. *Journal of Time Series Analysis* **23**(6): 667–685.

Lanne, M., Lütkepohl, H., Saikkonen, P. (2003). Test procedures for unit roots in time series with level shifts at unknown time. *Oxford Bulletin of Economics and Statistics* **65**(1): 91–115.

Lütkepohl, H., Krätzig, M. (2004). *Applied Time Series Econometrics*. Cambridge University Press, Cambridge.

MacKinnon, J.G. (1996). Numerical distribution functions for unit root and cointegration test. *Journal of Applied Econometrics* **11**(6): 601–618.

MacKinnon, J.G., Haug, A.A., Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics* **14**(5): 563–577.

Paruolo, P. (1996). On the determination of integration indices in I(2) systems. *Journal of Econometrics* **72**(1-2): 313–356.

Payne, J.E. (2010). Survey of the international evidence on the causal relationship between energy consumption and growth. *Journal of Economic Studies* **37**(1): 53–95.

Perron, P. (1989). The great crash, the oil price shock and the unit root hypothesis. *Econometrica* **57**(6): 1361–1401.

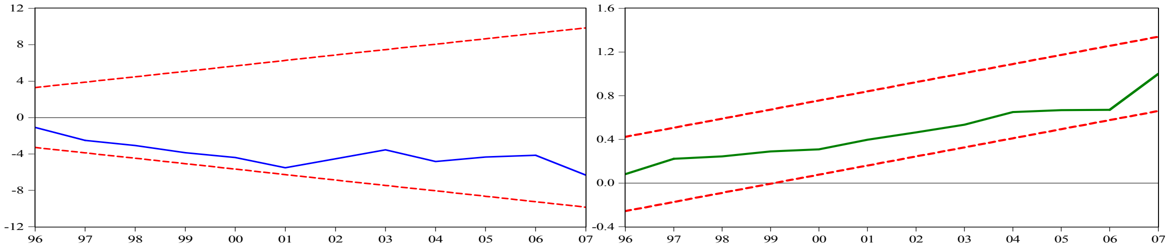
Pesaran H., Smith R.P., Akiyama T. (1998). *Energy Demand in Asian Developing Economies*. Oxford University Press, Oxford.

Polemis, M.L. (2007). Modeling industrial energy demand in Greece using cointegration techniques. *Energy Policy* **35**(8): 4039–4050.

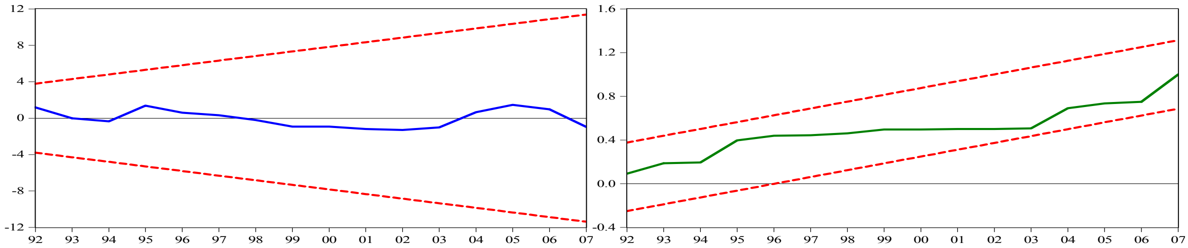
Saikkonen, P. (1992). Estimation and testing of cointegrated systems by an autoregressive approximation. *Econometric Theory* **8**(1): 1–27.

Saikkonen, P., Lütkepohl, H. (2002). Testing for a unit root in a time series with a level shift at unknown time. *Econometric Theory* **18**(2): 313–348.

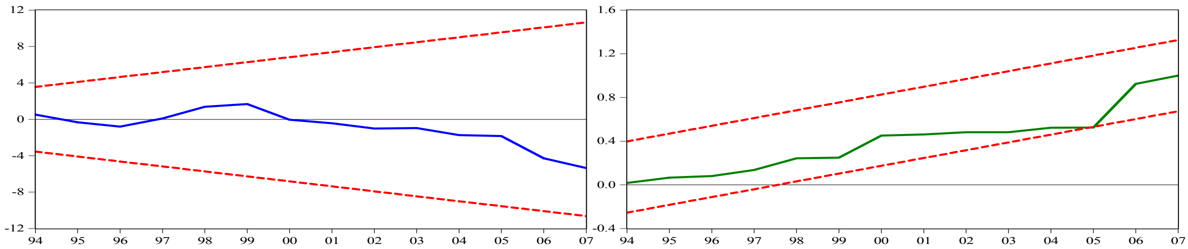
Appendix



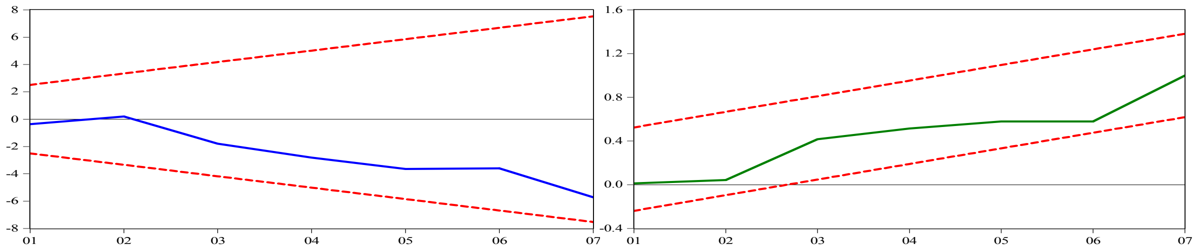
(a) Food & Tobacco **[1]**



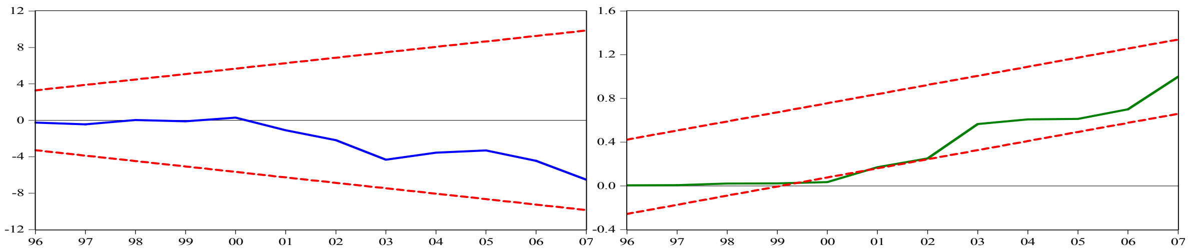
(b) Pulp & Paper **[4]**



(c) Chemicals **[5]**



(d) Non-metallic Minerals **[6]**



(e) Transport Equipment **[8]**

CUSUM ---- 5% Significance —— CUSUM of Squares

Fig. A.1: CUSUM and CUSUMSQ plots for the estimated ECM models.

List of FCN Working Papers

2010

Lang J., Madlener R. (2010). Relevance of Risk Capital and Margining for the Valuation of Power Plants: Cash Requirements for Credit Risk Mitigation, FCN Working Paper No. 1/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, February.

Michelsen C., Madlener R. (2010). Integrated Theoretical Framework for a Homeowner's Decision in Favor of an Innovative Residential Heating System, FCN Working Paper No. 2/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, February.

Harmsen - van Hout M.J.W., Herings P.J.-J., Dellaert B.G.C. (2010). The Structure of Online Consumer Communication Networks, FCN Working Paper No. 3/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, March.

Madlener R., Neustadt I. (2010). Renewable Energy Policy in the Presence of Innovation: Does Government Pre-Commitment Matter?, FCN Working Paper No. 4/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, April (revised June 2010).

Harmsen-van Hout M.J.W., Dellaert B.G.C., Herings, P.J.-J. (2010). Behavioral Effects in Individual Decisions of Network Formation: Complexity Reduces Payoff Orientation and Social Preferences, FCN Working Paper No. 5/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, May.

Lohwasser R., Madlener R. (2010). Relating R&D and Investment Policies to CCS Market Diffusion Through Two-Factor Learning, FCN Working Paper No. 6/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, June.

Rohlfs W., Madlener R. (2010). Valuation of CCS-Ready Coal-Fired Power Plants: A Multi-Dimensional Real Options Approach, FCN Working Paper No. 7/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, July.

Rohlfs W., Madlener R. (2010). Cost Effectiveness of Carbon Capture-Ready Coal Power Plants with Delayed Retrofit, FCN Working Paper No. 8/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August (revised December 2010).

Gampert M., Madlener R. (2010). Pan-European Management of Electricity Portfolios: Risks and Opportunities of Contract Bundling, FCN Working Paper No. 9/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Glensk B., Madlener R. (2010). Fuzzy Portfolio Optimization for Power Generation Assets, FCN Working Paper No. 10/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Lang J., Madlener R. (2010). Portfolio Optimization for Power Plants: The Impact of Credit Risk Mitigation and Margining, FCN Working Paper No. 11/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Westner G., Madlener R. (2010). Investment in New Power Generation Under Uncertainty: Benefits of CHP vs. Condensing Plants in a Copula-Based Analysis, FCN Working Paper No. 12/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Bellmann E., Lang J., Madlener R. (2010). Cost Evaluation of Credit Risk Securitization in the Electricity Industry: Credit Default Acceptance vs. Margining Costs, FCN Working Paper No. 13/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Ernst C.-S., Lunz B., Hackbarth A., Madlener R., Sauer D.-U., Eckstein L. (2010). Optimal Battery Size for Serial Plug-in Hybrid Vehicles: A Model-Based Economic Analysis for Germany, FCN Working Paper No. 14/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, October.

Harmsen - van Hout M.J.W., Herings P.J.-J., Dellaert B.G.C. (2010). Communication Network Formation with Link Specificity and Value Transferability, FCN Working Paper No. 15/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Paulun T., Feess E., Madlener R. (2010). Why Higher Price Sensitivity of Consumers May Increase Average Prices: An Analysis of the European Electricity Market, FCN Working Paper No. 16/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Madlener R., Glensk B. (2010). Portfolio Impact of New Power Generation Investments of E.ON in the UK, Sweden and Germany, FCN Working Paper No. 17/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Ghosh G., Kwasnica A., Shortle J. (2010). A Laboratory Experiment to Compare Two Market Institutions for Emissions Trading, FCN Working Paper No. 18/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Bernstein R., Madlener R. (2010). Short- and Long-Run Electricity Demand Elasticities at the Subsectoral Level: A Cointegration Analysis for German Manufacturing Industries, FCN Working Paper No. 19/2010, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

2009

Madlener R., Mathar T. (2009). Development Trends and Economics of Concentrating Solar Power Generation Technologies: A Comparative Analysis, FCN Working Paper No. 1/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Madlener R., Latz J. (2009). Centralized and Integrated Decentralized Compressed Air Energy Storage for Enhanced Grid Integration of Wind Power, FCN Working Paper No. 2/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November (revised September 2010).

Kraemer C., Madlener R. (2009). Using Fuzzy Real Options Valuation for Assessing Investments in NGCC and CCS Energy Conversion Technology, FCN Working Paper No. 3/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Westner G., Madlener R. (2009). Development of Cogeneration in Germany: A Dynamic Portfolio Analysis Based on the New Regulatory Framework, FCN Working Paper No. 4/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November (revised March 2010).

Westner G., Madlener R. (2009). The Benefit of Regional Diversification of Cogeneration Investments in Europe: A Mean-Variance Portfolio Analysis, FCN Working Paper No. 5/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November (revised March 2010).

Lohwasser R., Madlener R. (2009). Simulation of the European Electricity Market and CCS Development with the HECTOR Model, FCN Working Paper No. 6/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Lohwasser R., Madlener R. (2009). Impact of CCS on the Economics of Coal-Fired Power Plants – Why Investment Costs Do and Efficiency Doesn't Matter, FCN Working Paper No. 7/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Holtermann T., Madlener R. (2009). Assessment of the Technological Development and Economic Potential of Photobioreactors, FCN Working Paper No. 8/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Ghosh G., Carriazo F. (2009). A Comparison of Three Methods of Estimation in the Context of Spatial Modeling, FCN Working Paper No. 9/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Ghosh G., Shortle J. (2009). Water Quality Trading when Nonpoint Pollution Loads are Stochastic, FCN Working Paper No. 10/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Ghosh G., Ribaudo M., Shortle J. (2009). Do Baseline Requirements hinder Trades in Water Quality Trading Programs?, FCN Working Paper No. 11/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

Madlener R., Glensk B., Raymond P. (2009). Investigation of E.ON's Power Generation Assets by Using Mean-Variance Portfolio Analysis, FCN Working Paper No. 12/2009, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, November.

2008

Madlener R., Gao W., Neustadt I., Zweifel P. (2008). Promoting Renewable Electricity Generation in Imperfect Markets: Price vs. Quantity Policies, FCN Working Paper No. 1/2008, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, July (revised May 2009).

Madlener R., Wenk C. (2008). Efficient Investment Portfolios for the Swiss Electricity Supply Sector, FCN Working Paper No. 2/2008, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Omann I., Kowalski K., Bohunovsky L., Madlener R., Stagl S. (2008). The Influence of Social Preferences on Multi-Criteria Evaluation of Energy Scenarios, FCN Working Paper No. 3/2008, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, August.

Bernstein R., Madlener R. (2008). The Impact of Disaggregated ICT Capital on Electricity Intensity of Production: Econometric Analysis of Major European Industries, FCN Working Paper No. 4/2008, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

Erber G., Madlener R. (2008). Impact of ICT and Human Skills on the European Financial Intermediation Sector, FCN Working Paper No. 5/2008, Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University, September.

FCN Working Papers are free of charge. They can mostly be downloaded in pdf format from the FCN / E.ON ERC Website (www.eonerc.rwth-aachen.de/fcn) and the SSRN Website (www.ssrn.com), respectively. Alternatively, they may also be ordered as hardcopies from Ms Sabine Schill (Phone: +49 (0) 241-80 49820, E-mail: post_fcn@eonerc.rwth-aachen.de), RWTH Aachen University, Institute for Future Energy Consumer Needs and Behavior (FCN), Chair of Energy Economics and Management (Prof. Dr. Reinhard Madlener), Mathieustrasse 6, 52074 Aachen, Germany.