Energy Economics 48 (2015) 178–187

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Short- and long-run electricity demand elasticities at the subsectoral level: A cointegration analysis for German manufacturing industries

Ronald Bernstein, Reinhard Madlener *

Institute for Future Energy Consumer Needs and Behavior (FCN), School of Business and Economics / E.ON Energy Research Center, RWTH Aachen University, Mathieustraße 10, 52074 Aachen, Germany

ARTICLE INFO

Article history:
Received 18 March 2011
Received in revised form 30 December 2014
Accepted 31 December 2014
Available online 7 January 2015

JEL classification:
C1
Q4

Keywords:
Electricity demand elasticity
Disaggregated data
Cointegration
Granger causality
Structural break
German industry

ABSTRACT

We estimate electricity demand elasticities for eight subsectors of the German manufacturing industry using annual data from EU-KLEMS and the International Energy Agency for 1970–2007. The subsectoral approach allows to retain additional information otherwise blurred by aggregation and to benefit from lower intrasectoral heterogeneity. By employing a cointegrated VAR approach and accounting for structural breaks, we find long-run relationships for five of the eight subsectors studied. Short-run elasticities are estimated using single-equation error correction modeling. Granger causality tests and an impulse response analysis provide further insights into the relationships and dynamics of the variables, confirming the usefulness of the subsectoral approach adopted.

1. Introduction

Energy demand modeling on the basis of historical time series data has traditionally been conducted for a specific country, at an aggregated or disaggregated 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. Analyzing 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 possible.[1,2] 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 that makes use of disaggregated data at a subsectoral industry level for estimating energy demand elasticities with regard to economic activity and energy price within a standard cointegration framework. Specifically, the elasticities are estimated for each of the following eight subsectors of the German economy[3]: [FT] food and tobacco (15–16); [TL] textile and leather (17–19); [WW] wood and wood products (20); [PP] pulp, paper and printing (21–22); [CH] chemicals and chemical products (24); [NM] non-metallic minerals (26); [MM] metal and machinery (27–33); and [TE] 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 and Shukla, 1999; Kamerschen and 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 the country analyzed. Beenstock et al.

* Corresponding author. Tel.: +49 241 80 49820; fax: +49 241 80 49829.
E-mail addresses: ronald.bernstein@rwth-aachen.de (R. Bernstein), RMadlener@eonerc.rwth-aachen.de (R. Madlener).

[1] Implying that aggregation in general is aimed at stepwise compiling entities with similar characteristics and, hence, also similar consumption behavior and technologies.

[2] However, as one of the anonymous referees pointed out correctly, disaggregated data may suffer more from data problems such as outliers, measurement errors, etc., than data on a more aggregate level.

[3] 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.

http://dx.doi.org/10.1016/j.eneco.2014.12.019
0140-9883/

Table 1
Industrial electricity demand studies.

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

Note: SR and LR denote estimates for the short and long run, respectively.
[a] Also estimate demand for other sectors.
[b] Estimates an oil demand function separately.

(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 and Shukla (1999) estimate sectoral elasticities including industry (split into small/medium and large firms) 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 enterprises, and 1.06 and −0.45 for the large enterprises. Kamerschen and Porter (2004) employ a simultaneous equation approach for estimating price elasticities of electricity demand by U.S. industry.[4] 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.

A number of previous studies have used two-digit industry data for analyzing energy demand (see for example Caloghirou et al., 1997; Christopoulos, 2000; Christopoulos and Tsionas, 2002; Floros and Vlachou, 2005).[5] As these studies focus on interfuel substitution using a translog cost function approach and do not account for potential stochastic trends in the variables, their findings are not directly comparable to ours.

Further, Agnolucci (2009) uses disaggregated industrial data at the two-digit level of the NACE taxonomy in his energy demand study. 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 time series estimates mostly failed to show intuitive results. This presumably is due to the short time spans covered by the data. Finally, although information from disaggregated data is used in the estimation, the panel approach does not provide subsector-specific estimates of energy demand elasticities.

In sum, unlike the previous econometric literature on industrial electricity demand, we aim at examining data at the industrial subsector level of aggregation 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. As mentioned above, this study is the first of its kind estimating subsectoral electricity demand elasticities using standard cointegration techniques. Nevertheless, further research, especially with more advanced analysis techniques, would be desirable in order to corroborate our findings and hence to draw more reliable implications for policy design and guidance.

The paper proceeds as follows. In Section 2, we provide the analytical framework and methodology of the econometric analysis. Section 3 discusses the data, the application of the model and the results obtained from the analysis, while Section 4 concludes.

[4] Kamerschen and Porter (2004) also consider a partial adjustment approach, which, however, had to be dropped due to nonsensical estimates.
[5] We are grateful for this hint provided by two anonymous referees.

2. Analytical framework and methodology

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

$$E_t = f(V_t, P_t, \boldsymbol{X}_t, \boldsymbol{A}_t), \tag{1}$$

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 ($\boldsymbol{X}_t$) (which may include, for example, the real price of an electricity substitute and/or weather variables), and exogenous factors ($\boldsymbol{A}_t$), 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 the 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. Nevertheless, not taking this potential substitution effect into account in the model might be a limitation to the analysis and distort the results presented below. Altogether, the analytical framework described above is kept simple and resembles a very standard analysis of electricity consumption. In detail, the functional form of the electricity demand function looks as follows:

$$e_t = c_0 + dt + \beta_v v_t + \beta_p p_t + \varepsilon_t, \tag{2}$$

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 denotes the Gaussian error term. β_v and β_p are the constant elasticities of economic activity and price, respectively, with regard to electricity demand.

In the past, researchers have criticized that this kind of log-linear functional form (which has been chosen *a priori* in many studies) might not fully capture the complex relationships between the variables. Hsing (1990) for example, rejects the standard log-linear model in favor of the Box–Cox extended autoregressive (BCEA) model (see Savin and White, 1978). Other studies (see e.g. Pesaran et al., 1998, and Bhattacharyya and Timilsina, 2010) argue that alternative, more complex functional form specifications, such as translog cost functions, enjoy the advantage of having a more rigid theoretical foundation. Nevertheless, they conclude that despite the theoretical consistency of translog functions, the log-linear model performs better in that it shows an improved fit to the data.[6] Also, Amarawickrama and Hunt (2008) argue that the log-linear functional form above is favored in the energy demand literature for “its simplicity, straightforward interpretation and limited data requirements.”

[6] Pesaran et al. (1998) note that this might be due to important deficiencies in the underlying functional form of the indirect utility or cost functions.