Analyzing Industrial Electricity Demand: Applying Modern Econometric Time-Series Techniques

Christopher Hoeck, IER University of Stuttgart
Christoph Weber, IER University of Stuttgart

ABSTRACT

For any attempt to increase energy efficiency sufficient information about energy use and the underlying influencing factors is required. This paper analyses the factors which determine industrial energy use and especially electricity demand using an econometric approach based on time-series data. Besides the role of economic factors the impact of technological improvements on energy efficiency is investigated.

The analysis of energy demand in the industrial sector is accomplished by an econometric model based on the economic theory of production. Starting with the concept of production functions which are used to mathematically describe the transformation of inputs into output, demand functions for energy as well as for labor, capital and materials are derived from a profit maximization approach. The factors influencing demand are then the relative input prices, real output and technological progress. The demand equations are estimated using various co-integration approaches, notably the ADL- or ECM-model. These approaches allow in particular to distinguish short-term and long-term effects.

Despite the impact of economic variables, industrial energy demand very much depends on technological properties of the capital stock. Therefore in the empirical application 10 different types of German industries with different production structures are distinguished. For every single sector monthly data from 1991 to 2000 are analyzed.

The results indicate that electricity demand in the German industry depend very little if at all on energy prices. Hence autonomous energy efficiency improvements and industrial restructuring are much more affecting industrial electricity demand than energy prices. The most influential factor however is the output level. For most sectors it turns out that both short-term and long-term output elasticities are significantly below one, indicating that there are substantial economies of scale in industrial electricity use.

Introduction

Using modern econometric techniques on time series data is complementary to other approaches of analyzing energy demand like decomposition analysis or process analyses. The first decomposes the change in industrial energy demand into several effects. Mostly these are the production effect, the structural effect and the intensity effect (Ang & Lee 1994). This is a more or less descriptive approach neglecting any price influences on energy demand and assuming an output elasticity of one. The process analysis explicitly takes into account the technological details of several inter-related production processes, but as in decomposition analyses price influences are ignored. In contrast, although econometric regression of time series has a lower degree of technological detail than process analyses the role of economic factors like prices and output level may be accounted for in a consistent and theoretically founded way.

Demand Functions for Input Factors

Economic theory views production as a series of activities by which inputs are transformed through a technological process into output of goods and services. A production function *f(.)* is an analytical tool to abstractly characterize the transformation of inputs x_i into a single output y and therefore defines the limits of a firm's technical production possibilities (Thompson 1989). Basically production functions may be distinguished according to their ease of substitution between the input factors necessary to produce a given output. The limitational production functions always requires a fixed proportion of inputs. There are no variable factors of production. On the other hand the inputs of a substitutional production function can be replaced more or less easily (Fandel 1991). During the following analyses of energy demand this kind of production function will be assumed.

The inputs considered here are capital, labor, energy and materials. They can be either fixed or variable. This classification goes along with the division of time into short- and long-run and therefore into short- and long-run production functions. A fixed input's quantity cannot readily be changed in the short run and therefore determines an upper capacity limit or scale of operation for production. In contrast, the amount of a variable input can easily be adjusted in order to raise or lower output. In the short run these inputs are raw materials, energy and possibly labor. The long run usually starts at a point of time where all production factors become variable; no fixed inputs exist.

As a matter of fact a firm will only be able maintain production if it earns profit. To explain the behavior of industrial enterprises economic theory assumes that the primary goal of industrial production is the maximization of profit. Given a price w_i for the input the firm chooses an optimal x_i for which the first order condition for optimality holds. This is assumed to be done simultaneously for every input. The result of this optimization are the demand functions for every single input factor (Hansen 1993). The factors determining the demand of an input x_i are its own price, the price of all other inputs and the real output y. Thus, for all $j \neq i$ the demand function reads

$$x_i = f(w_i, w_j, y) \tag{1-1}$$

For example, for electricity x_E the input demand equation becomes

$$x_E = f(w_E, w_G, w_C, w_O, w_K, w_L, w_M, y, t) \tag{1-2}$$

Thus, industrial electricity demand is determined by its own price w_E and the price the other all energy sources like gas w_G, coal w_C, and oil w_O. In addition to that the prices of capital w_K, labor w_L and raw materials w_M as well as output y enter the demand function. All these prices are assumed to be real prices, thus they are relative to the prices existing on the sales market. Furthermore the time t enters as a proxy for autonomous technical progress. Because demand functions are viewed as the results of an economic optimization, three basic restrictions have to be met :

1. **Negativity** : The influence of the own price of an input factor must be negative. Thus, a rise in the price of energy must lead to a decrease in the demand of energy. This is a necessary condition for profit maximization to exist.
2. **Symmetry** : The influence on the demand for x_i due to a change in the price of an input $j \neq i$ must be identical to the impact of a change of w_i on the demand for the factor j.

Thus, economic theory implies that the impact from a rise of labor cost will have a similar effect on energy demand as will the rise of energy cost have on the demand of labor.

3. **Homogeneity** : The demand function is homogeneous of degree zero in all input prices. This means a change in all input prices by λ will result in a change of a given demand x_i by λ^0. Thus, if the prices of all inputs rise or fall by the same amount the demand for energy will not be affected, nor will the demand from all other factors.

Equation (1-2) is the basis for the following econometric time-series analysis on industrial energy demand. For the regression a log-linear specification is assumed. Thus, the long run equation to be estimated reads

$$x_E = \beta_0 + \beta_y y + \beta_E w_E + ... + \beta_T t + u_t \tag{1-3}$$

All variables except the time trend are in logarithms. The seasonal dummies used for estimation are not shown in (1-3). The residual term u_t captures all the influences not explained by the variables and is assumed to be a white noise process. By including lagged data for all variables equation (1-3) becomes an autoregressive distributed lag model, or ADL.

Properties of Time Series

In econometric analysis every time series is treated as the realization of a stochastic process. Thus, for every single observation as well as for the series as a whole there exists an underlying probability distribution determining the so called data generating process of the series. An important question is whether this process is stationary or not. Stationarity means that after an exogenous shock a time series will return to its conditional mean in the long run. Therefore stationarity has important implications for the economic and statistical properties of time series.

The types of non-stationary time series discussed in this paper are so called stochastic trends. The most common case of a stochastic trend is a random walk. Time series consisting of a random walk have a non-constant variance, i. e. the variance increases with time (Wojciech & Deadman 1997). An economic shock has a non-decaying influence on a stochastic trend. Clearly in the presence of a stochastic trend the concept of economic long run equilibria makes little sense. Therefore if energy demand is nonstationary an optimal long run energy demand derived as shown in the previous chapter does not exist in the first place.

A nonstationary time series that can be transformed into a stationary series by differencing *d* times is said to be integrated of order *d*, or *I(d)*. Because taking the first difference of a random walk will result in a stationary time series, it is called integrated of order one or *I(1)*. The reason why econometricians do not like to work with integrated data like *I(1)* is that the regression statistics of random walks does not have the familiar Student-t distribution. In addition, analysing time series data containing stochastical trends may result into a **spurious** regression. This term was first coined by Granger and Newbold (1986), who found out during their Monte Carlo analysis that the regression of *independent I(1)* variables does falsely indicate a significant statistical relation between these variables in three of four times. Therefore, including *I(1)* variables into a regression equation will very likely lead to wrong conclusions about their significance.

Many economic variables show signs of nonstationarity. Thus, only their first or second differences are stationary. Unfortunately using the difference of a time series is no remedy to the problem of integrated data, because such a model does not exhibit a long run solution. The desire to have a model with both short and long run solutions led to the concept of cointegration, first introduced by Engle and Granger (1987). The idea of cointegration is that although every single variable used in the regression is nonstationary there may exist a linear combination of these variables which is itself stationary. Assuming there are two variables y and x which are both $I(1)$ and a residual term u_t which is white noise, a static linear regression equation may have the form

$$y_t = \beta_0 + \beta_1 x_t + u_t \tag{1-4}$$

The two variables of interest y and x are called cointegrated if the residual term u_t is stationary. This means that the linear combination $y_t - \beta_0 - \beta_1 x_t$ has to be stationary. In this case β_1 is called the cointegration parameter. It forces the two nonstationary variables y and x to drift together in time i. e. the difference between both variables u_t never becomes too large. Thus, these deviations from the long run path (1-4) have to be stationary or $I(0)$. For variables to be cointegrated it is necessary that they are integrated of the same order. Hence, only if both x and y are $I(1)$ or both are $I(2)$ there may exist a cointegration parameter which assures that u_t is $I(0)$. In any other case using the regression equation (1-4) makes no sense (Wojciech & Deadman 1997).

The concept of cointegration allows for non spurious regressions between integrated variables of a positive order and therefore is a perquisite for the calculation of their long run coefficients. Despite that, even if equation (1-4) is stationary the distribution of the estimated parameter β_1 is non standard. In fact it asymptotically follows a Brown movement or Wiener process. Therefore the standard tables to test for significance must be used with caution. In addition to that, the estimators of variables containing a stochastic trend converge to their true values at a higher rate than those of $I(0)$ variables and therefore are called "superconsistent"(Holden & Perman 1994).

Using econometric regression analysis on time series data requires to find out whether these data are stationary or not. If for a time series the hypothesis of containing a stochastic trend cannot be rejected this series can only be used in a regression equation if it cointegrates with other time series of the same order. The Results from tests for the order of integration of the relevant time series are presented below.

The Structure of Energy Demand in the German Industry

In 1999 the industrial sector in Germany used 2433 PJ of final energy, which is more than 25% of the whole use of final energy from all sectors. More than 77% of this energy was used for process-and space heating while mechanical energy had a share of less than 20%. The remaining energy was used for light and communication. Almost 30% of the energy used in the industrial sector was electricity, nearly 40% was gas and the share of oil and coal was about 10% and 18%. For the 10 different types of industry analyzed in this paper the shares of the four sources of energy in final energy demand are presented in Figure 1.

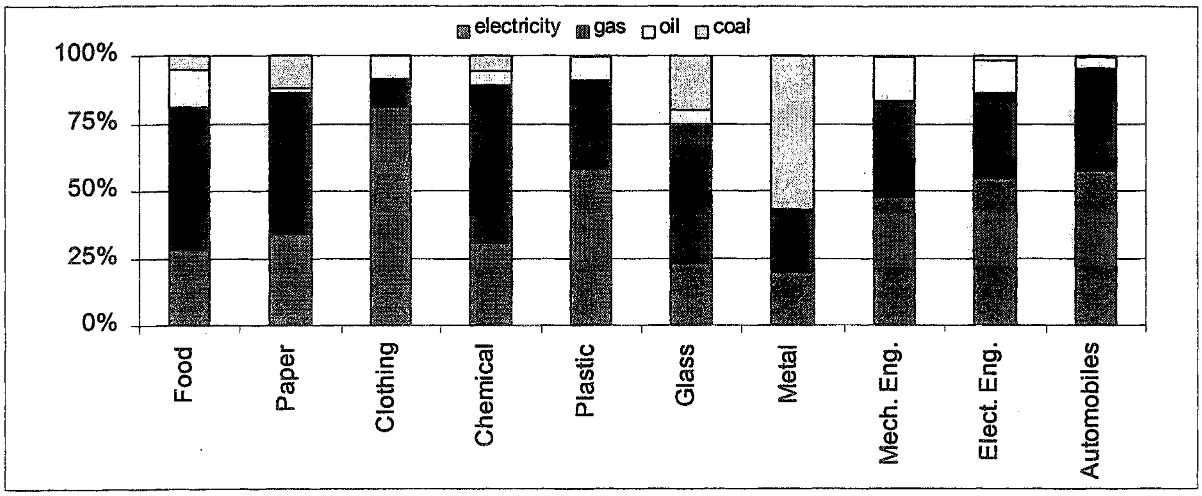

Figure 1. Share of Energy Consumption of 10 Industrial Sectors in Germany in 1999

Although the methodology described may be applied to any energy demand the focus in the rest of the paper is on total site electricity demand. Figure 2 shows this demand for the 10 industrial sectors of interest.

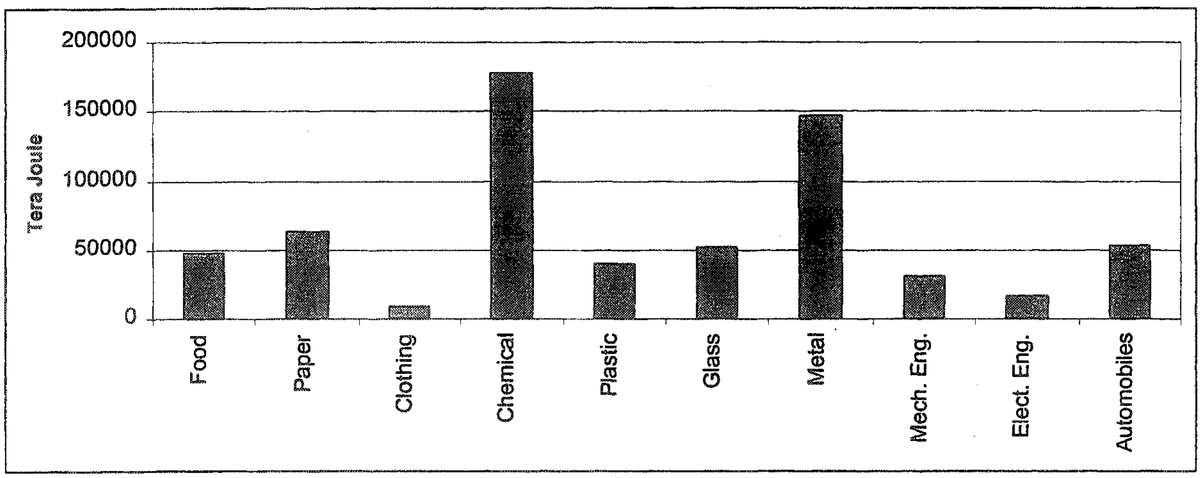

Figure 2. Electricity Demand of 10 Industrial Sectors in Germany in 1999

From Figure 2 it's easy to see that the chemical and metal industry had the largest demand for electricity. While paper industry used more than 60000 TJ, the food, glass and automobile industry all consumed around 50000 TJ of electricity. About 40000 TJ are used by the plastic industry followed by mechanical- and electrical engineering with 30000 and 17000 TJ. Clothing industry used the least electricity.

General Sample Statistics and Orders of Integration

For every sector of interest the mean and standard deviation of the real output, output prices and electricity demand are shown in Table 1. The output and output prices are indexed 1995 =1.0 while electricity demand is in TJ. All are monthly data from 1991:1 to 2000:4.

Table 1. Sample Statistics of Output, Output Prices and Electricity Demand

Industry	Output		Output Price		Electricity Demand	
	Mean	Stand. Dev	Mean	Stand. Dev	Mean	Stand. Dev
Food	1,11	0,055	1,012	0,019	3661	439
Paper	0,973	0,071	0,942	0,034	4924	348
Clothing	1,011	0,143	1,005	0,023	1154	187
Chemical	1,001	0,089	0,981	0,019	14272	689
Plastic	1,033	0,109	0,992	0,014	2991	248
Glass	1,365	0,227	0,987	0,021	3850	356
Metal	0,982	0,089	0,969	0,031	12037	661
Mechanical Eng.	1,315	0,170	1,007	0,038	2697	238
Electrical Eng.	0,956	0,122	0,998	0,018	1435	76
Automobiles	1,235	0,271	1,004	0,034	3802	530

The nominal prices of the input factors are shown in Table 2. All prices are monthly data indexed 1995=1.0. This prices apply to the whole industry sector. The time period is from 1991:1 until 2000:4.

Table 2. Sample Statistics Nominal Input Prices

Input prices	Mean	Stand. Dev
Electricity	0,928	0,095
Coal	0,728	0,281
Oil	1,209	0,221
Gas	1,081	0,080
Labor	1,094	0,161
Material	0,987	0,014
Capital	0,922	0,063

The nominal industrial price index for electricity remained at a somewhat constant level until the effects of the liberation of the German electricity market in 1998 lead to a decline starting in the middle of 1999. The price for coal has been a political one showing little to no volatility. With the suppression of the "Kohlepfennig" in 1995 the time series drops in a sudden kink containing world market prices from there on. Starting with a drop from a high level in the beginning of 1991 the price index for heating oil remained somewhat stable until 1996. After rising up to 50% in the beginning of 1997 it reached its lowest value in 1999:2. From that point until 2000:4 the nominal price for oil rose by nearly 100%. The gas price in Germany is connected to the price of oil and follows its movements but has smaller swings. Costs per hour steadily rose during the time of analysis but show a stabilization since 1998. The price index for raw materials had frequent changes of small magnitude. Finally the costs for investment is an artificial time series calculated by the price for capital goods and the interest rate for national bonds. Unfortunately apart from costs for labor price data for the individual sectors were not available. Therefore price indices for the whole industry were used to approximate the prices for the 10 industrial sectors. They were converted into real price indices using the output prices from Table 1. Those were available for every single sector.

Whether a time series in stationary or nonstationary is an important question for regression analysis. Therefore every time series involved in econometric analysis has to be tested for its order of integration to find out whether its *I(2)*, *I(1)* or *I(0)*. For the data from Tables 1 and 2 this was done by the augmented Dickey-Fuller test (Dickey & Fuller 1981). Because the power of this test can be quite low an improved procedure from Enders (1995) was used. The following results are mostly valid for all sectors considered.

Table 3. Results from the Augmented Dickey-Fuller Tests

Variable	x_E	y	w_E	w_O	w_G	w_C	w_L	w_K	w_M
Result	I(0)	I(0)	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)	I(1)

Table 3 shows that the real output y, electricity demand x_E and the real cost per hour w_L seem to be stationary. This is an interesting result, because output appears to be the most important explanatory variable for the demand for electricity and when both are stationary the normal t-test are valid without the need for cointegration. Apart from the cost of labor all real input prices seem to consist of a random walk. Therefore at least two of these variables have to be a significant part of the demand equation for a possible cointegration relation to exist.

It should be pointed that for certain sectors electricity demand, output and the price of electricity appear to be borderline between *I(0)* and *I(1)*. This is due to the fact that time series can be separated into a permanent component (random walks) and a temporary component (stationary influences). The less weight the permanent part has on the time series the harder it is to tell whether its variance is increasing in time (Cochrane 1988).

Results from Econometric Estimation

In this chapter the results of regressing equation (1-3) for total site electricity demand are presented. For the paper and food industry this will be done in detail. The 8 remaining industries are summarized in a single table.

The Paper Industry

The paper industry in Germany covers the production of paper, pulp, cardboard, hygiene goods, stationery, wallpaper and other goods made of paper. Approximately 95% of the electricity consumed in the paper industry is used for mechanical energy i.e. to run electric engines. The next figures shows the electricity demand, the real output and the real price for electricity from 1991:1 until 2000:4, while Table 4 summarizes the results from the estimation.

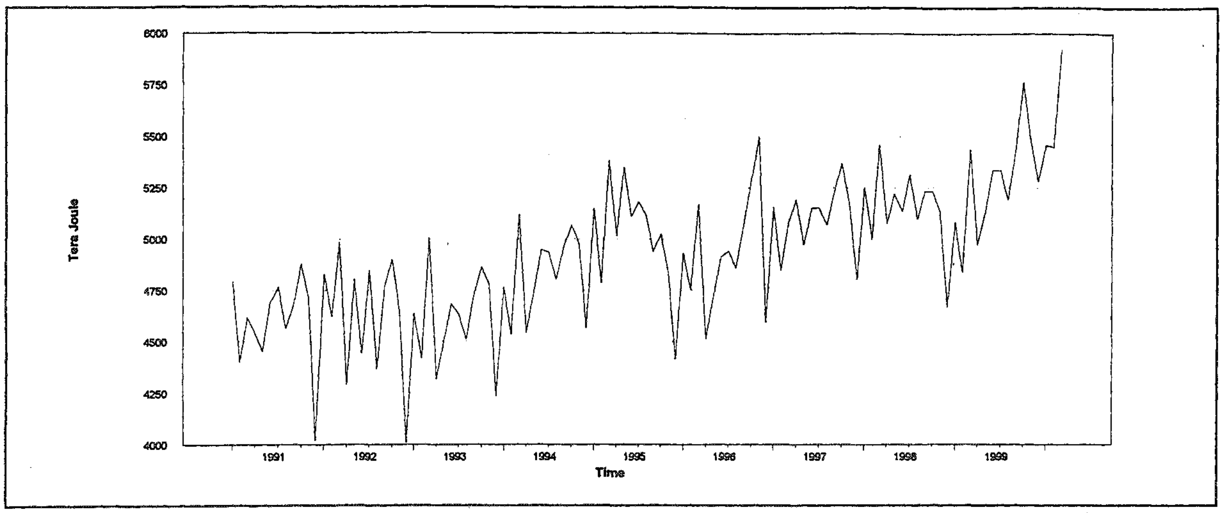

Figure 3. Electricity Demand in the German Paper Industry

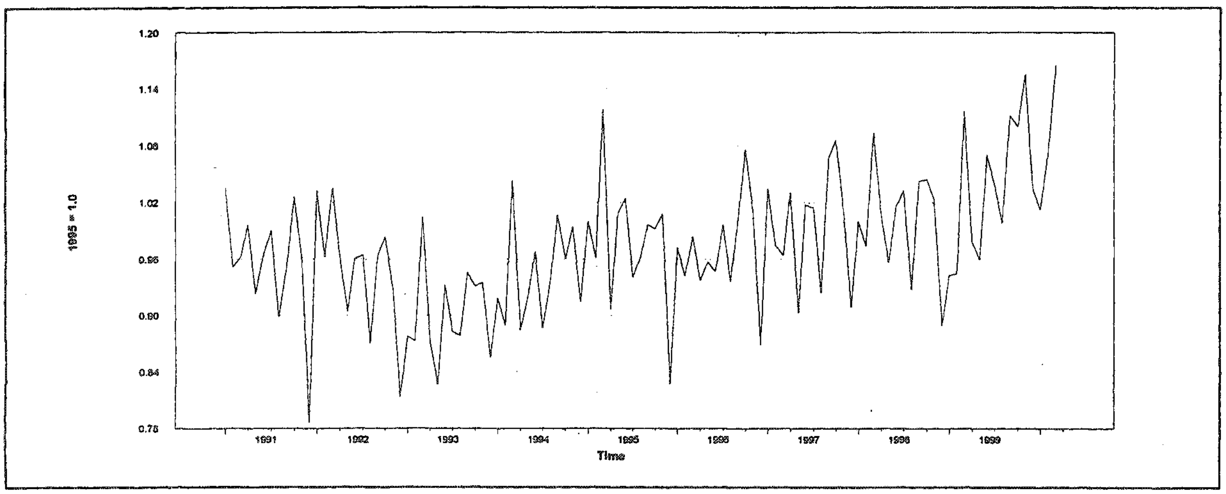

Figure 4. Real Output Index in the German Paper Industry

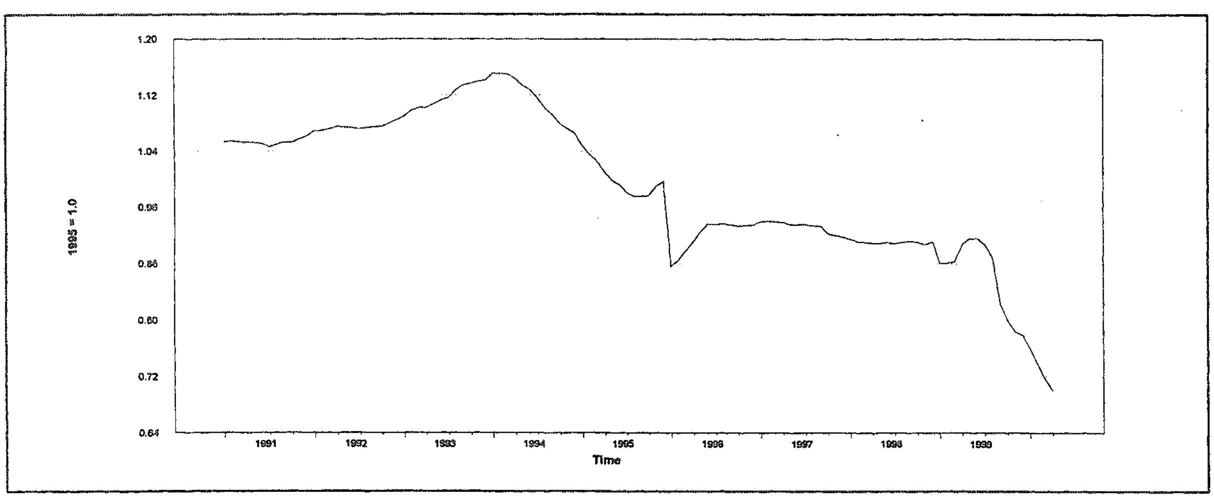

Figure 5. Real Price Index for Electricity in the German Paper Industry

Table 4. Estimation Results from Paper Industry

R^2=0,92	Paper Industry Long Run		Paper Industry Short Run	
Variables	Coefficient	Stand. Dev.	Coefficient	Stand. Dev.
Output	0,44	0,047	0,25	0,097
Electricity Price	-0,11	0,058	n.s.	n.s.
Gas Price	n.s.	n.s.	n.s.	n.s.
Oil Price	n.s.	n.s.	n.s.	n.s.
Coal Price	0,05	0,013	n.s.	n.s.
Price of Material	n.s.	n.s.	n.s.	n.s.
Price of Labor	n.s.	n.s.	n.s.	n.s.
Price of Capital	n.s.	n.s.	n.s.	n.s.
Time Trend	0,002	0,001	-	-

The significant factors for the electricity demand are output, electricity and coal price and a time trend. All other variables are not significant (n.s.). The coefficients presented in Table 4 correspond to the direct elasticities of energy demand for the variables. They describe the relative change in electricity demand due to a 1% change of the variable of interest. Therefore, a 1 % increase in the output of the paper industry leads to an additional demand for electricity of 0,44% in the long run. Short run output elasticity is about one half the size of long run elasticity. The regression results indicate little to no substitution possibilities for electricity in the paper industry. This seems quite reasonable because of the high share of mechanical energy in electricity use. The positive time trend indicates a small but steady autonomous increase in electricity demand in the paper industry.

Tests for stationarity of the residuals indicate that the two *I(1)* variables w_E and w_C are cointegrated. Hence, the estimation is not spurious and if both prices are weak exogenous they asymptotically follow a normal distribution. The negativity condition is fulfilled while homogeneity is not. Symmetry of the variables can only be investigated if the demand equations of other inputs are estimated. Further tests show no signs of autocorrelations in the error term and indicate constant coefficients in time. Ex post forecasts for the years 1998 and 1999 show that the observed values of electricity demand are all inside the forecast interval.

The Food Industry

The food industry covers the production of meat and fish, fruit and vegetables, fat and oil, milk, sugar, bread, pasta, beverage, animal fodder and other food. The largest consumers of electricity are the sugar industry, the dairy industry and brewery. Nearly 70% of electricity demand is transformed into mechanical energy.

Figures 6 show the time series of electricity demand for the food industry from 1991:1 until 2000:4 in Germany. Table 5 presents the results from regressing electricity demand. The long-run output elasticity is clearly higher than in the paper industry and labor and gas appear to be complements for electricity. The fact that gas and electricity should be complements seems rather dubious from a technical point of view. Electricity and gas are substitutes mainly to provide process heat. The output elasticity in the short run is nearly 2/3 of its value in the long run.

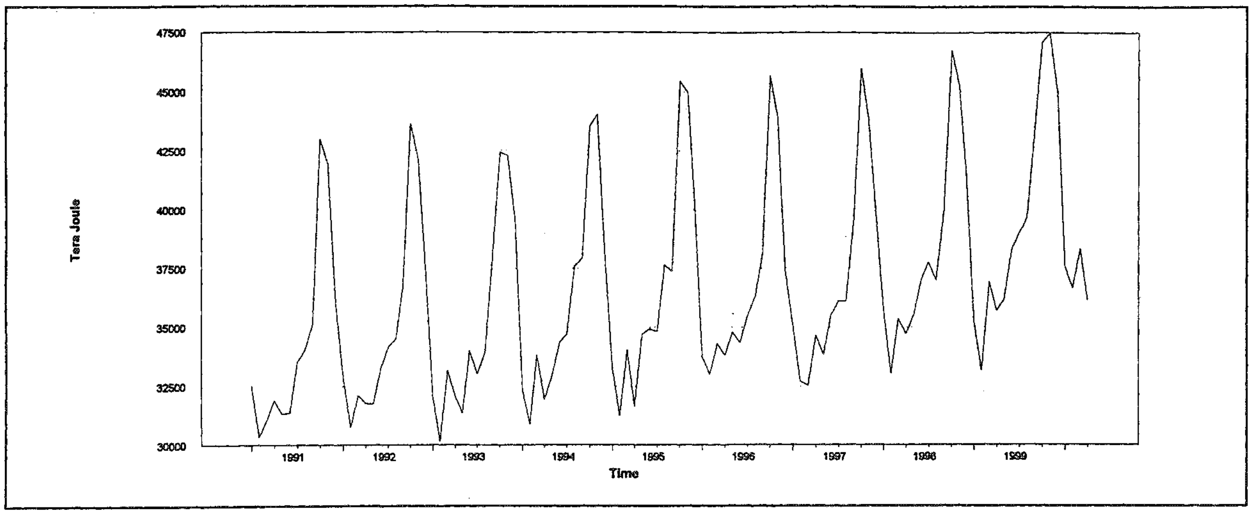

Figure 6. Electricity Demand in the German Food Industry

Table 5. Estimation Results from Food Industry

R^2=0,98	Food Industry Long Run		Food Industry Short Run	
Variables	Coefficient	Stand. Dev.	Coefficient	Stand. Dev.
Output	0,69	0,056	0,48	0,074
Electricity Price	n.s.	n.s.	n.s.	n.s.
Gas Price	-0,13	0,037	n.s.	n.s.
Oil Price	n.s.	n.s.	n.s.	n.s.
Coal Price	0,04	0,012	n.s.	n.s.
Price of Material	n.s.	n.s.	n.s.	n.s.
Price of Labor	-0,18	0,062	n.s.	n.s.
Price of Capital	n.s.	n.s.	n.s.	n.s.
Time Trend	0,002	0,003	-	-

Testing for stationarity of the residuals from the regression indicates that there exists a cointegration vector for the price of electricity, the price of gas and price of coal. Homogeneity of the demand function is not fulfilled and as mentioned before, the tests for symmetry would require information from the elasticities of demand from other inputs. The residual terms snow no signs of intertemporal correlation and the hypothesis of constant coefficients over the whole regression period can not be rejected at the standard significance levels.

The Remaining Sectors

The long-run coefficients from the remaining 8 sectors are summarized in Tables 6a and 6b.

Table 6a. Long Run Estimation Results from the Remaining sectors

Industry	Clothing		Chemical		Plastic		Glass	
Variables	Coeff.	St. Dev.	Coeff.	St. Dev.	Coeff.	St. Dev.	Coeff.	St. Dev.
Output	0,52	0,071	0,60	0,037	0,71	0,057	0,65	0,038
Electricity Price	-0,45	0,089	-0,11	0,036	-0,14	0,106	n.s.	n.s.
Gas Price	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Oil Price	-0,06	0,017	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Coal Price	0,05	0,037	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Price of Material	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Price of Labor	-0,58	0,069	-0,36	0,027	-0,16	0,086	-0,05	0,062
Price of Capital	n.s.	n.s.	-0,37	0,052	n.s.	n.s.	-0,04	0,007
Time Trend	0,001	0,0003	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.

Table 6b. Long Run Estimation Results from the Remaining Sectors

Industry	Metal		Mechanical Eng.		Electrical Eng.		Automobiles	
Variables	Coeff.	St. Dev.	Coeff.	St. Dev.	Coeff.	St. Dev.	Coeff.	St. Dev.
Output	0,56	0,033	0,49	0,038	0,36	0,026	0,42	0,071
Electricity Price	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Gas Price	0,60	0,037	n.s.	n.s.	0,20	0,032	n.s.	n.s.
Oil Price	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Coal Price	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Price of Material	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Price of Labor	-0,12	0,026	-0,47	0,051	-0,27	0,031	-0,31	0,115
Price of Capital	-0,11	0,043	n.s.	n.s.	-0,19	0,051	n.s.	n.s.
Time Trend	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	0,0025	0,0007

The most obvious result is that output is a significant factor of influence in all of the 10 sectors. The elasticities range from 0,36 to 0,71 indicating substantial economies of scale in industrial energy use. If the electricity price is significant for a sector its influence is quite low except for the clothing industry. Prices for gas, oil and coal also have little to no influence except the high elasticity of the gas price in the metal industry, where gas seems to be a substitute for electricity for process heat mainly. The negative coefficients for labor indicate that labor is a complementary input factor for electricity. The reason may be that higher prices for labor force the companies to invest in new machines which are more efficient i. e. need less electricity during production. A rise of the price for capital leads to a decline of electricity demand in some industries. This small complementary coherence must be seen with caution, because additional estimations on demand for capital goods showed no response to either the price of capital or the price of electricity. Finally the time trend is significant in 4 of 10 industries showing a small positive influence on electricity demand. It was difficult to compare this results to other econometric analysis because most of the papers regressing economic demand functions for the industrial sector focus on total energy demand.

All 10 estimated regressions on electricity demand seem to have stationary residuals. This result indicates, that if *I(1)* variables enter an equation they always cointegrate with another nonstationary variable. Looking at the plastic and glass industry this result seems rather strange because in both equations there exists only one *I(1)* variable and therefore the residuals should be nonstationary, too. But as mentioned earlier tests for orders of integration have low power in the case when a time series is close to a random walk, but in fact is stationary. Therefore finding stationary residuals in regression equations should be more convincing then relying completely on the test for stochastic trends in single variables. This does not mean at all that testing the order of integration prior to a regression analysis is useless. It is nevertheless an important analytical tool to avoid spurious regressions on time series.

Conclusion

From the results it is evident that the price elasticities of electricity demand in the industrial sectors is rather low. Also, a high adjustment speed to the long-term equilibrium is observed. It indicates that the price reaction is due to the adaptation of plant operation and not necessarily a consequence of investment decision. Output is the most influential factor on electricity demand showing a great spread of elasticities in different industries. With output elasticities as low as 0,36 there are substantial economies of scale in industrial energy use. The fact that short run output elasticity is below its long run value can be explained by a sluggish change of production in the short run i. e. goods are taken from or put on stock. The estimates of the time trend included in the regressions as a proxy for technical progress show a positive influence. This indicates that even if there is a technological drive towards increasing electricity efficiency, the resulting reduction of electricity input is offset by additional industrial uses for electricity.

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