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Substitution between Energy, Capital and Labour Within Danish Industrial Companies

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Preface

The report contains empirical analyses based on AKF's large micro panel database for industrial companies, where information from energy surveys, accounting statistics etc. has been merged. The database was constructed in association with Peter Sandager, Statistics Denmark.

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Summary

Based on micro panel data for industrial companies covering 1993 to 1997 we estimate factor demand models with electricity, other energy, labour and machine capital as flexible inputs using both the translog and the linear logit specification. As opposed to the few previous studies using micro (cross section) data we find that both electricity and other energy are complements with machine capital. It is also found that substitution between electricity and other energy is limited. The own-price elasticity for electricity is -0.32 in the translog model and -0.13 in the linear logit model. The corresponding own-price elasticities are -0.52 and -0.29 for other energy, -0.09 and -0.05 for labour and -0.53 and -0.34 for machine capital.

In the study special attention is devoted to the problems associated with the use of »accounting« values as indicator of the level of capital in the factor demand model. A generalized version of Arellano and Bond's GMM estimator is applied in order to correct for measurement errors of capital.

1 Introduction

During the last three decades considerable empirical efforts have been put into analyses of the substitution between energy, capital and labour in the manufacturing sector. This line of research is motivated by political objectives to reduce the use of energy, the need to forecast future energy demand and to understand the impact of environmental taxation, e.g. the effect of an energy tax on the use of energy and on the use of other production factors. In this study we employ micro panel data to analyse substitution between energy, labour and capital within Danish industrial companies. With respect to energy we distinguish between electricity and other types of energy.

One issue that has attracted attention from literature is the extent to which capital and energy are substitutes or complementary inputs in production. A seminal study by Berndt and Wood (1975) found that capital and energy were complements, while the study by Griffin and Gregory (1976) concluded that they were substitutes. In a review of the early literature Apostolakis (1990) found that most studies based on time-series data classify the two inputs as complements, while studies based on pooled cross section of countries or regions find that energy and capital are substitutes in the production process. According to Apostolakis the most prominent explanation for this difference is that time-series reflect short-term relationships, while cross-section analyses capture long-term effects.

It appears that nearly all previous empirical studies with a simultaneous determination of demand for capital, energy and labour have been carried out on the basis of aggregate data like macro time-series or cross-country data. However, it has been emphasized by Solow (1987) that studies based on macro data cannot capture the technical substitution between energy and capital, and that data at a more disaggregate level should be employed instead.

Despite the expected advantages of micro data it appears that only two previous studies apply micro data to estimate factor demand systems for capital, energy and labour for manufacturing companies (Woodland 1993; Nguyen and Streitwieser 1999). These two studies both use *cross-section* data at the micro level and both find that energy and capital are substitutes. As compared with these studies, we employ micro *panel* data, where industrial companies are followed over time. Panel data have the advantage that they make it possible to control for (time invariant) unobserved heterogeneity between the companies, which otherwise could result in biased estimates.

The two previous studies using micro data also both used the translog functional form, which is the most widely used form to estimate factor demand. As a robustness check of the results we estimate and compare two different functional forms. The first is the translog, while the second is the cost share linear logit following Considine and Mount (1984). The motivation for also using the linear logit model is that the translog model may only be »well-behaved« for a limited range of relative prices and factor cost shares. This potential drawback of the translog is more serious with micro data, because there are large variations between companies in the cost shares compared with the variations in cost shares typically observed with aggregate time-series.

In addition, while the two previous studies did not distinguish between different types of capital, we treat use of machines and equipment separately from building capital. It seems likely that the demand for the former type of capital is more flexible in the short run as compared with buildings.

While micro data offers some potential advantages they also raise other challenges than macro data. As an example, the inclusion of capital data deriving from accounting statistics needs to address the issue of how to calculate the gross capital stock from the »accounting« measure of stock, see Griliches and Mairesse (1995). The (unbalanced) panel we apply covers the years 1993, 1995, 1996 and 1997. For each company we observe the »accounting« measure of its capital stock (divided between financial assets, machinery and buildings/land) in these years, but we do not have information on investments over a long period of time, which could be used to calculate the remaining gross capital stock subject to a number of assumptions on the economic depreciation, as would be the normal procedure applied in time-series studies to calculate the gross capital stock. To approximate the gross capital stock we use the accounting value of the capital stock multiplied by a correction factor which basically scales the accounting value of the capital stock up to the same scale as the gross capital stock.

When modelling factor demand we include machinery as a flexible input, while building capital (including the value of the land) is a fixed input. That implies that the demand for energy (divided between electricity and other energy), labour and machinery is conditioned on the level of building capital, i.e. that building capital enters as an explanatory variable. It is well-known that measurement errors in the explanatory variables may yield biased estimates in a standard OLS model, so the approximated measure of the gross building capital may therefore be problematic. To get around this problem we estimate an instrumental variables model using companies output and a sector indicator as instruments. For efficiency we use the Generalized Methods of Moments estimator suggested by Arellano and Bond (1991), which is more efficient than the standard IV-estimator.

The main finding of the study is that machinery and energy, both electricity and other energy, are complementary inputs in production when the panel nature of the data is taken into account. This is contrary to the finding of the previous micro (cross-section) studies, but it can be argued that the estimates of the previous studies are biased due to endogeneity of some of the explanatory variables. When we estimate models based on a cross section in a single year we also find that machinery and energy are substitutes. In addition, we also find relatively small own and cross-price elasticities. Most of these are below 0.5 (numerically).

In section 2 previous studies are briefly described. The econometric models are briefly described in section 3, while the data are presented in section 4. Estimation results are presented and discussed in section 5, while summary and discussion are offered in section 6.

2 Previous Studies on Factor Demand in the Industrial Sector

It appears from reviews of the literature (e.g. Atkinson and Manning 1995), that most previous studies on the substitution between capital, labour and energy have been based on aggregated data. Most of these studies find a negative own-price elasticity for energy around -0.5, and in general there seems to be substitution between energy and labour.[1] However, with respect to capital a number of studies find it to be a substitute to energy, while others conclude it is a complementary input to energy. Apostolakis (1990) finds that most studies based on (macro) cross-section data yield substitution between the two factors, while studies on time-series often result in complementarity. Apostolakis suggests that the most prominent explanation for this difference is that cross-section studies capture long run relationships, while time-series reflect short-term effects. Atkinson and Manning seem to agree that this could be a potential explanation for the discrepancy between cross-section and time-series studies, but they also note that the time periods for which most studies are estimated covers periods of extreme flux in the energy market such as post-1973, 1979 and 1986, which means rapid movements in the relative factor prices. Cross-section studies from this period may therefore produce results that are neither short-run nor long-run estimates; rather they may be biased due to omitted (dynamic) factors.

As noted in the first section it has been pointed out that macro studies may provide biased estimates of the technical substitution between production factors due to aggregation bias:

> *....estimates of factor substitutability based on aggregate data are misleading because they capture more than simply technological substitution....[thus]...they are not measuring what they want. Factor substitution is a microeconomic phenomenon, and is best examined by looking at micro data....General equilibrium frameworks...can then serve to integrate the microeconomic aspects in a consistent fashion to permit the examination of energy-economy interactions at a detailed level.* (Solow 1987, p. 612)

The view expressed by Solow is an example of one of the general advantages attributed to micro data as opposed to macro data; namely that macro data do not really reveal the behaviour of the agents due to aggregation problems. In order to understand the behaviour of individual companies one has to employ information at the level of the decision unit.

To give an example suppose that the industrial sector consists of only two companies, one being energy intensive, and one being capital intensive. The energy-intensive company uses two units of energy and one unit of capital to produce one unit of output. The capital-intensive company uses one unit of energy and two units of capital to produce one unit of output. If it is further assumed that both produce and sell 10 units of output, then the aggregate (i.e. both companies) use of energy and capital units is 30. Assume further that it is impossible for the companies to substitute between the two inputs (leontief production function), but that demand for the two products depends on prices. An increase in the cost of energy will increase the price of the output of the energy-intensive company as compared with the capital-intensive company. Say that output of the energy-intensive company is reduced to five units (due to reduced demand), while the output of the capital-intensive company is increased to 15 units. Due to these demand changes the aggregate use of factors has changed. The aggregate use of energy is reduced to 25 units, while the aggregate use of capital is increased to 35 units. At the macro level it looks like the change in factor prices caused factor substitution, but in the example there was no technical substitution in any of the companies. The apparent substitution at the macro level derived from demand effects, which shifted the output shares of the companies.

Despite the potential aggregation bias in macro studies, it appears that only two previous studies have applied micro data to estimate own and cross-price elasticities (as well as substitution elasticities) for capital, energy and labour for manufacturing companies. The first study by Woodland (1993) uses repeated cross-section data for about 10,000 industrial establishments located in the Australian state of New South Wales in the years 1977-85. Woodland uses a translog system with capital, labour, coal, gas, electricity and oil included as variable production factors. In general, Woodland finds that capital, labour and the different types of energy are substitutes, though there in some cases is complementarity between some of the energy types. The second study by Nguyen and Streitwieser (1999) used cross-section data for 10,412 U.S. manufacturing plants for the year 1991. They also use a translog system to estimate the demand for capital, labour, energy and materials. They find that these factors are all substitutes in production.[2]

In addition to these two studies a number of micro studies (using cross-section or panel data) have looked on demand for energy, but without including the demand for other factors (Kleijweg et al. 1989; Doms and Dunne 1993; Bjørner et al. 2001; Bjørner and Jensen, 2002a). However, often these single factor studies restrict substitution between the factor in question and all other factors (treated as one factor) to be the same (strong a priori restrictions imposed). Furthermore, three studies use micro data to investigate interfuel substitution. In a methodological important article Lee and Pitt (1987) provide a general theoretical analysis of the estimation of factor demand, when there are binding non-negativity constraints, which results in »corner« solutions, where the company chooses not to use one or more inputs available to them. This is formulated as a joint discrete/continuous model. As an application they use a cross section of Indonesian companies to estimate demand for three energy inputs. Bousquet and Ivaldi (1998) apply the methodology from Lee and Pitt to estimate substitution between different fuels in the French dairy industry. Finally, panel data were applied by Bjørner and Jensen (2002b) to estimate interfuel substitution among Danish industrial companies.[3]

In our application of the factor demand model we distinguish between two types of energy (electricity and other energy). In principle, this opens up for discrete/continuous models as some companies only use electricity. However, there are only few industrial companies that only rely on electricity, and in general, these companies are small. Therefore, we only include companies that use both types of energy inputs.

The measure of factor prices in the previous micro studies deserves some discussion. Both Woodland (1993) and Nguyen and Streitwieser (1999) calculate the »price« of labour as the wage bill divided by the number of employees. The choice of labour quality (level of training, education etc.) is an important management decision. This firstly implies that the average wage per employee is endogenous, and secondly, that the differences in average wage of each company are more likely to reflect differences in labour quality rather than real exogenous differences in the »price« of labour. The use of the average wage rate is therefore likely to yield bias estimates in the factor demand system. This is especially pronounced in the case of Nguyen and Streitwieser (1999), who use cross-section data for one year (Woodland (1993) uses repeated cross-section data).

A similar type of problem appears to be present for the »price« of energy in Nguyen and Streitwieser (1999). They aggregate energy according to Btu (British thermal units) and presumably calculate the (average) price of energy of each company by dividing energy expenditure with the energy aggregate.[4] However, this means that the cross-section variation in energy »prices« capture differences in the quality of energy. E.g. electricity is more expensive per thermal unit than oil, gas and especially coal. Companies with energy-intensive industrial processes (e.g. steel processing) often use the cheapest type of energy, because it is relatively cheap for them – due to their high energy consumption – to process the raw (and cheap) types of energy. Thus, the low average »price« along with high energy intensity may look like a substitution effect without being so. Basically, the average energy »price« may be endogenous in cross-section data, which potentially leads to biased estimates.

Our calculation of the »price« of labour and energy is based on the same principles as Nguyen and Streitwieser (1999) and Woodland (1993), and potentially they also suffer from endogeneity. However, with panel data the problem with endogenous price of labour and energy is reduced as the variation over time (for each company) in average labour and energy cost can be used to identify the parameters in the model. It seems likely that the composition between high and low quality of labour is considerably more stable within the single companies (over time) as compared with the variation in the composition of high and low quality of labour between companies. The same applies to different forms of energy.

To summarize, we use the variation in average »prices« over time at company level to identify the parameters of the factor demand system. By this procedure we expect to reduce (or even eliminate) the potential endogeneity problems associated with the use of average costs as indicator of factor prices. The use of average costs as indicator of factor prices may have caused biased estimates in the previous cross-section applications of micro data to factor demand systems. In addition, we also distinguish between different types of capital in our model.

3 Factor Demand Models

A large number of studies on factor demand have used the translog (TL) model developed by Christensen et al. (1973). The translog function (as well as the linear logit) belongs to the class of »flexible functional forms« which have enough parameters to enable the function to approximate an arbitrary function up to the second order. However, it has been recognized that the translog model is only »well-behaved« for a limited range of relative prices and cost shares. Outside this range regularity conditions such as positive cost shares and negative own-price elasticities are not satisfied. This drawback is pronounced in our case, because there are large variations in the cost shares between the different companies. The cost share linear logit (LL) model developed and described in Considine and Mount (1984) and in Considine (1989a and 1989b) ensures that all cost shares are positive and all own-price elasticities are negative, *if* this is satisfied for a specific set of cost shares where symmetry is imposed.[5] Following Considine and Mount (1984) we have used the mean cost shares of each company as the point where symmetry is imposed.

As flexible production factors we include electricity *(E)*, other types of energy *(O)*, which mainly consists of fuel oil and natural gas, labour *(L)* and machine capital *(C)*. In addition, we also include building (including property value) capital *(B)* as a factor of production which is considered fixed in the short run. I.e. the level of building capital is included as an explanatory variable in the other factor equations. We do not include raw materials as a factor, because it has not been possible to obtain prices for raw materials relevant to the individual companies. To be consistent we therefore include value added *(V)* instead of production in the factor demand equations.[6]

The translog and the linear logit models are briefly presented below in specifications that allow for company specific variations in the distribution of the different factors. For a more thorough description of the models (including the formulas used to derive price and substitution elasticities from the estimated parameters) we refer to Christensen et al. (1973), Considine and Mount (1984) and Considine (1989a and 1989b). Besides individual fixed effects, factor prices, value added and buildings a trend variable is included in the models as a crude (but widely used) way to capture technical change.

3.1 Translog Model (TL)

From a translog cost function the following system of cost-share equations can be derived:

$$S_{\mathrm{int}} = b_{in} + \sum_{j=1}^{4} \alpha_{ij} \ln P_{jnt} + \alpha_{Ti} T_t + \alpha_{Vi} V_{int} + \alpha_{Bi} B_{int} + u_{int} \qquad (1)$$

where *i* and *j* are indices for the four inputs (electricity, other types of energy, labour and machine capital), while *n* and *t* are indices for respectively company and time. P_{int} is the price of input *i*. T_t is the trend variable, while V_{int} is the log to the value added and B_{int} is the log to the building capital stock.

The parameters b_{in} are the constants. In standard formulations of the TL model – based on aggregate time-series data or cross-section data – these constants are assumed to be identical for all observations (i.e. $b_{in} = b_i$). However, with panel data it is possible to allow these constants to be individual for each company. The individual share constants (time invariant unobserved heterogeneity) capture the effects of all unobserved time invariant factors that may influence the companies' use of the four inputs.

The system in (1) implies four equations – one for each of the four inputs (electricity, other energy inputs, labour and machine capital). When adding up and price homogeneity is imposed, the system to be estimated can be reduced to three equations where the typical equation is:

$$S_{\mathrm{int}} = b_{in} + \sum_{j=1}^{3} \alpha_{ij} \ln \frac{P_{jnt}}{P_{4nt}} + \alpha_{Ti} T_t + \alpha_{Vi} V_{int} + \alpha_{Bi} B_{int} + u_{int} \tag{2}$$

The fourth input is used as the numeraire good. Symmetry implies the restriction: $\alpha_{ij} = \alpha_{ji}$. The parameters of the fourth input equation are calculated using the adding up, price homogeneity and symmetry conditions.

3.2 Linear Logit Model (LL)

After imposing homogeneity and symmetry, the four factor Linear Logit model can be written as a three equation system, where the fourth good is used as the numeraire good. For normalisation $b_{4n} = \alpha_{T4} = \alpha_{V4} = \alpha_{B4} = 0$. These parameters are suppressed in equation (3).

$$\begin{aligned}
\ln \frac{S_{1\mathrm{nt}}}{S_{4\mathrm{nt}}} &= b_{1n} + \alpha_{12} \left(m_{2n} \ln \frac{P_{2nt}}{P_{4nt}} - m_{2n} \ln \frac{P_{1nt}}{P_{4nt}} \right) + \alpha_{13} \left(m_{3n} \ln \frac{P_{3nt}}{P_{4nt}} - m_{3n} \ln \frac{P_{1nt}}{P_{4nt}} \right) - \alpha_{14} \left(m_{4n} \ln \frac{P_{1nt}}{P_{4nt}} + m_{1n} \ln \frac{P_{1nt}}{P_{4nt}} \right) \\
&\quad - \alpha_{24} m_{2n} \ln \frac{P_{2nt}}{P_{4nt}} - \alpha_{34} m_{3n} \ln \frac{P_{3nt}}{P_{4nt}} + \alpha_{T1} T_t + \alpha_{V1} V_{1nt} + \alpha_{B1} B_{1nt} + u_{1nt} \\
\ln \frac{S_{2\mathrm{nt}}}{S_{4\mathrm{nt}}} &= b_{2n} + \alpha_{12} \left(m_{1n} \ln \frac{P_{1nt}}{P_{4nt}} - m_{1n} \ln \frac{P_{2nt}}{P_{4nt}} \right) + \alpha_{23} \left(m_{3n} \ln \frac{P_{3nt}}{P_{4nt}} - m_{3n} \ln \frac{P_{2nt}}{P_{4nt}} \right) - \alpha_{24} \left(m_{4n} \ln \frac{P_{2nt}}{P_{4nt}} + m_{2n} \ln \frac{P_{2nt}}{P_{4nt}} \right) \\
&\quad - \alpha_{14} m_{1n} \ln \frac{P_{1nt}}{P_{4nt}} - \alpha_{34} m_{3n} \ln \frac{P_{3nt}}{P_{4nt}} + \alpha_{T2} T_t + \alpha_{V2} V_{2nt} + \alpha_{B2} B_{2nt} + u_{2nt} \\
\ln \frac{S_{3\mathrm{nt}}}{S_{4\mathrm{nt}}} &= b_{3n} + \alpha_{13} \left(m_{1n} \ln \frac{P_{1nt}}{P_{4nt}} - m_{1n} \ln \frac{P_{3nt}}{P_{4nt}} \right) + \alpha_{23} \left(m_{2n} \ln \frac{P_{2nt}}{P_{4nt}} - m_{2n} \ln \frac{P_{3nt}}{P_{4nt}} \right) - \alpha_{34} \left(m_{4n} \ln \frac{P_{3nt}}{P_{4nt}} + m_{3n} \ln \frac{P_{3nt}}{P_{4nt}} \right) \\
&\quad - \alpha_{14} m_{1n} \ln \frac{P_{1nt}}{P_{4nt}} - \alpha_{24} m_{2n} \ln \frac{P_{2nt}}{P_{4nt}} + \alpha_{T3} T_t + \alpha_{V3} V_{3nt} + \alpha_{B3} B_{3nt} + u_{3nt}
\end{aligned}$$

(3)

In the system above m_{in} is the mean cost share of each company, where symmetry is imposed.

3.3 Econometric Method

The data for the estimations are conditioned on interior solutions for the cost shares, i.e. the data only include companies with all four cost shares greater than zero. The TL and LL models are linear models with three equations. Each equation includes unobserved time invariant heterogeneity (fixed effects) which may be correlated with the right-hand side variables of the model. The building capital variable (B_{int}) is measured with error, because we use the account value of the building capital stock to calculate a proxy for the building gross capital stock in the estimations. Thus, measurement errors are dumped into the unobserved term – implying that the unobserved terms are correlated with the building capital variables. The measurement errors also imply that the unobserved terms are correlated across the equations. Finally, the model contains several cross-equation restrictions among others due to the symmetry restrictions.

For the estimations we prefer the GMM first difference (GMM-dif) estimator suggested by Arellano and Bond (1991). This estimator can handle single equation models with fixed effects and endogenous right-hand side variables. Arnberg (2002) presents a trivial extension of the GMM-dif estimator to systems of equations which allow for cross-equation restrictions. For comparisons we also present results from estimating the first difference transformed model using the seemingly unrelated regressions method (SUR-dif).

The standard approach is to transform the TL and LL models into first differences to remove the time-invariant unobserved heterogeneity and to use instruments to control for the unobserved measurement errors. This will provide consistent estimates. The moment condition for the instruments is:

$$E[Z_{\mathrm{in(t}-s)}(u_{\mathrm{int}} - u_{\mathrm{in(t}-1)})] = 0 \quad \mathit{for} \quad i = 1, 2, 3, 4;\ 0 \le s \le (t-1);\ t = 1,..,T;\ n = 1,..,N \qquad (4)$$

where $(u_{\mathrm{int}} - u_{\mathrm{in(t}-1)})$ is the disturbance term of the first difference transformed model and $Z_{\mathrm{in(t}-s)}$ is an exogenous instrument. As suggested in equation (4): if Z_{int} is uncorrelated with $(u_{\mathrm{int}} - u_{\mathrm{in(t}-1)})$ then $Z_{\mathrm{in(t}-s)}$ may also be uncorrelated.

Thus, we can use both the present lag and the previous lags as instruments. This is similar to the approach suggested by Arellano and Bond (1991).

We use two types of weight matrices for the GMM-dif estimator. One weight matrix takes account of the MA(1) structure of the first differenced residuals and assumes no cross-equation correlation and homoscedasticity. This estimator can be estimated in one step and is denoted the one-step GMM estimator. The other weight matrix is consistent under heteroscedasticity and exploits all the cross-equation correlation both between disturbances of the same lag and between different lagged disturbances. This estimator uses the residuals from the one step estimator to calculate the heteroscedasticity and cross correlation consistent weight matrix after the same principle as in White (1980). The estimator is calculated in two steps and is thus denoted the two-step GMM estimator. In the results section primary attention will be given to two-step GMM estimates.

We test the validity of the instruments (that is the exogenous variables) using the Sargan test of the over-identifying restrictions assumption, where the null is that there is no correlation between the residuals and the instruments. The test statistic uses the residuals from the two-step GMM estimator and is chi-squared distributed with degrees of freedom equal to the number of instruments minus the number of estimated coefficients.

The cross-equation restrictions are imposed on the models and tested using the minimum chi-square test with degrees of freedom equal to the number of restrictions.

For comparisons we also present results from estimating using the Seemingly Unrelated Regressions (SUR) estimator. The reported SUR estimates are heteroscedasticity consistent using the covariance matrix suggested by White (1980). The SUR model assumes that all the explanatory variables are exogenous. Therefore, using the SUR estimator may give biased estimates due to the measurement errors on the building capital variable.

4 Description of the Data

The data on energy use are obtained from four *Energy Surveys* carried out by Statistics Denmark for the years 1993, 1995, 1996 and 1997 for industrial companies. Information on value added, production and accounting (book) value of capital was obtained from *Accounting Statistics*, while information on the number of employees and labour costs was obtained from other registers from Statistics Denmark. Primary data are collected for all industrial companies with more than 50 employees and half of the companies with 20-50 employees. The individual unit is the company, which in some cases may own a number of different plants. However, in most cases the company only owns one plant, in which case the data are similar to plant level data.

Deflators for value added were not available at the company level, so instead deflators were obtained from the Danish National Accounts. At the most disaggregate level the national accounts contain deflators representing 80 different industrial branches.

The energy surveys include information about expenditures as well as the consumption in physical units of electricity, which makes it possible to calculate the average electricity price for each company. The price of electricity varies between different companies, because the price of electricity is individual for each of the 100 electricity utilities in Denmark. For the other sources of energy (i.e. fuel oil, heating oil, natural gas, coal, district heating and LPG) general (list) prices are used. The price of the other types of energy is an average price calculated as the total cost of energy divided by the total energy content. For the majority of companies the other energy input consists of oil and/or natural gas.[7] The price of natural gas in Denmark is tied to the price of oil (due to political reasons), so the prices of the dominant fuels in the other energy input follow the same path over time. Some other types of fuels (e.g. coke, waste and wood) are not included, because it was not possible to obtain reliable indicators of prices, but the omitted fuel type accounts for less than 1% of the overall energy consumption. Also transport fuels (gasoline and diesel) have been left out, but this is due to the different nature of use.

The »price« of labour was calculated as the total labour costs divided by the number of employees (full-time equivalents). As discussed in section 2 this measure of the »price« of labour costs may be endogenous as it also measures each company's choice of labour quality. However, assuming that the quality of labour hired by a company does not vary over time, then the variation in the quality of the labour input (between companies) will be eliminated by the fixed effect. Thus, the bias caused by the measurement errors is reduced, when we use estimators which control for the fixed effect.[8]

For each company we observe the »accounting« measure of its capital stock, that is the value of the capital stock (divided between financial assets, machinery and buildings/land) in the four years, but we do not have information on investments over a long period of time, which could be used to calculate the gross capital. The gross capital measures the physical quantity of productive capital and is the relevant measure when estimating the demand for production factors, while the accounting value in principle should reflect the economic value of the capital stock as if it were to be sold. Thus, the accounting value reflects the productivity of the capital stock for its remaining lifetime – taking into account that the productivity is declining with time. The gross capital stock measures the present physical quantity of the productive capital corresponding to the productivity of the capital stock in the present period. The main difference to the accounting value is that the gross capital stock does not take into account that the productivity of the capital stock will decline in the future. Hence, the level of Danish companies' gross capital stock is higher than its accounting value.

The machine capital budget shares for firm *n* are: $S_{4nt} = (C_{nt}U_{nt}) / X_{nt}$. Here C_{nt} is the machine gross capital stock and U_{nt} is the user cost of machine capital, while X_{nt} is the total costs for the four inputs. We calculate a proxy for the gross capital stock by multiplying the value of the capital stock by a correction factor. The correction factor is calculated using two measures of the aggregate machine capital stock of industrial sectors. These measures are calculated and applied in the Danish macroeconomic model ADAM. It is basically the total machine gross capital stock of an industrial sector divided by the total accounting value of the machine capital stock of the sector. The correction factor is calculated for each of eight sectors. Hence, we scale up the accounting value so that the sector average of the proxy is similar to the sector average of the gross capital stock. Using the proxy instead of the machine gross capital stock implies that S_{4nt} particularly and the three other budget shares are measured with error. Since the budget shares are dependent variables this will not bias the estimates of the TL and LL models[9]. Assuming that the sector average of the proxy is similar to the sector average of the gross capital stock the bias on the calculated elasticities is neglectable.

The user cost of machine capital is obtained using the user cost calculated and applied in the macroeconomic model ADAM. The user costs are the same for companies in each of eight industrial sectors.

Building capital enters into the TL and LL models as a conditioning variable. We calculate a proxy for the building gross capital stock by multiplying the accounting value of the building capital stock by a correction factor. This correction factor is calculated after the same principle as for the machine capital stock using macroeconomic variables for the building gross capital stock and the value of the stock. Hence, we scale up the value of building capital stock so that the average level of the calculated proxy should be similar to the building gross capital stock. Using the proxy in the estimations instead of the true building gross capital stock implies measurement errors, which we control for using instrumental variables estimation methods. As instruments for the building gross capital stock we use the companies' output values and indicators of which sector each company belong to. The requirement of buildings varies with industrial sector. For instance, companies in the iron and metal industrial sector must be expected to have different requirements for building capital than food production companies. Also, we expect building capital to be positively correlated with the output value.

The panel is unbalanced. In the estimations presented companies which are present less than three years, industrial companies with their own local production of electricity and companies that only use electricity as energy input are excluded. Companies which in one year have had very large or very small factor cost shares (higher than 99.9% and lower than 0.1%) are also excluded. Altogether this leaves us with 3,278 observations covering 903 different companies.[10] Table 4.1 provides descriptive statistics of the cost shares for the data set. It appears from the table that cost shares of electricity and other types of energy generally are very small (medians at 2 and 1 per cent). Labour is the dominating cost with a median cost share of about 90 per cent. The median cost share of machine capital is 7 per cent.

Table 4.1 Quantiles and means of the cost shares

Quantiles	S_1 *(electricity)*	S_2 *(other energy)*	S_3 *(labour)*	S_4 *(machine capital)*
0.05	0.0048	0.0022	0.6692	0.0152
0.25	0.0103	0.0048	0.8293	0.0385
0.50 (median)	0.0178	0.0089	0.8952	0.0682
0.75	0.0329	0.0169	0.9374	0.1176
0.95	0.0768	0.0596	0.9673	0.2286
Mean cost share N=3,278	0.0268	0.0178	0.8673	0.0884

5 Results

In this section we report the results from estimating the models presented in section 3. First we present the estimated parameters of the models. Then the derived price elasticities and substitution elasticities are presented.

5.1 Estimation Results

The results from estimating the TL model are presented in table 5.1 and the results from estimating the LL model are presented in table 5.2. The models are estimated with the adding up, price homogeneity and symmetry restrictions imposed. For each model parameter estimates are presented for a level model based on data for only 1996, a first difference model, where all explanatory variables are assumed to be exogenous, and for a first difference model, where building capital is assumed to be endogenous due to measurement errors. The former models are estimated using the Seemingly Unrelated Regressions (SUR) estimator and thus exploiting the cross-equation correlation between residuals to gain efficiency. The SUR estimates may be biased due to the measurement errors on the building capital variable (and the cross-section level model may also be biased due to potential endogeneity of the price of labour and energy). The last model is estimated using GMM and building capital is assumed to be endogenous with sector indicators and the companies' output as the exogenous instrumental variables. All available lags of the sector indicator and output are included in the instrument set to increase the efficiency of the GMM estimates. The weight matrices and the covariance matrices of the GMM estimators are heteroscedasticity consistent. In both the TL and LL models machine capital is used as the numeraire good. The machine capital cost share equation and the parameters for the user cost of machine capital are not estimated in the TL model, but are calculated using the adding up, price homogeneity and symmetry restrictions. In the tables the simple mean of the individual fixed effects is also presented. The price and substitution elasticities are calculated using the estimates of the price parameters α_{11} to α_{44}.

Focussing on the two difference models it appears that the parameter estimates of the TL model which are significant using the SUR estimator are also significant using the GMM estimator, and the significant estimates do not vary much using the two estimators (see table 5.1). The price parameters are fairly similar, implying that the calculated elasticities do not vary much using GMM estimates compared to SUR estimates. Only half of these price parameters are significant, that is α_{11}, α_{13} and α_{22} (both SUR and GMM estimates). The parameters α_{ii} are all positive, in which case the own-price elasticities may change signs depending on the level of the cost shares.[11]

Building capital is error contaminated and the SUR estimates may be biased, but the GMM estimates are consistent, because building capital is instrumented. Thus, the GMM estimates are the preferred estimates. The Sargan test does not reject the over-identifying restrictions provided by the instruments. The GMM estimates of the building capital parameters tend to be more significant than when building capital is assumed to be exogenous.

Table 5.1 Translog

	Levels, exogenous[2]		First difference, exogenous		GMM-DIF: IV	
	Parameter	Std. error	Parameter	Std. error	Parameter	Std. error
Mean(b_1)	0.058	(0.064)	0.054		0.019	
mean(b_2)	-0.318***	(0.068)	0.013		0.045	
mean(b_3)	1.951***	(0.354)	0.314		0.358	
mean(b_4)	-0.690**	(0.322)[1]	0.619		0.578	
α_{11}	-0.014**	(0.006)	0.020***	(0.002)	0.017***	(0.001)
α_{12}	-0.008***	(0.001)	0.001	(0.001)	2.7 E-4	(0.001)
α_{13}	0.006	(0.005)	-0.013**	(0.005)	-0.009***	(0.003)
α_{14}	0.016***	(0.006)[1]	-0.008*	(0.004)[1]	-0.008***	(0.003)[1]
α_{22}	-3.4 E-4	(0.003)	0.010***	(0.001)	0.008***	(0.001)
α_{23}	0.028***	(0.006)	-0.004	(0.003)	-0.006**	(0.003)
α_{24}	-0.019***	(0.004)[1]	-0.006**	(0.003)[1]	-0.002	(0.002)[1]
α_{33}	-0.079***	(0.027)	0.044	(0.029)	0.039	(0.025)
α_{34}	0.045*	(0.023)[1]	-0.027	(0.024)[1]	-0.023	(0.022)[1]
α_{44}	-0.042*	(0.023)[1]	0.041*	(0.021)[1]	0.034*	(0.020)[1]
α_{T1}			2.8 E-4	(2.5 E-4)	1.2 E-4	(2.8 E-4)
α_{T2}			3.5 E-4	(2.7 E-4)	-1.8 E-4	(3.0 E-4)
α_{T3}			-1.9 E-5	(0.001)	7.7 E-4	(0.002)
α_{T4}			-6.2 E-4	(0.001)[1]	-7.1 E-4	(0.001)[1]
α_{V1}	-0.002	(0.001)	-0.001	(0.001)	-0.001	(0.001)
α_{V2}	-0.004***	(0.001)	-0.002	(0.002)	-0.003**	(0.001)
α_{V3}	0.008	(0.005)	0.015***	(0.006)	0.013**	(0.006)
α_{V4}	-0.002	(0.004)[1]	-0.012**	(0.005)[1]	-0.009*	(0.005)[1]
α_{B1}	0.004***	(0.001)	4.5 E-4	(0.001)	0.002	(0.003)
α_{B2}	0.004***	(0.001)	-5.3 E-4	(3.8 E-4)	0.007	(0.004)
α_{B3}	-0.024***	(0.004)	-0.014***	(0.003)	-0.017	(0.017)
α_{B4}	0.016***	(0.003)[1]	0.014***	(0.003)[1]	0.009	(0.014)[1]
Sargan					56.9(df=42)	p=0.06
N	813		2375		2375	

Notes:

1 Asymptotic standard error derived using the delta method

2 Sample includes observations of firms in 1995. A constant term for the only sample is estimated.

* indicates that the parameter is significant at a 10%-level.

** indicates that the parameter is significant at a 5% -level.

*** indicates that the parameter is significant at a 1% -level.

Turning next to the LL model (and still focussing on the difference models), it appears that most of the estimated parameters are significant (see table 5.2). The GMM estimates of the price parameters are all significant and not very different from the corresponding SUR estimates suggesting that the calculated elasticities using the GMM estimates are similar to the correspondent elasticities using the SUR estimates (which was also the case for the TL model). The Sargan test of the LL model does not reject the over-identifying restrictions provided by the instruments.

Table 5.2 Linear logit

	Levels, exogenous[2]		First difference, exogenous		GMM-DIF: IV	
	Parameter	Std. error	Parameter	Std. error	Parameter	Std. error
mean(b_1)	13.047***	(2.569)	-7.666		-6.538	
mean(b_2)	6.166***	(2.287)	-7.384		-10.591	
mean(b_3)	11.148***	(2.141)	-6.907		-6.877	
mean(b_4)	0[3]		0[3]		0[3]	
α_{11}	31.695***	(3.226) [1]	29.524***	(1.494) [1]	31.632***	(1.177) [1]
α_{12}	-2.189***	(0.793)	-0.024	(0.574)	-0.790***	(0.298)
α_{13}	-1.115***	(0.121)	-0.716***	(0.066)	-0.824***	(0.047)
α_{14}	2.096***	(0.384)	-1.848***	(0.457)	-1.267***	(0.327)
α_{22}	3.605	(4.199) [1]	42.112***	(2.421) [1]	39.030***	(2.174) [1]
α_{23}	-0.175**	(0.073)	-0.665***	(0.063)	-0.568***	(0.055)
α_{24}	1.712***	(0.406)	-1.950***	(0.454)	-2.046***	(0.344)
α_{33}	-0.008	(0.015) [1]	0.094***	(0.014) [1]	0.096***	(0.010) [1]
α_{34}	0.429***	(0.150)	-0.569***	(0.122)	-0.577***	(0.099)
α_{44}	-5.118***	(1.641)[1]	6.527***	(1.175) [1]	6.457***	(0.967) [1]
α_{T1}			0.044***	(0.008)	0.055***	(0.012)
α_{T2}			0.057***	(0.010)	0.001	(0.019)
α_{T3}			0.021**	(0.008)	0.028**	(0.013)
α_{T4}			0[3]		0[3]	
α_{V1}	-0.003	(0.042)	-0.051	(0.047)	-0.026	(0.047)
α_{V2}	0.075	(0.054)	-0.184***	(0.057)	-0.325***	(0.076)
α_{V3}	-0.036	(0.041)	0.057	(0.049)	0.049	(0.048)
α_{V4}	0[3]		0[3]		0[3]	
α_{B1}	0.038	(0.036)	-0.146***	(0.043)	-0.293**	(0.127)
α_{B2}	-0.104**	(0.049)	-0.190***	(0.043)	0.772***	(0.197)
α_{B3}	-0.191***	(0.036)	-0.186***	(0.041)	-0.256**	(0.130)
α_{B4}	0[3]		0[3]		0[3]	
Sargan					70.9(df=63)	p=23.10
N	813		2375		2375	

Notes: See table 5.1.
[3] The parameter is zero by the normalisation constraints of the LL model.

The GMM estimates of the building capital parameters are negative in the electricity and labour cost equations and positive in the other energy costs equation, which indicates that the electricity and labour costs relative to the machine capital costs decrease with the size of the building capital stock, and that the other energy costs relative to the machine capital costs increase.

5.2 Derived Demand Elasticities

The derived demand price elasticities of the TL and LL models are reported in table 5.3 and 5.4 for the cross-section level estimation (italic), the first difference SUR model (normal font) and the first difference GMM model (bold). In both tables, the elasticities are evaluated at the sample mean cost shares.

In general, the elasticities of the two difference models are small (numerically below 1). In most cases the price elasticities of the TL model estimated using GMM are numerically larger than the correspondent SUR estimates. The same does not apply to the elasticities of the LL model, where the relative size of the SUR and GMM price elasticity estimates varies. In the following, primary attention will be given to the GMM estimates of the price elasticities, because these estimates are consistent also when building capital is measured with error.

Table 5.3 Partial own and cross-price elasticities in the TL model

	P_1		P_2		P_3		P_4	
	*-1.517****	*(0.208)*	*-0.311****	*(0.052)*	*1.118****	*(0.191)*	*0.710****	*(0.220)*
Electricity	-0.214***	(0.060)	0.042	(0.045)	0.375*	(0.191)	-0.203	(0.158)
	-0.322* **	**(0.049)**	**0.028**	**(0.020)**	**0.523*** **	**(0.127)**	**-0.229** **	**(0.114)**
	*-0.507****	*(0.086)*	*-1.006****	*(0.176)*	*2.620****	*(0.383)*	*-1.106****	*(0.257)*
Other energy	0.063	(0.067)	-0.450***	(0.078)	0.628***	(0.188)	-0.242*	(0.141)
	0.042	**(0.030)**	**-0.523*** **	**(0.051)**	**0.514*** **	**(0.143)**	**-0.032**	**(0.112)**
	*0.033****	*(0.006)*	*0.048****	*(0.007)*	*-0.221****	*(0.032)*	*0.140****	*(0.027)*
Labour	0.011*	(0.006)	0.013***	(0.004)	-0.082**	(0.033)	0.057**	(0.027)
	0.016* **	**(0.004)**	**0.011*** **	**(0.003)**	**-0.088*** **	**(0.029)**	**0.061** **	**(0.025)**
	*0.206****	*(0.066)*	*-0.197****	*(0.045)*	*1.372****	*(0.262)*	*-1.382****	*(0.253)*
Machines	-0.061	(0.048)	-0.049*	(0.028)	0.563**	(0.268)	-0.453*	(0.235)
	-0.069 **	**(0.034)**	**-0.006**	**(0.023)**	**0.602** **	**(0.246)**	**-0.527** **	**(0.222)**

Notes:
Price elasticities based on sample mean cost shares. Levels estimates in Italics. First difference estimates, exogenous model in normal fonts. GMM-dif, IV estimates in bold. Asymptotic Standard errors – derived using the delta method - in brackets.

* indicates that the parameter is significant at a 10%-level.

** indicates that the parameter is significant at a 5% -level.

*** indicates that the parameter is significant at a 1% -level.

Table 5.4 Partial own and cross-price elasticities in the LL model

	P_1		P_2		P_3		P_4	
	*-0.156**	*(0.083)*	*-0.019*	*(0.013)*	*-0.100*	*(0.105)*	*0.275****	*(0.034)*
Electricity	-0.189***	(0.040)	0.017*	(0.010)	0.246***	(0.057)	-0.075*	(0.040)
	-0.132*	**(0.031)**	**0.004**	**(0.005)**	**0.153***	**(0.040)**	**-0.024**	**(0.029)**
	-0.031	*(0.020)*	*-0.927****	*(0.066)*	*0.717****	*(0.063)*	*0.241****	*(0.036)*
Other energy	0.026*	(0.015)	-0.233***	(0.043)	0.291***	(0.054)	-0.084**	(0.040)
	0.006	**(0.008)**	**-0.287***	**(0.039)**	**0.374***	**(0.047)**	**-0.092***	**(0.030)**
	-0.003	*(0.003)*	*0.013****	*(0.001)*	*-0.137****	*(0.013)*	*0.127****	*(0.013)*
Labour	0.008***	(0.002)	0.006***	(0.001)	-0.052***	(0.012)	0.038***	(0.011)
	0.005*	**(0.001)**	**0.008***	**(0.001)**	**-0.050***	**(0.009)**	**0.037***	**(0.009)**
	*0.080****	*(0.010)*	*0.043***	*(0.006)*	*1.243****	*(0.130)*	*-1.366****	*(0.146)*
Machines	-0.023*	(0.012)	-0.017**	(0.008)	0.374***	(0.106)	-0.335***	(0.104)
	-0.007	**(0.008)**	**-0.019***	**(0.006)**	**0.367***	**(0.085)**	**-0.341***	**(0.085)**

Notes: See table 5.3.

In general the price elasticities of the LL model are numerically smaller than the corresponding elasticities of the TL model. The own-price elasticities are rather small. The demand for labour is very inelastic to changes in the wage with own-price elasticities at -0.09 and -0.05. Thus, a 10 per cent wage increase only implies a 0.9 or 0.5 per cent reduction in the demand for labour (TL and LL model, respectively). The demand for machine capital is also inelastic, though the own-price elasticities are larger (-0.53 and -0.34 TL and LL estimates, respectively). The own-price elasticity for electricity is numerically lower than the own-price elasticity of other energy types, -0.32 compared to -0.52 (TL model estimates).

The TL and LL difference models give the same qualitative answers with respect to the substitution between machine capital and energy (electricity and other energy). Machine capital and energy are complements (or in some cases not significantly different from zero). In cross-section models the opposite result is obtained as the cross-price elasticities are positive in most cases. This was also found in the two previous studies based on cross-section micro data. In the TL cross-section case it appears that electricity and other energy are substitutes. In the difference models the cross energy price elasticities are positive (but insignificant).

Table 5.5 Elasticities of substitution in the TL model and in the LL model

	TL model		LL model	
Σ_{12}	*-19.66****	*(3.34)*	*-5.60****	*(0.79)*
	2.37	(2.52)	2.30***	(0.57)
	1.56	**(1.14)**	**0.03**	**(0.30)**
Σ_{13}	*1.29****	*(0.22)*	*-0.14*	*(0.12)*
	0.43*	(0.22)	0.28***	(0.07)
	0.60***	**(0.15)**	**0.17*****	**(0.05)**
Σ_{14}	*8.00****	*(2.51)*	*4.80****	*(0.38)*
	-2.30	(1.79)	-2.17***	(0.46)
	-2.59**	**(1.29)**	**-0.97*****	**(0.33)**
Σ_{23}	*3.01****	*(0.44)*	*0.82****	*(0.07)*
	0.72***	(2.17)	0.33***	(0.06)
	0.59***	**(0.16)**	**0.43*****	**(0.05)**
Σ_{24}	*-12.46****	*(2.88)*	*4.02****	*(0.41)*
	-2.73*	(1.60)	-2.38***	(0.45)
	-0.36	**(1.27)**	**-2.58*****	**(0.34)**
Σ_{34}	*1.58****	*(0.30)*	*1.40****	*(0.15)*
	0.65**	(0.31)	0.46***	(0.12)
	0.69**	**(0.28)**	**0.45*****	**(0.10)**

Notes: See table 5.3.

It appears from both the TL and the LL models, that labour is a substitute to each of the other three factors. The cross-price elasticities indicate that the labour demand is very inelastic to changes in the energy prices and to changes in the user costs of machinery. For the energy demand it appears that the own-price elasticities in most cases are smaller than the wage and the machine user cost elasticities. Thus, the demand for electricity and other energy seems to vary more with the wages and the machine user costs than with the energy prices (though this can partly be attributed to the differences in factor cost shares).

The input substitution can also be described by Allen elasticities of substitution. Table 5.5 reports the estimated Allen elasticities of substitution for the TL and LL models. By construction the substitution elasticities give the same qualitative answers as the corresponding cross-price elasticities.

The substitution elasticities between labour and the other inputs (machine capital and energy) are all positive and between 0.5 and 1.0 in the TL model and between 0.2 and 0.4 in the LL model. Thus, labour is a moderate substitute to the inputs energy and machine capital.

With respect to the performance of the TL model and the LL model, we have noted that the α_{ii} parameters all are positive. This may yield positive own-price elasticities in the TL model for low cost shares. In the difference TL model a high share of the estimated own-price elasticities has positive signs, when elasticities of the TL model are evaluated at the observed cost shares of each company. Thus, almost half of the own-price elasticities for the two energy inputs have wrong positive signs. For machine capital wrong signs on the own-price elasticity are observed only in one of five cases, while wrong signs for the own-price elasticity of labour are observed in only few cases (recall that all presented price elasticities in table 5.3 and 5.4 are based on the sample mean cost shares).

In the LL model the own-price elasticities are always negative. The large share of perverse price elasticities in the TL model illustrates the problems associated with the use of this model when low elasticities of substitution are combined with small input cost shares. The LL model appears to give more satisfactory results.

As described in section two there are two studies that previously have used micro level data to estimate factor demand in industrial companies. These studies used cross-section data (Nguyen and Streitwieser, 1999) and repeated cross sections (Woodland, 1993). In both these studies it appears that there is substitution between the energy inputs and capital (all types of capital included as one type). This was also the case in this study when cross-section data for a single year are used. When we instead use difference estimates we obtain complementarity between energy and machinery. The two former cross-section studies also generally obtain high own-price elasticities (numerically above unity) for energy, where we obtain small own-price elasticities for energy (between -0.1 and -0.6) in the first difference models. With respect to labour and capital Woodland generally obtains – in correspondence with our results – small own-price elasticities (in most cases between -0.1 and -0.5). Nguyen and Streitwieser find an overall own-price elasticity for labour at -1.6 and for capital at -1.1.

The limited interfuel substitution between electricity and an aggregate of other types of energy in our study is confirmed by a previous study by Bjørner and Jensen (2002b), relying partly on the same data as applied here. Their study focused on interfuel substitution without including the information on the use and cost of labour and capital.[12] It was also observed by Woodland (1993) that interfuel substitution in many cases appeared to be relatively low as compared with the substitution between the different fuel inputs and the other primary factors (labour and capital).

6 Summary and Discussion

Panel data at company level have been applied to estimate factor substitution between electricity, other energy, labour and machine capital for Danish industrial companies. Level of building capital was included as a fixed input. Fixed effects versions of the translog and linear logit model were estimated. In order to compare with results from previous micro studies cross-section models were also estimated. The fixed effects estimator utilizes the variation over time in the explanatory variables for each company to identify the parameters and allow for unobserved heterogeneity in the factor shares. The cross-section model uses the between variation in data to identify the parameters. The estimated fixed effects own-price elasticities using respectively the translog model and the linear logit model are -0.32 and -0.13 for electricity, -0.52 and -0.29 for other energy, -0.09 and -0.05 for labour and -0.53 and -0.34 for machine capital.

As opposed to the (few) previous factor demand studies using micro cross-section level data, it is found that there is complementarity between both energy input and (machine) capital when fixed-effects models are applied. When we look at a cross-section of our data we find results that are similar to the previous studies using micro cross-section data. In addition, the own-price elasticities are generally smaller (numerically) as compared with the previous micro (cross section) studies, especially for energy.

Previous surveys of the macro studies on factor substitution have pointed out that studies based on time-series generally result in complementarity between energy and capital, while cross-national studies often obtain substitution between these inputs. As an explanation it has been suggested that time-series studies reflect short-term relationships, while cross-national studies reveal long-term effects. It is tempting to extend the explanation from the macro studies to the micro studies, so that our panel (fixed effects) estimator reflects short-run effects, while the micro cross-section results show the long-term potentials for technical substitution in the companies. However, currently it seems premature to draw such a conclusion as the two available cross-section studies may have produced biased estimates due to problems in the calculation of the price of labour. In both cases the price of labour was calculated as the wage bill divided by the number of employees, but in this case the variation in labour »price« between different companies is more likely to reflect differences in the quality of labour than exogenously given wage differences.

In our study special attention has been devoted to the measurement of gross capital value of machines and buildings at the micro level when only book capital values are available. In our model building capital is assumed fixed, which leads to an empirical specification, where building capital enters as an exogenous variable. To correct for bias due to measurement errors in the gross building capital variable the instrumental variables method was applied using a generalized version of Arellano and Bond's GMM estimator. It appeared that the correction for measurement errors had some impact on the effect of building capital on factor shares etc. However, the instrumentation did not have any major impact on the own and cross-price elasticities of the flexible factors.

Both the translog and the linear logit factor models were estimated. By and large the two specifications gave similar results when elasticities from the translog model were calculated using sample mean factor shares. However, a relatively large share of the individual own-price elasticities of the translog model had wrong (positive) signs, which probably reflects that the translog model is not well suited for analysing factor demand when substitution is low and factor shares are small and heterogeneous. The linear logit model appears to give more satisfactory results in the current case.

Sammenfatning

Substitution mellem energi, arbejdskraft og kapital i industrien
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I rapporten foretages analyser af efterspørgslen efter energi, arbejdskraft og kapital i danske industrivirksomheder. Endvidere analyseres virksomhedernes muligheder for at substituere mellem de forskellige produktionsfaktorer. Denne type analyser er motiveret af det politiske ønske om at reducere energiforbruget samt behovet for at forstå effekten af miljøregulering, fx effekten af energiskatter på energiforbruget og på andre produktionsfaktorer. Et emne, som har fået stor opmærksomhed i energilitteraturen, er, hvorvidt kapital og energi er substitutter eller komplementære input. Det foreliggende studie adskiller sig fra hovedparten af tidligere undersøgelser ved at analysere denne sammenhæng med udgangspunkt i data på virksomhedsniveau, hvor de fleste af de hidtidige studier er lavet på grundlag af aggregerede makrodata, som fx tidsserier for hele den danske industri. Et argument imod at anvende aggregerede data til studier af faktorsubstitution er, at aggregerede data ikke kan opfange teknisk substitution mellem energi og kapital på grund af aggregeringsproblemer. Faktorsubstitution er et mikroøkonomisk fænomen, som undersøges bedst på mikrodata.

Den empiriske analyse er foretaget på baggrund af et panel af virksomheder, der følges i årene 1993 samt 1995-1997 (en forløbsdatabase).

Der skelnes i analysen mellem virksomhedernes brug af elektricitet, anden energi (olie, gas, kul og fjernvarme), arbejdskraft, maskin- og bygningskapital.

Analysen viser, at der er komplementaritet mellem begge energiinput og maskinkapital, mens arbejdskraft er substitut til både kapital og de to energiinput. Sammenlignet med de få øvrige studier på mikrodata giver analysen numerisk små egenpriselasticiteter, især for energi. Alt efter modelspecifikationen får vi egenpriselasticiteter for elektricitet på -0,32 til -0,13, for anden energi på -0,52 til -0,29, for arbejdskraft på -0,09 til -0,05 og for maskinkapital på -0,53 til -0,34. Resultaterne peger endvidere på, at energiforbruget i lige så høj grad afhænger af priserne på arbejdskraft som af energipriserne.

References

Apostolakis, B.E. (1990): Energy – capital substitutability/complementarity. The dichotomy. *Energy Economics*, 12(1): 48-58.

Arellano, M. and S. Bond (1991): Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies*, 58: 277-97.

Arnberg, S. (2002): Analysis of Static or Dynamic Linear Panel Data Models – Econometric Methods for Single or Multiple Equations Models. Chapter 4 in: *Empirical Studies of Agricultural Land Allocation*, PhD Thesis, University of Copenhagen.

Atkinson, J. and N. Manning (1995): A survey of international energy elasticities. In Barker, T.; P. Ekins and N. Johnstone (eds.): *Global Warming and Energy Demand*. Routledge, London.

Berndt, E.R. and D.O. Wood (1975): Technology, Prices and the Derived Demand for Energy. *Review of Economics and Statistics*, 57(3): 259-68.

Bjørner, T.B. and H.H. Jensen (2002a): Energy taxes, voluntary agreements and investment subsidies – a micro-panel analysis of the effect on Danish industrial companies' energy demand. *Resource and Energy Economics*, 24: 229-249.

Bjørner, T.B. and H.H. Jensen (2002b): Interfuel Substitution within Industrial Companies: An Analysis Based on Panel Data at Company Level. *The Energy Journal*, 23 (2).

Bjørner, T.B.; M. Togeby and H.H. Jensen (2001): Industrial Companies' Demand for Electricity: Evidence from a Micro Panel. *Energy Economics*, 23(5): 595-617.

Bousquet, A. and M. Ivaldi (1998): An individual choice model of energy mix. *Resource and Energy Economics*, 20: 263-286.

Christensen, L.R.; D.W. Jorgenson and L.J. Lau (1973): Transcendental Logarithmic Production Frontiers. *The Review of Economics and Statistics*, 55: 28-45.

Considine, T.J. (1989a): Separability, Functional Form and Regulatory Policy in Models of Interfuel Substitution. *Energy Economics*, 11(2): 82-94.

Considine, T.J. (1989b): Estimating the Demand for Energy and Natural Resource Inputs_ Trade-Offs in Global Properties. *Applied Economics*, 21(7): 931-45.

Considine, T.J. (1990): Symmetry Constraints and Variable Returns to Scale in Logit Models. *Journal of Business and Economic Statistics*, 8(3): 347-53.

Considine, T.J. and T.D. Mount (1984): The Use of Linear Logit Models for Dynamic Input Demand Systems. *Review of Economics and Statistics*, 66(3): 434-43.

Doms, M.E. and T. Dunne (1993): *Energy Intensity, Electricity Consumption and Advanced Manufacturing Technology Usage*. Bureau of the Census Centre for Economic Studies, Discussion Paper: CES 83-9.

Griffin, J.M. and P.R. Gregory (1976): An Intercountry Translog Model of Energy Substitution Responses. *American Economic Review*, 66(5): 845-57.

Griliches, Z. and J. Mairesse (1995): *Production Functions: The Search for Identification.* National Bureau of Economic Research, Working Paper 5067.

Kleijweg, A.; G. van Leeuwen, R. Huigen and K. Zeelenberg (1989): *The demand for energy in Dutch manufacturing: A study using panel data of individual firms, 1978-1986*. Research Paper 8906, Research Institute for Small and Medium-sized Business in the Netherlands, Department of Fundamental Research.

Lee, L.-F. and M. Pitt (1987): Microeconometric models of rationing, imperfect markets, and non-negativity constraints. *Journal of Econometrics*, 36: 89-110.

Nguyen, Sang V. and Mary L. Streitwieser (1999). Factor Substitution in U.S. Manufacturing: Does Plant Size Matter? *Small Business Economics*, 12: 41-57.

Solow, J.L. (1987): The Capital Energy Complementarity Debate Revisited. *American Economic Review*, 77: 605-14.

White, H. (1980): A Heteroscedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroscedasticity. *Econometrica*, 48: 817-38.

Woodland, A.D. (1993): A Micro-econometric Analysis of the Industrial Demand for Energy in NSW. *Energy Journal*, 14(2): 57-89.

Notes

1. The studies that include materials as a separate factor of production also generally find that energy and materials are substitutes.

2. In addition they also find that the degrees of substitution among inputs are quite similar cross-plant sizes.

3. Woodland (1993) and Bjørner and Jensen (2002b) avoided the complexity of corner solutions by conditioning on the observed fuel pattern. See their contributions for a discussion of the pros and cons of this approach as compared with discrete/continuous models.

4. Nguyen and Streitwieser (1999) do not explicitly describe how the »price« of energy was calculated, but as they used a Btu aggregation to measure energy, it seems natural that they divided energy expenditure with the Btu aggregate.

5. The applied version of the linear logit model has the drawback that symmetry only holds for one set of cost shares. Thus, global symmetry is sacrificed for global concavity. See Considine (1989a, 1989b and 1990).

6. More formally, it is assumed that materials are separable from the other inputs, so that the cost-minimizing mix of *E*, *O*, *L* and *C* is independent of the price of materials. Danish macro models estimated on aggregate time-series data offer support for the assumption that materials are separable.

7. Coal and LPG account for less than 10% of the overall use of other types of energy. The use of coal is restricted to a small number of companies.

8. Of course it could be argued, that IV estimation methods should be used to correct the price of labour and energy, but we also want to apply IV techniques to correct for measurement errors with respect to capital. Since we only have a limited number of instruments available some simplifications were required. In addition, results from Bjørner and Jensen (2002a) and Bjørner et al. (2001) suggest that the potential endogeneity bias associated with the use of average energy costs is limited in panel models (using fixed effects or first differences estimators).

9. This is under the standard assumptions that the expected value of the measurement errors is zero and that the errors are not correlated with the explanatory variables.

10. 334 of the companies are observed in three years, while 569 are observed in all four years.

11. The estimated parameters of the trend are all insignificant. Likelihood-ratio tests do not reject null that the trend variables all are equal to zero. Estimations of the TL model

without the trend show the same qualitative results as the model with the trend included. We report the results for the TL model with the trend included for comparisons, because the trend is significant in the LL model.

12. It should be noted that Bjørner and Jensen relied on micro panel data covering a longer period (eight years between 1983 and 1997). Unfortunately, the accounting data (especially the capital data) did not have a sufficient level of disaggregation in the whole period, so in the current study we are restricted to use data only covering 1993 to 1997).