Embodied and induced technological change and energy prices

Kurt Kratena[a,*]

Michael Wueger[a]

[a] Austrian Institute of Economic Research, P.O. Box 91, 1103 Vienna, Austria

*) Corresponding author: Tel:+ 43 1 7982601, fax: + 43 1 7989386, kurt.kratena@wifo.ac.at, URL: www.wifo.at

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Abstract:

The aim of this paper is the analysis of embodied and induced technological change that reduces energy input in production, based on dynamic factor demand models with K,L,E,M inputs. A dynamic factor demand model is set up for different industries including the variable cost function and an investment function for the short-run fixed input capital (K). From the solution of the dynamic optimization model we derive a forward looking investment function that depends on factor prices. The model is estimated based on WIOD and EUKLEMS data for 13 different industries by pooling across 5 EU countries.

The modelling framework allows for different sources of technological change: total factor productivity, increasing returns to scale, factor bias, embodied technical change, and induced technical change. We find energy saving technological change embodied in capital goods and induced by energy prices in four to six out of 13 industries, depending on the specification for returns to scale. In most industries the factor bias is also energy saving.

Key words: embodied and induced technological change, dynamic factor demand models, emission mitigation policies,

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1. Introduction

Technological change is seen as an important factor for quantifying the costs of adjustment of an economy to higher energy prices or to carbon prices stemming from the implementation of climate policy. Aggregate impact assessment models of climate policy like WITCH (Bosetti, et al., 2006) as well as CGE models of energy and emissions likeOtto, Löschel and Reilly (2008) have during the last decade increasingly attempted to integrate features of endogenous technological change, especially energy saving R&D and learning by doing for carbon free types of energy. This concept of energy saving innovation is based on the pioneer work of Popp (2002). The most important consequence of endogenous or induced technological change in the context of climate policy is that it substantially lowers the economic costs of climate policy. As Sue Wing (2006) has noted, this is due to the mechanism of extending the set of substitution possibilities between fossil fuels and other inputs in production. If technological change is further thought of induced by factors which are part of climate policy measures (effective energy and carbon prices, R&D subsidies), it is climate policy itself that creates the cost savings of its own measures.

There are different ways of modeling endogenous and induced technological change, like induced innovation, learning by doing and endogenous diffusion of technologies (Jaffe, et al., 2003). A first important analytical starting point for technological change in production is the distinction between substitution effects and technological change (see: Sue Wing, 2006). Substitution effects can occur between the fossil energy carriers and other types of energy or between aggregate energy (E) and other inputs like labor (L), capital (K) and intermediates without energy (M). The approach presented here is based on the latter mechanism and sets up a K,L,E,M cost function and factor demand functions in a dynamic cost minimization framework. The first generation of static K,L,E,M cost function and factor demand functions dealt with total factor productivity (TFP) and the bias in technical change (Jorgenson and Fraumeni, 1981, Jorgenson, 1984). This is based on the concept of factor-bias in technical change (Binswanger and Ruttan,1978) and for energy yields the AEEI (autonomous energy efficiency improvement) that can be built into long-term models. In general, this framework defines energy saving technological change as an exogenous factor and only a few studies have attempted to expand this concept towards induced technological change(Dowlatabadi and Oravetz, 2006). Another new approach of modeling the rate and the factor bias of technological change has been put forward by Jin and Jorgenson (2010). It replaces the deterministic trend for describing technological change by latent variables which are identified by applying the Kalman filter to the econometric model of cost and factor demand.

Another – from our point of view – not fully exploited line of research is extending the model that integrates the rate and the factor bias of technological change by explicitly describing embodied technological change. The main idea of embodied technical change is that the technology is incorporated in the stock of equipment and technological change therefore only occurs with the installation of a new vintage of equipment. The importance of embodied technical change in a K,L,E,M framework has first been shown empirically by Berndt, Kolstad and Lee (1993). Sue Wing and Eckaus (2007) apply the framework of factor demand equations with short-run fixed input of K and thereby derive short and long-run reactions of energy intensity to energy prices. They demonstrate the empirical relevance of embodied technological change by showing that energy intensity in U.S. industries continued to decline after the collapse of energy prices which cannot be explained by short-term substitution reactions, but only by the stepwise embodiment of energy saving innovations in the stock of physical capital. Embodied technological change therefore could also be thought of describing the process of diffusion of advanced energy saving technologies rather than the upstream process of energy saving innovation.

This concept has also been extended in Kratena (2007) by appending an investment equation that describes the dynamic adjustment process of the short-run fixed factor *K*. The basic idea behind this extension is that if investment depends on energy prices and energy and capital are substitutes, then embodied technological change is energy saving and becomes price induced. The empirical results in Kratena (2007) show that capital and energy are substitutes only in about half of the manufacturing industries in Europe. Therefore embodied and induced technological change is energy using in some industries. This result is in line with the results obtained by Sue Wing and Eckaus (2007), which worked with different asset types of physical capital and found energy using as well as energy saving embodied and induced technological change, depending on the asset type. One main shortcoming in Kratena (2007) was that the underlying dynamic model was not forward looking, but applied an *ex post* stock adjustment mechanism.

The analysis in this paper takes up this line of research and sets up a forward looking model of dynamic cost minimization based on the Translog function with short-run fixed input of *K*, as laid down in Pindyck and Rotemberg (1983). One main difference to the Pindyck and Rotemberg approach is that we do not assume explicit external adjustment costs, but stick to the stock adjustment model. This approach is set up for a panel data set of five European countries (Austria, Denmark, Finland, Netherlands, and United Kingdom), based on a combination of economic data from the EUKLEMS databank and on preliminary data from the environmental satellite accounts in the WIOD project. We identify embodied energy saving technological change only in four to six (depending on the specification for returns to scale) out of 13 manufacturing industries. In the other industries capital and energy are complements and our methodological approach can only identify energy saving factor bias of technological change, but no energy saving embodiment of technological change. The link to price-induced embodiment is introduced by the forward looking investment equation. Price induced and energy saving embodiment can be identified, if investment reacts positively to energy prices.

The remainder of the paper is organized as follows: in section 2 the theoretical model is set up and in section 3 data issues are laid down together with the estimation methodology and the empirical results.IIn section 4 some preliminary conclusions are drawn.

2. Dynamic factor demand and technical change

Starting point of the analysis is a dynamic optimization problem of production, based on a variable cost function with capital input as a short- run fixed factor. Galeotti (1996) describes several ways of specifying and solving the dynamic problem. Most models are based on the quadratic variable cost function and include internal costs of adjustment for the short-run fixed input K (Morrison, 1986, Watkins and Berndt, 1992). In these models the dynamic control problem can be solved starting from a point near the equilibrium given by the Euler equation and the specification of an expectation mechanism (Lasserre and Ouelette, 1999).

In this paper we start from the Translog approach like Pindyck and Rotemberg (1983). In order not to restrict the specification too much, we do not specify explicitly the external costs of adjustment. Instead we assume that due to the existence of such adjustment costs, the planned capital stock under rational expectations adjusts to the difference between the optimal stock and the actual stock in the current period. By this specification we conserve the forward looking mechanism for determining the path of capital accumulation of Pindyck and Rotemberg (1983) and at the same time allow for higher flexibility in the adjustment mechanism.

The representative producers in each industry all face a cost function G comprising short-run variable costs $VC[p_v, K, Q, t]$ as well as expenditure for (aggregate) investment I with the corresponding price index of (aggregate) investment goods p_I :

(1) $$G = VC[p_v, K, Q, t] + p_I I$$

where $\mathbf{p_v}$ is a vector of variable input prices for input quantities v, K is the level of the quasi-fixed capital input to production, Q is the level of gross output and t is time. Taking into account that gross investment in the stock K comprises changes in the stock plus depreciation with depreciation rate δ, we have:

(2) $$G = VC[p_v, K, Q, t] + p_I(\dot{K} + \delta K)$$

The producers choose a time path of K to minimize discounted costs over a time horizon τ for which values for the exogenous variables are given:

$$(3) \qquad \min \int_{\tau}^{\infty} e^{-r(t-\tau)} \left[VC_t(p_v, K, Q, t) + p_I(\dot{K} + \delta K) \right] dt$$

where $\dot{K}$ stands for the change in K.

The two main optimality conditions following from this cost minimization problem are given by Shephard's Lemma and the Euler condition:

$$(4) \qquad \frac{\partial VC}{\partial p_v} = v$$

$$(5) \qquad p_I(r + \delta) + \frac{\partial VC}{\partial K} = 0$$

As Galeotti (1996) has shown, the Euler condition in this simple case without explicit adjustment costs just reduces to the equilibrium condition of the simple static case. This condition requires that the shadow price of fixed assets must be equal to the user costs of capital. The shadow price of capital is given by the negative of the term that measures the impact of capital inputs on short- run variable costs.

2.1 Translog cost functions and technological change

The next step consists in parameterizing the variable cost function VC, which shall be assumed to be Translog with one aggregate capital stock K :

$$
\begin{aligned}
\log VC &= \alpha_0 + \alpha_Q \log Q + \alpha_E \log(p_E / p_M) + \log p_M + \alpha_L \log(p_L / p_M) \\
&+ \beta_K \log K + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + \frac{1}{2}\gamma_{QQ}(\log Q)^2 + \frac{1}{2}\gamma_{LL}(\log(p_L / p_M))^2 + \\
&+ \gamma_{LE} \log(p_L / p_M)\log(p_E / p_M) + \frac{1}{2}\gamma_{EE}(\log(p_E / p_M))^2 + \frac{1}{2}\gamma_{KK}(\log K)^2 + \\
&+ \rho_{QL} \log Q \log(p_L / p_M) + \rho_{QE} \log Q \log(p_E / p_M) + \\
&+ \rho_{QK} \log Q \log K + \rho_{KL} \log K \log(p_L / p_M) + \rho_{KE} \log K \log(p_E / p_M) + \\
&+ \rho_{tQ} t \log Q + \rho_{tK} t \log K + \rho_{tL} t \log(p_L / p_M) + \rho_{tE} t \log(p_E / p_M)
\end{aligned} \tag{6}
$$

In this equation p_E, p_L and p_M are the prices of the variable inputs energy (*E*), labor (*L*) and materials (*M*), and the α, β, γ and ρ are vectors of parameters to be estimated. The homogeneity restriction for the price parameters $\sum_i \gamma_{ij} = 0$, $\sum_j \gamma_{ij} = 0$ has already been imposed in (6), so that the terms for the price of materials p_M have been omitted. The usual parameter restrictions of the Translog function imply in this case:

$$\sum_i \alpha_i = 1, \ \sum_i \gamma_{ij} = 0, \ \sum_j \gamma_{ij} = 0, \ \sum_i \rho_{ti} = 0, \ \sum_i \rho_{Yi} = 0, \ \sum_i \rho_{Ki} = 0 \, .$$

with i,j = L, E, M (the variable factors). Assuming constant returns to scale implies another set of restrictions (Berndt, Hesse, 1986):

$\alpha_Y + \beta_K = 1$, $\gamma_{KK} + \rho_{YK} = 0$, $\gamma_{YY} + \rho_{YK} = 0$, $\rho_{tY} + \rho_{tK} = 0$, $\rho_{Yi} + \rho_{Ki} = 0$, with i= L, E, M,

That leads to the following more condensed cost function:

$$
\begin{aligned}
\log VC = {} & \alpha_0 + \alpha_Q \log Q + \alpha_E \log(p_E / p_M) + \log p_M + \alpha_L \log(p_L / p_M) + (1-\alpha_Q)\log K \\
& + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + \frac{1}{2}\gamma_{LL}(\log(p_L / p_M))^2 + +\gamma_{LE}\log(p_L / p_M)\log(p_E / p_M) \\
& + \frac{1}{2}\gamma_{EE}(\log(p_E / p_M))^2 + \rho_{KL}\log\left(\frac{K}{Q}\right)\log(p_L / p_M) + \rho_{KE}\log\left(\frac{K}{Q}\right)\log(p_E / p_M) \\
& + \rho_{QK}\left(\log Q \log K - \frac{1}{2}(\log Q)^2 - \frac{1}{2}(\log K)^2\right) + \\
& + \rho_{tL} t \log(p_L / p_M) + \rho_{tE} t \log(p_E / p_M) + \rho_{tK} t \log\left(\frac{K}{Q}\right)
\end{aligned} \tag{7}
$$

As is well known, Shepard's Lemma yields the cost share equations in the Translog case, for example: $\frac{\partial \log VC}{\partial \log p_E} = \frac{\partial VC}{\partial p_E}\frac{p_E}{VC} = \frac{p_E E}{VC} = s_E$, which for the case of non-constant returns to scale can be written as:

$$\text{(8)}\quad \frac{p_L L}{VC} = s_L = \left[\alpha_L + \gamma_{LL}\log(p_L / p_M) + \gamma_{LE}\log(p_E / p_M) + \rho_{KL}\log K + \rho_{QL}\log Q + \rho_{tL} t\right]$$

$$\text{(9)}\quad \frac{p_E E}{VC} = s_E = \left[\alpha \quad + \gamma_{LE}\log(p_L / p_M) + \gamma_{EE}\log(p_E / p_M) + \rho_{KE}\log K + \rho_{QE}\log Q + \rho_{tE} t\right]$$

In the case of constant returns to scale the cost shares of the variable factors are reduced to:

$$\text{(10)}\quad \frac{p_L L}{VC} = s_L = \left[\alpha_L + \gamma_{LL}\log(p_L / p_M) + \gamma_{LE}\log(p_E / p_M) + \rho_{KL}\log\left(\frac{K}{Q}\right) + \rho_{tL} t\right]$$

$$\text{(11)}\quad \frac{p_E E}{VC} = s_E = \left[\alpha_E + \gamma_{LE}\log(p_L / p_M) + \gamma_{EE}\log(p_E / p_M) + \rho_{KE}\log\left(\frac{K}{Q}\right) + \rho_{tE} t\right]$$

In this factor share equations we can clearly identify two of the three components of technical change we want to deal with in this study, namely the input-biases (measured by ρ_{tL} and ρ_{tE}) and the impact of the quasi fixed capital stock (measured by ρ_{KL} and ρ_{KE}) on factor demand. The first set of parameters describes disembodied or autonomous technical change and the second embodied technical change brought about by the installation of new capital equipment. If the ρ_{ti} with i= L, E, M are positive, autonomous technical change is factor using. Positive parameter values for the ρ_{Ki} imply factor using embodied technical change and can also be interpreted in a way that capital and energy are complements and not substitutes.

The variable cost equations (6) and (7) contain all components of technical change and show their impact on overall unit costs. That comprises components of autonomous and embodied technical change that exert an influence on total variable costs as well as on factor demand. Autonomous technical change can be found for the capital stock (ρ_{tK}) and for the factors (i.e. the factor biases ρ_{tL} , ρ_{tE} and ρ_{tM}). Another source of autonomous technical change that only influences costs is TFP, measured by α_t and α_{tt} . Embodied technical change only exerts an influence on variable cost measured by the same parameters as appear in the factor demand equations, namely ρ_{KL} and ρ_{KE} .

In the specification of the model with non-constant returns to scale (cost function (6)), these can also be interpreted as an additional source of technical change. The returns to scale are derived from the elasticity of variable cost to output:

$$(12)\ \rho = \frac{\partial \log VC}{\partial \log Q}\left[\alpha_Q + \gamma_{QQ}\log Q + \rho_{QL}\log(p_L / p_M) + \rho_{QE}\log(p_E / p_M) + \rho_{QK}\log K + \rho_{tQ}t\right]$$

If ρ < 1, the cost function exhibits increasing returns, and if ρ > 1, the returns to scale are decreasing.

Energy demand reacts immediately to the factor prices (energy and labor) and – as will be described in the next subsection – to long-run adjustment in the capital stock. The immediate reaction is given by the own and cross price elasticities. The own price elasticity of energy ε_{EE} demand can be written as:

$$(13) \qquad \varepsilon_{EE} = \frac{\partial \log E}{\partial \log p_E} = \frac{s_E^2 - s_E + \gamma_{EE}}{s_E}$$

2.2 Capital prices and forward looking capital stock adjustment

Capital is treated as a short-run fixed factor in this dynamic factor demand model and therefore only enters in quantity units in the variable cost function and the factor demand functions. Several prices of capital can be derived in this model. One is the user cost of capital $u_K = p_I(r+\delta)$ as described above. Another capital price is given by exhausting gross output and calculating operating surplus and put it into relation to the capital stock:

$p_K = \frac{p_Q Q - VC}{K}$. In purely static models like Berndt and Hesse (1986) equilibrium is defined by the equality between this capital price p_K and the user cost u_K. In the simple dynamic model without explicit adjustment costs applied here, long-run equilibrium defined by the Euler equation only comprises the shadow price of capital and the user cost u_K. The shadow price of capital $z_K = -\frac{\partial VC}{\partial K} = -\frac{\partial \log VC}{\partial \log K}\frac{VC}{K}$ can directly be derived from the cost function.

In the case of non- -constant returns to scale this shadow value is given with:

$$(14) -\frac{\partial VC}{\partial K} = -\frac{VC}{K}\left[\beta_K + \gamma_{KK}\log K + \rho_{KL}\log(p_L / p_M) + \rho_{KE}\log(p_E / p_M) + \rho_{QK}\log Q + \rho_{tK} t\right]$$

For constant returns to scale this expression is written as:

$$(15)\ -\frac{\partial VC}{\partial K} = -\frac{VC}{K}\left[(1-\alpha_Q) + \rho_{KL}\log(p_L / p_M) + \rho_{KE}\log(p_E / p_M) - \rho_{QK}\log\left(\frac{K}{Q}\right) + \rho_{tK} t\right]$$

Inserting this shadow value in the Euler condition (equation (5)) yields the explicit solution for the optimal stock K^* in both specifications for returns to scale:

$$(16) \qquad \log K^* = \frac{1}{\gamma_{KK}}\left[-\beta_K - \rho_{QK}\log Q - \rho_{KL}\log(p_L / p_M) - \rho_{KE}\log(p_E / p_M) - \rho_{tK} t - s_K\right]$$

$$(17) \qquad \log K^* = \frac{1}{\rho_{QK}}\left[(1-\alpha_Q) + \rho_{QK}\log Q + \rho_{KL}\log(p_L / p_M) + \rho_{KE}\log(p_E / p_M) + \rho_{tK} t + s_K\right]$$

In (16) the optimal stock for the case of non-constant returns to scale is presented, in (17) for constant returns. In both equations s_K represents the user cost of capital share

$s_K = \frac{u_K K}{VC} = \frac{p_I(r+\delta)K}{VC}$, where $u_K = p_I(r+\delta)$. It is a well known shortcoming of the Translog model (see: Kratena, 2007) that the optimal capital stock formulation also contains the capital stock on the right hand side of the equation. We deal with that by defining s_K as a separate variable.

In both specifications for returns to scale the optimal stock is influenced by scale effects (ρ_{QK}), by embodied (ρ_{KL} and ρ_{KE}), and autonomous (ρ_{tK}) technical change. For the elasticity of the optimal stock to changes in energy prices we derive the following relationships in the two specifications:

(18) $$\frac{\partial \log K^*}{\partial \log p_E} = -\frac{\rho_{KE}}{\gamma_{KK}}$$ for non-constant returns to scale

(19) $$\frac{\partial \log K^*}{\partial \log p_E} = \frac{\rho_{KE}}{\rho_{QK}}$$ for constant returns to scale

Therefore, if the parameter ρ_{KE} is negative, the industry faces energy saving technical change. In that case - in order to obtain a rise in the capital stock – the parameter γ_{KK} must be positive in the case of non- constant returns to scale and the parameter ρ_{QK} must be negative in the case of constant returns to scale. These different conditions on parameters nevertheless imply the same in both returns to scale specifications, namely that the term $(\log K)^2$ exerts a negative influence on variable cost.

The actual capital stock equals the optimal capital stock, when all actual values of the variables in (16) and in (17) are equal to the expected values for these variables at the point in time, when the investment has been installed. Errors in the expectations and unforeseen shocks lead to a gradual adjustment of the capital stock. In most dynamic factor demand models this gradual adjustment is given by the introduction of explicit internal or external costs of adjustment. In our approach it is assumed that adjustment costs play an important role for the short-run stickiness of the capital stock, but these costs are not treated in an explicit manner. Instead we formulate a traditional stock adjustment model (Egebo, et al., 1990) in a forward looking specification:

(20) $$\log K_{t+1} - \log K_t = \tau_1\left(\varepsilon_t(\log K^*_{t+1}) - \log K_t\right) + \tau_2\left(\log K_t - \log K_{t-1}\right)$$

Here $\varepsilon_t(\log K^*_{t+1})$ is the expected level of the optimal stock K^* in t+1, given the information on factor prices and output in t. The capital stock adjusts in a forward looking process and both adjustment terms of first and second order are included, where the equilibrium condition is given by $t_1 > 0$. The sign of the adjustment term of second order, t_2, is ambiguous and decides about the path of the adjustment process. Inserting the expressions for K^* into (20) yields the following investment equations that complement this dynamic factor demand model:

(21)

$$\Delta \log(K_{t+1}) = \tau_1 \left[\begin{pmatrix} -s_{K,t+1} - \beta_K + \\ \varepsilon_t \left(\rho_{KL} \log(p_{L,t+1} / p_{M,t+1}) - \rho_{KE} \log(p_{E,t+1} / p_{M,t+1}) - \rho_{QK} \log Q_{t+1} - \rho_{tK} t + 1 \right) \end{pmatrix} \frac{1}{\gamma_{KK}} - \log K_t \right] + \tau_2 \left[\log K_t - \log K_{t-1} \right]$$

(22)

$$\Delta \log(K_{t+1}) = \tau_1 \left[\begin{pmatrix} s_{K,t+1} + (1-\alpha_Q) + \\ \varepsilon_t \left(\rho_{KL} \log(p_{L,t+1} / p_{M,t+1}) + \rho_{KE} \log(p_{E,t+1} / p_{M,t+1}) + \rho_{QK} \log Q_{t+1} + \rho_{tK} t + 1 \right) \end{pmatrix} \frac{1}{\rho_{QK}} - \log K_t \right] + \tau_2 \left[\log K_t - \log K_{t-1} \right]$$

It is important to note that there is an input-output loop built in this model that works via the price system. We do not explicitly append any output price equation to our system, but a general version is a mark up on variable costs:

(23) $$\log p = (1+\mu) \log VC$$

This mark up takes into account differences between the capital price p_K, and the user costs of capital $u_K = p_I(r+\delta)$, caused either by imperfect competition or frictions on the capital market. The approach lined out here is set up on an industry level and therefore cost and price equations can be defined for each industry j (we simplify the notation by omitting this industry index). The investment goods price can be defined as a function of domestic output (commodity) prices and import prices, given the input structures for investment:

$$(24) \quad p_I = p\left(I - \hat{M}_B\right)B_{ij} + p_{im}\hat{M}_B B_{ij}$$

with $\mathbf{B_{ij}}$ as a gross fixed capital formation matrix in coefficients, showing the shares of different commodities i in the investment of industries j and $\mathbf{M_B}$ as a diagonal matrix of import shares of commodity i in the column vector of investment in the input-output table. The row vector of investment good prices p_I can therefore be written as a function of the row vector of output (commodity) prices $\mathbf{p}$ and import prices, $\mathbf{p_{im}}$. The elements of the matrix $\mathbf{B_{ij}}$ are concentrated in the investment commodities. Technical change occurs in the capital producing sectors and can lead to lower effective prices of energy efficient capital goods. Via capital imports this technical change then influences costs and inputs in all other sectors, this mechanism has for IT/CT capital goods been described by Jorgenson and Stiroh. The model could in a next stage be completed by explicitly describing the price setting mechanism in capital goods producing sectors and linking it to energy relevant characteristics of capital goods like in the seminal paper by Newell, et al. (1999).

Embodied technological change can now directly be measured by the elasticity of energy demand to the quantity input of capital. This relationship is for both specifications of returns to scale given with:

$$(25) \quad \varepsilon_{KE} = \frac{\partial \log E}{\partial \log K} = \frac{\rho_{KE}}{s_E} - \frac{z_K K}{VC}$$

The second term in (25) is the shadow price of capital share and can be interpreted as a measure of the impact of an additional unit of quantity capital input on variable costs. If this expression is large enough, i.e. $\frac{z_K K}{VC} > \frac{\rho_{KE}}{s_E}$, the energy – capital elasticity becomes negative even in cases, where the result $\rho_{KE} > 0$ would indicate capital – energy complementarity and energy using embodied technical change. This is due to the fact that in these cases the total cost saving-impact of capital is high and dominates the impact on energy input.

As Sue Wing and Eckaus (2007) and Kratena (2007) have shown, in this approach a long run own price elasticity of energy can be derived, capturing both the short-run substitution effects as described in (12) and the long-run effects stemming from capital stock adjustment. In the long run equilibrium, once the capital stock has adjusted to the optimal level *K**, the total impact of energy prices on energy demand can be seen as:

(26) $$\eta_{EE} = \frac{d\log E}{d\log p_E} = \frac{s_E^2 - s_E + \gamma_{EE}}{s_E} + \frac{\partial \log E}{\partial \log K^*}\frac{\partial \log K^*}{\partial \log p_E}$$

Inserting (18), (19) and (25) into (26) gives the full expression for this long-run own price elasticity of energy demand in both specifications for returns to scale:

(27) $$\eta_{EE} = \frac{s_E^2 - s_E + \gamma_{EE}}{s_E} + \left[\frac{\rho_{KE}}{s_E} - \frac{z_k K}{VC}\right]\left(-\frac{\rho_{KE}}{\gamma_{KK}}\right)$$

(28) $$\eta_{EE} = \frac{s_E^2 - s_E + \gamma_{EE}}{s_E} + \left[\frac{\rho_{KE}}{s_E} - \frac{z_k K}{VC}\right]\left(\frac{\rho_{KE}}{\rho_{QK}}\right)$$

The relation of these long-run elasticities to the short-run elasticities gives an indication for the role of embodied and induced technical change. The short to medium-term impact of a rise in effective energy prices, for example due to the introduction of a carbon price, is given by adding embodied and induced technical change effects to the short-run substitution effects according to the investment function (21) or (22).

3. Data, estimation method and results

The empirical application of the *K*,*L*,*E*,*M* model outlined above is based on a detailed data set comprising all input quantities as well as prices. As in Kratena (2007) and in Neuwahl, et al. (2009),the EUKLEMS database was one source for this dataset. The release of this database from November 2009 is the most recent version and has been fully incorporated into the WIOD database. We choose five EU countries for the empirical application of our model: Austria, Denmark, Finland, Netherlands, and the UK. This country group comprises large and small European economies as well as countries that have reacted with 'active' energy saving policies (Denmark). With Netherlands and the UK the data set also contains two economies with large structural changes after energy price shocks, partly in the form of a shift towards domestic energy extraction and production.

The EU KLEMS database, which was the original source for data on input structures at the detailed industry level for all 25 EU countries is described in O'Mahony and Timmer (2007). For the five countries covered in this study, long time series for output, labour, capital and intermediate inputs are available athe level of 32 industries, defined by NACE (see Table 1 for the classification in the WIOD database), starting in 1970. The limiting factor concerning data availability is the energy input by industry. In general, the 'YL files' of the WIOD database do not contain aggregate energy input, but the WIOD database contains detailed energy accounts in physical units from 1995 on. These data have been combined with data from the OECD "Energy Prices and Taxes" from 1980 on and with the March 2008 release of the EUKLEMS database, that still contained data about energy input. The combination of these data sets enabled us to calculate energy inputs in values from 1995 to 2006 and link these series with the energy input data in the former version of EUKLEMS. Using this link and the energy price data, we were able to interpolate an energy input dataset for the period 1980-1994. The price index for investment goods has been calculated using the investment matrix for Austria for all five countries. Due to the lack of soundly based import prices for commodities, we used the gross output deflators only for calculating the price for investment goods according to (23). In the end, this analysis has been limited to 13 manufacturing sectors (NACE 15 to 37). The variables used in this study are:

Values

$p_E E$ Intermediate energy inputs at current purchasers' prices (in millions of local currency)

$p_M M$ Intermediate material and service inputs at current purchasers' prices (in millions of local currency)

$p_L L$ Labour compensation (in millions of local currency)

Volumes

Q Gross output, volume indices, 1995 = 100

K Real gross fixed capital stock, 1995 prices

Prices

p Gross output price, 1995 = 100

p_E Energy input price, 1995 = 100, calculated from $p_E E$ and from energy input in TJ

p_M Intermediate input price, 1995 = 100

p_L Labour input price, 1995 = 100, calculated from labour compensation and hours worked

p_I Gross fixed capital stock formation price index, 1995 = 100, calculated from investment matrix (Austria) and gross output price

δ Rate of depreciation of total capital stock, calculated from K and total depreciation

The real rate of return, r, in the user cost term $u_K = p_I(r+\delta)$ was calculated by deflating the benchmark interest rate (treasury bills on the secondary market) with the deflator of GDP.

3.1 Estimation method

The econometric estimation is carried out for the system comprising the variable cost function ((6) or (7), depending on the returns to scale-specification), the factor demand functions ((8) and (9) or (10) and (11)), and the investment function ((21) or (22)). As in Pindyck and Rotemberg (1983) the system is forward looking and contains expected values of variables that determine the path of the capital stock. Using the actual values for the variables in the investment function in t+1 on the right hand side, shifts all expectational errors in the residuals of this equation. Therefore we can – like Pindyck and Rotemberg – use an instrumental variable estimator, where instruments are all known values in t for the expected values in t+1. That implies that expectations are formed for $t+1$ on the base of an information-set in t for all variables (output and input prices).

The systems for non-constant returns to scale and constant returns to scale have been estimated applying the Generalized Method of Moments (GMM) estimator for a panel data set of the five countries (data from 1980 to 2006) for each industry in the manufacturing sector. The total number of observations of the balanced panel that entered in the estimation procedure (adjusting for lags and leads) was 135. Table 2 shows descriptive statistics for input prices and cost shares of factors of production in manufacturing. Large standard deviations and differences between maximum and minimum values are found for input prices of labour and energy, but not for intermediate inputs. One general problem for the identification of significant own price elasticities of energy are the small cost shares of energy in all industries, except in the energy intensive manufacturing branches. In general, the variance of energy prices and the average price level of energy inputs is not higher in the energy intensive industries (with the exception of "Coke, refined petroleum and nuclear fuel").

3.2 Estimation results

The system estimation of the variable cost function, the labour and energy cost share and the investment function have been carried out in each manufacturing industry, for the specification of non-constant as well as of constant returns to scale. The estimation method applied was GMM in a balanced panel data set in EViews 6.0. The instruments used are the lagged values of gross output (constant prices), capital stock (constant prices), factor input prices, depreciation rates and the real rate of return.

As a first result, we derive all parameter estimates of the model, which have been estimated under the restrictions of homogeneity and symmetry of the Translog model. We did not in general enforce concavity of the cost function, but only forced parameters to certain values, when in a first step concavity was violated and some positive mean values of own price elasticities appeared. In the case of constant returns to scale we applied the additional restrictions on parameters following from constant returns to scale.

Table 3 shows selected parameter values for the non-constant returns to scale case. Out of the 91 crucial parameters exhibited in Table 3, only 25 turn out to be insignificant (not even at the 10% level). The parameter for embodied energy saving technical change (ρ_{KE}) turns out to be negative in the following six industries: wood and cork, pulp and paper/printing, chemicals, rubber and plastics, basic metals and fabricated metal, as well as electrical and optical equipment. This negative value indicates at a first sight energy-capital substitutability, but the exact *ceteris paribus* impact of *K* on *E* can only be deduced from the capital-energy elasticity (equation (25)). The parameter for embodied labour saving technical change (ρ_{KL}) turns out to be negative only in one industry (coke, refined petroleum and nuclear fuel).

In Table 4 the parameters for the autonomous components of technical change in the case of non-constant returns to scale are outlined, comprising the TFP parameters α_t and α_{tt} , as well as the parameters measuring the factor bias for *K*, *L* and *E*. Out of these 65 estimated parameters in total 19 turn out to be insignificant. We find autonomous negative impact of both TFP parameters in only four industries. The factor bias is labour saving in all industries and energy saving in: chemicals, other non-metallic minerals, basic metals and fabricated metal, machinery, electrical and optical equipment, and transport equipment. In the other seven manufacturing industries the factor bias is found to be energy using.

Table 5 and Table 6 show the same parameter results for the case of constant returns to scale. Out of the 91 crucial parameters (Table 5) in the case of constant returns to scale only 8 are insignificant. The number of industries with energy saving embodied technical change (according to the parameter ρ_{KE}) is reduced from six (in the case of non-constant returns to scale) to three industries: Coke, refined petroleum and nuclear fuel, chemicals, basic metals and fabricated metal. The latter two also exhibit negative values of ρ_{KE} in the case of non-constant returns to scale. The parameter for embodied labour saving technical change (ρ_{KL}) is negative in more than one industry in the case of constant returns. Out of the 65 estimated parameters for autonomous technical change in the case of constant returns only 10 turn out to be insignificant. A majority of industries (nine) exhibits an energy saving bias in technical change in this specification.

A more comprehensive picture of the different impacts and channels of prices and technical change on factor demand can be concluded from the calculation of the elasticities. The own price elasticities of energy are small across industries in both specifications for returns to scale, the unweighted average is about -0.2. The own price elasticities of labour are significantly larger across industries in both specifications for returns to scale, the unweighted average is about -0.5. In general, there is no indication that the own price elasticities of energy are larger in the energy intensive industries, where the cost share of energy is larger. The Translog model works with a variable own price elasticity and takes into account variations in the cost share during the time period of this analysis (1980 – 2006) and across countries. The only energy intensive manufacturing industry with a significantly above average own price elasticity of energy is chemicals.

In the case of non-constant returns to scale we find six industries exhibiting negative energy-capital elasticities: pulp and paper/printing, chemicals, rubber and plastics, basic metals and fabricated metal, machinery, electrical and optical equipment. This list includes all energy intensive industries except coke, refined petroleum and nuclear fuel and other non-metallic minerals. The industries with negative energy-capital elasticities can be clearly identified as industries where energy and capital are substitutes and where energy saving embodied technical change takes place.

In the case of constant returns to scale the industries with negative energy-capital elasticities are: coke, refined petroleum and nuclear fuel, chemicals, rubber and plastics, basic metals and fabricated metal. Therefore three industries turn out to be characterized by energy-capital substitutability (chemicals, rubber and plastics, and basic metals and fabricated metal) in both specifications for returns to scale, but in the case of constant returns to scale less industries with energy saving embodied technical change are identified. Two of the industries that reveal energy saving embodied technical change in the case of non-constant returns to scale, but not under constant returns, face increasing returns to scale (pulp and paper/printing, and electrical and optical equipment). Allowing for increasing returns might be seen as an option allowing for an additional source of technical change, so that technical change is split up into more components that can be identified. Those industries that show capital-energy complementarity in the case of non-constant returns to scale are not systematically characterized by increasing returns, so that the link between these two sources of technical change should not be overemphasized.

It is worth to recall that for energy saving induced and embodied technical change, additionally the restrictions on the parameters of equation (27) and (28) must be fulfilled. Mainly that boils down to a significant positive reaction of investment to a rise in energy prices. The idea behind this type of price inducement of energy saving technical change is that higher energy prices mean a stronger incentive to change to a more energy efficient technology that is embodied in new capital goods. Therefore, compared to a baseline scenario with lower energy prices, firms would scrap old vintages of capital on a faster pace and the diffusion of more energy efficient technologies would accelerate.

The role of induced and embodied technical change in our approach can be seen from a comparison of the short-run own price elasticities (covering pure substitution effects) with the long-run elasticities (including adjustment of investment to new factor prices) in Table 9.

For the industries for which we found embodied energy saving technical change in the case of non-constant returns to scale (pulp and paper/printing, chemicals, rubber and plastics, basic metals and fabricated metal, machinery, electrical and optical equipment), the long run own price elasticity of energy is higher than the short-run with the exception of basic metals and fabricated metal, and electrical and optical equipment. Therefore, only in four out of the six industries with embodied energy saving technical change, this technical change can also be characterized as price induced. The most prominent results are a much higher long-run own price elasticity of energy in chemicals and an even positive long run own price elasticity of energy in basic metals and fabricated metal.

In those industries where we found embodied energy saving technical change in the case of constant returns to scale (coke, refined petroleum and nuclear fuel, chemicals, rubber and plastics, basic metals and fabricated metal), the long-run own price elasticity is higher than the short-run only in chemicals.

The main conclusions from these results are that though embodied technical change can be identified in this approach, only in a few industries (mainly in chemicals) this leads also to the identification of price induced embodied technical change. In some cases (basic metals and fabricated metal) where investment reacts negatively to an increase in energy prices, the price inducement of embodied technical change is even reversed.

4. Conclusions

In this paper the role of embodied and induced technical change for the energy demand of 13 manufacturing industries in 5 EU countries (Austria, Denmark, Finland, Netherlands, UK) has been explored. The approach chosen was a dynamic Translog model, where capital does not adjust immediately, but according to a forward looking investment function. This work complements former studies where either only the long run impact of embodied technical change has been analysed (Sue Wing and Eckaus, 2007) or where the investment demand function added to the factor demand was backward looking (Kratena, 2007). The estimation procedure allows for introducing expectations about factor prices and output and identifies the different sources of technical change separately. The methodology has been applied in two different specifications for returns to scale (non-constant, constant) in order to check, if non-constant returns to scale might be seen as an additional source of technical change. As in Kratena (2007) we identify about half of the 13 manufacturing industries as industries with energy saving embodied technical change. This is partly also due to our methodological approach which only allows for energy saving embodied technical change when capital and energy are substitutes. The embodied technical change identified in a first step can then be identified as price induced, depending on the impact of energy prices on investment. This second step of the analysis further reduces the number of industries, where embodied and induced energy saving technical change can be found. A further proof for long-run induced energy saving technical change is derived from a comparison exercise between the short-run and the long-run price elasticity of energy. In fact these differences are only small in a number of sectors and only in one or two sectors the long-run elasticity is significantly higher than the short-run, clearly indicating the role of embodied and induced technical change.

One promising extension of this approach therefore is to introduce the option of embodied and price induced technical change also in the case of energy-capital complementarity. One important feature for this is the link between costs and price setting in the capital goods producing sectors and the price of investment goods in the other industries. Another possible extension is the explicit introduction of the energy efficiency of new and older capital goods, for example in a vintage model.

Table1 : WIOD industries and definition by NACE

WIOD industries	NACE
AGRICULTURE, HUNTING, FORESTRY AND FISHING	AtB
MINING AND QUARRYING	C
FOOD , BEVERAGES AND TOBACCO	15t16
Textiles and textile	17t18
Leather, leather and footwear	19
WOOD AND OF WOOD AND CORK	20
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	21t22
Coke, refined petroleum and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics	25
OTHER NON-METALLIC MINERAL	26
BASIC METALS AND FABRICATED METAL	27t28
MACHINERY, NEC	29
ELECTRICAL AND OPTICAL EQUIPMENT	30t33
TRANSPORT EQUIPMENT	34t35
MANUFACTURING NEC; RECYCLING	36t37
ELECTRICITY, GAS AND WATER SUPPLY	E
CONSTRUCTION	F
Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	50
Wholesale trade and commission trade, except of motor vehicles and motorcycles	51
Retail trade, except of motor vehicles and motorcycles; repair of household goods	52
HOTELS AND RESTAURANTS	H
Inland transport	60
Water transport	61
Air transport	62
Supporting and auxiliary transport activities; activities of travel agencies	63
POST AND TELECOMMUNICATIONS	64
FINANCIAL INTERMEDIATION	J
Real estate activities	70
Renting of m&eq and other business activities	71t74
PUBLIC ADMIN AND DEFENCE; COMPULSORY SOCIAL SECURITY	L
EDUCATION	M
HEALTH AND SOCIAL WORK	N
OTHER COMMUNITY, SOCIAL AND PERSONAL SERVICES	O
PRIVATE HOUSEHOLDS WITH EMPLOYED PERSONS	P

Table 2 : Descriptive statistics of cost shares (L, E) and input prices

Food, beverages and tobacco	Mean	Median	Maximum	Minimum	Std. Dev.
s_L	0.1727	0.1721	0.2558	0.1066	0.0378
s_E	0.0180	0.0159	0.0377	0.0108	0.0055
p_L	91.74	95.94	153.95	29.36	30.59
p_E	118.09	101.85	239.81	60.83	34.58
p_M	97.28	99.64	119.04	51.39	12.33
Textiles, leather and footwear					
s_L	0.2964	0.3078	0.3792	0.1952	0.0514
s_E	0.0166	0.0158	0.0416	0.0033	0.0061
p_L	97.16	96.77	210.15	29.40	35.55
p_E	109.19	100.00	222.60	56.55	29.30
p_M	90.79	96.16	112.14	49.74	15.41
Wood and cork					
s_L	0.2558	0.2543	0.3219	0.1678	0.0385
s_E	0.0203	0.0196	0.0593	0.0023	0.0105
p_L	92.15	93.47	161.51	29.82	31.26
p_E	124.43	107.20	312.50	56.60	45.20
p_M	90.84	94.18	117.14	48.67	14.79
Pulp and paper, printing					
s_L	0.2910	0.2956	0.3788	0.1824	0.0531
s_E	0.0415	0.0321	0.1361	0.0152	0.0272
p_L	91.68	92.67	156.11	29.64	32.57
p_E	106.52	99.12	199.40	55.07	24.86
p_M	89.40	93.10	117.92	42.79	17.15
Coke, refined petroleum and nuclear fuel					
s_L	0.0646	0.0508	0.2055	0.0082	0.0445
s_E	0.8104	0.8184	0.9498	0.5598	0.0774
p_L	95.71	95.00	185.74	27.62	35.00
p_E	208.43	139.11	560.59	48.57	134.93
p_M	94.87	97.56	156.41	48.23	18.15
Chemicals and chemical products					
s_L	0.2152	0.2191	0.3027	0.0959	0.0481
s_E	0.0825	0.0847	0.1851	0.0264	0.0356
p_L	92.13	93.50	169.10	26.77	35.64
p_E	120.22	108.58	213.60	60.81	32.54
p_M	94.87	97.56	156.41	48.23	18.15

Table 2 : continued

Rubber and plastics	Mean	Median	Maximum	Minimum	Std. Dev.
s_L	0.2994	0.3023	0.3632	0.2222	0.0314
s_E	0.0460	0.0308	0.2452	0.0108	0.0356
p_L	93.47	95.71	175.11	29.77	33.35
p_E	105.40	97.54	175.52	54.35	21.66
p_M	91.43	95.23	126.65	51.79	15.31
Other non-metallic minerals					
s_L	0.3154	0.3212	0.3747	0.2448	0.0338
s_E	0.0725	0.0552	0.2329	0.0281	0.0385
p_L	90.28	92.77	165.20	26.94	31.86
p_E	118.74	106.01	228.75	63.91	32.46
p_M	94.13	98.13	129.16	47.12	18.69
Basic metals and fabricated metal					
s_L	0.2770	0.2784	0.3665	0.1584	0.0528
s_E	0.0612	0.0577	0.1413	0.0190	0.0266
p_L	90.68	92.16	168.08	30.12	32.81
p_E	106.13	100.00	187.30	55.88	26.03
p_M	92.33	95.86	143.81	45.85	17.52
Machinery					
s_L	0.3226	0.3274	0.4078	0.2101	0.0466
s_E	0.0112	0.0097	0.0306	0.0046	0.0051
p_L	91.77	91.05	182.15	29.00	33.51
p_E	109.30	100.00	190.16	57.58	27.38
p_M	93.75	97.26	141.41	45.44	19.92
Electrical and optical equipment					
s_L	0.3036	0.3009	0.4293	0.1403	0.0713
s_E	0.0099	0.0091	0.0446	0.0033	0.0064
p_L	92.42	95.44	175.84	23.90	35.74
p_E	108.08	100.00	181.42	52.39	25.42
p_M	88.76	95.12	116.29	50.54	15.67
Transport equipment					
s_L	0.2542	0.2577	0.3773	0.1281	0.0661
s_E	0.0111	0.0108	0.0287	0.0042	0.0046
p_L	90.04	96.06	161.57	29.01	32.83
p_E	112.06	101.82	197.76	60.38	28.23
p_M	92.49	97.02	138.15	42.20	20.97
Other manufacturing					
s_L	0.3558	0.3355	0.5176	0.2479	0.0717
s_E	0.0233	0.0152	0.1658	0.0061	0.0243
p_L	91.47	97.15	159.63	22.62	33.24
p_E	138.53	102.07	842.25	65.44	137.72
p_M	91.78	96.25	124.16	50.35	16.10

Table 3: Selected parameter estimates: non-constant returns to scale

	β_K	γ_{LL}	γ_{LE}	γ_{EE}	γ_{KK}	ρ_{KL}	ρ_{KE}
Food, beverages and tobacco	-0.3064	0.0577	-0.0144	0.0121	-0.0337	0.0619	0.0148
	(0.1235) ***	(0.0245) **	(0.0022) ***	(0.0009) ***	(0.0811)	(0.0156) ***	(0.0015) ***
Textiles, leather and footwear	-0.7704	0.0168	-0.0051	0.0131	0.3874	0.0041	0.0025
	(0.1366) ***	(0.0329)	(0.0035) *	(0.0018) ***	(0.1214) ***	(0.0160)	(0.0017) *
Wood and cork	-1.8256	0.1528	-0.0156	0.0110	-1.1409	0.0340	-0.0003
	(0.3106) ***	(0.0262) ***	(0.0061) ***	(0.0000) ***	(0.1446) ***	(0.0173) **	(0.0045)
Pulp and paper, printing	-1.1688	0.0109	0.0085	0.0250	0.6118	0.0421	-0.0045
	(0.6125) **	(0.0285)	(0.0094)	(0.0001) ***	(0.3202) **	(0.0165) **	(0.0097)
Coke, refined petroleum and nuclear fuel	-0.1471	-0.0091	-0.0526	0.0658	-0.8335	-0.0240	0.0050
	(1.0648)	(0.0195)	(0.0062) ***	(0.0146) ***	(0.2745) ***	(0.0085) ***	(0.0181)
Chemicals and chemical products	1.5429	0.1510	-0.0008	0.0229	1.2024	0.1722	-0.1248
	(0.2262) ***	(0.0207) ***	(0.0092)	(0.0078) ***	(0.2953) ***	(0.0178) ***	(0.0136) ***
Rubber and plastics	-0.8230	0.0839	0.0027	0.0011	-1.1749	0.1260	-0.0149
	(0.6449)	(0.0195) ***	(0.0099) ***	(0.0122) **	(0.4804) *	(0.0259) ***	(0.0275) *
Other non-metallic minerals	-1.5436	-0.0326	-0.0249	0.0550	0.4000	0.0138	0.0441
	(0.2738) ***	(0.0219)	(0.0074) ***	(0.0001) ***	(0.1644) **	(0.0109)	(0.0105) ***
Basic metals and fabricated metal	-0.3972	0.1629	-0.0188	0.0417	-0.1735	0.1723	-0.0581
	(0.1947) **	(0.0211) ***	(0.0074) ***	(0.0052) ***	(0.1242)	(0.0104) ***	(0.0063) ***
Machinery	-0.2171	0.1076	-0.0012	0.0054	0.4780	0.1012	0.0000
	(0.2187)	(0.0132) ***	(0.0025)	(0.0011) ***	(0.1223) ***	(0.0066) ***	(0.0014)
Electrical and optical equipment	-0.0358	0.0690	-0.0005	0.0070	-0.1320	0.0639	-0.0019
	(0.1468)	(0.0316)	(0.0045)	(0.0000) ***	(0.0443) ***	(0.0130) ***	(0.0017)
Transport equipment	-0.2724	0.1700	0.0134	0.0072	-0.5835	0.0574	0.0009
	(0.3201)	(0.0000) ***	(0.0065) **	(0.0031) **	(0.1525) ***	(0.0187) ***	(0.0032)
Other manufacturing	-1.2236	0.0358	-0.0082	0.0136	-0.1043	0.1448	0.0016
	(0.1927) ***	(0.0328)	(0.0076)	(0.0006) ***	(0.0295) ***	(0.0144) ***	(0.0057)

standard error in parenthesis, *, **, and *** represent 10%, 5%, and 1% of significance, respectively.

Table 4: Parameter estimates for TFP and factor bias: non-constant returns to scale

	α_t		α_{tt}		ρ_{tK}		ρ_{tL}		ρ_{tE}	
Food, beverages and tobacco	-0.0380		0.0000		-0.0037		-0.0005		0.0006	
	(-0.0025)	***	(0.0001)		(-0.0010)	***	(0.0009)		(-0.0001)	***
Textiles, leather and footwear	-0.0236		-0.0002		0.0048		-0.0028		0.0005	
	(-0.0053)	***	(-0.0001)	*	(-0.0016)	***	(-0.0011)	***	(-0.0001)	***
Wood and cork	-0.0287		0.0002		0.0022		-0.0038		0.0003	
	(-0.0070)	***	(-0.0001)	*	(0.0028)		(-0.0007)	***	(-0.0001)	*
Pulp and paper, printing	-0.0408		-0.0001		-0.0062		-0.0028		0.0003	
	(-0.0144)	***	(0.0001)		(0.0058)		(-0.0009)	***	(0.0004)	
Coke, refined petroleum and nuclear fuel	0.1636		-0.0020		-0.0067		-0.0009		0.0036	
	(-0.0434)	***	(0.0007)	***	(0.0073)		(0.0007)		(0.0011)	***
Chemicals and chemical products	0.0146		0.0006		0.0161		-0.0037		-0.0030	
	(0.0076)	**	(0.0002)	***	(0.0053)	***	(0.0009)	***	(0.0005)	***
Rubber and plastics	-0.0591		0.0001		-0.0237		-0.0023		0.0006	
	(0.0102)		(0.0002)	**	(0.0063)		(0.0006)	***	(0.0005)	
Other non-metallic minerals	-0.0179		-0.0001		0.0157		-0.0007		-0.0009	
	(0.0045)	***	(0.0001)		(0.0019)	***	(0.0006)		(0.0003)	***
Basic metals and fabricated metal	0.0104		0.0004		-0.0088		-0.0046		-0.0003	
	(0.0066)	*	(0.0001)	***	(0.0027)	***	(0.0007)	***	(0.0003)	
Machinery	-0.0305		0.0002		-0.0012		-0.0059		-0.0002	
	(0.0070)	***	(0.0001)	*	(0.0025)		(0.0003)	***	(0.0001)	***
Electrical and optical equipment	0.0159		0.0013		0.0027		-0.0083		-0.0004	
	(0.0127)		(0.0001)	***	(0.0026)		(0.0012)	***	(0.0002)	***
Transport equipment	0.0019		0.0003		0.0002		-0.0073		-0.0004	
	(0.0056)		(0.0002)	**	(0.0022)		(0.0006)	***	(0.0002)	**
Other manufacturing	-0.0539		0.0001		-0.0103		-0.0033		0.0011	
	(0.0053)	***	(0.0002)		(0.0021)	***	(0.0011)	***	(0.0003)	***

standard error in parenthesis*, **, and *** represent 10%, 5%, and 1% of significance, respectively.

Table 5: Selected parameter estimates: constant returns to scale

	α_Q	γ_{LL}	γ_{LE}	γ_{EE}	ρ_{KL}	ρ_{KE}	ρ_{QK}
Food, beverages and tobacco	1.7855	0.0859	-0.0036	0.0151	0.0658	0.0090	0.8386
	(0.1243) ***	(0.0100) ***	(0.0017) **	(0.0000) ***	(0.0058) ***	(0.0006) ***	(0.1582) ***
Textiles, leather and footwear	1.5012	-0.0390	-0.0060	0.0123	-0.0561	0.0030	0.2458
	(0.0785) ***	(0.0213) *	(0.0037) *	(0.0013) ***	(0.0118) ***	(0.0011) ***	(0.1347) *
Wood and cork	1.1515	0.1358	0.0060	0.0163	0.0125	0.0084	0.5162
	(0.2228) ***	(0.0185) ***	(0.0057)	(0.0025) ***	(0.0123)	(0.0025) ***	(0.4424)
Pulp and paper, printing	0.0481	-0.1672	0.0464	0.0212	-0.0966	0.0423	-1.2639
	(0.2789)	(0.0392) ***	(0.0181) **	(0.0107) **	(0.0124) ***	(0.0038) ***	(0.4518) ***
Coke, refined petroleum and nuclear fuel	3.3571	-0.0430	-0.0463	0.0393	-0.0272	-0.0080	3.7159
	(0.5714) ***	(0.0177) **	(0.0066) ***	(0.0095) ***	(0.0075) ***	(0.0124)	(0.7940) ***
Chemicals and chemical products	0.9078	0.1553	0.0367	-0.0117	0.1763	-0.1656	-4.2503
	(0.0889) ***	(0.0000) ***	(0.0072) ***	(0.0063) *	(0.0146) ***	(0.0130) ***	(0.7219) ***
Rubber and plastics	0.9011	0.0542	0.0297	0.0266	0.0974	-0.0479	-0.1035
	(0.1146) ***	(0.0174) ***	(0.0102) ***	(0.0082) ***	(0.0154) ***	(0.0169) ***	(0.0553) *
Other non-metallic minerals	0.6591	0.1429	0.0101	0.0513	-0.0381	0.0160	-1.2287
	(0.2074) ***	(0.0156) ***	(0.0059) *	(0.0001) ***	(0.0077) ***	(0.0041) ***	(0.3890) ***
Basic metals and fabricated metal	1.1697	0.1699	-0.0115	0.0372	0.0914	-0.0325	0.3441
	(0.0752) ***	(0.0000) ***	(0.0112)	(0.0040) ***	(0.0071) ***	(0.0034) ***	(0.1777) *
Machinery	-0.0441	0.1694	0.0205	0.0047	0.1205	0.0064	-1.7631
	(0.0976)	(0.0141) ***	(0.0018) ***	(0.0013) ***	(0.0057) ***	(0.0008) ***	(0.2056) ***
Electrical and optical equipment	1.1576	0.0766	0.0062	0.0061	0.0719	0.0008	-0.0281
	(0.0234) ***	(0.0218) ***	(0.0035) *	(0.0013) ***	(0.0106) ***	(0.0010)	(0.0127) **
Transport equipment	2.0841	0.1703	0.1035	0.0141	0.0339	0.0179	1.0262
	(0.1248) ***	(0.0000) ***	(0.0097) ***	(0.0030) ***	(0.0101) ***	(0.0031) ***	(0.1425) ***
Other manufacturing	1.0372	-0.0429	-0.0301	0.0132	0.1364	0.0188	0.4420
	(0.0730) ***	(0.0224) *	(0.0036) ***	(0.0004) ***	(0.0072) ***	(0.0030) ***	(0.0990) ***

standard error in parenthesis*, **, and *** represent 10%, 5%, and 1% of significance, respectively.

Table 6: Parameter estimates for TFP and factor bias: constant returns to scale

	α_t	α_{tt}	ρ_{tK}	ρ_{tL}	ρ_{tE}
Food, beverages and tobacco	0.0014	0.0001	0.0143	-0.0017	0.0003
	(0.0047)	(0.0002)	(0.0039) ***	(0.0005) ***	(0.0001) ***
Textiles, leather and footwear	0.0159	-0.0008	0.0247	-0.0016	0.0004
	(0.0046) ***	(0.0002) ***	(0.0029) ***	(0.0009) *	(0.0001) ***
Wood and cork	-0.0315	0.0011	-0.0176	-0.0037	-0.0002
	(0.0063) ***	(0.0003) ***	(0.0085) **	(0.0007) ***	(0.0002)
Pulp and paper, printing	-0.0178	0.0002	-0.0122	0.0041	-0.0013
	(0.0071) **	(0.0003)	(0.0061) **	(0.0012) ***	(0.0006) **
Coke, refined petroleum and nuclear fuel	0.0737	-0.0043	0.0465	-0.0004	0.0044
	(0.0222) ***	(0.0013) ***	(0.0186) **	(0.0006)	(0.0007) ***
Chemicals and chemical products	-0.0122	0.0011	0.0643	-0.0026	-0.0060
	(0.0031) ***	(0.0002) ***	(0.0113) ***	(0.0004) ***	(0.0004) ***
Rubber and plastics	-0.0490	0.0026	-0.0062	-0.0013	-0.0017
	(0.0066) ***	(0.0004) ***	(0.0061)	(0.0006) **	(0.0004) ***
Other non-metallic minerals	-0.0298	0.0019	0.0109	-0.0044	-0.0014
	(0.0063) ***	(0.0004) ***	(0.0041) ***	(0.0004) ***	(0.0002) ***
Basic metals and fabricated metal	-0.0331	0.0017	-0.0003	-0.0037	-0.0009
	(0.0036) ***	(0.0002) ***	(0.0030)	(0.0003) ***	(0.0003) ***
Machinery	0.0120	-0.0002	0.0217	-0.0061	-0.0004
	(0.0069) *	(0.0002)	(0.0057) ***	(0.0004) ***	(0.0001) ***
Electrical and optical equipment	-0.0231	0.0014	0.0178	-0.0084	-0.0004
	(0.0019) ***	(0.0001) ***	(0.0012) ***	(0.0008) ***	(0.0001) ***
Transport equipment	-0.0040	0.0007	0.0224	-0.0053	-0.0020
	(0.0044)	(0.0002) ***	(0.0036) ***	(0.0004) ***	(0.0002) ***
Other manufacturing	-0.0371	0.0014	-0.0141	-0.0008	0.0020
	(0.0043) ***	(0.0002) ***	(0.0028) ***	(0.0009)	(0.0002) ***

standard error in parenthesis*, **, and *** represent 10%, 5%, and 1% of significance, respectively.

Table 7: Own price and capital elasticities of E and L: non-constant returns to scale

	ε_{EE}	ε_{LL}	ε_{EK}	ε_{LK}	ρ
Food, beverages and tobacco	-0.2595	-0.4773	0.8845	0.3742	1.0165
Textiles, leather and footwear	-0.0791	-0.6458	0.1587	-0.0010	1.0126
Wood and cork	-0.1494	-0.1316	0.0489	0.2075	0.8908
Pulp and paper, printing	-0.1339	-0.6706	-0.1159	0.1824	0.9614
Coke, refined petroleum and nuclear fuel	-0.1092	-1.1677	0.2276	-0.3925	0.8844
Chemicals and chemical products	-0.5682	-0.0404	-1.9717	0.7897	1.0518
Rubber and plastics	-0.4759	-0.4773	-0.2467	0.6514	0.7445
Other non-metallic minerals	-0.0160	-0.7898	0.5935	-0.0936	1.1096
Basic metals and fabricated metal	-0.0742	-0.1115	-1.1123	0.7391	0.9279
Machinery	-0.4165	-0.3362	-0.0240	0.3023	1.0028
Electrical and optical equipment	-0.0810	-0.4551	-0.1248	0.3502	0.8846
Transport equipment	-0.2061	-0.0220	0.1149	0.2678	1.0052
Other manufacturing	-0.0397	-0.6047	0.0783	0.3875	1.0005

Table 8: Own price and capital elasticities of E and L: constant returns to scale

	ε_{EE}	ε_{LL}	ε_{EK}	ε_{LK}
Food, beverages and tobacco	-0.0766	-0.3066	0.5721	0.4304
Textiles, leather and footwear	-0.1292	-0.8412	0.1972	-0.2049
Wood and cork	-0.1035	-0.1998	0.5357	-0.0466
Pulp and paper, printing	-0.2587	-1.3081	1.5026	-0.2380
Coke, refined petroleum and nuclear fuel	-0.1422	-2.0352	-0.0056	-0.6921
Chemicals and chemical products	-1.0836	-0.0191	-2.7513	0.6553
Rubber and plastics	-0.1107	-0.5175	-1.5797	0.2704
Other non-metallic minerals	-0.0772	-0.2258	0.3545	-0.0330
Basic metals and fabricated metal	-0.1676	-0.0853	-0.6477	0.3698
Machinery	-0.4928	-0.1390	0.5788	0.2823
Electrical and optical equipment	-0.2030	-0.4283	0.1732	0.3288
Transport equipment	-0.0906	-0.0208	1.9192	0.1459
Other manufacturing	-0.0702	-0.7703	1.3564	0.4615

Table 9: Short and long-run own price elasticities of E

	non-constant rs ε_{EE}	non-constant rs η_{EE}	constant rs ε_{EE}	constant rs η_{EE}
Food, beverages and tobacco	-0.2595	0.1276	-0.0766	0.0503
Textiles, leather and footwear	-0.0791	-0.0801	-0.1292	-0.1309
Wood and cork	-0.1494	-0.1494	-0.1035	-0.1036
Pulp and paper, printing	-0.1339	-0.1347	-0.2587	-0.2437
Coke, refined petroleum and nuclear fuel	-0.1092	-0.1078	-0.1422	-0.1422
Chemicals and chemical products	-0.5682	-0.7728	-1.0836	-1.3512
Rubber and plastics	-0.4759	-0.9150	-0.1107	-0.0920
Other non-metallic minerals	-0.0160	-0.0815	-0.0772	-0.1400
Basic metals and fabricated metal	-0.0742	0.2981	-0.1676	-0.0022
Machinery	-0.4165	-0.4165	-0.4928	-0.4928
Electrical and optical equipment	-0.0810	-0.0792	-0.2030	-0.2055
Transport equipment	-0.2061	-0.2059	-0.0906	0.5446
Other manufacturing	-0.0397	-0.0364	-0.0702	-0.0613

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