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Capital-Energy Relationships: An Analysis of Three Panel Data Estimation Methods

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Abstract

Policies that aim to reduce energy consumption in the industrial sector require knowledge of the elasticity of substitution (*EoS*) of capital-energy. In this paper, *first*, we extend Thomsen's (2000) methodology in the context of a Generalized Leontief (*GL*) to link short and long run in a panel data setting. This allows us to estimate short and long run elasticities of capital-energy. Furthermore, we disaggregate by industry, different kinds of capital and we control for technological change. We also propose a new method to estimate a system of input-output equations jointly with a dynamic equation for the capital motion by using a Generalized Method of Moments System (*GMM-SYS*) in two steps for short run elasticities; while long run elasticities are estimated by the Iterated Seemingly Unrelated Regression (*ISUR*) method. *Second*, we estimate an Error Correction Model (*ECM*) using a four factor specification and investment in R&D for Energy Efficiency to distinguish short from long run elasticities by applying *GMM-SYS* in one step. *Finally*, we estimate a system of equations jointly with a Translog Cost Function (*TCF*) by applying the *ISUR* method to compare the *EoS* with those obtained by the previous two methods.
Our results show clear evidence of complementarity when using the *TCF* while weak substitutability is found with the *GL*. Regarding the *ECM*, it is found that reductions in investment in machinery prompt bigger increases in energy consumption than reductions in investment in buildings. Therefore we argue that a policy of increasing energy prices via taxes to reduce energy consumption will seriously affect investment and it is especially harmful for the industries of basic metals, chemical, transport equipment and machinery, i.e., those showing stronger dependence between energy and capital. We recommend that a better policy is to encourage technological diffusion.

JEL-codes: C33, C51, C52, Q41, Q43. *Keywords:* Capital-Energy Relationships; Dynamic Panel Data Methods; Rebound Effect; Substitutability and Complementarity; Flexible Forms.

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Introduction

According to Saunders (2000), the design of policies that aim to reduce energy consumption in the industrial sector via taxes requires to know the Elasticity of Substitution (*EoS*) between capital and energy. If it is negative, then policies must encourage technological diffusion. However, if the elasticity is positive, taxes could then be used to reduce energy consumption. Berndt and Wood (1975) provided the first estimation of *EoS* between capital and energy and since then, the controversy about the nature of its relationship still continues.

Berndt and Wood (1975) found that energy price shocks will prompt reduction in the investment of capital**.** On the contrary, Griffin and Gregory (1976) found that changes in energy prices will encourage investment in capital to reduce energy consumption. These results were found for the United States economy. The former estimation used aggregate data and a four factor model whereas the later one used an international panel data and three factors[4]. Berndt and Wood (1979) argued that the omission of intermediate materials in Griffin and Gregory's (1976) model prompt a biased estimation and therefore, they concluded substitutability. In the early literature, the discussion was originated by the different conclusions based on the Translog Cost Function (*TCF*). Later on, Apostolakis (1990) argued that substitutability associated with long run adjustments in capital-energy (*K-E*) was related to the use of panel data settings. On the other hand, complementarity was related to the use of time series settings.

More recently, Frondel and Schmidt (2002) pointed out that in fact none of these arguments were important. They found that, under certain circumstances, the elasticities obtained by the *TCF* ended up being close to the ratio of factor costs and total cost, and therefore, the *TCF* cannot provide reliable estimates.

Two alternative approaches are the Generalized Leontief Cost Function (*GL*) and the Error Correction Model (*ECM*). Thomsen (2000) analyzed the former specification, and he suggested a two-step procedure to estimate Cross Price Elasticities ($CPEs$). In the first step, a function of capital prices is obtained by applying Shephard's lemma to a long run cost function. In the second step, the previous results are used to estimate the short run demand of factors. This approach is contrary to the one proposed by Morrison (1993), who obtains in the first step the short run demand functions based on a short run cost (*SRC*) function. According to Thomsen (2000), Morrison's approach is not only a more complicated procedure but also the SRC proposed by Morrison was found to be unrealistic.

After thirty years of studying *EoS* issues, researchers have learned that substitutability is a relative concept that depends on the country[5], industry and the kind of capital[6] that is analyzed. Furthermore, Popp (1997) argues that using a time trend, as a regular practice in the previous estimations, cannot capture technological changes particularly for energy efficiency and therefore, a trend just captures the general impact of technological changes on energy consumption. That is why one of the main challenges to improve on Thomsen's (2000) methodology is to control for the previous factors by using a panel data setting where we can disaggregate by industry and by kind of capital and also controlling at the same time for technological change. Hence, this is the first objective that we address in this paper.

Regarding the *ECM*, Apergis and Payne (2009) have analyzed the relationship between energy and economic growth by following a time series approach in a panel data context. However, to the best of our knowledge, there are still no estimation and testing results of short and long run elasticities of capital-energy by using an *ECM* in a panel data context where we can disaggregate by industry and different kinds of capital, and this is the second novel contribution of this paper.

Along these lines, *first,* we extend the Thomsen's (2000) methodology to link the short and long run in a panel data setting. In order to do so, we also propose a new method to estimate a system of input - output equations jointly with a dynamic equation for the motion of capital by using a General Method of Moments System (*GMM-SYS*) for the short run elasticities; whereas long run elasticities are estimated by using the Iterated Seemingly Unrelated Regression (*ISUR*) method. Since we are dealing with a dynamic panel, the dynamics in the *GMM-SYS* are introduced following Arellano and Bond (1991). Furthermore, we control for technological change using Investment in Research and Development for Energy Efficiency (denoted as $IR\&DEF$ from now onwards). In order to compare the results with Thomsen's methodology in the panel data context, *second,* we also estimate an *ECM* based on a Cobb-Douglas production function with four factors and $IR\&DEF$ to estimate the *Technical Elasticity of Substitution (TES)* proposed by Frondel (2004) . The estimation method involves applying the *GMM-SYS* in one step. *Finally* we estimate a *TCF* for three and four factors to investigate if we find evidence of the arguments in the

[4]Two of the most widely used specifications are the $KLEM$ and KLE models, where capital letters stand for capital (K), labour (L), energy (E) and intermediate materials (M).

[5]See Pindyck (1979).

[6]See Field (1980) and Morrison (1993).

literature (see e.g. Berndt and Wood (1979), Apostolakis (1990) and Frondel and Schmidt (2002)) about the effect of omitted variable bias and the panel data setting in the estimates when we disaggregate by industry and by kind of capital, and also for comparison purposes with the previous two methods.

The structure of this paper is as follows**.** Section 2 describes the three models and the methodologies that are used. Section 3 presents the dataset, the empirical results and evidence is shown that the industries of basic metals, chemical, transport equipment and machinery are the ones that show stronger dependence between energy and capital. Finally, Section 4 concludes. Appendix A contains the $CPEs$ for capital and energy, and Appendix B collects secondary results such as own price elasticities.

The models and methodology

In this paper two flexible forms (the *TCF* and the *GL*) and an *ECM* are used to estimate the relationship between capital and energy. Regarding the flexible forms, Diewert (1974) argued that a cost function is flexible if the level of cost and its first and second derivatives are homogeneous of degree one in prices. Flexible forms are considered as an approximation to a general cost function. They are the result of solving the classic microeconomics problem that firms face. That is, the cost function is given as $C(p,y,\tilde{t}) \equiv \min_i\{p'i : f(i), i \gg 0\}$, where p is the vector of N input prices with $p \equiv (p_1, p_2, \ldots, p_N)' \gg 0$, i is the demand of inputs, $f(\bullet)$ is a production function and $\tilde{t}$ denotes the technological level which, later in the empirical section, will be captured by the variable $IR \,\&\, DEF$. Finally, y corresponds to the output in a certain period of time. It is important to mention that the cost function $C(p,y,\tilde{t})$ is assumed to be homogeneous of degree 1 and concave in input prices. For simplicity in terms of notation, we write $C(p,y,\tilde{t}) = C$ from now onwards.

The translog cost function (TCF)

The first flexible form to be analyzed is the *TCF* which takes the following shape

$$\ln C \equiv \beta_0 + \sum_{i=1}^{N} \beta_i \ln p_i + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \beta_{ij} \ln p_i \ln p_j + \beta_{\tilde{t}}\tilde{t} + \frac{1}{2}\beta_{\tilde{t}\tilde{t}}\tilde{t}^2 + \beta_y \ln y$$
$$+ \frac{1}{2}\beta_{yy}(\ln y)^2 \sum_{i=1}^{N} \beta_{iy} \ln p_i \ln y + \sum_{i=1}^{N} \beta_{i\tilde{t}}\tilde{t} \ln p_i + \beta_{y\tilde{t}}\tilde{t}\ln y, \qquad \text{eq(1)}$$

where subscripts i and j stand for factors $1,..,N$. Moreover, symmetry and homogeneity of degree 1 in prices are imposed as follows

$$\beta_{ij} = \beta_{ji}, \sum_{i=1}^{N} \beta_i = 1, \sum_{i=1}^{N} \beta_{ij} = \sum_{i=1}^{N} \beta_{iy} = \sum_{i=1}^{N} \beta_{i\tilde{t}} = 0. \qquad \text{eq(2)}$$

Notice that it is assumed that the function is non homothetic, that is, $\beta_{iy} \neq 0$. This implies that the cost shares associated to this function will depend on the level of economic activity. Furthermore, $\beta_{i\tilde{t}} \neq 0$ implies that technology will affect each factor differently, and therefore non neutral technical change is assumed (see Barker (1995)).

Regarding concavity, if the cost function is concave in prices then its Hessian matrix has to be negative definite. However checking the curvature of the Hessian matrix is equivalent to checking the curvature of the matrix of Allen -- Uzawa, which is a matrix of the own and cross price elasticities. The *TCF* will be a second order Taylor expansion of a concave cost function if the matrix is itself definite negative. This can be tested by obtaining non-positive eigenvalues for the Hessian matrix. On the other hand assuming symmetry in the substitution coefficients (i.e. $\beta_{ij} = \beta_{ji}$) implies to assume Slutsky symmetry. According to Mass-Collel (1995), the Slutsky symmetry applies to the matrix of derivatives of the optimal demand of factors with respect to input prices, called substitution matrix, which is assumed to be negative semidefinite and symmetric. Regarding the system of share cost s_i of factor i , by applying Shephard's lemma to the *TCF* , the following system is generated

$$s_i = \frac{\partial \ln C}{\partial \ln p_i} = \frac{\partial C}{\partial p_i}\frac{p_i}{C} = \frac{p_i i}{C} = \beta_i + \sum_{j=1}^{N} \beta_{ij} \ln p_j + \beta_{iy} \ln y + \beta_{i\tilde{t}}\tilde{t}.$$

eq(3)

Monotonicity is another theoretical requirement and in order to hold, each share cost equation s_i must be positive at each point in time.

We now move to a panel data setting where in (eq1), we allow for H industries, and following Ma et al (2008), the following restrictions must hold

$$\beta_0 = \sum_{h=1}^{H} \beta_{0_h}, \beta_i = \sum_{h=1}^{H} \beta_{i_h}, \beta_{\tilde{t}} = \sum_{h=1}^{H} \beta_{\tilde{t}_h}, \beta_{\tilde{t}\tilde{t}} = \sum_{h=1}^{H} \beta_{\tilde{t}\tilde{t}_h}, \beta_y = \sum_{h=1}^{H} \beta_{y_h},$$

$$\beta_{yy} = \sum_{h=1}^{H} \beta_{yy_h}, \beta_{iy} = \sum_{h=1}^{H} \beta_{iy_h}, \beta_{i\tilde{t}} = \sum_{h=1}^{H} \beta_{i\tilde{t}_h}, \beta_{y\tilde{t}} = \sum_{h=1}^{H} \beta_{y\tilde{t}_h}.$$

eq(4)

where subscript $h = 1,...H$ stands for the H analyzed industries. As an example, β_{0_h} denotes the intercept in equation (eq1) for industry h. Moreover, according to Fuss (1977), the estimation method is a two-step optimization procedure, one where firms choose the optimal combination of fuels and another where they choose their optimal combination of factors; and this process is equivalent to optimizing in only one step. If weak separability[7] is assumed in energy, and energy is one of our factors and it is the object of interest, we define p_E as an index of energy price which can be estimated by the next translog function

$$\ln p_E \equiv \gamma_0 + \sum_{f=1}^{F} \gamma_f \ln p_f + \frac{1}{2}\sum_{f=1}^{F}\sum_{g=1}^{F} \gamma_{fg} \ln p_f \ln p_g + \sum_{f=1}^{F} \gamma_{f\tilde{t}} \ln p_f \tilde{t},$$

eq(5)

where $\ln p_E$ is the logarithm of the energy index that is substituted out to estimate the *TCF* given by (eq1) in the second step. Subscripts f and g stand for F fuels and $\tilde{t}$ is technological change, that we will capture by the IR & DEF for the industrial sector in the empirical application. Similarly to equation (eq1), it is assumed that

$$\sum_{f=1}^{F} \gamma_f = 1, \sum_{f=1}^{F} \gamma_{fg} = \sum_{f=1}^{F} \gamma_{f\tilde{t}} = 0, \gamma_{fg} = \gamma_{gf}.$$

eq(6)

Moreover, in the panel data setting we require that[8]

$$\gamma_0 = \sum_{h=1}^{H} \gamma_{0_h}, \gamma_{f\tilde{t}} = \sum_{h=1}^{H} \gamma_{f\tilde{t}_h} \text{ and } \gamma_f = \sum_{h=1}^{H} \gamma_{f_h},$$

eq(7)

where subscript h stands for each of the H industries. By applying Shephard's lemma to equation (eq5), the system of share cost $s_{f_{ht}}$ can be obtained for fuel f and industry h at time t

$$s_{f_{ht}} = \gamma_{f_h} + \sum_{g=1}^{F} \gamma_{fg} \ln p_{g_t} + \gamma_{f\tilde{t}_h}\tilde{t}_t,$$

eq(8)

[7]If a production function is weakly separable the marginal rate of technical substitution ($MRTS$) between a subset, say among the fuels that are used, is independent of the $MRTS$ among factors, see Berndt and Christensen (1973).

[8] Following Pindyck (1977), the parameter γ_{0_h} can be estimated by assuming that $\ln p_E$ is equal to 1 in a base year. That is, in our case, finding the value of γ_{0_h} that makes $e^{\ln p_E} = p_E = 1$ in the year 2000 where e is the base of the natural logarithm. Moreover, all the factor prices related to K_1, K_2, L and M have the same base year.

where p_{g_t} denotes the price of fuel g at time t and $\tilde{t}_t$ is the technological level at time t. Following Berndt (1991), one can introduce additive disturbances in the system of equations (eq8) that could be interpreted as random mistakes of firms in choosing their optimal quantities of inputs. Therefore we can add a term $U_{f_{ht}}$ that is assumed to be multivariate with mean zero and a constant covariance matrix.

The share cost $s_{f_{ht}}$ must add to unity and therefore H equations from the system of share cost (eq8) are a linear combination of the other $H(N-1)$ equations. Consequently, the covariance matrix is singular and non diagonal. An alternative to solve this problem is to estimate (eq8) equation by equation applying Ordinary Least Squares (*OLS*). However, symmetry in the parameters cannot be guaranteed. To estimate the system jointly, Berndt (1991) suggests dropping one equation from the system (eq8). The parameters of the dropped equation can be obtained by using the restrictions of homogeneity. Nevertheless, it raises a natural question about which equation should be dropped and consequently, the result will be dependent on the chosen equation. This drawback can be avoided by applying Maximum Likelihood (*ML*) methods. Nevertheless, *ML* is a complicated method to implement and besides one has to impose normality on the disturbances. Another alternative method is Three Stage Least Squares (*3SLS*) which does not have the aforementioned disadvantages. Moreover, according to Berndt (1991), if one iterates, the lack of invariance due to the dropped equation can be eliminated and the result will be numerically equivalent to the *ML* estimation. Furthermore, following Fuss (1975), fuel prices in the system (eq5) are assumed to be exogenous and consequently *3SLS* will be equivalent to the Iterated Zellner- efficient estimator (*IZEF*)[9]. This method is also known as the Iterated Seemingly Unrelated Regression (*ISUR*) method that assumes the following stochastic structure for factors f and g for industry h at any times t and r

$$E(U_{f_{ht}})=0,\ E(U_{f_{ht}}U_{g_{hr}})=\sigma_{fg} \text{ for } t=r. \qquad \text{eq(9)}$$

Hence, once the disturbances as in (eq9) are added to the system of equations (eq8), it can be estimated by the $ISUR$ method and then an energy index can be obtained as in equation (eq5). In our estimation, there is an energy index for each H industry at time t. On the other hand, a similar disturbance structure as in (eq9) is added to the system of cost share (eq3). The system of equations (eq3) along with the TCF are estimated by *IZEF* method. The β_{ij} coefficients are then used to estimate the $CPEs$ for industry h , which are computed as follows

$$\eta_{i_h p_{j_h}} = \frac{\partial \ln i_h}{\partial \ln p_{j_h}} = \frac{\partial \ln}{\partial \ln p_{j_h}}\left(\frac{\partial C}{\partial p_{i_h}}\right) = \frac{\partial \ln s_{i_h}}{\partial \ln p_{j_h}} + \frac{\partial \ln C}{\partial \ln p_{j_h}} - \frac{\partial \ln p_{i_h}}{\partial \ln p_{j_h}} = \frac{\beta_{ij}}{s_{i_h}} + s_{j_h}. \qquad \text{eq(10)}$$

Expression (eq10) uses the fact that $\frac{\partial C}{\partial p_{i_h}} = s_{i_h}\frac{C}{p_{i_h}}$ and it assumes that $\frac{\partial \ln p_{i_h}}{\partial \ln p_{j_h}} = 0$. We also apply the Iterated Seemingly Unrelated Regression[10] (*ISUR*) method as the estimation procedure in the application section. Therefore, $\eta_{i_h p_{j_h}}$ corresponds to the $CPEs$ for input i and price p_j of input j for industry h (i.e. $\eta_{i_h p_{j_h}}$) . The same procedure can be applied to obtain the own price elasticities. However, in this case we will have $\frac{\partial \ln p_{i_h}}{\partial \ln p_{i_h}} = 1$ and therefore

$$\eta_{i_h p_{i_h}} = \frac{\beta_{ii}}{s_{i_h}} + s_{i_h} - 1. \qquad \text{eq(11)}$$

The Generalized Leontief (GL) cost function and the $GMM-SYS$ estimation procedure

The second flexible form used in this paper is the *GL* cost function where, as in the case of the *TCF*, symmetry, monotonicity and homogeneity in prices have to hold. Thomsen (2000) estimated the *GL*, and he established a link between short and long run through a price function for the quasi -flexible factors. He also suggested a two-step procedure to estimate Cross Price Elasticities ($CPEs$). In the first step, a function of capital prices is obtained by applying Shephard's lemma to a long run cost function. In the second step, the previous results are used to estimate the short run demand of factors. Thomsen (2000) also estimated indices of energy efficiency based on a *TCF* and a

[9]Note that when obtaining the *3SLS* estimates in the first step of the instrumental variable method, we may have endogenous variables that could be on the right hand side of the system (eq3). Nevertheless, in this case it is assumed that all variables on the right hand side are exogenous and therefore the second and third steps in *3SLS* are the same than those followed in the *IZEF* method.

[10]See e.g. Greene (2008).

time trend.
We proceed now to enumerate the main novelties that we introduce to extend Thomsen (2000) estimation procedure. First, we propose a new method to estimate a system of input - output equations jointly with a dynamic equation for the motion of capital by using a General Method of Moments System (*GMM-SYS*) in two steps for the short run elasticities; whereas the long run elasticities are estimated by the Iterated Seemingly Unrelated Regression (*ISUR*) method.
The *GMM-SYS* estimation method proceeds as follows. The second main novelty that we introduce in contrast to Thomsen (2000) is that in the estimation of the *GL* , we will include the term $\tau_{\tilde{t}\tilde{t}}$ to control for technological change using IR & DEF (note that Thomsen (2000) simply included a time trend in an auxiliary TCF)

$$C = y\left[\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_{ij}(p_i p_j)^{0.5} \right] + \tau_{\tilde{t}\tilde{t}} \sum_{i=1}^{N} (p_{i\tilde{t}})\tilde{t}y, \qquad \text{eq(12)}$$

where all the variables are defined as in the *TCF*, p_i is the price of factor i, $\tilde{t}$ is technological progress and y is output. Additionally, symmetry is assumed and therefore $\alpha_{ij} = \alpha_{ji}$. According to Diewert et al (1984), the coefficients α_{ij} of this expression are just enough to guaranty flexibility. In this estimation we assume that the cost function is linear in output. We introduce the heterogeneity, following Addison et al (2005), by the following restriction across H industries

$$\tau_{\tilde{t}\tilde{t}} = \sum_{h=1}^{H} \tau_{\tilde{t}\tilde{t}_h}. \qquad \text{eq(13)}$$

As in the TCF estimation, applying Shepherd's lemma, one can obtain the following system of long run demand functions for industry h and factor i at time t

$$\frac{i_{ht}}{y_{ht}} = a_{i_{ht}} = \sum_{j=1}^{N} \alpha_{ij}(p_{j_{ht}}/p_{i_{ht}})^{0.5} + \tau_{\tilde{t}\tilde{t}_h}. \qquad \text{eq(14)}$$

Following Berndt (1991), the system of input-output equations can be estimated by *Ordinary Least Squares* (OLS) *- equation by equation*; although, symmetry in the coefficients is difficult to be guaranteed. Moreover, in this case, there is no need to drop any equation due to the singularity of the covariance matrix as in the *TCF* (as it happens in Berndt (1991)) and efficiency can only reached by using *ML*. An alternative estimation method is *ISUR* which does not impose normality in the residuals as the *ML* method. The system of equations (eq14) can stacked and represented as

$$Y_{i_{ht}} = X_{i_{ht}}\alpha + D_{ht}\eta + \epsilon_{i_{ht}}, \qquad \text{eq(15)}$$

Where $Y_{i_{ht}} = (a_{1_{11}}, .a_{i_{ht}}, ..., a_{N_{HT}})'$ is a vector of dimension $HNT \times 1, X_{i_{ht}}$ is a matrix of dimension $HNT \times (1/2)N(N+1),$ where T stands for time. The following matrix is arranged to guarantee symmetry as follows

$$X_{i_{ht}} = \begin{bmatrix} \begin{matrix} (\frac{p_{2_{11}}}{p_{1_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{2_{HT}}}{p_{1_{HT}}})^{0.5} \end{matrix} & \cdots & \begin{matrix} (\frac{p_{N_{11}}}{p_{1_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{N_{HT}}}{p_{1_{HT}}})^{0.5} \end{matrix} & 0 & 0 & 0 & \cdots \\ \begin{matrix} (\frac{p_{1_{11}}}{p_{2_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{1_{HT}}}{p_{2_{HT}}})^{0.5} \end{matrix} & \cdots & \cdots & \begin{matrix} (\frac{p_{N_{11}}}{p_{2_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{N_{HT}}}{p_{2_{HT}}})^{0.5} \end{matrix} & 0 & 0 & \cdots \\ 0 & \cdots & \cdots & \cdots & \begin{matrix} (\frac{p_{N_{11}}}{p_{3_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{N_{HT}}}{p_{3_{HT}}})^{0.5} \end{matrix} & 0 & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \begin{matrix} (\frac{p_{N_{11}}}{p_{(N-1)_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{N_{HT}}}{p_{(N-1)_{HT}}})^{0.5} \end{matrix} \\ 0 & \cdots & \begin{matrix} (\frac{p_{1_{11}}}{p_{N_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{1_{HT}}}{p_{N_{HT}}})^{0.5} \end{matrix} & \begin{matrix} (\frac{p_{2_{11}}}{p_{N_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{2_{HT}}}{p_{N_{HT}}})^{0.5} \end{matrix} & \begin{matrix} (\frac{p_{3_{11}}}{p_{N_{HT}}})^{0.5} \\ \vdots \\ (\frac{p_{3_{HT}}}{p_{N_{HT}}})^{0.5} \end{matrix} & \cdots & \begin{matrix} (\frac{p_{(N-1)_{11}}}{p_{N_{11}}})^{0.5} \\ \vdots \\ (\frac{p_{(N-1)_{HT}}}{p_{N_{HT}}})^{0.5} \end{matrix} \end{bmatrix},$$

η and α are the vectors that contain the coefficients $\tau_{\tilde{t}\tilde{t}_h}$ and α_{ij}, where η is of dimension $H \times 1$ and α is $(1/2)N(N+1) \times 1$. The matrix D_{ht} contains the variable $\tilde{t}_{ht}$ (i.e. the $IR\ \&\ DEF$ variable per industry) and its dimension is $HNT \times H$. The stochastic term, $\epsilon_{i_{ht}}$, has the same characterization as in (eq9) with dimension $HNT \times 1$.

Regarding the $CPEs$, they can be obtained by using the following expression

$$\eta_{i_h p_{j_h}} = \frac{\partial i_h}{\partial p_{i_h}} \frac{p_{j_h}}{C} = \frac{1}{2} \frac{\alpha_{ij} (p_{i_h} / p_{j_h})^{-0.5}}{a_{i_h}}, \qquad \text{eq(16)}$$

whereas the own price elasticities can be computed as[11]

$$\frac{-1/2 \sum_{j=1,\, j \neq i} \alpha_{ij} (p_{i_h} / p_{j_h})^{-0.5}}{a_{i_h}}. \qquad \text{eq(17)}$$

Following Thomsen (2000), the link between the long run and the short run is given by the demand function of

[11] We set $p_{i_h} = T^{-1} \sum_{t=1}^{T} p_{i_{ht}}$ and a_{i_h} is the value of $a_{i_{ht}}$ evaluated at the average of input prices.

capital obtained in the previous section. The intuition of this link is that the price of the demand function of the long run value of capital, K^* can artificially be changed until it reaches its short run level. For instance if factor 2 is quasi-fixed (i.e. in the short run, firms cannot choose optimally the amount of capital to be used in the productive process), the link between long and short run through factor 2 for industry h is then established as the following equation shows

$$\tilde{p}_{2_{ht}} = \left(\frac{\alpha_{12}(p_{1_{ht}})^{0.5} + \alpha_{23}(p_{3_{ht}})^{0.5} + \alpha_{24}(p_{4_{ht}})^{0.5} + \ldots + \alpha_{2N}(p_{N_{ht}})^{0.5}}{\frac{2_{ht}}{y_{ht}} - (\alpha_{22} + \tau_{\tilde{t}t_h})} \right)^2 . \qquad \text{eq(18)}$$

Notice that this function is estimated by using the coefficients obtained in (eq15). Once expression (eq18) is introduced in the flexible input-output equations (i.e. the ones for the N inputs), the short run demand function can be estimated. However, there is still one very important issue that we did not mention yet, and it is that in the case of energy, its adjustment in the short run depends on the investment in capital which will be adjusted fully only in the long run. Therefore this stickiness implies a dynamic adjustment cost. Furthermore, changes in the capital stock implies also adjustment costs. According to Nickell (1985), firms will try to minimize the distance between the long run target and its variation in the short run at certain period of time t. This fact can be summarized by the next optimization problem

$$\min_{\check{K}_{\bar{k}_{h(t+s)}}} Q = \sum_{s=0}^{\infty} \varphi^s \lambda_1 (\check{K}_{\bar{k}_{h(t+s)}} - \check{K}^*_{\bar{k}_{h(t+s)}})^2 + (\check{K}_{\bar{k}_{h(t+s)}} - \check{K}_{\bar{k}_{h(t+s-1)}})^2$$
$$- 2\lambda_2 (\check{K}_{\bar{k}_{h(t+s)}} - \check{K}_{\bar{k}_{h(t+s-1)}})(\check{K}^*_{\bar{k}_{h(t+s)}} - \check{K}^*_{\bar{k}_{h(t+s-1)}}), \qquad \text{eq(19)}$$

where φ is a discount factor $(0 < \varphi < 1)$ and $\lambda_1, \lambda_2 > 0$.
$\check{K}_{\bar{k}_{ht}} = \left(K_{1_{11}}, \ldots, K_{\bar{k}_{ht}}, \ldots, K_{\bar{k}_{HT}}\right)'$ and $\check{K}^*_{\bar{k}_{ht}} = (K^*_{1_{11}}, \ldots, K^*_{\bar{k}_{ht}}, \ldots, K^*_{\bar{k}_{HT}})'$ denote the short and long run values of the $\bar{k}$ different types of capital that we may include as factors. We allow for introducing $\bar{k}$ different kinds of capital and for example $K_{\bar{k}_{ht}}$ denotes the $\bar{k}-th$ type of capital for industry h at time t. Hence $\check{K}_{\bar{k}_{ht+s}}$ and $\check{K}^*_{\bar{k}_{ht+s}}$ are the value of vectors at time $t+s$. Nickell (1985) shows that when firms minimize the previous quadratic loss function Q, the first order condition is a difference equation and it can be written as an error correction equation[12]

$$\Delta \check{K}_{\bar{k}_{ht}} = \psi \Delta \check{K}^*_{\bar{k}_{ht}} + \phi(\check{K}^*_{\bar{k}_{ht-1}} - \check{K}_{\bar{k}_{ht-1}}), \qquad \text{eq(20)}$$

where $\psi = (1 - \mu_1(1 - \lambda_2))$, $\phi = 1 - \mu_1$ and μ_1 is assumed to be the stable root of the difference equation , ϕ is the speed of adjustment coefficient and Δ denotes the first difference operator. In this setting, the motion of capital is estimated by dividing equation (eq20) by the output per industry. Thomsen (2000) estimated the system of short run input-output equations along with the equation of the capital motion by using non linear- *ML* . However, as he pointed out, due to the inclusion of the lagged dependent variable in equation (eq20), the residuals of the jointly estimation can be autocorrelated. Since in our case (and contrary to Thomsen (2000)) we deal with a panel data setting, the application of *ML* to deal with the dynamics of the model is very complicated. A natural alternative is to use the method proposed by Arellano and Bond (1991) and Blundell and Bond (1998), for dynamic panel data. Therefore, since we are dealing with a dynamic panel, we introduce the dynamics in the *GMM-SYS* as in Arellano and Bond (1991). However, this method was developed originally for micro panels while since our setting in our application is a macro panel, therefore it is easy for the number of instruments to overtake the number of groups prompting singularity in the matrix of covariances. In this paper, the following method is proposed to estimate the system of input-output equations and the motion of capital jointly by using the previous method with the next specifications that allows to treat autocorrelation in the residuals prompted by the inclusion of a lagged dependent

[12] Note that equation (eq20) follows Thomsen's (2000) specification, where the stochastic process that generates $\check{K}^*_{\bar{k}_{ht}}$ follows a random walk without drift.

variable $\check{K}_{\bar{k}_{ht-1}}$. The proposed procedure to estimate the short run elasticities by using the *GMM-SYS* is as follows. Let us define the following vectors

$$\tilde{S}_{i_{ht}} = (a_{1_{11}},..,a_{i_{ht}},..,a_{N_{HT}},\frac{\Delta K_{1_{11}}}{y_{11}},..,\frac{\Delta K_{1_{ht}}}{y_{ht}},...,\frac{\Delta K_{\bar{k}_{HT}}}{y_{HT}})',$$

$$\frac{\hat{K}^*_{\bar{k}_{ht}}}{y_{ht}} = (0,0,0,...,\frac{K^*_{1_{11}}}{y_{11}},...,\frac{K^*_{1_{ht}}}{y_{ht}},...,\frac{K^*_{\bar{k}_{HT}}}{y_{HT}})',$$

$$\frac{\hat{K}_{\bar{k}_{h(t-1)}}}{y_{ht}} = (0,0,0,..,\frac{K_{1_{10}}}{y_{11}},...,\frac{K_{1_{1(t-1)}}}{y_{ht}},...,\frac{K_{\bar{k}_{H(T-1)}}}{y_{HT}})'.$$

$\tilde{S}_{i_{ht}}$ is a modified version of $Y_{i_{ht}}$ in equation (eq15) to include the motion equation of capital embedded in equation (eq20), and therefore its dimension is $(NT+\bar{k}HT)\times 1$, where $(\bar{k}HT)\times 1$ is the dimension of the vector $\frac{\Delta\check{K}_{\bar{k}_{ht}}}{y_{ht}}$. Furthermore, vectors $\frac{\check{K}^*_{\bar{k}_{ht}}}{y_{ht}}$, $\frac{\check{K}_{\bar{k}_{ht-1}}}{y_{ht}}$ and $\frac{\Delta\check{K}^*_{\bar{k}_{ht}}}{y_{ht}}$ are the elements of equation (eq20) and consequently they are not relevant for the system of input-output equations.[13] This is the reason of the existence of zeros at the beginning of those vectors $\frac{\hat{K}^*_{\bar{k}_{ht}}}{y_{ht}}$ and $\frac{\hat{K}_{\bar{k}_{ht-1}}}{y_{ht}}$. To estimate the short run input-ouput equations, the new short run equation can be written as

$$\tilde{S}_{i_{ht}} = \phi_h(\frac{\hat{K}^*_{\bar{k}_{ht}}}{y_{ht}} - \frac{\hat{K}_{\bar{k}_{ht-1}}}{y_{ht}}) + \tilde{F}_{i_{ht}}\nu + \tilde{\epsilon}_{i_{ht}}, \qquad \text{eq(21)}$$

where $\tilde{F}_{i_{ht}} = \left[\tilde{X}_{i_{ht}}, D_{ht}, \frac{\Delta K^*_{\bar{k}_{ht}}}{y_h}\right]$ and $\nu = (\tilde{\alpha},\tilde{\tau}_{\tilde{i}\tilde{t}_h},\psi)'$. Notice that $\tilde{X}_{i_{ht}}$ is used to stress that the equations referring to the flexible factors in equation (eq15) have been modified by substituting out the shadow prices equation as in (eq18) into them. Consequently, $\tilde{\alpha}$, $\tilde{\tau}_{\tilde{i}\tilde{t}_h}$ are the short run version of the coefficients defined in equation (eq15). Notice also the subscript h in the speed adjustment parameter ϕ_h implies a heterogeneous error correction term[14]. Furthermore, it is assumed that $E(\tilde{\epsilon}_{i_{ht}}) = 0, E(\tilde{\epsilon}_{i_{ht}}\tilde{\epsilon}_{i_{hr}}) = \sigma_i$ for $t = r$, and 0 otherwise. Notice that since $\tilde{S}_{i_{ht}}$ contains the first difference of the vectors $\frac{K_{\bar{k}_{ht}}}{y_h}$, and also their lag appears on the right hand side of expression (eq21), therefore the residuals of this expression $(i.e.\tilde{\epsilon}_{i_{ht}})$ are autocorrelated[15]. Therefore the *GMM-SYS* estimator that is used in the estimation is defined as

$$\gamma = (\tilde{G}'_{i_{ht}}Z_{i_{ht}}\Sigma Z'_{i_{ht}}\tilde{G}_{i_{ht}})^{-1}\tilde{G}'_{i_{ht}}Z_{i_{ht}}\Sigma Z'_{i_{ht}}\tilde{S}_{i_{ht}}, \qquad \text{eq(22)}$$

where $\gamma = (\phi_h,\tilde{\alpha},\tilde{\tau}_{\tilde{i}\tilde{t}h},\psi)'$, $\tilde{G}_{i_{ht}} = (1/y_{ht}(\hat{K}^*_{\bar{k}_{ht}} - \hat{K}_{\bar{k}_{ht-1}}),\tilde{F}_{i_{ht}})'$ and $Z_{i_{ht}}$ is the matrix of instruments that contains both the instruments for the model in levels and in first differences as proposed by Arellano and Bond (1991) and Blundell and Bond (1998). Σ is a weighting moments matrix that can determine the value of the parameter γ and it will weight moments in a inverse proportion to the variances. In special, Σ is given as

$$\Sigma = var[Z_{i_{ht}}\tilde{\epsilon}_{i_{ht}}]^{-1}.$$

[13]Where $\frac{\Delta K^*_{\bar{k}_{ht}}}{y_h}$ is estimated by applying first differences to the vector $K^*_{\bar{k}_{ht}}$ and dividing it by y_h.

[14]During the estimation in the application section, the parameter ψ of equation (eq20) was allowed also to vary across industries, however, the estimates that were obtained for them were not statistically significant.
[15]See Nickell (1981).

GMM-SYS is a two stage procedure where in the first step the value of γ is estimated, by assuming that Σ in expression (eq22) is the identity matrix. In the second step, expression (eq22) is estimated again by using the estimated value of Σ that was obtained when making use of the estimated parameters obtained in the first step. However, as noticed by Roodman (2006), in a finite sample a large number of instruments can prompt the matrix Σ to be singular and consequently its generalized inverse has to be used.

Regarding the diagnostic tests, in the empirical application in Section 3, we will also make use of two tests: the Sargan and Hansen ($S-H$) test of over identifying restrictions, as in Hansen (1982) and Sargan (1958); and the Arellano-Bond ($A-B$) test (1991) for autocorrelation. The $S-H$ statistic tests under the null, if the inner product of the instruments $Z_{i_{ht}}$ and the residuals $\tilde{\epsilon}_{i_{ht}}$ is orthogonal. To carry out this test, the moment weighting matrix must be estimated and if the matrix is singular due to the use of many instruments the test can have very low power as pointed out by Roodman (2006).

On the other hand, the autocorrelation test of $(A-B)$ evaluates under the null hypothesis the assumption that the inner product $\frac{1}{N}\sum \tilde{\epsilon}^{-l}_{i_{ht}} \tilde{\epsilon}_{i_{ht}}$ is zero, where l stands for the $l-th$ -lag that is tested .

Regarding the estimation of the elasticities, the expression used for the long run in (eq16) and (eq17) can be used for estimating also the $CPEs$ for the short run.

The Error Correction Model (ECM)

The last specification to be described, and that it will be used in Section 3, is the *ECM*. The estimation is carried out by applying the *GMM-SYS*. To estimate this specification instead of using a cost context, the model is based on the production side and therefore some modifications are needed. First, the concept of elasticity is based on the *Technical elasticity of substitution* (*TES*) for factors i and j proposed by Frondel (2004), and it is given for industry h by

$$TES_{i_h j_h} = \frac{\partial i_h}{\partial j_h}\frac{j_h}{i_h} = \frac{\partial \ln i_h}{\partial \ln j_h}. \qquad \text{eq(23)}$$

Where $TES_{i_h j_h} >> 0$. A decrease in the amount input j for industry h , implies an increment of input i equal to the amount $TES_{i_h j_h}$ to keep the same level of production. Following Frondel (2004), unlike the *TCF* and the *GL*, the *TES* does not imply any optimality assumptions and it captures a substitution process that is determined entirely by the technology that firms used in the production process. Moreover, in contrast with the *CPE* which measures a relationship between relative changes in quantities and prices, the *TES* is a measure of relative changes purely in quantities. Second, following Arpegis and Payne (2009), we also assume a Cobb-Douglas production function

$$y = \varrho 1^{\eta_1} 2^{\eta_2} \cdots N^{\eta_N} \tilde{t}^{\eta_{\tilde{t}}}. \qquad \text{eq(24)}$$

where $1,..,N$ are the number of factors and $\tilde{t}$ denotes technological level as before. Furthermore ϱ is the general level of technology which is assumed constant and η_i measures the changes in output due to changes in factor i . However, contrary to Arpegis and Payne (2009) who used a time trend for technological change, here we use the IR & DEF in our empirical application. Moreover, by applying logarithms in both sides of expression (eq24) and re-arranging for having the level of energy as dependent variable, we can analyze changes in this variable due to changes in the investment in capital. Finally, taking the procedure to a panel data context for industry h at time t, the following expression is obtained

$$\ln E_{ht} = A_h + \tilde{\eta}_{1_h} \ln 1_{ht} + \tilde{\eta}_{2_h} \ln 2_{ht} + \ldots + \tilde{\eta}_{(N-1)_h} \ln(N-1)_{ht} + \tilde{\eta}_{\tilde{t}_h} \ln \tilde{t}_{ht} + \theta_h \ln y_{ht}, \qquad \text{eq(25)}$$

where $\theta_h = \frac{1}{\eta_{E_h}}, \tilde{\eta}_{1_h} = \frac{\eta_{1_h}}{\eta_{E_h}}, \tilde{\eta}_{2_h} = \frac{\eta_{2_h}}{\eta_{E_h}}, \ldots, \tilde{\eta}_{(N-1)_h} = \frac{\eta_{(N-1)_h}}{\eta_{E_h}}, \tilde{\eta}_{\tilde{t}_h} = \frac{\eta_{\tilde{t}_h}}{\eta_{E_h}}, \ln\varrho_h = A_h$. Assuming that the factors $1,2,..,N$ are cointegrated, according to the *Granger Representation Theorem,* expression (eq25) can be reparameterized in an *ECM* form. Following Pesaran, Shin and Smith (1999), the autoregressive distributed lag model, ARDL(1,1), is specified as

$$\ln E_{ht} = \Psi_1 V_{ht} + \Psi_2 V_{h(t-1)} + \phi \ln E_{h(t-1)} + A_h + \xi_{ht}, \qquad \text{eq(26)}$$

here $V_{ht} = (\ln 1_{ht}, \ln 2_{ht}, \ln 3_{ht}, .., \ln(N-1)_{ht}, \ln \tilde{t}_{ht}, \ln y_{ht})'$ and $\Psi_1 = (\tilde{\eta}_{1h}, \ldots, \tilde{\eta}_{(N-1)h}, \tilde{\eta}_{\tilde{t}h}, \theta_h)'$.
Moreover, expression (eq26) can be reparameterized into an *ECM* framework as follows[16]

$$\Delta \ln E_{ht} = \Psi_1 \Delta V_{ht} + \Pi V_{h(t-1)} + (\phi - 1)\ln E_{h(t-1)} + A_h + \xi_{ht}. \qquad \text{eq(27)}$$

where $\Pi = \Psi_1 + \Psi_2$. Following Pesaran, Shin and Smith (1999), in the long run the industries can be subjects to common forces such as solvency constrain or common technology and therefore the parameters Π and ϕ can be assumed to be homogeneous across industries. Moreover, this assumption will reduce the number of parameters in the estimation, increasing efficiency and therefore the assumption of homogeneity implies that $\Pi = (\pi_1, \pi_2, .., \pi_{(N-1)}, \pi_{\tilde{t}}, \theta)'$. Notice that the inclusion of the lag of the logarithm of energy $(\ln E_{h(t-1)})$ in this equation will prompt problems of autocorrelation. For this reason, the *GMM-SYS* procedure, as described in the previous Section, has to be applied. Following Yasar (2006), short and long run elasticities can be estimated in only one step[17].

Short run elasticities are the coefficients contained in Ψ_1 from equation (eq27), while the long run counterparts are obtained by assuming $\Delta \ln E_{ht} = \Delta V_{ht} = 0.$ Therefore the Long Run (*LR*) total elasticity of substitution for energy and factor j are defined as

$$TES_{Ej}^{LR} = -\frac{\pi_j}{\phi - 1}. \qquad \text{eq(28)}$$

Following Enders (2004), the *Granger Representation Theorem* argues that assuming that the time series are integrated of the same order, one can estimate an *ECM*. Therefore, a unit root test has to be applied to all the series to test how many times the series need to be differentiated until they are stationary. The unit root test for panel data that will be used in the next Section follows a simple regression given as

$$\Delta i_{ht} = (\rho - 1)\Delta i_{ht-1} + \sum_{Lag=1}^{\breve{p}_h} \tilde{\theta}_{hLag} \Delta i_{ht-Lag} + \tilde{\xi}_{i_{ht}},$$

where it is assumed that $\tilde{\xi}_{i_{ht}}$ are i.i.d. and $E(\tilde{\xi}_{i_{ht}}) = 0$, $E(\tilde{\xi}^2_{i_{ht}}) = \sigma_i^2 < \infty$, $|\rho| < 1$ if i_{ht} is stationary with $\breve{p}_h$ being the maximum lags for factor i. The only issue is either to assume that the autorregressive term ρ is common or different across industries (i.e., if we allow an autoregressive term ρ_h for each industry h). Therefore, under the null hypothesis whereas under the alternative we have two options: either $\rho = \rho_h = ... = \rho_H$ and $\rho < 0$; or $\rho_1 < 0, ..., \rho_H < 0.$ The tests proposed by Levin, Lin, and Chu (2002, *LLC*)[18] and Breitung (2000) belong to the tests that follow the first option. Both tests use proxy variables to remove the possible existence of autocorrelation. However, the former assumes that the time dimension is larger than the cross section one and it requires, unlike the Breitung's test, to estimate the average standard deviation by using Kernel choices. The *LLC* is recommended for small samples[19]. An example of a test that follows the second option is the test proposed by Im, Pesaran and Shin (2003, *IPS*)[20], that it is based on computing the average of individual Augmented Dickey-Fuller (*ADF*) (1979) tests.

On the other hand the test proposed by Maddala and Wu (1999) is based on a Fisher-type test and it belongs also to

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[16]This expression is obtained by adding and subtracting the term $\Psi_1 V_{it-1}$ on the right hand side of equation (eq26), and by subtracting ln E_{ht-1} from both sides.

[17]Notice that more traditional methods are more complicated than the $GMM-SYS$ procedure that is proposed here in this paper, given that the estimation is usually carried out in two steps. In the first one, a long run relationship is estimated by using Full Modified OLS or Dynamic OLS. In the second step, the residuals from the previous step are used to estimate the short run specification.

[18]Denoted as LLC from now onwards.

[19]Cross-section dimension between 10 and 250 and time dimension between 25 and 250, according to Baltagi (2005).

[20]Denoted as *IPS* from now onwards.

the second group. The test is estimated by the following expression

$$q = -2\sum_{h=1}^{H} \log(q_h) \rightarrow \chi^2_{2H},$$

where q_h denotes the $p-$ value obtained for the h industry for the individual unit root tests. In the our case, in Section 3, the two tests are based on the *ADF* and the Philips-Perron (*PP*) (1988) test. The *PP* test allows us to estimate the regression

$$i_{ht} = \iota + \tilde{\rho} i_{ht-1} + u_{i_{ht}},$$

where ι and $\tilde{\rho}$ are the intercept and the autocorrelation coefficients respectively. We can use *OLS* even when $u_{i_{ht}}$ is correlated. However, a nuisance parameter is introduced in the statistic to allow for autocorrelation.

Regarding the cointegration test that we will use in our empirical application, Pedroni (2004) suggests a residual-based test. The null of no cointegration is evaluated based on a long run specification that allows for individual heterogeneity. Pedroni (2004)'s test is a two step procedure. In the first step a long run regression is estimated as

$$\tilde{u}_{ht} = \ln E_{ht} - \omega_h - \delta_h t - (\varpi_{1h} \ln 1_{ht} + \varpi_{2h} \ln 2_{ht} + \ldots + \varpi_{(N-1)h} \ln(N-1)_{ht} + \varpi_{\tilde{\iota}h} \ln \tilde{\iota}_{ht}) + \tilde{\tilde{\xi}}_{ht},$$

where energy consumption E_{ht} and the panel of factors $(i.e.\ \ln 1_{ht}, \ldots, \ln \tilde{\iota}_{ht})$ are assumed to be cointegrated of order 1. Moreover, ω_h and δ_h , (i.e. the fixed effect and time trend), are allowed to be heterogenous across individuals). In the second step, once we have obtained the estimated residuals from $\tilde{u}_{ht}$ (i.e. $\hat{\tilde{\tilde{\xi}}}_{ht}$), the regression is estimated.

$$\hat{\tilde{\tilde{\xi}}}_{ht} = \tilde{\phi}_{ht} \hat{\tilde{\tilde{\xi}}}_{ht-1} + e_{ht}$$

Pedroni (2004) offers two alternatives to test the null of no cointegration against the alternative that there is cointegration for some of the individuals. Under the null, it is assumed that either $\tilde{\phi}_{ht}$ is different or equal across individuals. If the former is assumed, the group of statistics are called the within dimension statistics, whereas the later is called the between dimension statistics.

For the within dimension statistics, four statistics are proposed by Pedroni (2004), the panel variance ratio, the panel-rho, the panel- t and the panel *ADF*. These are obtained by adding the numerator separately from the original test proposed for time series by Phillips and Ouliaris (1990) and Dickey-Fuller (1979). On the other hand, the between dimension statistics are basically the group mean of the original tests proposed by Phillips and Ouliaris (1990) applied individually to each element of the cross section.

Empirical results

The dataset

The empirical analysis is based from both the cost and production sides, and therefore the data set that we use contains information of four fuel inputs (i.e. $F = 4$)[21] and their corresponding prices. Additionally, we considered the eight industries with the highest energy consumption[22](i.e. $H = 8$) of the United Kingdom (UK) economy from 1970 to 2006, i.e., during thirty seven years ($T = 37$) which corresponds to the most updated dataset that was available when the analysis was carried out. Finally, we use five factors and IR & DEF (i.e. $N = 6$). The factors are constructed as net capital stock divided into buildings (K_1), machinery and equipment (K_2), labour (L) and

[21]The most important industrial fuels used are: natural gas (*G*), electricity (*El*), coal (*C*) and oil (*O*), IEA (2009).

[22]According to the IEA (2009), the following 8 industries are the ones that show the biggest energy consumption in the manufacture sector over the time period that is analyzed: Industry 1: basic metals, industry 2: chemical and petrochemical, industry 3: non-metallic minerals, industry 4: transport equipment, industry 5: machinery, industry 6: textiles, industry 7: food and industry 8: paper.

intermediate materials (M) together with energy (E) and $IR \& DEF$ [23]. Therefore, we use two types of capital and $\bar{k} = 2$. The dataset used was obtained from the *Economic and Social data Service* and the *National Statistics for the UK*[24].

On the other hand, regarding the factor prices, an index of energy is built as expression (eq5) shows. The price of capital is built using the implicit price of the net capital stock per industry. In the case of labour, its price is estimated by dividing labour compensation and the number of employees per industry. Finally, the price of M is an index of producer prices for intermediate materials[25].

Estimation and testing results

In this section, we report the results obtained from the *TCF*, the *GL* and the *ECM* [26].

The translog cost function (TCF)

The estimation of the *TCF* is based on the Fuss' methodology (1977) by using the *ISUR* estimation approach; and therefore, it is a two step estimation procedure. The results from the first step are shown in Table 1. The intuition is that, at this stage, firms choose the optimal combination of different energy sources and that the empirical utility is used to estimate an energy index to aggregate the four fuel prices per industry[27]. In the second step, according to Fuss (1977), firms will presumably choose the optimal amount of factors that minimizes their cost function, subject to the restrictions that the production technology imposes on the ability to substitute one factor by another. The coefficients related to this stage are displayed in Table 2. Notice that the coefficients that relate energy and capital are highly significant, although they cannot say anything about the magnitude of the relationship between capital and energy by themselves. In order to obtain the $CPEs$, they have to be estimated by expression (eq10).

The $CPEs$ for K_1, K_2 and E are reported in Table 3. They are highly statistically significant and all negative across the eight industries that are analyzed. Therefore the *TCF* model clearly provides evidence of complementarity. This implies that changes in the energy prices will prompt a reduction in the amount of investment, given that energy and capital move together. Furthermore, the $CPEs$ for machinery (i.e. K_2) are bigger than for buildings (i.e. K_1), which shows that firms find less flexibility by using better technology embedded in more efficient machinery to reduce energy consumption than increasing investment in buildings. Consequently, an increase in energy prices will be more harmful for industries 1,4-6 and 8 given that the $CPEs$ for K_2 show the biggest absolute value[28]. Koetse, de Groot and Florax (2008, Figure 1) show a range of different point estimates for estimated *CPE* in different studies in the literature. Our point estimates for the *CPE* for the different industries tend to be in absolute value larger than the ones reported there. However, notice that the estimations considered in Koetse, de Groot and Florax (2008, Figure 1) do not considered the effect of capital desegregation. In this estimation breaking down capital into different kinds prompt larger estimates like in the Field (1980)'s estimation.

Berndt and Wood (1979) argued that dropping M from the model could lead to bias the results towards substitutability. Furthermore, Apostolakis (1990) found that estimation based on panel data settings tends to conclude also substitutability. In our estimation results, as Table 4 shows, although the estimated $CPEs$ are not significant, when M was dropped from the estimation and the KLE model was estimated, the conclusion of complementarity did not change. We argue that the robustness of our results is due to the disaggregation of capital into buildings (K_1) and machinery (K_2 **)**. This does not allow the data structure to predetermine the value of the $CPEs$, as pointed out by Frondel and Schmidt (2002), and consequently in this case, like in the case of Field (1980), the distinction of different kinds of capital can improve the estimation when the *TCF* is used. Additionally even though it also used a panel data setting, the $CPEs$ clearly show that for both kinds of capital and across industries, we find a complementary relationship. Therefore, we argue that by disaggregating by industry and by kind of capitals, it allows us to obtain robust results in contrast to an omitted variable bias, and this offers a solution to the previous arguments given by Berndt and Wood (1979), Apostolakis (1990) and Frondel and Schmidt (2002).

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[23] $IR \& DEF$ is only available at aggregated level, and therefore, it is not possible to distinguish by industry. However, we have merged this database with the general investment in $R \& D$ in the industrial sector per industry in order to be able to differentiate the structure of investment in $R \& D$ per industry.

[24] See http://www.esds.ac.uk and http://www.statistics.gov.uk/statbase/Product.asp?vlnk=10730.

[25] There is not an available index for intermediate materials per industry in the UK, and therefore, the same index was used across industries.

[26] All the programming and routines have been written and coded in STATA: www.stata.com.

[27] Notice that the same prices for energy will be used in both the *TCF* and the GL . In the second step, the TCF is estimated by equation (eq1).

[28] I.e. basic metals, transport equipment, machinery, textiles and paper.

Finally, Table B1 shows the estimated results of the own price-elasticities based on the TCF .

The Generalized Leontief (GL) cost function

The second model to be estimated is the one based on the methodology proposed by Thomsen (2000) that distinguishes short and long run. The estimation procedure involves applying the *GMM-SYS* procedure described in the previous section in two steps. In the first step the long run demand functions are estimated and in the second step, a function for the capital price that is obtained from the previous step is substituted out into the short demand functions. This estimation is carried out by estimating the short run input-output system along with the dynamic motion equation for capital as expression (eq21) shows. For the long run, Table 5 presents the results of the estimated coefficients of the long run system of equations specified as in (eq15). From Table 5, we can see that the estimated parameters related to capital and energy are highly significant. Notice also that the estimated coefficients related to technological change for industries 1, 2, 4 and 8[29] are highly statistically significant and positive. Therefore it shows that there is a rebound effect. This effect has been analyzed by Saunders (2000), where improvements in energy efficiency make energy cheaper and consequently, energy consumption increases. The estimated $CPEs$ for the long run regression are displayed in Table 6. It can be seen that the $CPEs$ are highly significant and positive across the eight analyzed industries. As a result, the *GL* in the long run classified both kinds of capital across industries as substitutes. However, the estimated elasticities are quite small in magnitude, and this fact implies that there is a very narrow space for firms to substitute capital for energy. Therefore, we interpret this result arguing that the *GL* finds very weak evidence of substitutability between them.

Regarding the short run, the estimated coefficients of the short run input-output system along with the equation of capital motion estimated by the *GMM-SYS* can be found in Table 7. Contrary to the long run estimation, it is not found considerable statistical significance in the estimated coefficients related to the interaction capital-energy. Nevertheless, the capital-motion coefficient ψ is statistically significant and the speed adjustment parameters ϕ_h are also significant for four industries[30]. A natural concern is the fact that the inclusion of a lagged dependent variable for the capital motion can prompt biased estimates. However, as it is shown at the bottom of Table 7, the battery of tests for autocorrelation of order one and two that we performed by the ($A-B$) test, do not reject the null of lack of autocorrelation.

The estimated elasticities obtained from the previous estimates are displayed in Table 8. Notice that, the $CPEs$ for K_1 are positive and statistically significant at 10% level, whereas the ones related to K_2 were found to be not statistically significant across the industries analyzed. The fact that there is this lack of statistical significance is not surprising, since in the long run the $CPEs$ of capital and energy are weak substitutes and consequently, in the short run the lack of flexibility is even narrower, which is captured by the estimation results. Finally, Tables B2 and B3 show the estimated results of the long and short run own price-elasticities based on the *GL*.

The Error Correction Model (ECM)

The final specification presented in this section is the *ECM*. According to the *Granger Representation Theorem* (see Enders (2004)), it is required the time series to be integrated of the same order to express their long run relationship as an *ECM*. We apply first tests for unit root to the series in levels and in first differences, to verify that they are integrated of the same order. The first two columns of Table 9 show the results for the null of a common unit root process. Notice that the *LLC* (2002) test classifies 3 out of 7 of the series as non-stationary, whereas the Breitung (2000) test classifies 6 of the series as non-stationary. Furthermore, when the null hypothesis of an individual unit root was tested by the *IPS*, *ADF* and *PP*, it was found, as Table 10 shows, that the former test pointed out stationarity for almost all the series whereas the latter ones found generally non-stationarity . Nevertheless, when the first difference was applied to the series, in general they were found to be stationary under both common and individual hypothesis[31]; and therefore this result provides evidence that the series are integrated of the same order.

The next step is to apply the Pedroni's (2004) test for cointegration and the results are displayed in Table 11. Among all tests provided by Pedroni (2004), those based on Phillips-Perron (*PP*) (1988) are more reliable in our context were serial autocorrelation is an important issue, since they allow for more general types of neglected autocorrelation[32]. The null of no cointegration is rejected by the non parametric *PP* test and the panel v for the

[29] I.e., basic metals, transport equipment and paper.
[30] See equations (eq20) and (eq21).
[31] See the last two columns of Table 9 and the second part of Table 10.
[32] See Enders (2004).

within dimension, see Table 11. However, the rest of the tests do not reject the null hypothesis of no cointegration. Therefore Pedroni (2004) tests provide mix-evidence of the existence of cointegration although the test based on *PP* clearly supports the existence of cointegration. In order to provide even more solid evidence whether cointegration exists or not, we check if the residuals of the *EMC* in our own specification are stationary.

The *ECM* is estimated by using expression (eq27), and the results are displayed in Table 12. As it can be seen at the bottom of Table 12, the Arellano and Bond test for autocorrelation of first and second order cannot reject the null of no-autocorrelation. Moreover, according to Roodman (2006), when a one step *GMM* procedure is used as in this case (note that as described in the previous Section, we use the *GMM-SYS* procedure), the Sargan (1983) test is inconsistent and the Hansen (1982) test is more reliable. As it can be seen in Table 12, the Hansen (1982) test does not reject the null that the instruments are valid. However, the test can have a very low power due to large number of instruments that are employed. Therefore, the residuals obtained from the *ECM* were also tested for unit root test. Table 13 confirms that there is a long run relationship as the residuals are found to be stationary.

Regarding the estimated *Technical Elasticities of Substitution* (TES), the short run ones can be obtained directly from the estimated coefficients displayed in Table 14. One can see that the value of the estimates *TES* for machinery (K_2) are bigger than for buildings (K_1), showing that a decrease of 1% in the amount of K_2, implies an increase of more than 1% of energy consumption to keep the same level of production. Therefore, like in the *TCF*, the model shows that firms face limitations to substitute capital for energy when capital is embedded in machinery. Nevertheless, notice that some *TES* have wrong sign which can suggest that this model could not be suitable for the data set used in this estimation.

Summary of the three different specifications

As a conclusion from the different specifications, we find clear evidence of complementarity when using the *TCF*, while when using the *GL*, the results support weak substitutability between capital and energy. Moreover, it was found that the *TCF* and the *ECM* show that firms face more limitations to substitute capital for energy when capital is embedded in machinery than in buildings. Furthermore the estimated elasticities show that industries 1, 2, 4 and 5 are the most vulnerable ones to a change in energy prices via taxes[33].

Therefore we find evidence that a policy that aims to diminish energy consumption via changes in energy prices will have a more severe contraction in capital demand for those four industries.

Conclusions

Thirty years ago, the estimation of $CPEs$ for capital and energy began a controversy with the work of Berndt and Wood (1975) about its relationship that is still currently unsolved. The early literature found that the omission of M and the use of panel data settings lead the estimation results towards substitutability (see Frondel (2004)). The estimations in the literature usually were characterized by using a *TCF*, one kind of capital and a time trend to model technological change.

In this paper, a panel data setting was used to estimate three models to compute $CPEs$ and *TES* and also we control for technological change by using IR & DEF and two kinds of capital. In order to do so, *first*, we extend the Thomsen's methodology to be applied to a panel data context developing a new estimation method applied jointly with the *GMM-SYS* to deal with the dynamics of the system. *Second*, an *ECM* was estimated by using a Cobb-Douglas production function; and *finally*, we estimate a *TCF* with three and four factors to check if the results are robust to an omitted variable bias (as claimed in Frondel (2004)).

Regarding the *GL*, the estimated $CPEs$ in the long run show that all kinds of capital and energy are weak substitutes whereas in the short run, the scope for firms to substitute capital for energy is still weaker. Moreover, the estimation shows that, in the short run, there is only a relationship between buildings (K_1) and energy, since the $CPEs$ for machinery (i.e. K_2) were not statistically significant.

In relation to the *ECM*, it is found that with the actual level of technology, firms face more limitation to substitute capital for energy when capital is invested in machinery than when it is invested in buildings. Finally, it was found that the *TCF* suggests clear complementarity when we use both three (i.e. K, E and L) and four (i.e. K, L, E and M) factors. This result challenges the conclusion reached by Berndt and Wood (1979) and Frondel and Schmidt

[33] I.e. basic metals, chemical, transport equipment and machinery. These industries present the largest absolute value of the estimated elasticities and therefore, the strongest dependence between capital and energy.

(2002). It is shown that by using a panel data setting and also by the omission of M in the estimation cannot fully determine substitutability once we disaggregate by industry and by capital. Furthermore it is shown that using different kinds of capital can make the estimation more robust even when M is dropped from the specification.

In relation to each of the eight industries, there is clear evidence that those that are more vulnerable to changes in energy prices are industries 1, 2, 4 and 5 (i.e. basic metals, chemical, transport equipment and machinery), according to the *TCF*.

In short, we find clear evidence of complementarity when using the *TCF* while when using the *GL*, the conclusion was weak substitutability. Moreover, the substitution between capital and energy is more limited when capital is invested in machinery than when it is invested in buildings. Therefore, a policy of increasing energy prices to reduce energy consumption will seriously affect investment and, in particular, it will be more harmful for the industries of basic metals, chemical, transport equipment and machinery that are the ones that show stronger dependence between energy and capital. A better policy may be to encourage technological diffusion. Additionally, the *GL* also provide evidence that there is a rebound effect since the estimated IR & DEF coefficients are also positive. Using data to firm level may help to distinguish even further for which industries an increase of energy prices can be more harmful; however, there is still a pending issue about the proper way to measure the substitution among productive factors and this is an objective of future research.

References

Addison, T. J., Bellman L., Schank T. and Teixeira P. (2005), The Demand for Labor: An analysis Using Matched Employer-Employee Data from the German LIAB. Will the High Unskilled Worker Own-wage Elasticity Please Stand up?, *Institute for the study of Labor*, 1780,1- 33.

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

Arellano, M. and Bond, S. R. (1991), Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, *Review of Economic Studies* 58, 277-297.

Apergis, N. and Payne, J. E. (2009), Energy Consumption and Economic Growth in Central America: Evidence from a Panel Cointegration and Error Correction Model, *Energy Economics* 31, 2, 211-216.

Baltagi, B. H. (2005), *Econometric Analysis of Panel Data*, Wiley, UK.

Baker, T., Ekis P. and Johnstone N. (1995), Global Warming and Energy Demand, *Global Environmental Change Series*, 1995, 46-105.

Berndt, E. R. and Christensen L. R. (1973), The Internal Structure of Functional Relationship: Separability, Substitution, and Aggregation, *Review of Economic Studies*, 40, 3, 403-410.

Berndt, E. R. and Wood, D. O. (1975), Technology, Prices, and the Derived Demand for Energy, *The Review of Economics and Statistics* 57, 3, 259-268.

Berndt, E. R. and Wood D. O.(1979), Engineering and Econometric Interpretation of Energy- Capital Complementarity, *American Economic Review* 69, 3, 342-354.

Berndt, E. R. (1991), *The practice of Econometrics. Classical and Contemporary*, Addison-Wesley Publishing Company, USA.

Blundell, R. and Bond S. (1998), Initial Conditions and Moment Restriction in Dynamic Panel Data Models, *Journal of Econometrics* 87, 11-143.

Breitung, J. (2000), The Total Power of Some Unit Root Test for panel Data, *Advances in Econometrics* 15, 161-177.

Dickey, D. and W. Fuller (1979), Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association* 74, 427-431.

Diewert, W. E. (1974), Application of the Duality Theory in: Intrilligator, M. D., Kendrick, D. A., *Frontiers of Quantitative Economics*, Vol. II,. North Holland, Amsterdam, 106-171.

Diewert, W. E., Wales T. J. (1987), Flexible Functional Forms and Global Curvature Conditions, *Econometrica* 55, 1, 43-68.

Enders, W. (2004), *Applied Econometric Time Series*, Wiley, USA.

Field, B. C. (1980), Capital Energy Substitution in USA manufacturing, *The Review of Economics and Statistics* 62, 2, 207-212.

Frondel, M. and Schmidt, C. M. (2002), The Capital -- Energy Controversy: An Artefact of Cost Shares?, *The*

Energy Journal 23, 3, 53-80.
Frondel, M. (2004), Empirical Assessment of Energy-Price Policies: the Case for Cross-Price Elasticities, *Energy Policy* 32, 8, 989-1000.
Fuss, M. A. (1977), The Demand for Energy in Canada Manufacturing: An example of the estimation of production structure with many inputs, *Journal of Econometrics* 5, 89-116.
Greene, W. H. (2008), *Econometric Analysis,* sixth edition, Pearson International Edition.
Griffin, J. M. and Gregory P. R.(1976), An intercountry Translog Model of Energy Substitution Responses, *The American Economic Review* 66, 5, 845-857.
Hansen, L. P. (1982), Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica* 50, 1029-1054.
Im, K. S., M. H. Pesaran, and Y. Shi (2003), Testing for Unit Root in Heterogeneous Panels, *Journal of Econometrics* 115, 53-74.
International Energy Agency (IEA) (2009), Energy Balances of OECD countries, http://www.iea.org.
Koetse, M. J., H. L. F. de Groot and R. J. G. M. Florax (2008), Capital-energy substitution and shifts in factor demand: A meta-analysis, Energy Economics 30, 2236-2251.
Kuh, E. (1959), The validity of Cross- Sectionally Estimated Behaviour Equations in Time Series Applications, *Econometrica* 27, 2, 197-214.
Levin, A., C. Lin, and C. J. Chu (2002), Unit Root Test in Panel Data: Asymptotic and Finite Sample Properties, *Journal of Econometrics* 108, 1-24.
Ma, H., Oxley L.,Gibson J. and Kim B. (2008), China's energy economy: Technical change, factor demand and interfactor interfuel substitution, *Energy Economics* 30, 2167-2183.
Maddala, G. S. and Wu, S. (1999), A Comparative Study of Unit Root Test with Panel Data and a New Simple Test , *Oxford Bulletin of Economics and Statistics* 61 631-652.
Mas-Collel, Whinston D. M. and Green J. R., (1995), *Microeconomic Theory*, Oxford University Press, USA.
Morrison, C. (1993), Energy and Capital: Further Exploration of E-K Interactions and Economic Performance, *The Energy Journal* 14, 1, 217-244.
Nickell, S. (1981), Biases in dynamic models with fixed effects, *Econometrica*, 49, 1417-1426.
Nickell, S. (1985), Error Correction, Partial Adjustment and all that: an expository note, *Oxford Bulletin of Economics and Statistics* 47, 2, 119-129.
Pedroni, P. (2004), Panel Cointegration; Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the Purchasing Power Parity Hypothesis, *Econometric Theory* 20, 597-325.
Pesaran, M. H. Y. Shin and R. P. Smith (1999), Pooled Mean Group Estimation of Dynamic Heterogeneuos Panels, *Journal of the American Statistical Association* 94, 621-634.
Phillips, P. C. B. and Ouliaris (1990), Asymptotic Properties of Residuals Based Test for Cointegration, *Econometrica* 58, 165-193.
Phillips, P. C. B. and P. Perron (1988), Testing for a Unit Root in Time Series Regression, *Biometrika* 75, 335-46.
Pop, D.(1998), The Effect of New Technology on Energy Consumption, *Resource and Energy and Economics* 23, 3, 215-239.
Pindyck, R. S. (1979), Interfuel Substitution and the Industrial Demand for Energy: an International Comparison, *The Review of Economics and Statistics* 61, 2, 169-179.
Roodman, D. (2006), How to do xtabond2 : An introduction to Difference and System GMM in Stata, *Centre for Global Development*, 103, 1-51.
Sargan, J. (1953), The Estimation of Economic Relationship Using Instrumental Variables, *Econometrica* 26, 3, 393-415.
Saunders, H. D. (2000), A View from the Macro Side: Rebound, Backfire, and Khazzoom-Brookes, *Energy Policy* 28, 6-7, 439-449.
Thomsen, T. (2000), Short Cuts to Dynamic Factor Demand Modelling, *Journal of Econometrics* 97, 1, 1-23.
Yasar, M. (2006), The Dynamic of Exports and Productivity at the Plant Level : A panel Data Error Correction Model (ECM) approach, *Contributions to Economic Analysis*, Elsevier, Amsterdam, 1-37.

Appendix A

Table 1: Estimation results for the coefficients of the energy-price TCF given by equation (eq5).

γ_{GG}	0.0907***	(0.0163)
γ_{GEl}	-0.1613***	(0.0142)
γ_{GO}	0.0334**	(0.0104)
γ_{ElEl}	0.2077***	(0.0290)
γ_{EO}	-0.0010	(0.0126)
γ_{OO}	0.0116	(0.0136)
$\gamma_{G\tilde{t}_h}$	8DV	
$\gamma_{El\tilde{t}_h}$	8DV	
$\gamma_{O\tilde{t}_h}$	8DV	
γ_{G_h}	8DV	
γ_{El_h}	8DV	
γ_{O_h}	8DV	

Standard errors are given in parenthesis. 8DV denotes that eight dummy variables are used for the fixed effects in the regression. "*": significant at 10 percent level. "**": significant at 5 percent level. "***": significant at 1 percent level. Note that the value of the parameters related to Coal can be obtained by the constraint (eq6). The parameters related to the dummy variables are available upon request from the authors.

Table 2: Estimation results for the $KLEM$ parameters based on the share cost system given by equation (eq1).

β_{EE}	0.0066	(0.0072)	$\beta_{K_2\tilde{t}_5}$	0.0134***	(0.0035)
β_{EK_1}	-0.0249***	(0.0064)	$\beta_{K_2\tilde{t}_6}$	0.0103***	(0.0031)
β_{EK_2}	-0.0294***	(0.0070)	$\beta_{K_2\tilde{t}_7}$	-0.0061	(0.0043)
β_{EL}	0.01420**	(0.0058)	$\beta_{K_2\tilde{t}_8}$	0.0050	(0.0039)
$\beta_{K_1K_1}$	0.0759***	(0.0130)	$\beta_{L\tilde{t}_1}$	-0.0088***	(0.0031)
$\beta_{K_1K_2}$	-0.0456***	(0.0107)	$\beta_{L\tilde{t}_2}$	-0.0064	(0.0046)
β_{K_1L}	0.0124	(0.0080)	$\beta_{L\tilde{t}_3}$	-0.0017	(0.0037)
$\beta_{K_2K_2}$	0.1109***	(0.0175)	$\beta_{L\tilde{t}_4}$	0.0172***	(0.0045)
β_{K_2L}	-0.0279***	(0.0090)	$\beta_{L\tilde{t}_5}$	0.0091***	(0.0035)
β_{LL}	0.0267***	(0.0094)	$\beta_{L\tilde{t}_6}$	-0.0028	(0.0033)
$\beta_{E\tilde{t}_1}$	0.0003	(0.0029)	$\beta_{L\tilde{t}_7}$	0.0035	(0.0043)
$\beta_{E\tilde{t}_2}$	0.0042	(0.0044)	$\beta_{L\tilde{t}_8}$	0.0033	(0.0037)
$\beta_{E\tilde{t}_3}$	0.0073**	(0.0035)	β_{Ey_h}	8DV	
$\beta_{E\tilde{t}_4}$	0.0002	(0.0045)	$\beta_{K_1y_h}$	8DV	
$\beta_{E\tilde{t}_5}$	0.0021	(0.0034)	$\beta_{K_2y_h}$	8DV	
$\beta_{E\tilde{t}_6}$	-0.0012	(0.0026)	β_{Ly_h}	8DV	
$\beta_{E\tilde{t}_7}$	0.0005	(0.0040)	β_{yy_h}	8DV	
$\beta_{E\tilde{t}_8}$	0.0001	(0.0038)	$\beta_{\tilde{t}\tilde{t}_h}$	8DV	
$\beta_{K_1\tilde{t}_1}$	0.0086***	(0.0030)	$\beta_{\tilde{t}y_h}$	8DV	

Table 2: Estimation results for the $KLEM$ (Continuation)

$\beta_{K_1\tilde{t}_2}$	-0.0009	(0.0045)	β_{E_h}	8DV
$\beta_{K_1\tilde{t}_3}$	-0.0013	(0.0036)	$\beta_{K_{1_h}}$	8DV
$\beta_{K_1\tilde{t}_4}$	0.0092**	(0.0045)	$\beta_{K_{2_h}}$	8DV
$\beta_{K_1\tilde{t}_5}$	0.0067**	(0.0034)	β_{L_h}	8DV
$\beta_{K_1\tilde{t}_6}$	0.0026	(0.0030)	β_0	8DV
$\beta_{K_1\tilde{t}_7}$	0.0054	(0.0042)		
$\beta_{K_1\tilde{t}_8}$	0.0004	(0.0038)		
$\beta_{K_2\tilde{t}_1}$	0.0103***	(0.0031)		
$\beta_{K_2\tilde{t}_2}$	0.0040	(0.0046)		
$\beta_{K_2\tilde{t}_3}$	0.0053	(0.0037)		
$\beta_{K_2\tilde{t}_4}$	0.0062	(0.0047)		

See footnote in Table 1 for notation used in this Table. Additionally, note that the value of the parameters related to intermediate materials can be obtained by the constraint (eq2). The parameters related to the dummy variables are available upon request from the authors.

Table 3: Estimation results for $CPEs$ based on $KLEM$ model specification, given by equation (eq10).

$\eta_{K_{1_1}p_{E_1}}$	-0.1646***	(0.0464)	$\eta_{K_{2_1}p_{E_1}}$	-1.7064***	(0.4598)
$\eta_{K_{1_2}p_{E_2}}$	-0.2388***	(0.0668)	$\eta_{K_{2_2}p_{E_2}}$	-1.1845***	(0.3466)
$\eta_{K_{1_3}p_{E_3}}$	-0.1900***	(0.0593)	$\eta_{K_{1_3}p_{E_3}}$	-0.4697***	(0.1753)
$\eta_{K_{1_4}p_{E_4}}$	-0.1592***	(0.0437)	$\eta_{K_{1_4}p_{E_4}}$	-2.6993***	(0.6982)
$\eta_{K_{1_5}p_{E_5}}$	-0.2726***	(0.0735)	$\eta_{K_{1_5}p_{E_5}}$	-2.2466***	(0.5657)
$\eta_{K_{1_6}p_{E_6}}$	-0.1730***	(0.0477)	$\eta_{K_{1_6}p_{E_6}}$	-2.3240***	(0.6001)
$\eta_{K_{1_7}p_{E_7}}$	-1.4845***	(0.3883)	$\eta_{K_{1_7}p_{E_7}}$	-1.4322***	(0.3475)
$\eta_{K_{1_8}p_{E_8}}$	-0.2249***	(0.0608)	$\eta_{K_{1_8}p_{E_8}}$	-2.4585***	(0.6472)

Table 4: Estimation results for $CPEs$ based on the KLE model specification, given by equation (eq10).

$\eta_{K_{1_1}p_{E_1}}$	-0.0820	(0.2754)	$\eta_{K_{2_1}p_{E_1}}$	-0.6185	(2.9585)
$\eta_{K_{1_2}p_{E_2}}$	-0.1168	(0.3843)	$\eta_{K_{2_2}p_{E_2}}$	-0.2903	(2.2765)
$\eta_{K_{1_3}p_{E_3}}$	-0.0778	(0.3869)	$\eta_{K_{2_3}p_{E_3}}$	0.0633	(1.0108)
$\eta_{K_{1_4}p_{E_4}}$	-0.0878	(0.2669)	$\eta_{K_{2_4}p_{E_4}}$	-1.1789	(4.6816)
$\eta_{K_{1_5}p_{E_5}}$	-0.1193	(0.3809)	$\eta_{K_{2_5}p_{E_5}}$	-0.6220	(2.5815)
$\eta_{K_{1_6}p_{E_6}}$	-0.0865	(0.2822)	$\eta_{K_{2_6}p_{E_6}}$	-0.7466	(3.1930)
$\eta_{K_{1_7}p_{E_7}}$	-0.4105	(1.1970)	$\eta_{K_{2_7}p_{E_7}}$	-0.3601	(1.3720)
$\eta_{K_{1_8}p_{E_8}}$	-0.1263	(0.3804)	$\eta_{K_{2_8}p_{E_8}}$	-0.7608	(3.4683)

For table 3 and 4 ,see footnote in Table 1 for notation used in these tables.

Table 5: Estimation results of the long run GL specification given by equation (eq15).

α_{EE}	-0.0077	(0.0119)
α_{EK_1}	0.0252***	(0.0089)
α_{EK_2}	0.0251**	(0.0105)
α_{EL}	0.0115*	(0.0064)
α_{EM}	-0.0288***	(0.0095)
$\alpha_{K_1K_1}$	-0.0641**	(0.0260)
$\alpha_{K_1K_2}$	0.0937***	(0.0178)
α_{K_1L}	-0.0812***	(0.0112)
α_{K_1M}	0.1523***	(0.0196)
$\alpha_{K_2K_2}$	-0.0985	(0.0741)
α_{K_2L}	0.0706**	(0.0327)
α_{K_2M}	0.2235***	(0.0450)
α_{LL}	0.2772***	(0.0212)
α_{LM}	0.0065	(0.0203)
α_{MM}	0.2607***	(0.0360)
$\tau_{t\tilde{t}_1}$	0.0133***	(0.0030)
$\tau_{t\tilde{t}_2}$	0.0060**	(0.0030)
$\tau_{t\tilde{t}_3}$	-0.0003	(0.0040)
$\tau_{t\tilde{t}_4}$	0.0345***	(0.0040)
$\tau_{t\tilde{t}_5}$	-0.0010***	(0.0030)
$\tau_{t\tilde{t}_6}$	0.0047	(0.0030)
$\tau_{t\tilde{t}_7}$	0.0040	(0.0034)
$\tau_{t\tilde{t}_8}$	0.0127***	(0.0036)

See footnote in Table 1 for notation used in this Table.

Table 6: Estimation results of the long run EoS based on the GL specification given by equation (eq16).

$\eta_{K_{1_1}p_{E_1}}$	0.0962***	(0.0339)	$\eta_{K_{2_1}p_{E_1}}$	0.0430**	(0.0180)
$\eta_{K_{1_2}p_{E_2}}$	0.0918***	(0.0324)	$\eta_{K_{2_2}p_{E_2}}$	0.0415**	(0.0174)
$\eta_{K_{1_3}p_{E_3}}$	0.0980***	(0.0345)	$\eta_{K_{2_3}p_{E_3}}$	0.0424**	(0.0177)
$\eta_{K_{1_4}p_{E_4}}$	0.0852***	(0.0300)	$\eta_{K_{2_4}p_{E_4}}$	0.0398**	(0.0166)
$\eta_{K_{1_5}p_{E_5}}$	0.1028***	(0.0362)	$\eta_{K_{2_5}p_{E_5}}$	0.0436**	(0.0183)
$\eta_{K_{1_6}p_{E_6}}$	0.0946***	(0.0334)	$\eta_{K_{2_6}p_{E_6}}$	0.0424**	(0.0177)
$\eta_{K_{1_7}p_{E_7}}$	0.1035***	(0.0365)	$\eta_{K_{2_7}p_{E_7}}$	0.0394**	(0.0165)
$\eta_{K_{1_8}p_{E_8}}$	0.0928***	(0.0327)	$\eta_{K_{2_8}p_{E_8}}$	0.0412**	(0.0172)

See footnote in Table 1 for notation used in this Table.

Table 7: Estimation results of the short run parameters based on the GL specification of the equations input-output given by equation (eq21).

ψ	-2.0398***	(0.5532)
ϕ_1	-1.2674**	(0.7531)
ϕ_2	-0.8822***	(0.1486)
ϕ_3	2.9010	(1.8062)
ϕ_4	-0.9755	(1.0301)
ϕ_5	-1.8862**	(0.8258)
ϕ_6	-0.2544	(0.4848)
ϕ_7	2.2260	(1.7938)
ϕ_8	-2.2446*	(0.4364)
$\tilde{\alpha}_{EE}$	-0.0101	(0.0286)
$\tilde{\alpha}_{EK_1}$	0.0454*	(0.0266)
$\tilde{\alpha}_{EK_2}$	0.0052	(0.0396)
$\tilde{\alpha}_{EL}$	0.0225**	(0.0112)
$\tilde{\alpha}_{EM}$	-0.0379*	(0.0213)
$\tilde{\alpha}_{K_1K_1}$	-0.1238	(0.0987)
$\tilde{\alpha}_{K_1K_2}$	0.1472***	(0.0387)
$\tilde{\alpha}_{K_1L}$	-0.1038***	(0.0156)
$\tilde{\alpha}_{K_1M}$	0.1596***	(0.0423)
$\tilde{\alpha}_{K_2K_2}$	-0.1078	(0.2624)
$\tilde{\alpha}_{K_2L}$	0.0661	(0.0978)
$\tilde{\alpha}_{K_2M}$	0.2027	(0.1418)
$\tilde{\alpha}_{LL}$	0.2865***	(0.0556)
$\tilde{\alpha}_{LM}$	0.0142	(0.0548)
$\tilde{\alpha}_{MM}$	0.2752**	(0.0930)
$\tilde{\tau}_{t\tilde{t}_1}$	0.0136**	(0.0060)
$\tilde{\tau}_{\tilde{t}\tilde{t}_2}$	0.0055	(0.0113)
$\tilde{\tau}_{t\tilde{t}_3}$	-0.0001	(0.0074)
$\tilde{\tau}_{t\tilde{t}_4}$	0.0343***	(0.0116)
$\tilde{\tau}_{t\tilde{t}_5}$	-0.0096	(0.0099)
$\tilde{\tau}_{t\tilde{t}_6}$	0.0047	(0.0060)
$\tilde{\tau}_{t\tilde{t}_7}$	0.0040	(0.0141)
$\tilde{\tau}_{t\tilde{t}_8}$	0.0127***	(0.0044)
Arellano-Bond test for AR(1)	-1.76	$P-value$ =0.079
Arellano-Bond test for AR(2)	-0.22	$P-value$ =0.827

See footnote in Table 1 for notation used in this Table.

Table 8: Estimation results of the short run EoS based on the GL specification given by equation (eq16).

$\eta_{K_{1_1}p_{E_1}}$	0.1714*	(0.1005)	$\eta_{K_{2_1}p_{E_1}}$	0.0090	(0.0683)
$\eta_{K_{1_2}p_{E_2}}$	0.1648*	(0.0966)	$\eta_{K_{2_2}p_{E_2}}$	0.0087	(0.0656)
$\eta_{K_{1_3}p_{E_3}}$	0.1768*	(0.1036)	$\eta_{K_{2_3}p_{E_3}}$	0.0089	(0.0670)
$\eta_{K_{1_4}p_{E_4}}$	0.1533*	(0.0899)	$\eta_{K_{2_4}p_{E_4}}$	0.0083	(0.0630)
$\eta_{K_{1_5}p_{E_5}}$	0.1834*	(0.1075)	$\eta_{K_{2_5}p_{E_5}}$	0.0091	(0.0690)
$\eta_{K_{1_6}p_{E_6}}$	0.1686*	(0.0988)	$\eta_{K_{2_6}p_{E_6}}$	0.0089	(0.0671)
$\eta_{K_{1_7}p_{E_7}}$	0.2006*	(0.1176)	$\eta_{K_{2_7}p_{E_7}}$	0.0081	(0.0611)
$\eta_{K_{1_8}p_{E_8}}$	0.1672*	(0.0980)	$\eta_{K_{2_8}p_{E_8}}$	0.0086	(0.0652)

See footnote in Table 1 for notation used in this Table.

Table 9: Tests for a common unit root: Levin, Lin, and Chu (LLC , 2002) and Breitung (2000).

Null:common unit root process	Levels LLC	Levels Breitung t -stat	First differences LLC	First differences Breitung t -stat
E	-2.9319***	-2.0553**	-8.4115***	0.3418
K_1	-7.1817***	3.6483	-11.0840***	-8.9659***
K_2	-3.3529***	-0.7121	-4.3853***	-3.9532***
L	-3.6179***	-0.4884	-4.9019***	-4.0408***
M	2.6868	9.1312	-1.8084**	-4.5858***
$IR\&DEF$	-1.3199	-0.9862	-13.3448***	-4.6862***
y	0.3683	6.3036	-2.6277***	-4.8213***

"*" denotes rejection of the null hypothesis at 10 percent level, "**" at 5 percent level and "***" at 1 percent level.

Table 10: Tests for individual unit root: Im, Pesaran and Shin (IPS , 2003), Augmented Dickey Fuller (ADF) and Phillip-Perron (PP).

Series in levels			
	IPS	ADF -Fisher	PP -Fisher
E	-1.9874**	30.5644**	52.4336***
K_1	-4.4823***	46.9313***	40.5891***
K_2	0.1891	22.4298	10.1968
L	-0.2756	19.9994	4.1604
M	6.4112	1.8019	3.8321
$IR\&DEF$	-1.5712**	21.6382	34.8997***
y	3.5521	18.3578	6.0799
First differences			
E	-7.8269***	113.9340***	91.8918***
K_1	-9.3789***	104.2700***	49.5041***
K_2	-3.7331***	46.5842***	43.4554***
L	-6.2217***	65.3152***	87.7057***

Table 10 (Continuation)

M	-8.4268***	92.2833***	198.439***
$IR\&DEF$	-12.8364***	171.0940***	175.431***
y	-7.2094***	77.0375***	87.0090***

"*" denotes rejection of the null hypothesis at 10 % level, "**" at 5 percent level and "***" at 1 percent level.

Table 11: Pedroni (2004) test for cointegration.

Alternative hypothesis: common autoregressive coefficients (within-dimension)	
Panel v -Statistic	2.0895**
Panel rho -Statistic	0.3065
Panel PP -Statistic	-2.8598***
Panel ADF -Statistic	0.3754
Alternative hypothesis: individual autoregressive coefficients (between-dimension)	
Group rho -Statistic	2.0007
Group PP -Statistic	-0.6011
Group ADF -Statistic	0.5506

"*" denotes rejection of the null hypothesis at 10 % level, "**" at 5% level and "***" at 1 % percent level.

Table 12: Estimation results of the Error Correction parameters given by equation (eq27).

$\tilde{\eta}_{K_{1_1}}$	0.4353*	(0.2557)	$\tilde{\eta}_{M_1}$	-0.7343***	(0.2573)
$\tilde{\eta}_{K_{1_2}}$	0.05227	(0.2085)	$\tilde{\eta}_{M_2}$	0.1482	(0.1234)
$\tilde{\eta}_{K_{1_3}}$	0.5039***	(0.1420)	$\tilde{\eta}_{M_3}$	-0.0662	(0.325)
$\tilde{\eta}_{K_{1_4}}$	0.0765	(0.1766)	$\tilde{\eta}_{M_4}$	0.0621	(0.3594)
$\tilde{\eta}_{K_{1_5}}$	0.7650**	(0.3635)	$\tilde{\eta}_{M_5}$	-4.244***	(0.4156)
$\tilde{\eta}_{K_{1_6}}$	1.4190***	(0.3236)	$\tilde{\eta}_{M_6}$	-6.5127***	(0.7809)
$\tilde{\eta}_{K_{1_7}}$	-0.2559	(0.2666)	$\tilde{\eta}_{M_7}$	0.2880	(2.6086)
$\tilde{\eta}_{K_{1_8}}$	0.1693	(0.1580)	$\tilde{\eta}_{M_8}$	0.8302***	(0.2476)
$\tilde{\eta}_{K_{2_1}}$	1.5887***	(0.3264)	$\tilde{\eta}_{\tilde{t}_1}$	0.0179	(0.0426)
$\tilde{\eta}_{K_{2_2}}$	1.4008**	(0.5624)	$\tilde{\eta}_{\tilde{t}_2}$	0.0011	(0.0015)
$\tilde{\eta}_{K_{2_3}}$	-1.1477***	(0.4003)	$\tilde{\eta}_{\tilde{t}_3}$	-0.1544	(0.1279)
$\tilde{\eta}_{K_{2_4}}$	1.4035***	(0.2960)	$\tilde{\eta}_{\tilde{t}_4}$	0.0048**	(0.0023)
$\tilde{\eta}_{K_{2_5}}$	4.1575***	(0.7003)	$\tilde{\eta}_{\tilde{t}_5}$	-0.0108***	(0.003)
$\tilde{\eta}_{K_{2_6}}$	1.0160***	(0.2634)	$\tilde{\eta}_{\tilde{t}_6}$	0.3593***	(0.1365)
$\tilde{\eta}_{K_{2_7}}$	0.2369	(0.7513)	$\tilde{\eta}_{\tilde{t}_7}$	0.0993	(0.0674)
$\tilde{\eta}_{K_{2_8}}$	-0.7160	(0.6258)	$\tilde{\eta}_{\tilde{t}_8}$	0.36155***	(0.1316)
$\tilde{\eta}_{L_1}$	-1.4460***	(0.1708)	θ_1	1.3561***	(0.3778)
$\tilde{\eta}_{L_2}$	0.1498	(0.2971)	θ_2	-0.0811	(0.1815)
$\tilde{\eta}_{L_3}$	0.2143	(0.2967)	θ_3	-0.4009	(0.4318)
$\tilde{\eta}_{L_4}$	-0.3198	(0.2833)	θ_4	-0.3990	(0.339)

Table 12: (Continuation)

$\tilde{\eta}_{L_5}$	-3.5484***	(0.3807)	θ_5	5.7428***	(0.5822)
$\tilde{\eta}_{L_6}$	-3.5715***	(0.2760)	θ_6	8.9029***	(0.9225)
$\tilde{\eta}_{L_7}$	1.4399***	(0.4954)	θ_7	-0.8622	(4.5357)
$\tilde{\eta}_{L8}$	0.0478	(0.2663)	θ_8	-0.6908***	(0.2231)
π_{K_1}	-0.0371	(0.1270)			
π_{K_2}	-0.4440***	(0.1091)			
($\phi - 1$)	0.3189***	(0.1184)			
π_L	0.1364	(0.2225)			
π_M	0.1942	(0.2883)			
$\pi_{\tilde{t}}$	-0.0079**	(0.0036)			
θ	-0.2132	(0.3446)			
A_h	8DV				
$A-B$ for AR(1)	-2.51	$P-value$ =0.012			
$A-B$ for AR(2)	0.79	$P-value$ =0.431			
Hansen test	0	$P-value$ =1			
Sargan test	11.92	$P-value$ =0.03			

See footnote in Table 1 for notation used in this Table.
The parameters related to the dummy variables are available upon request from the authors.

Table 13: Alternative tests of cointegration based on the residuals of the ECM.

Null: Unit root (assumes common unit root process)	
Levin, Lin & Chu*	-19.1334***
Null: Unit root (assumes individual unit root process)	
ADF - Fisher Chi-square	481.4740***
PP - Fisher Chi-square	432.9090***

"*" denotes rejection of the null hypothesis at 10 percent level, "**" at 5 percent level and "***" at 1 percent level.

Table 14: Short and long run elasticities based on specification (eq27) and (eq28).

$TES_{E_1K_{1_1}}$	0.4353*	(0.2557)	$TES_{E_1K_{2_1}}$	1.5887***	(0.3264)
$TES_{E_2K_{1_2}}$	0.0523	(0.2085)	$TES_{E_2K_{2_2}}$	1.4008**	(0.5624)
$TES_{E_3K_{1_3}}$	0.5039***	(0.1420)	$TES_{E_3K_{2_3}}$	-1.1477***	(0.4003)
$TES_{E_4K_{1_4}}$	0.0765	(0.1766)	$TES_{E_4K_{2_4}}$	1.4034***	(0.2960)
$TES_{E_5K_{1_5}}$	0.7657**	(0.3635)	$TES_{E_5K_{2_5}}$	4.1575***	(0.7003)
$TES_{E_6K_{1_6}}$	1.4190***	(0.3236)	$TES_{E_6K_{2_6}}$	1.0161***	(0.2634)
$TES_{E_7K_{1_7}}$	-0.2560	(0.2666)	$TES_{E_7K_{2_7}}$	0.2369	(0.7513)
$TES_{E_8K_{1_8}}$	0.1694	(0.1580)	$TES_{E_8K_{2_8}}$	-0.7160	(0.6258)
$TES^{LR}_{EK_1}$	0.1162	(0.3845)	$TES^{LR}_{EK_2}$	1.3924***	(0.5159)

See footnote in Table 1 for notation used in this Table. Additionally, LR denotes Long Run.

Appendix B

Table B1: Estimated results of the own price-elasticities based on the TCF, given by equation (eq11).

Industries	E	K_1	K_2	L	M
1	-0.5490	-0.3134***	-0.2837***	-0.6675***	-0.5353***
	(0.4759)	(0.0941)	(0.0772)	(0.0477)	(0.0647)
2	-0.6520*	-0.1140	-0.3205***	-0.6734***	-0.5106***
	(0.3587)	(0.1355)	(0.0641)	(0.0583)	(0.0608)
3	-0.7942***	-0.1910	-0.3177***	-0.6623***	-0.5793***
	(0.1814)	(0.1203)	(0.0654)	(0.0445)	(0.0733)
4	-0.3290	-0.3370***	-0.2938***	-0.6682***	-0.5447***
	(0.7227)	(0.0885)	(0.0741)	(0.0483)	(0.0663)
5	-0.4520	-0.0440	-0.0260	-0.6384***	-0.4548***
	(0.5856)	(0.1491)	(0.1327)	(0.0365)	(0.0536)
6	-0.4200	-0.3021**	-0.2428***	-0.6600***	-0.5215***
	(0.6211)	(0.0966)	(0.0880)	(0.0434)	(0.0624)
7	-0.6510*	3.6049***	2.9302***	-0.6607***	-0.2559***
	(0.3596)	(0.7874)	(0.6147)	(0.0437)	(0.0380)
8	-0.3760	-0.1760	-0.3147***	-0.6545***	-0.5622***
	(0.6699)	(0.1233)	(0.0667)	(0.0411)	(0.0696)

See footnote in Table 1 for notation used in this Table.

Table B2: Estimated results of the long run own price elasticities based on the GL specification given by equation (eq17).

Industries	E	K_1	K_2	L	M
1	-0.6418**	-0.7176***	-0.6439***	-0.0110	-0.2779***
	(0.2881)	(0.0910)	(0.1104)	(0.0373)	(0.0309)
2	-0.4994**	-0.6933***	-0.6333***	-0.0090	-0.2765***
	(0.2237)	(0.0900)	(0.1091)	(0.0372)	(0.0305)
3	-0.7043**	-0.7353***	-0.6449***	-0.0060	-0.2789***
	(0.3116)	(0.0954)	(0.1090)	(0.0380)	(0.0310)
4	-0.3417**	-0.6382***	-0.6090***	-0.0080	-0.2692***
	(0.1516)	(0.0824)	(0.1035)	(0.0353)	(0.0300)
5	-1.2981**	-0.7838***	-0.6691***	-0.0110	-0.2854***
	(0.5657)	(0.1009)	(0.1163)	(0.0392)	(0.0313)
6	-0.7247**	-0.7314***	-0.6519***	-0.0110	-0.2807***
	(0.3122)	(0.0927)	(0.1134)	(0.0376)	(0.0308)
7	-0.5784**	-0.7665***	-0.6317***	0.0140	-0.2840***
	(0.2258)	(0.1161)	(0.1029)	(0.0393)	(0.0299)
8	-0.5065**	-0.6958***	-0.6299***	-0.0070	-0.2742***
	(0.2269)	(0.09)	(0.1058)	(0.037)	(0.0308)

See footnote in Table 1 for notation used in this Table.

Table B3: Estimated results of the short run own price elasticities based on the GL specification given by equation (eq17).

Industries	E	K_1	K_2	L	M
1	-0.7110	0.9203***	-0.6590*	0.0030	-0.2653***
	(0.7308)	(0.3405)	(0.3939)	(0.0969)	(0.0788)
2	-0.5450	-0.8959**	-0.6480*	0.0060	-0.2642***
	(0.4731)	(0.3361)	(0.3863)	(0.1010)	(0.0777)
3	-0.7720	-0.9537***	-0.6590*	0.0090	-0.2665***
	(0.7681)	(0.3616)	(0.3858)	(0.0985)	(0.0785)
4	-0.3690	-0.8259***	-0.6230*	0.0050	-0.2572***
	(0.3618)	(0.3092)	(0.3671)	(0.0914)	(0.0760)
5	-1.4800	-1.0070***	-0.6840*	0.0050	-0.2725***

Table B3: (Continuation)

	(1.5041)	(0.3761)	(0.4180)	(0.1023)	(0.0818)
6	-0.8080	-0.9381***	-0.6670*	0.0050	-0.2681***
	(0.8115)	(0.3472)	(0.4033)	(0.0983)	(0.0785)
7	-0.6110	-1.0676**	-0.6420*	0.0350	-0.2725***
	(0.6003)	(0.4965)	(0.3570)	(0.1037)	(0.0769)
8	-0.5520	-0.9011***	-0.6440*	0.0070	-0.2619***
	(0.5441)	(0.3389)	(0.376)	(0.0964)	(0.0782)

See footnote in Table 1 for notation used in this Table.