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Production Functions for Climate Policy Modeling: An Empirical Analysis

by

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Abstract

Quantitative models for climate policy modeling differ in the production structure used and in the sizes of the elasticities of substitution. The empirical foundation for both is generally lacking. This paper estimates the parameters of two-level CES production functions with capital, labour and energy as inputs, and is the first to systematically compare all nesting structures. Using industry-level data from 12 OECD countries, we find that the nesting structure where capital and labour are combined first, fits the data best, but for most countries and industries we cannot reject that all three inputs can be put into one single nest. These two nesting structures are used by most climate models. However, while several climate policy models use a Cobb-Douglas function for (part of the) production function, we reject elasticities equal to one, in favour of considerably smaller values. Finally we find evidence for factor-specific technological change. With lower elasticities and with factor-specific technological change, some climate policy models may find a bigger effect of endogenous technological change on mitigating the costs of climate policy.

JEL Classification: O13, Q32, Q43, Q55

Keywords: Climate policy, input substitution, technological change

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1 Introduction

The recent literature on the long run effects of climate policy focusses on the alleviating effect of endogenous technological change on the costs of climate policy. That is, it studies the welfare gains from research and development or from learning-by-doing effects when the economy faces some form of climate policy, compared to a scenario without endogenous technological change. Next to investing in new technologies, applied climate policy models allow firms to react to price changes, caused by climate policy, through input substitution, e.g. shifting away from energy towards capital or labour. Since the endogenous changes in technology are themselves determined by the price changes and the substitution possibilities – the easier it is to substitute away from energy, the smaller may be the need to invest in energy-saving technologies –, it is important that the substitution possibilities in applied climate policy models are not only empirically founded, but also disentangled from changes in the production isoquant that come from technological change: too high or too low elasticities may lead to under- or overestimates of the effects of endogenous technological change. In addition, the results of simulations without technological change are sensitive to the elasticity of substitution. Indeed, Jacoby et al. (2006) found that, in the MIT EPPA model, the elasticity of substitution between energy and value-added (the capital-labour composite) is the parameter that affects the costs of "Kyoto forever" for the U.S. economy the most.

Unfortunately, in most applied dynamic climate policy models, neither the production structure nor the accompanying elasticities of substitution have an empirical basis. The current paper therefore estimates production functions for climate policy models. We study all possible production structures, while taking into account that both substitution possibilities and technological change affect the production possibilities frontier.

In applied climate policy models the ease with which one can substitute one input for another is generally represented by elasticities of substitution. As they generally use constant elasticity of substitution (CES) production functions with capital, labour and energy as inputs, applied climate models can choose between different structures for the production function. For example, capital and energy can be combined first using a two-input CES function with a specific elasticity of substitution, and subsequently this composite can be 'nested' into another CES function, where it is combined with labour (with possibly a different elasticity).

Table 1 presents an overview of the production structures, elasticities of substitution and types of technological change of some dynamic models that simulate the effect of climate policy on the economy. The table shows that the nesting structure differs between the various papers. Moreover, 3 out of 10 models do not nest at all and treat all inputs at the same level. A second observation is that in all models but one, capital is in the same nest as labour. One could nevertheless argue that capital and energy should be combined first, as is done in the GREEN model (Burniaux et al., 1992), since (physical) capital and energy generally operate jointly.

When we look at the elasticities of substitution in Table 1, we see that models use different values for the elasticities of substitution, even when they use the same nesting structure. In addition, many models use the knife-edge case of a unit elasticity and hence neutral technological change in (part of) the production function. When the elasticity of substitution is equal to one, the CES function reduces to a Cobb-Douglas function, in which case relative factor productivity is unaffected by technological change. Hence the choice for a unit elasticity greatly affects the role of technological change in model simulations.

The way in which technological change enters the production function differs as well (we define technological change as a change in the position or shape of the production isoquant, for a given elasticity of substitution).

Table 1: Nesting structure and elasticities of substitution for several models

Author(s)	Nesting structure[a]	Elasticities[b]	Techn. change[c]
Bosetti et al. (2006)	(KL)E	$\sigma_{K,L} = 1$; $\sigma_{KL,E} = 0.5$	exog. TFP; endog. energy-specific
Burniaux et al. (1992)[d]	(KE)L	$\sigma_{K,E} = 0$ or 0.8; $\sigma_{KE,L} = 0$ or 0.12 or 1	exogenous
Edenhofer et al. (2005)	KLE	$\sigma_{K,L,E} = 0.4$	endog. factor-specific
Gerlagh and Van der Zwaan (2003)	(KL)E	$\sigma_{K,L} = 1$; $\sigma_{KL,E} = 0.4$	endog. energy-specific
Goulder and Schneider (1999)	KLEM	$\sigma_{K,L,E,M} = 1$	endog. TFP
Kemfert (2002)	(KLM)E	$\sigma_{KLM,E} = 0.5$	endog. energy-specific
Manne et al. (1995)	(KL)E	$\sigma_{K,L} = 1$; $\sigma_{KL,E} = 0.4$	exogenous
Paltsev et al. (2005)	(KL)E	$\sigma_{K,L} = 1$; $\sigma_{KL,E} = 0.4 - 0.5$	exogenous
Popp (2004)	KLE	$\sigma_{K,L,E} = 1$	endog. energy-specific
Sue Wing (2003)[e]	(KL)(EM)	$\sigma_{K,L} = 0.68 - 0.94$; $\sigma_{E,M} = 0.7$; $\sigma_{KL,EM} = 0.7$	endog. TFP

[a] (KL)E means a nesting structure in which capital and labour are combined first, and then this composite is combined with energy with a different elasticity of substitution. (KLE) means that all inputs are in a single-level CES function.

[b] $\sigma_{i,j}$ is the elasticity of substitution between inputs i and j and $\sigma_{ij,k}$ is the elasticity of substitution between the composite of inputs i and j on the one hand, and input k on the other.

[c] TFP = Total Factor Productivity growth.

[d] Lower elasticities for old capital, higher elasticities for new capital.

[e] Elasticities taken from Cruz and Goulder (1992).

Focussing on endogenous technological change, we see that four of the models in Table 1 use energy specific technological change, two models use total factor productivity (TFP) growth (both at the industry level), and only one model uses factor-specific technological change.

In sum, dynamic climate policy models differ along three dimensions: nesting structure, the sizes of the elasticities, and the way in which technological change affects marginal productivities. Surprisingly, the production functions used by the models in Table 1 generally lack empirical foundation. While authors refer to other papers – that don't have empirical validations themselves – for the nesting structures and elasticities chosen, technology is generally modeled in a way that the modeler suits best, or to best answer the question under scrutiny. The current paper offers an empirical analysis of all three dimensions by estimating CES production functions for all possible nesting structures. Accordingly, we report the accompanying elasticities of substitution for each nesting structure and conclude which nesting structure fits the data best.

We find that the (KL)E nesting structure, that is a nesting structure in which capital and labour are combined first, fits the data best, but we generally cannot reject that the production function has all inputs in one CES function (i.e. a 3-input 1-level CES function). These nesting structures are used by most of the models in Table 1. However, for the (KL)E nesting structure we reject that elasticities are equal to 1, in favour of considerably lower values, while several of the climate policy models in the table use a Cobb-Douglas function for (part of the) production function. Finally we test for different technology trends and reject the hypothesis that only energy-specific technological change matters, and the hypothesis of total factor productivity (TFP) growth, in favour of factor-specific technological change. That is, technology trends differ significantly between capital, labour and energy.

In all models in Table 1, firms minimize costs. Hence estimates of constant substitution elasticities for dynamic climate policy models should start from firms' optimizing behavior. Only a few papers have estimated CES production functions with capital, labour and energy as inputs, using equations that are derived from optimizing behavior by firms. Prywes (1986) and Chang (1994) both use ratios of first-order conditions to estimate the parameters of a (KE)L nesting structure, disregarding the (KL)E and (LE)K structures.[1] Both authors first use the ratio of the first-order conditions for capital and energy to estimate the elasticity of substitution between capital and energy, which we denote by $\sigma_{K,E}$. Using this estimate, they derive fitted values for composite input Z and its price P_Z, which are subsequently employed to estimate the elasticity of substitution between the capital-energy composite on the one hand and labour on the other, which we denote by $\sigma_{KE,L}$. For this they exploit the first-order conditions with respect to labour and Z. However, when taking ratios of first-order conditions, it becomes impossible to identify the individual technology parameters, which we need to study how technological change affects the production function.[2]

Prywes (1986) uses pooled data from 4-digit U.S. industries for the period 1971-1976 to estimate elasticities for 2-digit industries. He finds estimates for $\sigma_{K,E}$ ranging from -0.57 to 0.47. His estimates for $\sigma_{KE,L}$ range from 0.21 to 1.58. Chang (1994) uses time series data for Taiwan and finds the elasticity of substitution between capital and energy to be about 0.87, and the one for labour and the capital-energy nest to be around 0.45.

The remainder of the paper is organized as follows. We first introduce the

[1] In a footnote, Chang (1994) claims he compared several nesting structures and chose to combine capital and energy first, based on the R^2. However, he does not report his results.

[2] Prywes (1986) estimates total factor productivity growth separately from the first order conditions, using dummy variables. Hence his results on technological change do not affect his estimates of the substitution elasticities and are hence outside the scope of this paper.

nested CES production function and derive the equations to be estimated. We then describe our dataset and the econometric method in section 3. In section 4 we present our estimation results, where we first discuss which nesting structure fits the data best and then present the estimated elasticities of substitution for each nesting structure. We explicitly test whether substitution elasticities differ significantly from one and whether the production function should be nested. Section 4.4 presents our results regarding technological change. In section 5 we confront our results with the production functions used in the literature on dynamic climate policy modeling. We summarize and conclude in section 6.

2 Model specification

The two-level three-input CES production function can be nested in three ways: (KL)E, (KE)L and (LE)K. For the purpose of illustration we focus in this section on the (KL)E structure, although we estimate all three nesting structures and present the results for all nesting structures in section 4. The (KL)E nesting structure looks as follows:[3]

$$Q = \left(\alpha (A_E E)^{\frac{\sigma_{KL,E^{-1}}}{\sigma_{KL,E}}} + (1-\alpha)(Z)^{\frac{\sigma_{KL,E^{-1}}}{\sigma_{KL,E}}} \right)^{\frac{\sigma_{KL,E}}{\sigma_{KL,E^{-1}}}}, \tag{1}$$

with

$$Z = \left(\beta (A_K K)^{\frac{\sigma_{K,L^{-1}}}{\sigma_{K,L}}} + (1-\beta)(A_L L)^{\frac{\sigma_{K,L^{-1}}}{\sigma_{K,L}}} \right)^{\frac{\sigma_{K,L}}{\sigma_{K,L^{-1}}}}. \tag{2}$$

When (2) is substituted into (1) we have a nested CES function where inputs capital K and labour L are combined to form a composite input Z in the

[3]As in the literature on general equilibrium climate policy modeling, we assume constant returns to scale production functions. Note that in models with endogenous technological change the returns to scale need not be constant at the aggregate level, although they are for each individual goods producer.

lower nest, which in turn is combined with the energy input E to give final output Q. In the remainder of the paper we denote a composite of two inputs by Z. The A_j, $j \in \{E, K, L\}$, are parameters representing factor-specific levels of technology.[4] The elasticity of substitution between energy E and composite input Z equals $\sigma_{KL,E}$, and $\sigma_{K,L}$ is the elasticity of substitution between inputs K and L. Parameters α and β, $0 < \alpha, \beta < 1$, are share parameters.[5]

When an elasticity of substitution equals unity, the production function involved reduces to a Cobb-Douglas function with the share parameters in (1) and (2) as production elasticities. From (1) and (2) it is easy to see that if $\sigma_{KL,E} = \sigma_{K,L}$, then the nested function reduces to a one-level CES production function where all three inputs are equally easy to substitute for each other. On the other hand, if two inputs are not in the same nest, then the elasticity of substitution between these inputs is determined by the two CES elasticities and the cost-share of the composite. Hence a different nesting structure implies different values for the substitution elasticities.

One of the questions to be answered in this paper is whether a total factor productivity representation of technology in climate policy models is sufficient, or technology trends are input specific. With a purely total factor productivity representation of technology we have $A_E = A_K = A_L$, in which case we can multiply a total factor productivity parameter A_Q out of the right-hand side of (1). To test for factor-augmenting technological change versus total factor productivity growth we need to identify all (factor-specific) technology parameters. As noted in the introduction, this is not possible when the equations to be estimated are derived from ratios

[4]Note that we multiplied out any total factor productivity term A_Q and Z-specific technology parameter A_Z. Hence these are included in the factor-specific technology parameters A_j.

[5]The levels of output, inputs, Z, and of the five technology parameters are time- and possibly country- or industry-dependent, but we suppressed the subscripts to ease notation.

of first order conditions. We will show that, using a system of equations derived from cost-minimization, we can not only identify all factor-specific technology parameters but in addition we can explicitly test for TFP growth against the null hypothesis of factor-specific technological change.

Following Berndt (1991, p. 457), we assume that our 2-digit industry-level data (see section 3) are sufficiently disaggregated to assume that prices are exogenous, and derive our system of equations from the cost function approach. With a two-level CES production function, the cost minimization problem of a firm can be represented as a two-stage problem: in the case of the (KL)E nesting structure we first have to find the optimal demand for K and L per unit of Z, given prices and technology, and then use the resulting relative price of Z to solve for the optimal demand for E and Z in the upper nest.[6] We present the problem for the upper nest of the (KL)E nesting structure (the problems for the nest with K and L, and for the other nesting structures, are analogous):

$$\min_{E,Z} \; P_E E + P_Z Z \text{ s.t. } (1), \tag{3}$$

where the price of input j is denoted by P_j. From the first order conditions we can derive the cost function $c(P_E, P_Z, Q)$. After applying Shephard's lemma we find the conditional factor demands. Following the literature on climate policy modeling, we assume price-taking behaviour by firms, which implies that the unit cost function gives the price of output. Substituting this result into the conditional factor demands, taking logarithms, and

[6] The weak separability of the nested CES function allows us to first solve for the relative optimal factor demand for the lower nest. Since our functions are homogenous of degree one, we then know the input demand and cost price per unit of Z. This information can subsequently be used to find the optimal levels of E and Z, from which the optimal levels of K and L can be derived.

rearranging, gives for input E (the equation for Z is analogous):

$$\ln\left(\frac{E}{Q}\right) = \sigma_{KL,E}\ln\alpha + (\sigma_{KL,E} - 1)\ln A_E + \sigma_{KL,E}\ln\left(\frac{P_Q}{P_E}\right). \tag{4}$$

As is well-known in the literature on estimating constant substitution elasticities, not all parameters can be estimated, as usually the equation (or system of equations) to be estimated is under-identified. This is can be seen in (4): if we estimate this equation using price and quantity data (by adding an error term to the right-hand side), the first two terms on the right hand side would end up in the constant term and hence the share parameter α and technology parameter A_E cannot be individually identified. After taking first differences (i.e. for each variable X we take $X(t) - X(t-1)$), such that we get percentage changes in (4), the first term on the right-hand side drops out and we can identify (the growth rate of) the factor-specific technology parameter from the constant term, using the estimate for the elasticity of substitution. The same procedure can be applied for input Z and the lower nest. This gives us the following four equations for the (KL)E structure, where lower-case letters denote percentage changes:

$$\begin{aligned} e - q &= (\sigma_{KL,E} - 1)a_E + \sigma_{KL,E}(p_Q - p_E) && (5)\\ z - q &= \sigma_{KL,E}(p_Q - p_Z) && (6)\\ k - z &= (\sigma_{K,L} - 1)a_K + \sigma_{K,L}(p_Z - p_K) && (7)\\ l - z &= (\sigma_{K,L} - 1)a_L + \sigma_{K,L}(p_Z - p_L) && (8) \end{aligned}$$

On the left-hand side of each equation we see the percentage change in the ratio of two quantities. On the right-hand side of each equation we first see a term containing an elasticity of substitution, $\sigma_{i,j}$ or $\sigma_{ij,k}$, and a technology parameter a_j (except for (6), see footnote 4), and a term consisting of the product of a substitution elasticity and the percentage change of the ratio of two prices. Hence the first equation explains the growth rate of the energy-output ratio $e - q$ from the (negative of the) growth rate of their relative price $p_Q - p_E$, the substitution possibilities $\sigma_{KL,E}$, and the rate of energy-augmenting technological change a_E.

Unfortunately z and p_Z are unobservable, and they can neither be derived using the method used by Prywes (1986) and Chang (1994) (as in that case we would not be able to estimate the technology parameters), nor using an index method.[7] To circumvent this problem, we add $p_K - p_Q - (p_Z - p_Q)$ to both sides of (7), which gives us the growth rate of the share of capital costs in the costs of the intermediate input on the left-hand side. We then add $p_Z - p_Q$ to both sides of (6), divide both sides by $\sigma_{KL,E} - 1$, and substitute the resulting expression for $p_Z - p_Q$ into the right-hand side of (7). Applying the same procedure to (8) gives us the following system of equations:

$$e - q = (\sigma_{KL,E} - 1)a_E + \sigma_{KL,E}(p_Q - p_E) \quad (9)$$

$$\widetilde{\theta_{KZ}} = (\sigma_{K,L} - 1)a_K + \frac{\sigma_{K,L} - 1}{1 - \sigma_{KL,E}}\widetilde{\theta_{ZQ}} + (1 - \sigma_{K,L})(p_K - p_Q) \quad (10)$$

$$\widetilde{\theta_{LZ}} = (\sigma_{K,L} - 1)a_L + \frac{\sigma_{K,L} - 1}{1 - \sigma_{KL,E}}\widetilde{\theta_{ZQ}} + (1 - \sigma_{K,L})(p_L - p_Q) \quad (11)$$

where $\widetilde{\theta_{mn}} \equiv p_m + m - (p_n + n)$ is the percentage change of the cost share of input M in the costs of producing N. For the case of the (KL)E nesting

[7] To see this, write (2) in growth rates, which gives $z = \theta_{KZ}(a_K + k) + \theta_{LZ}(a_L + l)$, where the θs are cost-shares. This shows that we need data on technological change to construct data for z. However, as can be seen from (7) and (8), we need data on z and p_Z to be able to identify a_L and a_K. Hence constructing a series for z or p_Z using an index method, and using data on prices and quantities of capital and labour (that is, without knowledge of the technology parameters), will lead to measurement error and hence biased estimates of the coefficients.

structure, this leads to the following model to be estimated:

$$y_1 = \alpha_1 + \beta_1 x_1 + \varepsilon_1 \tag{12}$$

$$y_2 = \alpha_2 + \beta_{21} x_{21} + \beta_{22} x_{22} + \varepsilon_2 \tag{13}$$

$$y_3 = \alpha_3 + \beta_{31} x_{31} + \beta_{32} x_{32} + \varepsilon_3 \tag{14}$$

where the εs are error terms and the dependent variables are $y_1 = e - q$, $y_2 = p_K + k - d\ln(P_k K + P_L L)$ and $y_3 = p_L + l - d\ln(P_k K + P_L L)$, with $d\ln X$ denoting the first difference of the natural logarithm of X. The independent variables are $x_1 = p_Q - p_E$, $x_{21} = x_{31} = d\ln(P_k K + P_L L) - p_Q - q$, $x_{22} = p_K - p_Q$ and $x_{32} = p_L - p_Q$. From (10) and (11) we see that we have to impose the following cross-equation restrictions when estimating the system: $\beta_{22} = \beta_{32}$ and $\beta_{21} = \beta_{31} = -\beta_{22}/(1 - \beta_1)$.[8] We can then derive our parameters as follows: $\sigma_{KL,E} = \beta_1$, $\sigma_{K,L} = 1 - \beta_{22}$, $a_E = \alpha_1/(\beta_1 - 1)$, $a_L = -\alpha_2/\beta_{22}$ and $a_K = -\alpha_3/\beta_{22}$.

Following the analysis above, we see that if we assume that technology is not factor-specific but based on total factor productivity (that is if we do not normalize A_Q to 1 but instead assume that $A_E = A_K = A_L = 1$) we can derive the TFP growth parameter a_Q. For the (KL)E nesting structure this gives:

$$e - q = (\sigma_{KL,E} - 1)a_Q + \sigma_{KL,E}(p_Q - p_E) \tag{15}$$

$$\widetilde{\theta_{KZ}} = \frac{\sigma_{K,L} - 1}{1 - \sigma_{KL,E}}\widetilde{\theta_{ZQ}} + (1 - \sigma_{K,L})(p_K - p_Q) \tag{16}$$

$$\widetilde{\theta_{LZ}} = \frac{\sigma_{K,L} - 1}{1 - \sigma_{KL,E}}\widetilde{\theta_{ZQ}} + (1 - \sigma_{K,L})(p_L - p_Q) \tag{17}$$

Since the last model is a special case of the model with factor-specific technological change, we can test whether technological change is based on total

[8]Using the weak separability of the nested CES function, we first estimate (12) and use the result for β_1 to impose the restriction on β_{21} and β_{22}.

factor productivity growth (as modeled by Goulder and Schneider, 1999; Sue Wing, 2003) or factor-specific. To be more precise, we can test for the model of TFP growth by testing $-\alpha_2/\beta_{22} = -\alpha_3/\beta_{32} = 0$.[9]

In addition we can test for specific functional forms. We can test whether the production function is a one-level, non-nested CES by testing the restriction β_{21} $(= \beta_{31}) = 1$. We can test for a Cobb-Douglas function for one of the two levels by testing $\beta_1 = 1$ and $\beta_{22} = \beta_{32} = 0$, respectively.

3 Econometric model and data

We estimated the system (12)-(14) for each of our 3 nesting structures. To identify the parameters of our model, we first estimate (12) and use the resulting estimate for the elasticity of substitution for the outer nest in the restriction on the system (13)-(14) (see footnote 2). As described below, we have industry-level time series data for 12 countries. We estimate models with industry-specific elasticities and models with country-specific elasticities.[10] That is, we estimate the system (12)-(14) for each nesting structure with panels for each industry to estimate industry-specific elasticities, and estimate the same system for each nesting structure with panels for each country to estimate country-specific elasticities, which gives us in total 6 systems to estimate. We use country-industry fixed effects (i.e. a dummy for each country-industry combination) and estimated the fixed effects models using least squares dummy variable models. We then tested, for each equation in each model, whether the fixed effects where the same for all country-industry combinations. We were unable to reject this hypothesis

[9]We also tested for the model with TFP growth by testing $\alpha_2 = \alpha_3 = 0$, since both tests are statistically correct but may give different results. Our conclusions are qualitatively unaffected when using this alternative test.

[10]We have too few observations per country-industry combination (12 on average, with for some country-industry combinations as few as 6 observations) to estimate elasticities using panels at the combined country-industry level.

for any equation (at the 10% significance level). As a consequence, pooled regressions are more efficient than regressions using fixed effects, and the remainder of the paper contains results from pooled regressions.

The data are derived from the IEA Energy Balances and from the OECD International Sectoral Database.[11] They form an unbalanced panel for 12 OECD countries, with up to 7 industries (6 sub-industries of the manufacturing industry plus the construction industry), and up to 19 years of observations. The countries involved are Belgium, Canada, Denmark, Finland, France, United Kingdom, Italy, the Netherlands, Norway, Sweden, USA and West-Germany. The industries involved are basic metal products, construction, food & tobacco, textiles & leather, non-metallic minerals, transportation equipment, and the paper, pulp & printing industry. Data come from the time period 1978-1996. We drop the first and last percentile of observations for q, e, l, k, and their prices, to correct for outliers without having to judge on individual observations. This gives us in total 1024 observations.

All prices are in 1990 U.S. dollars, PPP. The price of value added is the numeraire. Industry output is the sum of value added and the value of energy at 1990 market prices. Energy is energy use in kiloton of oil equivalents (IEA Energy Balances). Price of energy is per kiloton of oil equivalent (IEA Energy Balances). Capital is gross capital stock (OECD International Sectoral Database). Price (user cost) of capital is foregone interest plus depreciation minus capital gain. Here the interest rate is the nominal bond rate (IMF, International Financial Statistics), depreciation is the ratio of consumption of fixed capital and gross capital stock (both OECD International Sectoral Database) or 3.5%, capital gain is the percentage change in the ratio of gross capital stock in current national prices and gross capital stock. Labour is total employment in man hours (OECD International Sectoral Database). Price of labour is compensation of employees, per man

[11] We use the same database as van Soest et al. (2006).

hour (OECD International Sectoral Database).

4 Estimation results

Before we move to our results regarding goodness of fit, the elasticities of substitution and technological change, we first discuss the cross-equation restrictions that were mentioned before.

4.1 Cross-equation restrictions

As noted in section 2, we have to impose some cross-equation restrictions on the system (13)-(14) to estimate the elasticity of substitution for the inner nest. Before we did so, we first estimated the unrestricted system for all nesting structures, both for country- and industry-specific elasticities. In most cases, the cross-equation restriction $\beta_{22} = \beta_{32}$ was rejected. More precisely, for the model with country-specific elasticities the restriction was rejected for all countries for the (KL)E and (LE)K nesting structures, and for the (KE)L structure it was rejected for 8 out of 12 countries. For the model with industry-specific elasticities the restriction was rejected for all sectors for the (KL)E and (LE)K nesting structures, and for the (KE)L nesting structure it was rejected for 5 out of 7 industries.

However, the purpose of this paper is to estimate elasticities of substitution that can be used in the dynamic climate policy modeling literature, by making the exactly the same assumptions as in the climate policy modeling literature. That is, we started from a nested constant returns to scale CES production function, and assumed perfect competition at all levels. Although a 3-input translog production function is much more flexible, it would have given a range of (non-constant) elasticities, which would not be suitable for climate policy models without having to make additional assumptions. We therefore proceed with our analysis, imposing the cross-

Table 2: Goodness of fit

	(KL)E	(LE)K	(KE)L
Industry σs	0.4090	0.3299	0.1356
Country σs	0.4124	0.3117	0.1612

Note: R^2 adjusted for degrees of freedom.

equation restrictions even for those equations where they are rejected ex ante, to find the parameters of the nested CES production function that fits the data best.

4.2 Goodness of fit

As noted in the introduction, the literature on climate policy modeling lacks a systematic comparison of the empirical relevance of the nesting structures (KL)E, (KE)L and (LE)K. We present the goodness of fit of the three nesting structures in table 2.

Table 2 shows that there are substantial differences in how well each nesting structure fits the data. For both the model with industry-specific elasticities and the model with country-specific elasticities the $\overline{R}^2$ is highest for the (KL)E nesting structure. The (LE)K nesting structure fits the data much better than the (KE)L structure. This is quite surprising, as one might expect the decision on capital investment to be determined jointly with the decision on labour demand or energy demand, instead of the demand for labour to be determined jointly with the demand for energy. Compared to the other nesting structures, the (KE)L structure fits the data poorly.

4.3 Elasticities of substitution

Table 3 presents our results for the elasticities of substitution. We will discuss them by nesting structure.[12]

4.3.1 The (KL)E nesting structure

Several dynamic climate policy models use the (KL)E or ((KL),(EM)) nesting structure. That is, they first combine capital and labour, and this composite is subsequently combined with energy (or an energy-materials composite) using a different elasticity of substitution. The first column of Table 3 shows our estimates for the elasticity of substitution between energy and the capital-labour composite. We see a considerable amount of variation over industries and countries. The industry estimates range from 0.16 to 0.62, while the country estimates range from 0.15 to 0.61. Note that we cannot reject perfect complementarity (i.e. an elasticity equal to zero) between energy and the capital-labour composite for one sector (transport equipment) and 3 countries (Canada, the Netherlands and Sweden). The elasticities for capital and labour are reported in the second column and show quite some variation as well, with estimates ranging from 0.22 to 0.59 for the industry elasticities and from 0.26 to 0.62 for the country estimates.

Table 4 presents the probability values for the two sided tests whether each elasticity is equal to one, in which case we would have a Cobb-Douglas production function.[13] For all countries and industries the null-hypothesis

[12]We tested whether the elasticities were the same for all countries or all industries. We rejected this hypothesis for all nests and for all nesting structures at the 5% significance level, except for the elasticity of substitution for the outer nest of the (KE)L structure, i.e. $\sigma_{KE,L}$. Here we could reject the null hypothesis at the 10% level for country elasticities, but not for industry elasticities. Note that the (KE)L structure is the structure with the lowest goodness of fit.

[13]A p-value smaller than 0.05 implies that we can reject the null-hypothesis at the 5% significance level.

Table 3: Estimated elasticities of substitution

	(KL)E		(LE)K		(KE)L	
	$\sigma_{KL,E}$	$\sigma_{K,L}$	$\sigma_{LE,K}$	$\sigma_{L,E}$	$\sigma_{KE,L}$	$\sigma_{K,E}$
Industry σs						
Basis metals	0.6223**	0.5940**	0.4784**	0.8616**	0.8283**	0.8808**
	(0.0655)	(0.0222)	(0.0208)	(0.0189)	(0.0416)	(0.0208)
Construction	0.2892**	0.2246**	0.1796**	0.5176**	0.9450**	0.9923**
	(0.0564)	(0.0304)	(0.0302)	(0.0438)	(0.1077)	(0.0028)
Food & Tob.	0.3988**	0.4599**	0.4240**	0.8482**	0.9188**	0.9912**
	(0.0583)	(0.0220)	(0.0218)	(0.0249)	(0.0694)	(0.0053)
Transport Eq.	0.1577	0.4441**	0.3723**	0.7999**	0.9826**	0.9966**
	(0.0818)	(0.0321)	(0.0327)	(0.0390)	(0.0792)	(0.0012)
Non-metal. Min.	0.2543**	0.4544**	0.3924**	0.8226**	0.9423**	0.9998**
	(0.0652)	(0.0235)	(0.0233)	(0.0258)	(0.0630)	(0.0041)
Paper etc.	0.3950**	0.3677**	0.3190**	0.7667**	0.8122**	0.9675**
	(0.0732)	(0.0228)	(0.0221)	(0.0312)	(0.0714)	(0.0145)
Textiles etc.	0.2939**	0.2739**	0.2320**	0.7882**	1.0368**	0.9991**
	(0.0647)	(0.0187)	(0.0183)	(0.0318)	(0.0705)	(0.0015)
Country σs						
Belgium	0.6053**	0.6161**	0.5379**	0.8579**	1.0277**	0.9988**
	(0.0759)	(0.0364)	(0.0375)	(0.0326)	(0.0736)	(0.0029)
Canada	0.1719	0.5291**	0.3664**	0.7941**	0.8840**	0.9853**
	(0.1222)	(0.0466)	(0.0516)	(0.0443)	(0.0695)	(0.0146)
Denmark	0.4952**	0.4189**	0.4066**	0.8626**	0.8201**	0.9456**
	(0.0940)	(0.0338)	(0.0316)	(0.0320)	(0.0838)	(0.0191)
Finland	0.5263**	0.5333**	0.4269**	0.8343**	0.8987**	0.9658**
	(0.0715)	(0.0295)	(0.0290)	(0.0290)	(0.0631)	(0.0098)
France	0.3280**	0.3952**	0.3648**	0.7706**	0.9941**	0.9998**
	(0.0727)	(0.0276)	(0.0276)	(0.0353)	(0.1051)	(0.0004)
UK	0.2480**	0.2755**	0.2280**	0.7188**	0.7975**	0.9411**
	(0.0758)	(0.0272)	(0.0274)	(0.0419)	(0.0752)	(0.0141)
Italy	0.2417**	0.5218**	0.4650**	0.8061**	0.9154**	0.9759**
	(0.0761)	(0.0343)	(0.0349)	(0.0320)	(0.0821)	(0.0086)
Netherlands	0.1789	0.2562**	0.2199**	0.7783**	0.9324**	1.0002**
	(0.0939)	(0.0262)	(0.0257)	(0.0471)	(0.1007)	(0.0052)
Norway	0.3034**	0.3634**	0.3089**	0.7155**	0.6812**	0.8046**
	(0.0897)	(0.0296)	(0.0289)	(0.0405)	(0.0856)	(0.0334)
Sweden	0.1474	0.4264**	0.3731**	0.7867**	0.9740**	0.9979**
	(0.0823)	(0.0264)	(0.0262)	(0.0342)	(0.0827)	(0.0017)
USA	0.5465**	0.3194**	0.2852**	0.8618**	0.9735**	0.9994**
	(0.1092)	(0.0271)	(0.0271)	(0.0478)	(0.1163)	(0.0017)
West-Germany	0.3308**	0.4271**	0.3746**	0.7480**	1.1692**	0.9904**
	(0.0961)	(0.0420)	(0.0406)	(0.0554)	(0.1580)	(0.0150)

Note: Standard errors in parentheses. */** indicates that coefficient differs from zero at 5/1% level of significance. Regressions with fixed effects for the second equation for the inner nest of the (KL)E structure and for the equation for the outer nest for the (LE)K structure, for both the model with industry-specific elasticities and the model with country-specific elasticities. Pooled regressions for all other equations.

Table 4: Tests for Cobb-Douglas function.[a]

	(KL)E		(LE)K		(KE)L	
	$\sigma_{KL,E}$	$\sigma_{K,L}$	$\sigma_{LE,K}$	$\sigma_{L,E}$	$\sigma_{KE,L}$	$\sigma_{K,E}$
Industry σs						
Basis metals	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
Construction	0.0000	0.0000	0.0000	0.0000	0.6098	0.0066
Food & Tob.	0.0000	0.0000	0.0000	0.0000	0.2421	0.0986
Transport Eq.	0.0000	0.0000	0.0000	0.0000	0.8265	0.0032
Non-metal. Min.	0.0000	0.0000	0.0000	0.0000	0.3602	0.9575
Paper etc.	0.0000	0.0000	0.0000	0.0000	0.0087	0.0253
Textiles etc.	0.0000	0.0000	0.0000	0.0000	0.6023	0.5269
Country σs						
Belgium	0.0000	0.0000	0.0000	0.0000	0.7073	0.6810
Canada	0.0000	0.0000	0.0000	0.0000	0.0952	0.3159
Denmark	0.0000	0.0000	0.0000	0.0000	0.0322	0.0044
Finland	0.0000	0.0000	0.0000	0.0000	0.1087	0.0005
France	0.0000	0.0000	0.0000	0.0000	0.9551	0.5702
UK	0.0000	0.0000	0.0000	0.0000	0.0072	0.0000
Italy	0.0000	0.0000	0.0000	0.0000	0.3029	0.0049
Netherlands	0.0000	0.0000	0.0000	0.0000	0.5023	0.9758
Norway	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Sweden	0.0000	0.0000	0.0000	0.0000	0.7529	0.2204
USA	0.0000	0.0000	0.0000	0.0038	0.8200	0.7477
West-Germany	0.0000	0.0000	0.0000	0.0000	0.2847	0.5225

[a] Two-sided p-values for H_0: elasticity equal to 1.

of a unit elasticity is rejected.

In addition we tested for common elasticities over the two nests (i.e. $\sigma_{KL,E} = \sigma_{K,L}$). That is, we tested whether the production function could have a single elasticity of substitution and hence could be non-nested. As is shown in Table 5, we cannot reject a non-nested production function for 5 industries and 8 countries.

4.3.2 The (LE)K nesting structure

The substitution elasticities for both nests of the (LE)K nesting structure differ significantly from zero for all countries and all industries. Values for $\sigma_{LE,K}$ range from 0.18 to 0.48 for the industry estimates and from 0.22 to 0.54 for the country estimates. Industry and country elasticities for the inner nest range from 0.52 to 0.86 and from 0.72 to 0.86, respectively. For all elasticities we can reject the null of a unit elasticity at the 1% level. Contrary to the (KL)E structure we can reject the null-hypothesis of a common elasticity for both nests for all countries and all industries for the (LE)K nesting structure.

4.3.3 The (KE)L nesting structure

The (KE)L nesting structure, which has the lowest $\overline{R}^2$, shows remarkably high elasticities when compared to the (KL)E and (LE)K nesting structures. For the outer nest, $\sigma_{KE,L}$, the values range from 0.81 to 1.04 for the industry estimates, and from 0.68 to 1.16 for the country estimates (see Table 3). The values for the elasticity of substitution between capital and energy range from 0.88 to 0.9996, for countries and from 0.80 to 1.00 for industries.

When we test for Cobb-Douglas production functions for the outer nest, we can only reject it for the basis metals industry and for the paper, pulp and printing industry (at the 1% significance level) and for Denmark (at the 5% level, but not at the 1% level), the UK and Norway (at the 1% level). For the inner nest we reject a Cobb-Douglas production function for 4 countries and 5 industries. We cannot reject a common elasticity for both nests, for 6 out of 7 industries and for all countries.

4.4 Technological change

The models in Table 1 not only differ in nesting structure and sizes of substitution elasticities, but also in the way productivity improvements enter

Table 5: Tests for common elasticities (no nesting).[a]

	(KL)E	(LE)K	(KE)L
Industry σs			
Basis metals	0.6832	0.0000	0.2600
Construction	0.3131	0.0000	0.6609
Food & Tob.	0.3276	0.0000	0.2984
Transport Eq.	0.0012	0.0000	0.8604
Non-metal. Min.	0.0039	0.0000	0.3630
Paper etc.	0.7221	0.0000	0.0333
Textiles etc.	0.7879	0.0000	0.5933
Country σs			
Belgium	0.8976	0.0000	0.6956
Canada	0.0064	0.0000	0.1537
Denmark	0.4452	0.0000	0.1447
Finland	0.9269	0.0000	0.2934
France	0.3877	0.0000	0.9567
UK	0.7335	0.0000	0.0606
Italy	0.0008	0.0000	0.4639
Netherlands	0.4285	0.0000	0.5019
Norway	0.5254	0.0000	0.1797
Sweden	0.0013	0.0000	0.7724
USA	0.0439	0.0000	0.8238
West-Germany	0.3588	0.0000	0.2604

[a] Two-sided p-values for H_0: $\sigma_{i,j} = \sigma_{ij,k}$.

the production function. We saw in Table 1 that, of those models with endogenous technological change, 4 models use energy-specific technological change, 2 models use industry-specific total factor productivity changes and 1 model uses factor-specific technological change. Since all these models either use a (KL)E or (KLE) nesting structure, and since this is the structure that fits the data best, we focus on the results for technological change for the (KL)E nesting structure (recall that for the (KL)E nesting structure we could not reject a (KLE) structure for most countries and most industries).

Table 6 shows the factor-specific technology trends for the (KL)E nesting structure. We find rates of energy-augmenting technological change of 1.2-2.7% per year. Interestingly we find the highest rate of energy-specific technological change (over industries) in the energy-intensive basis metals industry. The rates of labour-augmenting technological change are generally higher than the rate of energy-augmenting technological change, with values around 3%, while the rates of capital-augmenting technological change are found to be negative and around -2.3%.

For our purpose it is interesting to see whether the technology trends for the three inputs differ from each other. Table 7 presents, for each country and each industry, tests whether the technology trends are equal. We can reject that the rate of energy-augmenting technological change and the rate of labour-augmenting technological change are equal, for 4 out of 7 industries and 8 out of 12 countries (at the 1% significance level). When testing the equality of either of these two technology trends and the rate of capital-augmenting technological change, we can reject the null-hypothesis for all industries and countries. We therefore conclude that rates of factor-specific technological change tend to differ over factors.

As noted in Section 2, we can test for the model of total factor productivity growth by testing $a_L = a_K = 0$. As can be inferred from Tables 6 and 7, we can reject $a_L = a_K = 0$ for all countries and industries for the (KL)E

Table 6: Rates of factor-specific technological change, (KL)E nesting structure

	Energy	Labour	Capital
Industry σs			
Basis metals	0.0273**	0.0406**	−0.0317**
	(0.0092)	(0.0044)	(0.0036)
Construction	0.0145**	0.0213**	−0.0166**
	(0.0044)	(0.0022)	(0.0018)
Food & Tob.	0.0172**	0.0306**	−0.0238**
	(0.0053)	(0.0032)	(0.0026)
Transport Eq.	0.0122**	0.0297**	−0.0231**
	(0.0038)	(0.0033)	(0.0027)
Non-metal. Min.	0.0138**	0.0302**	−0.0236**
	(0.0042)	(0.0032)	(0.0026)
Paper etc.	0.0170**	0.0261**	−0.0203**
	(0.0055)	(0.0027)	(0.0021)
Textiles etc.	0.0146**	0.0227**	−0.0177**
	(0.0044)	(0.0023)	(0.0018)
Country σs			
Belgium	0.0275**	0.0420**	−0.0347**
	(0.0093)	(0.0056)	(0.0047)
Canada	0.0131**	0.0342**	−0.0283**
	(0.0041)	(0.0047)	(0.0039)
Denmark	0.0215**	0.0278**	−0.0229**
	(0.0071)	(0.0032)	(0.0026)
Finland	0.0229**	0.0346**	−0.0285**
	(0.0072)	(0.0040)	(0.0033)
France	0.0161**	0.0267**	−0.0220**
	(0.0048)	(0.0029)	(0.0024)
UK	0.0144**	0.0223**	−0.0184**
	(0.0043)	(0.0023)	(0.0019)
Italy	0.0143**	0.0337**	−0.0278**
	(0.0042)	(0.0040)	(0.0034)
Netherlands	0.0132**	0.0217**	−0.0179**
	(0.0039)	(0.0023)	(0.0019)
Norway	0.0156**	0.0253**	−0.0209**
	(0.0047)	(0.0028)	(0.0022)
Sweden	0.0127**	0.0281**	−0.0232**
	(0.0037)	(0.0031)	(0.0026)
USA	0.0239**	0.0237**	−0.0196**
	(0.0087)	(0.0025)	(0.0021)
West-Germany	0.0162**	0.0281**	−0.0232**
	(0.0050)	(0.0034)	(0.0029)

Note: Standard errors in parentheses. */** indicates that coefficient differs from zero at 5/1% level of significance.

Table 7: Tests for $a_i = a_j$, for (KL)E structure

	$a_E = a_L$	$a_E = a_K$	$a_L = a_K$
Industry σs			
Basis metals	0.1905	0.0000	0.0000
Construction	0.1734	0.0000	0.0000
Food & Tob.	0.0306	0.0000	0.0000
Transport Eq.	0.0006	0.0000	0.0000
Non-metal. Min.	0.0019	0.0000	0.0000
Paper etc.	0.1374	0.0000	0.0000
Textiles etc.	0.1009	0.0000	0.0000
Country σs			
Belgium	0.1804	0.0000	0.0000
Canada	0.0007	0.0000	0.0000
Denmark	0.4192	0.0000	0.0000
Finland	0.1582	0.0000	0.0000
France	0.0612	0.0000	0.0000
UK	0.1071	0.0000	0.0000
Italy	0.0009	0.0000	0.0000
Netherlands	0.0627	0.0000	0.0000
Norway	0.0730	0.0000	0.0000
Sweden	0.0014	0.0000	0.0000
USA	0.9824	0.0000	0.0000
West-Germany	0.0502	0.0000	0.0000

Note: Two-sided p-values for H_0: $a_i = a_j$.

nesting structure.

5 Discussion

Comparing the results of the previous section with the climate policy models in Table 1, we can draw four conclusions.

The first conclusion refers to the nesting structure chosen by the climate policy models. Nearly all models have capital and labour in the same nest. This nesting structure is supported by our results as the (KL)E nesting structure seems to fit the data best. The (KE)L nesting structure, as used in Burniaux et al. (1992), on the other hand, performs rather poorly in terms of goodness of fit. The argument that the demand for capital and energy is determined jointly, as machines use energy, is only partly valid. Capital is not just the stock of available machines, but money invested in general, or foregone consumption. Our results suggest that, given the (KL)E nesting structure, substitution elasticities may be the same for both nests for several countries and industries. Indeed, several of the models in Table 1 do not have a separate nest for the capital-labour composite, but model both inputs together with energy in a non-nested function. Hence our results support the nesting choice for most of the models in Table 1.

It should be noted, however, that our results suggest that there is considerable variation over countries and industries in substitution possibilities. Our second conclusion therefore is that both the sizes of the elasticities, and whether the nesting structure is (KL)E or non-nested KLE, vary considerably over both countries and industries.

Our third conclusion refers to the sizes of the elasticities of substitution. Several climate models that use a (KL)E or KLE (or KLEM) nesting structure use a unit elasticity of substitution for (part of the) production function. However, our results for the (KL)E nesting structure, which is the nesting structure that fits the data best, show that we can reject the Cobb-Douglas function for all industries and for all countries. We find that $\sigma_{KL,E}$ ranges from 0.1 to 0.6, while $\sigma_{K,L}$ ranges from 0.2 to 0.6. The recent literature on capital-labour production functions rejects unit elasticities, in favour of smaller values, as well (see e.g. Antràs (2004) and references therein). We therefore conclude that the elasticities of substitution in (parts of) the production functions in some of the papers in Table 1 are too high.

Our results for factor-specific technological change suggest that technology trends differ significantly over inputs. Energy, labour and capital all have a significant rate of technological change, and they generally differ significantly from each other. This is ignored in climate policy models that use Cobb-Douglas production functions, since they do not allow technological change to affect relative marginal productivities of inputs. In addition, our results go against models with total factor productivity growth. Our fourth conclusion is therefore that most papers in Table 1 put too many restrictions on their models regarding the possibilities for technological change.

What are the possible effects of elasticities that are too high, and of a rigid way of modeling changes in the production isoquant, on the results that are found by climate policy models? First of all, changes in the elasticity of substitution affect the model results when there is no endogenous technological change. As noted in the introduction, Jacoby et al. (2006) found that the MIT EPPA model is most sensitive to changes in the elasticity of substitution between the capital-labour composite and energy. Both the model of Goulder and Schneider (1999) and the model of Popp (2004) use a unit elasticity, which is rejected by the data.

Secondly the higher an elasticity of substitution, the easier it is to substitute away from an input that faces an increase in its relative price, and the lower will be the need to invest in input-saving technological change. As a consequence, climate policy models that use elasticities of substitution that are too high may underestimate the role of endogenous technological change in reducing the costs of climate policy. In addition, models with a Cobb-Douglas production function neglect the role of factor-specific technological change, since with a Cobb-Douglas production function technological change does not affect the relative marginal productivity of inputs. It is therefore impossible to aim innovations at energy-saving technologies: changes in the production isoquant are always total factor productivity improvements. Hence the costs of achieving a certain improvement in the productivity of energy may be lower when moving away from a unit elasticity of substitution.

Finally, energy-specific technological change and total factor productivity growth (even at the industry or country level) all take away degrees of freedom from an economy. Adding additional flexibility to a model could lead to a lower burden of climate policy on an economy.

6 Summary and conclusions

This paper contributes to the literature on climate policy modeling by estimating nested CES production functions using capital, labour and energy as inputs. We find that the nesting structure in which first capital and labour are combined using a CES function, and then this composite of capital and labour is combined with energy in a second CES function, fits the data best. For this (KL)E nesting structure we were, for most countries and most industries, not able to reject the hypothesis that the elasticities are equal for both nests. The (KL)E nesting structure, or its non-nested form with equal elasticities for both nests, is used by most models in the applied climate policy modeling literature. However, our estimates for the elasticities of substitution vary substantially over countries and over industries, and are lower than those used in some of the models. In addition we explicitly reject unit elasticities of substitution (i.e. Cobb-Douglas production functions). Regarding technological change, we find factor-specific growth rates that are significant and that mostly significantly differ from each other. We reject total factor productivity growth (in favour of factor-specific technological change) and 'only energy-augmenting technological change', both of which are used by several papers in the climate policy literature.

Given that lower elasticities imply that it becomes harder to substitute away from energy, and given that most models in the climate policy modeling literature put too many restrictions on their models, we suggest that the role of endogenous technological change in reducing the costs of climate policy may be bigger than has been found by some climate policy models. Whether this claim holds, should of course be tested by adapting the models in Table 1 to our empirical findings, and comparing the additional effect of endogenous technological change in the original model with that from the adapted model.

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