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Factor-Augmenting Technical Change: An Empirical Assessment

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Abstract This paper estimates factor-specific technical change and input substitution using a structural approach. It contributes to the existing literature by introducing various technology drivers for factor productivities and by assessing the impact of endogenous technical change on the elasticity of substitution. The empirical results suggest that factor productivities are indeed endogenous. In addition, technology drivers are factor-specific. Whereas the R&D stock and machinery imports are important determinants of energy and capital productivity, the education stock is statistically related to labour productivity. The rate of energy-augmenting technical change is larger than that of either labour or capital. By contrast, the productivity of these two factors grows at similar rates. Estimates of the elasticity of substitution are within the range identified by previous literature. In addition, we show that endogenous technical change reduces substitution. Because the elasticity of substitution is lower than one, knowledge and human capital can ultimately have an energy-using effect. The estimated structure of endogenous technical change suggests that Integrated Assessment models focusing on energy-saving technical change might underestimate climate policy costs.

Keywords Endogenous technical change · Integrated assessment models · Panel regression

JEL Classifications C3 · O47 · Q55 · Q56

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1 Introduction

Over the past decades, our understanding of the relationship between technological change, economic growth, and the environment has greatly improved. The literature has advanced from early models with exogenous technical change to representations of endogenous processes driven by various factors such as innovation [1, 44, 45], human capital [34] and experience [2]. Technical change has also become an important element in the design of climate policies. It is widely accepted that GHGs emission reduction is possible only if carbon-free technologies become attractive from the economic viewpoint and if energy efficiency improves. As a consequence, a growing number of models used for climate policy analysis have looked at the dynamics of technical change. Models describing technical change as an endogenous process make it possible to study the relationship between climate policy and technical change and to evaluate the implications of policy-induced technical change (ITC) on the macroeconomic costs of climate policy. Results in this literature show that ITC substantially influences the long-run costs of climate policy, the dynamics of technical change itself, the timing of action, and the design of optimal policy [9, 12, 27].

Nevertheless, the appropriate way to model technical change is still debated. Most Integrated Assessment Models (IAMs) suffer from three limitations. First, most models endogenise technical change in the energy sector. Other forms of technical change such as improvements in total factor productivity or labour productivity either follow autonomous trends or are simply omitted. However, recent empirical studies indicate that technical change can also be energy-using [47, 53]. Whether technical change is good or bad for the environment depends on the direction it takes. In order to have sustainable growth, pollution-saving technical change must dominate other types of technical change, such as neutral technical change or labour-augmenting technical change, which tend to increase pollution [6, 7, 35].

Models that omit endogenous technical change in the *energy sector* tend to *overestimate* the cost of climate policies [20, 22, 36]. When technical progress is exogenous, the only way to reduce emissions is to substitute fossil fuel inputs with cleaner inputs, such as renewables. Endogenous technical change introduces the additional option of improving the efficiency with which energy inputs are used, for example by investing in energy R&D. However, omitting endogenous technical change in the *non-energy sector* might actually *underestimate* policy costs because the opportunity cost of energy-saving R&D is not fully captured. By neglecting the dynamics of technical change in the non-energy sector, where the majority of R&D investments occur, the impact of climate policy on economy-wide technical change is omitted. Climate policy stimulates energy-saving technical change, which comes at the costs of R&D in other sectors. As a consequence, the pace of overall technological change might be reduced, with negative influences on welfare and economic growth [13, 28, 41, 51].

The degree of complementarity between the energy input and non-energy inputs, such as labour and capital, is a major explanation of the direction of policy-induced technical change and of its implications on the use of energy. When technical change increases the productivity of inputs that are gross complements to energy, the demand of energy increases, with negative implications on the environment, ceteris paribus [13, 41, 49]. As a consequence, climate policy would re-direct resources away from these sources of technical change.

This finding underlines the key role played by the elasticity of substitution and the deep interconnections between factor substitution and technical change [51]. Estimates of substitution elasticities are provided by a number of empirical studies (see Markandya and Pedroso-Galinato [39] for a review). Despite the significant heterogeneity, most estimates point at a relationship of complementarity between capital, labour and energy, and most studies find a substitution elasticity lower than one. However, all estimates are based on the assumption that factor productivities are exogenous, therefore neglecting the interactions with endogenous technical change.

A second main limitation of state-of-the-art IA models is the weak empirical foundation of key technology parameters such as the elasticity of substitution, the dynamics of factor productivities, and their elasticities with respect to endogenous-technology drivers. Despite significant improvements during the last decades, the empirical research that can provide useful information for the parameterisation of IA models is still surprisingly limited. Most of the empirical literature focuses on the magnitude of neutral technical change. Early approaches measured indicators of neutral technical change as Solow residuals [50] or as a coefficient of an exogenous trend using translog production functions [32]. Econometric methods were used to infer technical change from the dynamics of other economic variables. Slade [48] and Bonne and Kemball-Cook [5] developed a model of factor demands in which the nature of technical change as a latent variable is emphasised. Technical change is broken down into an unobservable time trend and other factors that endogenously influence it. A similar methodology is used in Carraro and Galeotti [10]. In this latter work, the dynamics of technical change were inferred from the time evolution of capital stock rather than from factor demands.

In addition, fewer studies have addressed factor-biased or factor-augmenting technical change.[1] Kendrick [33] analysed and compared trends in labour and capital productivity, measured as a ratio of output over labour and capital respectively for 33 American industries from 1899 to 1953. Despite the heterogeneities across industry, in the long-run technical change is labour- and capital-saving. Labour technical change tends to increase faster than capital technical change. Sue Wing and Eckaus [52] revised the work by Jorgenson and Fraumeni [31] on energy-saving technical change in the US economy. Technical change has been an important explanatory factor of the decline in aggregate energy intensity since 1980. Another important driver is sectoral change, whereas energy prices play only a minor role. Sanstad et al. [47], using a translog production function, estimated sectoral productivity trends and energy-augmenting technical change for several energy- intensive industries in India, South Korea, and the United States. They concluded that there is significant heterogeneity in energy productivity not only across countries, but also across sectors. Van der Werf [53] estimated factor-augmenting technical change using a two-level Constant Elasticity of Substitution (CES) production function for the inputs capital, labour, and energy. He found larger rates of improvement for labour, followed by energy, whereas the rates of capital-augmenting technical change are negative.

Finally, the almost total absence of empirical studies on the drivers of factor productivities has led IA models to follow the mainstream growth theory (Arrow [2]; Romer [44, 45]; Grossman and Helpman [26]) and assume that the engine of technical change is the accumulation of knowledge or experience, neglecting other important drivers such as trade and human capital.

Because of the growing relevance of IAMs in climate policy analysis, empirical results are needed to guide modellers in the implementation of accurate descriptions of technical change [12]. This paper addresses this issue by

[1] Hicks neutral technical change can be represented as a parallel shift in isoquants. Factor-biased technical change shifts the slopes of the isoquants, thereby affecting the relative marginal product of inputs. Technical change is factor-augmenting if it increases the productivity of factors.

estimating factor-specific technical change and input substitution using a structural approach. It infers the dynamics of technical change from a system of factor demands. It improves upon the existing literature by introducing endogenous-technology drivers for factor productivities (energy, labour and capital) and by assessing the impact of endogenous technical change on the estimate of elasticity of substitution. By using a model of production that is commonly used in IAMs, the empirical results described in this paper can be directly applied to IAMs.

Results indicate that factor productivities are endogenous, thus rejecting models with exogenous technical change. Second, it shows that technology drivers are factor-specific. Knowledge is an important driver of capital and energy productivity, whereas human capital is a better explanatory variable of labour productivity. Imports of machinery and equipment from OECD are also energy-augmenting, but their effect is much smaller than that of the R&D stock. Third, the rate of energy-augmenting technical change tends to be larger than that of either labour or capital, which instead have similar growth rates.

Because the elasticity of substitution is less than one, we can conclude that R&D stock, imports of machinery and equipment, and education stock have an input-saving effect. Therefore, knowledge is not only energy-saving, but also capital-saving. Human capital is labour-saving. Because the estimated elasticity of substitution is less than one, knowledge and human capital can ultimately have an energy-using effect. This result suggests that climate–economy models focusing on energy-saving technical change tend to underestimate climate policy costs.

The remainder of the paper is organised as follows: in Section 2, we introduce the Constant Elasticity Production Function (CES) and briefly discuss the strategy that can be employed to identify different components of technical change. Section 3 describes the specification of the empirical model and the data. Section 4 presents the results. Section 5 discusses the implications on the nexus between technical change and environmental policy in the specific context of climate change. Section 6 summarises our main results and outlines further research directions.

2 Model Specification

Climate–economy models represent the production side of the economy by using production functions that can be parameterised in different ways to reflect alternative assumptions on technology and factors substitution. Most IAMs use CES production functions to describe how different inputs are combined to produce final output.

Large differences exist with respect to the assumed nesting structure, the size of the elasticity of substitution, and the way technical change is represented. Van der Werf [53] reviews the production structure of ten state-of-the-art IAMs. All models except one, nest labour together with capital, whereas three models consider a non-nested production function, assuming an equal elasticity of substitution between energy, capital, and labour.[2] The specification that best fits the data combines capital and labour first, and then the capital–labour bundle with energy. However, a non-nested production function cannot be rejected for eight out of twelve countries, and for five out of seven industries. In addition, most IAMs share the assumption of exogenous technical change and only one model [18] is characterised by factor-specific technical change.

In this paper, we consider a non-nested production function with endogenous factor-augmenting technical change.[3] We assume that a representative firm produces total output (X) using the CES technology with constant-return-to-scale, a standard assumption in IA modelling literature:

$$X(t) = H(t)\left\{(A_K(t)K(t))^\rho + (A_L(t)L(t))^\rho + (A_E(t)E(t))^\rho\right\}^{\frac{1}{\rho}} \tag{1}$$

The elasticity of substitution σ is related to ρ according to the standard relationship, $\rho=(\sigma-1)/\sigma$.

This formulation (David et al. [17]) can account for factor-specific technical change, differentiating the dynamics of technical change across inputs. The coefficients that pre-multiply the three inputs, capital, labour, and energy (A_f with $f=K,L,E$), describe the productivity of production factors, that is the efficiency with which inputs are used in production. The higher the productivity coefficient, the lower the quantity of input is required to produce the same level of output. Technical change is factor-augmenting if an increase in productivity leads to higher output, keeping everything else constant, i.e. $\frac{\partial X(t)}{\partial A_f(t)} > 0$. Neutral technical change is also included as an additional parameter (H), which pre-multiplies the whole production function.

This production structure makes it possible to differentiate factor-specific technical change, while accounting for changes in overall productivity. Indeed, factor-specific technical change and overall productivity can take different and opposite paths. The industrial revolution in the eighteenth century and the introduction of information technologies in the seventies are both examples of rapid technical change in specific sectors associated with aggregate productivity slowdown (Greenwood and Yorukoglu [24]). Learning about new technologies and initial lack of experience explain

[2] These are the models described by Edenhofer et al. [19], Goulder and Schneider [28] and Popp [43].

[3] Given the focus of the paper, which is the identification of the endogenous determinants of factor-augmenting technical change, we decided to start with one of the simplest CES structure that has an empirical foundation.

why the introduction of new technologies may be associated with lower productivity growth.

Factor-augmenting technical change is input-saving or input-using depending on the elasticity of substitution. The interplay between neutral and factor-specific technical change and the interaction between substitution and technical change can be better understood by looking at conditional factor demands derived from the cost-minimisation problem of the representative firm.[4]

Using logarithms and differentiating with respect to time, conditional factor demands can be expressed as a linear relationship,[5] as in system (2). The percentage change in factor demands on the left-hand side depends on the percentage change of final output (x), technology parameters ($a_f + h$) and relative input prices ($p_f - p$):

$$\begin{aligned} k &= x + (\sigma - 1)(a_K + h) + (1 - \sigma)(p_K - p) \\ l &= x + (\sigma - 1)(a_L + h) + (1 - \sigma)(p_L - p) \\ e &= x + (\sigma - 1)(a_E + h) + (1 - \sigma)(p_E - p) \end{aligned} \tag{2}$$

Technical change is broken down into two components, neutral technical change (h), which affects all inputs equally, and factor-augmenting technical change (a_f with $f{=}K,L,E$). Factor-augmenting technical change ($a_f{>}0$) is input-saving if the elasticity of substitution is lower than one and if total technical change remains positive, ($a_f{+}h){>}0$.

Totally differentiating and dividing by the value of final output (PX), the zero profit condition ($PX = P_K K + P_L L + P_E E$), neutral technical change (h) can be decomposed into total factor productivity growth (tfp) and share-weighted input efficiency improvements:

$$h = \mathrm{tfp} - (a_K\theta_K + a_L\theta_L + a_E\theta_E) \tag{3}$$

where tfp is defined as a unit cost reduction not due to factor price reductions:

$$\mathrm{tfp} = (a_K p_K + a_L p_L + a_E p_E) - p \tag{4}$$

and θ_i being the input cost shares $\theta_i = \frac{P_i V_i}{PX}$ with $V_i = K, L, E$.

Total factor productivity is a correct measure of neutral technical change only if technical change does not differ across inputs, i.e. $a_K{=}a_E{=}a_L$.

A well-known problem that clearly stands out from system (2) is the impossibility to fully identify both neutral and factor-specific technical change. The most straightforward way to deal with this issue is to focus on factor-specific technical change, assuming no time variation in neutral technical change (i.e. $h{=}0$). This is also the assumption shared by the literature on CES production functions with factor-augmenting technical change and on directed technical change (e.g., van der Werf [53] and Acemoglu [1]).

Factor-specific technical change consists of two components. A constant term, which captures the growth rate of autonomous technical change, δ_f^0, and an endogenous component, which relates factor productivities to one or more technology driver, y_j:

$$a_f = \delta_f^0 + \sum_{j=1} \delta_f^j y_j \forall f = K, L, E \tag{5}$$

where δ_f^j describes the elasticity of factor productivity a_f with respect to the technology driver y_j, $\delta_f^j = \frac{\partial a_f}{\partial y_j}\ \forall f = K, L, E$.

With this formulation we can test the hypothesis of endogenous technical change by looking at the statistical significance of the elasticity with respect to y_j. In addition, the role of various technology drivers can be assessed. Three different possible sources of factor-specific technical change are considered: knowledge, measured by the stock of R&D expenditure, trade, in particular imports of machinery and equipment, and human capital, approximated by the stock of education expenditure. These variables were selected among the main determinants of neutral technical change identified by the empirical growth literature .The role of knowledge as an engine of productivity growth has been acknowledged since the early models of endogenous growth [43, 44]. Important contributions include studies by Griliches [25], Nadiri [40] and Mansfield [37, 38]. Coe and Helpman [15] found empirical evidence of international technology spillovers. R&D has an effect not only on the productivity of the innovating country, but also on the productivity of trading partners. The more open to trade a country is, the greater this effect [8, 16].

Engelbrecht [21] extended the analysis of Coe and Helpman [15] by including the role of human capital. He found that both R&D stock and human capital, measured in terms of school attainment, are important determinants of productivity growth. Other empirical studies found a positive relationship between aggregate productivity and other indicators of human capital, such as education attainment [3] and education expenditure [14].

Another indicator of knowledge is the stock of capital [2]. Rosenberg [46] stressed how technical improvements are often tied to capital goods such as machinery and equipment. Therefore, the purchase of these goods is fundamental for the translation of technical change into productivity growth. Machinery is considered to be an important source of economic growth and technical progress [18]. Historically, capital goods were manufactured in a small number of countries because they required a mature stage of industrialisation, technical competency and high skill levels. Moreover, the capital goods industry is highly specialised and requires a large market. For this reason, capital production

[4] Cost minimisation is also a standard assumption made in IA modelling literature. As in the IA modelling literature we also assume price-taking behaviour and therefore the unit cost function gives the price of final output, $C(1; P_K, P_L, P_E){=}P$.

[5] Small letters denote percentage changes, e.g. $x = dX / X = dlnX$.

has been concentrated in OECD countries, especially in the United States, the United Kingdom and Germany. These countries are also among the most R&D-intensive. It follows that the machinery produced in these countries are particularly knowledge-intensive and therefore they have high potentials to transfer technology and knowledge.

3 Empirical Model and Data

System (2) can be expressed in percentage change of cost shares that depend on prices and technology. Technology is a function of time and of three technology drivers, namely the stock of R&D expenditure (y_1), imports of machinery and equipment from OECD countries (y_2) and the stock of education expenditure (y_3):

$$\begin{aligned}
\widetilde{\theta}_K &= (\sigma-1)\delta_K^0 + (\sigma-1)\sum_{j=1}^{3}\delta_K^i y_j + (1-\sigma)(p_K - p)\\
\widetilde{\theta}_L &= (\sigma-1)\delta_L^0 + (\sigma-1)\sum_{j=1}^{3}\delta_L^i y_j + (1-\sigma)(p_L - p)\\
\widetilde{\theta}_E &= (\sigma-1)\delta_E^0 + (\sigma-1)\sum_{j=1}^{3}\delta_E^i y_j + (1-\sigma)(p_E - p)
\end{aligned} \tag{6}$$

Country and time effects are captured using country dummies and a logarithmic time trend.[6] As a consequence, the rate of autonomous technical change ($\delta^0{}_f$) consists of a country-specific term and of a time trend common to all countries. In discrete time, the empirical model reads as follows:

$$\begin{aligned}
\Delta\theta_{Kit} &= \sum_{i=1}^{12}\alpha_{Ki}Di + \alpha_{K1}\ln t + \gamma_{K1}R\&D + \gamma_{K2}M\&E\\
&\quad + \gamma_{K3}EDU + \gamma_{K4}\Delta(P_{Kit} - P_{it}) + \varepsilon_{it}\\
\Delta\theta_{Lit} &= \sum_{i=1}^{12}\alpha_{Li}Di + \alpha_{L1}\ln t + \gamma_{L1}R\&D + \gamma_{L2}M\&E\\
&\quad + \gamma_{L3}EDU + \gamma_{L4}\Delta(P_{Lit} - P_{it}) + \varepsilon_{it}\\
\Delta\theta_{Eit} &= \sum_{i=1}^{12}\alpha_{Ei}Di + \alpha_{E1}\ln t + \gamma_{E1}R\&D + \gamma_{E2}M\&E\\
&\quad + \gamma_{E3}EDU + \gamma_{E4}\Delta(P_{Eit} - P_{it}) + \varepsilon_{it}
\end{aligned} \tag{7}$$

where $\Delta\theta_{fit} = \frac{\theta_{fit}-\theta_{fit-1}}{\theta_{fit-1}}\ \forall f = K, L, E;\ \Delta(P_{fit} - P_{it}) = \frac{(P_{fit}-P_{fit-1})}{P_{fit-1}} - \frac{(P_{it}-P_{it-1})}{P_{it-1}}$ and ε_{it} are error terms. The parameters of interest can be retrieved using the following constraints:

Autonomous technology component

$$\begin{aligned}
&\alpha_{Ki} + \alpha_{K1} = (\sigma-1)\delta_{Ki}^0\\
&\alpha_{Li} + \alpha_{L1} = (\sigma-1)\delta_{Li}^0\\
&\alpha_{Ei} + \alpha_{E1} = (\sigma-1)\delta_{Ei}^0
\end{aligned}$$

Endogenous technology component

$$\begin{aligned}
&\gamma_{K1} = (\sigma-1)\delta_K^1 R\,\&\,D;\ \gamma_{K2} = (\sigma-1)\delta_K^2 M\,\&\,E;\ \gamma_{K3} = (\sigma-1)\delta_K^3 EDU\\
&\gamma_{L1} = (\sigma-1)\delta_L^1 R\,\&\,D;\ \gamma_{L2} = (\sigma-1)\delta_L^2 M\,\&\,E;\ \gamma_{L3} = (\sigma-1)\delta_L^3 EDU\\
&\gamma_{E1} = (\sigma-1)\delta_E^1 R\,\&\,D;\ \gamma_{E2} = (\sigma-1)\delta_E^2 M\,\&\,E;\ \gamma_{E3} = (\sigma-1)\delta_E^3 EDU
\end{aligned}$$

Elasticity of substitution

$$\gamma_{K4} = \gamma_{L4} = \gamma_{E4} = (1-\sigma)$$

A set of tests can be performed to better assess the dynamics of endogenous technical change (Test 1), autonomous technical change (Test 4), and substitution (Test 2 and 3):

Test 1 :

$\mathrm{H}_0\ :\ \gamma_{Kj} = \gamma_{Lj} = \gamma_{Ej}$ for $\forall j = 1, 2, 3$

Test 2 :

$\mathrm{H}_0\ :\gamma_{K4} = \gamma_{L4} = \gamma_{E4} = 0$

Test 3 :

$\mathrm{H}_0\ :\ \gamma_{K4} = \gamma_{L4} = \gamma_{E4}$

Test 4 :

$\mathrm{H}_0\ :\ \alpha_{Ki} + \alpha_{K1} = \alpha_{Li} + \alpha_{L1} = \alpha_{Ei} + \alpha_{E1} \forall i = 1, \cdot\cdot, N$

Test 1 assesses whether the role of different technology drivers differs across inputs. Test 2 evaluates the hypothesis of a Cobb–Douglas production function. Test 3 checks the assumption of common elasticity between capital, labour and energy. Test 4 evaluates the hypothesis of neutral technical change when technical change is exogenous (i.e., $\gamma_{f1}=\gamma_{f2}=\gamma_{f3}=0$ for all $f=K,L,E$) by testing the equality of the time trend and dummy coefficients across equations.

Estimation of system (7) requires data on prices and quantities of output, labour, capital and energy. The estimation is carried out using aggregate data, although an extension to sectoral data is left for future research.

Aggregate data was collected from the OECD STAN Industry Database 2006,[7] the International Energy Agency (IEA) Databases 2006 on Prices and Taxes and Extended Energy Balance. The methodology of Pindyck [42] is used to compute values for the variables of interest. The share of labour was computed using labour compensation. The

[6] The time effect can also be made country-specific by interacting country dummies with the time trend. Although all of these specifications were estimated, the model with a common time trend was preferred because it is more parsimonious.

[7] Data available from http://www.sourceoecd.org/

compensation to capital was computed as the difference between value added and labour compensation. Using data on the labour force from either the OECD STAN Industry Database 2005 or the Penn World Table [29], the price of labour was obtained implicitly, dividing labour compensation by the labour force. The price of capital was computed in a similar way. Energy prices were taken from dataset on real index of industry price, IEA Prices and Taxes, and they are expressed in constant US$ (base year 2000) per tonnes of oil equivalent. Energy quantities that come from IEA OECD Energy Balance are expressed in thousand tonnes of oil equivalent. Total output was defined as value added plus the value of energy quantities. All values, in national currency, were converted into current US$ using the Purchasing Power Parity Conversion Factor from the World Development Indicators[8] (WDI). Using the US implicit deflator of GDP, current prices were converted into constant prices at 2000 US$. All units are therefore expressed in millions of US $ relative to the base year 2000. Prices were finally expressed as indices, with the base year 2000.

Data on R&D expenditure[9] is limited to 13 OECD countries, from 1987 to 2002. The stock of R&D was computed using the perpetual inventory method with a depreciation rate of 5 %, although the choice of different depreciation values does not affect the results significantly. The initial value of the stock was set equal to the level of investments in the first available year, divided by the average annual growth rate over the observation period, plus the rate of depreciation, as suggested in [14].

Data on machinery and equipment imports are from the OECD STAN Industry Database 2006.[10] Data are available for 12 countries over 13 years (1989–2001). The OECD STAN Industry Database provides data on bilateral trade flows and makes it possible to distinguish imports from different trading partners. In the case of machinery, only imports from the OECD countries were selected. Machinery and equipment imports are classified as a two-digit industry according to the International Standard Industrial Classification (ISIC classification number 29).

Education is measured as current and capital expenditure on all types of education, from both private and public sources. Data are from the OECD.[11] The stock was computed using the perpetual inventory method, with a depreciation rate of 2 % [30].[12] Table 4 in the Appendix summarises descriptive statistics for the main variables.

[8] World Bank, 2006.
[9] ANBERD—R&D Expenditure in Industry 2006 available from http://www.sourceoecd.org/
[10] Data available from http://www.sourceoecd.org/
[11] Education Expenditures by Country, Nature, Resource Category, and Level of Education Vol. 2006 issue 01.
[12] A higher depreciation rate was also experimented, yielding very similar results.

Given the theoretical set-up from which the empirical model was derived, the three equations are correlated. The representative firm chooses the optimal demand of all three inputs simultaneously. Therefore, the system error terms have a variance covariance matrix that does not satisfy the assumptions of zero covariance and constant variance. As a consequence, the model is estimated with a feasible generalised least square estimator (FGLS).

Although there are economic reasons that justify the inclusion of country dummies, their relevance is also assessed statistically. The null hypothesis of an equal constant term is always rejected at 10 % significance level when technology is endogenous. The specification with exogenous technical change rejects two cases out of three.

4 Estimation Results

Before imposing the restrictions that make it possible to identify a unique value for the parameters of interest, we estimate the system without cross-equation constraints. We also test the hypothesis of common elasticity (Test 3) and of Cobb–Douglas production function (Test 2), both in the case of exogenous and endogenous technical change.

When technical change is assumed to be exogenous (i.e., $\gamma_{f1}=\gamma_{f2}=\gamma_{f3}=0$ for all $f=K,L,E$), we reject the hypothesis of common elasticity between capital and energy and labour and energy. The same hypothesis cannot be rejected between capital and labour (at 1 % significance level). Similar results are obtained with endogenous technical change, but at a lower level of significance (10 %). The equations for capital, labour and energy yield the following values of the elasticity of substitution, 0.7, 0.8 and 0.1, respectively. Endogenous technical change slightly reduces the elasticity to 0.6, 0.7 and 0.1, respectively. All estimates point at a value less than one. Indeed, the test of Cobb–Douglas production structure is rejected in all equations, both with exogenous and endogenous technical change.

The main contribution of this paper is twofold: (a) the empirical assessment of the impact of endogenous technical change on the elasticities of substitution, and (b) the determination of how different technology drivers affect factor-augmenting technical change. We present the results with exogenous factor productivities (Table 1) essentially for comparison with the existing literature. The case with exogenous technical change provides a benchmark to assess the implications of endogenous technical change.

Exogenous technical change is captured by the constant term, which is country-specific, and a time trend. Results are in line with previous findings, although there are some differences with van der Werf [53], especially regarding capital-augmenting technical change. Our results are similar to Kendrick [33]. He found that technical change is labour-

Table 1 Exogenous technical change (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	p value	Coeff	p value	Coeff	p value
γ_{f4} $(p_i - p)$	0.62	0.00***	0.62	0.00***	0.62	0.00***
$\alpha_{f\mathrm{BE}}$	0.00	0.63	−0.01	0.08*	−0.01	0.32
$\alpha_{f\mathrm{CA}}$	0.00	0.84	−0.01	0.18	−0.04	0.00***
$\alpha_{f\mathrm{DE}}$	0.00	0.51	0.00	0.89	−0.06	0.00***
$\alpha_{f\mathrm{DK}}$	0.00	0.45	−0.01	0.01***	−0.02	0.12
$\alpha_{f\mathrm{ES}}$	−0.02	0.01***	−0.02	0.00***	−0.02	0.15
$\alpha_{f\mathrm{FI}}$	0.00	0.81	−0.02	0.00***	−0.03	0.04**
$\alpha_{f\mathrm{FR}}$	0.00	0.66	−0.01	0.11	−0.04	0.00***
$\alpha_{f\mathrm{IT}}$	−0.03	0.00***	−0.01	0.08*	−0.02	0.16
$\alpha_{f\mathrm{JP}}$	0.00	0.48	0.00	0.60	−0.03	0.01***
$\alpha_{f\mathrm{NL}}$	−0.01	0.07*	0.00	0.39	−0.04	0.00***
$\alpha_{f\mathrm{UK}}$	0.00	0.66	−0.01	0.03**	−0.05	0.00***
$\alpha_{f\mathrm{US}}$	−0.02	0.01***	−0.01	0.18	−0.05	0.00***
α_{f1} $(\ln T)$	0.00	0.44	0.00	0.93	0.01	0.00***
R^2	0.52		0.16		0.67	
T	14		14		14	
N	12		12		12	
Factor-augmenting technical change (country average)	0.010		0.011		0.024	
Elasticity of substitution	0.376		0.376		0.376	

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

***p=0.01; **p=0.05; *p=0.1

saving and capital-saving in the long-term and that labour technical change tends to grow faster than capital. In addition, the rate of energy-augmenting technical change is larger than that of labour, with values of 2.4 and 1.1 % per year respectively.

The hypothesis of neutral technical change (Test 4) is rejected in most countries. We can reject that energy-augmenting technical change is equal to either labour or capital in respectively 7 and 8 countries out of 12. The equality between labour- and capital-augmenting technical change is rejected in only 2 out of 12 countries.

Table 2 reports the estimation results with endogenous technical change. We start by including all drivers mentioned above, namely the stock of R&D expenditure (R&D), imports of machinery (M&E), and the stock of education expenditure (EDU).[13]

The selected drivers of endogenous technical change partly explain the variation in input cost shares. We can reject the null hypothesis of exogenous technical change for the capital and energy equation, whereas at this stage the three drivers do not explain changes in the labour cost share.

The inclusion of endogenous-technology proxies reduces the role of the exogenous component. It decreases the significance and the coefficient of the time trend in the energy equation and it diminishes the number of significant country dummies in the labour equation. In the case of labour, the time trend is not significant. This means that the rate of labour-augmenting technical change is significantly different from zero only when country dummies are significant, namely in Denmark, Spain and Finland. On average, the rate of labour-specific technical change is 1.4 % per year, very close to what was found in the specification with exogenous technical change. Indeed, the endogenous drivers included here do not explain improvements in labour productivity.

In contrast, energy-augmenting technical change is well explained by imports of machinery and the R&D stock, although at this stage the latter driver is significant only at 11 % significance level. The time trend and country dummies are no longer significant, suggesting that the two technology drivers are able to capture most of the dynamics of energy-augmenting technical change. The negative sign of their coefficients implies that, at constant prices, an increase in R&D and machinery imports reduces energy cost share. This is exactly what Binswanger and Ruttan [4] defined as input-saving technical change.

Capital-augmenting technical change is explained by the R&D stock and machinery imports, which have a capital-saving effect. On average, the rate of both energy and capital productivity growth is larger when accounting for the endogenous drivers. Growth rates are respectively 3 % and 5.3 % per year.

[13] The correlation between these three variables is low and therefore they could be included simultaneously.

Table 2 Endogenous technical change (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	p value	Coeff	p value	Coeff	p value
γ_{f4} ($p_i - p$)	0.63	0.00***	0.63	0.00***	0.63	0.00***
γ_{f1} R&D	−0.64	0.00***	0.18	0.13	−0.46	0.11
γ_{f2} M&E	−0.01	0.09*	0.00	0.78	−0.05	0.01***
γ_{f3} EDU	0.15	0.25	0.02	0.90	0.07	0.81
$\alpha_{f\mathrm{BE}}$	0.04	0.01***	−0.02	0.16	0.03	0.46
$\alpha_{f\mathrm{CA}}$	0.06	0.00***	−0.02	0.12	0.01	0.75
$\alpha_{f\mathrm{DE}}$	0.03	0.00***	−0.01	0.47	−0.03	0.20
$\alpha_{f\mathrm{DK}}$	0.06	0.00***	−0.04	0.05**	0.03	0.44
$\alpha_{f\mathrm{ES}}$	0.03	0.12	−0.04	0.09*	0.02	0.62
$\alpha_{f\mathrm{FI}}$	0.07	0.00***	−0.04	0.03**	0.03	0.49
$\alpha_{f\mathrm{FR}}$	0.04	0.01***	−0.02	0.19	0.00	1.00
$\alpha_{f\mathrm{IT}}$	−0.02	0.18	−0.01	0.44	−0.01	0.88
$\alpha_{f\mathrm{JP}}$	0.05	0.00***	−0.01	0.29	0.01	0.77
$\alpha_{f\mathrm{NL}}$	0.02	0.11	−0.01	0.26	−0.01	0.75
$\alpha_{f\mathrm{UK}}$	0.02	0.38	−0.02	0.27	−0.03	0.49
$\alpha_{f\mathrm{US}}$	0.02	0.30	−0.02	0.35	−0.01	0.79
α_{f1} ($\ln T$)	0.00	0.34	0.00	0.90	0.01	0.30
R^2	0.67		0.20		0.68	
T	13		13		13	
N	12		12		12	
Technology parameters						
Exogenous component (country average)	−0.039		0.014		0.000	
Endogenous Drivers						
R&D stock	1.016					
M&E	0.023				0.085	
EDU stock						
Factor-augmenting technical change	0.03		0.014		0.053	
Elasticity of substitution	0.368		0.368		0.368	

Factor-augmenting technical change was calculated by adding the exogenous and endogenous component. The endogenous component was computed for average values of the technology drivers (See Table 4 in Appendix I)

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

***p=0.01; **p=0.05; *p=0.1

We tested whether the R&D stock and machinery imports have the same effect on capital and energy input shares. Although we reject that machinery has the same impact on energy and capital at 10 % significance level (p value 0.07), we cannot reject the same hypothesis for R&D at 1 % significance level (p value 0.55).

The model with endogenous technology also rejects the hypothesis of neutral technical change in most cases. We reject the hypothesis that labour has the same rate of factor-augmentation of any other input, but we could not reject that energy and capital productivities have similar growth rates for 11 countries out of 12.

The introduction of endogenous-technology drivers tends to reduce the elasticity of substitution by about 2 %, from 0.376 to 0.368. This result suggests that the effect of prices on cost shares is upward biased when endogenous technical change is omitted. This result has already been emphasised by Carraro and Siniscalco [9]. It suggests that part of the change that is attributed to substitution is due to technical change. It is difficult to know whether a new combination of inputs is adopted because a new technology has become available (technical change) or because variations in input prices have made an existing technology more attractive (substitution). When the elasticity of substitution is low, most of the variation is likely to be due to technical change (Sue Wing [50]).

To improve the efficiency of our estimates, we re-estimate the model with endogenous technical change excluding the technology drivers that were not statistically significant and the time trend. Only statistically significant country dummies are preserved.[14] Results are reported in Table 3.

[14] We used an iterative selection technique that drops regressors one by one, selecting those with the lowest significance level, until all variables are significant.

Table 3 Endogenous technical change including only significant variables (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	p value	Coeff	p value	Coeff	p value
γ_{f4} $(p_i - p)$	0.63	0.00***	0.63	0.00***	0.63	0.00***
γ_{f1} R&D	−0.59	0.00***			−0.34	0.00***
γ_{f2} M&E					−0.06	0.00***
γ_{f3} EDU			−0.09	0.00***		
$\alpha_{f\mathrm{BE}}$	0.04	0.00***			0.04	0.01***
$\alpha_{f\mathrm{CA}}$	0.05	0.00***			0.02	0.18
$\alpha_{f\mathrm{DE}}$	0.02	0.00***				
$\alpha_{f\mathrm{DK}}$	0.06	0.00***	−0.01	0.04**	0.04	0.01***
$\alpha_{f\mathrm{ES}}$	0.04	0.00***	−0.01	0.10*	0.04	0.01***
$\alpha_{f\mathrm{FI}}$	0.07	0.00***	−0.01	0.00***	0.03	0.02**
$\alpha_{f\mathrm{FR}}$	0.04	0.00***				
$\alpha_{f\mathrm{IT}}$	−0.02	0.00***				
$\alpha_{f\mathrm{JP}}$	0.05	0.00***			0.02	0.13
$\alpha_{f\mathrm{NL}}$	0.01	0.03**				
$\alpha_{f\mathrm{UK}}$	0.02	0.00***				
$\alpha_{f\mathrm{US}}$	0.03	0.00***				
R^2	0.64		0.15		0.66	
T	13		13		13	
N	12		12		12	
Technology parameters						
Exogenous component (country average)	−0.047		0.004		−0.019	
Endogenous drivers						
R&D stock	0.941				0.538	
M&E					0.093	
EDU stock			0.140			
Factor-augmenting technical change	0.015		0.014		0.021	
Elasticity	0.370		0.370		0.370	

Factor-augmenting technical change was calculated by adding the exogenous and endogenous component

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

***p=0.01; **p=0.05; *p=0.1

The effect of R&D stock and machinery imports is quite stable, although the latter variable is no longer significant in the capital equation. The effect of the education stock on labour is less robust and it becomes significant and labour-saving. The autonomous term remains significant in the capital equation, suggesting that a considerable part of capital dynamics is still captured by an exogenous component.

As for the rate of factor-augmenting technical change, we confirm the results obtained with the previous less efficient specification. Energy-augmenting technical change grows at a faster rate, on average at 2 % per year, whereas labour and capital have slightly lower and similar rates of improvement, 1.5 and 1.4 % respectively.

Together the two drivers of energy-augmenting technical change, R&D stock and machinery imports, have an effect on energy productivity that is statistically equivalent to the effect R&D stock has on capital productivity (p value 0.20). In contrast, the contribution of human capital to labour-augmenting technical change is statistically different at 1 % significance level.[15]

Estimation residuals reveal the presence of first-order autocorrelation. However, the correlation between residuals is weak, between 0.26 in the endogenous specification with selected variables and 0.4 in the endogenous specification with all variables. We did not correct for correlation in the estimation results reported in Tables 1, 2 and 3, but Appendix II reports bootstrap estimates of the standard errors. They confirm the validity of inference analysis presented in the main text of the paper.[16]

[15] As in Table 2, we reject that labour and either capital or energy have the same rate of factor-augmentation, but we could not reject that energy and capital have the same growth rate.

[16] Bootstrap methods provide an alternative to inference based on parametric assumptions ,when those assumptions are in doubt.

Two are the main conclusions that have emerged so far. First, we confirm that technology trends are factor-specific. Second, and perhaps most importantly, the underlining technology drivers differ across inputs. Knowledge (R&D) is the most important variable explaining capital- and energy-augmenting technical change. Human capital is the variable driving labour productivity. Imports of machinery also play a role, especially for the energy input, but its contribution is much smaller compared to that of the R&D stock.

5 Factor-Augmenting Technical Change: Implications on Energy Use, Climate Policy Modelling and Assessment

The dynamics of macroeconomic data analysed in the previous section suggest that the productivities of inputs typically used in IA models, namely labour, capital, and energy, are endogenous and they grow with different drivers. It also shows that substitution possibilities between capital, labour and energy are low, especially when technical change is endogenous.

These results have important implications for IAMs because they suggest that technical change is not necessarily energy-saving and other forms of technical change (labour- and capital-saving) are equally relevant. As argued in the introduction, models that overlook the macroeconomic dynamics of technical change cannot track how climate policy redistributes resources across different R&D sectors [12]. As a consequence, these models tend to underestimate the policy costs in terms of Gross World Product losses. In addition, our results indicate that substitution possibilities are low, which implies that input-saving technical change can actually have an energy-using effect.

Although a full-fledged general equilibrium analysis is beyond the scope of the present analysis, the joint estimation of endogenous technical change and substitution allows us to highlight some implications in terms of energy use and induced technical change dynamics. Consider the cost-minimising factor demands, estimated in Section 4:

$$\frac{K}{Y} = H^{\sigma-1}\left(\frac{P_Y}{P_K}\right)^{\sigma} A_K{}^{\sigma-1} \tag{8}$$

$$\frac{L}{Y} = H^{\sigma-1}\left(\frac{P_Y}{P_L}\right)^{\sigma} A_L{}^{\sigma-1} \tag{9}$$

$$\frac{E}{Y} = H^{\sigma-1}\left(\frac{P_Y}{P_E}\right)^{\sigma} A_E{}^{\sigma-1} \tag{10}$$

Consider now the ratio of energy demand with respect to labour and capital using the specification of technical change estimated in Table 3. The relative demand of energy reads as follows:

$$\begin{aligned}
\frac{E}{L} &= \left(\frac{P_L}{P_E}\right)^{\sigma}\left(\frac{e^{\delta_L^0} EDU^{\delta_L^3}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2}}\right)^{1-\sigma} \\
\frac{E}{K} &= \left(\frac{P_K}{P_E}\right)^{\sigma}\left(\frac{e^{\delta_K^0} R\ \&\ D^{\delta_K^1}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2}}\right)^{1-\sigma} \\
&= \left(\frac{P_K}{P_E}\right)^{\sigma}\left(\frac{e^{\delta_K^0} R\ \&\ D^{\delta_K^1-\delta_E^1}}{e^{\delta_E^0} M\ \&\ E^{\delta_E^2}}\right)^{1-\sigma}
\end{aligned} \tag{11}$$

This implies that, *with positive elasticity* $\delta_L^1 = 0.140$*, human capital has an energy-using effect if, ceteris paribus, the elasticity of substitution is less than one:*

$$\frac{\partial\left(\frac{EN}{L}\right)}{\partial EDU} = (1-\sigma)\delta_L^3\left(\frac{P_L}{P_{EN}}\right)^{\sigma}\left(\frac{e^{\delta_L^0} EDU^{\delta_L^3}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2}}\right)^{-\sigma}\left(\frac{e^{\delta_L^0} EDU^{\delta_L^3-1}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2}}\right) > 0 \text{ since } \sigma < 1 \text{ and } \delta_L^3 > 0$$

What can be said regarding the relative impact of the R&D stock? The conditional demand for energy (Eq. 10) indicates that the direct impact of knowledge on energy demand is negative (energy-saving) if the elasticity of substitution is less than one. However, the indirect impact via capital productivity (Eq. 8) is energy-using, as for human capital. The net effect ultimately depends on the relative size of the two elasticities, $\delta_K{}^1$and $\delta_E{}^1$. *Since the estimated value of* $\delta_K{}^1$*is larger than* $\delta_E{}^1$, $\delta_K^1 = 0.941$ *and* $\delta_E^1 = 0.538$*, the net effect of knowledge is energy-using, if, ceteris paribus, the elasticity of substitution is less than one*:

$$\begin{aligned}
\frac{\partial\left(\frac{E}{L}\right)}{\partial R\ \&\ D} &= (1-\sigma)(\delta_K^1-\delta_E^1)\left(\frac{P_K}{P_E}\right)^{\sigma}\left(\frac{e^{\delta_K^0} R\ \&\ D^{\delta_K^1-\delta_E^1}}{e^{\delta_E^0} M\ \&\ E^{\delta_E^2}}\right)^{-\sigma} \\
&\times\left(\frac{e^{\delta_K^0} R\ \&\ D^{\delta_K^1-\delta_E^1-1}}{e^{\delta_E^0} M\ \&\ E^{\delta_E^2}}\right) > 0 \\
&\text{since } \sigma < 1 \text{ and } (\delta_K^1-\delta_E^1) > 0
\end{aligned}$$

In contrast, since $\delta_E^2 = 0.093$ the *net effect of machinery and equipment imports is energy-saving, if, ceteris paribus, the elasticity of substitution is less than one*:

$$\begin{aligned}
\frac{\partial\left(\frac{EN}{L}\right)}{\partial M\ \&\ E} &= (1-\sigma)(-\delta_E^2)\left(\frac{P_L}{P_{EN}}\right)^{\sigma}\left(\frac{e^{\delta_L^0} EDU^{\delta_L^3}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2}}\right)^{-\sigma} \\
&\times\left(\frac{e^{\delta_L^0} EDU^{\delta_L^3}}{e^{\delta_E^0} R\ \&\ D^{\delta_E^1} M\ \&\ E^{\delta_E^2+1}}\right) < 0 \\
&\text{since } \sigma < 1 \text{ and } \delta_E^2 > 0
\end{aligned}$$

What can be said regarding the potential impact of climate policy on induced technical change? Consider cost-effective analyses of climate goals, such as stabilising GHG concentrations at a given level. Since the objective is to reduce emissions, investments will be reallocated to the activities that allow achieving the goal at the minimum possible cost. As a consequence, climate policy will stimulate energy-saving technical change at the of cost energy-using technical change, in the present analysis education and R&D. Carraro, De Cian and Tavoni [11] assess the general equilibrium implications of human capital-driven technical change and find that climate policy discourages investments in education because human capital is labour-augmenting and gross complement with energy. Carraro et al. [13] find a similar result in a model with directed technical change where R&D is both capital–labour- and energy-augmenting. They show that climate policy reduces capital–labour-augmenting R&D, but stimulates energy-saving innovation.

Some caveats should be mentioned. Most studies, as well as the present analysis, only consider the direct effects of human capital and knowledge, neglecting possible indirect interactions that could actually have energy-saving effects. For example, a higher level of human capital can make mitigation policies more effective. Human capital is an essential input in the creation of new knowledge and new products and therefore it could stimulate energy-saving innovation, leading to the development of technologies that can replace or reduce the use of fossil fuels. A second potential energy-saving effect is that human capital increases the ability to adopt new technologies. Finally, there might be international as well intrasectoral spillovers. A better understanding of the relationship between the supply of specific skills, innovation, and clean technologies diffusion is certainly an important area for future research.

6 Summary and Conclusions

The debate on technical change and the environment has emphasised the existence of a gap between the climate–economy modelling literature and empirical work. Climate–economy models simulate the consequences of different specification of technical change over time. Empirical works attempt to identify production and technology structures that best explain observed patterns. However, these two strands of literature have addressed similar, but not comparable questions.

This paper tackles the existing divide from the empirical point of view. Starting from a production structure widely used by climate–economy modellers, it provides an empirical background to technology parameters that are essential to describe the dynamics of technical change. This paper estimates factor-specific technical change and input substitution using a structural approach. It improves upon exiting works by introducing endogenous-technology drivers for factor productivities (energy, labour and capital).

The main contribution of this paper is twofold. It provides an empirical assessment of the impact of endogenous technical change on the elasticity of substitution, and it identifies the drivers of factor-augmenting technical change.

First, factor productivities are endogenous, thus rejecting models with exogenous technical change. Second, technology drivers are factor-specific. Whereas knowledge is an important driver of capital and energy productivity, human capital is a better explanatory variable of labour productivity. Imports of machinery and equipment from OECD drive the productivity of energy and have an energy-saving effect, although the elasticity is much smaller than that of the R&D stock. Thirdly, the rate of energy-augmenting technical change tends to be larger than that of either labour or capital, which instead have similar growth rates. Because the elasticity of substitution is less than one, we can conclude that knowledge, machinery imports, and human capital have an input-saving effect. Finally, our results suggest that endogenous technical change tend to lower the elasticity of substitution. This result is not new in literature, yet it has never been fully assessed empirically.

These results have important implications for Integrated Assessment Models and climate policy analysis. The joint estimation of endogenous productivities and substitution allows us to highlight some implications in terms of energy use and induced technical change dynamics. The estimated structure of technical change suggests that climate policy might reduce economy-wide knowledge as well as human capital accumulation, if their energy-using effect prevails. As a consequence, omitting endogenous technical change at the macroeconomic level might underestimate climate policy costs.

Two lines of research follow from this paper. On the one hand, empirical work should aim at a better understanding of the interplay between different components of technical change, technology drivers, and factor substitution. On the other hand, IA models should broaden the representation of endogenous technical change outside of the energy sector. Few attempts in this direction already exist [11, 13, 23], but modelling choices should be better grounded on the empirical evidence.

Appendix I

Table 4 provides descriptive statistics of the main variables.

Table 4 Descriptive statistics of main variables

Variable	N	T	Obs	Mean	Std. dev.	Min	Max
Labour price (growth rate)	12	14	168	0.015	0.017	−0.076	0.067
Capital price (growth rate)	12	14	168	0.010	0.042	−0.154	0.138
Energy price (growth rate)	12	14	168	0.011	0.063	−0.101	0.289
Labour cost share (growth rate)	12	14	168	0.000	0.016	−0.080	0.051
Capital cost share (growth rate)	12	14	168	0.001	0.023	−0.076	0.121
Energy cost share (growth rate)	12	14	168	−0.005	0.071	−0.190	0.273
M&E (growth rate)	12	13	156	0.057	0.163	−0.379	0.860
R&D (growth rate)	12	14	168	0.066	0.030	0.014	0.140
Edu (growth rate)	12	14	168	0.068	0.037	0.011	0.163
Tfp (growth rate)	12	14	168	0.013	0.018	−0.034	0.061

Appendix II

This Appendix reports the same results as in the main text from Tables 1 to 4, but with bootstrap standard errors. Results confirm the validity of the inference analysis carried out in the main text is valid.

Table 5 Exogenous technical change (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	p value	Coeff	p value	Coeff	p value
γ_{f4} $(p_i - p)$	0.62	0.00	0.62	0.00	0.62	0.00
$\alpha_{f\mathrm{BE}}$	0.00	0.52	−0.01	0.03	−0.01	0.31
$\alpha_{f\mathrm{CA}}$	0.00	0.78	−0.01	0.14	−0.04	0.00
$\alpha_{f\mathrm{DE}}$	0.00	0.53	0.00	0.95	−0.06	0.00
$\alpha_{f\mathrm{DK}}$	0.00	0.38	−0.01	0.00	−0.02	0.13
$\alpha_{f\mathrm{ES}}$	−0.02	0.00	−0.02	0.00	−0.02	0.27
$\alpha_{f\mathrm{FI}}$	0.00	0.83	−0.02	0.01	−0.03	0.03
$\alpha_{f\mathrm{FR}}$	0.00	0.52	−0.01	0.03	−0.04	0.00
$\alpha_{f\mathrm{IT}}$	−0.03	0.00	−0.01	0.06	−0.02	0.10
$\alpha_{f\mathrm{JP}}$	0.00	0.35	0.00	0.56	−0.03	0.04
$\alpha_{f\mathrm{NL}}$	−0.01	0.08	0.00	0.32	−0.04	0.01
$\alpha_{f\mathrm{UK}}$	0.00	0.56	−0.01	0.03	−0.05	0.00
$\alpha_{f\mathrm{US}}$	−0.02	0.14	−0.01	0.03	−0.05	0.01
α_{f1} $(\ln T)$	0.00	0.46	0.00	0.92	0.01	0.01

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

Table 6 Endogenous technical change (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	p value	Coeff	p value	Coeff	p value
γ_{f4} $(p_i - p)$	0.63	0.00	0.63	0.00	0.63	0.00
γ_{f1} R&D stock	−0.64	0.00	0.18	0.25	−0.46	0.15
γ_{f2} M&E	−0.01	0.26	0.00	0.79	−0.05	0.05
γ_{f3} EDU stock	0.15	0.27	0.02	0.89	0.07	0.85
$\alpha_{f\mathrm{BE}}$	0.04	0.00	−0.02	0.14	0.03	0.49
$\alpha_{f\mathrm{CA}}$	0.06	0.00	−0.02	0.12	0.01	0.77
$\alpha_{f\mathrm{DE}}$	0.03	0.00	−0.01	0.61	−0.03	0.32
$\alpha_{f\mathrm{DK}}$	0.06	0.00	−0.04	0.05	0.03	0.49
$\alpha_{f\mathrm{ES}}$	0.03	0.06	−0.04	0.06	0.02	0.69
$\alpha_{f\mathrm{FI}}$	0.07	0.00	−0.04	0.07	0.03	0.51
$\alpha_{f\mathrm{FR}}$	0.04	0.00	−0.02	0.16	0.00	1.00
$\alpha_{f\mathrm{IT}}$	−0.02	0.19	−0.01	0.42	−0.01	0.90
$\alpha_{f\mathrm{JP}}$	0.05	0.00	−0.01	0.31	0.01	0.79
$\alpha_{f\mathrm{NL}}$	0.02	0.06	−0.01	0.24	−0.01	0.76
$\alpha_{f\mathrm{UK}}$	0.02	0.33	−0.02	0.24	−0.03	0.56
$\alpha_{f\mathrm{US}}$	0.02	0.27	−0.02	0.29	−0.01	0.83
α_{f1} $(\ln T)$	0.00	0.31	0.00	0.90	0.01	0.38

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

Table 7 Endogenous technical change including only significant variables (constrained system estimation, FGLS estimator)

	Capital		Labour		Energy	
	Coeff	*p* value	Coeff	*p* value	Coeff	*p* value
γ_{f4} (p_i-p)	0.63	0.00	0.63	0.00	0.63	0.00
γ_{f1} R&D stock	−0.59	0.00			−0.34	0.00
γ_{f2} M&E					−0.06	0.06
γ_{f3} EDU stock			−0.09	0.00		
$\alpha_{f\mathrm{BE}}$	0.04	0.00			0.035	0.01
$\alpha_{f\mathrm{CA}}$	0.05	0.00			0.017	0.18
$\alpha_{f\mathrm{DE}}$	0.02	0.00				
$\alpha_{f\mathrm{DK}}$	0.06	0.00	−0.01	0.01	0.04	0.01
$\alpha_{f\mathrm{ES}}$	0.04	0.00	−0.01	0.02	0.04	0.02
$\alpha_{f\mathrm{FI}}$	0.07	0.00	−0.01	0.06	0.03	0.01
$\alpha_{f\mathrm{FR}}$	0.04	0.00				
$\alpha_{f\mathrm{IT}}$	−0.02	0.00				
$\alpha_{f\mathrm{JP}}$	0.05	0.00			0.02	0.27
$\alpha_{f\mathrm{NL}}$	0.01	0.03				
$\alpha_{f\mathrm{UK}}$	0.02	0.00				
$\alpha_{f\mathrm{US}}$	0.03	0.01				

BE Belgium, *CA* Canada, *DE* Germany, *DK* Denmark, *ES* Spain, *FI* Finland, *FR* France, *IT* Italy, *JP* Japan, *NL* Netherlands, *UK* United Kingdom, *US* United States

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