Fondazione Eni Enrico Mattei

NOTA DI LAVORO

18.2009

Factor-Augmenting Technical Change: An Empirical Assessment

By **Enrica De Cian**, Fondazione Eni Enrico Mattei and School of Advanced Studies in Venice

Carlo Carraro, University of Venice, Fondazione Enrico Mattei, CEPR, CESifo and CMCC

SUSTAINABLE DEVELOPMENT Series
Editor: Carlo Carraro

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Summary

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Keywords: Technical Change, Technology Spillovers, Endogenous Growth, Panel Regression

JEL Classification: C3, O47, Q55, Q56

The authors gratefully acknowledge comments and support from Reyer Gerlagh and Ignazio Musu. Useful comments were also received from participants at SURED 2008, June 4-9, Ascona, Switzerland.

Address for correspondence:

Enrica De Cian
Fondazione Eni Enrico Mattei
Campo S. Maria Formosa 5252
30122 Venezia
Italy
E-mail: enrica.decian@feem.it

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Carlo Carraro, University of Venice, Fondazione Enrico Mattei, CEPR, CESifo and CMCC
and
Enrica De Cian[1], University of Venice, Fondazione Enrico Mattei, and CMCC

Abstract

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[1] **Corresponding author:** Enrica De Cian. Fondazione Eni Enrico Mattei, Campo S. Maria Formosa, Castello 5252, 30122 Venice, Italy. E-mail: enrica.decian@feem.it. *The authors gratefully acknowledge comments and support from Reyer Gerlagh and Ignazio Musu. Useful comments were also received from participants at SURED 2008, June 4-9, Ascona, Switzerland.*

1. Introduction

Over the past decades, our understanding of the role of technological change in economic growth has improved greatly. Literature has advanced from early models with exogenous technical change to representations of endogenous processes driven by various factors such as innovation (Romer, 1986; 1990; Acemoglu, 2002), human capital (Lucas, 1988) and experience (Arrow, 1962).

Technical change has also become an important element in the design of climate policies. Recent climate-economy models include modules describing technical change as an endogenous process. These models make it possible to understand how endogenous and policy-induced technical change (ITC) affects the macroeconomic costs of climate policy. Overall, this literature shows that ITC substantially affects both the costs and the timing of mitigation policies (Grubb et al. 2002; Clarke and Weyant 2002; Carraro, et al. 2006).

Nonetheless, even the most recent climate-economy models suffer from two limitations. First, most models endogenise technical change in the energy sector. Other forms of technical change such as total factor productivity or labour productivity either follow autonomous trends or are simply omitted. However, increasing evidence supports the existence of both energy-saving and energy-using technical change (see van der Werf, 2008; De Cian, 2009). The effect of technical change on pollution or greenhouse gas emissions depends on the substitution possibilities among inputs. If technical change increases the productivity of inputs that are gross complement to energy, it may also increase pollution (Lopez, 1994). This underlines the key role played by the elasticity of substitution across factors and the deep interconnections between factor substitution and technical change (Sue Wing, 2006). Estimates of substitution elasticities are provided by a number of empirical studies (see Markandya, 2007 for a review). Despite the large heterogeneity, most estimates point at a complementarity relationship between capital, labour and energy. In most cases, a substitution elasticity lower than one is estimated.

A second main limitation of most state-of-the-art climate-economy models is the weak empirical foundation of key technology parameters such as the elasticity of substitution, the growth rates 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 climate-economy models is still limited.

Most empirical literature focuses on the magnitude of neutral technical change. Early approaches measured indicators of neutral technical change as Solow residuals (Solow 1957) or as a coefficient of an exogenous trend using translog production functions (Jorgenson and Wilcoxen, 1990). Econometric methods were used to infer technical change from the dynamics of other economic variables. Slade (1989) and Bonne and Kemball-Cook (1992) 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 (1996). 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[2]. Kendrick (1995) analysed and compared trends in labour and capital productivity, measured as 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 et al. (2007) revised the work by Jorgenson and Fraumeni (1981) 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. (2006), 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 large heterogeneity in energy productivity not only across countries, but also across sectors. Van der Werf (2008) estimated factor-augmenting technical change using a 2-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[3].

This paper addresses these two previously described limitations of climate-economy models by estimating factor-specific technical change and input substitution using a structural approach. It

[2] 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.

[3] Another branch of empirical research has investigated the determinants of neutral technical change, identifying several explanatory variables, which include human capital (Engelbrecht, 1997; Barro and Sala-i-Martin, 2004; Caselli, 2005), domestic R&D (Griliches, 1980; Nadiri, 1970; Mansfield, 1979;1980), foreign R&D (Coe and Helpman, 1995), trade openness (Grossman and Helpman, 2001; Cameron, 2005), and capital goods (Delong and Summers, 1991).

infers the dynamics of technical change from a system of factor demands. It improves upon van der Werf (2008) 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. This paper contributes to the debate on technology and the environment by providing new empirical results that are consistent with the underlying production structure of Integrated Assessment Models (IAMs) and is therefore suitable for improving the empirical foundations of those models.

First, this paper shows that factor-productivities are endogenous, thus rejecting models with exogenous technical change. Second, it shows that technology drivers are factor-specific. Innovation is an important driver of capital and energy productivity, whereas education 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 R&D. 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 innovation, imports of machinery and equipment, and education have an input-saving effect. Therefore, innovation is not only energy-saving, but also capital-saving. Human capital is labour-saving. As long as labour and capital are gross complements to energy, technical change can be energy-using. This is a relevant conclusion for the development of climate-economy models.

In Section 2, we introduce the Constant Elasticity Production Function (CES) and briefly discuss the strategies 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 re-estimates factor-augmenting technical change using an alternative identification strategy. 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 integrated assessment models describe the production side of the economy using a CES production function.

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 (2008) reviews the production structure of 10 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[4]. 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 (Edenhofer et al. 2005) is characterised by factor-specific technical change.

In this paper, we consider a non-nested production function with endogenous factor-augmenting technical change[5]. 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:

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

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

This formulation (David et al. 1965) 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 or efficiency of production factors. 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.

[4] These are the models described by Edenhofer et al. (2005), Goulder and Schneider (1999) and Popp (2004).

[5] 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. This assumption simplifies the analytical derivation of the empirical model, especially when neutral technical change is explicitly accounted for, see Section 5.

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, 1997). Learning about new technologies and initial lack of experience explain 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[6].

Using logarithms and differentiating with respect to time, conditional factor demands can be expressed as a linear relationship[7], 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:

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

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

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

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

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

Therefore, 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 stands out clearly 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, 2008 and Acemoglu, 2002). This identification strategy is discussed further in Section 5, which proposes an alternative methodology.

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

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

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: innovation, approximated by the stock of R&D expenditure, trade, in particular imports of machinery and equipment, and human capital, proxied by the stock of education expenditure. These variables were selected among the main determinants of neutral technical change (see Barro and Sala-i-Martin, 2004).

The role of R&D as an engine of productivity growth has been acknowledged since the early models of endogenous growth (Romer 1986; 1990). Important contributions include studies by Griliches (1980), Nadiri (1970) and Mansfield (1979; 1980). Coe and Helpman (1995) 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 (Cameron 2005; Coe et al. 1997).

Engelbrecht (1997) extended the analysis of Coe and Helpman (1995) by including the role of human capital. He found that both R&D 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 (Barro and Sala-i-Martin, 2004) and education expenditure (Caselli, 2005).

Another indicator of knowledge is the stock of capital (Arrow, 1962). Rosenberg (1983) 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 was considered to be an important source of economic growth (DeLong and Summers, 1991) and technical progress. 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 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):

$$\tilde{\theta}_K = (\sigma - 1)\delta_K^0 + (\sigma - 1)\sum_{j=1}^{3} \delta_K^i y_j + (1-\sigma)(p_K - p)$$

$$\tilde{\theta}_L = (\sigma - 1)\delta_L^0 + (\sigma - 1)\sum_{j=1}^{3} \delta_L^i y_j + (1-\sigma)(p_L - p) \qquad (6)$$

$$\tilde{\theta}_E = (\sigma - 1)\delta_E^0 + (\sigma - 1)\sum_{j=1}^{3} \delta_E^i y_j + (1-\sigma)(p_E - p)$$

Country and time effects are captured using country dummies and a logarithmic time trend[8]. As a consequence, the rate of autonomous technical change (δ^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:

$$\Delta\theta_{Kit} = \sum_{i=1}^{12} \alpha_{Ki} Di + \alpha_{K1} \ln t + \gamma_{K1} R\&D + \gamma_{K2} M\&E + \gamma_{K3} EDU + \gamma_{K4} \Delta(P_{Kit} - P_{it}) + \varepsilon_{it}$$

$$\Delta\theta_{Lit} = \sum_{i=1}^{12} \alpha_{Li} Di + \alpha_{L1} \ln t + \gamma_{L1} R\&D + \gamma_{L2} M\&E + \gamma_{L3} EDU + \gamma_{L4} \Delta(P_{Lit} - P_{it}) + \varepsilon_{it} \qquad (7)$$

$$\Delta\theta_{Eit} = \sum_{i=1}^{12} \alpha_{Ei} Di + \alpha_{E1} \ln t + \gamma_{E1} R\&D + \gamma_{E2} M\&E + \gamma_{E3} EDU + \gamma_{E4} \Delta(P_{Eit} - P_{it}) + \varepsilon_{it}$$

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

Autonomous technology component

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

Endogenous technology component

$$\gamma_{K1} = (\sigma - 1)\delta_K^1 R\&D; \; \gamma_{K2} = (\sigma - 1)\delta_K^2 M\&E; \; \gamma_{K3} = (\sigma - 1)\delta_K^3 EDU$$
$$\gamma_{L1} = (\sigma - 1)\delta_L^1 R\&D; \; \gamma_{L2} = (\sigma - 1)\delta_L^2 M\&E; \; \gamma_{L3} = (\sigma - 1)\delta_L^3 EDU$$

Elasticity of substitution

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

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[8] 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.

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).

$$
\begin{aligned}
&\text{Test 1:}\\
&\mathrm{H}_0 : \gamma_{Kj} = \gamma_{Lj} = \gamma_{Ej} \text{ for } \forall j = 1,2,3\\
&\text{Test 2:}\\
&\mathrm{H}_0 : \gamma_{K4} = \gamma_{L4} = \gamma_{E4} = 0\\
&\text{Test 3:}\\
&\mathrm{H}_0 : \gamma_{K4} = \gamma_{L4} = \gamma_{E4}\\
&\text{Test 4:}\\
&\mathrm{H}_0 : \alpha_{Ki} + \alpha_{K1} = \alpha_{Li} + \alpha_{L1} = \alpha_{Ei} + \alpha_{E1} \forall i = 1,..,12
\end{aligned}
$$

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[9], the International Energy Agency (IEA) Databases 2006 on Prices and Taxes and Extended Energy Balance. The methodology of Pindyck (1979) is used to compute values for the variables of interest. The share of labour was computed using labour compensation. The 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 (Heston et al. 2006), 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

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

the Purchasing Power Parity Conversion Factor from the World Development Indicators[10] (WDI). Using the US implicit deflator of GDP, current prices were converted into constant prices at 2000 US$. All unites 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[11] 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 Caselli (2005).

Data on machinery and equipment imports are from the OECD STAN Industry Database 2006[12]. 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[13]. The stock was computed using the perpetual inventory method, with a depreciation rate of 2% (Jorgenson and Fraumeni, 1992)[14]. Table A1 in the Appendix summarises descriptive statistics for the main variables.

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).

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[10] World Bank, 2006.
[11] ANBERD - R&D Expenditure in Industry 2006 available from http://www.sourceoecd.org/

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

[13] Education Expenditures by Country, Nature, Resource Category, and Level of Education Vol. 2006 issue 01.
[14] A higher depreciation rate was also experimented, yielding very similar results.

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: (i) the empirical assessment of the impact of endogenous technical change on the elasticities of substitution, and (ii) the determination of how different technology drivers affect factor-augmenting technical change. We present the results when factor productivities are exogenous (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 (2008), especially regarding capital-augmenting technical change. Our results are similar to Kendrick (1956). He found that technical change is labour-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.

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

	Capital		**Labour**		**Energy**	
	coeff	p-value	coeff	p-value	coeff	p-value
γ_{f4} $(p_i\text{-}p)$	0.62	0.00***	0.62	0.00***	0.62	0.00***
α_{fBE}	0.00	0.63	-0.01	0.08*	-0.01	0.32
α_{fCA}	0.00	0.84	-0.01	0.18	-0.04	0.00***
α_{fDE}	0.00	0.51	0.00	0.89	-0.06	0.00***
α_{fDK}	0.00	0.45	-0.01	0.01***	-0.02	0.12
α_{fES}	-0.02	0.01***	-0.02	0.00***	-0.02	0.15
α_{fFI}	0.00	0.81	-0.02	0.00***	-0.03	0.04**
α_{fFR}	0.00	0.66	-0.01	0.11	-0.04	0.00***
α_{fIT}	-0.03	0.00***	-0.01	0.08*	-0.02	0.16
α_{fJP}	0.00	0.48	0.00	0.60	-0.03	0.01***
α_{fNL}	-0.01	0.07*	0.00	0.39	-0.04	0.00***
α_{fUK}	0.00	0.66	-0.01	0.03**	-0.05	0.00***
α_{fUS}	-0.02	0.01***	-0.01	0.18	-0.05	0.00***
α_{f1} (lnt)	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	

*** Significant at 1% level

** Significant at 5% level

* Significant at 10% level

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*)[15].

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 reduce 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.

On the contrary, energy-augmenting technical change is well explained by imports of machinery and R&D, 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 (1978) defined as input-saving technical change.

Capital-augmenting technical change is explained extensively by R&D and machinery, 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.

[15] 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} $(p_i\text{-}p)$	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
α_{fBE}	0.04	0.01***	-0.02	0.16	0.03	0.46
α_{fCA}	0.06	0.00***	-0.02	0.12	0.01	0.75
α_{fDE}	0.03	0.00***	-0.01	0.47	-0.03	0.20
α_{fDK}	0.06	0.00***	-0.04	0.05**	0.03	0.44
α_{fES}	0.03	0.12	-0.04	0.09*	0.02	0.62
α_{fFI}	0.07	0.00***	-0.04	0.03**	0.03	0.49
α_{fFR}	0.04	0.01***	-0.02	0.19	0.00	1.00
α_{fIT}	-0.02	0.18	-0.01	0.44	-0.01	0.88
α_{fJP}	0.05	0.00***	-0.01	0.29	0.01	0.77
α_{fNL}	0.02	0.11	-0.01	0.26	-0.01	0.75
α_{fUK}	0.02	0.38	-0.02	0.27	-0.03	0.49
α_{fUS}	0.02	0.30	-0.02	0.35	-0.01	0.79
α_{f1} (lnT)	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	1.016					
M&E	0.023				0.085	
Edu						
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 A.I in Appendix I).

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

We tested whether R&D 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 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, (1994). 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 due to technical change (Sue Wing, 2006).

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[16]. Results are reported in Table 3.

The effect of R&D and machinery is quite stable, although machinery is no longer significant in the capital equation. The effect of education on labour is less robust, which is now 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

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

average at 2% per year, whereas labour and capital have slightly lower and similar rates of improvement, respectively 1.5% and 1.4%.

Together the two drivers of energy-augmenting technical change, R&D and machinery imports, have an effect on energy productivity that is statistically equivalent to the effect R&D has on capital productivity (p-value 0.20). Alternatively, the contribution of education to labour-augmenting technical change is statistically different at 1% significance level[17].

[17] 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.

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} $(p_i\text{-}p)$	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***		
α_{fBE}	0.04	0.00***			0.04	0.01***
α_{fCA}	0.05	0.00***			0.02	0.18
α_{fDE}	0.02	0.00***				
α_{fDK}	0.06	0.00***	-0.01	0.04**	0.04	0.01***
α_{fES}	0.04	0.00***	-0.01	0.10*	0.04	0.01***
α_{fFI}	0.07	0.00***	-0.01	0.00***	0.03	0.02**
α_{fFR}	0.04	0.00***				
α_{fIT}	-0.02	0.00***				
α_{fJP}	0.05	0.00***			0.02	0.13
α_{fNL}	0.01	0.03**				
α_{fUK}	0.02	0.00***				
α_{fUS}	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	0.941				0.538	
M&E					0.093	
Edu			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.

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

Estimation residuals reveal the presence of first-order autocorrelation. However, the correlation between residuals is not very strong, ranging from 0.26 in the endogenous specification with selected variables to 0.4 in the endogenous specification with all variables. We did not correct for correlation in the estimation results reported in Table 1 to 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[18].

Two are the main conclusions that have emerged so far. First, we confirm results by van der Werf (2008) that technology trends are factor-specific. Second, and perhaps most importantly, the underlining technology drivers differ over inputs. Innovation (R&D) is the most important variable explaining capital- and energy-augmenting technical change. Education 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 R&D.

The crucial assumption that makes it possible to identify factor-specific technology trends is that all technical change is captured by factor productivity coefficients, leaving no role for neutral technical change. Section 5 generalises the model to include neutral technical change. In the next section we clarify that when factor-augmenting technical change is endogenous and the drivers are input-specific, we can partly solve the identification problem described in Section 2.

5. Factor-augmenting technical change: an alternative specification

The production structure described in equation (1) makes it possible to differentiate factor-specific technical change from changes in overall productivity, approximated by neutral technical change. Neutral and factor-augmenting technical change appear in the demand equation of each input with the same coefficient. Therefore their effect cannot be separately identified. These two technology components can only be identified if neutral and factor-augmenting technical change are characterised as different processes. This is one of the major findings in Section 2. Technical change is input-specific and therefore factor productivities should be described by different innovation frontiers. This result allows us to estimate a model including neutral and factor-specific technical change simultaneously.

The remainder of this Section describes this alternative approach. It shows how the input-specific relationship between technology drivers and productivity growth makes it possible to completely identify the endogenous component of technical change even in the presence of neutral technical change.

[18] Bootstrap methods are often used as an alternative to inference based on parametric assumptions when those assumptions are in doubt.

Instead of assuming no variations in neutral technical change as before, i.e. $h=0$, the relationship between neutral technical change and factor-augmenting technical change described in equation (3) is used to replace h into the system of factor demands (2). Equation (3) describes a relationship between neutral technical change, total factor productivity growth rate, and factor-augmenting technical change. It describes neutral technical change as total factor productivity net of the improvement in input productivities. With this substitution the system of factor demands reads as follows:

$$
\begin{aligned}
k &= x+(\sigma-1)a_K+(\sigma-1)tfp+(\sigma-1)(1-\theta_K)a_K-(\sigma-1)\theta_L a_L-(\sigma-1)\theta_E a_E+(1-\sigma)(p_K-p) \\
l &= x+(\sigma-1)a_L+(\sigma-1)tfp+(\sigma-1)(1-\theta_L)a_L-(\sigma-1)\theta_K a_K-(\sigma-1)\theta_E a_E+(1-\sigma)(p_L-p) \\
e &= x+(\sigma-1)a_E+(\sigma-1)tfp+(\sigma-1)(1-\theta_E)a_E-(\sigma-1)\theta_K a_K-(\sigma-1)\theta_L a_L+(1-\sigma)(p_E-p)
\end{aligned}
\qquad (8)
$$

The zero profit assumption leads to a linear combination among some regressors. To solve this problem, labour productivity is replaced by the following relationship $\theta_L = 1-\theta_K-\theta_E$ [19]. The corresponding equation becomes redundant and can be dropped:

$$
\begin{aligned}
k &= x+(\sigma-1)a_K+(\sigma-1)tfp+(\sigma-1)(1-\theta_K)(a_K-a_L)-(\sigma-1)\theta_E(a_E-a_L)+(1-\sigma)(p_K-p) \\
e &= x+(\sigma-1)a_E+(\sigma-1)tfp+(\sigma-1)(1-\theta_E)(a_E-a_L)-(\sigma-1)\theta_K(a_K-a_L)+(1-\sigma)(p_E-p)
\end{aligned}
\qquad (9)
$$

The technology parameters that can be identified at this stage are the elasticity of substitution (σ) and the rate of factor augmentation relative to that of labour, (a_K-a_L, a_E-a_L). Compared to system (2) we have an additional explanatory variable, which is total factor productivity growth rate.

Results described in Table 3 suggest that R&D is a common source of capital- and energy-augmenting technical change, whereas education drives labour productivity. Based on this evidence, we consider a model in which energy and capital depend on R&D and labour on education:

$$
\begin{aligned}
a_f &= \delta_f^0+\delta_f^1 R\&D \qquad \forall f = K,E \\
a_L &= \delta_L^0+\delta_L^1 Edu
\end{aligned}
\qquad (10)
$$

Replacing these equations into (9), the model to be estimated becomes:

[19] The choice of normalising with respect to labour is driven by the fact that labour has a different technology driver and this is exactly what makes it possible to identify technical change.

$$\tilde{\theta}_K = \gamma_{K1}(tfp - (p_K - p)) + \gamma_{K2}(\theta_K - 1) + \gamma_{K3}\theta_E + \gamma_{K4}(\theta_K - 1)R\&D + \gamma_{K5}\theta_E R\&D + \gamma_{K6}\theta_L Edu$$

$$\tilde{\theta}_E = \gamma_{E1}(tfp - (p_E - p)) + \gamma_{E2}(\theta_E - 1) + \gamma_{E3}\theta_K + \gamma_{E4}(\theta_E - 1)R\&D + \gamma_{E5}\theta_K R\&D + \gamma_{E6}\theta_L Edu \quad (11)$$

The following constraints are to be imposed in order to identify the technology parameters:

$$\begin{aligned}
\gamma_{K1} &= \gamma_{E1} = (\sigma - 1) \\
\gamma_{K2} &= \gamma_{E3} = -(\sigma - 1)(\delta_K^0 - \delta_L^0) \\
\gamma_{K3} &= \gamma_{E2} = -(\sigma - 1)(\delta_E^0 - \delta_L^0) \\
\gamma_{K4} &= \gamma_{E5} = -(\sigma - 1)\delta_K^1 \\
\gamma_{K5} &= \gamma_{E4} = -(\sigma - 1)\delta_E^1 \\
\gamma_{K6} &= \gamma_{E6} = -(\sigma - 1)\delta_L^1
\end{aligned}$$

The autonomous component can be identified only in relative terms. However, the endogenous part can be fully determined.

Table 4 reports estimation results[20]. All variables are significant explanatory factors of the percentage change in input cost shares, but for the autonomous component of energy productivity, relative to labour. Regarding the sources, results confirm the role of R&D as technology driver of capital and energy productivities and of education as driver of labour productivity. R&D has a larger effect on energy than capital, though we could not reject the null hypothesis that R&D has the same effect on capital and energy productivity.

[20] The estimation of system (11) involves an additional issue, namely the endogeneity of the input cost shares that appear also on the right hand side of the equation. This problem was addressed by considering a temporal shift between the dependent and the independent variables.

Table 4. Factor-augmenting technical change in the presence of neutral technical change (constrained system estimation, FGLS estimator)

Variables	Parameters	Estimated coefficients	p-value	Technology parameters	
$(tfp-(p_K-p))$	$\gamma_{K1}=\gamma_{E1}=(\sigma-1)$	-0.732***	0.000	σ	0.27
(θ_K-1)	$\gamma_{K2}=\gamma_{E3}=-(\sigma-1)(\delta_K^0-\delta_L^0)$	-0.014**	0.026	$(\delta_K^0-\delta_L^0)$	-0.02
(θ_E)	$\gamma_{K3}=\gamma_{E2}=-(\sigma-1)(\delta_E^0-\delta_L^0)$	-0.007	0.595	$(\delta_E^0-\delta_L^0)$	-0.01
$(\theta_K-1)x$	$\gamma_{K4}=\gamma_{E5}=-(\sigma-1)\delta_K^1$	0.228**	0.026	δ_K^1 $(R\&D)$	0.31
$(\theta_E)x$	$\gamma_{K5}=\gamma_{E4}=-(\sigma-1)\delta_E^1$	0.333*	0.072	δ_E^1 $(R\&D)$	0.46
$(\theta_L)y$	$\gamma_{K6}=\gamma_{E6}=-(\sigma-1)\delta_L^1$	0.127**	0.051	δ_L^1 (Edu)	0.17

R^2: 0.69;0.65; T=12, N=12. Logarithm time trend was not statistically significant. Only significant country dummies have been included

*** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level

As for the elasticity of substitution, these results confirm a tendency already observed with the previous models. The inclusion of additional variables that explain technical change, in this case total factor productivity, reduces the value of the elasticity of substitution. Accounting for neutral technical change reduces its value even further, to 0.27.

Observing the relationship between neutral technical change and factor productivities described in equation (3), we can conclude that total factor productivity is a biased measure of neutral technical change. Total factor productivity growth is an accounting measure of technical progress that is exclusively based on output and input quantity changes, and neglects variations in factor productivities. A corrected measure of neutral technical change should explicitly account for the improvements in input efficiencies. When technical change is factor-augmenting, the total factor productivity tends to over-estimate neutral technical change, i.e. $tfp = h + (a_K\theta_K + a_L\theta_L + a_E\theta_E)$.

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 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 determines how different technology drivers affect factor-augmenting technical change.

First, factor-productivities are endogenous, thus rejecting models with exogenous technical change. Second, technology drivers are factor-specific. Where innovation is an important driver of capital and energy productivity, education 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 R&D. 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 innovation, machinery imports and education 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 has never been fully assessed empirically. These results indicate that innovation and human capital are not necessarily energy-saving. As long as labour and capital are gross complements to energy, technical change can be energy-using.

The paper explores the relationship between neutral and factor-augmenting technical change. Total factor productivity is a widely used measure of neutral technical change, but it neglects improvements in factor productivities. As a consequence, when technical change is factor-augmenting, it tends to overestimate neutral technical change. When both neutral and factor-augmenting technical change are considered in the estimated system, the elasticity of substitution is further reduced, confirming the link between technical change and substitution previously observed.

Two lines of research can depart from the findings of 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, climate-economy models should broaden the representation of endogenous technical change outside the energy sector. Few attempts in this direction already exist (Gerlagh, 2008; Carraro et al. 2009), but modelling choices should be better grounded on the empirical evidence.

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Appendix I

Table AI.1 provides descriptive statistics of the main variables.

Table AI.1. 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 Table 1 to 4, but with bootstrap standard errors. Results confirm the validity of the inference analysis carried out in the main text is valid. The only notable change is the reduction of the significance level of the education driver in table AII.4, which is diminished from 5% to 10%.

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

	Capital		Labour		Energy	
	coeff	p-value	coeff	p-value	coeff	p-value
γ_{f4} $(p_i\text{-}p)$	0.62	0.00	0.62	0.00	0.62	0.00
α_{fBE}	0.00	0.52	-0.01	0.03	-0.01	0.31
α_{fCA}	0.00	0.78	-0.01	0.14	-0.04	0.00
α_{fDE}	0.00	0.53	0.00	0.95	-0.06	0.00
α_{fDK}	0.00	0.38	-0.01	0.00	-0.02	0.13
α_{fES}	-0.02	0.00	-0.02	0.00	-0.02	0.27
α_{fFI}	0.00	0.83	-0.02	0.01	-0.03	0.03
α_{fFR}	0.00	0.52	-0.01	0.03	-0.04	0.00
α_{fIT}	-0.03	0.00	-0.01	0.06	-0.02	0.10
α_{fJP}	0.00	0.35	0.00	0.56	-0.03	0.04
α_{fNL}	-0.01	0.08	0.00	0.32	-0.04	0.01
α_{fUK}	0.00	0.56	-0.01	0.03	-0.05	0.00
α_{fUS}	-0.02	0.14	-0.01	0.03	-0.05	0.01
α_{f1} (lnT)	0.00	0.46	0.00	0.92	0.01	0.01

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

	Capital		Labour		Energy	
	coeff	p-value	coeff	p-value	coeff	p-value
γ_{f4} $(p_i\text{-}p)$	0.63	0.00	0.63	0.00	0.63	0.00
γ_{f1} $R\&D$	-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	0.15	0.27	0.02	0.89	0.07	0.85
α_{fBE}	0.04	0.00	-0.02	0.14	0.03	0.49
α_{fCA}	0.06	0.00	-0.02	0.12	0.01	0.77
α_{fDE}	0.03	0.00	-0.01	0.61	-0.03	0.32
α_{fDK}	0.06	0.00	-0.04	0.05	0.03	0.49
α_{fES}	0.03	0.06	-0.04	0.06	0.02	0.69

α_{fFI}	0.07	0.00	-0.04	0.07	0.03	0.51
α_{fFR}	0.04	0.00	-0.02	0.16	0.00	1.00
α_{fIT}	-0.02	0.19	-0.01	0.42	-0.01	0.90
α_{fJP}	0.05	0.00	-0.01	0.31	0.01	0.79
α_{fNL}	0.02	0.06	-0.01	0.24	-0.01	0.76
α_{fUK}	0.02	0.33	-0.02	0.24	-0.03	0.56
α_{fUS}	0.02	0.27	-0.02	0.29	-0.01	0.83
α_{fI} *(lnT)*	0.00	0.31	0.00	0.90	0.01	0.38

Table AII.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	0.06
γ_{f3} *Edu*			-0.09	0.00		
α_{fBE}	0.04	0.00			0.035	0.01
α_{fCA}	0.05	0.00			0.017	0.18
α_{fDE}	0.02	0.00				
α_{fDK}	0.06	0.00	-0.01	0.01	0.04	0.01
α_{fES}	0.04	0.00	-0.01	0.02	0.04	0.02
α_{fFI}	0.07	0.00	-0.01	0.06	0.03	0.01
α_{fFR}	0.04	0.00				
α_{fIT}	-0.02	0.00				
α_{fJP}	0.05	0.00			0.02	0.27
α_{fNL}	0.01	0.03				
α_{fUK}	0.02	0.00				
α_{fUS}	0.03	0.01				

Table AII.4: Factor-augmenting technical change in the presence of neutral technical change (constrained system estimation, FGLS estimator)

Variables	**Parameters**	**Estimated coefficients**	**p-value**	**Technology parameters**	
$(tfp-(p_K-p))$	$\gamma_{K1}=\gamma_{E1}=(\sigma-1)$	-0.732	0.00	σ	0.27
(θ_K-1)	$\gamma_{K2}=\gamma_{E3}=-(\sigma-1)(\delta_K^0-\delta_L^0)$	-0.014	0.09	$(\delta_K^0-\delta_L^0)$	-0.02
(θ_E)	$\gamma_{K3}=\gamma_{E2}=-(\sigma-1)(\delta_E^0-\delta_L^0)$	-0.007	0.56	$(\delta_E^0-\delta_L^0)$	-0.01

$(\theta_K - 1)x$	$\gamma_{K4} = \gamma_{E5} = -(\sigma - 1)\delta_K^1$	0.228	0.01	δ_K^1	0.31
$(\theta_E)x$	$\gamma_{K5} = \gamma_{E4} = -(\sigma - 1)\delta_E^1$	0.333	0.05	δ_E^1	0.46
$(\theta_L)y$	$\gamma_{K6} = \gamma_{E6} = -(\sigma - 1)\delta_L^1$	0.127	0.10	δ_L^1	0.17

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