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August, 2008

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The empirical findings suggest that technical change is directed. Technical change tends to be more energy-saving than capital- and labour-saving. Both R&D investments and international trade are important determinants of growth in energy and capital productivity whereas technical change for labour is positively related to education expenditure. Therefore, the sources of factor-augmenting technical change go beyond R&D investments, as proposed in the theory of directed technical change, and they differ across inputs. In other words, not only is technical change directed, the sources of factor-augmenting technical change appear to be input specific.

Keywords: Factor-augmenting technical change, Technology spillovers, Panel data;
JEL classifications: C3; O47; Q55; Q56;

1 Introduction

Technical change is an increasingly interesting issue for economists specialised in fields other than economic growth or the microeconomic theory of innovation (Hicks, 1932), where the process of technical change was first analyzed. Starting from the first models of economic growth, technical change has always been considered as the key engine of long-run economic growth (Solow, 1956). In the nineties, a group of environmental economists investigated the relationships between growth and pollution, and discovered a negative relationship for some pollutants (Grossman and Krueger, 1993; de Bruyn et al., 1997). This result suggested a positive correlation between growth and environmental efficiency. Technical change also plays a crucial role in climate economy models used to assist the analysis of climate policy. It is now well established that the assumptions about technical change are among the most important drivers of the macroeconomic costs of stabilizing the concentration of carbon emissions in the atmosphere (Edenhofer et al., 2006). Increasing concerns about climate change call for more empirical evidence on the dynamics and the sources of technical change.

The difficulties of dealing with technical change are mostly due to its non-observability. A simple way of measuring technical change is to approximate it with a deterministic trend

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(Jorgenson and Wilcoxen, 1990). More sophisticated models infer technical change by observing the dynamics of other economic variables. Slade (1989) and Bonne et al. (1992) developed a model of factor demands in which the nature of technical change as a latent variable is preserved. Technical change is broken down into an unobservable component, a time trend, and other factors that endogenously influence technical change. In this way, technical change is modeled as a stochastic trend. A similar methodology was used by Carraro and Galeotti (1996) who inferred the dynamics of technical change from the time evolution of capital stock rather than factor demand.

The economic approach to technical change typically treats it as a cost reducing process, abstracting from elements such as productivity improvements and productivity sources. Building upon the analytical framework developed by the economic approach, this paper attempts to quantify the dynamics and the sources of technical change, with consideration for input productivity changes (e.g. factor-augmenting technical change). The dynamics of the technical change process are inferred from the dynamics of factor demands. Using a structural approach, the growth rate of factor-augmenting technical change is estimated.

This paper strengthens the empirical foundation of three aspects of technological change: the substitution possibilities between inputs; the direction and magnitude of factor-augmenting technical change; and the sources of factor-augmenting technical change. Two definitions of factor-augmenting technical change are used. First, factor-augmenting technical change is defined as the change in input shares that is not due to variations in prices. In this first model technical change is exogenous and its growth rate is a parameter to be estimated. In the second definition technical change is specified as an endogenous function of other macroeconomic variables, plus an exogenous component that captures its autonomous evolution over time.

The results of this paper have a stand-alone value as they add to the empirical literature on substitution and technical change. At the same time, they provide empirical based specifications of factor-augmenting technical change to be implemented in applied economic models. These results might have an important role if applied in climate economy models and models for international trade policies. Those models are affected by uncertainty in the choice of parameter values. The empirical results on the structure of technical change described in this paper can help to reduce both the parameter and structural uncertainty that characterise most climate economy models.

The rest of the paper is structured as followed. Section 2 introduces the theoretical background upon which the empirical model is based and deals with the estimation of productivity growth rates in the case of exogenous technical change. Section 3 estimates different specifications of endogenous factor-augmenting technical change. Section 4 concludes.

2 Theoretical set up

This section describes the theoretical background to the the empirical model used to estimate different components of technical change. As noted in the introduction, technical change cannot be observed and therefore it must be inferred from related observable entities. This paper infers the dynamics of factor-augmenting technical change from observable changes in factor demands. Different components of technical change can be identified if the demand of different inputs is considered jointly. A representative firm is assumed to produce the aggregate output of the economy using energy, labour and capital. Optimality conditions determine the demand of the three inputs, which are interdependent. The amount of labour to use is related to how much energy and capital can be used and to the way these three inputs can be substituted with each other. Prices and substitution play a key role as the firm will minimise its costs and therefore it will substitute expensive inputs with cheap inputs. Once this effect is accounted for, the other way in which the input mix can vary is through changes in factor productivities, namely in factor-augmenting technical change. The availability of a machine that uses less labour can be classified as labour-saving technical change. Such technological change could be deduced by observing a reduction in the labour cost share given constant prices. This is the idea behind the econometric approach used in this paper to quantify factor-augmenting technical change. In the next section we translate this concept into more formal language.

2.1 Modeling factor augmenting technical change

Technical change can affect all inputs equally (neutral technical change) or it can affect the proportion with which inputs are combined. The latter type of technical change is also called factor-augmenting or input-saving technical change[1] and it can be represented as a change in input efficiency or productivity (David and van Der Klundert, 1965). The direction of technical change describes whether technical change reduces or increases input cost share. Technological change is input-saving if the input share decreases at constant factor prices. It is input-using if the input share increases. The final effect of technical change on the production structure and input combination depends also on the substitution possibility among inputs, which is represented by the elasticity of substitution, henceforth denoted with σ. It describes the relative percentage change in input quantities induced by a one percent change in relative input prices, maintaining constant output quantity and price. A sufficiently flexible production function that can accommodate for different degrees of substitution and for different types of technical change is the Constant Elasticity of Substitution production function (CES). The final aggregate output of the economy, X, is produced using this constant return to scale production technology and combine labour, energy and capital:

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

The elasticity of substitution σ is related to the parameter ρ according to the standard definition, $\rho = \frac{\sigma-1}{\sigma}$. Given the wide uncertainty about input substitution,[2] we assume the simplest structure with an empirical foundation. The elasticity of substitution between any pair of these three inputs, σ, is the same, according to the empirical results found in van der Werf (2007). That paper estimates different input nesting structures and finds that a production model using equal substitution elasticity fits the data well. This type of CES is also called non-nested, since all inputs can be substituted with each other in the same way. The linkage between energy use and carbon emissions makes it possible to draw some conclusions about the environmental implications of technical change. From this perspective, the important questions are whether technical change is energy-saving or energy-using and whether inputs are gross substitutes or gross complements.

The coefficients that premultiply each input (A_i) describe the productivity of the corresponding input[3]. The higher the productivity coefficient, the lower the quantity of input required to produce the same level of output. Technical change is input i-augmenting if an increase in this coefficient leads to higher outputs, keeping everything else constant, $\frac{\partial X}{\partial A_i} > 0$. The coefficient

[1]Technical change is input-augmenting, or following Binswanger and Ruttan (1978) input-saving, if the input cost share decreases at constant factor prices.

[2]For an exhaustive review on the empirical literature on substitution elasticity see, among others, Markandya et al. 2007.

[3]This formulation of the CES production function is the variant introduced by David and van Der Klundert (1965). There are several variants of CES and the major difference is the interpretation given to the parameters that premultiply inputs. The most popular form is that introduced by Arrow (1962), where each input is premultiplied by a distributive parameter, the sum of which must be one. His formulation was considered unsatisfactory for a representation of technical change, which was assumed to be neutral. Instead, in the formulation of David and van Der Klundert (1965), technical change can be input specific. A particular feature of this production function is that inputs are expressed in efficiency units and that augmentation coefficients can be differentiated among inputs. For a discussion on this point see Klump et al. (2000)

standing in front of all inputs (H) represents neutral technical change in the sense of Hicks' neutral technical change, meaning that a change in H does not affect the rate of input marginal productivity (Barro et al. 2004).

Different assumptions can be made about the time evolution of augmentation coefficients. To start with, we fix the rates of input augmentation over time and so they are treated as parameters. In this case factor-augmenting technical change is exogenous. This assumption is relaxed in the second part of the paper in which technical change is specified as an endogenous function of other variables.

Cost minimization under the constraint of unit production function yields the standard unit cost function:[4]

$$C(1; P_K, P_L, P_E) = \frac{1}{H}[\frac{P_K}{A_K}^{\sigma-1} + \frac{P_L}{A_L}^{\sigma-1} + \frac{P_E}{A_E}^{\sigma-1}]^{\frac{1}{\sigma-1}} \tag{2}$$

By differentiating the unit cost function with respect to input prices, the respective conditional input demands are obtained. By replacing the assumption of zero profit condition in the output market, $C(1, P_K, P_L, P_E) = P$, unit input demands can be expressed as follow:

$$\frac{K}{X} = H^{\sigma-1} \frac{P}{P_K}^{\sigma} A_K^{\sigma-1} \frac{L}{X} = H^{\sigma-1} \frac{P}{P_L}^{\sigma} A_L^{\sigma-1} \frac{E}{X} = H^{\sigma-1} \frac{P}{P_E}^{\sigma} A_E^{\sigma-1} \tag{3}$$

These equations can be linearised so as to obtain a linear relationship between percentage changes or log changes of the variables. We denote the percentage changes with small letters $x = dX/X = dlnX$:

$$\begin{aligned} k &= x - \sigma(p_K - p) + (\sigma - 1)(h + a_K) \\ l &= x - \sigma(p_L - p) + (\sigma - 1)(h + a_L) \\ e &= x - \sigma(p_E - p) + (\sigma - 1)(h + a_E) \end{aligned} \tag{4}$$

The transformation of the system from level into percentage changes makes the interpretation of comparative static exercises more straightforward. We can immediately tell how a change in the right hand side variables affects input demand growth rates. The growth rates of input demands (k, l,e) depend on the growth rate of output (x) and of relative input prices ($p_i - p$). In addition, the way technical change varies over time also affects input demand. Technical change relative to each input has been broken down into two components:

- Neutral technical change, h, which is the part of technical change affecting all inputs equally. This term appears in all three equations;

- Input-specific or factor-augmenting technical change, a_i, which is specific to each input i;

The total impact of technical change on input demand is determined by the sum of these two components, henceforth referred to as net technical change, $h + a_i$. The direction of technical change depends on the elasticity of substitution, σ. Positive net technical change, $h + a_i > 0$, reduces input demand only if the substitutability among inputs is sufficiently low, $\sigma < 1$.

What can be observed in these three equations are prices and quantities. However, when a change in input demand is observed, at constant prices, the three equations do not tell whether such change comes from h or a_i. In other words the two forms of technical change cannot be identified. To address this issue, this paper assumes that all technical change is factor-augmenting and thus total factor productivity can be broken down into factor productivity

[4]For the sake of clarity time indexes are omitted, but all variables remain time-varying.

growth rates[5]:

$$tfp = (a_K\theta_K + a_L\theta_L + a_E\theta_E) \tag{5}$$

This assumption is also shared by the theory of directed technical change (Acemoglu, 2002), in which all technical change is factor-augmenting technical change. Therefore, this setup makes it possible to assess that theoretical model. Using this assumption, system (4) simplifies as follows:

$$\begin{array}{l} k - x = -\sigma(p_K - p) + (\sigma - 1)a_K \\ l - x = -\sigma(p_L - p) + (\sigma - 1)a_L \\ e - x = -\sigma(p_E - p) + (\sigma - 1)a_E \end{array} \tag{6}$$

The empirical model that will allow estimating the parameters of interest is obtained after some algebraic manipulations of system (6). Adding $(p_i - p)$ to each side of each equation, the system can be written in terms of cost share percentage changes, denoted with $\widetilde{\theta_i} = (i - x) + (p_i - p)$ for all $i = E, L, K$:

$$\begin{array}{l} \widetilde{\theta_K} = \gamma_{K0} + \gamma_{K1}(p_K - p)] \\ \widetilde{\theta_L} = \gamma_{L0} + \gamma_{L1}(p_L - p)] \\ \widetilde{\theta_E} = \gamma_{E0} + \gamma_{E1}(p_E - p)] \end{array} \tag{7}$$

Factor-augmenting technical change is identified by the three constant terms. More precisely, the γ_{i0} and γ_{i1} coefficients are associated with the parameters to be estimated according to the following constraints:

$$\begin{array}{l} \gamma_{E0} = (\sigma - 1)a_E \\ \gamma_{L0} = (\sigma - 1)a_L \\ \gamma_{K0} = (\sigma - 1)a_K \end{array} \tag{8}$$

The elasticity of substitution is identified by the coefficient associated with relative prices (γ_{i1}). Since input demands are derived from the same production function, the elasticity of substitution is constrained to be equal across the three equations:

$$\gamma_{E1} = \gamma_{L1} = \gamma_{K1} = (1 - \sigma) \tag{9}$$

The next section describes the construction of the dataset used to estimate the technology parameters highlighted in system (8) and (9).

2.2 Data description

The 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[6].

[5] It can be shown (De Cian, 2008) that neutral and factor-augmenting technical change are related through the following equation, which can be derived from the zero profit condition:

$$h = tfp - (a_K\theta_K + a_L\theta_L + a_E\theta_E)$$

In this model, assuming that all technical change is factor-augmenting implies that neutral technical change does not change over time, $h \neq 0$.

[6] On March 15, 2007 a new dataset, EUKLEMS became available. It contains this type of data for 60 industries in European countries. More information can be found in the website www.euklems.net.

Aggregate data have been collected from the OECD STAN Industry Database 2005[7], and the International Energy Agency 2005 (IEA) databases Energy Prices and Taxes - Energy End Use Prices and Extended Energy Balance[8]. To compute values for the variables of interest we used Pindyck's methodology(1979). 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 (Feenstra et al. (2005)) depending on data availability, the price of labour was obtained implicitly, dividing labour compensation, $PL * L$, by the labour force. An attempt to use hours worked was made, but there were too many missing data. The price of capital was computed as the indirect price from the ratio $\frac{PK*K}{K}$[9].

The price of energy was measured using the real index of industry price from IEA Energy Prices and Taxes. It was converted to constant US$ (base year 2000) per tonne of oil equivalent. The price in the base year was normalised to 1. Energy quantities are from IEA Extended Energy Balance and they are expressed in thousand tonnes of oil equivalent. Total output has been defined as value added plus the value of energy quantities. All values, in national currency, have been converted into current US$ using the Purchasing Power Parity Conversion Factor from the World Development Indicators 2006. Using the US implicit deflator of GDP, current prices were converted into constant prices at 2000 US$. The implicit deflator was computed using the GDP expressed in current and constant US$. All units are therefore expressed in millions of US$ relative to the base year 2000. Finally, prices were expressed as indices, with base year 2000. TFP was computed using the unit cost function measure[10].

The final sample consists of time series from 1978 to 2001 for 15 countries. Table 9 in Appendix A reports descriptive statistics for the main variables used in the estimation. Table 10 reports the variable values for the first and the last year of the series. While variation between countries accounts for most of the variation in the cost factor shares, factor prices and total factor productivity growth (tfp) vary more over time than across countries. Cost factor shares are in fact quite stable for each country.

The pattern of the data show some heterogeneity across countries and not all of them are characterised by trends that were recognised as stylised facts for the US economy during the postwar period (Jones, 2002). The four stylised facts recalled in Smulders et al. (2003) are improving energy efficiency, increases in per capita energy use, the decline of the share of energy costs over GDP and the decline of energy prices per unit of labour costs. Whereas increases in energy efficiency and in per capita energy use are common to most industrialised countries, the trend of energy cost over GDP and of energy price over labour cost is different across countries. Most countries show a downward trend for the energy-labour price ratio with the exception of New Zealand, the Netherlands, Luxembourg, Italy and Denmark.

2.3 Empirical specification and estimation method

The major econometric issues to be considered in the estimation of system (7) are the correlation among equations and the role of country and time effects. Given the theoretical background from which the empirical model has been derived, the three equations can be expected to be correlated with each other. The representative firm chooses the optimal demand of all three

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

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

[9]This price was compared with the user cost of capital computed as lending interest rate (World Development Indicators 2006 Data available from http://devdata.worldbank.org/wdi2006/contents) plus depreciation (6%) minus capital gain (World Development Indicators 2006). Capital gains were computed as the ratio between gross fixed capital formation in constant and current local currency. The two measures of capital price, however, compare well only in the case of US. However, the method described in the main text was preferred as yielding more reasonable time series.

[10]TFP was also computed as a Solow residual using quantity data which yielded very similar results to the unit cost function methodology.

inputs at the same time. Therefore, the system error terms has a variance covariance matrix that does not satisfy the assumptions of zero covariance and constant variance. In order to explicitly account for the correlation across equations, the model is estimated with a Feasible Generalised Least Square Estimator (FGLS). The estimation of the three equations as a system yields more efficient estimates than estimating each single equation individually. The model to be estimated explains the variation in input cost shares with the variation in relative input prices and a constant, which in this setting identifies the growth rate of factor-augmenting technical change.

Country and time effects are captured using country dummies and a logarithmic time trend. The hidden assumption behind pooled estimation is that all countries have similar production functions (Nordhaus, 1977) and that different values for the right hand side variables lead to different changes in the dependent variable, in this case the input cost shares. In the model with autonomous technical change the differences in prices account for the variation in cost shares, but the effect of an equal price change is assumed to be the same across countries. In fact, only one coefficient, common to all countries, will capture the effect of prices. However, what *can* be differentiated is the role of technical change, which is associated with the constant. Country dummies can be used to estimate a different constant for each country and therefore to differentiate technical change among countries. The time effect can also be made country specific by interacting the country dummies with the time trend. Although all these types of specifications were estimated, the model with a common time trend was preferred because it is more parsimonious. The system was originally derived in continuous time, but what is actually estimated is a discrete approximation of it:

$$
\begin{aligned}
\Delta\theta_{Kit} &= \gamma_{K0} + \gamma_{K1}\Delta(P_{Kit} - P_{it}) + \textstyle\sum_{i=1}^{14} \gamma_{K2i} D_i + \gamma_{K3} Lnt + u_{Kit} \\
\Delta\theta_{Lit} &= \gamma_{L0} + \gamma_{L1}\Delta(P_{Lit} - P_{it}) + \textstyle\sum_{i=1}^{14} \gamma_{L2i} D_i + \gamma_{L3} Lnt + u_{Lit} \\
\Delta\theta_{Eit} &= \gamma_{E0} + \gamma_{E1}\Delta(P_{Eit} - P_{it}) + \textstyle\sum_{i=1}^{14} \gamma_{E2i} D_i + \gamma_{E3} Lnt + u_{Eit}
\end{aligned}
\tag{10}
$$

where $: \Delta\theta_{jit} = \dfrac{\theta_{jit} - \theta_{jit-1}}{\theta_{jit-1}}$ and $\Delta(P_{jit} - P_{it}) = \dfrac{(P_{jit} - P_{it}) - (P_{jit-1} - P_{it-1})}{P_{jit-1} - P_{it-1}}$ for $j = K, L, E;$

Factor-augmenting technical change is identified by the three constants, which can be made country specific$i$:

$$
\begin{aligned}
\gamma_{E0} + \gamma_{E2i} + \gamma_{E3} &= (\sigma - 1)a_{Ei} \\
\gamma_{L0} + \gamma_{L2i} + \gamma_{L3} &= (\sigma - 1)a_{Li} \\
\gamma_{K0} + \gamma_{K2i} + \gamma_{K3} &= (\sigma - 1)a_{Ki}
\end{aligned}
\tag{11}
$$

As mention above, the introduction of country and time dummies allows differentiating the constant term across countries and over time. Although there are economic reasons that justify the inclusion of dummies, their relevance is also assessed statistically. To this end, the three equations are estimated independently and the hypotheses of an equal constant term across countries and over time is tested with an $F - test$. Country dummies are significant for the capital and energy equations.

2.4 Estimation results

Table 1 reports the estimation results relative to system (10). The estimator used was a feasible generalised least square estimator where the estimated variance-covariance matrix accounts for the correlation across equations. The reported results refer to the estimation under the constraint of equal elasticity across the three equations[11]. At first, all country dummies were included. In following estimations, only the country dummies that appeared significantly different from zero were kept in the estimated model, leading to more efficient estimates.

In table 1, the time trend is significant only in the equation explaining capital share growth rate, whereas it is not significant in the other two. However, its inclusion increases the significance of the constant term. By explicitly including a time component common to all countries, the identification of input-augmenting technical change is more precise because the effect of other time components is taken away.

The estimated coefficient of the regressor $(p_i - p)$ is associated with the value of the elasticity of substitution. This parameter is always significant and positive. An increase in the relative input price increases the corresponding cost share. This result may appear counterintuitive at first, since the substitution effect should reduce the demand of inputs whose prices increase. However, the cost shares measure the value of input and therefore if the quantity reduction is lower than the price increase, the overall value of input goes up. This is the case when the elasticity of substitution is lower than one because a 1% increase in prices reduces input demand by σ%. When constrained to be equal among inputs, the estimated elasticity of substitution is quite low, around 0.39[12].

What is left after the price effect has been taken into account is defined here as technical change. Technical change in this specification consists of a country specific component, which is captured by the country dummies, and another term common to all countries, which is represented by the constant and time effect. The negative sign of the constant suggests that at constant prices input-augmenting technical reduces input cost shares. When inputs become more productive, a lower quantity yields the same output, if everything else is kept constant. These results are consistent with the definition of input-biased technical change given by Binswanger and Ruttan (1978). They define technical change as input-saving if it reduces the input cost shares at constant prices.

The benchmark country associated with the constant is the United States. Other country dummies are to be interpreted relative to the benchmark. The significance of the country dummies varies with the input considered. It tells whether that country's input technical change is significantly different from the benchmark country's. In the case of capital, more than half countries in the sample[13] are characterised by their own capital-augmenting technical change, which reflects other country specific factors. labour-augmenting technical change is rarely significant. Moreover, on average the magnitude is very close to zero. Finally, energy-augmenting technical change is common to most countries except for Spain, Finland, Luxembourg and New Zealand.

The average value of factor-augmenting technical change, computed using the constraints (11), has been reported in the bottom part of table 1. Energy technical change is the largest in size, followed by capital and then labour technical change. Technical change therefore *does* appear to be input specific. Energy technical change is particularly high and on average it increases by 5% a year, with a growth rate that is almost twice that of capital and labour. Figure 1 highlights the presence of some heterogeneity in the patterns of input-augmenting technical change across countries. Most of them behave similarly to the US, except for Spain, Finland,

[11] The system was first estimated including only country effects. A log time trend, aimed at isolating the time effects common to all countries, was then introduced. A specification with a country specific time component was experimented, but the large number of parameters to be estimated led to very inefficient results. Country specific time effects were rarely significant and the specification with only one common time component was preferred. This result is not surprising considering that the sample of countries is relatively homogeneous, as they are all OECD countries. Only the results relative to best specification are reported here.

[12] It should be mentioned that when the system was estimated without constraints, the three equations yielded very different substitution elasticities and the hypothesis of equal elasticity was always rejected. The labour equation yields an elasticity very close to one whereas the elasticity obtained from the energy equation is much lower than 0.38. The results from the capital equation were in between.

[13] Belgium, Canada, Finland, France, Italy, Japan, New Zealand, the Netherlands and UK.

France, Italy, Japan, Luxembourg, New Zealand and the United Kingdom which differ from the US in the growth rate of at least one input productivity. In at least one equation, the dummy variable relative to these countries was significant, meaning that the intercept for that country was significantly different from the US's. Compared to the US, energy technical change is very low in New Zealand and nearly zero in Spain and Finland. It is extremely high in Luxembourg. Capital technical change is very small in Belgium, France and UK. labour technical change is always positive, particularly so in Spain and Finland, which in fact are the only countries with a significant value for the corresponding dummy. The explanation behind these results can be partly found in the pattern of relative input prices (table 11, Appendix A). In Spain and Finland, the price of labour has been increasing substantially over time. Countries characterised by low capital technical change are those where capital price, relative to the other input prices, has been decreasing (Belgium and UK). Since input prices reflect marginal input productivity, increasing prices can be associated with increasing productivity. Significant productivity improvements are then explained with big changes in technical change and thus productivity parameters. Table 2 reports the values of factor-augmenting technical change for countries other than the US [14].

Table 1 about here

Figure 1 about here

Table 2 about here

Another interesting result is that the elasticity of substitution is reduced when a time trend is included in the model. When the time effects are explicitly accounted for, the role of input substitution in explaining the change in input cost shares is lower and part of the effect that was attributed to factor substitution is captured by technical change. Technical change and input substitution are difficult to distinguish because they both show up as a change in input cost shares. It is difficult to know whether the new combination of input is adopted because a new technology has become available (technical change) or because the change in input prices has made an existing technology more attractive (substitution). When the elasticity of substitution is low, it is more unlikely that substitution occur and therefore most of the change in input shares is due to technical change[15].

2.5 Comparison with existing results

To date, there are no empirical works that quantify input augmenting technical change in a systematic way, but the work of van der Werf (2007). The author estimated and compared substitution and technical change for different countries. Different CES production structures with factor augmenting technical change are estimated using industry data for a panel of OECD countries. The specification that fits best the data assumes that the elasticity between labour and capital differs from the one between the capital labour nest and energy. The structure with equal elasticity among the three inputs also fits well the data. The estimates of input augmenting technical change are negative for capital and positive for labour and energy. Energy technical change ranges between 1% and 4% whereas labour technical change goes from 2% to 4%. The elasticity of substitution varies between 0.1 and 0.8. These results are in line with those obtained here, except for capital technical change which in this paper is found to be on average positive.

Other existing studies dealing with input-augmenting technical change are mostly country studies - very often about specific industrial sectors - that look at only one of the possible components of technical change. Starting with the work of Jorgenson and Fraumeni (1992) several

[14] Those not reported in the table have the same values as the US.

[15] An extensive discussion on this issue can be found in Sue Wing, 2006.

studies have assessed the role of energy technical change in explaining the decline in US energy intensity. Jorgenson and Fraumeni found that technical progress was energy-using and this was at odds with the stylised fact of a declining trend in energy intensity. The historical decline in energy intensity coupled with increasing economic growth suggest that, at the aggregate level, technical progress was energy saving. Sue Wing (2007), using more recent data for the US economy, revisited the work of Jorgenson and Fraumeni. Of particular interest is the methodology used in that work which disentangles the contribution of several factors to explain the pattern of energy intensity at the aggregate level. Technical change was found to be an important explanatory factor for the decline in aggregate energy intensity after 1980. Moreover, most of this improvement was autonomous and not driven by energy prices. The most important component was the change in the sectoral composition of the economy whereas energy prices play only a minor role.

Changes in sectoral composition are not explicitly considered in this paper, but they could explain some results such as the reduction in energy technical change in New Zealand. In 1983 the share of capital used in New Zealand took over the share of labour, so one explanation for the peculiarity of technical change in this country might be a restructuring of the sectoral composition of the economy toward more energy intensive sectors.

Most existing works on labour and capital productivity have measured the productivity of these two inputs as a ratio of output to labour and capital. Kendrick (1956) analyzed and compared trends in capital and labour productivity for 33 industries in the US from 1899 to 1953. Despite the across-industry heterogeneities, in the long run technical change is labour- and capital-saving. However, within shorter time periods technical change has been input-using, especially capital-using. The magnitude of capital and labour technical change ranges between 1% and 3 %. labour technical change tends to increase faster than capital technical change. The estimation results for the US in this paper compare relatively well with those findings. The rate of labour technical change is almost 2% and it is higher than capital technical change, which is about 0.18%[16].

Much larger is the number of empirical works on substitution elasticities (Markandya, 2007). Most of them are country or sector specific studies (Berndt and Wood, 1975; Hudson and Jorgenson, 1974). Fewer are empirical works with international or multi-country coverage, whose results are more comparable to those obtained in this paper. In particular, Griffin and Gregory (1976), using manufacturing data in ten countries estimated elasticity ranges between labour and capital of 0.39-0.52, between capital and energy of 0.36-1.48 and between labour and energy of 0.72-0.87. More recently, van der Werf (2007) found values between 0.22 and 0.59 for the elasticity between capital and labour and between 0.15 and 0.61 for the elasticity between the capital labour nest and energy. To conclude, the results found for exogenous factor-augmenting technical change compare well with the existing literature.

3 Technology spillovers and endogenous factor productivity

So far, technical change has been defined as the change in input cost share that could not be explained by factor substitution, accounting for other countries and time effects. However, technical change is a process that responds to incentives and that is likely to depend on other economic activities.

The role of R&D as an engine of productivity growth has been acknowledged since the very first models of endogenous growth (Romer, 1986; 1990). However, empirical literature limits attention to the relationship between R&D and total factor productivity growth, tfp. Important contributions are the works of Griliches (1980) and Nadiri (1980). They both found evidence for a positive relationship between these two variables. Mansfield (1979; 1980) estimated the effect

[16] A similar pattern for labour and capital technical change characterises Belgium, Spain, Finland, France and New Zealand.

on productivity growth of R&D flow over GDP, finding an elasticity between 0.20 and 0.50. 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 greater this effect, the more open to trade a country is (Cameron, 2005; Coe et al., 1997).

Countries can also import new technologies from abroad, through imports. When innovations are incorporated in products that are available on the world market, all buyers of those products can enjoy them and thus international trade is one important channel for the diffusion of technology and innovation. Grossman and Helpman (2001) in their seminal book identified four major mechanisms by which trade can have an impact on domestic productivity. A wider transmission of knowledge increases the stock of global knowledge. Trade increases the market size and competition. More contacts and deeper communication can eliminate the duplication of research. Countries can benefit from accessing a global pool of knowledge. If countries are integrated through trade, participation in the world economy gives access to a larger variety of inputs, machineries and capital equipment.

Engelbrecht (1997) extended the analysis of Coe and Helpman (1995) to include the role of a more general measure of innovation, that is human capital measured in terms of school attainment, suggesting that education and R&D are both important determinants of productivity growth. Empirical studies found a positive relationship between aggregate productivity and different measures of education, such as education attainment (Barro et al., 2004) and education expenditure (Caselli, 2004).

Another measure used to approximate innovation or the stock of knowledge available is the stock of machinery. This notion dates back to Arrow (1962), who introduced the view of capital stock as a picture of the knowledge incorporated in those goods. Rosenberg (1983) stressed how the technical improvements are often tied to capital goods such as machinery and equipment and therefore the purchase of these goods is fundamental for the translation of technical change into productivity growth. Capital goods, or machinery, have some characteristics that make them an important vehicle of technology transmission. Historically, capital goods have only been manufactured in a small number of countries because it requires a mature stage of industrialization, 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 can be expected to be particularly knowledge-intensive and therefore have a higher potential for the transfer of technology. Finally, since machinery is energy-using, high quality machinery in terms of energy requirements can be expected to reduce aggregate energy use. Machinery has been considered to be an important source for economic growth (DeLong and Summers, 1991) and technological progress.

On the theoretical side, a model for directed technical change that relates input productivity and R&D investments was developed by Acemoglu (2002). R&D can be allocated to improve the productivity of different inputs, depending on profit considerations. Profit maximizing firms direct invention efforts toward those factors that are more profitable, either because they command a higher price or because they have bigger market potential.

In light of these theoretical and empirical studies, it can be expected that trade, capital goods, R&D, and education all relate to factor-augmenting technical change, an issue still to be explored by empirical literature on growth determinants. The remaining part of this paper contributes to filling that gap by describing a model in which factor-augmenting technical change is endogenously linked to R&D and education expenditure, imports and imports in capital goods (machinery). The sources of factor productivity growth can be made input specific, identifying the sources of economic growth in a more precise way.

3.1 Modeling endogenous factor-augmenting technical change

This model is derived by the same input demand system (7). Input-augmenting technical change is no longer treated as a parameter to be estimated, instead it has a functional form that describes its relationship with other economic variables, generally denoted by X. The rate of change in factor productivity, a_i, now consists of two components. The first component is constant over time and it is denoted by δ_i^0. The second component depends on the growth rate of other variables, x, in proportion to the coefficient δ_i:

$$a_i = \delta_i^0 + \delta_i x, \quad \text{for all } i = E, L, K \tag{12}$$

This definition of technical change corresponds to an innovation function that includes an exponential component, which captures autonomous technical change, and an endogenous component, which captures the endogenous effect of X[17] :

$$A_i = e^{\delta_i^0 t} X^{\delta_i} \text{ for each i = E, L, K} \tag{13}$$

If the elasticity with respect to X is zero, the previous model with constant, exogenous, technical change is obtained ($a_i = \delta_i^0$). This formulation makes it possible to assess the role of different variables as productivity sources for different factors.

Substituting the definition of technical change given in equation (10) into the input demand system (7), the system to be estimated is obtained. As in the case of constant technical change, after some algebraic manipulations the dependent variable can be expressed as the growth rate in the input cost shares. The explanatory variable is the rate of change in relative prices $(p_i - p)$ a constant term that captures the effect of autonomous technical change (γ_{i0}) and the variable x:

$$\begin{aligned}
\widetilde{\theta_K} &= \gamma_{K0} + \gamma_{K1}(p_K - p)] + \gamma_{K2}x \\
\widetilde{\theta_L} &= \gamma_{L0} + \gamma_{L1}(p_L - p)] + \gamma_{L2}x \\
\widetilde{\theta_E} &= \gamma_{E0} + \gamma_{E1}(p_E - p)] + \gamma_{E2}x
\end{aligned} \tag{14}$$

From the estimated coefficients, γ_{ij} for $i = E, L, K$ and $j = 0, 1, 2$, the structural parameters of the model can be recovered using the following constraints:

$$\begin{aligned}
\gamma_{E0} &= (\sigma - 1)\delta_E^0 \\
\gamma_{L0} &= (\sigma - 1)\delta_L^0 \\
\gamma_{K0} &= (\sigma - 1)\delta_K^0 \\
\gamma_{E2} &= (\sigma - 1)\delta_E \\
\gamma_{L2} &= (\sigma - 1)\delta_L \\
\gamma_{K2} &= (\sigma - 1)\delta_K \\
\gamma_{E1} &= \gamma_{L1} = \gamma_{K1} = (1 - \sigma)
\end{aligned} \tag{15}$$

As in the model considered in the previous section, the elasticity of substitution is common to all three equations. Therefore, a constraint is imposed across equations.

3.2 Data description

Three different sources of technical change are evaluated: R&D expenditure, aggregate imports and imports of machinery and equipment. A specification in which labour productivity depends on education expenditure is also estimated.

[17] This functional form was introduced by Mansfield (1956) and then used by most studies aimed at estimating the elasticity of productivity with respect to R&D. Important contributions are those by Griliches (1973, 1980).

The most recent available data on R&D expenditure[18] is limited to a small number of countries. Therefore, the sample used in the estimation of this specification is slightly different from the one used in the previous section: only 13 countries are included[19], from 1987 to 2002. The stock of R&D has been computed using the perpetual inventory method with a depreciation rate of 5%, although the choice of different 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.

Imports data are from the Feenstra trade database (Feenstra et al., 2005). They are aggregate imports from the world. Data on machinery and equipment imports are from the OECD STAN Industry Database 2006[20]. Data are available for 13 countries[21] 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 have been selected. The focus on imports from the OECD is justified by the high concentration of R&D world expenditure in OECD countries, which channel most of their R&D activity into just a few sectors, among which machinery. As a consequence, the machinery produced and exported from these countries is regarded as particularly knowledge intensive. Machinery and equipment imports are classified as a two-digit industry according to the International Standard Industrial Classification[22] (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[23]. The sample was chosen to be compatible with the R&D database and so 13 countries are considered over the period 1987-2001. As in the case of R&D, the variable that enters into the system is the growth rate of the education expenditure stock. The stock was computed using the perpetual inventory method, with a depreciation rate of 2% (Jorgenson and Fraumeni, 1992)[24]. Table 3 summarises the major statistics for the variables used to model endogenous technical change. The remaining data (price and quantities of output, labour, capital and energy) were described in section 2.2.

Table 3 about here

3.3 Estimation results

Table 4 reports the estimation results when factor-augmenting technical change is endogenously related to the stock of R&D expenditure. The country dummies that were not statistically different from zero have been excluded so as to obtain more efficient estimates. It emerges that R&D is significantly related to all inputs. Compared to capital and energy, the impact on labour technical change is less significant. An increase in aggregate R&D saves all inputs. The effect is greater on capital productivity, followed by energy and labour productivity. These results support the theory of directed technical change according to which R&D affects inputs differently, depending on the market and the price effect.

Comparing the results in table 4 with those obtained from the model of autonomous technical change (table 1) two major observations can be made. First of all, when there are no additional variables, all technical change is accounted for by autonomous technical change, captured by the constant term, and the elasticity of substitution, which tends to be larger. The introduction of

[18]ANBERD - R&D Expenditure in Industry 2006 available from http://www.sourceoecd.org/

[19]For Luxembourg and New Zealand the OECD Database does not provide R&D data and therefore they were excluded from the sample.

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

[21]Austria and Luxembourg were excluded because of too many missing values.

[22]http://unstats.un.org/unsd/cr/registry/

[23]Education Expenditures by Country, Nature, Resource Category, and Level of Education Vol 2006 issue 01. The database distinguishes education expenditure by nature, source and type of education. However, the data have many missing values and so the choice of expenditure type depends also on data availability.

[24]A higher depreciation rate was also experimented, yielding very similar results.

R&D reduces the elasticity of substitution, approximately from 0.39 to 0.36. Moreover, in the first model autonomous technical change was significant in all three equation and, on average, it was positive, meaning that it was input-saving. The introduction of R&D reduces the role of autonomous technical change, which in some cases can even be negative. In particular, it can be noted that negative technical change occurs only when the endogenous component is significant and sufficiently big (e.g. for capital and energy). In the case of labour, where the effect of R&D is small, the autonomous component remains positive. The overall growth rate of factor-augmenting technical change, consisting of both the autonomous and endogenous component, is positive, as it can be seen from the values reported in the second column of table 8[25]. Energy technical change tends to be the bigger one, followed by labour and capital technical change.

Another variable that can be expected to explain the growth rate of labour productivity is education. Education attainment, measured as years of schooling, or education expenditure have been considered as a possible determinant of aggregate productivity growth by the empirical literature on growth determinants. Barro et al. (2004) found that public education spending has an effect on the growth rate of real GDP of 0.009 whereas Cullison (1993) found that an increase in the growth rate of government spending on education has an effect on output growth rate equal to 0.269. Caselli (2004) also found that the elasticity of human capital with respect to education spending is 0.2.

Table 5 reports the estimation results when R&D increases energy and capital productivity and education augments labour productivity. As expected, education expenditure increases labour productivity. The magnitude of the effect is lower than the effect R&D has on both capital and energy productivity and it is within the rages found by previous studies. It can be noted that when education is specified as source of labour productivity, the effect of R&D on the other two inputs is reversed. R&D increases energy productivity more than capital productivity. When both education and R&D are included as possible sources of labour productivity, only education remains a significant explanatory variable. This result seems to suggest that education expenditure is more important in sustaining labour productivity[26].

Table 4 about here

Table 5 about here

The next model looks at the relationship between factor productivity and international trade. First aggregate imports are experimented, extending the work of Coe et al. (1997) on neutral technical change to factor-augmenting technical change. Secondly, the effect of machinery imports is considered. As discussed at the beginning of this section, capital goods are an important vehicle of technology diffusion because they incorporate the knowledge available in the economy, at a given point in time.

Table 6 and 7 report the estimation results when technical change is assumed to have an autonomous component and an endogenous part related respectively to machinery and aggregate imports. A first comparison of the R^2 shows the model has a higher explanatory power when machinery imports are included than when aggregate imports are included. Machinery imports have a positive effect on both energy and capital productivity, whereas aggregate imports positively impact capital productivity only, with a coefficient that has a little less than half the effect of machinery.

Machinery imports have a stronger effect related to energy probably because they are a specific type of goods, whereas aggregate imports are a more generic aggregate, and include many different goods. Machinery and equipment are energy-using goods since they include engines, motors, and appliances. Moreover, they absorb a significant fraction of R&D expenditure. As

[25] These values have been computed using the mean change in the endogenous variable, x, which in this case is R&D.

[26] These results have not been reported here but they are available upon request.

for the growth in labour productivity, imports are not the appropriate explanatory variable under this specification

As in the model with R&D, the total effect of technical change, $\delta_i + \delta_i^0 x$, depends on the values of x. Results for the mean values of x are summarised in table 8. When the source of technical change is machinery imports, energy technical change has the highest growth rate. Capital technical change grows more than labour technical change only in the model with aggregate imports and exogenous technical change.

To summarise, both intertemporal (R&D and education) and international (imports) technology spillovers are important sources of factor-augmenting technical change. If these sources are not specified in the model, the process of technical change is explained mostly by input substitution and autonomous technical change. It can be noted that in all different specifications of endogenous technical change, the introduction of further explanatory variables for the input cost shares reduces the elasticity of substitution. In other words, when other factors are accounted for, less is due to substitution. This result was discussed in Carraro and Siniscalco (1994) who observed that if endogenous technical change is omitted, the effect of prices on cost shares is upward biased. To distinguish between technical change and substitution is not an easy task, because they have the same effect, they both affect input cost shares. On this point, the estimated elasticity of substitution is very stable across different specifications. Moreover, the use of panel data helps to identify the effect of technical change, which is a long-run process, whereas substitution can also occur in the short run.

Table 6 about here

Table 7 about here

Table 8 about here

4 Conclusions

This paper considers a new way of modeling endogenous technical change. Not only neutral technical change is endogenous, as extensively found by the existing literature on growth determinants, factor productivities can also be endogenous. Moreover, the relationship between factor-augmenting technical change and different sources of technical change is input specific.

This paper has developed a simple analytical framework that makes it possible to estimate factor productivity growth and identify its determinants. Two definitions of factor-augmenting technical change were used. First, all input technical change was assumed to be autonomous or exogenous. Secondly, technical change was broken down into two components, one autonomous and one endogenous. Several sources of endogenous technical change were considered, namely R&D and education investments, aggregate imports and machinery imports.

The different specifications of technical change estimated in the paper led to consistent and similar results. Technical change is input-specific and, on average, it is input-saving. The growth rate of energy technical change tends to be the greatest, followed by labour and capital technical change, which grow at similar rates. Energy productivity increases with R&D and machinery imports, whereas capital productivity increases with R&D, aggregate and machinery imports. Education expenditure rather than R&D expenditure appears to better explain labour productivity.

It can be concluded that a model of production that represents technical change only with one parameter, e.g. tfp, would be unsatisfactory because it does not make it possible to differentiate the effect of technical change on each input and the sources of factor productivity improvements. The crucial assumption that makes it possible to identify the different components of technical change is that all technical change is factor-augmenting, leaving no role for neutral technical change. Ongoing research is dealing with a more comprehensive model of technical change, where factor-augmenting and neutral technical change are considered simultaneously.

The results obtained in this paper may be valuable in other economic fields, such as in applied economic literature. In fact, these results provide an empirical basis for different specifications of endogenous technical change that can be implemented in applied models used for policy relevant analysis. Two important applications are in the context of climate and trade policy. Climate economy models are extensively used to assist the analysis of climate policies. Technical change is a key feature of those models, especially because of the long term horizon and global dimension of climate issues.

5 Appendix A

Table 9 about here

Table 10 about here

Table 11 about here

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7 Figures and Tables

Figure 1: Average yearly growth rate of input augmenting technical change

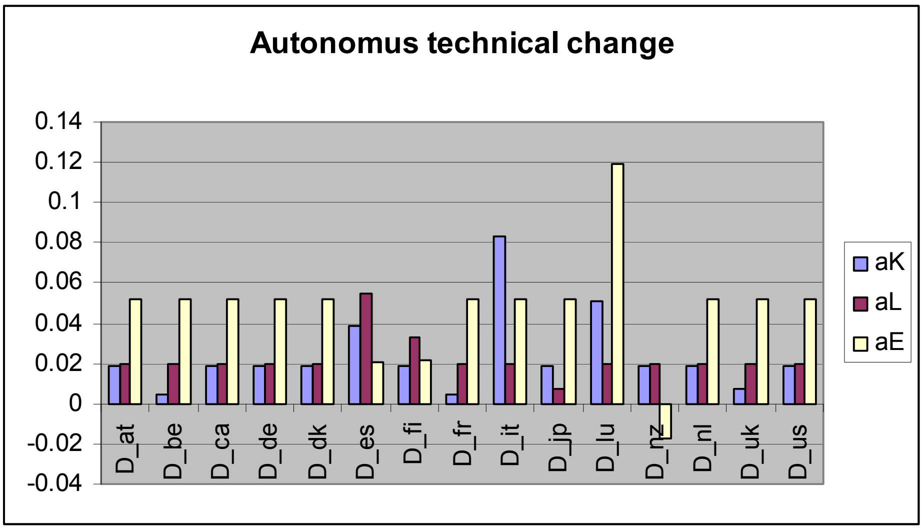

Table 1: Constrained system regression with fewer country dummies and a log temporal trend

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR	ENERGY
$(p_i - p)$ $[\gamma_{i1}]$	0.610***(0.000)	0.610***(0.000)	0.610***(0.000)
D_{be}	0.009*(0.076)		
D_{es}	-0.012**(0.016)	-0.022***(0.000)	0.019*(0.082)
D_{fi}		-0.008**(0.038)	0.019*(0.085)
D_{fr}	0.008*(0.086)		
D_{it}	-0.039* (0.000)		
D_{jp}		0.007* (0.080)	
D_{lu}	-0.020***(0.000)		-0.041***(0.000)
D_{nz}			0.042***(0.000)
D_{uk}	0.007(0.171)		
lnT	0.005**(0.004)	0.002 (0.284)	0.005 (0.196)
D_{us}(cons.)	-0.017*** (0.001)	-0.012*(0.004)	-0.032*(0.002)
R^2	0.427	0.011	0.623
N	15	15	15
T	23	23	23
σ	0.390	0.390	0.390
Average a_K	0.024*		
Average a_L		0.022*	
Average a_E			0.048*

P-value in brackets
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Average a_i have been computed as the value of the constant plus the significant dummies and the temporal trend, when significant.

Table 2: Autonomous technical change by country

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR	ENERGY
D_{be}	0.004	0.019	0.052
D_{es}	0.039	0.055	0.021
D_{fi}	0.018	0.033	0.021
D_{fr}	0.005	0.019	0.052
D_{it}	0.083	0.019	0.052
D_{jp}	0.018	0.008	0.052
D_{lu}	0.051	0.019	0.119
D_{nz}	0.018	0.019	-0.017
D_{uk}	0.008	0.019	0.052
D_{us}	0.018	0.019	0.052

Table 3: R&D and imports data summary

Variable (growth rates)	Mean	Std. Dev.	Min	Max	T	N	Obs
$R\&Dstock$	0.069	0.031	0.014	0.140	14	13	182
Aggregate Imports from World	0.071	0.124	-0.201	0.448	15	23	345
Machinery and equipment imports from OECD	0.0564	0.162	-0.379	0.860	13	13	169
Education expenditure stock	0.068	0.035	0.011	0.1631	14	13	182

Table 4: Constrained system regression: Aggregate R&D

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR	ENERGY
$(p_i - p)$ $[\gamma_{i1}]$	0.639***(0.000)	0.639***(0.000)	0.639***(0.000)
AGG. R&D	-0.522***(0.000)	-0.106***(0.000)	-0.248***(0.000)
D_{at}	0.047***(0.000)		0.025**(0.046)
D_{be}	0.036***(0.000)		0.024**(0.028)
D_{ca}	0.047 ***(0.000)		
D_{it}	-0.019***(0.000)		
D_{de}	0.020 ***(0.003)		-0.024**(0.023)
D_{dk}	0.055*** (0.000)		0.027**(0.033)
D_{es}	0.033*** (0.004)	-0.010**(0.032)	0.025**(0.034)
D_{fi}	0.059***(0.000)	-0.006 (0.193)	0.022*(0.079)
D_{fr}	0.031***(0.000)		
D_{jp}	0.042***(0.000)		
D_{nl}	0.013*(0.056)		
D_{uk}	0.020***(0.002)		
D_{us}(cons)	0.017**(0.033)		-0.020*(0.052)
R^2	0.566	0.090	0.652
T	14	14	14
N	13	13	13
σ	0.361***	0.361***	0.361***
δ_K^0	-0.048*		
δ_L^0		0.002*	
δ_E^0			-0.010*
δ_K	0.817***		
δ_L		0.165***	
δ_E			0.389***

P-value in brackets
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Average δ_i^0 have been computed as the value of the constant
plus the significant dummies and the temporal trend, when significant.

Table 5: Different sources of productivity growth: aggregate R&D and education

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR(EDU)	ENERGY
$(p_i - p)$ $[\gamma_{i1}]$	0.642***(0.000)	0.642***(0.000)	0.642***(0.000)
AGG. R&D (EDU)	-0.188***(0.000)	-0.082***(0.000)	-0.256***(0.000)
D_{at}	0.012 *(0.068)		0.026** (0.044)
D_{be}	0.013** (0.018)		0.024** (0.031)
D_{ca}	0.018 ***(0.003)		
D_{it}	-0.026*** (0.000)		
D_{de}			-0.024** (0.024)
D_{dk}	0.018*** (0.005)	-0.010** (0.020)	0.028 **(0.025)
D_{es}		-0.017*** (0.000)	0.026** (0.031)
D_{fi}	0.022 ***(0.001)	-0.012*** (0.006)	0.023 *(0.070)
D_{fr}	0.012** (0.033)		
D_{jp}	0.019*** (0.001)		
D_{uk}			-0.018*(0.087)
R^2	0.521	0.102	0.653
T	14	14	14
N	13	13	13
σ	0.358***	0.358***	0.358***
δ_K^0	-0.011*		
δ_L^0		0.005*	
δ_E^0			-0.010*
δ_K	0.293***		
δ_L		0.128***	
δ_E			0.398***

P-value in brackets
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Average δ_i^0 have been computed as the value of the constant
plus the significant dummies and the temporal trend, when significant.

Table 6: Constrained regression with country and time trend: Machinery Imports

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR	ENERGY
$(p_i - p)$ $[\gamma_{i1}]$	0.619***(0.000)	0.619***(0.000)	0.619***(0.000))
MACH	-0.017*(0.059)	-0.006 (0.480)	-0.057***(0.003)
lnt	-0.003 (0.118)	-0.002 (0.201)	0.005 (0.206)
D_{be}			0.022**(0.043)
D_{dk}		-0.012**(0.011)	
D_{es}		-0.008*(0.073)	0.018 (0.113)
D_{fi}		-0.011**(0.021)	
D_{it}	-0.027***(0.000)		
D_{jp}	0.010*(0.057)		
D_{nz}			0.020*(0.066)
D_{us}(cons)	0.004(0.334)	-0.002(0.535)	-0.019**(0.022)
R^2	0.550	0.119	0.638
T	13	13	13
N	13	13	13
σ	0.381***	0.381***	0.381***
δ_K^0	0.025*		
δ_L^0		0.071 *	
δ_E^0			-0.017*
δ_K	0.027*		
δ_L		0.009	
δ_E			0.093***

P-value in brackets
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Average δ_i^0 have been computed as the value of the constant plus the significant dummies and the temporal trend, when significant.

Table 7: Constrained system regression with country and time trend: Aggregate Imports

$\frac{\theta_{it}-\theta_{it-1}}{\theta_{it-1}}$	CAPITAL	LABOR	ENERGY
$(p_i - p)$ $[\gamma_{i1}]$	0.600***(0.000)	0.600***(0.000)	0.600***(0.000)
IMPORTS	-0.027***(0.006)	0.008 (0.367)	-0.010(0.669)
lnT	0.004**(0.020)	0.002 (0.162)	
D_{be}	0.014 ***(0.004)		
D_{ca}	0.012 ***(0.009)		
D_{es}		-0.020***(0.000)	0.024**(0.037)
D_{fi}	0.010***(0.044)	-0.007*(0.095)	0.023**(0.042)
D_{fr}	0.013***(0.005)		
D_{it}	-0.033***(0.000)		
D_{jp}	0.006(0.200)		
D_{nz}	0.013***(0.005)		0.047 ***(0.000
D_{nl}			0.007 (0.518)
D_{uk}	0.012**(0.012)		
D_{us}(cons)	-0.017***(0.000)	-0.007*(0.095)	-0.023***(0.000)
R^2	0.477	0.010	0.603
T	22	22	22
N	15	15	15
σ	0.400***	0.400***	0.400***
δ_K^0	0.044*		
δ_L^0		0.045*	
δ_E^0			-0.042*
δ_K	0.016***		
δ_L		-0.018	
δ_E			0.400

P-value in brackets
* Significant at 10%
** Significant at 5%
*** Significant at 1%

Average δ_i^0 have been computed as the value of the constant plus the significant dummies and the temporal trend, when significant.

Table 8: Factor augmenting technical change and substitution elasticity

	Exogenous	R&D	R&D(EDU)	MACH	IMP.
a_K	0.024	0.008	0.009	0.002	0.024
a_L	0.022	0.013	0.014	0.003	0.022
a_E	0.048	0.017	0.017	0.005	0.056
σ	0.39	0.361	0.358	0.38	0.378

Table 9: Descriptive statistics of the major variables

Variable	Obs	Mean	Std. Dev.	Min	Max
P_K	360	0.889	0.187	0.161	1.334
P_L	360	0.883	0.121	0.346	1.177
P_E	360	0.974	0.191	0.528	1.587
θ_L	360	0.530	0.046	0.405	0.631
θ_K	360	0.416	0.047	0.322	0.548
θ_E	360	0.054	0.025	0.014	0.155
p_K	345	0.018	0.055	-0.154	0.444
p_L	345	0.014	0.022	-0.079	0.132
p_E	345	0.010	0.081	-0.321	0.331
tfp	345	0.016	0.026	-0.045	0.228
$\widetilde{\theta_L}$	345	-0.001	0.020	-0.083	0.131
$\widetilde{\theta_K}$	345	0.004	0.026	-0.112	0.129
$\widetilde{\theta_E}$	345	-0.011	0.087	-0.323	0.347
$tfp - p_E$	345	0.006	0.081	-0.281	0.341
$tfp - p_K$	345	-0.002	0.034	-0.216	0.124
$tfp - p_L$	345	0.002	0.025	-0.066	0.144

Table 10: Data summary: first and last value for major variables

			P_K	P_L	P_E	S_L	S_K	S_E	tfp
1	Austria	1978	0.473	0.783	0.997	0.613	0.340	0.047	
	Austria	2002	1.019	0.995	0.948	0.547	0.423	0.029	-0.001
2	Belgium	1978	0.991	0.742	0.900	0.550	0.375	0.075	
	Belgium	2002	0.972	1.077	0.950	0.542	0.404	0.055	0.001
3	Canada	1978	0.971	0.855	1.016	0.547	0.350	0.104	
	Canada	2001	0.980	1.018	1.049	0.536	0.389	0.075	0.015
4	Denmark	1978	0.903	0.701	0.677	0.593	0.379	0.028	
	Denmark	2002	0.954	1.033	0.977	0.597	0.382	0.021	-0.009
5	Finland	1978	0.836	0.672	1.038	0.542	0.365	0.093	
	Finland	2002	0.971	1.044	1.034	0.503	0.406	0.091	0.024
6	France	1978	1.009	0.760	0.787	0.572	0.385	0.042	
	France	2002	0.996	1.034	0.926	0.554	0.418	0.028	0.010
7	Germany	1978	0.686	0.905	1.098	0.548	0.367	0.085	
	Germany	2002	1.019	1.016	1.059	0.555	0.408	0.038	0.018
8	Italy	1978	0.161	0.847	0.655	0.506	0.464	0.031	
	Italy	2002	0.968	0.986	1.049	0.428	0.540	0.032	0.005
9	Japan	1978	1.256	0.733	1.089	0.425	0.507	0.068	
	Japan	2002	0.946	1.016	1.005	0.521	0.439	0.040	0.007
10	Luxembourg	1978	0.374	0.629	0.640	0.451	0.395	0.155	
	Luxembourg	2002	0.916	1.043	0.936	0.531	0.431	0.038	0.045
11	Netherlands	1978	0.606	0.982	0.598	0.583	0.367	0.050	
	Netherlands	2002	1.035	1.066	0.976	0.545	0.412	0.043	0.008
12	New Zealand	1978	0.899	1.154	0.916	0.518	0.443	0.039	
	New Zealand	2000	1.000	1.000	1.000	0.405	0.522	0.0736	0.043
13	Spain	1978	0.594	0.346	0.669	0.516	0.453	0.031	
	Spain	2002	1.090	1.085	0.981	0.518	0.446	0.036	0.055
14	United Kingdom	1978	1.009	0.662	1.190	0.576	0.358	0.066	
	United Kingdom	2002	1.040	1.088	0.963	0.591	0.385	0.024	0.060
15	United States	1978	0.618	0.744	0.982	0.538	0.387	0.075	
	United States	2002	1.028	1.022	0.944	0.561	0.404	0.036	0.009

Table 11: Trend of the ratio of price growth rates: $p_i = \frac{\dot{p_i}}{p_i}$

	$p_K - p_L$	$p_E - p_K$	$p_E - p_L$
AT	+	+	-
BE	-	-	-
CA	-	-	-
DE	+	-	-
DK	-	+	+
ES	-	-	-
FI	-	-	-
FR	-	+	-
IT	+	-	+
JP	-	+	-
LU	+	-	+
NL	+	+	+
NZ	+	-	+
UK	-	-	-
USA	+	-	-