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The impact of R&D on factor-augmenting technical change – an empirical assessment at the sector level

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Abstract.

The understanding of the drivers of technological progress and their impact on food security is still limited. The paper contributes to the lacking empirical evidence on the speed of technical change affecting various sectors and production factors differently, which leads to contradicting projections of food demand in the global ex-ante assessment models. The aim of the paper is to quantify endogenous factor-augmenting technical change driven by R&D investments in a panel of 13 OECD countries over 1987-2006.

A CES framework with cost minimization behavior was chosen to derive the system of equations that were estimated by GMM system estimator. Statistically significant effects of domestic and foreign manufacturing R&D were found on labor-augmenting technical change in manufacturing, agriculture, transport and retail sector. The results of this study provide a starting point for incorporating endogenous factor-biased technical change in impact assessment models aimed at policy analysis of food security.

Keywords: factor-biased technical change, R&D, CES function, production sectors, GMM regression.

JEL codes: C3, O3, Q16

1. Introduction

Food security is one of the largest challenges facing mankind in the next half century (as acknowledged for instance by UNDP, 2012 and UNEP, 2012). Since the price shocks of 2007 and 2008, agricultural markets have experienced larger price fluctuations than ever before, illustrating the fragility of the world food supply system. Moreover, the projections of population growth warn that by 2050 the agricultural sector will have to feed 9 billion people, which requires doubling the current levels of food production. However, satisfying expected increases in food demand by a proportional increase in food supply will be limited due to the constrained availability of additional agricultural land. To overcome these challenges, technical progress is required that will drive agricultural productivity and therefore will make an important contribution to future improvements of global food security.

Yet, the understanding of the drivers of the technological progress and their impact on food security is still limited. It may be argued that there is convincing empirical evidence that cumulative domestic R&D and knowledge stocks are important determinants of agricultural (see Alston et al., 2000 for a meta-analysis). However, all the mentioned studies aim at quantifying the *neutral technical change*, assuming that all factors benefit equally from the innovation efforts. Nevertheless, some production factors benefit from technical change more than others: technical change is *factor-biased*, as shown by Acemoglu (2002) and Acemoglu and Aghion et al. (2012). Factor-biased technical change might result from induced innovation that directs technical change towards a scarcer production factor (for instance in Japan, specific crop varieties were developed that increased the productivity of land, as explained in Hayami and Ruttan, 1970). Acemoglu (2002) shows that factor-biased technical change can be also directed to the more abundant production factor if the elasticity of substitution between production factors is larger than one.

This significant progress in the theoretical understanding of the direction of technical change has not been sufficiently reflected in empirical studies. For instance Carraro and De Cian (2013), highlight a "*total absence of empirical studies on the drivers of factor productivities*" leading to weak empirical foundation of key technology parameters. This is confirmed by Robinson (2013) who argues that "in most global CGE models total factor productivity (representing a measure of neutral technical change) is calibrated residually with rather ad hoc assumptions on future productivity change and furthermore homogenously across different countries and sectors". By neglecting the endogeneity of technical change, crucial dynamics in the factor markets are not accounted for which leads to contradicting projections in the global impact assessment models[1].

Similar conclusion was derived by Von Lampe et al. (2013) who point out that the *"black box of macro and sectoral technical change*", referring to the lacking empirical evidence on the speed of technical change affecting various sectors and production factors differently, leads to contradicting projections of food prices and demand in the key global ex-ante assessment models. As a result, their ability to guide policy makers in defining long-term food security strategies is weakened.

To elaborate this notion in greater detail, it is well known that food security is a multi-dimensional problem with food availability and accessibility being the key dimensions. How much will be produced (food availability) and at what prices (food accessibility) depends largely on advances in productivity, i.e. on technical change. However, the usual treatment of technical change purely as a Solow residual to predict future production and prices is insufficient. First, technical change does not come as *manna-from-heaven*, but it is provoked by various technology drivers, such as the R&D investments. Second, technical change might be directed to production factors differently, as for instance advances in agricultural machinery are usually labor-saving, whereas advances in fertilizers are land-saving. The factor-bias in technical change consequently affects production factor markets and price transmission mechanism. Third, technical change affects various industries differently and these industries benefit from large spillover effects. In this respect, the productivity growth of agriculture might be well driven by technological advances in other industries outside of agriculture. Ignoring these spillover effects would underestimate the evolution of productivity in agriculture and would cause a bias in food security predictions. To summarize, we need to understand better how R&D and other technology drivers affect technical change and how technical change varies across production factors and across all sectors in the economy.

This paper aims at contributing to the lack of empirical evidence on the understanding of endogenous technical change related to R&D investments[2]. On a macro-level, there has been a "*revival of the CES production function*" with corresponding advances in estimation techniques aiming to quantify simultaneously the elasticity of substitution and factor-bias, however, without an explicit link to technology drivers such as R&D or human capital. On the sector-level, the number

[1] In an experiment performed by Robison et al. (2013), under higher labor-saving technical change in agriculture compared to manufacturing and services, agricultural prices are rising, whereas under a uniformly distributed labour augmenting technical change, projected prices are stable.

[2] The paper contributes to Marie Curie Project METCAFOS which aims at investigating the links between drivers of technical change and sectoral growth that will be integrated into a global CGE model MAGNET with the purpose of improving projections of food security.

of studies that quantify biased technical change is even more limited and with a predominant focus on manufacturing industries. The contribution of this study is that it estimates the endogenous factor-biased technical change in a panel data framework including all sectors of the economy. The timeliness of this research is supported by the availability of high quality data provided by the KLEMS project where capital and labor are expressed as services flows and corrected for differences in labor and capital quality, and the availability of R&D datasets for major OECD countries[3].

The main objective of the paper is to quantify the relationship between R&D stocks and parameters representing technology in the CES function for eight aggregated sectors of the economy.

Partial goals were defined as:

- To quantify the endogenous elasticity of substitution between capital and labor and to assess whether technical change on a sector level has been neutral or factor-biased.
- To analyze whether selected categories of R&D stocks are significant in explaining factor-augmenting technical change related to capital and labor, i.e. to prove the endogeneity of technical change.
- To compare the speed of factor-augmenting technical change across different industries.

2. Review of approaches to estimate factor-biased technical change in CES framework

In the macro literature, researchers have long time favored the assumption of a Cobb-Douglas functional form for the aggregate production function with unitary elasticities of substitution and Hicks-neutral representation of technology (based on seminal work of Berndt, 1976, cit. in Antras, 2004). However, Antras (2004) showed that restricting the analysis to Hicks-neutral technological change biases results towards the Cobb-Douglas production function and argued, that a Cobb-Douglas specification of the U.S. aggregate production function may be misleading. This has spurred a revival of aggregate CES production function research in the macro-economic literature and the stimulated discussion on how to reliably estimate the substitution elasticity and factor-biased technology parameters together and overcome the identification problem. A similar conclusion was derived in a recent study by León-Ledesma (2013) who showed analytically that, imposing Hicks-neutrality leads to biases towards Cobb–Douglas when the true nature of technical progress is factor-augmenting. The authors followed-up on Klump et al. (2007) who made a significant contribution to empirical research on CES functions by estimating a normalized

[3] KLEMS project is funded by the European Commission and aims to create a database on measures of economic growth, productivity, employment creation, capital formation and technological change at the industry level for all European Union member states from 1970 onwards: www.euklems.net.

production function in a supply-side system of the US economy from 1953 to 1998. The authors compared the evolution of factor-augmenting technical change and found an asymmetrical pattern where the growth of labor-augmenting technical progress is almost exponential, while capital-augmenting technical progress is hyperbolic or logarithmic.

Dong et al. (2013) contributed to the discussion about factor-biased technical change and the appropriateness of Cobb-Douglas in a study on China and argued that factor-biased production functions are more suitable that neutral. The authors found that in most of the periods of 1970-2010, technical change derived from CES function was biased towards capital, at the rate of 3.6%. Only in selected periods, technical change was labor-augmenting, which is related to institutional measures that motivated workers for higher productivity.

The approach of Antras for the United States was followed by Young (2013), who estimated factor biased technical change both on aggregate and sector level in the US economy from the first-order conditions associated with a CES production function. Using data on 35 industries from 1960 to 2005, he found that technical change in the aggregate appears to be net labor-augmenting and on the industry level, certain sectors might be net capital-augmenting.

Another evidence of a factor biased technical change on industry level is provided by Van der Werf (2008) who addresses the issue of missing empirical foundation of substitution elasticities in climate policy models. Using industry-level data from 12 OECD countries, the author found evidence for factor-specific technological change and concludes that some climate policy models may find a bigger effect of endogenous technological change on mitigating the costs of climate policy.

The approach of Van der Werf was used recently in Dissou et al. (2012), who focused on ten Canadian manufacturing industries for the period 1962-1997 and estimated seemingly unrelated regressions for each industry. However, their results on biased technical change were not conclusive.

Juselius (2008) provided a novel approach to test for Cobb-Douglas or CES specification using quarterly data on Finish manufacturing with a time series approach. Juselius argued that in studies with short periods, prices might not be equal to marginal products due to market imperfections such as labor regulations. To prevent biased estimates, he derived elasticity parameter from long-term negative relationship between wages and capital-labor share.

Another innovative approach of modeling technical change is presented in Jorgenson (2010). He proposed a more flexible alternative to the exponential function that is commonly used to quantify factor-biased technical change (he points out that the constant time trends might rule out the fact that technical change may be capital-using at one point of time and capital-saving at another). Jorgenson quantified the factor-biased technology parameter from a latent variable that was isolated from using a Kalman filter, in a system of equations derived from a translog specification of production function. The novel econometric approach was applied to 35 sectors of the US economy in 1960 – 2005.

All the above mentioned approaches consider factor-biased technical change exogenously determined by alternative trend functions. However, factor biased technical change as well as elasticity of substitution might be endogenous, i.e. they might be influenced by technology drivers such as R&D investments, education or imports of technologies. Whereas multiple empirical evidence that links R&D to TFP exists in the literature, so far only one available study attempts to link R&D to factor – biased technical change, which is the study of Carraro and de Cian (2013) who estimate factor augmenting technical change considering three endogenous drivers for manufacturing industry in 13 OECD countries. This paper follows the approach of Carraro and de Cian, but it concentrates on R&D stocks that are distinguished in various types. Moreover, the estimates are carried out using a KLEMS dataset with longer time horizon and they include all major sectors of the economy.

3. Data and Methodology

3.1 Description of the dataset

The dataset used in this study contains observations for the period 1987 – 2006 for the following 13 OECD countries: Austria, Belgium, Canada, Denmark, Spain, Finland, France, Germany, Great Britain, Ireland, Italy, Japan, the Netherlands and USA.

Data characterizing the production process for each industry was obtained from the KLEMS database (2011), ISIC Revision 3, March 2011 update. This study focuses on a broad set of production sectors that span the whole economy, at the cost of higher aggregation. The choice of aggregation is in line with the availability of the R&D datasets. Ideally, the availability of business R&D expenditures would be corresponding to sector-level economic data, but such detail of R&D expenditures is often not available. The classification of aggregated production sectors used in the analysis is provided in Table 1.

In order to obtain a homogenous dataset, all nominal values were first expressed in constant prices of 2005 and consequently converted to US dollars using sector-specific purchasing power parities (PPPs) (Inklaar and Timmer, 2014). The use of sector-specific PPPs is strongly recommended in an analyses of international productivity at the sector level. Aggregate GDP PPPs and currency exchange rates are not appropriate as conversion factors because of differences in relative prices between tradable and non-tradable sectors will introduce a bias (Sørensen, 2001; Sørensen and Schjerning, 2008).

3.2. Construction of R&D stocks

The study focuses on R&D stocks as the major technological driver that can be linked to sector-level technical change (other important drivers such as education and human capital are not considered). The R&D stocks are further classified into four R&D categories:

R&D stocks in agriculture: It is assumed the R&D stocks in agriculture have direct productivity effects, i.e. they drive technical change in agriculture. Examples are inventions in seeds varieties developed during the Green revolution, or GMO technologies of respective agricultural crops, that are hardly adopted in other industries.

R&D stocks in manufacturing: They represent the most substantial part of R&D investments. As described in Roeger et al. (2008), manufacturing R&D is mostly patented and supplies a large amount of innovative goods that are used in other industries. In relation to new technologies supplied by the manufacturing sector, organizational changes occur that stimulate productivity of services (as occurred for instance in retail, wholesale and banking due to ICT investments in the USA). Therefore, it is assumed that R&D stocks in manufacturing affect not only productivity of manufacturing itself (intra-industry effects), but also productivity of other domestic industries (inter-industry effects) and foreign sectors (foreign inter-industry spillovers).

R&D stocks in services: A study by the European Commission (2008) points out that R&D in services is still a relatively unknown area. However, the importance is not negligible as around 80 % of science and technology jobs are located in services sectors. For instance, services sector with a high content of knowledge are financial, insurance and retail sectors, where typical R&D activities include insurance and financial mathematics or IT systems development. Business and legal services, wholesale and retail on the other hand invest in R&D oriented towards socio-economic and customer research. Transportation services, such as airlines also carry out R&D, which is designed towards logistics simulation and system management. Based on this evidence, R&D in services is considered as a specific R&D category in the paper.

Total Business R&D stocks: Total Business R&D stocks are included as a separate category for two reasons. First, they capture the aggregated effect of R&D spending of private businesses and they can be understood as a technological frontier of the respective country, built from private funds. Second, they provide a representative value of R&D for sectors with inadequate availability of R&D data such as mining or construction. It is assumed that total R&D stocks affect productivity both of domestic and foreign industries.

Total Public R&D stocks: Total public R&D stocks are considered as the last R&D category. They are represented by total governmental budget appropriations and their positive effect on productivity captures the public goods nature of R&D. Foreign spillover effects are considered as well as in case of private R&D stocks.

Data on business R&D expenditures (total and manufacturing) were obtained from the OECD ANBERD Database (2014a). Values are provided in constant prices of 2005 expressed in PPP dollars. Data for Belgium, Spain and Ireland were adjusted due to the occurrence of structural breaks or missing observations. Regarding public R&D expenditures, given that GERD datasets by sector and field of sciences (OECD 2014b) are incomplete, the indicator of Governmental Budget Appropriations for R&D was used as a proxy for total public R&D expenditures and agricultural R&D expenditures (OECD 2014c). Multiple structural breaks were removed by approximating the growth rate from the past. As for Italy, values between 2002 – 2005 were calculated taking growth rates of GERD from the OECD database.

Values of R&D expenditures were used to calculate R&D stock categories (equation 1) using the Perpetual Inventory Method (PIM) (originally proposed by Griliches, 1979), where *RD_stock* represents accumulated R&D expenditures (*RD_exp*) corrected for depreciation (*dep*). The depreciation rate was set at 0.05 following common practice in the literature.

$$RD\_stock_t = (1 - dep).RD\_stock_{t-1} \quad + RD\_exp_t \tag{1}$$

The initial value of R&D stock was calculated from the steady-state condition taking into account the compound growth rate of R&D expenditures (RD_{gr}) calculated over 1987 – 2007:

$$RD\_stock_{t0} = \frac{RD\_exp_{t0}}{(RD_{gr}+dep)} \tag{2}$$

Calculation of manufacturing R&D spillovers

It is assumed that manufacturing R&D has inter-industry effects. However, each industry absorbs different types of R&D. For instance, agricultural productivity might be stimulated mostly from R&D in machinery and chemical industry, whereas productivity in services might be boosted by R&D in ICT technologies. In order to capture this difference, R&D manufacturing stocks were adjusted using shares of intermediate consumption of individual manufacturing subsectors in the aggregated 7 sectors of the economy (Table 2), following the approach of Keller (2002) and other scholars:

$$manRD\_stock_{i,r,t} = \frac{IC_{i,j,r,t}}{\sum_j IC_{i,j,r,t}} . manRD\_stock_{j,r,t} \quad , \qquad (3)$$

where *manRD_stock* represents inter-sectoral manufacturing R&D stocks in reporting country *r*, aggregated sector *i* and time *t*, *IC* represents flow of intermediate consumption of aggregated sector *i* from manufacturing subsector *j*.

Intermediate consumption figures were obtained from the STAN input-output database (OECD 2014d). The values are reported in million USD for three periods. The observations of R&D manufacturing in 1986-1999 were adjusted using input-out structure of mid1999s, the observations of 2000-2003 were adjusted using structure of beginning 2000s and the remaining observations 2004-2007 were adjusted using data of the period mid-2000s. Since each production sector has a different structure of intermediate consumption, the R&D manufacturing stock series differ per sector.

Calculation of foreign R&D spillovers

There are various ways to measure foreign R&D spillovers. Typically it is assumed that R&D is embedded in trade flows and the transaction matrices composing of input-output and bilateral import shares are used to calculate foreign spillovers. This approach was first adopted by Coe and Helpman (1995) and modified later by Lichtenberg and van Pottelsberghe de la Potterie (1998). Consequently, Keller (1998) showed that the simple sum of the foreign R&D stock performs better than the import-weighted sum used in Coe and Helpman.

As already pointed out by Van Meijl (1995), not all technological innovations lead to user-producer relationships and thus the real magnitude of pure knowledge spillovers might be underestimated when using the transaction flow matrices. Thus, various scholars proposed alternative approaches to measure R&D spillovers rather than trade channels such as technology proximity based on patents, FDI or geographic proximity (for instance Verspagen, 1997, Cincera, 2005 or Krammer, 2010). Nevertheless, significant evidence of trade-embodied R&D spillovers on productivity cannot be denied. For instance Keller (2002) concludes that the input-output specification performs better than the technology flow matrix adopted from Evenson (1994). In line with this finding, Scherer (2003) suggests that the R&D spillover measured by patent matrices can be replaced by a combination of intermediate goods and capital flows matrices (cited in Cerulli and Potti, 2009). Krammer (2010) finds that imports remain the main channel of diffusion for developing and developed countries, while FDI, although statistically significant, has a lower impact on productivity of the recipients.

Recently, Ang and Mandsen (2013) consider six channels of international knowledge transmission and conclude that knowledge spillovers through imports are the most significant variables for TFP growth in the Asian miracle economies. Based on the strong evidence in favor of trade-embodied knowledge spillovers, R&D spillovers are calculated using trade flows in this paper. Moreover, in sectors with low level of internal R&D, such as mining or construction, knowledge spills over mostly via inputs that embody R&D.

Two alternatives to calculate knowledge spillover are considered: the Coe and Helpmans approach using bilateral import shares (CH approach) and the approach using Lichtenberg Potterie's ratio of imports to value added (LP approach). Using the CH approach, own-sector foreign knowledge stocks of reporting country *r* in time *t (fRD_stock_CH)* are calculated as a weighted sum of R&D stocks of partner countries *p*. The import shares m_{rpt} are calculated from bilateral imports designed for intermediate use, as reported in the STAN Database (OECD 2014e).

$$\boldsymbol{fRD\_stock\_CH_{r,t} = \sum_p m_{r,p,t} \,.\, RD\_stock_{p,t}} \tag{4}$$

Alternatively, own-sector foreign knowledge stocks are calculated using the LP approach *(fRD_stock_CLP)* where weights are calculated as share of imports ($M_{r,p,t}$) in value added of the partner country ($VA_{r,p,t}$), obtained from the STAN Structural Database (OECD 2014f).

$$\boldsymbol{fRD\_stock\_LP_{r,t} = \sum_p \frac{M_{r,p,t}}{VA_{r,p,t}} . RD\_stock_{p,t}} \tag{5}$$

The own-sector foreign knowledge stocks are consequently used to calculate inter-sectoral foreign manufacturing knowledge spillovers using the input-output structure as described in equation 3.

3.3. Theoretical framework and derivation of the econometric model

Among the state-of-the-art modeling techniques that estimate CES function there are at least four different approaches: (i) estimation of first order conditions (FOC) derived either from profit maximization or cost minimization; (ii) a joint estimation of FOC together with the CES function; (iii) a Kmenta linearization (1967), and (iv) a non-linear estimation of the original functional form. Whereas the Kmenta linearization method only considers neutral technical change parameters, nonlinear estimations of the direct CES often do not converge (Leon-Ledesma, 2010). Therefore, the most common approach to estimate CES function jointly with factor-biased technical change is the estimation of the system of FOCs, which is also adopted in this paper.

A cost minimization framework with a CES production technology and constant returns to scale is chosen here to derive the first order conditions for capital and labor. This is in line with the producers' behavior embedded in CGE models, which ensures the consistency of the empirical estimates with their consequent incorporation into the CGE model.

The functional form of CES with factor-specific technology parameters (for simplicity, sub-indices for sector *i*, country *r* and year *t* were omitted) is written as:

$$Y \ = \left[\alpha_K.(A_K.K)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.(A_L.L)^{\left(\frac{\sigma-1}{\sigma}\right)}\right]^{\left(\frac{\sigma}{\sigma-1}\right)} \tag{6}$$

Where *Y*, *K*, and *L* represent production, capital and labor, respectively. Furthermore, α_K and α_L are distribution parameters corresponding to factors share, σ represents a sector-specific elasticity of substitution and A_K and A_L represent sector-specific factor-augmenting technology parameters.

Under the assumption of cost minimization, the first order condition for capital and labor can be expressed as (for detailed derivation, see Appendix):

$$ln\frac{K}{Y} = \sigma.ln\alpha_K + (\delta-1).lnA_K + \sigma.ln\frac{PY}{PK} \tag{7}$$

$$ln\frac{L}{Y} = \sigma.ln\alpha_L + (\delta-1).lnA_K + \sigma.ln\frac{PY}{PL} \tag{8}$$

where P_Y is the output price, P_K the input price of capital and P_L the input price of labor, respectively. Following Carraro and de Cian (2013), it is assumed that the factor-biased technical change parameter A_K can be linked to various categories of R&D investments, which represents the endogenous part of technical change. As not all technical change can be explained by R&D stocks (other drivers that are not captured in this paper might be relevant, such as human capital) the remaining part of technical change is exogenous and represented by a time vector. Equation 9 describes the relation of factor-augmenting technical change to R&D stocks :

$$A_K = A_{K0}.e^{\delta_t.t}.\prod_1^j RD_j{}^{\delta_j} \tag{9}$$

where RD_j is the respective *j*-th category of R&D stocks, *t* stands for a time vector and parameters δ_j indicate the elasticity of factor-augmenting technical change with respect to R&D stock category.

Expressing equation (9) in growth rates shows that growth of factor biased technical change consists of an autonomous part (exogenous) and an endogenous part, which is dependent on R&D (where R&D stocks are represented in growth rates rd_j).

$$a_k = \ \delta_t + \sum_1^j \delta_j rd_j \qquad \text{(analogically for labor } a_L\text{)} \tag{10}$$

Substituting a_K from equation (10) into the demand equation for capital (7) expressed in growth rates yields:

$$(k-y) = (\sigma-1).\delta_t + \ (\sigma-1).\delta_j.rd_j + \sigma.(p_y\text{-}p_k) \qquad \text{(analogically for labor demand)} \tag{11}$$

In order to reflect the panel character of the data, country dummies were added to the equation to account for the heterogeneity. The final specification of the system of equation that is estimated separately for each production sector is:

$$FOC_{Capital}: \ (k-y) = \sum_1^{13}(\sigma-1).\delta_{Ki}.D_i + (\sigma-1).\delta_{Kj}.rd_j + \sigma.(p_y\text{-}p_k) \tag{12}$$

$$FOC_{Labor}: \ (l-y) = \sum_1^{13}(\sigma-1).\delta_{Li}.D_i + (\sigma-1).\delta_{Lj}.rd_j + \sigma.(p_y\text{-}p_l) \tag{13}$$

Where (k-y) is calculated as *D.ln(K) - D.ln(Y)* and represents difference of growth rates of capital services and real value added, expressed in 2005 international PPP dollars, *(l-y)* is calculated as *D.ln(L) - D.ln(Y)* and represents the difference of growth rates of labor services and real value added, expressed in 2005 international PPP dollars. Analogically, price indices of value added, labor and capital were used to calculate the differences of growth rates of variables *(py-pk)* and *(py–pL)*. Price of capital was calculated by dividing nominal capital compensations by capital services, analogically for labor. rd_j represents growth rates of j^th R&D stock categories *D.ln(RD_stock)*. Finally, country dummies D_i represent 13 individual country intercepts.

Regarding the parameters in the system (12) and (13), σ indicates the elasticity of substitution between capital and labor, parameters δ_{Ki} and δ_{Li} represent country specific exogenous rate of capital and labor augmenting technical change and parameters δ_{Kj} and δ_{Lj} indicate the elasticity of capital (labor) augmenting technical change with respect to selected R&D category. The total rate of capital (labor) augmenting technical change can be calculated by substituting the mean rate of exogenous technical change δ_K (δ_L) and the elasticities δ_{Kj} (δ_{Lj}) to equation (10). The Cobb-Douglas technology can be verified by testing if the elasticity of substitution is equal to one. Rejecting the null hypothesis confirms the correctness of the CES technology specification.

In case of a neutral technical change, parameters δ_{Ki} in the capital demand equation are equal to δ_{Li} in the labor demand equation. The presence of a neutral technical change can be tested by a Wald test :

H_0: δ_{Ki} (FOC_Capital) = δ_{Li} (FOC_Labor)

3.4 Econometric approach

There are several econometric methods that could be used to estimate the system of equations (12) and (13), such as the method of Seemingly Unrelated Regressions (SUR) that takes into account the fact that the residuals in both FOC are correlated and enables to impose the constraint of equal substitution elasticities in each equation, or a non-linear version of SUR (NLSUR) that enables to estimate a direct structural form of the equations instead of a reduced form that is obtained by SUR.

In this paper, the Generalized Method of Moments (GMM) system estimator was applied as it provides the advantages of NLSUR and it also enables to deal with a potential endogeneity problem that might be present due to high aggregation of the dataset. The procedure for dealing with endogeneity in the paper was the following: at first, a default version of the model was estimated using two-step GMM with heteroscedasticity-autocorrelation consistent standard errors (Newey and West algorithm). Consequently, a modified version of the model with lagged ratio of prices by one and two periods (l1.log(py/pk) and l2.log(py/pl)) was applied as instruments for the py_pk and py_pl variables (in most cases, the Breusch-Godfrey test rejected the presence of autocorrelation in the model). The endogeneity problem was tested by comparing the overidentifying restriction test statistics (Hansen's J Chi^2) of this model with the test statistics of a model with instrumental variables including the potential endogenous variables py_pk and py_pl. Provided that there is an endogeneity problem, the overidentifying restrictions test in the model with included endogenous variable will strongly reject H_0. In this case, the default GMM estimates might not be consistent and instead, parameters obtained from GMM with instrumented prices are reported.

4. Results

4.1. Descriptive statistics - growth of output, input, prices and R&D stocks in OECD countries

Positive values of growth rates of *k_y* and *l_y* variables reported in Table 3 indicate increasing intensity of input uses in the production process in the last two decades. It is observed that capital deepening occurred in most sectors, with largest rates recorded in mining and construction. Contrary to capital, most of the sectors reported a declining use of labor in value added, with the largest negative growth occurring in agriculture and the public utilities sector. Only in the construction sector, growth of labor input was moderately positive, which can be complementary to higher capital intensification. It can be noted that in case of agriculture and public utilities, both capital and labor input shares declined which can be a sign of a neutral technical progress.

Observing the evolution of prices, it is found that in most sectors, the ratio of output and input prices declined, suggesting a decline of producer margins. Regarding capital prices, only in financial services, the price of output grew quicker than that of capital. In the remaining sectors, relative prices of capital increased. Besides, capital prices exhibit very high variation, especially in the construction, agriculture and retail. This is associated with volatility of capital compensations that were even negative in specific years. As for labor, growth rates of output to labor prices were negative for all sectors except for construction, suggesting that relative prices of labor increased over the whole period in the selected OECD countries.

The descriptive statistics of R&D stocks used in the analysis is provided in Table 4. It can be noted that business expenditures to research and development grew moderately with a rate of 1% annually in the period of 1987-2006. The most dynamic R&D category was R&D in business services, where growth rates reached almost 4%. This justifies the increased interest of policy makers in the role of R&D services in the economy, as pointed out in the European Commission Report cited above.

A closer look at the R&D stocks growth across OECD countries is shown in Figures 1-4. It is apparent that countries that contributed the most to growth of R&D stocks were Ireland, Australia, Finland, Spain, Canada and Japan. According to the Innovation Union Scoreboard (EC, 2014), Finland belongs to the innovation leaders and Ireland is leading in the economic dimension of the Scoreboard. Particularly striking is the growth of R&D in Irish services, which reached 15%. On the other hand, R&D investments in agriculture (from public sources) remained rather low and most countries reported growth less than 1%.

Growth rates of calculated foreign R&D spillovers are provided in Table 5. Whereas total domestic R&D stocks grew by 1.2%, the growth of foreign R&D spillovers was either very low as in case of the LP approach (0.08%) or even negative as in case of the CH approach (-0.23%). This shows that only a negligible proportion of domestic knowledge can potentially be spilled over abroad via imports of intermediate goods. The main reason for this is the fact that countries that are highly active in R&D are not important exporters or, large exporters are not strong innovators.

Figures 5-6 show country detail of foreign R&D spillovers calculated by the CH and LP approaches. Whereas the CH method assigns the highest weight to the R&D stock generated by the largest trading partner, the LP method assigns the highest weight to the R&D stock generated in the country that trades the highest proportion in domestic production. This leads to considerable differences in ranking of R&D spillovers (e.g. compare Germany vs. Spain).

Table 5 also reports growth rates of inter-industry manufacturing R&D spillovers for each sector. The positive values indicate that growth of domestic manufacturing R&D stocks has a higher potential in spilling abroad to other industries via imports of intermediate consumption.

4.2. Estimation of the system of equations

The results of the GMM estimates of the first order conditions of capital (FOC_K) and labor (FOC_L) for all aggregated sectors are reported in Table 6. The estimated elasticities of substitution are highly significant. The parameters range from 0.18 in the whoselale/retail sector to 0.53 in the construction sector and are statistically different from unity, confirming the appropriateness of the CES specification over a restrictive C-D specification. Concerning *agriculture*, the unconstrained estimates provided highly inconsistent substitution elasticities (σ_{FOC_K}=0.01, σ_{FOC_L}=0.15). This might be related to a measurement error in capital stock due to exclusion of land in KLEMS database, leading to biased estimates for the capital equation. Therefore, only the FOC of labor was estimated for agriculture. The disadvantage is that the results only allow to quantify the role of endogenous drivers on labor augmentation, but they cannot be used to assess whether technical change in agriculture was neutral or factor-biased. Most of the exogenous labour-augmenting technical change parameters are positive and significant. The positive values imply that the exogenous component of technical change in agriculture was labor-saving. Concerning the endogenous drivers of technical change, only domestic manufacturing R&D stocks are found to be significant in explaining labor augmentation. However, no evidence was found for the agricultural R&D to improve labor productivity, which is not in line with our expectations and it may be related to the construction of agricultural R&D stocks (distributed lagged forms would be probably more appropriate, as used by Alston et al. (2008) or Thirtle et al. (2008). Regarding the role of foreign spillovers, the results show that labour augmenting technical change in agriculture was declining due to foreign manufacturing R&D stock, which is also not in line with the prevailing evidence.

Concerning the *mining sector*, from all considered R&D stock categories, only total foreign R&D spillovers proved to significantly affect labor-augmenting technical change in mining. This confirms the assumption that sectors with lower own R&D activity benefit mostly from international spillovers transported via imported intermediate consumption. Regarding *manufacturing*, multiple exogenous augmenting technical change parameters were significant in the direction of labor saving. Concerning the endogenous drivers, both domestic manufacturing and foreign R&D manufacturing stocks significantly improved productivity of manufacturing industries. This provides a positive evidence on the role of business R&D expenditures in industrial productivity. The estimates for the public utilities sector show that manufacturing R&D investments proved significant in explaining capital augmenting technical change. On the other hand, labor-augmenting technical change in public utilities was positively stimulated by R&D in services , but it was not found to be significant. Regarding the *construction* sector, the estimates are less reliable due to data issues related to capital prices. The unconstrained estimates provided inconsistent substitution elasticities and if estimated separately by OLS, the elasticity of substitution in the capital equation was not significant. Thus, similar to agriculture, only the equation of FOC labor is reported, which produces a reliable value of the substitution elasticity. None of the R&D stock categories were proven to be significant in explaining labor-biased technical change in construction, although the total R&D stocks had at least the expected direction. Regarding the sector of *wholesale, retail and hotels*, the test of over identifying restrictions rejected H0 indicating a possible endogeneity problem in the model. Therefore, GMM with instruments of lagged price ratios was applied. The results show that most of the exogenous rates of technical change are significant in direction of labor-saving technical change but the effect of R&D investments is dubious – only foreign R&D spillovers proved significant, but in form of labor-using rather than labor-saving effect. Concerning the *transport, storage and communication* sector, the original moment conditions of GMM were also invalid according to the over-identifying restrictions test and therefore, the results are reported for GMM with instrumented prices. Similarly as in other sectors, the rates of exogenous technical change were indicated as labor-saving. Manufacturing R&D stocks were identified as important drivers of labor-saving technical change in this sector. As for the sector of *finance, insurance and real estate* it was not possible to relate labor-augmenting technical change to any of the R&D drivers. Contrary to the expectations, R&D stocks in services were not proved significant in explaining factor augmenting technical change

4.3. Explaining factor-biased technical change

The test of neutral technical change was applied to the estimates testing if the 13 country specific rates of exogenous technical change differ across the FOC equations. In mining, manufacturing, wholesale and retail and transportation sectors, the evidence of neutral technical change was rejected in most cases. However, in public utilities the evidence was mixed – in some countries, technical change exhibited neutral rates, which is in line with the descriptive statistics which showed that the share of both inputs declined along the period. For financial services, the hypothesis of neutral technical change in most cases cannot be rejected, which is probably related to the insignificant rates of factor augmenting technical change in both equations, implying that in most countries, technical change in financial services did not occur or was negligible.

Figures 7-12 report how exogenous labor augmenting technical change rates vary across the OECD countries. Regarding manufacturing, almost all countries report significant evidence of exogenous labor augmenting technical change, with the highest rate recorded in Ireland (6%), Finland (4.5%) and Japan (3.4%). Significant evidence is also found in the transport and communication sector, where rates of technical change reached up to 5% in case of Germany and Finland. High rates of labor augmenting technical change are also observed in agriculture, particularly for Germany (5%), Finland (4.5%) and Spain (3.4%). The sectors of financial services and construction are not reported because of limited evidence of labor-augmenting technical change.

For calculating the endogenous part of technical change, the elasticities of augmenting technical change are multiplied with mean growth rates of respective R&D drivers. The ranking of the elasticities is reported in Table 7. The elasticities range between 0.69% in mining to 0.02% in financial services. It is observed that the domestic manufacturing R&D stocks were the most common drivers of productivity, where 1% growth of domestic R&D stimulated labor augmenting technical change by 0.49% in agriculture and 0.40% in the transport and communication sector. In case of the public utilities and financial services sectors, manufacturing R&D positively affected the productivity of capital.

Finally, Table 8 reports the decomposition of total factor augmenting technical change on endogenous and exogenous drivers. The exogenous rates were computed as an average over the individual country rates. It is observed that the rates of endogenous technical change are considerably smaller than the exogenous rates, which is related to low dynamics of R&D expenditures in the past two decades.

5. Discussion

The estimated technology parameters can be only partially compared with other works, as there is limited evidence on endogenous technical change in the empirical literature. Regarding the substitution elasticities, the results are in line with other estimates. For instance Young (2013) finds substitution elasticities less than 0.5 for major US industries. Using industry-level data for 12 OECD countries, Van der Werf (2008) estimated σ_{KL} for 7 manufacturing sub-sectors in range of 0.2 – 0.6. Carraro and de Cian (2013) estimated the endogenous elasticity of substitution in a nested production function including energy to 0.38 for the aggregated manufacturing industry, which is almost identical to our estimate (0.34).

The estimated technology parameters showed that in most sectors, the technical change was biased towards labor with labor-saving and capital-using effects. This finding is consistent with other works, for instance Van der Werf (2008) finds rates of labor-augmenting technical change around 3% and negative rates of capital-augmenting technological change. Furthermore, it is consistent with Jorgenson (2010) who concluded that technical change for most sectors of US economy was labor-saving and capital-using, except for services where it is slightly capital-saving, which corresponds to the capital-saving effect of the R&D manufacturing spillovers on financial services found in our study.

The role of endogenous R&D drivers in explaining technical change seems to be small, as it captures only small part of the exogenous factor-biased technical change. This finding can be most directly compared with Carraro and de Cian (2013) who estimated factor augmenting technical change considering three endogenous drivers for manufacturing industries in 13 OECD countries. Carraro and de Cian find aggregated R&D stocks to be significant drivers of capital productivity, which is in contrast to our findings that show evidence of labor augmentation. They also found larger R&D effects (with an elasticity of 0.94% compared to 0.37% in our study). This can be related to the difference in the period of analysis that the authors used (1987 – 2002), the origin of their dataset and the estimation method.

6. Conclusion

The aim of the paper was to quantify endogenous factor-augmenting technical change driven by accumulated R&D investments. This is the first attempt to quantify endogenous technical change on a broader number of sectors. The study focused on a panel of 13 OECD countries over 20 years. A CES framework with cost minimization behavior was chosen to derive the system of equations that were estimated by GMM system estimator.

Several conclusions can be made from the obtained results. First, there is strong evidence that technical change in selected OECD countries has been directed towards labor in most of the sectors and the hypothesis of neutral technical change can be rejected for most sectors. However, the growth of labor augmenting technical change is offset by negative capital augmentation, thus total productivity effects are moderate in most sectors.

Second, statistically significant effects of domestic and foreign manufacturing R&D were found on labor-augmenting technical change in manufacturing, agriculture, transport and the retail sector. This confirms the initial hypothesis that productivity on a sector level is driven by technology drivers from outside, as for instance in agriculture, labor augmenting technical change was partially explained by R&D spillovers from manufacturing. Concerning the foreign R&D spillovers, their positive effect on factor-augmenting technical change is proved mostly in case of manufacturing R&D, which had higher potential of transfer via technology imports than the total R&D stock.

Third, contrary to expectations, it was found that the effect of R&D drivers on factor-augmenting technical change seems rather small as major part of technical change still remains unexplained. One of the reasons may be the omission of other possible technology drivers such as human capital. However, it may be also related to quality of R&D data. For instance concerning agriculture, data for public agricultural R&D expenditures in OECD countries is not available in consistent and sufficiently long time series. This applies also to the category of total public R&D expenditures, which are not adequately recorded neither in Eurostat nor in OECD databases.

Despite of these challenges, the outcomes of the study can be used to enhance the specification of technical change in global CGE models that are frequently used to assess important global issues, such as climate change, food security and land use change. They provide a starting point for incorporating endogenous factor-biased technical change in these models. With the estimated elasticities, it is possible to model the relationship between investments in R&D and factor-augmenting technical change. For example, with these additions, CGE model MAGNET (LEI Wageningen UR, 2014) can be extended to simulate the impact of public agricultural R&D on food security. Such an analysis will be particularly interesting for developing countries, where the returns from R&D are expected to particularly high (Alston, 2000). Besides, the extensions can be used in other Magnet policy applications such as the impacts of CAP policies, climate change or biofuel directive (Kavallari et al., 2014).

Tables and Figures

Table 1: Mapping of KLEMS production sectors into the aggregation used in the analysis

KLEMS	KLEMS sector description	Abbreviation	Aggregated sector description
AtB	Agriculture, Hunting, forestry and fishing	agr	Agriculture, Hunting, Forestry and Fishing
C	Mining and quarrying	min	Mining and Quarrying
D	Total manufacturing	man	Manufacturing
E	Electricity, gas and water supply	pu	Public Utilities (Electricity, Gas, and Water)
F	Construction	con	Construction
G	Wholesale and retail trade	wrt	Wholesale and Retail Trade, Hotels and Restaurants
H	Hotels and restaurants		
I	Transport storage and communication	tsc	Transport storage and communication
J	Financial intermediation	fire	Finance, Insurance, Real Estate and Business Services
K	Real estate, renting and business activities		

Note: governmental and community services were excluded due to lack of data on for this sector.

Table 2: Manufacturing sub-sectors *j* used in calculating manufacturing R&D spillovers

Total manufacturing sector
C15T16: Food products, beverages and tobacco
C17T19: Textiles, textile products, leather and footwear
C20T22: Wood, paper, printing, publishing
C23T25: Chemical, rubber, plastics and fuel products
C26: Other non-metallic mineral products
C27: Basic metals
C28: Fabricated metal products, except machinery and equipment
C29T35: Machinery and equipment, instruments and transport equipment
C36T37: Manufacturing n.e.c. and recycling

Table 4: Descriptive statistics of domestic R&D stocks growth rates

Variable	Mean	Std. Dev.	Min	Max
dlog_RDagri	0.5%	1.9%	-6%	12%
dlog_RDman	0.8%	2.0%	-2%	13%
dlog_RDserv	3.9%	7.3%	-15%	67%
dlog_RDtot	1.2%	2.3%	-1%	15%
dlog_RDpub	0.7%	1.9%	-2%	15%

Source: : Authors' calculations

Table 3: Descriptive statistics of output, inputs and price growth for 13 OECD countries (1987-2006)

	Variable	Obs	Mean	Std. Dev.
Agriculture	k_y	242	-1.0%	7.3%
	l_y	242	-3.2%	7.0%
	py_pk	204	-0.8%	30.0%
	py_pl	242	-3.4%	8.8%
Mining	k_y	242	2.4%	12.6%
	l_y	242	-2.2%	12.5%
	py_pk	229	0.9%	21.1%
	py_pl	242	-0.2%	15.1%
Manufacturing	k_y	242	0.6%	3.9%
	l_y	242	-2.9%	3.2%
	py_pk	242	0.0%	9.1%
	py_pl	242	-2.5%	3.1%
Public utilities	k_y	242	-0.6%	6.7%
	l_y	242	-3.4%	7.7%
	py_pk	242	-1.4%	12.8%
	py_pl	242	-2.3%	7.6%
Construction	k_y	242	3.0%	5.3%
	l_y	242	0.1%	3.5%
	py_pk	221	-1.5%	58.4%
	py_pl	242	0.3%	4.0%
Wholesale, retail, hotels	k_y	242	1.6%	4.0%
	l_y	242	-1.8%	3.6%
	py_pk	242	-0.1%	13.3%
	py_pl	242	-1.3%	3.6%
Transport, storage, communication	k_y	242	0.4%	4.0%
	l_y	242	-3.1%	3.7%
	py_pk	242	-0.8%	8.9%
	py_pl	242	-2.4%	3.6%
Finance, insurance, real estate and business	k_y	242	1.0%	2.9%
	l_y	242	-0.2%	2.9%
	py_pk	242	1.0%	4.6%
	py_pl	242	-0.4%	3.6%

Table 5: Growth of Foreign R&D stocks

Variable	Mean	Std. Dev.
Total Business Foreign Spillovers		
Foreign R&D_stock_CH	-0.23%	4%
Foreign R&D_stock_LP	0.08%	8%
Manufacturing foreign R&D spillovers (CH)		
agriculture	0.3%	18%
mining	0.9%	19%
Public utilities	1.4%	33%
construction	0.1%	18%
Wholesale, retail	-0.3%	14%
Transport	0.8%	14%
Finance, real estate	0.8%	19%

Table 7: Overview of elasticities of factor augmenting technical change w.r.t. R&D drivers

Sector	Equations	Elasticity of A_K/A_L to R&D stock (%)	Endogenous driver
Mining	FOC_L	0.69	RD total spillovers
Agriculture	FOC_L	0.49	RD man
Transport	FOC_L	0.4	RD man
Manufacturing	FOC_L	0.37	RD man
Public utilities	FOC_K	0.32	RD man
Manufacturing	FOC_L	0.23	RD man spillovers
Manufacturing	FOC_K	0.09	RD man spillovers
Financial Services	FOC_K	0.02	RD man spillovers

Source: authors calculation

Table 8: Quantification of factor-augmenting technical change

Sector	Equations	Exo factor-augmenting TC (%)	Endo factor-augmenting TC (%)	Total factor-augmenting TC (%)	Total factor-augmentation
Agriculture	FOC_L	2.8%	0.5%	3.3%	NA
	FOC_K	-6.2%	0.0%	-6.2%	
Mining	FOC_L	3.5%	-0.2%	3.3%	-2.9%
	FOC_C	-1.1%	0.1%	-1.0%	
Manufacturing	FOC_L	2.5%	0.6%	3.1%	2.2%
	FOC_K	0.3%	-0.4%	-0.2%	
Public utilities	FOC_L	3.6%	0.0%	3.6%	3.5%
Construction	FOC_L	-0.2%	0.0%	-0.2%	NA
	FOC_K	-2.1%	0.0%	-2.1%	
Wholesale, retail, hotels	FOC_L	1.8%	0.0%	1.7%	-0.3%
	FOC_K	-1.2%	0.0%	-1.2%	
Transport, storage	FOC_L	3.5%	-0.2%	3.2%	2.0%
	FOC_K	-1.1%	0.02%	-1.08%	
Financial services	FOC_L	0.2%	0.0%	0.2%	-0.9%

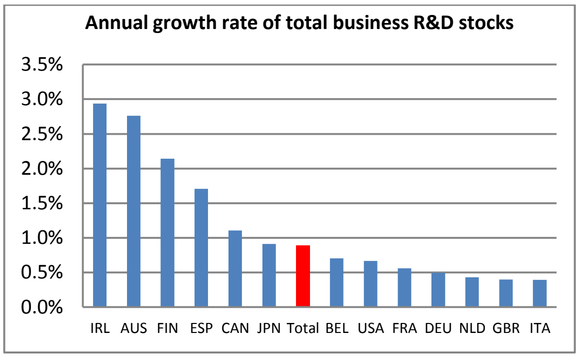
Source: authors calculation

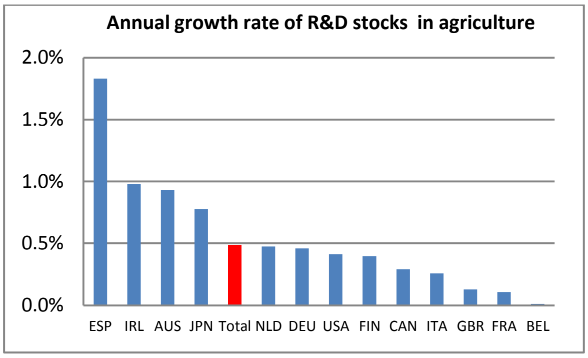
Table 6: Two-step GMM Estimates of the system of equations (with Newey-West HAC errors)

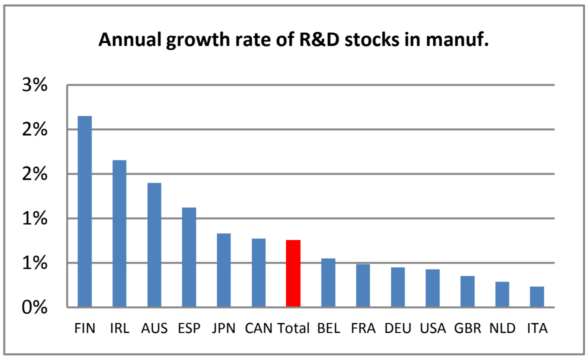
	Agr	Min	Man	Pu	Con	Wtr	Tsc	Fire
FOC Capital - dependent variable = k_y								
deltak1 - AUS		-0.014 (0.01)	-0.029 (0.00***)	-0.019 (0.01***)		-0.014 (0.01**)	-0.003 (0.009)	-0.004 (0.003)
deltak2 - BEL		-0.1 (0.03***)	-0.033 (0.01***)	0.016 (0.00***)		-0.047 (0.01***)	-0.018 (0.01**)	0.006 (0.004)
deltak3 - CAN		-0.025 (0.01**)	0.001 (0.006)	0.004 (0.005)		-0.019 (0.01***)	-0.009 (0.01*)	-0.06 (0.00***)
deltak4 - DEU		0.011 (0.027)	-0.014 (0.00***)	0 (0.006)		-0.033 (0.00***)	-0.01 (0.006)	-0.011 (0.00***)
deltak5 - ESP		-0.043 (0.01***)	-0.013 (0.00***)	0.02 (0.01***)		-0.043 (0.00***)	-0.033 (0.01***)	-0.002 (0.005)
deltak6 - FIN		-0.011 (0.021)	0.01 (0.01)	-0.004 (0.005)		-0.003 (0.013)	0.003 (0.01)	-0.012 (0.001*)
deltak7 - FRA		-0.033 (0.01***)	0.001 (0.004)	0.038 (0.01***)		-0.018 (0.00***)	0.018 (0.00***)	-0.003 (0.002)
deltak8 - GBR		-0.024 (0.01***)	-0.002 (0.007)	-0.016 (0.00***)		-0.023 (0.00***)	-0.03 (0.00***)	-0.035 (0.02**)
deltak9 - IRL		-0.088 (0.03***)	-0.01 (0.009)	0.016 (0.018)		-0.025 (0.01**)	-0.003 (0.019)	-0.005 (0.005)
deltak10 - ITA		-0.028 (0.01***)	-0.023 (0.00***)	-0.032 (0.01***)		-0.036 (0.01***)	-0.036 (0.02*)	0 (0.003)
deltak11 - JPN		-0.025 (0.01***)	-0.022 (0.00***)	0.007 (0.006)		-0.005 (0.003)	-0.02 (0.01***)	-0.012 (0.00***)
deltak12 - NLD		-0.008 (0.008)	-0.001 (0.002)	-0.004 (0.01)		0.003 (0.003)	-0.001 (0.01)	-0.002 (0.003)
deltak13 - USA		-0.026 (0.016)	-0.009 (0.004)	0.008 (0.006)		-0.006 (0.01***)	-0.018 (0.01***)	-0.003 (0.004)
delta_RDagri								
delta_RDman			0.029 (0.105)	0.32 (0.09***)			-0.138 (0.213)	
delta_RDserv				-0.186 (0.07***)				0.022 (0.026)
delta_RDtot							-0.3 (-0.46)	
delta_fRDtot_CH		-0.269 (0.306)						
delta_fRDtot_LP						0.067 (0.05)		
delta_fRD_man_CH								0.022 (0.01*)
delta_fRD_man_LP			0.087 (0.03**)					
sigma		0.4 (0.04***)	0.337 (0.03***)	0.49 (0.02***)		0.183 (0.04***)	0.344 (0.12***)	0.426 (0.10***)
FOC Labor - dependent variable = l_y								
deltal1 - AUS	0.032 (0.01***)	0.03 (0.01***)	0.013 (0.00***)	0.045 (0.033)	0.004 (0.01)	0.023 (0.00***)	0.039 (0.01**)	-0.007 (0.006)
deltal2 - BEL	0.008 (0.015)	0.086 (0.02***)	0.02 (0.00***)	0.02 (0.01***)	0.023 (0.01***)	0 (0.0026796)	0.026 (0.01**)	0.001 (0.004)
deltal3 - CAN	0.034 (0.01***)	0.002 (0.01)	0.016 (0.00***)	-0.021 (0.01***)	0.003 (0.008)	0.021 (0.01***)	0.018 (0.00***)	0.001 (0.003)
deltal4 - DEU	0.05 (0.01***)	0.049 (0.01***)	0.026 (0.00***)	0.035 (0.02**)	-0.01 (0.00**)	0.019 (0.00***)	0.055 (0.00***)	-0.001 (0.006)
deltal5 - ESP	0.034 (0.01***)	0.041 (0.01***)	-0.012 (0.00***)	0.032 (0.02*)	-0.01 (0.006)	0 (0.004)	0.017 (0.00***)	0.005 (0.006)
deltal6 - FIN	0.045 (0.01***)	0.034 (0.02***)	0.046 (0.00***)	0.0747 (0.01***)	0.01 (0.005)	0.018 (0.01**)	0.055 (0.01***)	0.003 (0.009)
deltal7 - FRA	0.039 (0.01***)	0.023 (0.023)	0.023 (0.00***)	0.024 (0.01*)	-0.001 (0.003)	0.01 (0.00***)	0.035 (0.00***)	-0.001 (0.003)
deltal8 - GBR	0.021 (0.01***)	0.074 (0.02***)	0.025 (0.00***)	0.062 (0.01***)	0.01 (0.008)	0.016 (0.00***)	0.042 (0.00***)	0.0165 (0.01***)
deltal9 - IRL	0.012 (0.009)	-0.008 (0.015)	0.063 (0.00***)	0.041 (0.037)	-0.01 (0.007)	0.03 (0.01***)	0.021 (0.013)	0.01 (0.014)
deltal10 - ITA	0.033 (0.01***)	0.023 (0.02)	0.011 (0.007)	0.062 (0.01***)	-0.01 (0.006)	0.007 (0.006)	0.041 (0.01***)	-0.008 (0.00**)
deltal11 - JPN	0.025 (0.01***)	0.038 (0.02**)	0.034 (0.00***)	0.027 (0.01**)	-0.019 (0.01**)	0.032 (0.01***)	0.027 (0.01***)	0.008 (0.005)
deltal12 - LND	0.017 (0.013)	0.018 (0.024)	0.025 (0.00***)	0.043 (0.027107)	-0.01 (0.00***)	0.022 (0.00***)	0.036 (0.01***)	-0.005 (0.00***)
deltal13 - USA	0.011 (0.008)	0.039 (0.01***)	0.034 (0.00***)	0.031 (0.01***)	-0.014 (0.00***)	0.028 (0.00***)	0.037 (0.01***)	-0.002 (0.004)
delta_RDagri	-0.34 (0.289)							
delta_RDman	0.491 (0.24**)		0.368 (0.08***)	-0.463 (0.366)			0.396 (0.17**)	
delta_RDserv				0.343 (0.347)				
delta_RDtot					0.236 (0.17)		-0.577 (0.29**)	
delta_fRDtot_CH		0.692 (0.33**)						
delta_fRDtot_LP						-0.124 (0.04***)		
delta_fRD_man_CH	-0.069 (0.03**)							
delta_fRD_man_LP			0.226 (0.04***)					
sigma	0.263 (0.03***)	0.4 (0.04***)	0.337 (0.03***)	0.489 (0.02***)	0.525 (0.05***)	0.183 (0.04***)	0.344 (0.12***)	0.426 (0.1***)
Test of neutral TC	Does not apply	Cannot reject H0 for D3, D4, D12	Cannot reject H0 for D5	Reject H0 for D1,D3,D6,D8,D10,D12	Does not apply	Reject H0 in all cases	Cannot reject H0 for D9	Reject H0 for D3, D4, D8
Test of C-D	reject H0	reject H0	reject H0	reject H0	reject H0	reject H0	reject H0	reject H0
Test of overid restr./Hausman for agri and con	H0 (Hausman), weak instruments	cannot reject H0	cannot reject H0	cannot reject H0	Cannot reject H0 (Hausman)	reject H0 - GMM instruments	reject H0 - GMM instruments	cannot reject H0

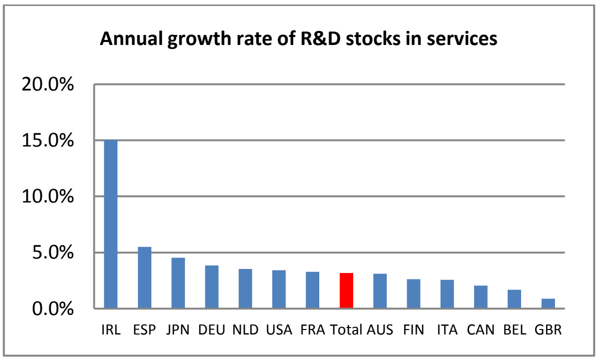
Note: for sector abbreviations see Table 1, fRtot_CH and fRDtot_LP are total foreign R&D spillovers, fRD_man_CH and fRD_man_LP are foreign manufacturing R&D spillovers absorbed in other industries. Coefficient sigma indicates elasticity of substitution. Standard errors are in the brackets, ***/**/* indicate significance the parameter at 0.01/0.05/0.1 level.

Figures 1-4: Annual growth rates of Business R&D stocks in selected OECD countries (1987-2006)



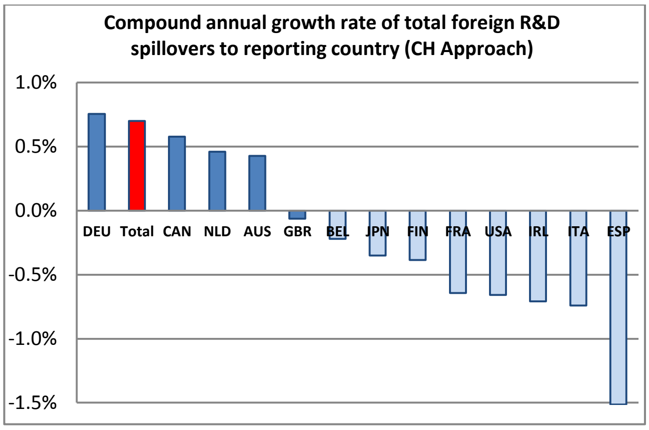


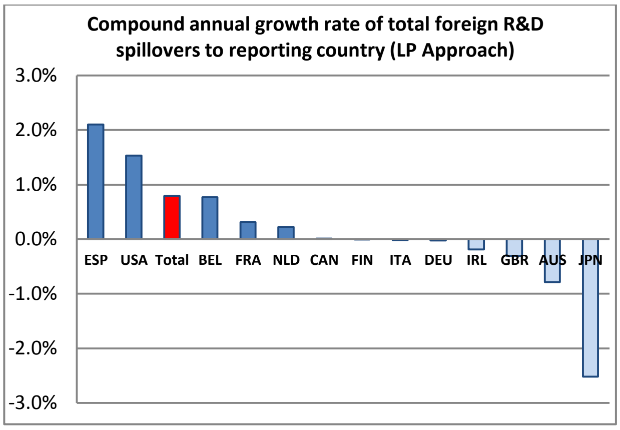




Note: In case of agriculture, R&D stocks are calculated from governmental budget appropriations.

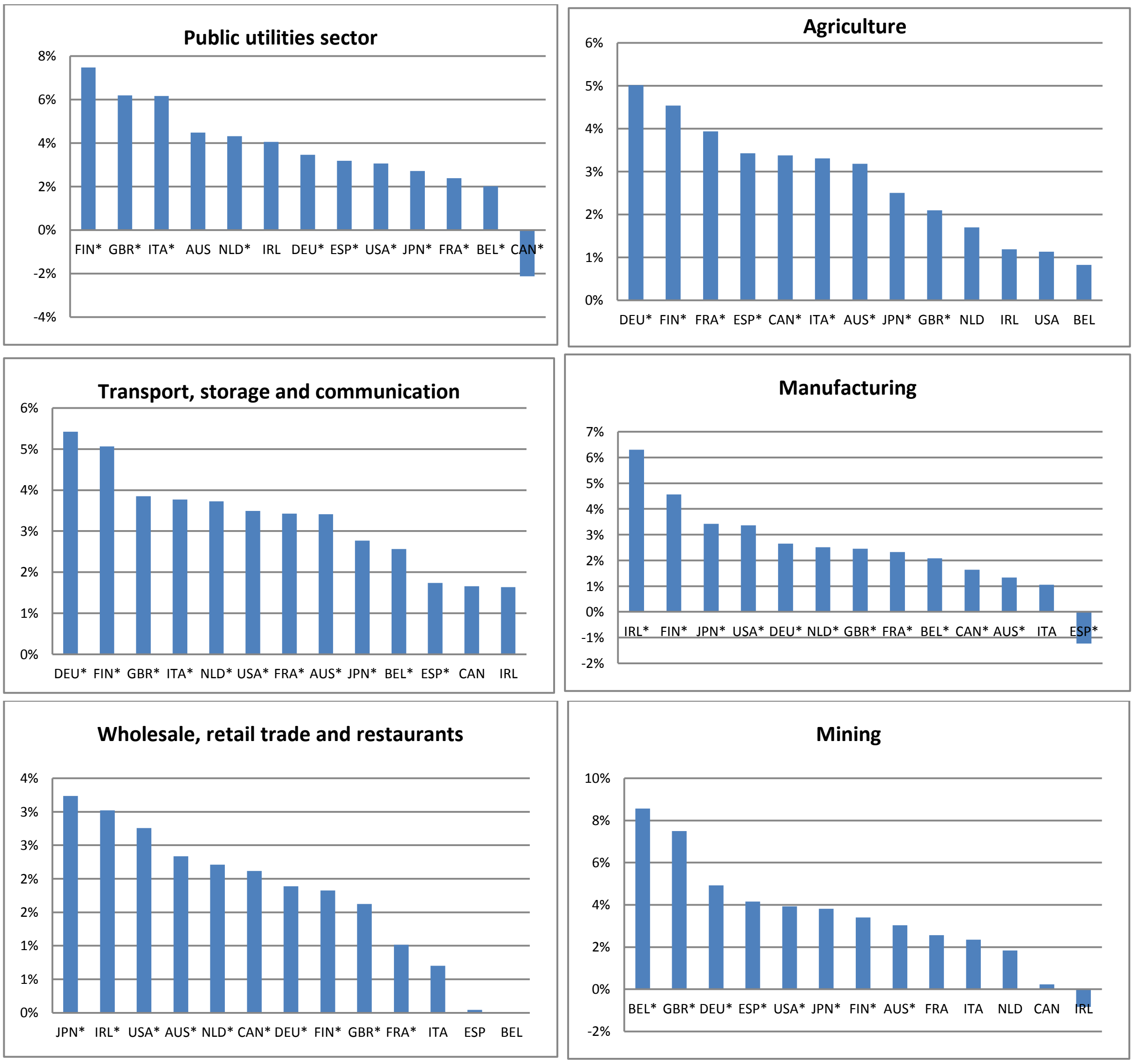
Figures 5-6: Annual growth rates of R&D stocks in selected OECD countries (1987-2006)





Source: authors calculation

Figures 7-12: Exogenous rates of labor augmenting technical change across OECD countries



Note: Countries with * have significant parameters of exogenous labor augmenting technical change.

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Appendix: Derivation of the demand conditions of capital and labor

Under constant returns to scale and perfect competition, producers minimize costs subject to CES production technology. The constrained optimization problem is written as:

$$minTC = P_k.K + P_L.L \quad \textit{subject to:} \qquad Y = \left[\alpha_K.(A_k.K)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.(A_L.L)^{\left(\frac{\sigma-1}{\sigma}\right)}\right]^{\left(\frac{\sigma}{\sigma-1}\right)}$$

The corresponding Lagrangian function writes as:

$$L(K,L,\lambda) = P_k.K + P_L.L - \lambda.\left\{\left[\alpha_K.(A_k.K)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.(A_L.L)^{\left(\frac{\sigma-1}{\sigma}\right)}\right]^{\left(\frac{\sigma}{\sigma-1}\right)} - Y\right\} \qquad (1)$$

Applying the first order derivations with respect to K,L and λ and equalizing to zero yields the following tangency condition, which equalizes ratio of input prices to marginal products:

$$\frac{P_k}{P_L} = \frac{M_k}{M_L} = \frac{\alpha_k.A_k.K^{\frac{-1}{\sigma}}}{\alpha_L.A_L.L^{\frac{-1}{\sigma}}} \qquad (2)$$

Solving for K and L from equation 2 yields:

$$L = \left(\frac{\alpha_L.P_K}{\alpha_K.P_L}\right)^{\sigma}.\left(\frac{A_L}{A_k}\right)^{\sigma-1}.K \qquad K = \left(\frac{\alpha_K.P_L}{\alpha_L.P_K}\right)^{\sigma}.\left(\frac{A_K}{A_L}\right)^{\sigma-1}.L \qquad (3,4)$$

Substituting L into the CES function and collecting terms yields:

$$Y^{\frac{\sigma-1}{\sigma}} = K^{\frac{\sigma-1}{\sigma}}.\left(\frac{P_K}{\alpha_K}\right)^{\sigma-1}.\left(\alpha_K.P_K{}^{1-\sigma}.A_K{}^{\frac{\sigma-1}{\sigma}} + \alpha_L.P_L{}^{1-\sigma}.A_L{}^{\frac{\sigma-1}{\sigma}}.\left(\frac{A_L{}^{\sigma-1}}{A_K{}^{\sigma-1}}\right)^{\left(\frac{\sigma-1}{\sigma}\right)}\right) \qquad (5)$$

Solving for K from equation 5 yields:

$$K = Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.\left(\alpha_K.P_K{}^{1-\sigma}.A_K{}^{\frac{\sigma-1}{\sigma}} + \alpha_L.P_L{}^{1-\sigma}.A_L{}^{\frac{\sigma-1}{\sigma}}.\left(\frac{A_L{}^{\sigma-1}}{A_K{}^{\sigma-1}}\right)^{\left(\frac{\sigma-1}{\sigma}\right)}\right)^{\left(\frac{-\sigma}{\sigma-1}\right)} \qquad (6)$$

$$L = Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.\left(\alpha_K.P_K{}^{1-\sigma}.A_K{}^{\frac{\sigma-1}{\sigma}}.\left(\frac{A_K{}^{\sigma-1}}{A_L{}^{\sigma-1}}\right)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.P_L{}^{1-\sigma}.A_L{}^{\frac{\sigma-1}{\sigma}}.\right)^{\left(\frac{-\sigma}{\sigma-1}\right)} \qquad (7)$$

Substituting K and L from equations 6 and 7 into total costs function yields:

$$TC = P_k.Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.\left(\alpha_K.P_K{}^{1-\sigma}.A_K{}^{\frac{\sigma-1}{\sigma}}.\left(\frac{A_K{}^{\sigma-1}}{A_L{}^{\sigma-1}}\right)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.P_L{}^{1-\sigma}.A_L{}^{\frac{\sigma-1}{\sigma}}.\right)^{\left(\frac{-\sigma}{\sigma-1}\right)} + P_L.Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.\left(\alpha_K.P_K{}^{1-\sigma}.A_K{}^{\frac{\sigma-1}{\sigma}}.\left(\frac{A_K{}^{\sigma-1}}{A_L{}^{\sigma-1}}\right)^{\left(\frac{\sigma-1}{\sigma}\right)} + \alpha_L.P_L{}^{1-\sigma}.A_L{}^{\frac{\sigma-1}{\sigma}}.\right)^{\left(\frac{-\sigma}{\sigma-1}\right)} \qquad (8)$$

Assuming that under perfect competition, firms operate with zero profits and output price equals to unit costs. Dividing equation 8 by total output and using substitution for repeated terms yields:

$$P = \frac{TC}{Y} = a.A_K{}^{-1}.\left(\frac{A_K}{A_L}\right)^{\sigma}.\mathrm{z}^{\frac{-\sigma}{\sigma-1}} + b.A_L{}^{-1}.\mathrm{z}^{\frac{-\sigma}{\sigma-1}} \qquad (9)$$

Where $a = \alpha_K.P_K{}^{1-\sigma}$ and $b = \alpha_L.P_L{}^{1-\sigma}$ and z $=\left[a + b.\left(\frac{A_L}{A_K}\right)^{1-\sigma}\right]$ (10, 11, 12)

Collecting z term in equation 9 provides:

$$P = \mathrm{z}^{\frac{-\sigma}{\sigma-1}}.A_L{}^{-1}.\left[a.\left(\frac{A_K}{A_L}\right)^{\sigma-1} + b\right] = \mathrm{z}^{\frac{-\sigma}{\sigma-1}}.A_L{}^{-1}.\mathrm{z} \qquad (13)$$

Solving for z in equation 13 results in:

$$z = (P.A_L\ )^{1-\sigma}$$

Substituting z into demand equation for capital (6) yields:

$$K = Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.A_K{}^{-1}.\left(\frac{A_K}{A_L}\right)^{\sigma}.\mathrm{z}^{\frac{-\sigma}{\sigma-1}}. = Y.\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}.A_K{}^{-1}.\left(\frac{A_K}{A_L}\right)^{\sigma}.(P.A_L\ )^{\sigma} \qquad (14)$$

Arranging the terms in equation 14 yields:

$$\frac{K}{Y} = \left(\frac{\alpha_K.P}{P_K}\right)^{\sigma}.A_K{}^{\sigma-1} \qquad (15)$$

Finally, applying logarithm yields 16:

$$ln\frac{K}{Y} = \sigma. ln\alpha_K + (\delta - 1). lnA_k + \sigma. ln\frac{Py}{Pk} \tag{16}$$

Substituting z into demand equation for labor yields:

$$L = Y . \left(\frac{P_L}{\alpha_L}\right)^{-\sigma} . {A_L}^{-1}. \mathrm{z}^{\frac{-\sigma}{\sigma-1}}. \quad = Y . \left(\frac{P_L}{\alpha_L}\right)^{-\sigma} . {A_L}^{-1}. (P. A_L \quad)^{\sigma} \tag{17}$$

Arranging the terms in equation 17 yields:

$$\frac{L}{Y} = \left(\frac{\alpha_L.P}{P_L}\right)^{\sigma} . {A_L}^{\sigma-1} \tag{18}$$

Finally, applying logarithm yields:

$$ln\frac{L}{Y} = \sigma. ln\alpha_L + (\delta - 1). lnA_L + \sigma. ln\frac{Py}{Pk} \tag{19}$$