Economic Systems Research

ISSN: 0953-5314 (Print) 1469-5758 (Online) Journal homepage: http://www.tandfonline.com/loi/cesr20

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ECONOMIC SYSTEMS RESEARCH, 2017
https://doi.org/10.1080/09535314.2017.1316707

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

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ABSTRACT

The aim of the paper is to quantify endogenous factor-augmenting technical change driven by R&D investments in a panel of 11 OECD countries over 1987–2007. This paper contributes to the scant empirical evidence on the speed, sources and direction of technical change for various sectors and production factors. Assuming cost-minimization behavior, a CES framework is used to derive a system of equations that is estimated by a GMM system estimator. The estimated factor-augmenting technology parameters show that in most sectors, technical change was labor-augmenting and labor-saving. Statistically significant effects of manufacturing and services R&D were found on factor-augmenting technical change (with the highest R&D elasticities found in the high-tech manufacturing and transport, storage and communication sectors). Whereas 'in-house' R&D stimulates total factor productivity, R&D spilled over to other sectors has a capital-augmenting effect accompanied by a higher use of labor. The results of this study provide a starting point for incorporating endogenous factor-augmenting technical change in impact assessment models aimed at broad policy analysis including economic growth, food security or climate change.

ARTICLE HISTORY
Received 16 December 2014
In final form 5 March 2017

KEYWORDS
Factor-augmenting technical change; R&D; CES function; GMM regression

1. Introduction

There is convincing empirical evidence that cumulative domestic R&D and knowledge stocks are important determinants of productivity. Griliches (1964; 1998) has made major contributions. Since then, an extensive literature has analyzed various aspects of the links between R&D and productivity, including returns to R&D (see Hall et al., 2010 for a review), international R&D spillovers (see Keller, 2004 for a review), returns to R&D in the agricultural sector (see Alston et al., 2000 for a meta-analysis) and firm-level R&D-productivity linkages (Mairesse and Sassenou, 1991 or Cincera and Ravet, 2012). Almost all existing studies that investigate the impact of R&D on productivity quantify

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'neutral technical change', by assuming that all factors of production benefit equally from innovation.

Acemoglu (2002) and Acemoglu et al. (2012) show, however, that some production factors benefit more from technical change than do others: technical change is 'factor-augmenting' and 'factor-biased'. Factor-augmenting technical change might result from induced innovation that directs technical change towards those production factors that are scarcer. For instance, in Japan some specific crop varieties have been developed to increase the land productivity (Hayami and Ruttan, 1970). Acemoglu (2002) shows that factor-augmenting technical change can be also directed to the more abundant production factors if the elasticity of substitution between any two production factors is larger than one.

Empirical estimates of the speed and the direction of factor-augmenting technical change are key inputs for multicountry, multisector computable general equilibrium (CGE) models. Such models are increasingly being used to assess major global and highly complex issues such as food security, climate change, biodiversity and land use-change. Key examples of such assessments are the OECD Environmental Outlook (2012), AgMIP food-climate model comparison (Nelson et al., 2013), Alternative Futures (OECD, 2016) and the IPCC Assessment Reports. Future productivity growth and its principal component, technical change, are key drivers of sectoral and macro-economic growth projections that are generated by these models (von Lampe et al., 2014). Most models assume labor-augmenting or Harrod-neutral technical change, which is predicated on a long-run constant capital-output ratio (Uzawa, 1961; Jones and Scrimgeour, 2008; Robinson et al., 2014). But, at present, the empirical foundation of key technology parameters is weak, which likely results in biased projections of future economic development. Indeed, Carraro and De Cian (2013, p. 14) find a "total absence of empirical studies on the drivers of factor productivities". Robinson et al. (2014) further argues that in most global CGE models, total factor productivity (TFP) (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, the models fail to account for crucial dynamics related to the investment and diffusion of knowledge, which might lead to biased projections in the global impact assessment models.[1] When technical change is endogenized via R&D, CGE and integrated assessment models can evaluate R&D policies and their impacts on economic growth, land use and food security, which makes their findings potentially very interesting to policy-makers.

By quantifying the relationship between R&D stocks and parameters representing technology in the CES function, we confront the lack of empirical evidence on the role of R&D investments head on. In so doing, (1) we quantify the endogenous elasticity of substitution between capital and labor and, thereby, assess whether technical change on a sector level has been neutral or factor-augmenting; (2) we analyze whether selected categories of R&D stocks are statistically significant in explaining factor-augmenting technical change related to capital and labor, that is, we demonstrate the endogeneity of technical change and (3) we examine the relative speed of factor-augmenting technical change across industries.

[1] In an experiment performed by Robinson et al. (2014), under higher labor-saving technical change in agriculture compared to manufacturing and services, agricultural prices are rising, whereas under a uniformly distributed labor-augmenting technical change, projected prices are stable.

On a macro-level, the CES production function has been revived, according to Klump et al. (2007). Advances in estimation techniques simultaneously quantify the elasticity of substitution and factor-augmentation but they lack an explicit link to technology drivers such as R&D or human capital. The number of studies that quantify factor-augmenting technical change by sector is even more limited, and those that do strictly focus on manufacturing industries.

This study's contributions are threefold. For one, it is the first that estimates endogenous factor-augmenting technical change using a panel data framework that includes all sectors of the economy. Second, it uses the KLEMS project's high-quality data, in which capital and labor inputs are expressed as services flows and thereby corrected for differences in labor and capital quality.[2] Third, it reveals empirical evidence on factor-augmenting technical change that can be integrated into leading impact assessment models; this action will, in turn, improve the quality of policy simulations that rely on those models.

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

For many years macro-economic researchers favored the Cobb–Douglas function to estimate aggregate production. Its unitary elasticities of substitution and Hicks-neutral representation of technology were not perceived to pose major problems (Berndt, 1976). But then Antràs (2004) showed that Hicks-neutral technological change produced bias in the elasticity of substitution and, hence, argued that Cobb–Douglas specifications of US aggregate production were likely misleading. His work spurred a revival of aggregate CES production function research and stimulated a discussion on how to reliably and jointly estimate the substitution elasticity and factor-augmenting technology parameters to overcome the identification problem. Analytically, León-Ledesma et al. (2015) also showed that imposing Hicks-neutrality leads to biases towards Cobb–Douglas when the true nature of technical progress is factor-augmenting. This followed-up Klump et al. (2007), who had contributed to the argument in favor of CES functions by estimating a normalized production function in a supply-side system of the US economy from 1953 to 1998. They examined the evolution of factor-augmenting technical change and found its effects were asymmetric. While the growth of labor-augmenting technical progress was essentially exponential, that for capital-augmenting technical progress was hyperbolic or logarithmic.

Dong et al. (2013) argued that aggregate factor-augmenting production functions are more suitable than functions assuming neutral technical change. In a study of China from 1970 to 2010, they found that technical change derived from a CES function was biased towards capital, at an annualized rate of 3.6%. Only in selected periods was technical change labor-augmenting, which suggests that institutional measures motivated workers to attain higher levels of productivity.

Inspired by Antràs (2004), Young (2013) estimated factor-augmenting technical change both in aggregate and by sector for the US economy based on the first-order conditions (FOCs) of a CES production function. Using data on 35 two-digit industries from 1960 to

[2] The KLEMS project, funded by the European Commission, has created 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.

2005, Young found that technical change in aggregate is, in net, labor-augmenting and that only certain industries could possibly be capital-augmenting. Van der Werf (2008) found more industry-level support by addressing the issue of missing empirical foundations for substitution elasticities in climate policy models. Also using two-digit industry-level data, but for 12 OECD countries, he found evidence of factor-specific technological change and concluded that some climate policy models may obtain larger effects of endogenous technological change for policies that mitigate costs of climate change. Using the same basic approach, Dissou et al. (2012), who focused on 10 Canadian manufacturing industries for the period 1962–1997 but using seemingly unrelated regressions (SURs) approach by industry obtained inconclusive results on the bias of technical change.

Jorgenson (2010) presented an innovative approach to modeling technical change. His was a more flexible alternative to the exponential function that had been typically used to quantify factor-biased technical change. Through a system of equations derived from a translog specification of production function, Jorgenson isolated the factor-biased technology parameter from a latent variable via a Kalman filter. He applied this novel econometric approach to 35 sectors corresponding to a two-digit level of the US economy in the period from 1960 to 2005.

Fairly recently, Villacorta (2015) derived an innovative Bayesian procedure to estimate aggregate country-specific substitution elasticities and factor-augmenting parameters using the KLEMS database for 20 OECD countries. He accounted for country heterogeneity using the Bayesian approach and found substantial variability in the technology parameters amongst the OECD countries.

All the aforementioned approaches consider factor-augmenting technical change as identified exogenously by alternative trend functions or latent variables. Still, factor-augmenting technical change as well as the elasticity of substitution could be endogenous, that is, they might be influenced by technology drivers such as R&D investments, education or technology transfer.

In this regard, Doraszelski and Jaumandreu (2013) present a specific approach to estimate endogenous productivity. They do so using a Markov process linked to R&D expenditures. This approach takes random shocks into account and capturing uncertainties inherent in the R&D processes. Kancs and Siliverstovs (2016) adopt Doraszelski and Jaumandreu's approach to estimate nonlinear effects of R&D on productivity on a micro-level dataset of OECD countries. Although the approaches provide insights, neither Cobb–Douglas production technology nor the use of a latent variable is suitable for our study. This is because they cannot yield empirical support that calibrates technical change in impact assessment models – an objective of the research reported in this paper.

In light of the above, the only available study that links R&D to factor-augmenting technical change is that by Carraro and de Cian (2013), who estimate factor-augmenting technical change via three endogenous drivers for an aggregate manufacturing industry for each of 11 OECD countries. We follow their approach but concentrate on R&D stocks, which are distinguished in various types. Moreover, we estimate parameters using the KLEMS dataset that has a longer time horizon and that includes all major sectors of the economy. As pointed out in Ortega-Argilés et al. (2015), technological opportunities and appropriability conditions are different across sectors. Therefore, it is both interesting and important to compare the impact of R&D on endogenous technical change across sectors.

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

Aggregated code	KLEMSsector	Code	Description	Share VA
Agr	AtB	agr	Agriculture	2%
Min	C	min	Mining	1%
High-tech	23t25	chem	Chemical, rubber, plastics	4%
	29	mac	Machinery n.e.c.	2%
	30t33	ele	Electrical and optical equipment	3%
	34t35	tre	Transport equipment	3%
Low-tech	15t16	food	Food, beverages and tobacco	3%
	17t19	text	Textiles	1%
	21t22	pulp	Pulp, paper	2%
	27t28	met	Basic metals and fabricated metals	3%
	36t37	nec	Manufacturing n.e.c.	1%
Pu	E	pu	Public utilities (Electricity, gas, and water)	3%
Con	F	con	Construction	8%
Wrt	G	wrt	Wholesale and retail trade	15%
Hot	H	hot	Hotels and restaurants	3%
Tsc	I	tsc	Transport storage and communication	8%
Fin	J	fin	Financial services	9%
Res	K	res	Real estate, renting and business activities	29%

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

Table 2. Sectors reported in the analysis.

Sector	Description	Share value added
Res	Real estate, renting and business activities	29%
Wrt	Wholesale and Retail Trade	15%
High-tech	High-tech sectors	12%
Low-tech	Low-tech sectors	10%
Fin	Financial services	9%
Con	Construction	8%
Tsc	Transport storage and communication	8%
Total		91%

3. Data and method

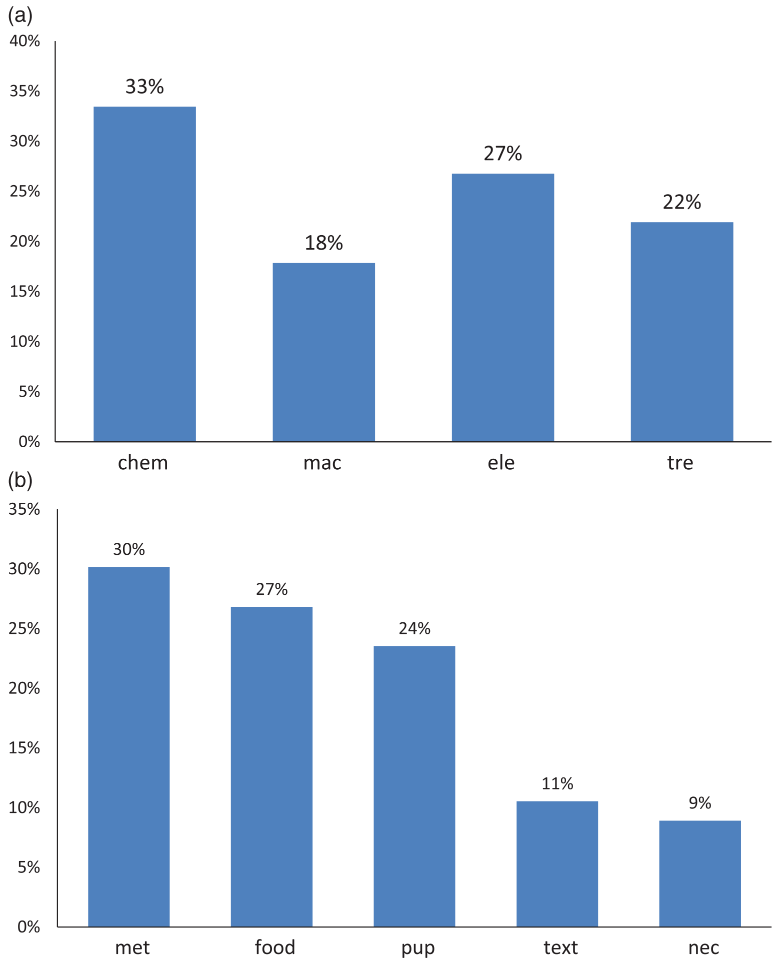
3.1. Description of the dataset

The dataset that is used in this study covers 1987–2007 for the following eleven OECD countries: Austria, Canada, Spain, Finland, France, Germany, Great Britain, Italy, Japan, the Netherlands and USA.[3] The ISIC Revision 3 March 2011 update of the KLEMS database by industry is used, and included the following variables: gross value added at current prices, gross value added price indices (1995 = 100), labor and capital compensations, volume indices of labor and capital services and number of persons employed. The price of capital was calculated by dividing nominal capital compensations by capital services obtained from the KLEMS database, analogically for the price of labor.

This study focuses on a broad set of production sectors that span the whole economy. The R&D datasets limits the level of disaggregation of the analysis. As a result, the analysis uses 19 aggregate sectors of the economy that follow the KLEMS data classification. Table 1 lists the sectors with their corresponding average share in value added. Some sectors comprise negligible shares of the economy (as in case of mining or hotels and restaurants), so Table 2 reports only the most relevant seven sectors, which comprise 91% of value added

[3] Observations for Belgium were removed from the original dataset due to lack of non-negative capital compensations provided by KLEMS. Observations for Ireland were removed due to large fluctuations of returns to capital.

Figure 1. (a) Average share of high-tech sectors in value added. (b) Average share of low-tech sectors in value added.



Source: authors' calculations based on KLEMS.

from 1987 to 2007. While agriculture is of interest to our analysis, results for that sector are not reported due to omission of land values in capital stock measurement within the KLEMS database; thus its inclusion could lead to potential estimation bias.

For the sake of the analysis, we grouped individual subsectors by their level of their technological advancement as expressed in their shares of R&D in value added. The high-tech sector consists of the sectors chemicals, machinery, electrical and optical equipment and machinery not elsewhere classified (n.e.c.). Figure 1(a) shows that all high-tech sectors are important in total value added, with significant cross-country variation. (For instance, in Italy machinery has a 30% share, whereas in the Netherlands 50% of high-tech sector production is in the chemical industry.) The low-tech sector consists of the remaining manufacturing sectors, which are pulp and paper, food industry, textiles and metals. Figure 1(b) shows that the metals and food industry comprises more than 50% of low-tech value added, followed by pulp and paper. Whereas the remaining two sectors – textiles and manufacturing n.e.c. – are of negligible importance. Again, there are notable cross-country differences. In Finland, for instance, the paper and pulp industry's share alone is almost 50%, whereas in Italy textile's share is almost 30%.

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

3.2. Construction of R&D stocks

3.2.1. R&D stock categories

The study focuses strictly on R&D stocks as the major technological driver at the sector level. (Other important drivers such as education and human capital are not considered.) R&D stocks are further classified into two categories:

- *R&D stocks in manufacturing* represent a substantial part of all R&D investments. As described in Roeger et al. (2008), manufacturing R&D is largely patented and also supplies the bulk of innovative goods 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 information and communication technology (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 enhance the productivity of other domestic industries (interindustry effects).
- *R&D stocks in services*: A study by the European Commission (2008) points out that R&D in services remains relatively invisible and unknown. But its importance is non-negligible since around 80% of science and technology jobs are in services sectors. For instance, services sectors with a high content of knowledge are financial, insurance and retail sectors, where typical R&D activities include the development of new insurance and financial metrics and IT systems development. Business and legal services, wholesale trade and retail trade, on the other hand, largely invest in socio-economic and customer research. Transportation services, such as airlines also carry out R&D, mostly in the form of logistics simulation and system management. Based on this evidence, R&D in services is accorded their own R&D category in this research.

Data on business R&D expenditures (manufacturing and services) were obtained from the OECD ANBERD Database (2014). Values are in constant 2005 prices in PPP dollars. Data for Spain were adjusted due for a structural break.[4]

[4] A structural break in Spanish data occurred in 2002 when companies started to participate more heavily in the survey. The pre-break values were corrected to the post-break levels by assuming a growth rate for 2002/2001 that was equal to that in 2001/2000 and recalculating backwards using the pre-break trend.

We calculated R&D stocks (Equation 1) from R&D expenditures using the Perpetual Inventory Method as proposed by Griliches (1979): *RD_stock* is defined current R&D expenditure (*RD_exp*) plus R&D stock from the previous period corrected for depreciation (*dep*). The depreciation rate was set at 0.15 following common practice in the literature (Kumbhakar et al., 2012). A depreciation rate of 15% corresponds to the average for the high-tech, medium and low-tech sectors and, hence, is representative for the general category of manufacturing and services R&D.

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

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 from 1987 to 2007. The compound growth rate refers to the country-level growth rate for each of the two R&D stocks categories:

$$RD\_stock_{t0} = \frac{RD\_exp_{t1}}{(RD_{gr} + dep)}. \tag{2}$$

3.2.2. Calculation of intersectoral R&D spillovers

We assumed that manufacturing and services R&D have interindustry effects but also that each industry absorbs different types of R&D. For instance, productivity in Construction might be stimulated mostly from R&D in machinery, whereas productivity in services might be boosted by R&D in ICT. To capture such differences, R&D stocks were adjusted using shares of intermediate consumption of manufacturing and services sectors in the aggregated seven sectors of the economy (Table 2), following the approach of Van Meijl (1997a; 1997b) and Keller (2002):

$$intersectoralRD\_stock_{i,r,t} = \frac{IC_{i,j,r,t}}{\sum_j IC_{i,j,r,t}} \cdot RD\_stock_{j,r,t}, \tag{3}$$

where *intersectoralRD_stock* represents intersectoral manufacturing R&D stocks in reporting country r, aggregated sector i and year t, and IC represents flow of intermediate consumption of aggregated sector i from manufacturing and services sector j.

Intermediate consumption shares were obtained from the World Input–Output Database (Timmer et al., 2015). The values are available in annual updates from 1995 on (for the period 1987–1994, shares of 1995 were used). Since each sector has a different structure of intermediate consumption, the R&D manufacturing stock series differ per sector.

3.3. Theoretical framework and derivation of the econometric model

Among the state-of-the-art modeling techniques used to estimate CES function there are at least four different approaches: (1) estimation of FOCs derived either from profit maximization or cost minimization; (2) joint estimation of FOCs together with the CES function; (3) Kmenta's (1967) linearization and (4) nonlinear estimation of the original functional form. Whereas Kmenta's linearization method only considers neutral technical change parameters, direct nonlinear estimation of the CES function often does not converge (León-Ledesma, 2010). Therefore, the most common approach to estimate a CES function jointly with factor-augmenting technical change is the system of FOCs, which we adopt here.

We selected a cost-minimization framework with CES technology and constant returns to scale here to derive the FOCs 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 a CES production function with sub-indices for country i ($i = 1 \ldots 11$), sector j ($j = 1 \ldots 7$), year t ($t = 1 \ldots 21$) and sub-indices for factor-specific parameters for capital $_K$ and labor $_L$ is written as

$$Y_{ijt} = \left[\alpha_{Kj}(A_{Kj} \cdot K_{ijt})^{((\sigma_j - 1)/\sigma_j)} + \alpha_{Lj}(A_{Lj} \cdot L_{ijt})^{((\sigma_j - 1)/\sigma_j)}\right]^{(\sigma_j/(\sigma_j - 1))}, \tag{4}$$

where Y, K, and L represent production, capital and labor, respectively. Furthermore, α_K and α_L are distribution parameters corresponding to factor shares, 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 FOCs for capital and labor can be expressed as (for detailed derivation, see Appendix):

$$\ln \frac{K_{ijt}}{Y_{ijt}} = \sigma_j \cdot \ln \alpha_{Kj} + (\sigma_j - 1) \cdot \ln A_{Kj} + \sigma_j \cdot \ln \frac{PY_{ijt}}{PK_{ijt}}, \tag{5}$$

$$\ln \frac{L_{ijt}}{Y_{ijt}} = \sigma_j \cdot \ln \alpha_{Lj} + (\sigma_j - 1) \cdot \ln A_{Lj} + \sigma_j \cdot \ln \frac{PY_{ijt}}{PL_{ijt}}, \tag{6}$$

where P_Y is the output price, P_K is the price of capital and P_L is the labor wage rate, respectively. Following Carraro and de Cian (2013), we assume that the factor-augmenting technical change parameter A_K can be linked to various categories of R&D, 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 remainder of technical change is exogenous and represented by a time vector. Equation 7 describes the relationship of capital-augmenting technical change to R&D stocks:

$$A_{Kj} = A_{K0j} \cdot e^{\delta_{Kj} \cdot t} \cdot RDm_{jit}^{\delta RD_{mKj}} \cdot RDs_{jit}^{\delta RD_{sKj}} \quad \text{(analogously for labor } A_L\text{)}, \tag{7}$$

where RD_m stands for manufacturing R&D stocks and RD_s represents R&D stocks in services, t stands for a time vector and parameters δRD_{mK} *and* δRD_{sK} indicate the elasticity of capital-augmenting technical change with respect to R&D stock category (analogously for labor).

Expressing Equation 7 in growth rates shows that the growth of factor-augmenting technical change consists of an autonomous part (exogenous) and an endogenous part, where the latter depends on R&D (where both R&D stock categories are represented in growth rates $d\log\_RDm$ and $d\log\_RDs$).

$$a_{Kj} = \delta_{Kj} + \delta RD_{mKj} \cdot d\log\_RDm_{jit} + \delta RD_{sKj} \cdot d\log\_RDs_{jit} \quad \text{(analogously for labor } a_L\text{)}. \tag{8}$$

Substituting a_K from Equation 8 into the demand equation for capital (5) expressed in growth rates yields:

$$\begin{aligned}(k_{ijt} - y_{ijt}) = {} & (\sigma_j - 1) \cdot \delta_{Kj} + (\sigma_j - 1) \cdot \delta RD_{mKj} \cdot d\log\_RDm_{jit} \\ & + (\sigma_j - 1) \cdot \delta RD_{sKj} \cdot d\log\_RDs_{jit} + \sigma_j(py_{ijt} - pk_{ijt}) \\ & \times \text{(analogously for labor demand)},\end{aligned} \tag{9}$$

where $(k_{ijt}-y_{ijt})$ is calculated as $(\ln K_{ijt}-\ln K_{ijt-1})-(\ln Y_{ijt}-\ln Y_{ijt-1})$ and represents the difference of growth rates for capital services and for real value added as expressed in 2005 international PPP dollars, $(l_{ijt}-y_{ijt})$ is calculated as $(\ln L_{ijt}-\ln L_{ijt-1})-(\ln Y_{ijt}-\ln Y_{ijt-1})$ and represents the difference in growth rates for labor services and for real value added as expressed in 2005 international PPP dollars. Analogously, price indices of value added, labor and capital were used to calculate the differences in growth rates for $(py_{ijt}-pk_{ijt})$ and $(py_{ijt} - pl_{ijt})$. Variables $d\log\_RDm_{ijt}$ and $d\log\_RDs_{ijt}$ are the growth rates of R&D stock categories calculated as $(\ln RDman_{ijt} - \ln RDman_{ijt-1})$ (analogously for services).

To reflect the panel character of the data, country dummies were added to the equation to account for country-specific heterogeneity. The final specification of the system of equations that is estimated separately for each production sector j is

$$\begin{aligned}(k_{ijt} - y_{ijt}) = {} & \sum_{1}^{11} (\sigma_j - 1) \cdot \delta_{Kij} \cdot D_{ij} + (\sigma_j - 1) \cdot \delta RD_{mKj} \cdot d\log\_RDm_{jit} \\ & + (\sigma_j - 1) \cdot \delta RD_{sKj} \cdot d\log\_RDs_{jit} + \sigma_j(py_{ijt} - pk_{ijt}),\end{aligned} \tag{10}$$

$$\begin{aligned}(l_{ijt} - y_{ijt}) = {} & \sum_{1}^{11} (\sigma_j - 1) \cdot \delta_{Lij} \cdot D_{ij} + (\sigma_j - 1) \cdot \delta RDm_{Lj} \cdot d\log\_RDm_{jit} \\ & + (\sigma_j - 1) \cdot \delta RD_{sLj} \cdot d\log\_RDs_{jit} + \sigma_j(py_{ijt} - pl_{ijt}),\end{aligned} \tag{11}$$

where the binary variables D_i represent 11 individual country intercepts ($i = 1,2,..11$).

In the Equation systems 10 and 11, the parameter σ is the elasticity of substitution between capital and labor, $\delta_K$and δ_L are parameters for the country-specific exogenous rates of capital and labor-augmenting technical change and $\delta RDm_{K(L)}$ and $\delta RDs_{K(L)}$ are parameters for the elasticity of capital- (labor-) augmenting technical change with respect to the indicated 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 $\delta RDm_{K(L)}$ and $\delta RDs_{K(L)}$ into Equation 8. Cobb–Douglas (C–D) technology can be verified by testing if the elasticity of substitution is equal to one. Rejecting the null hypothesis confirms a preference for a CES technology specification. We can test for neutral technical change by examining whether the δ_{Ki}in the capital demand equation are equal to δ_{Li} in the labor demand equation.

3.4. Econometric approach

There are several econometric methods that can be used to estimate the Equation systems 10 and 11. One is SUR, which accounts for correlated residuals in both FOCs and enables the imposition of the constraint of equal substitution elasticities across the two equations. Alternatively, a nonlinear version of SUR (NLSUR) enables to estimate a direct structural form of the equations instead of a reduced form required by use of SUR. We apply the generalized method of moments (GMM) system estimator since it has all the advantages of NLSUR and also deals with a potential endogeneity problem that might be present due to the high degree of aggregation in the dataset.

We dealt with endogeneity in the paper by first estimating a default version of the model using two-step GMM with heteroscedasticity-autocorrelation consistent standard errors (Newey and West algorithm). We then investigated the endogeneity of prices by comparing overidentifying restriction test values (Hansen's $J\chi^2$) of the basic model to those of a model estimated via instrumental variables. If an endogeneity problem exists, the overidentifying restrictions test in the standard model variable should strongly reject the H_0. In this case, the standard GMM estimates might not be consistent; if so, we report parameters obtained from the GMM with instrumented prices.

As instruments for $p_y - p_k$ and $p_y - p_L$, we lagged price ratios by both one and two periods [$\log(p_y/p_k)_{t-1}$ and $\log(p_y/p_l)_{t-2}$]. (In most cases, the Breusch–Godfrey test rejected the presence of autocorrelation in the model, a requirement for the validity of these lagged prices as instrumental variables.) We did not consider higher-order lags because then (1) the number of observations becomes prohibitively low and (2) there is no economic reason to believe that earlier prices would much inform those for more recent periods. We checked the strength of the instruments by using the F-test of the reduced-form regression; we tested the validity of instruments by performing Durbin–Wu–Hausman test.

Finally, we performed two versions of the tests for global significance of the parameters. First, we used a Wald test for a common intercept to test whether the exogenous rates of factor-augmenting technical change are statistically different across countries. Second, we performed a joint test of all parameters to evaluate their global significance.

3.5. Calculation of returns to research

Calculating returns to research is an important component of R&D-productivity studies. So we devote a section of the present to estimating R&D returns. Griliches (1979) and Hall et al. (2010) describe a common way of estimating returns to research. Such returns are usually approximated from the marginal product of R&D stock. In the case of a Cobb–Douglas production function, they are estimated directly by regressing TFP on the R&D to output ratio. Alternatively, one can derive the marginal product of research (corresponding to returns to research) from the estimated research elasticity (δ_{RD}) when multiplied by the output to R&D stock ratio:

$$\frac{\partial Y}{\partial RD} = \delta_{RD} \cdot \frac{Y}{RD}. \tag{12}$$

As we work with a CES production function, the means of estimating returns to research must be modified. Moreover, our focus is factor-augmenting technical change and not neutral technical change. Substituting the equation for factor-augmenting technical change (7) into the CES function (Equation 4) yields[5]:

$$Y = [\alpha_K (X_1)^{((\sigma-1)/\sigma)} + \alpha_L (X_2)^{((\sigma-1)/\sigma)}]^{(\sigma/(\sigma-1))}, \tag{13}$$

where $X_1 = A_{K0} \cdot e^{\delta kt} \cdot RD^{\delta RDk} \cdot K$ and $X_2 = A_{L0} \cdot e^{\delta Lt} \cdot RD^{\delta RDL} \cdot L$.

The marginal product of R&D stock is then

$$\frac{\partial Y}{\partial RD} = Z^{1/(\sigma-1)} (\alpha_K (X_1)^{(-1/\sigma)} \cdot X_1' + \alpha_L (X_2)^{(-1/\sigma)} \cdot X_2'), \tag{14}$$

where $Z = \alpha_K (X_1)^{((\sigma-1)/\sigma)} + \alpha_L (X_2)^{((\sigma-1)/\sigma)} = Y^{(\sigma-1)/\sigma}$,

$$X_1' = \frac{\partial X1}{\partial RD} = A_{K0} \cdot e^{\delta kt} \cdot \delta RD_k . RD^{\delta RD_k - 1} \cdot K \quad \text{and}$$

$$X_2' = \frac{\partial X2}{\partial RD} = A_{L0} \cdot e^{\delta Lt} \cdot \delta RD_L \cdot RD^{\delta RD_L - 1} \cdot L.$$

Substituting Equation 14 into the expression for the elasticity of output with respect to R&D stock and collecting terms Y and RD results in

$$\begin{aligned} elasRD &= \frac{\partial Y}{\partial RD} . \frac{RD}{Y} \\ &= Y^{(1-\sigma)/\sigma} (\alpha_K (A_K \cdot K)^{((\sigma-1)/\sigma)} \cdot \delta RD_k + \alpha_L (A_L \cdot L)^{((\sigma-1)/\sigma)} \cdot \delta RD_L). \end{aligned} \tag{15}$$

By solving for the marginal product of R&D from Equation 15, we get

$$\begin{aligned} \frac{\partial Y}{\partial RD} &= elasRD \cdot \frac{Y}{RD} \\ &= \frac{Y^{1/\sigma}}{RD} (\alpha_K (A_K \cdot K)^{((\sigma-1)/\sigma)} \cdot \delta RD_k + \alpha_L (A_L \cdot L)^{((\sigma-1)/\sigma)} \cdot \delta RD_L). \end{aligned} \tag{16}$$

Equation 16 shows that the marginal product of R&D stock in the CES production function is an extended case of the marginal product obtained from the Cobb–Douglas function (Equation 12). The first extension concerns the ratio of output to R&D stock where output is exponentiated to the inverse power of sigma. Clearly, in case of a Cobb–Douglas production function, in which sigma is unitary, this is reduced to a simple output-R&D ratio. Second, compared to the Cobb–Douglas case, there are factor-specific R&D elasticities (δRD_k and δRD_L) and their total effect on the marginal product is a weighted sum of both elasticities using effective capital and labor inputs as weights.

4. Results

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

Table 3 reports descriptive statistics of input and output quantities and prices, expressed as logarithmic differences. The number of observations differs per sector due to the elimination for extreme values.[6] Positive values of growth rates for $k-y$ and $l-y$ indicate

[5] For simplicity, time, sector and country indices are omitted and only one type of R&D stocks is assumed.

[6] In the construction sector, observations for Finland were removed due to large fluctuations in its returns to capital. Extreme values (variations exceeding 100%) were removed for Japan in low-tech and for Great Britain in financial services.

Table 3. Descriptive statistics of output, inputs and price growth for 11 OECD countries (1987–2007).

	Variable	Obs	Mean	Std. dev.	Min	Max
High-tech	k_y	211	0.001	0.046	−0.110	0.186
	py_pk	211	−0.005	0.133	−0.616	0.638
	l_y	211	−0.033	0.039	−0.132	0.089
	py_pl	211	−0.036	0.046	−0.160	0.120
Low-tech	k_y	209	0.012	0.034	−0.117	0.094
	py_pk	209	0.011	0.088	−0.239	0.364
	l_y	209	−0.015	0.028	−0.115	0.069
	py_pl	209	−0.014	0.036	−0.139	0.137
Construction	k_y	188	0.021	0.043	−0.117	0.192
	py_pk	188	0.024	0.176	−0.642	0.819
	l_y	188	0.005	0.032	−0.132	0.117
	py_pl	188	0.004	0.035	−0.122	0.117
Wholesale, retail, hotels	k_y	211	0.011	0.037	−0.117	0.186
	py_pk	211	−0.004	0.102	−0.392	0.495
	l_y	211	−0.021	0.030	−0.109	0.102
	py_pl	211	−0.016	0.030	−0.113	0.089
Transport, storage, communication	k_y	211	0.005	0.034	−0.078	0.121
	py_pk	211	−0.005	0.069	−0.239	0.255
	l_y	211	−0.030	0.030	−0.109	0.056
	py_pl	211	−0.024	0.030	−0.101	0.065
Financial services	k_y	208	0.018	0.064	−0.268	0.192
	py_pk	208	0.016	0.170	−0.527	0.692
	l_y	208	−0.018	0.046	−0.152	0.111
	py_pl	208	−0.014	0.077	−0.360	0.320
Real estate and business services	k_y	211	0.005	0.023	−0.077	0.097
	py_pk	211	0.007	0.039	−0.360	0.121
	l_y	211	0.008	0.030	−0.098	0.128
	py_pl	211	0.001	0.037	−0.099	0.237

increasing intensity of input use in the production process over the last two decades. Observe that capital-deepening occurred in most sectors, with the largest rates recorded in the low-tech sector, construction and financial services. Contrarily, most sectors reported a declining use of labor in value added, with the largest negative growth occurring in the high-tech sector and the transport, storage and communication sector. In construction, labor input growth was moderately positive and, in this industry, possibly complementary to capital intensification. As for capital in real estate and business services both had positive growth; this suggests that input intensification occurred, as higher capital input may require increased use of labor, but it can also be a sign of declining technical progress.

An examination of the evolution of prices suggests that the ratio of output to input prices declined for high-tech, wholesale and retail and transport, storage and communication sectors. In others – financial services and the low-tech sector, the price of output grew more quickly than did that of capital. But higher growth in wages compensated, suggesting that the relative price of labor increased over the full period in some OECD countries. In the two remaining sectors – construction and business services, the ratio of output to input prices increased, which suggests increasing producer margins. Typically for both real estate and the construction sector, output prices are tied to business cycles and, hence, tend to fluctuate somewhat radically.

The descriptive statistics for R&D stocks are shown in Table 4. Total R&D stocks in manufacturing grew moderately, at a rate of 0.5% annually, from 1987 to 2007. R&D in business

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

R&D absorbed by sector	Variable	Mean	Std. dev.	Min	Max
R&D stocks in manufacturing absorbed by the sectors					
High-tech and low-tech	*dlog_RDmtot*	0.5%	1.3%	−2.0%	8.1%
Construction	*dlog_RDm*	−1.1%	4.2%	−22.0%	15.8%
Wholesale and retail	*dlog_RDm*	−1.1%	5.0%	−40.8%	21.7%
Transport, storage and comm	*dlog_RDm*	−0.4%	6.9%	−29.1%	32.6%
Financial services	*dlog_RDm*	−2.1%	7.4%	−51.3%	35.0%
Real estate and business serv.	*dlog_RDm*	−0.9%	5.5%	−17.1%	44.1%
R&D stocks in services					
Wrt, tsc, fin and res	*dlog_RDstot*	2.9%	5.1%	−16.5%	30.2%
High-tech	dlog_*RDs*	3.4%	5.8%	−15.4%	36.9%
Low-tech	dlog_*RDs*	3.7%	5.6%	−19.2%	33.6%
Construction	dlog_*RDs*	2.7%	6.2%	−24.3%	32.9%

Notes: *dlog_RDmtot* and *dlog_RDstot* are own R&D stocks in manufacturing and services. *d*log_*RDm* and *d*log_*RDs* are obtained by premultiplication of *d*log_*RDmtot* and *d*log_*RDstot* by the share of intermediate consumption of the respective sectors. Sector abbreviations: Wrt = wholesale retail and trade, Tsc = transport, storage and communication, Fin = financial services, Res = real estate and business services.

services was more dynamic; its growth rates reached almost 3%. This justifies the increased interest of policy-makers in the role of R&D services in the economy, as pointed out by the European Commission (2008). Table 4 also contains intra-sectoral R&D spillovers, measured as R&D stocks absorbed by other sectors of the economy (pre-multiplied by the share in intermediate consumption). As for the manufacturing intra-sectoral spillovers, the average growth rates are negative due to a declining share of manufacturing in other sectors' intermediate consumption (and vice-versa for services sectors).

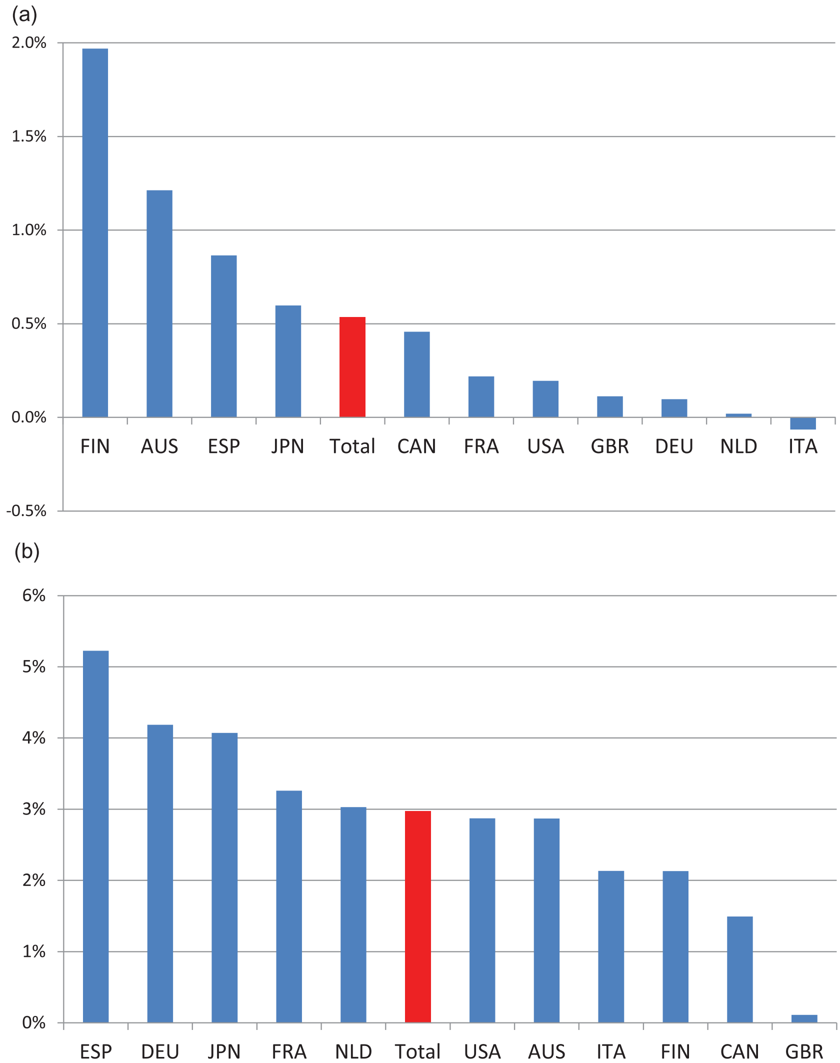
Figure 2(a) and (b) gives a more detail on the growth of R&D stocks by OECD country. It is apparent from them that Finland, Australia, Spain, Canada and Japan contributed most to growth of manufacturing R&D stocks. According to the Innovation Union Scoreboard (EC, 2014), Finland is among the innovation leaders. On the other hand, growth of R&D stocks in Italy was negative. This is likely because R&D stocks are built with a depreciation rate of 0.15. As a result, Italy's manufacturing R&D expenditures over the study period fail in net to create new knowledge (it would have taken a depreciation rate of 0.05 to enable its R&D stocks to be moderately positive). Spain, Germany, Japan and France enjoyed growth rates of R&D stocks in services that were greater than 3% annually.[7]

4.2. Estimation of the system of equations

The results of the GMM estimates of the FOCs of capital and labor following Equations 10 and 11 for the selected sectors are reported in Table 5. The estimated elasticities of substitution (σ) are all statistically significant. The parameters range from 0.13 in the construction sector to 0.42 in the real estate and business services and are statistically different from unity, which suggest a preference for a CES specification over a restricted Cobb–Douglas one. Concerning the *high-tech sector*, the overidentifying restrictions test confirms that we cannot reject the null hypothesis that the overidentifying restrictions are zero, at least given the parameters at hand. All exogenous augmenting technical change parameters

[7] The absolute maximum was recorded for Ireland (which had to be excluded from the estimations), where R&D stocks grew by 14%.

Figure 2. (a) Annual growth of R&D stocks in manufacturing. (b) Annual growth of R&D stocks in services.



are statistically significant and in a direction suggesting labor augmentation. Concerning endogenous drivers, both domestic manufacturing and services R&D stocks reveal statistical significance in explaining productivity of high-tech industries (see parameters δRDm and δRDs). The elasticities of manufacturing R&D are comparable in both demand equations, leading to supporting the hypothesis that labor and capital benefit similarly from productivity effects of business R&D expenditures. The impact of R&D for services is statistically significant but negative and the related elasticity values are substantially lower than those for manufacturing.

Although moments in the original equation were correctly specified, using wages as instruments for labor price notably improved the results of the overidentifying restrictions test in the case of *low-tech industries*. So we used this version since we can then use the fact

Table 5. Two-step GMM Estimates of the system of equations (with Newey–West HAC errors).

	High-tech		Low-tech		Con		Wrt		Tsc		Fin		Res	
	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error
FOC Capital – dependent variable = k_y														
σ	**0.242**	(0.041)***	**0.222**	(0.029)***	**0.135**	(0.061)**	**0.214**	(0.05)***	**0.402**	(0.109)***	**0.201**	(0.037)***	**0.424**	(0.08)***
δk_{AUS}	**−0.028**	(0.008)***	**−0.035**	(0.003)***	**0.006**	(0.003)*	**−0.021**	(0.007)***	0.002	(0.006)	**−0.011**	(0.006)*	−0.002	(0.005)
δk_{CAN}	**0.007**	(0.004)*	−0.001	(0.007)	**−0.018**	(0.007)***	**−0.026**	(0.006)***	−0.008	(0.006)	**−0.045**	(0.007)***	−0.001	(0.004)
δk_{DEU}	−0.003	(0.005)	**−0.023**	(0.004)***	**−0.010**	(0.004)**	**−0.027**	(0.005)***	−0.012	(0.01)	**−0.023**	(0.009)**	**−0.008**	(0.003)***
δk_{ESP}	**−0.014**	(0.004)***	**−0.014**	(0.005)***	**−0.013**	(0.006)**	**−0.033**	(0.003)***	**−0.027**	(0.005)***	−0.036	(0.028)	0.004	(0.008)
δk_{FIN}	−0.007	(0.018)	0.003	(0.012)			0.005	(0.015)	0.003	(0.008)	−0.015	(0.012)	−0.008	(0.005)
δk_{FRA}	**0.019**	(0.003)***	**−0.013**	(0.006)**	**−0.028**	(0.004)**	**−0.013**	(0.005)***	**0.018**	(0.006)***	**−0.023**	(0.004)***	0.000	(0.003)
δk_{GBR}	0.002	(0.007)	−0.005	(0.007)	**−0.033**	(0.016)*	**−0.022**	(0.004)***	**−0.025**	(0.005)***	−0.008	(0.017)	−0.023	(0.013)*
δk_{ITA}	**−0.015**	(0.004)***	**−0.017**	(0.003)***	**−0.033**	(0.003)***	**−0.035**	(0.002)***	**−0.033**	(0.017)*	−0.011	(0.011)	**0.005**	(0.003)*
δk_{JPN}	**−0.019**	(0.006)***	**−0.041**	(0.01)***	**−0.016**	(0.008)**	−0.004	(0.005)	**−0.021**	(0.007)***	**−0.017**	(0.007)**	**−0.008**	(0.004)*
δk_{NLD}	**0.032**	(0.005)***	−0.001	(0.002)	**−0.025**	(0.006)***	0.008	(0.005)	0.002	(0.006)	−0.016	(0.019)	0.003	(0.006)
δk_{USA}	−0.012	(0.01)	**−0.012**	(0.003)***	**−0.059**	(0.009)***	**−0.008**	(0.003)**	**−0.018**	(0.006)***	**−0.032**	(0.013)**	0.004	(0.004)
$\delta kRDm$	**0.531**	(0.276)**	**0.310**	(0.154)**	−0.004	(0.077)	0.011	(0.056)	**0.117**	(0.053)**	0.065	(0.058)	**0.084**	(0.03)***
$\delta kRDs$	**−0.070**	(0.024)***	−0.007	(0.049)	−0.043	(0.049)	0.035	(0.027)	−0.038	(0.056)	**0.187**	(0.098)*	**0.054**	(0.033)*
FOC Labor – dependent variable = l_y														
σ	**0.242**	(0.041)***	**0.222**	(0.029)***	**0.135**	(0.061)**	**0.214**	(0.05)***	**0.402**	(0.109)***	**0.201**	(0.037)***	**0.424**	(0.08)***
δL_{AUS}	**0.022**	(0.005)***	**0.010**	(0.004)**	0.004	(0.005)	**0.030**	(0.003)***	**0.028**	(0.011)***	**0.021**	(0.004)***	**−0.021**	(0.009)**
δL_{CAN}	**0.027**	(0.007)***	**0.013**	(0.003)***	0.005	(0.004)	**0.026**	(0.006)***	**0.016**	(0.003)***	0.008	(0.007)	−0.004	(0.005)
δL_{DEU}	**0.043**	(0.007)***	**0.017**	(0.003)***	**−0.007**	(0.003)**	**0.015**	(0.003)***	**0.062**	(0.008)***	0.005	(0.006)	**−0.020**	(0.007)***
δL_{ESP}	**0.015**	(0.004)***	−0.004	(0.004)	−0.007	(0.006)	0.005	(0.003)	**0.017**	(0.004)***	0.021	(0.018)	**−0.024**	(0.007)***
δL_{FIN}	**0.037**	(0.012)***	**0.037**	(0.005)***			**0.020**	(0.01)*	**0.052**	(0.008)***	0.020	(0.011)*	**−0.013**	(0.007)*
δL_{FRA}	**0.053**	(0.006)***	**0.006**	(0.003)*	0.001	(0.003)	**0.013**	(0.003)***	**0.037**	(0.004)***	0.003	(0.009)	−0.002	(0.003)
δL_{GBR}	**0.041**	(0.005)***	**0.015**	(0.004)***	**0.008**	(0.004)**	**0.021**	(0.002)***	**0.040**	(0.005)***	**0.022**	(0.005)***	0.002	(0.004)
δL_{ITA}	**0.015**	(0.006)**	**0.017**	(0.006)***	**−0.011**	(0.003)***	**0.010**	(0.005)**	**0.039**	(0.009)***	**0.020**	(0.006)***	**−0.030**	(0.006)***
δL_{JPN}	**0.040**	(0.006)***	**0.015**	(0.003)***	**−0.011**	(0.005)**	**0.038**	(0.009)***	**0.031**	(0.006)***	**0.025**	(0.006)***	−0.006	(0.006)
δL_{NLD}	**0.047**	(0.004)***	**0.022**	(0.002)***	**−0.009**	(0.004)**	**0.027**	(0.006)***	**0.038**	(0.006)***	**0.011**	(0.004)***	**−0.013**	(0.004)***
δL_{USA}	**0.037**	(0.009)***	**0.011**	(0.002)***	**−0.023**	(0.01)**	**0.030**	(0.004)***	**0.038**	(0.005)***	**0.015**	(0.003)***	−0.003	(0.006)
$\delta LRDm$	**0.603**	(0.202)***	**0.452**	(0.142)***	−0.100	(0.07)	**−0.087**	(0.029)***	−0.034	(0.037)	0.045	(0.044)	**−0.095**	(0.05)*
$\delta LRDs$	**−0.169**	(0.062)***	−0.030	(0.039)	−0.033	(0.032)	−0.003	(0.047)	−0.080	(0.048)*	**0.164**	(0.072)**	**−0.105**	(0.057)*

(*continued*).

Table 5. Continued.

	High-tech		Low-tech		Con		Wrt		Tsc		Fin		Res	
	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error	Coef.	st. error
Test of neutral TC	Reject H0 for all		Reject H0 for all except delta 5		Cannot reject H0 for delta 1, 4, 5, 11		Reject H0 for all		Reject H0 for all except delta 1		Reject H0 except delta 8 and delta 12		Reject H0 for delta 5, 10 and 12	
Test of C–D	$\chi^2(1) = 339.200$ ($p = .000$)		$\chi^2(1) = 700.590$ ($p = .000$)		$\chi^2(1) = 201.690$ ($p = .000$)		$\chi^2(1) = 248.650$ ($p = .000$)		$\chi^2(1) = 30.060$ ($p = .000$)		$\chi^2(1) = 464.230$ ($p = .000$)		$\chi^2(1) = 51.650$ ($p = .000$)	
Test of overid restr	Hansen's J $\chi^2(1) = 0.816$ ($p = .366$)		Hansen's J $\chi^2(1) = 0.451$ ($p = .502$)		Hansen's J $\chi^2(1) = 0.145$ ($p = .704$)		Hansen's J $\chi^2(1) = 0.324$ ($p = .570$)		Hansen's J $\chi^2(1) = 1.025$ ($p = .311$)		Hansen's J $\chi^2(1) = 0.010$ ($p = .922$)		Hansen's J $\chi^2(1) = 0.511$ ($p = .475$)	
Use of instruments for prices	py_pk, py_pl		py_pk, py_pl2		l2.log_py_pk and l2.log_py_pl		L2.log_py_pk and L2.py_pl2		L2.log_py_pk and L.log_py_pl2		py_pk, py_pl		py_pk, py_pl	
F-test of reduced equation	No endogeneity problem		py_pl: F(1, 197) = 1421 ($p = .000$)		py_pk: F(1, 162) = 9.180, ($p = .003$), py_pl: F(1, 162) = 35.380 ($p = .000$)		py_pk: F(1, 188) = 30.340, ($p = .000$), py_pl: F(1, 177) = 3.78 ($p = .054$)		py_pk: F(1, 188) = 22.690, ($p = .000$), py_pl: F(1, 199) = 8.93 ($p = .003$)		No endogeneity problem		No endogeneity problem	
Test of common intercept	FOC_K: $\chi^2(11) = 152.440$ ($p = .000$), FOC_L: $\chi^2(11) = 302.890$ ($p = .000$)		FOC_K: $\chi^2(11) = 205.390$ ($p = .000$), FOC_L: $\chi^2(11) = 224.510$ ($p = .000$)		FOC_K: $\chi^2(10) = 231.100$ ($p = .000$), FOC_L: $\chi^2(10) = 35.310$ ($p = .000$)		FOC_K: $\chi^2(11) = 352.440$ ($p = .000$), FOC_L: $\chi^2(11) = 238.390$ ($p = .000$)		FOC_K: $\chi^2(11) = 90.340$ ($p = .000$), FOC_L: $\chi^2(11) = 198.380$ ($p = .000$)		FOC_K: $\chi^2(11) = 73.960$ ($p = .000$), FOC_L: $\chi^2(11) = 83.280$ ($p = .000$)		FOC_K: $\chi^2(11) = 30.920$ ($p = .001$), FOC_L: $\chi^2(11) = 52.380$ ($p = .000$)	
Joint test of parameters' significance	FOC_K: $\chi^2(14) = 168.890$ ($p = .000$), FOC_L: $\chi^2(14) = 537.940$ ($p = .000$)		FOC_K: $\chi^2(14) = 545.530$ ($p = .000$), FOC_L: $\chi^2(14) = 556.490$ ($p = .000$)		FOC_K: $\chi^2(13) = 309.750$ ($p = .000$), FOC_L: $\chi^2(13) = 59.560$ ($p = .000$)		FOC_K: $\chi^2(14) = 471.620$ ($p = .000$), FOC_L: $\chi^2(14) = 681.60$ ($p = .000$)		FOC_K: $\chi^2(14) = 174.190$ ($p = .000$), FOC_L: $\chi^2(14) = 387.380$ ($p = .000$)		FOC_K: $\chi^2(14) = 182.780$ ($p = .000$), FOC_L: $\chi^2(14) = 260.200$ ($p = .000$)		FOC_K: $\chi^2(14) = 357.270$ ($p = .000$), FOC_L: $\chi^2(14) = 110.070$ ($p = .000$)	

Notes: Coefficient σ indicates elasticity of substitution, δL_i and δK_i are country-specific rates of exogenous factor-augmenting TC, δRDm and δRDs are elasticities of factor-agumenting TC w.r.t. R&D manufacturing and services. Standard errors are in the brackets, ***, ** and * indicate significance the parameter at .01, .05 and .1 levels.
Sector abbreviations: Con = construction, Wrt = wholesale retail and trade, Tsc = transport, storage and communication, Fin = financial services, Res = real estate and business services.

that wages correlate very strongly with the price of labor calculated from labor services. The estimation results are comparable to those for the high-tech industry, although the elasticity of substitution is slightly lower as are the exogenous rates of factor-augmenting technical change and the R&D elasticities. A 1% increase in manufacturing R&D stocks has led to a 0.45% increase in labor-augmenting TC in the low-tech industry (0.6% in case of high-tech) and 0.31% in capital-augmenting technical change. From this, we can also conclude that both factors have benefited positively from business R&D expenditures. The effect of R&D stocks for services is not statistically significant for low-tech industries.

For the *construction* sector, the overidentifying test rejected the null, suggesting a possible endogeneity problem, so *py_pl* and *py_pk* were instrumented by two-period lagged ratios of prices, $\log(py/pk)_{t-2}$ and $\log(py/pl)_{t-2}$. Despite the use of these instruments, the overidentifying restrictions were not statistically significantly different from zero, as required. In the resulting estimates, the elasticity of substitution is the lowest ($\sigma = 0.135$), perhaps due to the quality of the instruments. Furthermore, no R&D stocks were found statistically significant in explaining technical change. This could be related to the decelerating absorption of R&D stocks from manufacturing (intermediate consumption of construction sector from manufacturing declined over time). But manufacturing R&D stocks uncorrected for intermediate consumption were also not statistically significant. This could be related to the absence of any positive productivity growth in construction – both labor- and capital-augmenting technical change was negative. Indeed, this finding is in line with the descriptive statistics reported earlier; the construction sector is a sector in which capital and labor input per unit of output increased over time.

In the case of the *wholesale and retail trade* sector, the overidentifying restrictions test rejected the H_0, indicating a possible endogeneity problem in the model. Therefore, as for construction, we instrumented the GMM with lagged price ratios. Here, the elasticity of substitution was statistically significant with a value of 0.214 – comparable to other sectors. But R&D stocks in services were not statistically significant in explaining technical change in wholesale and retail. The effect of manufacturing R&D was a small and negative but statistically significant for labor-augmenting technical change. It turns out there was a 1% decline in the share of manufacturing in the intermediate consumption of wholesale and retail trade. Thus, given its negative effect, manufacturing R&D growth, in fact, had in a positive influence on labor-augmenting technical change in this sector.

For the *transport*, *storage and communication* sector overidentifying restrictions were invalid in the standard GMM estimation; so again results are reported for a GMM with instrumented prices. As for other sectors, the rates of exogenous technical change were labor-augmenting and statistically significant across all countries. Manufacturing R&D stocks were identified as important drivers of capital-augmenting technical change in this sector. Given that R&D manufacturing investments absorbed in this sector actually declined, the positive effect of R&D tell us how much of the negative capital augmentation was caused by a decline of R&D absorption. Clearly, if R&D investments had increased, capital-augmenting technical change should also have risen. Despite the positive role of R&D here, a large part of this sector's technical change remains unexplained.

For *financial services*, moment conditions were correctly specified in in the standard GMM. The elasticity of substitution is statistically significant with a value of 0.201. R&D in services proved significant in explaining both capital- and labor-augmenting technical change. Its direction and magnitude are comparable in both equations suggesting a neutral R&D effect on technical change. Estimation shows that 1% growth of R&D stocks in services yields about 0.18% growth of TFP. Although the elasticity is rather low, given that R&D stocks in services grew much more robustly than in manufacturing, the total contribution of R&D services to productivity in the financial sector was nonnegligible.

Finally, for *real estate and business services* the overidentifying restrictions were again valid and the elasticity of substitution was 0.424 – the second highest among the sectors examined. Both categories of R&D stocks had statistically significant effect on technical change in business services, but their directions differ. Clearly, R&D absorbed in real estate and business services has benefited productivity of capital rather than labor.

4.3. Decomposing and explaining factor-augmenting technical change

The test of neutral technical change was applied to see if the 11 country-specific rates of exogenous technical change differed across the FOC equations. In most countries, the high-tech, low-tech, wholesale and retail trade, transport, storage and communication, and the financial sector, the evidence of neutral technical change was rejected in favor of factor-augmenting technical change. In the construction and real estate and business services sector, the evidence was mixed due to negligible rates of productivity growth.

Table 6(a) reports how exogenous labor-augmenting technical change rates vary across OECD countries. All countries report significant evidence of exogenous labor-augmenting technical change for the high-tech sector; the highest rate was recorded for France (5.3%), the Netherlands (4.7%) and Germany (4.3%), whereas Italy and Spain lagged with rates below 2%. Labor-augmenting technical change parameters for the low-tech sector are statistically significant in all but Spain. The values range around 1% with outstanding rates for Finland (3.7%) and the Netherlands (2.2%). In construction, most of the labor-augmenting technical change was negative. For wholesale and retail trade, average rates center around 2% with the strong performances in Japan (3.8%), the USA and Australia (both 3%). In transport, storage and communication, labor-augmenting rates of technical change are the highest among all sectors; high rates were achieved by Germany (6.5%), Finland (5.4%), Great Britain (4.8%) and the Netherlands (4.5%). Rates of labor-augmenting technical change in the financial sector were more moderate (closer to 2%) and in four countries even not statistically significant. Finally, the real estate and business services sector had negative labor-augmenting technical change with lowest values recorded in Italy, Spain and Australia.

Table 6(b) reports the rates for capital-augmenting technical change. Clearly, most of the values are negative across all industries; although in some cases the rates of capital-augmenting technical change are not statistically significant. There are some individual outliers too. For instance, the high-tech sector in the Netherlands and France exhibited statistically significant positive values of capital-augmenting technical change.

Table 7 reports the decomposition of total factor-augmenting technical change via endogenous and exogenous drivers as well as information on the significant R&D driver. The reported exogenous rates are averages of the individual country rates. Note that the rates of endogenous technical change are considerably smaller than the exogenous rates; this is due to the relatively small changes in R&D expenditures experienced during the past two decades. In fact, R&D causes the biggest share of technical change in the financial sector (0.5%). An important contribution of R&D is also found in the low-tech sector. In case

Table 6. (a) Exogenous rates of labor-augmenting technical change and (b) exogenous rates of capital-augmenting technical change.

	High-tech	Low-tech	Con	Wrt	Tsc	Fin	Res
AUS	**2.2%**	**1.0%**	0.4%	**3.0%**	**2.8%**	**2.1%**	**−2.1%**
CAN	**2.7%**	**1.3%**	0.5%	**2.6%**	**1.6%**	0.8%	−0.4%
DEU	**4.3%**	**1.7%**	**−0.7%**	**1.5%**	**6.2%**	0.5%	**−2.0%**
ESP	**1.5%**	−0.4%	−0.7%	0.5%	**1.7%**	2.1%	**−2.4%**
FIN	**3.7%**	**3.7%**	NA	**2.0%**	**5.2%**	**2.0%**	**−1.3%**
FRA	**5.3%**	**0.6%**	0.1%	**1.3%**	**3.7%**	0.3%	−0.2%
GBR	**4.1%**	**1.5%**	**0.8%**	**2.1%**	**4.0%**	**2.2%**	0.2%
ITA	**1.5%**	**1.7%**	**−1.1%**	**1.0%**	**3.9%**	**2.0%**	**−3.0%**
JPN	**4.0%**	**1.5%**	**−1.1%**	**3.8%**	**3.1%**	**2.5%**	−0.6%
NLD	**4.7%**	**2.2%**	**−0.9%**	**2.7%**	**3.8%**	**1.1%**	**−1.3%**
USA	**3.7%**	**1.1%**	**−2.3%**	**3.0%**	**3.8%**	**1.5%**	−0.3%
Mean	3.4%	1.6%	−0.9%	2.3%	3.6%	1.9%	−2.0%
AUS	**−2.8%**	**−3.5%**	**1%**	**−2%**	0%	**−1%**	0%
CAN	**0.7%**	−0.1%	**−2%**	**−3%**	−1%	**−5%**	0%
DEU	−0.3%	**−2.3%**	**−1%**	**−3%**	−1%	**−2%**	**−1%**
ESP	**−1.4%**	**−1.4%**	**−1%**	**−3%**	**−3%**	−4%	0%
FIN	−0.7%	0.3%	NA	0%	0%	−2%	-1%
FRA	**1.9%**	−1.3%	**−1%**	**−1%**	**2%**	**−2%**	0%
GBR	0.2%	−0.5%	**−3%**	**−2%**	**−3%**	−1%	**−2%**
ITA	**−1.5%**	**−1.7%**	**−3%**	**−4%**	**−3%**	−1%	**1%**
JPN	**−1.9%**	**−4.1%**	**−2%**	0%	**−2%**	**−2%**	**−1%**
NLD	**3.2%**	−0.1%	**−2%**	1%	0%	−2%	0%
USA	−1.2%	**−1.2%**	**−6%**	**−1%**	**−2%**	**−3%**	0%
Mean	−0.3%	−2.2%	−2.1%	−2.3%	−1.8%	−2.5%	−0.8%

Notes: Values in bold indicate parameters significance at.05 level. Mean is calculated only from statistically significant parameters.
Sector abbreviations: Con = construction, Wrt = wholesale retail and trade, Tsc = transport, storage and communication, Fin = financial services, Res = real estate and business services.

of the high-tech sector, the impact of R&D is reduced by the negative effect of services R&D. If the effect of R&D services is left out, the endogenous growth rates of factor-augmenting technical changes in the high-tech sector are the second highest after the financial sector.

By summing rates of technical change over each factor, we derived total factor-augmentation. From this we can find that construction, low-tech manufacturing and real estate and business services suffered overall declines in productivity over time and space. In the cases of construction and real estate and business services, note this finding is limited to the pre-crisis period (before 2008–2009). Uppenberg and Strauss (2010) tell us that many EU countries, particularly Spain and Ireland, experienced strong employment growth in construction due to a real estate boom. This later proved to be an unsustainable bubble, subsequently leading to a sharp employment decline in the sector.

On the other hand, the high-tech sector exhibited positive productivity growth. (If the effect of R&D for services is excluded, its productivity grew by 6.64% – by far the highest value among sectors.) Transport, storage and communication also enjoyed positive productivity growth and, to a lesser extent, so did financial services. Productivity in the wholesale and retail sector remained fairly constant as the growth of labor-saving technical change was compensated by negative capital augmentation.

4.4. Implications for directed technical change

Acemoglu (2002) suggest that under a CES technology with non-unitary elasticity of substitution, factor-augmenting technical change produces bias in the ratio of factor marginal

Table 7. Decomposition of factor-augmenting technical change.

Sector	Equation	Elasticity of subs.	Significant endogenous driver	(*a*) Exo factor-augmenting TC (%)	(*b*) Endo factor-augmenting TC (%)	(*c*) = (*a*) + (*b*) Total factor-augmenting TC (%)	(*d*) = (c_L) + (c_K) Total factor-augmentation (%)
High-tech	FOC Capital	0.242	*RDman*, *RDserv* (neg)	−0.26%	0.05% (0.28% [a])	−0.21% (0.02% [a])	3.0% (6.64% [a])
	FOC Labor		*RDman*, *RDserv* (neg)	3.43%	−0.25% (0.32% [a])	3.18% (6.62%[a])	
Low-tech	FOC Capital	0.222	*RDman*	−2.21%	0.17%	−2.04%	−0.2%
	FOC Labor		*RDman*	1.64%	0.24%	1.89%	
Construction	FOC Capital	0.135	None	−2.07%	0.00%	−2.07%	
	FOC Labor		None	−0.87%	0.00%	−0.9%	−2.9%
Wholesale and retail	FOC Capital	0.214	None	−2.31%	0.00%	−2.31%	
	FOC Labor		*RDman* (neg)	2.30%	0.10%	2.39%	0.1%
Transport, storage and communication	FOC Capital	0.402	*RDman*	−1.77%	−0.05%	−1.82%	
	FOC Labor		None	3.63%	0.00%	3.63%	1.8%
Financial services	FOC Capital	0.201	*RDserv*	−2.53%	0.54%	−1.99%	
	FOC Labor		*RDserv*	1.92%	0.47%	2.39%	0.4%
Real estate and business services	FOC Capital	0.424	*RDman*, *RDserv*	−0.84%	0.07%	−0.76%	
	FOC Labor		*RDman*, *RDserv* (neg)	−2.02%	−0.21%	−2.23%	−3.0%

Notes: Total factor-augmentation is calculated by summing labor- and capital-augmenting technical change in each sector.
[a]When negative R&D services in high-tech sector is excluded.

Table 8. Directed technical change.

	A_K/A_L	K/L	Correlation
High-tech	−0.02	0.03	−0.31
Low-tech	−0.76	0.03	−0.27
Construction	2.38	0.02	−0.24
Wholesale and retail trade	−1.04	0.03	−0.43
Transport, storage, com.	−0.31	0.03	−0.47
Financial services	−0.80	0.05	−0.46
Real estate and business services	0.80	−0.02	−0.47

productivities. That is, if labor and capital are complements (the elasticity of substitution is less than one), labor-augmenting technical change induces an excess demand for capital with a labor-saving effect (with elasticity higher than one, labor augmentation produces a labor-using effect). Acemoglu also shows when the elasticity of substitution less than one, the *price-effect* prevails over the *market-effect*, so that it is more profitable to invest in technologies that save scarcer production factors. In other words, countries that accumulate capital faster wind up investing more into labor-augmenting technology than they do into capital-augmenting technology. And, conversely, countries that accumulate labor faster opt to invest more into capital-augmenting technology than they do into labor-augmenting technology.

In all production sectors, we can see that the elasticity of substitution is far below one. Thus we can conclude that production factors behave as gross complements. Therefore the strong evidence on labor-augmenting technical change found in all sectors (except for construction and real estate and business services) suggest that technical change has been labor-saving and capital-using.

Table 8 shows that, in all cases, growth in the capital/labor ratio was negatively related to the capital/labor ratio for augmenting technical change, which confirms the hypothesis. The strongest positive correlation was found for the financial, as well as the transport, storage and telecommunication, sector, which indicates the highest effect of capital accumulation for labor-saving technical change. An interesting exception is the real estate and business services sector for which technical change was directed towards capital in response to its faster accumulation of labor. In this sector, evidence for technical change points toward capital-savings rather than labor-savings.

The role of R&D in explaining the direction of technical change can also be discussed. Based on the findings from the previous chapter, we can classify the effect of R&D stocks as follows:

A neutral effect of own-R&D on technical change. In high-tech and low-tech sectors both production factors benefited from increased productivity from 'in-house' R&D activities, that is, Hicksian technical change. A similar conclusion can be drawn for the effect of services R&D on the financial sector. These activities stimulate productivity in the financial sector and save the use of both factors.

A capital-saving effect of intersectoral R&D on technical change. Manufacturing R&D stocks are important drivers of capital-augmenting technical change in the transport, storage and telecommunication sector. This suggests the implementation of new capital varieties to stimulate capital productivity. It supports a discussion of Solow-type technological progress as core to Romer (1994) endogenous growth.

Table 9. Estimated returns to R&D.

Sector	R&D stock category	RD to Y[a]	RD return	K-part	L-part
High-tech	RD manuf.	9.72	0.48	0.46	0.02
Low-tech	RD manuf.	10.25	0.94	0.90	0.05
Transport, storage, com.	RD manuf.	0.52	0.41	0.41	0.00
Financial services	RD services	0.13	38.34	36.36	1.98

[a]Ratio of R&D stock category in value added.

A capital-saving and *labor-using* effect of R&D on technical change. Investments in both manufacturing and services R&D investments enabled capital-saving and labor-using effects in real estate and business services. Manufacturing R&D suggests new capital varieties for both manufacturing and services, which in turn require higher-quality labor. R&D in services also favors capital productivity leading to a greater demand for labor with greater skills.

4.5. Calculation of returns to research

We used Equation 16 to calculate returns to research for sectors in which R&D proved significant in explaining productivity, that is, the high-tech sector, low-tech sector, the transport, storage and communication sector and financial services. But first some terms had to be simplified. For example, marginal product is in levels, whereas the estimated CES FOCs are in growth rates. So the level constants A_{K0} and A_{L0} in the equation for factor-augmenting technical change and the CES share parameters α_K and α_L are not known after estimation. To overcome this problem, one could normalize all variables (see Klump et al., 2007; Baccianti, 2013); but this would result in normalized marginal returns to R&D, which are rather difficult to interpret. So we opted to modify relying on two simplifications. First, we gave all countries the same factor-augmenting technical change A_K and $A_L$the same starting point – the value 1.0. Using this, we could then derive country-specific level constants A_{K0i} and A_{L0i} via the following equation:

$$A_{K0i} = \frac{1}{e^{\delta_{ki \cdot t}} \cdot RD_{it}^{\delta RD_k}} \text{ for } t = 1. \tag{17}$$

Second, to estimate the share parameters α_K and α_L, we used mean shares of capital and labor in value added, calculated over the whole dataset. We then substituted the mean values of capital, labor, value added and R&D stocks into Equation 16

$$R\,\&\,Dreturn = \frac{\bar{Y}^{1/\sigma}}{\overline{RD}} \cdot (\bar{s}_K \cdot (\bar{A}_K \cdot \bar{K})^{((\sigma-1)/\sigma)} \cdot \gamma k + \bar{s}_L \cdot (\bar{A}_L \cdot \bar{L})^{((\sigma-1)/\sigma)} \cdot \gamma L). \tag{18}$$

Results with the average returns to R&D for the selected sectors are displayed in Table 9. A remarkable difference exists between the R&D intensity of manufacturing and services sectors. For manufacturing the value of R&D stocks is almost 10 times that of value added (this particularly applies to France, Great Britain, the Netherlands and the USA); Australia, Spain and Finland exhibit considerably lower shares. Contrarily, R&D intensity in the financial services sector is quite low – especially in Germany, for which value added is 20 times higher than R&D stocks in services.

These findings are in line with those of Uppenberg and Strauss (2010) who claim that services sector innovation, in contrast to that in manufacturing, draws less on in-house knowledge creation in the form of R&D. The lower level of in-house knowledge creation partially reflects the smaller average size of service firms. Jankowski et al. (2005) add that little research occurs in house within the service sector and that any development activity there is primarily related to enhancing, redesigning or reconfiguring the proprietary technologies of others.

Average R&D returns also reflect differences in R&D intensities. Table 9 shows for sectors with the main driver being manufacturing R&D that derived returns are around 0.5, which is in line with other findings in the literature.[8] As for the R&D services, the estimated returns are implausibly high. According to Dorwick (2003, cited in Shanks and Zheng, 2006), industry-level returns should be around 40% or more and the economy-wide returns above 80%. The rates of return derived here are in line with this rule of thumb, with exception of those for the financial services. But it is possible to find rates of return well above 100% in the literature; Shanks and Zheng found a return of 438% in the wholesale, retail and trade sector.

Insight can be found when decomposing the R&D returns on factor-specific contribution (by multiplying both terms in Equation 18). Clearly, the capital component of R&D returns dominates total R&D returns. This also confirms the directed technical change hypothesis – labor-saving technical change results in capital-bias. This suggests that the marginal product of capital grew more quickly than did labor's, as reflected in its major contribution to R&D returns.

Table 10 shows more detailed country-level calculations of R&D returns (as opposed to total averages, here country-specific averages were the main variables). In the case of manufacturing, Table 10 reveals reasonable values of R&D returns for the USA, Japan, Finland, Canada and the Netherlands. But estimated returns to R&D are too high for Australia, Spain, Italy and Great Britain, undoubtedly due to high output/R&D-stock ratios. This raises questions about using a uniform R&D elasticity across the countries. Clearly, this assertion is too strong given the wide dispersion of country differences in R&D profiles. On the other hand, one might argue that above-average returns in some OECD countries simply reflect the effect of R&D spillovers that were not captured by the R&D series (either not properly recorded in the data collection process or the spillovers 'traveled' within OECD countries via another way than intermediate consumption). In other words, the above-average returns in some OECD countries might indicate that these countries are free-riding on R&D investments made by other countries.

In financial services, country-specific returns to services R&D are one to two magnitudes higher than those for manufacturing. We also find unrealistically high rates for some countries, for example, Germany. In such cases, the returns are undoubtedly social rather than private returns. Apparently services R&D have vast productivity impacts in financial services, so this phenomenon deserves more detailed examination. That is, this is a call for more micro-level evidence based on company R&D expenditures data and for more insight into the modeling of R&D services stocks, particularly functional forms and depreciation rates.

[8] For instance, Leijten (2014) claims that €1 invested in manufacturing leads to more than €1.5 investment in other sectors.

Table 10. Estimated country-specific returns to R&D.

Country	High-tech	Low-tech	Transport, storage, com.	Financial services
AUS	7.2	18.8	2.3	21.5
CAN	0.6	0.7	1.5	137.1
DEU	1.5	1.7	0.5	697.4
ESP	4.8	7.8	3.4	56.1
FIN	0.4	0.5	0.5	10.7
FRA	0.2	2.1	0.4	292.4
GBR	2.0	5.0	3.0	25.4
ITA	2.4	4.7	0.7	63.9
JPN	0.5	1.6	0.4	21.3
NLD	0.1	0.4	0.5	37.6
USA	0.5	0.7	0.3	57.2
Average	0.48	0.94	0.41	38.34

5. Discussion

It is interesting to compare our results with those of other studies. Results on the substitution elasticities, which range from 0.2 to 0.4, are in line with other estimates. For instance, Young (2013) obtains substitution elasticities less than 0.5 for major US industries at the two-digit level. Using two-digit industry-level data for 12 OECD countries, Van der Werf (2008) estimates σ_{KL} ranging from 0.2 to 0.6 in seven manufacturing subsectors. Carraro and de Cian (2013) estimate the endogenous elasticity of substitution in a nested production function including energy to be 0.38 for an aggregate manufacturing industry – slightly higher than our estimate of 0.24. Some authors (e.g. Baccianti, 2013) argue that substitution elasticities tend to be lower when estimated from growth rates instead of levels since they yield short-run rather than long-run relationships (i.e. long-run elasticities are higher). Nevertheless, the approach for estimating factor-augmenting technical change in growth rates fits our purposes well since it yields parameters identical to the linearized solution of our CGE model. Recall, due to the high levels of aggregation applied, that the substitution elasticities are, in fact, averages across individual subsectors.

The estimated factor-augmenting technology parameters in most sectors show that technical change is biased towards labor with labor-saving and capital-using effects. This is consistent with Van der Werf (2008), for instance, who finds rates of labor-augmenting technical change around 3% and negative rates of capital-augmenting technological change. Jorgenson (2010) also concluded that technical change for most sectors of the US economy was labor-saving and capital-using, except for services where it is slightly capital-saving; this corresponds to the capital-saving effect of the R&D in real estate and business services obtained here.

Our estimated R&D elasticities are directly comparable with those of Carraro and de Cian (2013) who derived factor-augmenting technical change via three endogenous drivers for an aggregate manufacturing industry for each of 13 OECD countries. In their piece, aggregate R&D stocks are statistically significant drivers of capital productivity, a finding confirmed here for intersectoral manufacturing R&D spillovers. They also obtained larger R&D effects – an elasticity of 0.94% versus 0.53% here. These differences could be related to the use of dissimilar periods of analysis (in their case, 1987–2002), the origin of their dataset and their use of aggregate R&D.

According to expectations the estimated R&D elasticities differ across sectors with the highest values recorded for high-tech manufacturing. This follows the Ortega-Argilés et al. (2015) who claims that high-tech manufacturing firms achieve greater productivity gains through research than do their low-tech counterparts. Kancs and Siliverstovs (2016) similarly claim that high-tech sectors achieve more productivity gains through R&D than do other sectors.

Findings regarding the direction of technical change show that manufacturing R&D stocks created 'in-house' stimulate TFP in both high- and low-tech manufacturing, whereas they exhibit a capital-augmenting effect on technical change when captured by service sectors via spillover effects. In the former case, apparently 'in-house' R&D improves access to information and enhances the speed of innovation, enabling new products to be developed faster and less expensively (Connolly and Fox, 2006); this naturally improves productivity of both production factors.

In case of the latter, new capital varieties are complementary with new productivity-enhancing strategies and business processes in services. The so-called general purpose technologies such as railways, motor vehicles, ICT and digital technologies are concrete examples of capital varieties that manufacturing R&D provides to the transport, storage and telecommunication sector (Connolly and Fox, 2006). Similarly stocks of computers, communication equipment and software have grown significantly since 1995 in financial services (Uppenberg and Strauss, 2010). Other examples of capital varieties relevant to financial services are automatic teller machines, electronic funds transfer point of sale and mobile banking. In wholesale and retail trade e-commerce-oriented innovations have enhanced productivity.

In some services sectors, resulting productivity effects of R&D were often capital-saving and labor-using. This may be due to the nature of the R&D process in services where improved customer satisfaction can be as important as improved productivity. Leijten (2014) notes that innovations can have a notable effect on social conditions and even lead to higher-quality jobs. He adds that new technologies in advanced manufacturing can diversify the set of activities performed by and firms in an industry, leading to employment growth. It therefore should not be surprising that R&D processes in services are labor-using rather than labor-saving, and yield positive effects on employment and an enhanced demand for highly qualified labor.

Services R&D had statistically significant impacts on productivity in the financial sector, real estate and business services, and high-tech manufacturing. They engendered particularly high R&D returns in the financial sector, which attained the highest share of technical change. Ortega-Argilés et al. (2015) also found an important role for R&D in service firms and as a result called for further investigation of its effects on services.

A last issue that is worth noting is the unintuitive negative role of R&D services in explaining factor-augmenting technical change in high-tech manufacturing. Results suggest that employing manufacturing R&D saves both capital and labor, whereas services R&D in turn require more-intensive use of them. This is possibly due to complementarities between different types of R&D products and services. Uppenberg and Strauss (2010) note that many manufacturers have, over time, transformed into service-providing companies. That is, the production of physical goods has become a secondary function, focusing instead on providing 'business solutions', which has occasionally been called the 'servitisation' of products. For instance, IBM, which started out as a computer manufacturer, has developed a strong background in both software and consulting. Similarly, instead of using internal R&D services, most pharmaceutical companies now contract R&D services (or purchase technologies from nascent firms) and some even outsource a significant amount of drug testing (Jankowski et al., 2005). Therefore, 'servitisation' of manufacturing generally suggests an enlarged portfolio of activities for a firm as well as higher demand for labor, as observed in services.

6. Conclusion

In this paper, we investigated the extent to which accumulated R&D investments drive endogenous factor-augmenting technical change. This paper therefore marks a first attempt to quantify R&D driven factor-augmenting technical change on a fairly broad set of sectors for a panel of 11 OECD countries over 2 decades. We apply a CES framework with cost-minimizing behavior to derive a system of equations and obtain estimates via a GMM system.

For all sectors, we obtain a substitution elasticity below one, thereby rejecting use of Cobb–Douglas technology. Second, we find evidence that OECD countries have faced massive capital accumulation that has directed technical change towards labor-saving, so a hypothesis of neutral technical change was rejected for most sectors. We derive the highest growth rates of labor-saving technical change for the high-tech sector as well as for transport, storage and communication. For example, France's high-tech sector and the transport, storage and communication sector in Germany and Finland have growth rates over 5%. They also exhibit the highest R&D elasticities implying they extract more productivity gains from R&D than do other sectors.

Manufacturing and services R&D stocks created 'in-house' stimulate TFP, whereas they exhibit a capital-saving and labor-using effect when they spill over to the other sectors. This is related to the complementarity of manufacturing and services R&D as well as the social role of R&D in creating employment and customer satisfaction.

We also quantified returns to research using a CES production framework with factor-augmenting technical change. Elasticities for returns to manufacturing R&D were around 0.5. Elasticities were extremely high for services R&D probably because they capture social returns and R&D embedded in manufacturing inputs.

Important processes of technical change are going on within the sectors that cannot be readily captured by simple TFP measures; that is, while sectors reported moderately low productivity growth, the factor-biases used to measure them may be large. Moreover, a report of a negative impact of R&D on labor productivity in some services sectors does not mean it is necessarily a negative phenomenon in net, as it also relates to increased employment and capital productivity growth. The financial sector clearly stands out from other services; the main part of its technical change is explained by R&D. This highlights the importance of retaining sectoral disaggregation even for services sectors.

Some findings are likely unique to the study period. Over-employment during the construction boom prior to 2008 resulted in negative rates of technical change and zero R&D effects in the construction and real estate sector. Therefore, it would be interesting to analyze technical change using only the post-crisis data, which should reflect the restructuring of many sectors, but particularly the construction, real estate and financial sectors. Furthermore, new innovations are becoming increasingly important, such as nanotechnologies, new types of biotechnologies and big data applications.

From the modeling perspective, the findings can be used to specify technical change in global applied CGE models, which are increasingly being used to assess important global issues, such as climate change, energy security and food security. In this regard, this study provides country- and sector-specific rates of exogenous factor-augmenting technical change, which can be used to improve projections of labor and capital with respect to both their demands and prices. The latter are key when projecting product prices, production patterns, land uses and international trade patterns. Such developments are crucial starting points for policy analyses.

Planned technological change can channel economic growth, reduce greenhouse gas emissions and reduce food security. Thus, with R&D elasticities in hand one can model the relationship between investments in R&D and factor-augmenting technical change and, thereby, open up the black box of technical change. Technological change is not only 'manna from heaven' but it requires resources that are also used to produce other goods, so it does have opportunity costs. Estimating the opportunity cost of technological change that is used to facilitate economic growth, employment, international trade and climate change is undoubtedly valuable policy work.

In this paper, input–output data were used to calculate intersectoral R&D spillovers. The commodity flows among sectors are a mechanism for knowledge diffusion within an economy. But most substitution elasticities in the analysis were between 0.1 and 0.4, suggesting moderate substitution among production factors. This does not jibe well with fixed coefficient technologies underlying input–output analyses. Still, it is likely that the degree of substitution is limited. Some of the elasticities derived here, particularly those on sectoral labor-saving technical change can be used to adjust input–output coefficients in the future. Factor-augmenting technical change also can be partly endogenized in input–output analyses by using the estimated rates of return to own and intersectoral R&D in combination with constructed intersectoral R&D stocks.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This research was supported by a Marie Curie Intra European Fellowship within the 7th European Community Framework Programme [grant agreement number PIEF-GA-2013-625278].

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Appendix 1. Derivation of the demand conditions for 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

$$minTC = P_K \cdot K + P_L \cdot L \quad \text{subject to}: Y = [\alpha_K(A_K \cdot K)^{((\sigma-1)/\sigma)} + \alpha_L(A_L \cdot L)^{((\sigma-1)/\sigma)}]^{(\sigma/(\sigma-1))}.$$

The corresponding Lagrangian function writes as

$$L(K, L, \lambda) = P_K \cdot K + P_L \cdot L - \lambda\{[\alpha_K(A_K \cdot K)^{((\sigma-1)/\sigma)} + \alpha_L(A_L \cdot L)^{((\sigma-1)/\sigma)}]^{(\sigma/(\sigma-1))} - Y\}. \tag{A1}$$

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

$$\frac{P_K}{P_L} = \frac{M_K}{M_L} = \frac{\alpha_K \cdot A_K \cdot K^{-1/\sigma}}{\alpha_L \cdot A_L \cdot L^{-1/\sigma}}. \tag{A2}$$

Solving for K and L in Equation A2 yields:

$$L = \left(\frac{\alpha_L \cdot P_K}{\alpha_K \cdot P_L}\right)^{\sigma} \left(\frac{A_L}{A_K}\right)^{\sigma-1} \cdot K, \tag{A3}$$

$$K = \left(\frac{\alpha_K \cdot P_L}{\alpha_L \cdot P_K}\right)^{\sigma} \left(\frac{A_K}{A_L}\right)^{\sigma-1} \cdot L. \tag{A4}$$

Substituting L into the CES function and collecting terms yields:

$$Y^{(\sigma-1)/\sigma} = K^{(\sigma-1)/\sigma}\left(\frac{P_K}{\alpha_K}\right)^{\sigma-1} \times \left(\alpha_K \cdot K^{1-\sigma} \cdot A_K^{((\sigma-1)/\sigma)} + \alpha_L \cdot P_L{}^{1-\sigma} \cdot A_L^{((\sigma-1)/\sigma)}\left(\frac{A_L^{\sigma-1}}{A_K^{\sigma-1}}\right)^{((\sigma-1)/\sigma)}\right). \tag{A5}$$

Solving for K in Equation A5 yields:

$$K = Y\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}\left(\alpha_K \cdot P_K^{1-\sigma} \cdot A_K^{((\sigma-1)/\sigma)} + \alpha_L \cdot P_L^{1-\sigma} \cdot A_L^{((\sigma-1)/\sigma)}\left(\frac{A_L^{\sigma-1}}{A_K^{\sigma-1}}\right)^{((\sigma-1)/\sigma)}\right)^{(-\sigma/(\sigma-1))}, \tag{A6}$$

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

Substituting K and L from Equations A6 and A7 into the total cost function yields:

$$TC = P_k \cdot Y\left(\frac{P_K}{\alpha_K}\right)^{-\sigma} \times \left(\alpha_K \cdot P_K^{1-\sigma} \cdot A_K^{((\sigma-1)/\sigma)}\left(\frac{A_K^{\sigma-1}}{A_L^{\sigma-1}}\right)^{((\sigma-1)/\sigma)} + \alpha_L \cdot P_L^{1-\sigma} \cdot A_L^{((\sigma-1)/\sigma)}\right)^{(-\sigma/(\sigma-1))} \tag{A7}$$

$$+ P_L \cdot Y\left(\frac{P_K}{\alpha_K}\right)^{-\sigma}\left(\alpha_K \cdot P_K^{1-\sigma} \cdot A_K^{(\sigma-1)/\sigma} \cdot \left(\frac{A_K{}^{\sigma-1}}{A_L{}^{\sigma-1}}\right)^{((\sigma-1)/\sigma)} + \alpha_L \cdot P_L^{1-\sigma} \cdot A_L^{((\sigma-1)/\sigma)}\right)^{(-\sigma/(\sigma-1))}. \tag{A8}$$

Assume, under perfect competition, that firms operate with zero profits and that their output price is equal to unit costs. Then by dividing Equation A8 by total output and substituting for repeated terms yields:

$$PY = \frac{TC}{Y} = a \cdot A_K^{-1}\left(\frac{A_K}{A_L}\right)^{\sigma} \cdot z^{-\sigma/(\sigma-1)} + b \cdot A_L^{-1} \cdot z^{-\sigma/(\sigma-1)}, \tag{A9}$$

where

$$a = \alpha_K \cdot P_K^{1-\sigma}, \tag{A10}$$

$$b = \alpha_L \cdot P_L^{1-\sigma}, \tag{A11}$$

$$z = \left[a + b\left(\frac{A_L}{A_K}\right)^{1-\sigma}\right]. \tag{A12}$$

Collecting the z terms in Equation A9 provides:

$$PY = z^{-\sigma/(\sigma-1)} \cdot A_L^{-1}\left[a\left(\frac{A_K}{A_L}\right)^{\sigma-1} + b\right] = z^{-\sigma/(\sigma-1)} \cdot A_L^{-1} \cdot z. \tag{A13}$$

Then, solving for z in Equation A13 results in

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

Substituting z into demand equation for capital (A6) yields:

$$K = Y\left(\frac{P_K}{\alpha_K}\right)^{-\sigma} \cdot A_K^{-1}\left(\frac{A_K}{A_L}\right)^{\sigma} \cdot z^{-\sigma/(\sigma-1)} = Y\left(\frac{P_K}{\alpha_K}\right)^{-\sigma} \cdot A_K^{-1}\left(\frac{A_K}{A_L}\right)^{\sigma}(PY \cdot A_L)^{\sigma}. \tag{A14}$$

Rearranging the terms in Equation A14 yields:

$$\frac{K}{Y} = \left(\frac{\alpha_K \cdot PY}{P_K}\right)^{\sigma} A_K^{\sigma-1}. \tag{A15}$$

Finally, taking the natural logarithm yields:

$$\ln\frac{K}{Y} = \sigma \cdot \ln\alpha_K + (\sigma - 1) \cdot \ln A_K + \sigma \cdot \ln\frac{PY}{PK}. \tag{A16}$$

Substituting z into demand equation for labor yields:

$$L = Y\left(\frac{P_L}{\alpha_L}\right)^{-\sigma} \cdot A_L^{-1} \cdot z^{-\sigma/(\sigma-1)} = Y\left(\frac{P_L}{\alpha_L}\right)^{-\sigma} \cdot A_L^{-1}(PY \cdot A_L)^{\sigma}. \tag{A17}$$

Rearranging the terms in Equation 17 yields:

$$\frac{L}{Y} = \left(\frac{\alpha_L \cdot PY}{P_L}\right)^{\sigma} \cdot {A_L}^{\sigma-1}. \tag{A18}$$

Finally, taking the natural logarithm yields:

$$\ln \frac{L}{Y} = \sigma \cdot \ln \alpha_L + (\sigma - 1) \cdot \ln A_L + \sigma \cdot \ln \frac{PY}{PK}. \tag{A19}$$