



MONROE - Modelling and evaluating the socio-economic impacts of research and innovation with the suite of macro- and regional-economic models

## D6.5.1 Technical description of the MONROE metamodel

March 2019: Public deliverable

## Contents

Contents .....	2
Document Details .....	3
Version History .....	3
Project Involvement.....	3
1. Introduction .....	4
2. R&D and endogenous productivity growth.....	5
2.1 Human capital and technology diffusion.....	6
2.2 The role of R&D in knowledge creation and knowledge adoption.....	7
3. Empirical setting and data description .....	8
4. Results of the econometric analysis .....	14
5. Practical implementation in the online tool.....	24
References .....	28
Annex: Java code for calculations .....	31

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727114

### Document Details

<b>Authors</b>	Olga Ivanova, Moustafa Chatzouz
<b>Creation Date</b>	19-03-2019
<b>Date of Last Revision</b>	
<b>Version</b>	1.0
<b>Description</b>	

### Version History

<b>Version</b>	<b>Updated By</b>	<b>Date</b>	<b>Changes / Comments</b>
1.0	Olga Ivanova	19-03-2019	Initial draft

### Project Involvement

<b>Project Director</b>	Olga Ivanova
<b>Project Manager</b>	Iason Diafas
<b>WP Manager</b>	Sebastian Voigt
<b>Project Leads</b>	Olga Ivanova

## 1. Introduction

The present deliverable describes the empirical setup, database and the results of econometric analysis that have been used as the basis for the construction of the meta-model used in the interactive part of the MONROE online tool. The goal of the MONROE online tool is to provide a broader audience of policy makers, students and other interested citizens information about the importance of R&D, the channels of impact and likely effects of sectoral economic growth of various R&D related policy measures.

The empirical econometric setup used in this deliverable relates to a limited body of literature that aims to investigate the structural determinants of TFP growth. This literature usually pools information on country level data on TFP growth rates and constructs a reduced form specification of the innovation-imitation processes as implied by the basic Schumpeterian growth theory (Nicoletti and Scarpetta (2003), Aghion and Howitt (2008), and Benhabib and Spiegel, (2005)). In this so-called, multi-factor productivity growth model, a number of control variables are usually added to understand the effects of the variables of interest on TFP growth.

Nicoletti and Scarpetta (2003), for example, used this approach to show the positive impact of trade liberalization and privatization on TFP growth . Similarly, Griffith and Howitt (2003), using firm level data document the positive role of product market competition on innovation. Our analysis follows a similar approach except that we are looking at different, compared to the literature, policy measures that affect innovation. In addition, and unlike most other studies, our paper extends the analysis across different sectors often considered important to growth dynamics of a country. In this respect, our paper is more closely related to the well-known study of Griffith et al (2004), who were the first to use industry level data in the context of multi-factor productivity model. Their analysis, however, relies on OECD/STAN data unlike ours which is based on the EU-KLEMS data and hence allow us to look at sectors beyond manufacturing. This is especially important given that some studies

point out the role of other than manufacturing industries, and in particular market services, as a key driver for the productivity gaps between countries, and especially between EU and the US (Havik et al (2008)).

The rest of the deliverable is structured as follows. Section 2 present the theoretical framework used for the econometric analysis in the paper. Section 3 describes the database used for econometric analysis and functional form of regressions. Section 4 presents the results of econometric analysis both at the aggregate level and for each of six aggregate economic sectors separately. Section 5 describes the practical implementation of the empirically estimated regressions in the online interactive tool.

## 2.R&D and endogenous productivity growth

The theoretical underpinnings of our approach follow Acemoglu et al, (2006) who analyze an economy where firms undertake both innovation and adoption of technologies from the world technology frontier. In this context, the selection of high-skill managers and firms is more important for innovation than for adoption. As the economy approaches the frontier, selection becomes more important. Countries at early stages of development pursue an investment-based strategy, which relies on existing firms and managers to maximize investment but sacrifices selection. Closer to the world technology frontier, economies switch to an innovation-based strategy with short-term relationships, younger firms, less investment, and better selection of firms and managers. They show that relatively backward economies may switch out of the investment-based strategy too soon, so certain policies such as limits on product market competition or investment subsidies, which encourage the investment-based strategy, may be beneficial. However, these policies may have significant long-run costs because they make it more likely that a society will be trapped in the investment-based strategy and fail to converge to the world technology frontier.

Let us denote the growth of the world technology frontier,  $\bar{A}_t$  by  $g$  so that

$$\bar{A}_t = \bar{A}_0(1+g) \quad (1)$$

For each representative country its state of technology is less than the frontier technology  $A_t \leq \bar{A}_t$ . The productivity of sector that produces intermediate good  $v$  at time  $t$  is expressed as

$$A_t(v) = s_t(v) [\eta \bar{A}_{t-1} + \gamma_t(v) A_{t-1}] \quad (2)$$

Where  $s_t(v) \in \{1, \sigma\}$  denotes the size of the investment with  $s_t(v) = 1$  for large sectors,  $\gamma_t(v)$  denotes the probability of new innovation. Equation above captures the two dimensions of productivity growth: adoption and innovation. By adopting existing technologies firms benefit from the world state of technological knowledge. In addition to it there is a productivity growth due to innovation building on the local sector-specific knowledge  $A_{t-1}$  and success of innovation depends on the probability of new innovation. The larger is investment the higher is the productivity growth. If we rearrange the terms we get the following equation that includes the distance to the technological frontier  $\bar{A}_{t-1} / A_{t-1}$

$$A_t(v) / A_{t-1} = s_t(v) [\eta \bar{A}_{t-1} / A_{t-1} + \gamma_t(v)] \quad (3)$$

In case when the country and sector is far from the technological frontier the major source of growth is the technology adoption. In case when the technological gap becomes close to unity that is the country is close to the frontier innovation becomes an important source of productivity growth.

## 2.1 Human capital and technology diffusion

This part of the model is based on the papers by Benhabib and Spiegel (2002) "Human capital and technology diffusion" and Helson and Phelps (1966) "Investment in human, technological diffusion and economic growth". Helson and

Phelps (1966) assume that there is a difference between actual level of the state-of-the-art technology and the theoretical level of technology that would prevail if technological diffusion was instantaneous. The technology diffusion can be modelled as follows:

$$\frac{\dot{TFP}_{i,t}}{TFP_{i,t}} = g(H_{it}) + c(H_{it}) \left( \frac{TFP_{m,t}}{TFP_{i,t}} - 1 \right) \quad (4)$$

Where  $TFP_{i,t}$  is the TFP of the country and  $TFP_{m,t}$  is the TFP of the technological leader (country with the highest TFP) and  $H_{i,t}$  is the human capital that is measured as the average number of years of education of the labour force/employed.

Another variation of the technology diffusion and catch-up processes is the logistic technology diffusion model which adds an extra term that captures the difficulty of adopting distant technologies:

$$\frac{\dot{TFP}_{i,t}}{TFP_{i,t}} = g(H_{it}) + c(H_{it}) \frac{TFP_{i,t}}{TFP_{m,t}} \left( \frac{TFP_{m,t}}{TFP_{i,t}} - 1 \right) \quad (5)$$

TFP in our framework is explained by the combination of technology adoption via the technological diffusion process described above and technological innovation linked to the knowledge created by the industry itself ( $I_{i,t}$ ):

$$\frac{\dot{TFP}_{i,t}}{TFP_{i,t}} = aH_{it} + bH_{it} \left( \frac{TFP_{m,t}}{TFP_{i,t}} - 1 \right) + cI_{i,t} \quad (6)$$

## 2.2 The role of R&D in knowledge creation and knowledge adoption

Following the paper of Griffith, Redding and Van Reenen (2001) our model assumes that R&D has two roles in the development of TFP. The first role is in knowledge creation or stimulation of innovation that has received a lot of attention in both theoretical and empirical literature. The second role is in facilitation of adoption or imitation of knowledge that has been created in other countries or sectors. Griffith, Redding and Van Reenen (2001) use a panel of OECD countries and find a strong

empirical evidence for the second role of R&D in adoption of knowledge. Griffith, Redding and Van Reenen (200) present a general equilibrium model of endogenous growth through increasing productivity that incorporates both role of R&D investments. They augment the conventional quality ladder model to allows the size of innovations to be a function of the distance behind the technological frontier and an equation for TFP growth of the following form is derived:

$$\begin{aligned} \Delta \ln A_{ijt} = & \beta \Delta \ln A_{Fjt} - \delta_1 \ln \left( \frac{A_i}{A_F} \right)_{jt-1} - \delta_2 \left( \frac{R}{Y} \right)_{ijt-1} \ln \left( \frac{A_i}{A_F} \right)_{jt-1} - \delta_3 H_{ijt-1} \ln \left( \frac{A_i}{A_F} \right)_{jt-1} \\ & + \rho_1 \left( \frac{R}{Y} \right)_{ijt-1} + \rho_2 H_{ijt-1} + u_{ijt} \end{aligned} \quad (7)$$

Where the growth is TFP over a certain period of time  $\Delta \ln A_{ijt}$  depend of the knowledge adoption that is captured by the growth of the technological frontier  $\Delta \ln A_{Fjt}$  and interaction between technological gap  $\ln \left( \frac{A_i}{A_F} \right)_{jt-1}$  and R&D per unit of sectoral output  $\left( \frac{R}{Y} \right)_{ijt-1}$  as well as the interaction between technological gap  $\ln \left( \frac{A_i}{A_F} \right)_{jt-1}$  and human capital  $H_{ijt-1}$ . The level of human capital and R&D capture the absorptive capacity of the particular sector. The growth of TFP is also linked to knowledge creation that is explained by R&D  $\left( \frac{R}{Y} \right)_{ijt-1}$  and human capital stocks  $H_{ijt-1}$ .

### 3. Empirical setting and data description

The empirical specification of our methodology follows Nicoletti and Scarpetta (2003), Aghion et al. (2004), Griffith et al. (2006) and Bourlès et al. (2013), where TFP growth is modelled as follows:



$$\ln\left(\frac{TFP_{cst}}{TFP_{cst-1}}\right) = b_1 \ln\left(\frac{TFP_{st}^*}{TFP_{st-1}^*}\right) + b_2 \ln\left(\frac{TFP_{cst-1}}{TFP_{st-1}^*}\right) + b_3 H_{t-1} + b_4 H_{t-1} \ln\left(\frac{TFP_{cst-1}}{TFP_{st-1}^*}\right) + b_5 RD_{t-1} + b_6 RD_{t-1} \ln\left(\frac{TFP_{cst-1}}{TFP_{st-1}^*}\right) + b_7 X_{st-1} + d_s + d_{sc} + d_{ct} \quad (9)$$

where the subscripts  $c$ ,  $s$  are country and sector indexes respectively, while  $t$  denotes the time period taken to be 5 years. The level of total factor productivity is given by  $TFP$ , with  $TFP^*$  being leader’s total factor productivity. The variable  $H$  denotes the level of human capital stock as measured by the share of high skilled people to total employment, and  $RD$  is the level of R&D intensity as measured by the private expenditures per value added (output). We estimate equation (9) using the least square dummy approach (or within group estimator), where we also add three different types of dummy variables that capture industry specific fixed effects ( $d_s$ ), country-industry specific fixed effects ( $d_{sc}$ ) and country specific trends ( $d_{ct}$ ),.

The first two terms in equation (9) are standard in the literature and measure productivity growth at the frontier and the technological gap between the frontier and non-frontier sectors (“catch-up” term) respectively. The productivity growth of the technological leader captures the link between TFP growth for the catching-up sector through the innovation and knowledge spillovers. On the other hand, the catch-up term aims to explain how the adoption of new technologies affect the innovation process of sectors. The idea here is that there are greater potentials in adopting new technologies the higher the technological gap is. In other words, we assume that the adoption of existing technology and knowledge could occur via different channels (machinery and equipment, trade, employment, networks etc.) that show up in the productivity gap between industries.

Since there is no data on the number of patents per economic sector readily available we choose to use the R&D intensity directly in the econometric equation as another potential driver to multi-factor productivity. According to Griffith et al. (2006), R&D

usually plays two separate roles in this equation: firstly because higher R&D spending could create new knowledge and secondly because it facilitates the adoption of knowledge or technology created elsewhere. For this reason, we directly include in our regression the interaction of RD and productivity gap. Benhabib and Spiegel (2005) have also proposed a similar idea holds for human capital. On the hand, higher human capital could create more knowledge in the economy, on the other hand, could increase the ability of a firm to adopt new technologies. To check, therefore, the latter effect we decided to include another interacting in our regression term between human capital and productivity gap.

In the baseline specification described above we then investigate the impact of specific governmental policies by adding to the econometric model six different variables: a) barriers to trade and investments, b) barriers to entrepreneurship, c) state control, namely governmental distortion in the market such as price ceilings d) government-financed R&D expenditures, e) public expenditures on R&D, and finally f) public expenditures on education and social programs. To limit possible reverse causality and multi-collinearity problems the policy vector is lagged one period, which in our case we took this to be 5 years, and include each variable one by one. Each among these variables have received, in various different contexts, the attention of the literature with their effects being disputed, and thus no unanimity exists about their impact on TFP growth. The inclusion of these variables therefore serve to contribute in this debate, and thus offer new evidence about their impact based on a new data sample.

For our econometric exercise we combine four different databases that provide information about the variables of our model. For sectoral level data, we use the EU-KLEMS database which covers 28 countries of which most of them are OECD countries until the year 2015. Depending on the variable, the data series spans a wide time period from roughly 1970 for mainly Western European countries, Korea and Japan and from the 1990s from non-Western European countries.

In this database information is given for totally 107 categories of industries of which 37 categories form head categories on a 2-digit level of which one is a 1-digit level for total industries. The coverage for services counts 45 sectors in which both 3-and 2-digit category levels are included. Within the business services category 12 out of totally 32 represent head categories on a 2-digit level. The personal services category have in total 7 head categories on 2- digit level of which two services sector no data is given. We use the latest release of the database from end 2017 that uses NACE Rev2 sectoral classification that is presented in the table below.

For the sectoral analysis we grouped our industrial data into six different sectors and run different regression based on the sector specific sample. The sectors we decided to create are a) Traditional b) the high-, c) medium- and d) low-technology sectors, e) high knowledge intensity service sector and f) other services. The classification we used are presented in Table 1 and follow Eurostat's definitions where for the purpose of our analysis we put together the groups "High-technology" and "medium-high technology" together and call them "High-technology".

For measuring Human capital stock we used OECD country level data on the share of high skilled people to total employment. Regulation data rely on OECD's Product Market Regulation (PMR) dataset. The PMR dataset is an internationally-comparable set of indicators that measure the economy-wide regulatory and market environments in 34 OECD countries and in another 22 non-OECD countries in 1998, 2003, 2008 and 2013. Among those indicators we use the indices on state control, barriers to investments and trade, and on barriers to entrepreneurship. The scale of each index is 0-6 from least to most restrictive regulation. The state control index captures the degree of governments involvement in business operations. It includes, for example, information about the pervasiveness of state ownership, governments stakes in the largest firms operating within the network sectors (i.e. electricity, gas, rail and air transport,

postal services and communication), the degree of coercive regulation used by the government, price controls, existence of special voting rights by the government in privately-owned firms, and so on. The barriers to investments and trade index, as the name suggest, summarize information covering specific barriers to investments or trade and include barriers such as barriers to FDI, tariffs, differential treatment of foreign suppliers. Similarly, the barriers to entrepreneurship index, capture the scale of governmental regulation on issues related to the complexity of regulatory framework in setting up or dissolving a business, the administrative burdens on start-ups, as well as the regulatory protection of incumbents.

Finally, we supplement our dataset with OECD’s main science and innovation indicators (MSTI). From this database we use series on government-financed expenditures on R&D, on education and social programs as percentage of government budget allocations for R&D, and on government expenditures on R&D policies. For the regressions we dropped countries with few or no observations and created a database of an unbalanced panel of thirteen OECD countries between 1995-2015 period.

*Table 1 Sectoral classification used for econometric analysis*

<i>Sectoral classification</i>	<i>NACE Rev2 codes</i>	<i>Names of the sectors</i>
<i>Traditional</i>	A01 A02 A03 B	Products of agriculture, hunting and related services; Products of forestry, logging and related services; Fish and other fishing products; aquaculture products; support services to fishing; Mining and quarrying
<i>Low-technology manufacturing</i>	C10-C12 C13-C15 C16 C17 C18 C31_C32	Food products, beverages and tobacco products; Textiles, wearing apparel and leather products; Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials; Paper and paper products; Printing and recording services; Furniture; other manufactured goods

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727114

<i>Medium-technology manufacturing</i>	C19	C22	Coke and refined petroleum products; Rubber and plastics products;
	C23		Other non-metallic mineral products; Basic metals; Fabricated metal
	C24	C25	products, except machinery and equipment; Repair and installation
	C33		services of machinery and equipment
<i>High-technology manufacturing</i>	C21	C26	Basic pharmaceutical products and pharmaceutical preparations;
	C20		Computer, electronic and optical products; Chemicals and chemical
	C27	C28	products; Electrical equipment; Machinery and equipment n.e.c.;
	C29		Motor vehicles, trailers and semi-trailers; Other transport equipment
	C30		
<i>Knowledge intensive service sectors</i>	H50	H51	Water transport services; Air transport services; Publishing services;
	J58		Motion picture, video and television programme production services,
	J59_J60		sound recording and music publishing; programming and
	J61		broadcasting services; Telecommunications services; Computer
	J62_J63		programming, consultancy and related services; information services;
	K64		Financial services, except insurance and pension funding; Insurance,
	K65 K66		reinsurance and pension funding services, except compulsory social
	M69_M70		security; Services auxiliary to financial services and insurance
	M71 M72		services; Legal and accounting services; services of head offices;
	M73		management consulting services; Architectural and engineering
	M74_M75		services; technical testing and analysis services; Scientific research
	N78	N80-	and development services; Advertising and market research services;
	N82		Other professional, scientific and technical services; veterinary
	O84 P85		services; Employment services; Security and investigation services;
	Q86		services to buildings and landscape; office administrative, office
	Q87_Q88		support and other business support services; Public administration
R90-R92		and defense services; compulsory social security services; Education	
R93		services; Human health services; Social work services; Creative, arts	
		and entertainment services; library, archive, museum and other	
		cultural services; gambling and betting services; Sporting services and	
		amusement and recreation services	
<i>Other service sectors</i>	C33 D35		Repair and installation services of machinery and equipment;
	E36	E37-	Electricity, gas, steam and air-conditioning; Natural water; water
	E39		treatment and supply services
	F G45 G46		Sewerage; waste collection, treatment and disposal activities;
	G47 H49		materials recovery; remediation activities and other waste
H52 H53		management services; Constructions and construction works;	

I L68B	Wholesale and retail trade and repair services of motor vehicles and
L68A N77	motorcycles; Wholesale trade services, except of motor vehicles and
N79 S94	motorcycles; Retail trade services, except of motor vehicles and
S95 S96	motorcycles; Land transport services and transport services via
T U	pipelines; Warehousing and support services for transportation; Postal and courier services; Accommodation and food services; Real estate services (excluding imputed rent); Imputed rents of owner-occupied dwellings; Rental and leasing services; Travel agency, tour operator and other reservation services and related services; Services furnished by membership organizations; Repair services of computers and personal and household goods; Other personal services; Services of households as employers; undifferentiated goods and services produced by households for own use; Services provided by extraterritorial organizations and bodies

## 4. Results of the econometric analysis

We start the analysis by presenting our results for the traditional sector. In Column 1 of Table 2 below we present our estimates for the baseline model. Columns (2) – (7) incorporate our new estimates by adding one-by-one into baseline specification our chosen policy variables. We maintain the same style of presenting our results throughout the rest of this paper.

*Table 2 Results of econometric analysis for “Traditional sector” regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.14*	0.14*	0.14*	0.14*	-0.00	0.14*	0.07
Gap	-0.66***	-0.66***	-0.66***	-0.66***	-0.80***	-0.67***	-0.73***
HC	-1.65***	-1.65***	-1.65***	-1.65***	-1.74***	-1.67***	-1.80***
HC # Gap	-0.55	-0.55	-0.55	-0.55	-0.78*	-0.56	-0.43
RD	0.43	0.43	0.43	0.43	2.93	0.26	1.56
RD # Gap	2.54	2.54	2.54	2.54	4.99**	2.58	3.47**
State Control		0.42					
Barriers to Entrepreneurship			-1.54				
Barriers to Trade and Investment				-0.61			
Gov. Financed R&D expenditures					-3.15		

Education and Social Programs Gov. Expenditures Gov.						-0.05	
Expenditures on R&D							10.87
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	372	372	372	372	300	352	342
Adjusted $R^2$	0.535	0.535	0.535	0.535	0.571	0.511	0.585

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Looking at the baseline specification, our estimates show that technological spillovers and technological transfers are important for this sector. This can be seen by the statistically significant estimated coefficients of leader’s productivity growth, which aims to capture technological spillovers, and of the negative sign in the catch-up term, which captures growth potentials via the adoption processes of newly created knowledge. A unit increase in the growth rate of the leader can bring about 0.14 percentage increase in the productivity growth of this sector over the long-run. Respectively, a unit reduction in the productivity gap via the adoption of new technologies, increases the growth rate of TFP for this sector by about 0.66 percentage points. However, the effectiveness of technological transfers in increasing growth potentials are not, according to our evidence, necessarily linked to R&D expenditures or to human capital. Human capital itself is found to be rather detrimental to the growth dynamics of this sector, though if one controls for government financed R&D expenditures or for public investments in R&D, human capital seems to make the adoption of new technologies easier (Column 5). These latter policies, however, may well hinder the TFP development of this sector by nullifying the effects from technological spillovers or by letting more difficult to adopt new technologies via R&D expenditures as is captured by the positive sign in the interacting terms between the R&D and the productivity gap variables (Columns 5 and 7) .

With regards to policies, none was found to be particularly relevant as all of them are statistically insignificant at all levels.

This, however, may well be attributed to the nature of our data, which lacks sectoral specific information, and not necessary on the nature of these policies. Nevertheless, our evidence here is still useful, as we can explicitly see that broad based policies have a rather negligible role in affecting the rate of innovation at this particular sector. As we will see later, this outcome is a recurrent pattern in most of our regressions, and change only when all information across sectors is pooled.

Table 3 Results of econometric analysis for “High-technology industrial sector” regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.18***	0.18***	0.18***	0.18***	0.13**	0.17***	0.15***
Gap	-0.59***	-0.59***	-0.59***	-0.59***	-0.56***	-0.64***	-0.61***
HC	-7.30	-7.30	-7.30	-7.30	-7.03	-6.63	-7.49
HC # Gap	-0.24	-0.24	-0.24	-0.24	-0.11	-0.21	-0.14
RD	0.16	0.16	0.16	0.16	-0.86*	0.26	-0.29
RD # Gap	0.34	0.34	0.34	0.34	-0.36	0.43	0.02
State Control		0.38					
Barriers to Entrepreneurship			-1.41				
Barriers to Trade and Investment				-0.56			
Gov. Financed R&D expenditures					0.11		
Education and Social Programs Gov. Expenditures						-0.02	
Gov. Expenditures on R&D							0.54
Country- Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	744	744	744	744	600	704	684
Adjusted R <sup>2</sup>	0.750	0.750	0.750	0.750	0.764	0.750	0.764

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



A similar picture emerges when looking at the “High-Tech” manufacturing sector (Table 3). Technological spillovers and technological transfers, as in the case of the traditional sector, are important to the TFP growth. As before, the adoption of new technologies does not require human capital or other forms of investments. R&D expenditures themselves, also do not play any particular role, while they may well contribute negatively to the pace of technological innovation when financed by the government (Column 5). Most governmental policies, as in the previous case, are statistically insignificant and thus ineffective in increasing the growth rate of this sector. Guided by this evidence, we again cannot identify sector specific development policies according to our results.

*Table 4 Results of econometric analysis for “Medium-technology industrial sector” regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.05	0.05	0.05	0.05	-0.05	0.15	0.12
Gap	-0.90***	-0.90***	-0.90***	-0.90***	-1.02***	-0.98***	-0.90***
HC	3.39	3.39	3.39	3.39	-1.49	2.55	21.95
HC # Gap	-1.85**	-1.85**	-1.85**	-1.85**	-1.73**	-1.91**	-2.10***
RD	3.69	3.69	3.69	3.69	4.07	2.49	3.56
RD # Gap	0.27	0.27	0.27	0.27	0.94	-0.16	-1.44
State Control		-3.48					
Barriers to Entrepreneurs hip			12.88				
Barriers to Trade and Investment				5.11			
Gov. Financed R&D expenditures					-1.41		
Education and Social Programs Gov. Expenditures						0.44	
Gov. Expenditures on R&D							-14.31
Country- Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	572	568	568	572	460	542	527
Adjusted R <sup>2</sup>	0.472	0.476	0.476	0.472	0.521	0.543	0.485

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

For the “medium-tech” sector we find that technological transfers are the single most important factor affecting its TFP development (Table 4). Technological transfers that decrease the productivity gap by one unit, may well lead to as much

as a 0.90 percent increase in TFP growth. Unlike, the previous cases, however, for this sector human capital is now found to be linked to the adoption processes of new knowledge or technology, despite the fact that itself may well be an insignificant factor. This result goes through regardless of the policies being implement and is robust to all specifications we considered. Perhaps the most surprising finding from this analysis is that technological spillovers play no particular role in increasing the pace of innovation or of the technological efficiency of this sector. This, for example, can be attributed to the non-exposure to trade or a limited cross-border interaction. Similarly, as in the previous cases, no policies were found to be important in increasing the growth potentials of this sector, repeating therefore our earlier arguments about the ineffectiveness of broad measured policies.

*Table 2 Results of econometric analysis for “Low-technology industrial sector” regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.11***	0.10***	0.10***	0.11***	0.08*	0.10***	0.12***
Gap	-0.58***	-0.62***	-0.62***	-0.58***	-0.54***	-0.59***	-0.58***
HC	0.61	0.63	0.63	0.61	-1.75	0.50	8.22
HC # Gap	0.42	0.38	0.38	0.42	0.37	0.41	0.45
RD	0.86	0.63	0.63	0.86	-1.26	1.28	0.98
RD # Gap	0.52	0.34	0.34	0.52	-0.80	0.87	0.62
State Control		-1.51					
Barriers to Entrepreneurs hip			0.13				
Barriers to Trade and Investment				2.19			
Gov. Financed R&D expenditures					-0.56		
Education and Social Programs Gov. Expenditures						0.17	
Gov. Expenditures on R&D							-5.62
Country- Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	788	776	776	788	631	748	728
Adjusted R <sup>2</sup>	0.610	0.608	0.608	0.610	0.615	0.595	0.616

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 5 above shows the results for the last manufacturing sector considered in the present study, namely the “low-tech” sector. As in most other cases, both technological transfers and technological spillovers are found to be statistically significant, and thus important to the growth dynamics of this sector. Their effects are comparable to the magnitude found in the traditional sector, and seem relatively unchanged regardless the policy variable we control for. Again, neither human capital or R&D expenditures are linked to the process of the technological development and are found to be statistically insignificant. Similarly, the policy variables considered here are found ineffective in increasing the TFP growth of this sector, and hence playing no role to this sector’s innovation dynamics.

*Table 3 Results of econometric analysis for “Knowledge intensive services sector” regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.02*	0.02*	0.02*	0.02*	0.02	0.01	0.02
Gap	-0.43***	-0.44***	-0.44***	-0.43***	-0.51***	-0.43***	-0.44***
HC	0.00	0.00	0.00	0.00	0.05	-0.03	0.01
HC # Gap	0.04	0.03	0.03	0.04	0.06	0.04	0.04
RD	0.36**	0.91*	0.91*	0.36**	0.24*	0.36**	0.28*
RD # Gap	0.02	0.31	0.31	0.02	0.07	0.02	0.06
State Control		-0.75					
Barriers to Entrepreneurs hip			0.05				
Barriers to Trade and Investment				1.10			
Gov. Financed R&D expenditures					-0.14		
Education and Social Programs Gov. Expenditures						-0.00	
Gov. Expenditures on R&D							0.23
Country- Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1863	1831	1831	1863	1491	1766	1720
Adjusted R <sup>2</sup>	0.682	0.683	0.683	0.682	0.704	0.710	0.691

We now turn our discussion to the service sector, starting from the “Knowledge-intensive” sector (Table 6). Repeating the pattern from the previous analysis, our evidence here again suggests that technological transfers and spillovers from the

technological frontier are important to growth. Their magnitude, however, especially with regards to the spillover effects, are weaker compared to the previous sectors analyzed thus far, while technological spillovers are nullified once we control for government expenses (columns 5 – 7). Moreover, and unlike all previous cases, R&D expenditures are found to be important to knowledge creation but not necessary be associated with the process of adopting new technologies. Their effectiveness could be particularly strong and could increase the TFP growth of this sector, from 0.30 to about 0.91 percentage points after a percentage increase in R&D spending, once we control for barriers to trade or investment or to entrepreneurship (columns 2-3). We do not identify any case in which R&D expenditures could become insignificant, which is reassuring given that knowledge in this sector by default is a key input to the production of services. Despite, however, this finding human capital, as in most of the previous cases, is insignificant to the innovation dynamics and play no role either by itself or for the adoption of new technologies. With regards to policies, our results here again indicate that none of them could improve TFP growth of this sector.

*Table 4 Results of econometric analysis for “Other services sector” regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.00	0.00	0.00	0.00	-0.00	0.01	0.00
Gap	-0.48***	-0.52***	-0.52***	-0.48***	-0.49***	-0.49***	-0.50***
HC	-0.06	-0.05	-0.05	-0.06	-0.07	-0.04	-0.02
HC # Gap	-0.16	-0.16	-0.16	-0.16	-0.17	-0.13	-0.13
RD	2.61***	2.52***	2.52***	2.61***	2.65***	2.63***	2.80***
RD # Gap	4.44***	4.41***	4.41***	4.44***	3.26***	4.47***	4.24***
State Control		-0.40					
Barriers to Entrepreneurs hip			1.47				
Barriers to Trade and Investment				0.48			
Gov. Financed R&D expenditures					-0.17		
Education and Social Programs Gov. Expenditures						0.01	
Gov. Expenditures on R&D							0.53

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727114

Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1411	1391	1391	1411	1136	1333	1283
Adjusted $R^2$	0.719	0.732	0.732	0.719	0.728	0.700	0.729

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Finally, we conclude this section by looking at the last sector we used for the purpose of this analysis comprising all service industries which are not knowledge intensive. Compared to the knowledge intensive category, one key difference that emerges from our analysis is that technological spillovers are rather unimportant to this sector, hence mimicking the case of some other sectors like “medium-tech” manufacturing sector. Interestingly, R&D expenditures themselves seem to be important determinant to TFP. Their quantitative impact is found to be particular large, and much larger than the “knowledge-intensive” sector, being able to increase TFP growth by about 2.61 percentage points in the baseline regression when RD expenditures increase by one percent. Nevertheless, according to our results an increase in R&D spending for this sector it also makes more unlikely or more difficult to adopt technologies invented elsewhere. All these hold true, regardless the inclusion of policy variable or not, which found to play no role in the development of this sector.

We conclude our analysis by presenting the results from the pooled regression. This allow us to investigate how the overall picture looks like by pooling all available information. It is also a robustness check against the small size sample bias that the previous regressions might suffer, given the limited number of observations used in some of our earlier regressions.

*Table 5 Results of econometric analysis for pooled regressions*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D.TFP*	0.05	0.05	0.05	0.05	0.01	0.07	0.06
Gap	-0.77***	-0.79***	-0.79***	-0.77***	-0.88***	-0.82***	-0.80***
HC	0.06	0.04	0.04	0.06	0.12	0.09	0.06
HC # Gap	0.04	0.02	0.02	0.04	0.07	0.06	0.04
RD	0.76*	1.47*	1.47*	0.76*	0.49	0.82*	0.64
RD # Gap	0.19	0.73	0.73	0.19	0.24	0.12	0.13

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 727114

State Control		-0.79***					
Barriers to			-0.33***				
Entrepreneurs							
hip							
Barriers to				-1.15***			
Trade and							
Investment							
Gov. Financed					2.08***		
R&D							
expenditures							
Education and						0.00	
Social							
Programs Gov.							
Expenditures							2.15***
Gov.							
Expenditures							
on R&D							
Country-	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE							
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE							
Observations	5750	5682	5682	5750	4618	5445	5284
Adjusted R <sup>2</sup>	0.507	0.511	0.511	0.507	0.536	0.549	0.514

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 2 shows the main results of the pooled regression. While technological spillovers were found to be very relevant to some sectors, the fact that for some other industries – especially those classified as medium-tech and non-knowledge intensive service sectors - do not play any important role implies that their overall importance is not robust. This can be seen, for example, by the statistically insignificant coefficients we found for leader’s TFP growth as opposed to the estimated coefficients of the catch-up term, which looks a robust driver in accelerating innovation. Our evidence, therefore, identifies technological transfers into a common determinant, though with a varying degree of impact, of TFP growth for all sectors, whereas technological spillovers exhibit a much more varied pattern with their relevance to rather depend on the sector we wish to look at. In this respect, our results compare against most of the theoretical or empirical work that tests the assumptions of the Schumpeterian growth theory and which views technological spillovers as a key driver to TFP growth.

The creation of new knew knowledge or technologies is most likely to be stemming from private or public R&D expenditures. In all specifications, private R&D

expenditures are found to be statistically significant, unless we control for government expenses such as public R&D expenditures or government-financed R&D expenditures. The latter result is in line with the empirical work of Adams (1990), who showed that public R&D has positive impact on TFP growth. Consistent with earlier findings, human capital or RD spending still found to be unimportant factors in absorbing new technologies. Except the medium-tech sectors, we observe here that there is a systematic pattern rejecting the dual face hypothesis about the role of RD and of human capital in affecting TFP growth by increasing the likelihood of better absorbing new technologies (See Griffith et al. (2006) and Benhabib and Spiegel (2005)) . With regards to human capital, in particular, our results are in line with the hypothesis that human capital has become a largely irrelevant factor to TFP growth, most notably because of the decrease in the quality of education over the last few decades, as well as because of the decline in returns to education which affects labor productivity and, by extension, the capacity to absorb new knowledge (See Prichett (2001) ). Our analysis in this and previous sections, helps to establish that this pattern may well be a common development relevant to all sectors of the economy.

Our second key insight relates to the relevance of public policies. In the previous section we did not identify any particular policy that affects the TFP growth of specific sector. This does not hold true, once we pool all the information we have into one sample. Our pooled estimates suggests that most of these policies have their expected sign and are important to TFP growth.

Our results here, identify three key regulation policies that could have detrimental consequences to innovation. Theoretical and empirical studies suggests that should be an inverted U relationship between regulation and economic growth. That is, deregulating market products could improve growth potential up to particular point after which more regulation is required. In our case, state control,

which captures the case of regulating markets mostly via price caps or ceilings, found to have a rather negative impact to TFP growth across industries. A unit increase to the score index about the state control, may well bring a decline to TFP growth equal to about 0.79 percentage points.

A similar, but less severe, impact could result from policies that reduce market competition, for example, by making harder to set-up a business. The most severe regulatory policy according to our results, however, come from an increases in the barriers to trade or investments. This is not surprising, given that many key technological developments are attributed to an exchange of know-how between trading patterns, and therefore imposing any sort of barriers such as tariff could deter such an exchange and, by extension, reduce productivity growth. On the other hand, public expenditures such as those considered here, we find to be effecting in boosting productivity growth, at least when the full sample is utilized. Of particular interest here, is the relatively large scale on growth that expenditures such as public RD investments or government-sponsored private RD have on growth. Depending on which among these two public policies we look at, TFP growth could increase by about 2.08-2.15 percentage point placing, therefore, these public policies on top of the most effective policy measure in boosting technological innovation.

## 5. Practical implementation in the online tool

Previous sections of the deliverable have described the database, empirical setup and the results of econometric estimations for the multi-factor productivity equations of the six aggregated economic sectors: traditional, high-tech, medium-tech, low-tech, knowledge intensive and other services. The grouping of the economic sectors is based on their clustering according to the R&I intensity and has been done by Eurostat.



The six estimated regressions form the basis for the MONROE meta-model that calculates the development of sectoral productivity for each EU28 country separately as the function of changes in various policies. Our econometric estimations have resulted in some insignificant parameters for several economic sectors. In cases when the regression coefficients were insignificant we have replaced them with the coefficients from the pooled regression that we thought to be more reliable in these particular cases.

The six estimated regressions and calculations around them are implemented in Java script inside of the online interactive tool for the calculation of (1) baseline scenario until 2050 under the assumption of no policy changes and of (2) policy scenario until 2050 under the assumptions of changes in policies as specified by the users of the online tool via the policy leavers. The comparison between the values of the baseline and policy scenario informs the visualizations of the online tool. Under the baseline scenario in the online tool we assume that the share of higher educated (use as measure of human capital) as well as the R&I intensity increase each 5 year period with 1.8%. We also assume sector specific growth rates for the productivity of the leader. These growth factors are based on the averages from the historical data of EU-KLEMS.

In order to calculate the baseline scenario using sector specific regressions with the parameters estimated on EU-KLEMS and OECD database we use the starting values of the EU-KLEMS data by aggregated sector and country in combination with the OECD data for all EU28 countries separately for the year 2015. We proceed as follows in each 5 year time period starting from 2020 and ending with 2050:

1. Update the share of highly educated and R&I intensity by sector and country using the growth rate of 1.8%

2. Update the interaction terms between the share of highly educated and R&I intensity and the technological gap to the leader
3. Calculate the new 5 year growth rate of the multi-factor productivity for each of the sectors and EU28 countries separately based on the functional form and estimated coefficients described in the previous sections of the deliverable
4. Recalculate the multi-factor productivity (TFP) of sectors in EU28 countries on the basis of the new 5 year growth rate
5. Recalculate the productivity of the technological leader using exogenous growth rates by sector
6. Update the technological gap to the leader

Figure below presents the results of the baseline scenario for the high-tech industry in Germany. The growth rate of the TFP flattens after a number of time periods and the technological gap to the leader reduces over time and stabilizes as well.

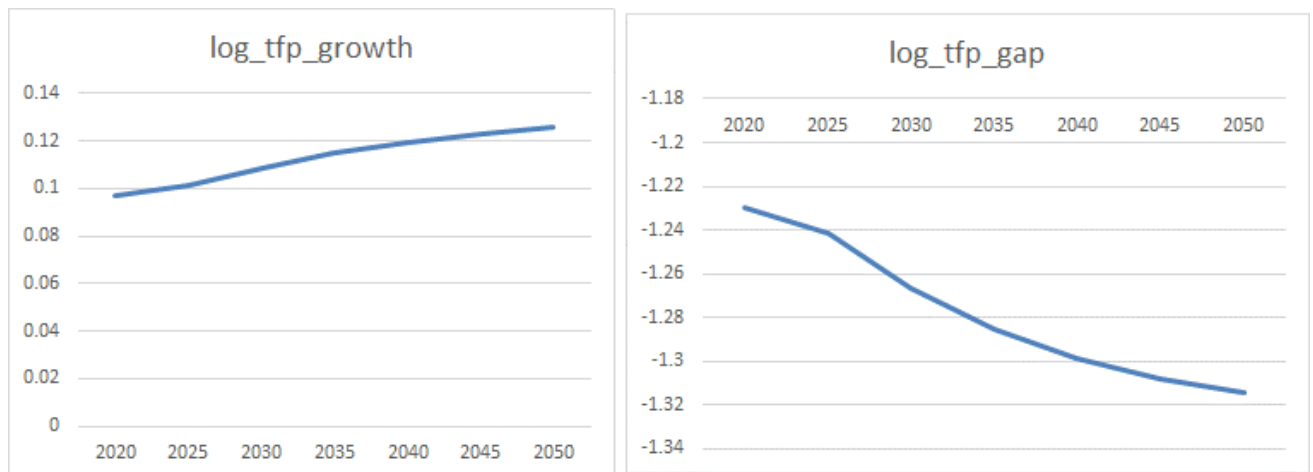


Figure 1 Development of growth rate of TFP and the technological gap to the technological leader for high-tech sector in Germany in the baseline scenario

Figure below provides the information about the baseline growth rates and the total value added (GDP) of EU28 countries in the period between 2015 and 2050 due to the increase in the sectoral multi-factor productivity TFP. These growth

rates are calculated using the following simple formula that updates the values of the sectoral value added based on the calculated changes in their TFP levels between 2015 and 2050:

$$VA\_growth = \frac{\sum_{sector} VA_{2015}^{sector} \cdot \frac{TFP_{2050}^{sector}}{TFP_{2015}^{sector}}}{\sum_{sector} VA_{2015}^{sector}} - 1 \quad (1)$$

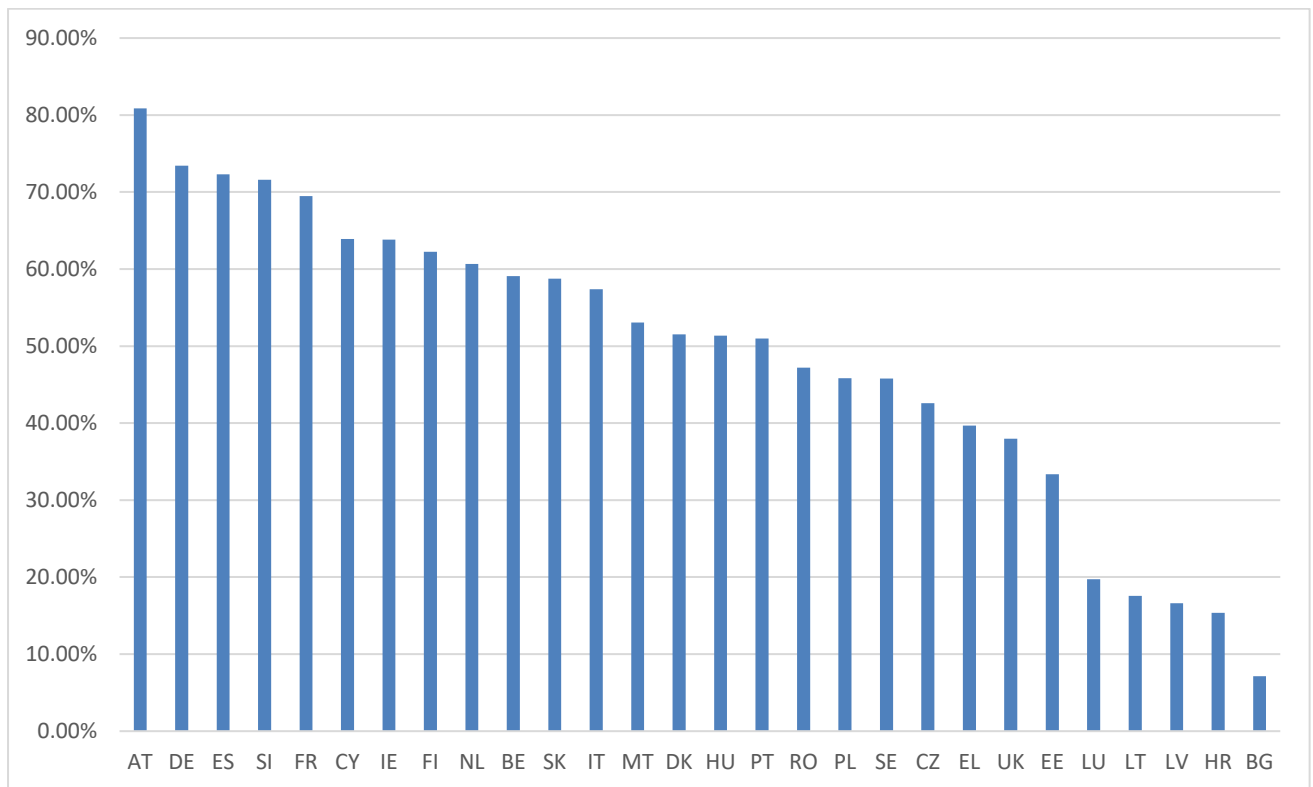


Figure 2 Growth rates of value added of the countries between 2015 and 2050 due to increased productivity of the sectors

The effects of the following policies can be illustrated using the online tool and changing its policy leavers:

- ✓ Barrier to entrepreneurship
- ✓ Barriers to trade and investment
- ✓ State Control
- ✓ Governmental subsidies to private R&D

- ✓ Public expenditures on education and welfare
- ✓ R&D expenditures in the Public Sector

These policies have been included into the multi-factor productivity regressions estimated on panel data using EU-KLEMS sectoral and OECD country-level data. The same step by step calculation procedure is followed as for the baseline scenario with the only difference that the values of the policies differ from the baseline ones (from the OECD database). Changes in policies result in deviations of the TFP developments from the baseline path and one can calculate the differences in TFP between the baseline and policy scenario for the year 2050 for each of the six sectors and each EU28 country. These differences drive the results of the visualizations in the interactive part of the online tool.

Changes in the value added of the sectors (and value added per hour worked) are directly attributed to the differences in TFP in 2050 between the baseline and policy scenarios. The overall country-level changes in the total value added (GDP) and the total value added per hour worked are calculated similar to the formula (1) above using the sum over the value added of the six aggregated groups of economic sectors.

$$VA\_growth = \frac{\sum_{sector} VA_{2015}^{sector} \cdot \frac{TFP_{2050}^{Sector, Policy}}{TFP_{2015}^{Sector}}}{\sum_{sector} VA_{2015}^{sector} \cdot \frac{TFP_{2050}^{Sector, Baseline}}{TFP_{2015}^{Sector}}} - 1 \quad (2)$$

## References

Acemoglu, Daron and Guerrieri, Veronica, (2008), Capital Deepening and Nonbalanced Economic Growth, Journal of Political Economy, 116, issue 3, p. 467-498,

Acemoglu D, Aghion P, Lelarge , Van Reenen J, Zilibotti, F (2007). "Technology, Information, and the Decentralization of the Firm," *The Quarterly Journal of Economics*, Oxford University Press, vol. 122(4), pages 1759-1799.

Adams, J. (1990), 'Fundamental stocks of knowledge and productivity growth', *Journal of Political Economy* No. 98(4), p. 673-702.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, 120(2), 701-728.

Aghion, Philippe, and Peter W. Howitt. *The economics of growth*. MIT press, 2008.

Baumol, William J., 1967. Performing arts: The permanent crisis, *Business Horizons*, Elsevier, vol. 10(3), pages 47-50.

Benhabib, Jess & Spiegel, Mark M., 2005."Human Capital and Technology Diffusion," *Handbook of Economic Growth*, in: Philippe Aghion & Steven Durlauf (ed.), *Handbook of Economic Growth*, edition 1, volume 1, chapter 13, pages 935-966, Elsevier.

Bond-Smith, S. C. (2014). *Innovation and Growth: Theoretical Models and Analytical Simulations of Spatial, Clustering and Competition Effects* (Thesis, Doctor of Philosophy (PhD)). University of Waikato, Hamilton

Herrendorf, Berthold & Herrington, Christopher & Valentinyi, Akos, 2013."Sectoral Technology and Structural Transformation," *CEPR Discussion Papers 9386*, C.E.P.R. Discussion Papers.

Havik, K., Mc Morrow, K., Röger, W., & Turrini, A. (2008). The EU-US total factor productivity gap: An industry perspective (No. 339). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Griffith R, Redding S, Van Reenen J (2004). "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries," *The Review of Economics and Statistics*, MIT Press, vol. 86(4), pages 883-895, November.

Kuznets, Simon (1973) *Modern Economic Growth: Findings and Reflections*, *American Economic Review*, American Economic Association, vol. 63(3), pages 247-258, June.

Loichinger E, (2015 ), Labor force projections up to 2053 for 26 EU countries, by age, sex, and highest level of educational attainment, Demographic research, Vol31 p.15.

Maddison, Angus, 1980. Monitoring the Labour Market: A Proposal for a Comprehensive Approach in Official Statistics (Illustrated by Recent Developments in France, Germany and the U.K.), Review of Income and Wealth, International Association for Research in Income and Wealth, vol. 26(2), pages 175-217, June.

Nelson, Richard R., and Edmund S. Phelps. "Investment in Humans, Technological Diffusion, and Economic Growth." The American Economic Review 56, no. 1/2 (1966): 69-75.

Nicoletti, G. and S. Scarpetta (2003), "Regulation, Productivity and Growth: OECD Evidence", Economic policy, 36, pp. 9-72, April  
Ngai, L, Pissarides, C (2007). "Structural Change in a Multisector Model of Growth," American Economic Review, American Economic Association, vol. 97(1), pages 429-443, March.

OECD (2016), 'Technological slowdown, technological divergence and public policy: A firm level perspective', ECO/CPE/WP1(2016)26.

Prichett, L. (2001), 'Where Has All the Education Gone?', World Bank Economic Review 15, 367-391

Rimmer, MT and Powell, AA (1992) *Demand Patterns Across the Development Spectrum: Estimates for the AIDADS System*. Working Paper. Centre of Policy Studies.

Stehrer , Dietzenbacher B, H.W.A. & Timmer, Marcel & Gaaitzen J. de Vries, 2014. "The World Input-Output Database: Content, Concepts and Applications," GGDC Research Memorandum GD-144, Groningen Growth and Development Centre, University of Groningen.

## Annex: Java code for calculations

```
const years = [2020,2025,2030,2035,2040,2045,2050];

// ----- constants from excel -----

const coeff_names =
["log_tfp_leader_growth","log_tfp_gap","years_schooling","years_schooling_log
_tfp_gap","i_rd_go","i_rd_go_log_tfp_gap","state_control","lbte","lbt","lg_f
gxgdp","lc_eduxcv","lgv_xgdp"]; // global

// ----- policy columns for table and for sliders -----

const policyColumns=["lbte", "lbt", "state_control", "lg_fgxdp",
"lc_eduxcv", "lgv_xgdp" ]

var countryNameById = d3.map();

var yAxis;

///// ----- functions-----

/*----- calculating values for all countries -----*/

function calculateNationalGDP(data, value_added, policies_variation,
policies_means, allCoefficients){
    // policy means are the difference between new and original values

    var allCountriesNationalGDP =[];
    // var test=[] //- FOR TESTING PURPOSES
    policies_variation.forEach(function(country){ // looping through
countries
        var allSectorsCalculated =[], nationalValues = [], allGDPData={};
        var country_policies_variation =
policies_variation.filter(function(k) {return k.cou == country.cou; })[0];

        sectors.forEach(function(sector, i){
            var sectorCountryData = data.filter(function(k){ return
k.sector == sector && k.cou == country.cou })[0];
            var sectorCountryValue_added =
value_added.filter(function(k){ return k.sector == sector && k.cou ==
country.cou })[0];
            var sectorCountryCoefficients =
allCoefficients.filter(function(k){ return k.sector == sector && k.cou ==
country.cou})[0];

            // calculating country values for one sector for all years
            var values = calculateSectorCountryValues(sectorCountryData,
Number(sectorCountryValue_added.va_per_sector),
```

```

Number(sectorCountryValue_added.gdp), country_policies_variation,
sectorCountryCoefficients,
Number(sectorCountryValue_added.VA_PerHourWorked_in_Euros))

        // looping through values to extract va for each year
        values.forEach(function(d) {
            if (i == 0) allGDPData[d.year] = d.va;    // create
year objects
            else allGDPData[d.year] += d.va;
        })
        allSectorsCalculated.push({"sector":sector,"values":values})
    })

    //----test.push(allSectorsCalculated)  //- FOR TESTING PURPOSES
    // once all sectors have been calculated, calculate shareVAtogDP
    allSectorsCalculated.forEach(function(g,i) {
        g.values.forEach(function(d) {
            d.shareVAtogDP = d.va / allGDPData[d.year];
        })
    })

    // looping through the years to calculate national values
    years.forEach(function(year) {
        var countryValues = {};
        countryValues.year = year;
        allSectorsCalculated.forEach(function(g,i) {
            countryValues.GDP = allGDPData[year]
        })
        nationalValues.push(countryValues)
    })

    allCountriesNationalGDP.push({'country':country.cou,'values':nationalVa
lues})
    })
    // -- download('test.json',JSON.stringify(test)) // - FOR TESTING
PURPOSES
    var GDP_2015;
    allCountriesNationalGDP.forEach(function(d) {
        VAperHourWorked = policies_means.filter(function(k) {return k.cou
== d.country; })[0]['VA_PerHourWorked_in_Euros']; //country value for va per
hour worked

        d.values.forEach(function(k,i) {
            if (i == 0) {
                GDP_2015 = k.GDP;
                k.VAperHourWorked = VAperHourWorked;
                k.GDPgrowth = 0;
            }
            else{
                k.GDPgrowth = (k.GDP- GDP_2015) / GDP_2015;
                k.VAperHourWorked = VAperHourWorked * (1 +
k.GDPgrowth);

```



```
        }
    })
})

return allCountriesNationalGDP;
}

/* ----- calculating values for single country-----*/

//// --- for sectors visualisation ----
function calculateAllSectorCountryValues(data, country_value_added,
country_policies_variation, allCoefficients ){
    // data is country related data
    // country_policies_variation is the difference between new value and
original value
    // country_value_added is country/sector related value_added
    // coefficients are country/sector related from the coefficients file

    var allSectorsCalculated =[], allGDPData={};

    sectors.forEach(function(sector,i){
        var sectorData = data.filter(function(k){ return k.sector ==
sector })[0];
        var sector_values = country_value_added.filter(function(d){ return
d.sector == sector })[0];
        var sectorCoefficients = allCoefficients.filter(function(d){
return d.sector == sector})[0];

        /// calculating country values for one sector for all years
        var values = calculateSectorCountryValues(sectorData,
Number(sector_values.va_per_sector), Number(sector_values.gdp),
country_policies_variation, sectorCoefficients,
Number(sector_values.VA_PerHourWorked_in_Euros))

        // looping through values to extract va for each year
        values.forEach(function(d){
            if (i == 0) allGDPData[d.year] = d.va;    // create year
objects
            else allGDPData[d.year] += d.va;
        })
        allSectorsCalculated.push({"sector":sector,"values":values})
    })
    //// ---- to be added here: calculation for VaperHourWorked

    allSectorsCalculated.forEach(function(g,i){
        g.values.forEach(function(d){
            d.shareVAtoGDP = d.va / allGDPData[d.year];
        })
    })
    return allSectorsCalculated;
}
```

```
function calculateSectorCountryValues(sectorData, VA_2015, GDP,
country_policies_variation, coefficients, VAperHourWorked_2015){
  var allYearsValues = [];
  var previousYearValues = cloneObject(sectorData);

  for (var property in country_policies_variation) { // difference with
original value, will be 0 first time or by reset
    if (country_policies_variation.hasOwnProperty(property) &&
property != "cou") {
      previousYearValues[property] =
Number(country_policies_variation[property])
    }
  }

  var annualGrowthRate = Number(sectorData['annual_growth_rate']);
  var mean_OECD_years_schooling =
Number(sectorData['mean_OECD_years_schooling']);

  // ----- calculated constants -----

  var growthRate_5 = Math.pow((1 + annualGrowthRate),5) -1;

  previousYearValues.year = 2015;
  previousYearValues.tfp_growth = previousYearValues.log_tfp_growth;
  previousYearValues.TFP_cumulative_growth = 1;
  previousYearValues.va = VA_2015;
  previousYearValues.vaPerHourWorked = VAperHourWorked_2015;
  TFP_2015 = previousYearValues.TFP;

  allYearsValues.push(previousYearValues)
  presentYearValues = {};

  years.forEach(function(year,i){
    //console.log(year)
    presentYearValues.year = year;
    if (year == 2020) { // in 2020 the same value as 2016 is used for
TFP_leader and log_tfp_gap
      presentYearValues.TFP_leader =
Number(previousYearValues.TFP_leader);
      presentYearValues.log_tfp_gap =
Number(previousYearValues.log_tfp_gap);
    }
    else {
      presentYearValues.TFP_leader =
Number(previousYearValues.TFP_leader) * (1 + growthRate_5);
      presentYearValues.log_tfp_gap =
Math.log(Number(previousYearValues.TFP) / presentYearValues.TFP_leader)
    }
    //

    presentYearValues.log_tfp_leader_growth = Math.log(1 +
growthRate_5)
```

```
        presentYearValues.years_schooling =
Number(previousYearValues.years_schooling) * (1 + mean_OECD_years_schooling);
        presentYearValues.i_rd_go = Number(previousYearValues.i_rd_go) *
(1 + mean_OECD_years_schooling);

        presentYearValues.years_schooling_log_tfp_gap =
presentYearValues.log_tfp_gap * presentYearValues.years_schooling;
        presentYearValues.i_rd_go_log_tfp_gap = presentYearValues.i_rd_go
* presentYearValues.log_tfp_gap; // changed this formula 23-1

        for (var policy in country_policies_variation) {
            if (country_policies_variation.hasOwnProperty(policy) &&
policy != "cou") {
                presentYearValues[policy] =
Number(country_policies_variation[policy]) // always same value for all years
            }
        }
        presentYearValues.tfp_growth = tfp_growth_calc(presentYearValues,
coefficients, coeff_names)+ Number(coefficients.intercept);
        presentYearValues.TFP = Number(previousYearValues.TFP) * (1 +
presentYearValues.tfp_growth)

        presentYearValues.TFP_cumulative_growth = presentYearValues.TFP /
TFP_2015;
        presentYearValues.va = VA_2015 *
presentYearValues.TFP_cumulative_growth;
        presentYearValues.vaPerHourWorked = VAPERhourWorked_2015 *
presentYearValues.TFP_cumulative_growth;
        presentYearValues.TFP_relative_growth = (presentYearValues.TFP -
TFP_2015) / TFP_2015

        previousYearValues = cloneObject(presentYearValues)
        allYearsValues.push(previousYearValues)
    })

    return allYearsValues;
}
function tfp_growth_calc(values, coefficients, coeff_names){
    var value = 0
    coeff_names.forEach(function(d,i){
        value += Number(coefficients[d]) * Number(values[d])
    })
    return value
}
function addLegend(gdpExtent, GDPpcExtent){

    //// legend
    var legendGDP =
d3.select('.legendGDP').append('svg').attr("height",115).attr("width",170)
```

```
var legendGDPpc =
d3.select('.legendGDPpc').append('svg').attr('viewBox', '0 0 350
50')//.attr("height",70).attr("width",350)

var gdpLegend =
legendGDP.append('g').attr('transform','translate(10,0)')
gdpLegend.selectAll('circle')
    .data(gdpExtent)
    .enter()
    .append('circle')
    .attr('r', function(d){ return sqrtScale(d)})
    .attr('fill','none')
    .attr('stroke','#888')
    .attr('cx', function(d,i) { return i * (2 * sqrtScale.range()[0] +
sqrtScale.range()[1]) + sqrtScale.range()[0]})
    .attr('cy', function(d){ return sqrtScale.range()[1] + 10})

gdpLegend.selectAll('text')
    .data(gdpExtent)
    .enter()
    .append('text')
    .attr('x', function(d,i) { return i * (2 * sqrtScale.range()[0] +
sqrtScale.range()[1]) + sqrtScale.range()[0]})
    .attr('y', function(d,i){ return (i == 0)? 90: 65 })
    .text(function(d){ return d3.format(",d")(d)})
    .attr('text-anchor','middle')

var GDPpcLegend =
legendGDPpc.append('g').attr('transform','translate(0,10)')

var col_range_low = colorScale(0), col_range_high =
colorScale(GDPpcExtent[1]*1.2);

var defs = GDPpcLegend.append("defs")

var linearGradient = defs.append("linearGradient")
    .attr("id", "linear-gradient");

linearGradient
    .attr("x1", "0%")
    .attr("y1", "0%")
    .attr("x2", "100%")
    .attr("y2", "0%");

linearGradient.append("stop")
    .attr("offset", "0%")
    .attr("stop-color", col_range_low);

linearGradient.append("stop")
    .attr("offset", "100%")
    .attr("stop-color", col_range_high);

GDPpcLegend.append("rect")
```

```
.attr("width", 347)
.attr("height", 16)
.style("fill", "url(#linear-gradient)");

GDPpcLegend.append("text").attr("class", "low-
country").attr('x', 0).attr('y', 30).attr('text-
anchor', 'start').text((GDPpcExtent[0]).toFixed(0)) // min value
GDPpcLegend.append("text").attr("class", "high-
country").attr('x', 347).attr('y', 30).attr('text-
anchor', 'end').text((GDPpcExtent[1]*1.2).toFixed(0))

///// policies sliders
}

function updateLegend(gdpExtent, GDPpcExtent){
  var legendGDP = d3.select('.legendGDP')
  var legendGDPpc = d3.select('.legendGDPpc')

  legendGDP.selectAll('text')
    .data(gdpExtent)
    .text(function(d) { return d3.format(",d")(d) })

}

///// ---- help functions--
function cloneObject(obj){
  var newObj = {};
  for (var property in obj) {
    if (obj.hasOwnProperty(property)) {
      newObj[property] = obj[property]
    }
  }
  return newObj;
}

/// --- resizing window ----
jQuery(window).on("resize", function() {
  var wrapperWidth =
d3.select('.chart').node().getBoundingClientRect().width;

  //console.log('wrapperWidth', wrapperWidth)

  var visWidth = wrapperWidth - margin.left- margin.right;
  d3.select('.vis').attr('width', wrapperWidth )

  if (layout== 'geo') {
    circleDist.range([visWidth/2 + margin.left, visWidth])
    scaleVis.attr('transform', 'translate('+ visWidth/2 +',0)')
    d3.select('.axisName').attr('transform',
'translate('+visWidth/2+')')
    var tickSize = -visWidth /2;
  }
  else {
```

```
        circleDist.range([paddingVis, visWidth]);
        var tickSize = -visWidth;
        if (layout == 'sectors')
            d3.selectAll('.sector').attr('transform', function(d,i){ return
'translate('+ circleDist(i) +', '+ growthScale(d.values[d.values.length -
1].TFP_relative_growth) +')' });
            else d3.selectAll('.country').attr('transform', function(d,i){
return 'translate('+ circleDist(i) +', '+ growthScale(d.values[d.values.length
- 1].GDPgrowth) +')' });
        }

        yAxis.call(d3.axisLeft(growthScale)
            .tickSize(tickSize)
            .ticks(5)
            .tickFormat(d3.format(".0%"))
        )

        yAxis.select(".domain").remove()
        yAxis.selectAll('text').attr('x',"30px").attr('dy',"-.4em")

        vertical.selectAll('.verticalLines').attr('transform', function(d,i){
return 'translate('+ circleDist(i) +', '+ visHeight +')' });

        if (wrapperWidth < 992) d3.selectAll('.policyColumn').classed('hidden',
true)
        else d3.selectAll('.policyColumn').classed('hidden', false)

    });

    //// file download
    function download(filename, text) {
        var element = document.createElement('a');
        element.setAttribute('href', 'data:text/plain;charset=utf-8,' +
encodeURIComponent(text));
        element.setAttribute('download', filename);

        element.style.display = 'none';
        document.body.appendChild(element);

        element.click();

        document.body.removeChild(element);
    }
```

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 727114