The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0144-3585.htm

Received 3 November 2023
Revised 5 June 2024
11 June 2024
Accepted 12 June 2024

Tangible, intangible assets and labour productivity growth

Chiara Castelli
Vienna Institute for International Economic Studies, Wien, Austria
Nicola Comincioli
Department of Economics and Management, Università degli Studi di Brescia, Brescia, Italy and
Fondazione Eni Enrico Mattei, Milano, Italy
Chiara Ferrante
University College Dublin, Dublin, Ireland, and
Nicola Pontarollo
Department of Economics and Management, Università degli Studi di Brescia, Brescia, Italy

Abstract

Purpose – The aim of this study is to investigate the contribution of tangible and intangible investments in driving labour productivity growth in the European Union over the period 2000–2017 and their role in the short and medium run. Additionally, heterogeneity across countries is accounted for by performing estimates separately for Eastern and Western European countries.

Design/methodology/approach – The methodology used to conduct the analysis of the determinants of productivity is the two-way fixed-effect and the system generalised method of moments. We also include country-specific dummies in place of our variable on national innovative capacity as a means to further reduce the number of instruments.

Findings – The results reveal a long-term relationship of investment in intangible assets with labour productivity growth, more specifically of investment in R&D. This relationship holds both when considering the whole set of European countries and for Western European countries, demonstrating that R&D is key to enhancing labour productivity growth. On the contrary, the effect for Eastern countries is negative, probably due to the lack of capacity to turn this investment into an efficient and effective way to foster productivity.

Originality/value – Besides confirming the well-known role of tangible and intangible assets in productivity, the heterogeneity shown in our analysis highlights the need for improving capabilities in Eastern countries. Diversifying the decisions on the investments in European countries, depending on the specific needs and their heterogeneity, could help bridge the productivity gap and enhance specific capabilities of the country systems.

Keywords European Union, Productivity, Intangible assets, Tangible assets

Paper type Research paper

1. Introduction

In recent decades, European countries experienced a slowdown in productivity (European Central Bank, 2017), struggling to drive investment growth. Though positive cyclical effects occurred between 2006 and 2007, the following Great Recession in 2008 saw European countries experiencing a combined decline both in labour productivity and in the whole economy (Hintzmann *et al.*, 2021). In understanding the reasons behind the prolonged decline, scholars have analysed, among the other possible drivers, the role of the accumulation of both

Journal of Economic Studies
Vol. 51 No. 9, 2024
pp. 272-289
Emerald Publishing Limited
0144-3585
DOI 10.1108/JES-11-2023-0620

tangible and intangible assets. On the one hand, tangible assets refer instead to information and communication technology (ICT), real estate and machinery. On the other hand, intangible assets mainly refer to research and development (R&D), computerised databases, know-how, innovation property, etc. Most of the studies analyse the role of R&D and ICT, providing evidence on how ICT, informatization and innovation play a leading role in driving productivity growth as well as investment in R&D, scientific activities and the use of knowledge (Hintzmann *et al.*, 2021; Corrado *et al.*, 2009, 2017, 2018; Roth, 2020).

European productivity slowdown contributed to widening the so-called “transatlantic EU–US productivity gap” (Ortega-Argilés, 2012; Cette *et al.*, 2016). While the US was able to increase productivity, thanks to investments in the knowledge economy, therefore transitioning towards the use and diffusion of ICT technologies, Europe lagged behind in the technological change, mainly due to the low ICT specialisation of the labour force, the rigidity of labour markets and the low capacity of firms to build or adopt new managerial practices (Ortega-Argilés, 2012; Cirillo and Guarascio, 2015). A combination of inadequate or delayed economic policies to deal with the financial crisis and the sovereign debt crisis exacerbated the divergence among European countries and their recovery (Gräbner *et al.*, 2020). Moreover, a productivity divergence is indeed visible also within Europe, in terms of differences in the production structure and also in the labour productivity growth, which leads to an increasing polarisation between “core” (Northern and Central EU countries such as Germany or Austria) and “peripheral” (Southern countries such as Italy or Greece) countries (Bruno *et al.*, 2021; Gräbner *et al.*, 2019). While Germany quickly restored the pre-crisis levels of production and income, Southern countries suffered indeed a long period of stagnation, being in 2019 still behind their pre-crisis level. Other examples, such as Ireland, Spain and Portugal, instead, started recovering after 2014, though with some problems. Relich (2017) highlights indeed how the impact of ICT on labour productivity is much greater in European transition economies entering the EU from 2004, such as Poland, the Czech Republic, Slovenia, with respect to EU15. The crisis period also highlighted heterogeneity among European countries from an industry-level perspective: German-centred core together with Central and Eastern European countries increased specialisation in technologically advanced tradable sectors (i.e. manufacturing). Southern countries, instead, shifted towards low-tech or non-tradable sectors (i.e. construction and market services). These countries suffered most therefore from the recession, and the subsequent sovereign debt crisis further worsened their economic conditions, especially in Italy, with a huge decrease in tangible investments.

This research aims at investigating the contribution of tangible and intangible investments in driving labour productivity growth in the European Union over the period 2000–2017 and their role in the short and medium run. Additionally, the nature of the relationship of tangible and intangible assets with labour productivity is examined as well as the duration of this relationship.

In the next Section, an overview of the main studies on the role of tangible and intangible investments on productivity and labour productivity growth is presented. Section 3 and 4 describe the data and methodology, respectively. Section 5 collects the results of the analyses carried out, while Section 6 draws conclusions and final remarks.

2. The relation between tangible and intangible assets and labour productivity

The literature on the role of tangible and intangible investment and their relationship with productivity growth is quite wide. For both categories of investment, many studies find a positive association with productivity growth. The seminal work of Griliches (1958) defines investments in R&D as one of the key drivers of productivity growth. Harhoff (1998) identifies R&D to have a positive and significant role on labour productivity, as well as Roth and Thum (2013), who demonstrate that intangible capital investment is positively related to labour productivity growth in Europe between 1998 and 2005. Bruno *et al.* (2021) show that R&D intensity is significantly and negatively associated with the productivity gap in the European Union, though the new Member States seem to take a smaller benefit. Since the first decades of the 1990s, many studies have emerged, analysing also the role of ICT as a catalyst for productivity growth. Dimelis and Papaioannou (2011) demonstrate the positive and significant effect of ICT on labour productivity growth and in country efficiency. This result is also confirmed by the results of Pieri *et al.* (2018), who prove how ICT contributes to reducing production inefficiency and generates inter-industry spillovers.

However, recently, many studies on the complementary effect of ICT and intangible investment are emerging. Corrado *et al.* (2017) find that the effect of intangible capital, R&D and innovative activities is greater when complemented with investment in ICT capital in ICT-intensive industries. Similarly, Zhu *et al.* (2021) demonstrate that in China both R&D and ICT positively affect innovation and, as a consequence, they also indirectly affect productivity, improving resource allocation and reducing costs. Hintzmann *et al.* (2021) find a general positive effect of intangible assets on labour productivity growth in European countries, and they also investigate the complementary effect of tangible and intangible assets as drivers of productivity growth. They demonstrate that this combination has positive effects on labour productivity, especially in Northern and Southern European regions, while there is no effect in central regions, where physical capital is the main driver of productivity. These results also suggest that investment's decisions should account for territorial heterogeneity.

3. Tangible and intangible assets and productivity in Europe

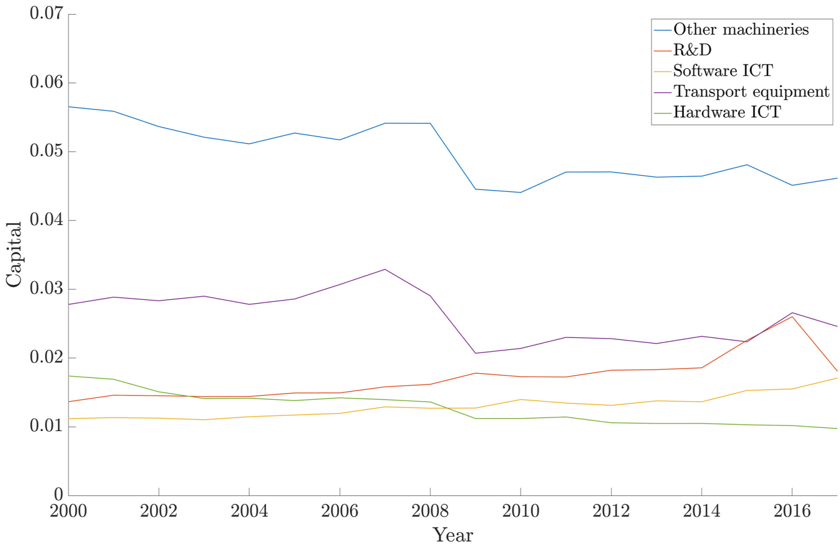
The dataset used for the analysis consists of balanced panel data coming from EU KLEMS [1], an annual-based dataset providing information on measures of economic growth, sectoral productivity and employment at industry level (NACE Rev.2), from 1995 to 2017, for all member countries of the EU. For the monetary measures, we adopt the power purchasing parities (PPPs) approach, developed by the joint International Comparison Programme (ICP) of the World Bank, Organisation for Economic Co-operation and Development (OECD) and Eurostat, which allows cross-country comparisons, accounting for the different price systems and returning the amount of local currency needed to purchase an equivalent level of utility across countries. To measure labour productivity, our outcome variable, we use the gross value added (GVA) per engaged person, taken in constant prices with 2010 as reference year and computed as the ratio of GVA with respect to the total number of people engaged. To measure the role of tangible assets, we distinguish between ICT and non-ICT investment. The former considers two assets: the first, which includes computers and hardware and telecommunication equipment, can be recognized as "hardware ICT", while the second is "software-ICT" and accounts for computer software and databases. Among non-ICT investments we have transportation equipment, given the importance of logistics and transportation and other machinery equipment and weapons related to the manufacturing sector, and not only. The role of intangible assets is, instead, measured by the investment in R&D. Since ICT contains computer software and databases, they cannot be included among intangible assets. Appendix 1 provides further details on the variables used, including the descriptive statistics.

Figure 1 shows the time trends of the tangible and intangible assets over the period 2020–2017. We observe that traditional tangible assets like machinery and transport equipment declined markedly with the financial crisis, while investments in software and R&D steadily increased. ICT, on the other hand, is constantly declining.

Figure 2 shows that in Europe productivity growth had a negative peak in 2009, in correspondence to the global financial crisis and, after an initial rebound, it stabilised to a level well below the pre-crisis trend. This means that EU countries are slowing down their productivity growth.

4. The model

The methodology used to conduct the analysis is the two-way fixed effect and the system generalised method of moments (GMM-system) (Arellano and Bover, 1995; Blundell and



Source(s): Authors' own work

Figure 1.
Tangible and intangible assets over gross value added 2000–2017 in EU28

Source(s): Authors' own work

Figure 2.
Productivity levels (left-axis) and growth (right-axis) 2000–2017 in EU28

Bond, 1998). Generally, GMM is implemented for both linear and nonlinear models and does not require the knowledge of the entire distribution of the variables, making it more efficient than the maximum likelihood methodology (Hansen, 1982). It relies on assumptions about the specific moments of the variables, called moment conditions, which are the expected values specifying the model's parameters in terms of the true moments. The GMM estimates the closest parameters to solving the weighted sample moment conditions. Since in this model the number of parameters is the same as the number of moment conditions, we use the one-step specification. Moreover, the choice of using the one-step GMM is also reinforced by the observation that, while certain asymptotic theories suggest the two-step approach as potentially more efficient, this superiority often becomes negligible in the context of finite sample sizes (Hansen and Lee, 2021; Hwang and Sun, 2018). We also introduce country-fixed effects to account for specific national trends. In our framework, a GMM-system is more suited than a GMM difference due to the high degree of persistence in our data (Roodman, 2009a). We also include country-specific dummies in place of our variable on national innovative capacity to further reduce the number of instruments. We obtain the standard equation for GVA per engaged person specified in levels with a lagged dependent variable:

$$lny_{i,t} = \beta lny_{i,t-1} + \eta Inv_i + \vartheta ln(0.03 + PopChg_i) + \delta Edu_i + \gamma CAPB_i + \phi Open_i + \tau_i + \epsilon_i \quad (1)$$

From Equation (1), as $\Delta lny_{i,t} = lny_{i,t} - lny_{i,t-1}$, the following empirical model for productivity growth can be derived:

$$\Delta lny_{i,t} = (\beta - 1) lny_{i,t-1} + \eta Inv_i + \vartheta ln(0.03 + PopChg_i) + \delta Edu_i + \gamma CAPB_i + \phi Open_i + \tau_i + \epsilon_i \quad (2)$$

where $i = 1, \cdots, N$ are the countries and $t = 1, \cdots, T$ are the years. Our dependent variable is the labour productivity growth rate $\Delta lny_{i,t}$, calculated as the logarithmic first difference between the GVA per engaged at year t and at year $t-1$. The right-side of the model contains the first lag of the log of GVA per engaged $\ln y_{i,t-1}$, then the investment in tangible or intangible assets Inv_i (at each stage we introduce ICT, non-ICT or R&D, respectively) or their temporal lag (from 1 to 3, in each specification), calculated as share of GVA. Furthermore, following the Solow model, we include the logarithm of the yearly population change $PopChg_i$ plus the common exogenous rate of technical change (g), which has been set equal to 0.03 in line with the literature originating from the Solow model (Heshmati, 2001; Kontsas and Mylonakis, 2009). As in the augmented Solow model, we also include a measure of human capital, such as the logarithm of the share of people with upper secondary education Edu_i (Bond *et al.*, 2001). In addition to the variables above, to improve the identification strategy of our model to avoid a significant risk of omitted variable bias, we considered adding two additional factors, accounting for fiscal policy $CAPB_i$ and trade openness $Open_i$, respectively. On the one hand, recent empirical literature has suggested that fiscal policy is a crucial determinant of productivity (Schoonackers and Heylen, 2011; Danquah *et al.*, 2014; Everaert *et al.*, 2015; Bardaka *et al.*, 2021; Carvelli, 2023a) because of the more general effect of government activity (Barro, 1990). In addition, fiscal policy also impacts productivity in an indirect way through investments (Afonso and Aubyn, 2010; Afonso and Jalles, 2015; Abiad *et al.*, 2016; Baussola and Carvelli, 2023; Carvelli, 2023b), which, in terms of tangible and intangible assets, are a key variable in our model. In doing so, we also take care of the issue of endogeneity of investment. To that end, we introduced in the model the cyclical adjusted primary balance (CAPB), [2] whose role in identifying discretionary fiscal policy adjustments is well recognized by scientific literature (Bardaka *et al.*, 2021). On the other hand, as economic openness is widely recognized to play a relevant role in accessing technology (Grossman and Helpman, 1993; Danquah *et al.*, 2014; Everaert *et al.*, 2015), including the openness index within our model can effectively help in capturing cross-country differences in terms of productivity. For this purpose, we used the openness to trade index, i.e. trade as a percentage of GDP [3].

Following Roodman (2009b), in the estimation of Equation (2), the lagged dependent variable is instrumented by its own past lags (from order 13 onwards). Furthermore, as we are estimating a growth model, following the literature we include education as an explanatory variable (Bond *et al.*, 2001). According to the authors, the use of this lagged variable is also possible as an instrument, providing more consistent estimates using the GMM. In our work, we have chosen tertiary education since it is relevant in affecting productivity (Nedić *et al.*, 2020), which is our focus. In addition, since the hiring process of highly skilled workers is costly and time-consuming, we do not expect tertiary education to be strictly exogenous. Thus, it is instrumented with its own lags (from order 13 onwards). This approach is aimed at avoiding instruments' proliferation [4]. Results of the analysis will be provided and discussed in the following section, where we estimate Equation (2) for the full sample of 23 countries [5] and for two subsamples, consisting of Western and Eastern European countries, to account for the possible heterogeneity due to the different levels of development of the two groups [6].

5. Results

This section shows the results of the analysis in the tables below. Firstly, the results of the investment in tangible and intangible assets on labour productivity growth are depicted. Secondly, we explore if these findings hold over the years and for how many years.

Tables 1–4 show our outcomes, taking one variable at a time, including the investigation of the role of investment, both simultaneous and lagged until order 3. Referring to Hansen

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	−0.000003	−0.000001	−0.000071*	−0.000017	−0.000010
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000086***	−0.000089***	−0.000006	−0.000058	−0.000086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000092***	0.000088***	0.000056***	0.000078***	0.000077***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.038966	−0.027890	−0.003441	−0.043909**	0.010858
	(0.0328)	(0.0327)	(0.0200)	(0.0204)	(0.0540)
Tertiary edu	−0.001388	−0.001492	−0.001709*	−0.001308	−0.002506
	(0.0011)	(0.0009)	(0.0010)	(0.0009)	(0.0015)
CAPB	−0.000544	−0.001323	−0.001116	−0.001627*	−0.000384
	(0.0008)	(0.0010)	(0.0010)	(0.0009)	(0.0018)
Openness	0.000481*	0.000435**	0.000434*	0.000350**	0.000647
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Inv. Computer hardw./ GVA	2.372510*				
	(1.3164)				
Inv. Mach./GVA		0.294647			
		(0.5469)			
Inv. R&D/GVA			1.450779***		
			(0.4910)		
Inv. Transp. Eq./GVA				0.918857***	
				(0.3523)	
Inv. Database/GVA					2.031217
					(2.4547)
Constant	−0.110315	−0.018216	0.184313*	−0.113683	0.264199
	(0.1981)	(0.1897)	(0.1061)	(0.1242)	(0.3266)
N	272	294	301	301	301
Instruments	17	17	17	17	17
Hansen, *p*-value	0.304151	0.298662	0.202174	0.287249	0.395333
AR(1) test, *p*-value	0.009921	0.007286	0.085892	0.050899	0.017328
AR(2) test, *p*-value	0.121875	0.105903	0.679640	0.194391	0.241127

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 1. GMM estimation results

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	−0.000005	−0.000001	0.000003	0.000003	−0.000006
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000076**	−0.000087***	−0.000088***	−0.000077*	−0.000088***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000087***	0.000089***	0.000083***	0.000082***	0.000085***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.045381	−0.033426	−0.033926*	−0.051983**	−0.016726
	(0.0364)	(0.0384)	(0.0206)	(0.0238)	(0.0543)
Tertiary edu	−0.001168	−0.001603	−0.001298	−0.000865	−0.001822
	(0.0015)	(0.0010)	(0.0009)	(0.0008)	(0.0019)
CAPB	−0.000012	−0.001221	−0.001598*	−0.001009	−0.001136
	(0.0009)	(0.0010)	(0.0008)	(0.0014)	(0.0016)
Openness	0.000470	0.000447*	0.000411**	0.000214	0.000526
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0004)
Inv. Computer hardw./GVA$_{-1}$	3.658096*				
	(2.1732)				
Inv. Mach./GVA$_{-1}$		0.508401			
		(0.9128)			
Inv. R&D/GVA$_{-1}$			0.194925		
			(0.5422)		
Inv. Transp. Eq./GVA$_{-1}$				1.798307**	
				(0.7328)	
Inv. Database/GVA$_{-1}$					0.972730
					(3.2340)
Constant	−0.184879	−0.054347	−0.040091	−0.210648	0.078028
	(0.2787)	(0.2290)	(0.1062)	(0.1769)	(0.3579)
N	271	294	301	301	301
Instruments	17	17	17	17	17
Hansen, *p*-value	0.360477	0.306646	0.239545	0.311909	0.310898
AR(1) test, *p*-value	0.023018	0.004321	0.006052	0.012417	0.015237
AR(2) test, *p*-value	0.177762	0.078145	0.105221	0.280840	0.147589

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 2.
GMM estimation results, lag 1

(2019), we added up to the third lag of the dependent variable to avoid autocorrelation (AR) of order 2 in the first-differenced residuals (Arellano and Bond, 1991). Furthermore, the *p*-value associated with the Hansen J-test (Hansen, 1982) is generally acceptable as its range is 0.15–0.30, pointing to the validity of our instruments (productivity and education lagged from the 13 onward).

Looking at the relationship between tangible assets and labour productivity growth, the coefficients are, in the beginning, positive and significant, in particular for the investments in computer hardware and telecommunication, transport equipment and other machinery and weapons. Computer software, instead, shows no significance in the coefficient, independently from the time lag considered, in contrast with the results presented by Corrado *et al.* (2013) and by Van Ark and Jäger (2017), but in line with the results obtained by Hintzmann *et al.* (2021). The role of computer hardware and telecommunication is positive and significant at the 10% level up to the first time lag, and then its significance increases to the 1% level from the second lag onwards. The role of other machinery and weapons appears instead to be non-significant, regardless of the lag considered for the estimation, and so does computerised software.

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	0.000002	0.000001	0.000007	0.000008	−0.000002
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000081***	−0.000081***	−0.000092***	−0.000064**	−0.000095***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000084***	0.000081***	0.000084***	0.000061**	0.000088***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.039950*	−0.031344	−0.035878*	−0.042208*	−0.014502
	(0.0235)	(0.0209)	(0.0191)	(0.0242)	(0.0337)
Tertiary edu	−0.000996	−0.001445	−0.001248	−0.000944	−0.001795
	(0.0013)	(0.0009)	(0.0010)	(0.0009)	(0.0013)
CAPB	0.000542	−0.001049	−0.001611*	−0.000419	−0.001088
	(0.0010)	(0.0010)	(0.0009)	(0.0013)	(0.0011)
Openness	0.000437	0.000415*	0.000404*	0.000236	0.000522
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Inv. Computer hardw./ GVA$_{-2}$	3.676103***				
	(1.2265)				
Inv. Mach./GVA$_{-2}$		0.507273			
		(0.4868)			
Inv. R&D/GVA$_{-2}$			0.037187		
			(0.8771)		
Inv. Transp. Eq./GVA$_{-2}$				1.707315*	
				(1.0003)	
Inv. Database/GVA$_{-2}$					1.065922
					(2.0045)
Constant	−0.169049	−0.055278	−0.056431	−0.157318	0.087454
	(0.1503)	(0.1499)	(0.1122)	(0.2085)	(0.1986)
N	270	294	301	301	301
Instruments	17	17	17	17	17
Hansen, *p*-value	0.494329	0.205703	0.252234	0.102340	0.235352
AR(1) test, *p*-value	0.012524	0.004285	0.003639	0.010341	0.004961
AR(2) test, *p*-value	0.206336	0.106313	0.073960	0.909765	0.083448

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 3. GMM estimation results, lag 2

The relationship between R&D and labour productivity is positive and significant at a 1% level when looking at the simultaneous relation. It however loses significance when the estimation is executed using the lags of R&D, regardless of the order. At this stage, this result appears not to be in line with previous studies at the European level (see Roth and Thum (2013) for example) suggesting that, while investment in tangible assets has a short-term and variable effect on labour productivity growth, investment in intangible assets, in particular in R&D, may have a prolonged effect in time.

To further dig into the relation between tangible and intangible assets on productivity growth, we interact our key variable with a geographical dummy for Eastern EU countries. Given the deep differences between the economic structures of Western and Eastern EU countries, with the latter being more reliant upon agriculture, manufacturing and other low-added value industries, we might expect a different productivity effect of tangible and intangible assets (Disdier and Mayer, 2004).

Tables 5–8 present the results over the years 1995–2017. In this model specification, the role of computer hardware and transportation is confirmed to be almost always positive, however significant only when interacted with the Eastern EU dummy variable and between

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	−0.000002	−0.000001	−0.000002	0.000012	0.000003
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000042	−0.000078***	−0.000112***	−0.000045	−0.000087***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000061*	0.000079***	0.000097***	0.000042	0.000086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.068575**	−0.028125*	−0.012620	−0.039596*	−0.041003*
	(0.0277)	(0.0166)	(0.0258)	(0.0223)	(0.0241)
Tertiary edu	0.000046	−0.001305	−0.001730*	0.000041	−0.001053
	(0.0019)	(0.0010)	(0.0010)	(0.0008)	(0.0014)
CAPB	0.000338	−0.001001	−0.001585*	−0.000089	−0.001766*
	(0.0012)	(0.0010)	(0.0010)	(0.0013)	(0.0010)
Openness	0.000267	0.000401*	0.000499**	0.000042	0.000373
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Inv. Computer hardw./ GVA$_{-3}$	5.390234***				
	(2.0845)				
Inv. Mach./GVA$_{-3}$		0.422114			
		(0.4167)			
Inv. R&D/GVA$_{-3}$			2.014214		
			(1.8607)		
Inv. Transp. Eq./GVA$_{-3}$				2.197790***	
				(0.7074)	
Inv. Database/GVA$_{-3}$					−0.397421
					(1.7864)
Constant	−0.427460*	−0.044207	0.117255	−0.240531	−0.094943
	(0.2487)	(0.1358)	(0.1585)	(0.1866)	(0.1703)
N	269	294	301	301	301
Instruments	17	17	17	17	17
Hansen, *p*-value	0.251975	0.341382	0.328066	0.156155	0.452883
AR(1) test, *p*-value	0.027226	0.007837	0.005105	0.002317	0.004596
AR(2) test, *p*-value	0.222882	0.168992	0.078869	0.498832	0.073170

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 4.
GMM estimation results, lag 3

first and second lag. This result confirms the findings of Relich (2017) and Dimelis and Papaioannou (2011) in transition economies, where computer hardware and telecommunications have a positive impact on labour productivity growth and in reducing country inefficiencies. Moreover, the previously found low significance of other machinery and weapons and computerised software is confirmed, regardless of the interaction term. The results about R&D are however quite interesting. We notice that this variable is positive and significant for the Western EU countries for the simultaneous effect as well as for the first and third lags. This result confirms the well-known persistence of R&D on these countries (Roth and Thum, 2013). With regard to Eastern EU countries, the effect inferred by the interaction variable is negative and significant, with the only exception of the second lag. These results confirm how the R&D effect can be region-specific (Spithoven and Merlevede, 2023).

The differences highlighted by the interaction with the Eastern EU dummy variable are aligned with the results by Hintzmann *et al.* (2021), who found that in Northern European regions the role of intangible assets is key and, in particular, investing in R&D leads to an increase in labour productivity, as it happens also in the Western countries considered in the analysis. In Southern regions, which also include Eastern countries, they find that both

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	0.000002	0.000001	−0.000054	−0.000007	−0.000004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000087***	−0.000090***	−0.000020	−0.000065**	−0.000086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000089***	0.000087***	0.000066***	0.000078***	0.000081***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.028608	−0.022339	−0.020636	−0.033575*	−0.016323
	(0.0238)	(0.0241)	(0.0167)	(0.0193)	(0.0273)
Tertiary edu	−0.001776	−0.001544	−0.001488	−0.001810*	−0.002008
	(0.0013)	(0.0013)	(0.0011)	(0.0011)	(0.0017)
CAPB	−0.000057	−0.000971	−0.001216	−0.001128	−0.001057
	(0.0011)	(0.0011)	(0.0009)	(0.0010)	(0.0010)
Openness	0.000416*	0.000390	0.000415*	0.000320	0.000544
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0004)
East EU	−0.005737	−0.006102	0.040838	0.014313	0.008338
	(0.0546)	(0.0413)	(0.0376)	(0.0360)	(0.0632)
Inv. Computer hardw./GVA	0.143312				
	(1.9463)				
East EU × Inv. Computer hardw./GVA	2.667713				
	(2.1268)				
Inv. Mach./GVA		−0.108674			
		(0.5825)			
East EU × Inv. Mach./GVA		0.331227			
		(0.7736)			
Inv. R&D/GVA			0.983618**		
			(0.4251)		
East EU × Inv. R&D/GVA			−3.280805*		
			(1.8286)		
Inv. Transp. Eq./GVA				0.237657	
				(0.6440)	
East EU × Inv. Transp. Eq./GVA				0.744901	
				(0.7536)	
Inv. Database/GVA					1.124845
					(1.4826)
East EU × Inv. Database/GVA					−0.489219
					(1.5474)
Const	−0.032648	0.028963	0.039459	−0.053476	0.086931
	(0.1308)	(0.1147)	(0.1047)	(0.1080)	(0.1463)
N	272	294	301	301	301
Instruments	19	19	19	19	19
Hansen, *p*-value	0.235051	0.293465	0.270642	0.294174	0.267499
AR(1) test, *p*-value	0.004612	0.004928	0.018446	0.025527	0.007213
AR(2) test, *p*-value	0.106015	0.091665	0.783224	0.127456	0.124252

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 5. GMM estimation results with interaction for Eastern Europe

tangible and intangible assets contribute to labour productivity. Moreover, our study surprisingly highlights a negative relationship of R&D with labour productivity growth in Eastern European countries, which might be due to the difficulty of transforming this kind of investment into revenues (Samoilenko, 2008). In the next section, we will discuss these results and conclude.

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	−0.000002	0.000000	−0.000004	−0.000001	−0.000008
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000066**	−0.000091***	−0.000074***	−0.000073***	−0.000088***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000080***	0.000088***	0.000077***	0.000077***	0.000084***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.039995*	−0.022759	−0.023323	−0.029179	−0.012587
	(0.0238)	(0.0243)	(0.0165)	(0.0182)	(0.0269)
Tertiary edu	−0.001676	−0.001496	−0.001341	−0.001304	−0.001759
	(0.0012)	(0.0013)	(0.0010)	(0.0009)	(0.0016)
CAPB	0.000825	−0.000861	−0.001115	−0.000740	−0.001149
	(0.0012)	(0.0012)	(0.0009)	(0.0013)	(0.0010)
Openness	0.000357	0.000398*	0.000311*	0.000354	0.000556
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
East EU	−0.009446	−0.020726	0.055815	−0.033434	−0.003775
	(0.0557)	(0.0491)	(0.0385)	(0.0465)	(0.0604)
Inv. Computer hardw./GVA$_{-1}$	0.910217				
	(1.8730)				
East EU × Inv. Computer hardw./GVA$_{-1}$	4.203294**				
	(1.9806)				
Inv. Mach./GVA$_{-1}$		−0.152411			
		(0.7130)			
East EU × Inv. Mach./GVA$_{-1}$		0.514845			
		(1.0034)			
Inv. R&D/GVA$_{-1}$			0.875413**		
			(0.4146)		
East EU × Inv. R&D/GVA$_{-1}$			−3.248405*		
			(1.7828)		
Inv. Transp. Eq./GVA$_{-1}$				0.156424	
				(0.7010)	
East EU × Inv. Transp. Eq./GVA$_{-1}$				1.932710**	
				(0.9627)	
Inv. Database/GVA$_{-1}$					1.102269
					(1.5687)
East EU × Inv. Database/GVA$_{-1}$					−0.278818
					(1.9724)
Const	−0.141133	0.031167	−0.014128	−0.058370	0.101330
	(0.1538)	(0.1107)	(0.0951)	(0.1111)	(0.1576)
N	271	294	301	301	301
Instruments	19	19	19	19	19
Hansen, *p*-value	0.526516	0.232180	0.176579	0.700655	0.251600
AR(1) test, *p*-value	0.013002	0.004605	0.003106	0.005910	0.011219
AR(2) test, *p*-value	0.235904	0.100108	0.082824	0.312021	0.126891

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 6. GMM estimation results with interaction for Eastern Europe, lag 1

Finally, even though our panel is balanced, as there are missing values in Tables B1 to B8 in Online Appendix 2, we run our GMM estimates via the forward-orthogonal deviations, a technique that is robust to the presence of many missing values (see Roodman, 2009b). In Table B9 to B16 we run a fixed effect model. Results hold in both cases.

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	−0.000004	0.000001	0.000016	0.000007	−0.000004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000069**	−0.000089***	−0.000094***	−0.000065***	−0.000093***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000080***	0.000082***	0.000080***	0.000058**	0.000087***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.035589**	−0.019441	−0.026856	−0.019147	−0.013898
	(0.0175)	(0.0144)	(0.0185)	(0.0152)	(0.0265)
Tertiary edu	−0.000836	−0.001276	−0.001637	−0.000408	−0.001733
	(0.0013)	(0.0011)	(0.0015)	(0.0008)	(0.0016)
CAPB	0.001392	−0.000858	−0.000928	−0.000863	−0.001142
	(0.0013)	(0.0010)	(0.0009)	(0.0011)	(0.0010)
Openness	0.000358	0.000395*	0.000278	0.000386	0.000532
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
East EU	−0.048325	−0.033599	0.070019	−0.084041	0.000501
	(0.0322)	(0.0630)	(0.0516)	(0.0640)	(0.0626)
Inv. Computer hardw./GVA$_{-2}$	1.123925				
	(1.3510)				
East EU × Inv. Computer hardw./GVA$_{-2}$	4.984967***				
	(1.6721)				
Inv. Mach./GVA$_{-2}$		−0.208040			
		(0.7744)			
East EU × Inv. Mach./GVA$_{-2}$		0.592450			
		(1.0273)			
Inv. R&D/GVA$_{-2}$			0.945141		
			(1.0168)		
East EU × Inv. R&D/GVA$_{-2}$			−3.212976		
			(2.0240)		
Inv. Transp. Eq./GVA$_{-2}$				−0.377223	
				(0.6512)	
East EU × Inv. Transp. Eq./GVA$_{-2}$				3.058210**	
				(1.2987)	
Inv. Database/GVA$_{-2}$					1.097806
					(1.4472)
East EU × Inv. Database/GVA$_{-2}$					−0.327040
					(1.9669)
Constant	−0.152747	0.045695	−0.032078	−0.055342	0.088234
	(0.1202)	(0.0754)	(0.1034)	(0.0863)	(0.1476)
N	270	294	301	301	301
Instruments	19	19	19	19	19
Hansen, *p*-value	0.620521	0.225502	0.229800	0.192000	0.208730
AR(1) test, *p*-value	0.020750	0.005232	0.002214	0.002989	0.007155
AR(2) test, *p*-value	0.480680	0.131439	0.060977	0.721638	0.103189

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 7. GMM estimation results with interaction for Eastern Europe, lag 2

6. Conclusion

The results obtained in the previous sections reveal a long-term relationship of investment in intangible assets with labour productivity growth, more specifically of investment in R&D. This relationship holds both when considering the whole set of European countries and the Eastern countries. For the Western Europe countries, we demonstrate that R&D is key to

	(1)	(2)	(3)	(4)	(5)
Log(GVA/engaged)$_{-1}$	0.000002	0.000001	−0.000054	−0.000007	−0.000004
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-2}$	−0.000087***	−0.000090***	−0.000020	−0.000065**	−0.000086***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(GVA/engaged)$_{-3}$	0.000089***	0.000087***	0.000066***	0.000078***	0.000081***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log(pop.change)	−0.028608	−0.022339	−0.020636	−0.033575*	−0.016323
	(0.0238)	(0.0241)	(0.0167)	(0.0193)	(0.0273)
Tertiary edu	−0.001776	−0.001544	−0.001488	−0.001810*	−0.002008
	(0.0013)	(0.0013)	(0.0011)	(0.0011)	(0.0017)
CAPB	−0.000057	−0.000971	−0.001216	−0.001128	−0.001057
	(0.0011)	(0.0011)	(0.0009)	(0.0010)	(0.0010)
Openness	0.000416*	0.000390	0.000415*	0.000320	0.000544
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0004)
East EU	−0.005737	−0.006102	0.040838	0.014313	0.008338
	(0.0546)	(0.0413)	(0.0376)	(0.0360)	(0.0632)
Inv. Computer hardw./GVA$_{-3}$	0.143312 (1.9463)				
East EU × Inv. Computer hardw./GVA$_{-3}$	2.667713 (2.1268)				
Inv. Mach./GVA$_{-3}$		−0.108674			
		(0.5825)			
East EU × Inv. Mach./GVA		0.331227 (0.7736)			
Inv. R&D/GVA			0.983618**		
			(0.4251)		
East EU × Inv. R&D/GVA$_{-3}$			−3.280805* (1.8286)		
Inv. Transp. Eq./GVA$_{-3}$				0.237657 (0.6440)	
East EU × Inv. Transp. Eq./GVA$_{-3}$				0.744901 (0.7536)	
Inv. Database/GVA$_{-3}$					1.124845
					(1.4826)
East EU × Inv. Database/GVA$_{-3}$					−0.489219 (1.5474)
Constant	−0.032648	0.028963	0.039459	−0.053476	0.086931
	(0.1308)	(0.1147)	(0.1047)	(0.1080)	(0.1463)
N	272	294	301	301	301
Instruments	19				
Hansen, *p*-value	0.235051	0.293465	0.270642	0.294174	0.267499
AR(1) test, *p*-value	0.004612	0.004928	0.018446	0.025527	0.007213
AR(2) test, *p*-value	0.106015	0.091665	0.783224	0.127456	0.124252

Note(s): Standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Instruments are the log of GVA per engaged person and tertiary education, going from the 13th to 18th lags
Source(s): Authors' own work

Table 8.
GMM estimation results with interaction for Eastern Europe, lag 3

enhancing labour productivity growth, while the effect for Eastern countries is negative, probably due to the lack of capacity to turn this investment into an efficient and effective way to foster productivity. Investment in computer hardware and telecommunication and in tangible assets positively impact labour productivity growth in all countries, while having a variable persistence.

These findings are in line with the literature, confirming the studies of Roth and Thum (2013), Bruno *et al.* (2021) and Relich (2017) on the contribution of tangible and intangible assets to productivity. Our results suggest that investment in R&D, mostly connected to competences and "know-how", is particularly effective in Western countries yet needs to be incentivized. However, the heterogeneity showed in our analysis highlights the need for improving capabilities in Eastern countries. Regarding investment in computer hardware and telecommunication and tangible assets, policies should aim at making them able to contribute to labour productivity growth, especially in transition economies. Diversifying the decisions on the investments in European countries, depending on the specific needs and their heterogeneity, could help bridge the productivity gap and enhance specific capabilities of the country systems (Peiró-Palomino, 2016).

Notes

1. The EU KLEMS database is run by the Vienna Institute for International Economic Studies (WIIW) in accordance with the European Commission DG Economic and Financial Affairs. For further information, please visit the website: https://euklems.eu/.
2. See: https://data.imf.org/.
3. See: https://wits.worldbank.org/visualization/openness-to-trade-visualization.html.
4. As customary for system GMM, we used both levels and differences of our instruments (Bond *et al.*, 2001).
5. Belgium, Croatia, Slovenia and Malta were excluded because they do not have data on tangible and intangible assets, while Luxemburg has not been included due to its small size (Gómez-Tello *et al.*, 2020).
6. Western European countries include Austria, Germany, Denmark, Greece, Spain, Finland, France, Ireland, Italy, the Netherlands, Portugal, Sweden and the UK; Eastern European countries include Bulgaria, Cyprus, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia.

References

Abiad, A.A., Furceri, D. and IMF, P.T. (2016), "The macroeconomic effects of public investment: evidence from advanced economies", *Journal of Macroeconomics*, Vol. 50, pp. 224-240, doi: 10.1016/j.jmacro.2016.07.005.

Afonso, A. and Aubyn, M. St. (2010), "Public and private investment rates of return: evidence for industrialized countries", *Applied Economics Letters*, Vol. 17 No. 9, pp. 839-843, doi: 10.1080/13504850802599425.

Afonso, A. and Jalles, J.T. (2015), "How does fiscal policy affect investment? Evidence from a large panel", *International Journal of Finance & Economics*, Vol. 20 No. 4, pp. 310-327, doi: 10.1002/ijfe.1518.

Arellano, M. and Bond, S. (1991), "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations", *The Review of Economic Studies*, Vol. 58 No. 2, pp. 277-297, doi: 10.2307/2297968.

Arellano, M. and Bover, O. (1995), "Another look at the instrumental variables estimation of error components models", *Journal of Econometrics*, Vol. 68 No. 1, pp. 29-51, doi: 10.1016/0304-4076(94)01642-d.

Bardaka, I., Bournakis, I. and Kaplanoglou, G. (2021), "Total factor productivity (TFP) and fiscal consolidation: how harmful is austerity?", *Economic Modelling*, Vol. 94, pp. 908-922, doi: 10.1016/j.econmod.2020.02.032.

Barro, R.J. (1990), "Government spending in a simple model of endogeneous growth", *Journal of Political Economy*, Vol. 98 No. 5, Part 2, pp. S103-S125, doi: 10.1086/261726.

Baussola, M. and Carvelli, G. (2023), "Public and private investments: long-run asymmetric effects in France and the US", *Finance Research Letters*, Vol. 58, 104317, doi: 10.1016/j.frl.2023.104317.

Blundell, R. and Bond, S. (1998), "Initial conditions and moment restrictions in dynamic panel data models", *Journal of Econometrics*, Vol. 87 No. 1, pp. 115-143, doi: 10.1016/s0304-4076(98)00009-8.

Bond, S., Hoeffler, A. and Temple, J. (2001), "GMM estimation of empirical growth models, C.E.P.R.", Discussion Papers, No. 3048, University of Bristol, Bristol, UK.

Bruno, R.L., Douarin, E., Korosteleva, J. and Radosevic, S. (2021), "The two disjointed faces of R&D and the productivity gap in Europe", *Journal of Common Market Studies*, Vol. 60 No. 3, pp. 580-603.

Carvelli, G. (2023a), "Fiscal adjustments and TFP dynamics: addressing reverse causality within a heterogeneous panel framework with global shocks", *Journal of Economic Studies*, Vol. 51 No. 9, pp. 112-136, doi: 10.1108/jes-08-2023-0447.

Carvelli, G. (2023b), "The dynamic effects of public investments on private capital formation: modelling a heterogeneous asymmetric cointegration with unobserved global factors", *International Economics*, Vol. 177, 100473, doi: 10.1016/j.inteco.2023.100473.

Cette, G., Fernald, J. and Mojon, B. (2016), "The pre-Great Recession slowdown in productivity", *European Economic Review*, Vol. 88, pp. 3-20, doi: 10.1016/j.euroecorev.2016.03.012.

Cirillo, V. and Guarascio, D. (2015), "Jobs and competitiveness in a polarised Europe", *Intereconomics*, Vol. 50 No. 3, pp. 156-160, doi: 10.1007/s10272-015-0536-0.

Corrado, C., Hulten, C. and Sichel, D. (2009), "Intangible capital and US economic growth", *Review of Income and Wealth*, Vol. 55 No. 3, pp. 661-685, doi: 10.1111/j.1475-4991.2009.00343.x.

Corrado, C., Haskel, J., Jona-Lasinio, C. and Iommi, M. (2013), "Innovation and intangible investment in Europe, Japan, and the United States", *Oxford Review of Economic Policy*, Vol. 29 No. 2, pp. 261-286, doi: 10.1093/oxrep/grt017.

Corrado, C., Haskel, J. and Jona-Lasinio, C. (2017), "Knowledge spillovers, ICT and productivity growth", *Oxford Bulletin of Economics and Statistics*, Vol. 79 No. 4, pp. 592-618, doi: 10.1111/obes.12171.

Corrado, C., Haskel, J., Jona-Lasinio, C. and Iommi, M. (2018), "Intangible investment in the EU and US before and since the Great Recession and its contribution to productivity growth", *Journal of Infrastructure, Policy and Development*, Vol. 2 No. 1, pp. 11-36, doi: 10.24294/jipd.v2i1.205.

Danquah, M., Moral-Benito, E. and Ouattara, B. (2014), "TFP growth and its determinants: a model averaging approach", *Empirical Economics*, Vol. 47 No. 1, pp. 227-251, doi: 10.1007/s00181-013-0737-y.

Dimelis, S. and Papaioannou, S. (2011), "Technical efficiency and the role of ICT: a comparison of developed and developing countries", *Emerging Markets Finance and Trade*, Vol. 47, sup3, pp. 40-53, doi: 10.2753/ree1540-496x4704s303.

Disdier, A.C. and Mayer, T. (2004), "How different is Eastern Europe? Structure and determinants of location choices by French firms in Eastern and Western Europe", *Journal of Comparative Economics*, Vol. 32 No. 2, pp. 280-296, doi: 10.1016/j.jce.2004.02.004.

European Central Bank (2017), *The Slowdown in Euro Area Productivity in a Global Context*, ECB, Frankfurt.

Everaert, G., Heylen, F. and Schoonackers, R. (2015), "Fiscal policy and TFP in the OECD: measuring direct and indirect effects", *Empirical Economics*, Vol. 49 No. 2, pp. 605-640, doi: 10.1007/s00181-014-0872-0.

Gómez-Tello, A., Murgui-García, M.J. and Sanchis-Llopis, M.T. (2020), "Exploring the recent upsurge in productivity disparities among European regions", *Growth and Change*, Vol. 51 No. 4, pp. 1491-1516, doi: 10.1111/grow.12414.

Gräbner, C., Heimberger, P., Kapeller, J. and Schültz, B. (2019), "Is the Eurozone disintegrating? Macroeconomic divergence, structural polarisation, trade and fragility", *Cambridge Journal of Economics*, Vol. 44 No. 3, pp. 647-669, doi: 10.1093/cje/bez059.

Gräbner, C., Heimberger, P., Kapeller, J. and Schütz, B. (2020), "Is the Eurozone disintegrating? Macroeconomic divergence, structural polarisation, trade and fragility", *Cambridge Journal of Economics*, Vol. 44 No. 3, pp. 647-669, doi: 10.1093/cje/bez059.

Griliches, Z. (1958), "Research costs and social returns: hybrid corn and related innovations", *Journal of Political Economy*, Vol. 66 No. 5, pp. 419-431, doi: 10.1086/258077.

Grossman, G.M. and Helpman, E. (1993), *Innovation and Growth in the Global Economy*, MIT Press, Cambridge, MA.

Hansen, L.P. (1982), "Large sample properties of generalized method of moments estimators", *Econometrica*, Vol. 50 No. 4, pp. 1029-1054, doi: 10.2307/1912775.

Hansen, B.E. (2019), *Econometrics*, University of Wisconsin, Madison, WI.

Hansen, B.E. and Lee, S. (2021), "Inference for iterated GMM under misspecification", *Econometrica*, Vol. 89 No. 3, pp. 1419-1447, doi: 10.3982/ecta16274.

Harhoff, D. (1998), "R&D and productivity in German manufacturing firms", *Economics of Innovation and New Technology*, Vol. 6 No. 1, pp. 29-50, doi: 10.1080/10438599800000012.

Heshmati, A. (2001), "On the causality between GDP and health care expenditure in augmented Solow growth model (No. 423)", SSE/EFI Working Paper Series in Economics and Finance.

Hintzmann, C., Lladós-Masllorens, J. and Ramos, R. (2021), "Intangible assets and labor productivity growth", *Economies*, Vol. 9 No. 2, p. 82, doi: 10.3390/economies9020082.

Hwang, J. and Sun, Y. (2018), "Should we go one step further? An accurate comparison of one-step and two-step procedures in a generalized method of moments framework", *Journal of Econometrics*, Vol. 207 No. 2, pp. 381-405, doi: 10.1016/j.jeconom.2018.07.006.

Kontsas, S. and Mylonakis, J. (2009), "A conceptual analysis of economic growth based on the Solow model", *European Journal of Economics, Finance and Administrative Sciences*, No. 15, pp. 74-93.

Nedić, V., Turanjanin, D. and Cvetanović, S. (2020), "Empirical investigation of the impact of tertiary education on the economic growth of the European Union countries", *Economic Analysis*, Vol. 53 No. 1, pp. 163-178, doi: 10.28934/ea.20.53.1.pp163-178.

Ortega-Argilés, R. (2012), "The transatlantic productivity gap: a survey of the main causes", *Journal of Economic Surveys*, Vol. 26 No. 3, pp. 395-419, doi: 10.1111/j.1467-6419.2012.00725.x.

Peiró-Palomino, J. (2016), "European regional convergence revisited: the role of intangible assets", *Annals of Regional Science*, Vol. 57 No. 1, pp. 165-194, doi: 10.1007/s00168-016-0767-4.

Pieri, F., Vecchi, M. and Venturini, F. (2018), "Modelling the joint impact of R&D and ICT on productivity: a Frontier analysis approach", *Research Policy*, Vol. 47 No. 9, pp. 1842-1852, doi: 10.1016/j.respol.2018.06.013.

Relich, M. (2017), "The impact of ICT on labor productivity in the EU", *Information Technology for Development*, Vol. 23 No. 4, pp. 706-722, doi: 10.1080/02681102.2017.1336071.

Roodman, D. (2009a), "How to do xtabond2: an introduction to difference and system GMM in Stata", *The Stata Journal*, Vol. 9 No. 1, pp. 86-136, doi: 10.1177/1536867x0900900106.

Roodman, D. (2009b), "How to do xtabond2: an introduction to difference and system GMM in Stata", *The Stata Journal*, Vol. 9 No. 1, pp. 86-136, doi: 10.1177/1536867x0900900106.

Roth, F. (2020), "Revisiting intangible capital and labour productivity growth, 2000-2015: accounting for the crisis and economic recovery in the EU", *Hamburg Discussion Papers in International Economics*, Vol. 21 No. 3, pp. 671-690, doi: 10.1108/jic-05-2019-0119.

Roth, F. and Thum, A.-E. (2013), "Intangible capital and labor productivity growth: panel evidence for the EU from 1998–2005", *Review of Income and Wealth*, Vol. 59 No. 3, pp. 486-508, doi: 10.1111/roiw.12009.

Samoilenko, S. (2008), "Contributing factors to information technology investment utilization in transition economies: an empirical investigation", *Information Technology for Development*, Vol. 14 No. 1, pp. 52-75, doi: 10.1002/itdj.20087.

Schoonackers, R. and Heylen, F. (2011), *Fiscal Policy and TFP in the OECD: A Non-stationary Panel Approach (No. 11/701)*, Ghent University, Faculty of Economics and Business Administration, Ghent.

Spithoven, A. and Merlevede, B. (2023), "The productivity impact of R&D and FDI spillovers: characterising regional path development", *The Journal of Technology Transfer*, Vol. 48 No. 2, pp. 560-590, doi: 10.1007/s10961-022-09918-0.

Van Ark, B. and Jäger, K. (2017), "Recent trends in Europe's output and productivity growth performance at the sector level, 2002-2015", *International Productivity Monitor*, Vol. 33, pp. 8-23.

Zhu, F., Li, Q., Yang, S. and Balezentis, T. (2021), "How ICT and R&D affect productivity? Firm level evidence for China", *Economic Research-Ekonomska Istraživanja*, Vol. 34, pp. 1-19, doi: 10.1080/1331677x.2021.1875861.

Appendix 1

Table A1. Description of the variables

Variable Name	Unit of measure	Notes
GVA per engaged	PPP, constant 2010 international dollars	
Investment	GVA share	*Tangible assets* Non-ICT - Transportation equipment - Other machinery equipment and weapons ICT - Computer and hardware and telecom. equipment - Computer software and databases *Intangible assets* - Research and development (RD)
Number of people engaged (Thousand)	Number	
Share of 15–64 population with tertiary education	Share population	Tertiary education is ISCED 5–8
Cyclical adjusted primary balance (CABP)	Percentage	
Openness index	Trade share of GDP	

Source(s): Authors' own work

Statistic	N	Mean	St. Dev	Min	Max
Log(GVA/engaged)	414	8.635	0.354	7.529	9.546
Inv. Mach./GVA	397	0.051	0.019	0.01	0.115
Inv. R&D/GVA	404	0.018	0.017	0.002	0.228
Inv. Database/GVA	404	0.013	0.007	0.002	0.04
Inv. Computer hardw./GVA	369	0.013	0.005	0.002	0.03
Inv. Transp. Eq./GVA	404	0.025	0.013	−0.003	0.08
Log(pop.change)	414	−3.497	0.287	−4.871	−2.827
Tertiary edu	410	70.6	12.678	21	88
CAPB	367	−0.427	2.617	−8.937	5.906
Openness	378	102.585	38.061	45.419	228.144
Eastern EU countries	414	0.435	0.496	0	1

Source(s): Authors' own work

Table A2. Descriptive statistics

Appendix 2

The supplementary material for this article can be found online.

Corresponding author
Nicola Comincioli can be contacted at: nicola.comincioli@unibs.it