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Abstract: This study attempts to investigate the impact of digitalisation on labour productivity in a sample of EU countries over the years 2014–2019. This sample has been fixed as a function of data availability collected by the European Commission through the digital economic and society index (DESI). Panel data analysis reveals a strong impact of digitalisation on labour productivity. Nevertheless, instrumental variable estimates suggest that digitalisation alone cannot significantly increase labour productivity. We find sizable differences across countries, with the Southern and Eastern European countries lagging behind the Central and Northern European countries, probably because of the low public investment in research and development (R&D) and human capital and the smaller size of firms. Findings suggest, in turn, that it would be useful for policymakers to provide enough support to small-sized firms in R&D and human resources management, especially in Southern and Eastern European countries.

Keywords: labour productivity; digitalisation; digital economic and society index; DESI; panel data analysis; EU.

JEL codes: O33, J24, J21.

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1 Introduction

In the last decades, EU countries have experienced a sharp slowdown in economic growth. The most recognised causes for this outcome have been the decelerating labour force and a substantial decline in productivity growth, especially labour productivity (a broad overview was proposed by Erber et al. (2017). However, not all European countries have suffered a slowdown in economic growth to the same extent. Evidence supports the view of a strong divide within the EU. For many countries, such as Italy, the decline started from 1990 to 2004 (Clementi et al., 2015; Storm, 2019; Balcerovicz et al., 2013; Pastore, 2020). According to World Bank (2020) data, the last decade's global economic and financial crisis further worsened the economic scenario, increasing the gap between the Continental and Nordic economies, especially in the already weakest European economies, such as the Mediterranean area. At the same time, Mediterranean economies also lost ground compared to the less developed economies of Eastern Europe.

The reasons for the low economic growth in the Southern European countries are manifold. Looking at the recipe implicit in Europe 2030 objectives, this depends not only on investments in technological innovation lower than the EU average but also on human capital. According to Eurostat (2024) data, the R&D expenditure on the GDP was always less than 1.5% in 2018 in the Mediterranean and Eastern European countries, much less than in Northern countries, except for Luxemburg and Ireland. A similar conclusion applies to public investment in human capital as a share of the GDP. Both factors are related, among others, to the substantial prevalence of small businesses (which are the least likely to invest in R&D and human resources management; Knott, 2017) and the insufficient State support that small businesses receive (Mazzucato, 2013), despite the EU emphasis on R&D and human capital in the Lisbon strategy, recently relaunched with the EU 2030 objectives (Pastore, 2020).

One of the factors contributing to the lower labour productivity may also be the low degree of digitalisation in all production and consumption fields, wherever possible. Many researchers emphasised the positive impact of intangible assets on labour and factor productivity (Bertani et al., 2020; Sahu et al., 2020). The first is software, which is one of the most relevant digital assets, followed by hardware, big data and so on. The issue of digitalisation is indeed very complex and articulated since it affects every aspect of labour management, production and consumption. Digitalisation represents a significant issue because, besides being an instrument allowing the improvement of productive activities and businesses, it also has positive macroeconomic implications, such as a stimulus for revamping education and designing new forms of collaborations (Brynjolfsson and McAfee, 2014; Rifkin, 2014; North et al., 2020; Casalet and Stezano, 2021; Ghasemzadeh et al., 2022). The recent pandemic due to the COVID-19 virus has determined an unprecedented boost in digitalisation, with a sudden transformation of many economic activities and jobs in all OECD countries. In particular, ILO (2020) estimates that around 18% of workers in this area could be occupied at home-based work, with a peak of about 30% in North American and Western European countries. This means an average yearly growth rate of 4% over 2019.

In this paper, we provide a framework of analysis focusing not only on the effects on labour productivity of digitalisation as a whole but also on its specific dimensions (connectivity, human capital, use of internet services, Integration of digital technology, digital public services) for 23 European countries in the years from 2014 to 2019. We resort to the digital economic and society index (DESI) computed by the European Commission to measure these different dimensions of digitalisation; in addition, as a measure of labour productivity, we use the ratio between the GDP and the number of employees in each country.

By highlighting the impact of digitalisation on labour productivity, we hope that our analysis provides a useful insight into the EU divide. Indeed, the emergency crisis related to the pandemic has represented a great opportunity for Southern countries to suddenly reduce the digital gap with the most advanced EU countries.

We will seek to answer the following general questions: What is the extent of the digital gap in Europe, if any? What is the impact of digitalisation on labour productivity? What are the consequences of the digital gap on labour productivity? Can a low average level of education be a constraint to digital transformation? Is digitalisation responsible for the different levels of labour productivity, or are there other factors that could influence both digitalisation and labour productivity? A more precise specification of the research hypothesis is defined further in this current paper.

We add to the existing literature in several respects. We are among the first to use the DESI scores to analyse the impact of digital transformation on labour productivity. DESI is a composite indicator of several sub-indicators, representing proxies of specific digitalisation dimensions. This important information allows us, for the first time, to jointly study the different aspects of this complex phenomenon on labour productivity. Moreover, we provide an assessment of cross-country differences in digitalisation and their impact on labour productivity through interactive dummies between DESI and country fixed-effects. From the methodological point of view, our paper starts from the findings of Evangelista et al. (2014) for EU countries and Aly (2020) for a group of developing countries. However, through DESI, we propose a more accurate measure of digitalisation and try to address the issue of omitted heterogeneity and reverse causality associated with digitalisation in several ways. First, we control for omitted heterogeneity with our fixed effects panel estimates, which also allows us to check for omitted variable bias due to the lack of control variables that are able to explain labour productivity in full. Second, we address reverse causality by implementing an instrumental variable (IV) approach and running our estimates with lagged independent variables. Our best estimates based on the total unemployment rate (TUR) as an IV suggest that digitalisation might not affect productivity per se, but as a consequence of a higher degree of innovativeness in the country.

As a robustness check, we confirm the validity of our main findings in estimates where productivity is measured by the GDP per hour worked. This assumption allows a different definition of labour productivity, which is more likely to be affected by digitalisation, than labour productivity itself.

The rest of the paper is structured as follows: Section 2 reviews the theoretical background and motivates the paper. Section 3 presents the methodology. Section 4 shows the results of our panel data analysis and discusses their implications. Sections 5–6 concern the discussion and conclusions. Section 7 concludes with limitations and future research.

2 Theoretical background and hypotheses development

2.1 The impact of digitalisation on economic growth and productivity

In the last decades, many economists have paid attention to technology as a significant driver of productivity and economic growth (Kügler et al., 2023; Moura, 2021; Braña, 2019; OECD, 2019; Marelli and Signorelli, 2010). Some of them considered the classical Solow's model with the inclusion, first, of technological progress and, in recent years, of the level of digitalisation and Artificial Intelligence adoption (Syverson, 2011; Brynjolfsson and McAfee, 2014). A broad stream of literature has emphasised how digital transformation – a revolution started initially with a strong adoption of technology – is nowadays deeply integrated into all business dimensions, resulting in changes in business operations and delivery of value to customers (see, among others, Mićić, 2017; Cassetta et al., 2020; Iandolo and Ferragina, 2021). Brynjolfsson and McAfee (2014) and Rifkin (2014) analysed the opportunities offered by digitalisation in terms of significant transformations and strong effects on employment, labour productivity, real wages and many other social and economic aspects.

An important effort to quantify the effects of digitalisation on economic growth for the Chinese economy was made by Kvochko (2013), while Toader et al. (2018) applied a similar analysis to EU countries for the years 2000–2017. These authors found that the information and communication technology (ICT) infrastructure was an important driver of economic growth, just like the employment and inflation rates. However, the extent of this impact on economic growth strictly depends on the ability of productive systems to take advantage of the digital transformation, and not all countries register the same high levels of economic growth. Therefore, in the last decade, a broad stream of literature has included digitalisation among the factors that explain the growth gap among EU countries and the US (Mazzucato, 2013; Feldstein, 2017).

Contributions to this literature can be distinguished, first of all, in relation to the micro or macro approach used. Among those who analyse the phenomenon at the micro-level, Bloom et al. (2012) identified the productivity miracle of US multinational enterprises using ICT and compared them to non-US multinationals, estimating a production function where capital was split in non-ICT and ICT capital and also controlling for the firm's organisational capital. The same conclusion on the relevant role of ICT on productivity was reached by Draca et al. (2009) a few years earlier. Examining the micro and macro literature on this topic, they rejected the 'Solow Paradox' of the slowdown in productivity growth despite the rapid development of ICT and found that the impact of ICT on productivity was much more significant than one would expect from the standard neoclassical model.

More recently, following a macroeconomic approach, Goldfarb and Tucker (2019) tried to identify the reasons for the remarkable increase in productivity due to ICT. Their study shows the strong impact of ICT in reducing costs of storage, computation and transmission of data. Most of these studies refer to the US framework; the digital transformation started before compared to the EU area, and it is widely recognised as one of the main factors explaining the strong US economic growth. Among the others, Brynjolfsson and Hitt (2000) tried to quantify the impact of digitalisation on US productivity in the short and medium-term through firm-level micro data in the years between the '80s and '90s. They found that the contribution of digitalisation on productivity is five times larger in the long run (5–7 years lag).

The same large effects on productivity and growth were not found in the EU economy. Instead, Van Ark (2008) identified, among others, the following causes for the lower economic growth in Europe: lower growth contributions from investment in ICT, the relatively small share of industries producing technology, and slower multifactor productivity growth. More recently, Acharya (2016) added to the previous causes also the fact that EU economies pointed mainly to productive externalities rather than capital accumulation, which was instead at the core of the US growth. Similarly, Corrado et al. (2017) showed that ICT-intensive industries have better productivity outcomes in countries that are more knowledge-based capital-intensive, such as the US economy, particularly with relatively higher investments in organisational capital.

Last but not least, the effect of digitalisation on economic growth also depends on its link with the inflation rate. A recent strand of the literature focuses on estimating a deflator of the prices of digital goods and services and their impact on the measurement of GDP. Several research papers (see, among others, Ahmad et al., 2017; Byrne et al., 2016; Moulton, 2018; Reinsdorf and Schreyer, 2019) reported an estimate of the consumer price index (CPI) taking into account the effect of digital products in OECD countries. They conclude that the price effect of the underestimation of the price level of digital products is around -0.6% and could affect productivity growth, but the long-run impact should be irrelevant.

This paper focuses on the EU context, which presents strong differentials in productivity. As mentioned in the introduction, we start with the recent contributions of Evangelista et al. (2014) and Aly (2020). These authors found that within the EU framework, the mere accessibility to ICT facilities is only a pre-condition for moving towards a digitalised society. For this reason, we focus on the importance of the 'level' and the 'quality' of using these technologies and their connection with human capital. We try to understand whether digitalisation directly impacts labour productivity or through different factors, such as the human capital endowment and the ability to innovate.

This is extremely important because finding a strong direct effect of digitalisation on labour productivity would suggest investing in digitalisation. Conversely, if digitalisation is only a condition needed to increase productivity, policy efforts should probably address other aims, such as improving the ability to innovate and invest public funds in the quantity and quality of tertiary education and other immaterial infrastructures. Indeed, if opportunely driven, digital technologies could contribute to bridging the gap between the most favoured and the disadvantaged parts of the population and may also represent an opportunity for the weakest European economies.

2.2 The role of human capital

The relationship between human capital and digitalisation is quite complex, and the literature on this topic is full of contributions. Human capital and education systems have a primary role in the digital revolution because digitalisation strongly affects the skills and competencies required by the labour market, being closely connected to productivity (Pérez and Frutos Rogriguez, 2017). Formal education is critical in affecting the propensity and predisposition to digital adoption, but it also needs to adapt to provide the skills and competencies required by the progress of digitalisation. Acemoglu and Restrepo (2018) have developed a framework for the analysis of the effect of new technologies on labour. They found that automation reduces the cost of producing through the use of labour and thus encourages the creation of new tasks. In the same vein, using microdata from the National Longitudinal Survey on Youth 1979, which contains accurate measures of worker skills, Deming (2017) found that ICT increased the demand for soft and social skills because machines cannot perform them. Therefore, in times of fast growth in ICT, even if digitalisation increases inequality in the short run (due to a massive process of job destruction), introducing new tasks tends to restabilise the equilibrium in the long run. All researchers agree, indeed, that the low-skilled profiles are the most penalised in terms of job destruction (Autor et al., 2003). Recently, analysing data from 9 European countries, the US and Japan over 25 years, Michaels et al. (2014) highlighted how digitalisation generates job destruction, especially in medium-skilled jobs, which determines an intense job polarisation. Balsemeier and Woerter (2019) found the same conclusion using data from a unique representative survey on the digitalisation activity of Swiss firms.

With the outbreak of the pandemic, traditional teaching and working methods have been totally overturned, leading to massive use of remote teaching and smart working (Joint Research Center, 2020). The rapid and dramatic digitalisation process requires a significant effort to develop a new educational paradigm to convey to students the latest competencies and skills needed in their future work. The speed of these recent transformations requires strong support from teachers to allow them to develop the necessary digital competencies (Benner, 2017). It also requires converting the skills of adult workers to the new paradigm.

An education system readily responsive to the new challenges coming from the future world of labour would be a relevant asset to avoid the possible negative effects of digitalisation in terms of lower labour demand since increased productivity allows many industries 'to do more with less' (Department of Economic and Social Affairs, 2017). Furthermore, digitalisation also leads to a higher demand for university education (Stiglitz, 2012; Dorn, 2015), especially in the STEM fields. On the one hand, this is because the digital revolution requires ever higher skills and competencies. On the other hand, the risks of job losses due to digitalisation are higher for manual jobs, which machines can more easily replace.

Stimulating these transformations of the education system requires supporting schools and Universities to face the efforts needed by providing them with high public funding. The literature is full of contributions on the strong direct relationship between low levels of economic growth and productivity on the one side and low investment in education on the other side (Barro, 1991; Mankiw et al., 1992; Adelakun, 2011; Aisen and Veiga, 2013). In other words, increasing investment in education is still more important nowadays than in the past because higher levels of human capital enhance technology adoption and increase productivity (Bodman and Le 2013; Silva and Teixeira 2011). There are sizeable differences in the amount of public spending for education among EU countries. In 2017, Eastern and Southern European countries, plus Ireland and Luxembourg, registered the lowest GDP percentages, while the Scandinavian countries (mainly Denmark, Sweden and Finland) reported the highest.

Significant differences also exist in the share of the tertiary educated, even in the younger population (25–34 years old): while in Ireland and Lithuania, more than 1 out of 2 were tertiary educated, the corresponding share in Italy and Portugal was only of 26.9 and 35%, respectively (source: Eurostat Statistics – Europa.eu – online database)

However, investing in education and increasing its digital content can lead to significant productivity increases only if well managed. Digitalisation works only if institutions, managers, and workers create the conditions for adequately adopting these new paradigms. To test this hypothesis, we will include a measure of human capital endowment in the econometric analysis and study its combined effect on labour productivity.

Based on the dissertation mentioned above, our hypothesis is derived as follows:

H1 If digitalisation has a relevant role in explaining the variations in labour productivity, the former is not a direct driver for the latter, but its effects are conditioned by other factors, such as human capital and the ability to innovate.

3 Methodology

The first attempts to adapt the classical Cobb-Douglas production function to catch the growing importance of technology in the production process were made by the Nobel Prize winner Robert Solow. He analysed the United Nations economy in 1909–1949 and found that technological progress accounted for 80% of all economic growth (Solow, 1956, 1957; Jorgenson, 1995). However, the most important result of Solow's study was that technological progress might produce a positive shift in the production function, also controlling for the same amount of capital and labour. According to this theory, we have the classical Cobb-Douglas production function:

$$Y = AL^{\beta}K^{\alpha} \tag{1}$$

where Y is total production; L and K, respectively, the labour and capital inputs; A is total factor productivity; $0 < \alpha < 1$ and $0 < \beta < 1$ are constants representing the output elasticities of capital and labour, respectively, determined by the available technology. Introducing the effect of technological progress over time (1) becomes:

$$Y(t) = K(t)^{\alpha}(A(t)L(t))^{1-\alpha} \tag{2}$$

where t denotes time and, since A also refers to labour-augmenting technology or 'knowledge', AL represents effective labour.

We may think of digitalisation as an additional production factor to the classical Cobb-Douglas production function depicted above. Starting from the previous contributions of Evangelista et al. (2014) and Aly (2020), we propose the following model to evaluate the impact on labour productivity of the level of digitalisation across European countries:

$$\log LP_{t,i} = \alpha + \beta_J \log DESI_{t,i}^{J} + \delta \log K_{t,i} + \gamma \log HC_{t,i} + \varepsilon_{t,i} \tag{3}$$

where $LP_{t,i}$ is labour productivity; $DESI_{t,i}^{J}$ is our indicator of digitalisation; $HC_{t,i}$ is the human capital level; K is the amount of fixed capital; $\varepsilon_{t,i}$ is the stochastic noise; i = 1, 2, …, 23 countries; j = 0, 1, …, 5 dimensions of DESI index (0 denotes the global DESI indicator); t = 2014, …, 2019. Variables are in logs, so that equation (3) is a linear transformation of the exponential model in (2).

In order to verify how different levels of digitalisation affect labour productivity in each country, we also propose an alternative model where country dummies interact with the levels of DESI index:

$$\log LP_{t,i} = \alpha + \beta_J C_i \log DESI_{t,i}^{J} + \delta \log K_{t,i} + \gamma \log HC_{t,i} + \varepsilon_{t,i} \tag{4}$$

where C_i are country-specific fixed effects so that $C_i \log DESI_{t,i}^{J}$ represent DESI dimensions interacted with each i-th country dummy variable.

However, in studying the factors affecting labour productivity, some problems of heterogeneity and endogeneity could arise (Ugur and Vivarelli, 2021). The first one is connected to different countries' characteristics and dimensions. The issue of endogeneity could arise because it is tough to identify – and measure – factors affecting labour productivity, so we could, on the one hand, omit some relevant regressors, and, on the other hand, there could be a reverse causality problem. In fact, there could be the problem of countries' digitalisation being affected by labour productivity.

We address the possible endogeneity of digitialisation in several ways. First, we estimate equation (4) with a fixed effect panel regression model, which allows us to control for omitted heterogeneity. Second, we run a fixed effect IV procedure to deal with the possible omitted heterogeneity (Stock, 2015). This approach implies estimating a two-step set of equations:

$$\log DESI_{t,i} = \alpha + \delta_J \log IV_{t,i}{}^J + \delta \log K_{t,i} + \gamma \log HC_{t,i} + \varepsilon_{2,t,i} \tag{5}$$

$$\log LP_{t,i} = \alpha + \gamma \log \widehat{DESI}_{t,i}{}^J + \delta \log K_{t,i} + \gamma \log HC_{t,i} + \varepsilon_{1,t,i} \tag{6}$$

where equation (5) includes only the exogenous variables, and the IV and equation (6) predict labour productivity using the values of predicted DESI from equation (5).

Identifying the IV is not easy because it should satisfy the following conditions:

1 being strongly correlated with DESI (*relevance condition*)

2 not being correlated with LP, the dependent variable of the main equation.

In other words, ii) implies $E(\varepsilon_{1i}\}|IV_i) = 0$ (*exclusion condition*). The *exclusion condition* may be tested by estimating a regression where our endogenous variable DESI is regressed on the IV and, then, by including the residuals of this equation in the main model estimation. If the coefficient of the residuals is statistically significant, the exclusion condition is not satisfied.

The reverse causality problem is addressed considering the lagged values for independent variables so that the (3) is transformed into the following:

$$\log LP_{t,i} = \alpha + \beta_J \log DESI_{t-1,i}{}^J + \delta \log K_{t-1,i} + \gamma \log HC_{t-1,i} + \varepsilon_{t,i} \tag{7}$$

because it is reasonable that the current levels of digitalisation and human and fixed capital will affect labour productivity in the following year.

3.1 Data

The analysis is based on the 2014–2019 years for the following 23 European countries: Austria (AT), Belgium (BE), the Czech Republic (CZ), Denmark (DK), Estonia (EE), Finland (FI), France (FR), Germany (DE), Greece (EL), Hungary (HU), Ireland (IE), Italy (IT), Latvia (LV), Lithuania (LT), Luxembourg (LU)[1], the Netherlands (NL), Poland (PL), Portugal (PT), Slovakia (SK), Slovenia (SI), Spain (ES), Sweden (SE), the UK[2].

Digitalisation is proxied by DESI. This latter index represents a composite indicator measuring EU countries' progress towards a digital economy and society. It is constructed with the same methodology for all EU countries, allowing for spatial and temporal analysis. The composite dimensions are as follows: connectivity, human capital, internet services, integration of digital technology, and digital public services, which we identify as DESI1 to DESI5. The indicators included in each dimension are collected mainly by the European Commission services (DG CNECT, Eurostat; European Commission, 2020) and by ad-hoc studies launched by the Commission services. The construction methodology of the composite indicator follows the OECD (2018) guidelines. It is based

1 on the min-max normalisation

2 the aggregation of the indicators into the pillars that identify the different dimensions, while the usage of pillars in the composite index is based on weighted arithmetic averages.

Table 1 Descriptive statistics

Countries (*)	*DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*	*Labour productivity*	*Employees with tertiary education*	*Physical capital*	*Δ DESI*	*Δ Labour productivity*	*Δ Physical capital*	*Δ Employees with tertiary education*
AT	47.977	12.165	13.095	6.841	6.873	9.002	80.398	34.140	0.235	30.445	2.557	0.021	8.025
BE	52.996	15.180	11.766	7.406	10.545	8.099	86.897	45.475	0.240	30.320	3.172	0.018	3.324
CZ	43.720	12.368	11.086	6.422	7.975	5.869	35.951	22.552	0.264	38.257	13.821	0.012	4.308
DE	48.591	13.560	13.131	7.879	7.357	6.663	73.712	31.835	0.204	27.137	2.755	0.012	8.752
DK	63.469	15.855	15.151	10.334	10.697	11.433	106.476	54.515	0.206	21.508	6.033	0.023	–0.389
EE	53.477	12.978	14.311	8.496	6.208	11.484	30.604	40.155	0.270	27.971	15.281	0.011	13.817
EL	32.048	8.144	8.252	4.982	5.797	4.873	50.839	31.762	0.109	41.860	–5.600	–0.005	10.037
ES	48.442	12.710	10.893	7.008	7.405	10.425	60.957	43.217	0.201	38.602	1.498	0.017	6.068
FI	62.972	13.896	18.381	9.581	9.712	11.401	83.796	48.118	0.228	24.475	4.992	0.017	6.330
FR	44.221	11.406	11.111	6.962	6.861	7.880	82.816	38.592	0.222	35.250	5.708	0.018	12.073
HU	38.754	12.261	10.022	6.635	4.418	5.417	27.303	21.758	0.231	42.212	12.139	0.045	–3.276
IE	51.610	12.537	12.282	6.718	11.413	8.659	121.692	51.428	0.324	47.052	38.346	0.277	7.702
IT	35.695	10.118	7.835	5.140	5.564	7.036	71.522	21.510	0.177	52.010	1.212	0.015	13.899
LT	43.485	9.818	9.449	6.741	8.467	9.010	27.420	41.773	0.208	47.184	15.496	0.032	10.389
LU	55.192	16.035	16.711	9.427	6.613	6.406	185.020	49.840	0.191	25.692	–1.019	–0.032	1.572
LV	42.059	13.481	9.576	6.675	4.131	8.196	25.896	34.307	0.214	47.074	15.492	–0.005	10.381
NL	61.981	16.600	14.294	9.756	10.625	10.705	88.460	44.260	0.212	26.079	4.152	0.038	10.024
PL	34.951	10.085	8.437	5.348	4.123	6.958	28.177	34.455	0.202	43.780	20.215	–0.009	22.031
PT	43.318	12.019	8.455	5.736	7.605	9.503	40.629	24.640	0.170	33.750	3.513	0.031	10.679
SE	62.682	15.691	16.203	9.912	10.210	10.666	92.288	43.245	0.245	22.281	5.655	0.010	11.221
SI	43.727	12.253	10.973	6.301	6.885	7.314	43.001	35.647	0.184	38.097	9.138	0.004	15.183
SK	39.423	10.619	10.017	6.340	6.559	5.889	32.722	24.035	0.219	39.602	8.155	0.012	14.667
UK	54.593	13.800	14.608	9.071	8.604	8.510	71.666	43.890	0.173	28.928	2.096	0.010	–0.0614
All	48.060	12.764	12.002	7.379	7.593	8.322	67.315	37.441	0.214	–	–	–	–

Notes: Mean values by country. (*)Austria – AT; Belgium – BE; the Czech Republic – CZ; Denmark – DK; Estonia – EE; Finland – FI; France – FR; Germany – DE; Greece – EL; Hungary – HU; Ireland – IE; Italy – IT; Latvia – LV; Lithuania – LT; Luxembourg – LU; the Netherlands – NL; Poland – PL; Portugal – PT; Slovakia – SK; Slovenia – SI; Spain – ES; Sweden – SE; the United Kingdom – UK. (**) The last three columns report the percentage change that occurred in the respective indicators in 2019 in comparison to 2014.

Source: Authors' elaboration on European Commission (2020)

These weights attributed to the five dimensions are the following: connectivity, 25%; human capital, 25%; use of internet services, 15%; integration of digital technology, 20%; digital public services, 15% (for more information on DESI, see European Commission, 2020, and DESI database https://digital-agenda-data.eu/datasets/desi/indicators).

Studying the determinants of labour productivity is very difficult in many respects. Firstly, labour productivity is not directly measurable and can only be proxied by other variables. Second, it depends on many factors, all complicated to measure. In the case of European countries, it depends not only on the countries' economies but also on their stage of economic development. Indeed, the average labour productivity is the highest in Ireland and some Eastern countries (Lithuania, Latvia and Poland), probably because they are recovering the gap from the rest of the continent.

As a proxy of labour productivity, we have chosen the ratio between the GDP in chain-linked volumes in millions of euros and the number of employees for each country; in more detail, the total production is divided by the number of employed labour force concurring with it. This choice is motivated by the need to consider the amount of production relativised to the effective labour force concurring to realise it. Anyway, each measure has several weaknesses because – in international comparisons – industrial composition, cultural and/or institutional factors can produce international differences in the average number of hours worked. For this reason, in the robustness check section, we propose an alternative measure of labour productivity based on the GDP per hour worked.

Even if many factors affect labour productivity, as many are highly correlated, we include only a small number of regressors in each model. The human capital endowment has been measured by the share of employees with tertiary education, while the amount of physical capital has been measured by the ratio between the gross fixed capital in chain-linked volumes and the total GDP (*physical capital*). In a first attempt, we tried to include in the model many other determinants of labour productivity, as follows: population density; the share of elderly people (people aged 65 years and more); the degree of innovation, proxied by the expenses in research and development (R&D) as a share of the GDP; the TUR; the share of employees in the manufacturing sector, as a proxy of the industry composition. Their contribution to productivity is apparent in reality. However, from an econometric point of view, the high correlation among these variables prevented us from including them in the model specification, and the coefficients appear biased in omitted estimates that include these variables. After all, panel estimates allow us to correct for unobserved heterogeneity across countries.

The same collinearity concern applies to the different components of DESI. Indeed, as the appendix shows (Table 7), the correlation among DESI components is very high, as well as the correlation between DESI and, for example, the TUR (–0.456) or between the share of employees in the manufacturing sector and the share of tertiary educated employees (–0.62). Consequently, to avoid biased estimates of the impact of the DESI components, we add each at a time rather than all together.

All data are extracted from the online Eurostat database and on our ad hoc elaborations based on Labour Force Survey data for the years involved in the analysis. In Table 1, we report the main descriptive statistics for each variable. Based on theoretical considerations, all the indicators considered are expected to have a positive relationship with labour productivity.

4 Results

4.1 Descriptive analysis

The DESI overall rank allows us to identify the countries' global position in terms of ranking in the degree of digitalisation, as shown in Table 1. Countries at the top of the rank have been able to implement and benefit from computing power, data storage capacity, and communication speed. All the EU Scandinavian countries – in the order Denmark, Finland and Sweden – occupy the first positions with DESI values higher than 60. At the bottom of the rank is a selection of Southern and Eastern European countries. The countries with the lowest ranking are Greece, Poland, and Italy, with DESI values under 36. Overall, the global ranking is in accordance with each pillar's rank. A few exceptions include Luxembourg, which is second for the first two pillars and occupies a lower-than-average position in the last two pillars. At the bottom of the pillars' rankings, we also find Portugal for the second dimension and Slovakia for the fifth. The first dimension concerns connectivity and measures, in each Member country, the implementation and quality of the broadband infrastructure. In 2018[3], 80% of European households were covered by fast broadband (at least 30 Mbps2). This dimension accounts for both fixed and mobile broadband coverage, 4 G technology, and fast and ultrafast broadband. They are all relevant conditions for competitiveness. The best-performing countries for this dimension are Denmark, Luxembourg, Sweden, Belgium, and the UK, while at the bottom of the classification, we find Greece, Lithuania and Italy. DESI2 allows quantifying the skills needed to exploit the possibilities offered by digitalisation and measures, on the one hand, the use of the internet and the possession of digital skills and, on the other hand, the share of ICT specialists and STEM graduates.

While 81% of Europeans had internet access at least once a week in 2018 (+2 points compared to 2017), 43% do not have basic digital skills. This measure of digital skills proxies the effectiveness of the education system in transferring the competencies and skills required by the labour market. Consequently, it represents the potential in terms of productivity coming from the current and future workforce. The Scandinavian countries of Finland and Sweden, Luxembourg and Denmark show the highest levels of competency and result in contrast to the Southern and Eastern countries of Italy and Greece. The third pillar pertains to the use of Internet services and takes into account a variety of online activities, such as the consumption of video calls, online content (videos, music, games, etc.), and online shopping and banking services. The percentage of Internet users engaging in various online activities, such as reading online news (72%), making video or audio calls (46%), using social networks (65%), shopping online (68%) or using online banking (61%) has increased slightly in the last two years. The classification of countries for this pillar is very similar to that found for the previous pillar because internet services require appropriate skills. For this pillar, Denmark and the UK add the other mentioned countries at the top of the ranking. The integration dimension of digital technology (DESI4) attains specifically to the use of technology by enterprises in their activities. The indicators included in this pillar measure, among others, the percentage of enterprises sharing electronic information and using e-Invoices, the share of SMEs (Small and medium-sized enterprises) selling online and the levels of e-commerce turnover. By adopting digital technologies, companies become more efficient, reducing costs and better engaging customers and business partners.

Moreover, internet as a point of sale offers high growth potential with access to larger and directly accessible markets, effectively eliminating sunk costs that create rigid entry barriers for new enterprises. European companies are increasingly adopting digital technologies, such as the use of business software for sharing electronic information (from 26% in 2013 to 34% of businesses in 2017), sending e-invoices (from 10% in 2013 to 18% of businesses in 2016) or using social media to interact with customers and partners (from 15% in 2013 to 21% of businesses in 2017). E-commerce by SMEs also increased slightly (from 14% in 2013 to 17% of SMEs in 2017). The best-performing countries in the years analysed are Ireland, Denmark, the Netherlands, and Belgium while the worst-performing countries are the Eastern countries of Latvia and Poland.

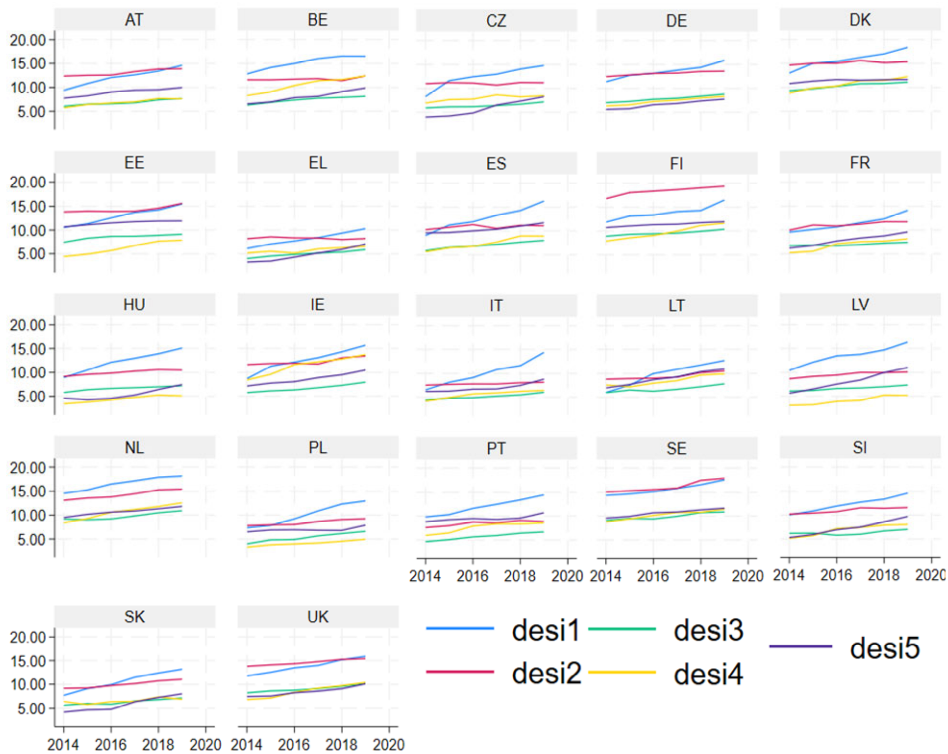
Figure 1 DESI by country (years 2014–2019) (see online version for colours)

Source: Authors' elaboration on European Commission (2020)

Finally, DESI5 is proxied by the offer of digital public services, addressed mainly to businesses and citizens, by the availability of open data and eHealth services. The modernisation and digitalisation of public services can lead to a more efficient and competitive business environment. The quality of European online public services improved in the last years with an increase of 5 points in pre-filled forms (measurement of re-use of user data already known to the public administration), 2 points in business services and 2 points in the completion of online services. The most digitalised countries for public services are Estonia, Denmark and Finland, while the worst performers are Greece and Slovakia. Overall, the trend for digitalisation is increasing for all countries, as we can see from Figures 1–2 and the third last column of Table 1. The highest increases concern Italy, Ireland, Lithuania and Latvia. The pillar which drove this increase is mainly connectivity, almost everywhere. Finland and Estonia showed instead human capital as the pillar driving the growth. Concerning labour productivity (see again

Table 1), the contrast among Luxembourg and Nordic countries (Ireland, Denmark and Sweden) and all the Eastern and Southern countries is very clear. Nevertheless, the trend in both digitalisation and productivity appears positive for all of them, with Ireland and Eastern countries showing the highest growth rates (except only Greece and Luxemburg in terms of labour productivity growth in the period analysed).

Figure 2 DESI dimensions by country (years 2014–2019) (see online version for colours)



Source: Authors' elaboration on European Commission (2020)

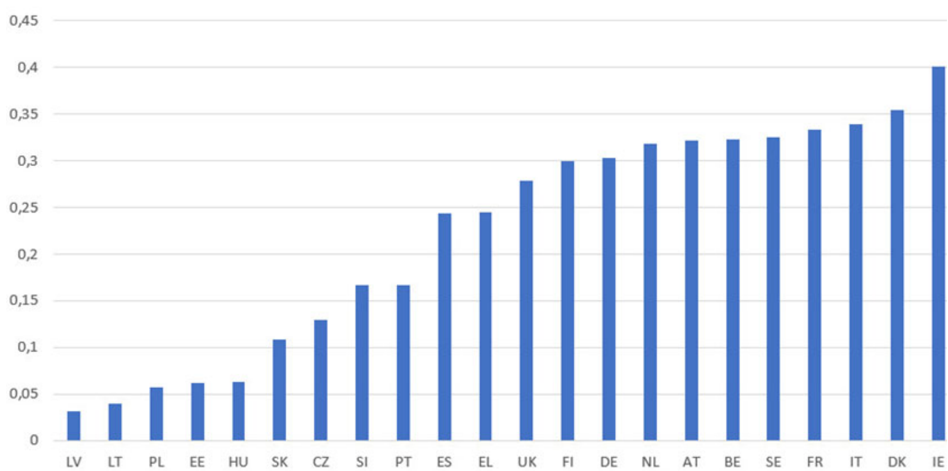
4.2 Regression model

The heterogeneity due to the different countries' dimensions is overcome by normalising all the indicators by the population size. The specifications chosen are panel random-effects, selected on the basis of the Hausman test results. In Table 2, we start our analysis from a simple regression model of labour productivity conditioned on digitalisation and then proceed to introduce a variable at each step to verify the stability of the regression coefficient for digitalisation, measured by the general DESI index and each dimension separately (equation (3) of the methodology section).

The Appendix (Table 8) shows the corresponding models with fixed effects and the corresponding Hausman test results. As the model specification is based on the logarithms of the respective indicators, the estimated coefficients can be interpreted in terms of elasticities, therefore representing the sensitivity of labour productivity to digitalisation changes. The DESI indices exert a statistically significant and positive effect on labour productivity. An exception is the use of internet services (DESI3) and digital public services (DESI5), which do not significantly impact labour productivity, while human capital and the integration of digital technologies strongly and positively affect productivity. This effect is also confirmed when other production factors are added to the model. The human capital endowment and fixed capital are both statistically significant in all model specifications.

In the time fixed-effects models (Table 8 in the Appendix), digital public services coefficients are still not statistically significant, while the use of internet services coefficient is significant, at least in model 1. The Hausman test is not statistically significant in most cases. The model estimates referring to the 4th pillar DESI are an exception (Integration of digital technology). However, the models' fixed and random effects specifications are substantially similar[4]. We take this as evidence in favour of the random effect model. Figure 3 reports the coefficients for the countries' dummy variables interacted with DESI in a regression model where labour productivity is the dependent variable while human and fixed capital are included as control variables (see equation (4) in the above methodology section). The coefficients of these interactions allow us to quantify each country's specific effect of a variation in digitalisation on labour productivity.

Figure 3 Estimated coefficients of country's interactions with DESI (random effects) (see online version for colours)



Notes: (*) The bars of the histogram represent the estimated coefficients of interactions between dummies for countries and DESI in a random-effects model also controlling for physical capital and share of the labour force with tertiary education. The corresponding estimates are reported in Table 9. All coefficients are statistically significant at 0.01 level with the exception of Estonia, Hungary Latvia, and Poland. All variables have been transformed in a natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 2 Panel estimates of the determinants of labour productivity

Variable	Total DESI			1 Connectivity			2 Human capital		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
DESI	0.4388**	0.3878*	0.3166**						
	(0.2052)	(0.2145)	(0.1675)						
DESI1				0.1299*	0.1082	0.0909			
				(0.0819)	(0.0812)	(0.0685)			
DESI2							0.3122***	0.2629*	0.2267*
							(0.1278)	(0.1436)	(0.1365)
Employees with tertiary educat.	0.1633	0.2577**			0.2184***	0.3031***		0.1925***	0.2805**
	(0.1109)	(0.1233)			(0.0910)	(0.1140)		(0.1129)	(0.1366)
Physical capital		0.1703***			0.1799***				0.1800***
		(0.0366)			(0.0401)				(0.0468)
2015y	–0.0113	–0.0112	–0.0135	0.0030	0.0012	–0.0041	0.0104	0.0078	0.0013
	(0.0098)	(0.0100)	(0.0098)	(0.0074)	(0.0075)	(0.0082)	(0.0108)	(0.0106)	(0.0083)
2016y	–0.0306	–0.0307	–0.0307	–0.0010	–0.0055	–0.0109	0.0128	0.0070	–0.0007
	(0.0223)	(0.0226)	(0.0197)	(0.0135)	(0.0137)	(0.0147)	(0.0121)	(0.0116)	(0.0096)
2017y	–0.0360	–0.0363	–0.0382	0.0082	0.0014	–0.0088	0.0259	0.0174	0.0044
	(0.0317)	(0.0321)	(0.0276)	(0.0177)	(0.0181)	(0.0189)	(0.0163)	(0.0156)	(0.0139)
2018y	–0.0455	–0.0459	–0.0480	0.0156	0.0061	–0.0071	0.0306	0.0204	0.0043
	(0.0420)	(0.0424)	(0.0359)	(0.0214)	(0.0220)	(0.0223)	(0.0200)	(0.0198)	(0.0181)
2019y	–0.0549	–0.0530	–0.0576	0.0199	0.0114	–0.0072	0.0408*	0.0306	0.0083
	(0.0519)	(0.0527)	(0.0452)	(0.0263)	(0.0267)	(0.0282)	(0.0230)	(0.0227)	(0.0207)

Notes: Random effects. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$. (*) 22 European countries analysed over the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. In random effects, rho is the estimated proportion of the between–variance (sigma_u) at the total variance (sum of sigma_u and sigma_e). It is calculated like: sigma_u/(sigma_u+ sigma_e).

Source: Authors' elaboration on European Commission (2020)

Table 2 Panel estimates of the determinants of labour productivity (continued)

Variable	*Total DESI*			*1 Connectivity*			*2 Human capital*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
_cons	2.3532***	1.9661***	2.1697***	3.6758***	2.9558***	2.9859***	3.2277***	2.6670***	2.7323***
	(0.7658)	(0.8176)	(0.8062)	(0.2134)	(0.4097)	(0.5082)		(0.4220)	(0.5174)
N	132	132	132	132	132	132	132	132	132
R2	0.3542	0.3887	0.3345	0.1208	0.3231	0.2807	0.2973	0.3673	0.3182
R2 within	0.5469	0.5505	0.6312	0.5226	0.5285	0.6176	0.5237	0.5295	0.6203
R2 between	0.3725	0.3979	0.3369	0.2288	0.3477	0.2857	0.3189	0.3777	0.3206
Wald chi2	34.28***	37.69***	138.77***	37.00***	58.21***	164.51***	41.76***	46.81***	130.56***
sigma_u	0.4129	0.4149	0.4170	0.4577	0.4284	0.4355	0.4302	0.4218	0.4277
sigma_e	0.0285	0.0285	0.0260	0.0293	0.0292	0.0264	0.0292	0.0292	0.0263
rho	0.9953	0.9953	0.9961	0.9960	0.9954	0.9963	0.9954	0.9952	0.9962

Notes: Random effects. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) 22 European countries analysed over the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. In random effects, rho is the estimated proportion of the between-variance (sigma_u) at the total variance (sum of sigma_u and sigma_e). It is calculated like: sigma_u/(sigma_u+ sigma_e).

Source: Authors' elaboration on European Commission (2020)

Table 2 Panel estimates of the determinants of labour productivity (continued)

Value	*3 Use of internet services*			*4 Integration of digital technology*			*5 Digital public services*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
DESI3	0.0432	–0.0045	–0.0297						
	(0.1477)	(0.1276)	(0.1255)						
DESI4				0.1716**	0.1657**	0.1239*			
				(0.0808)	(0.0815)	(0.0682)			
DESI5							0.0215	0.0201	0.0259
							(0.0633)	(0.0631)	(0.0612)
Employees with tertiary education		0.2797***	0.3670***		0.2928***	0.3620***		0.2741**	0.3529**
		(0.1068)	(0.1300)		(0.1202)	(0.1427)		(0.1238)	(0.1536)
Physical capital			0.1877***			0.1713***			0.1880***
			(0.0465)			(0.0412)			(0.0436)
2015y	0.0174*	0.0145*	0.0083	0.0069	0.0010	–0.0027	0.0191**	0.0132	0.0053
	(0.0093)	(0.0085)	(0.0095)	(0.0086)	(0.0086)	(0.0086)	(0.0088)	(0.0087)	(0.0060)
2016y	0.0240**	0.0163	0.0089	–0.0046	–0.0159	–0.0164	0.0249***	0.0134	0.0033
	(0.0106)	(0.0104)	(0.0125)	(0.0146)	(0.0152)	(0.0157)	(0.0105)	(0.0095)	(0.0063)
2017y	0.0409***	0.0304**	0.0180	0.0014	–0.0149	–0.0177	0.0424***	0.0260**	0.0094
	(0.0165)	(0.0160)	(0.0186)	(0.0210)	(0.0220)	(0.0225)	(0.0149)	(0.0129)	(0.0094)
2018y	0.0544***	0.0413**	0.0258	0.0052	–0.0161	–0.0198	0.0566***	0.0352**	0.0139
	(0.0230)	(0.0218)	(0.0250)	(0.0261)	(0.0278)	(0.0277)	(0.0205)	(0.0175)	(0.0141)
2019y	0.0674**	0.0557**	0.0345	0.0150	–0.0073	–0.0160	0.0700***	0.0477**	0.0189
	(0.0295)	(0.0270)	(0.0310)	(0.0295)	(0.0309)	(0.0306)	(0.0263)	(0.0221)	(0.0191)

Notes: Random effects. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) 22 European countries analysed over the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. In random effects, rho is the estimated proportion of the between-variance (sigma_u) at the total variance (sum of sigma_u and sigma_e). It is calculated like: sigma_u/(sigma_u+ sigma_e).

Source: Authors' elaboration on European Commission (2020)

Table 2 Panel estimates of the determinants of labour productivity (continued)

Value	*3 Use of internet services*			*4 Integration of digital technology*			*5 Digital public services*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
constant	3.8906***	2.9932***	3.0339***	3.6656***	2.6447***	2.7508***	3.9290***	2.9661***	2.9798***
	(0.2840)	(0.4779)	(0.6109)	(0.1604)	(0.4780)	(0.5632)	(0.1595)	(0.4579)	(0.5660)
N	132	132	132	132	132	132	132	132	132
R^2	0.0426	0.2854	0.2615	0.4399	0.4552	0.3788	0.0183	0.2892	0.2683
R^2 within	0.4868	0.5027	0.6004	0.5160	0.5324	0.6150	0.4884	0.5039	0.6019
R^2 between	0.2313	0.3014	0.2650	0.5275	0.4659	0.3827	0.1673	0.3039	0.2712
Wald chi^2	36.68***	54.30***	128.24***	35.82***	45.03***	118.79***	31.54***	37.27***	171.39***
sigma_u	0.4570	0.4383	0.4493	0.3582	0.3604	0.3664	0.4757	0.4462	0.4584
sigma_e	0.0303	0.0300	0.0270	0.0294	0.0290	0.0265	0.0303	0.0300	0.0270
rho	0.9956	0.9953	0.9964	0.9933	0.9936	0.9948	0.9959	0.9955	0.9965

Notes: Random effects. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) 22 European countries analysed over the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. In random effects, rho is the estimated proportion of the between-variance (sigma_u) at the total variance (sum of sigma_u and sigma_e). It is calculated like: sigma_u/(sigma_u+ sigma_e).

Source: Authors' elaboration on European Commission (2020)

Table 3 Random effects estimates with lagged regressors

Variable	*Total DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*
$DESI_{t-1}$	0.3806***					
	(0.1411)					
$DESI1_{t-1}$		0.1147**				
		(0.0510)				
$DESI2_{t-1}$			0.1902			
			(0.1345)			
$DESI3_{t-1}$				–0.0017		
				(0.1041)		
$DESI4_{t-1}$					0.1020*	
					(0.0638)	
$DESI5_{t-1}$						0.0258
						(0.0593)
Employees with tertiary $educat_{t-1}$	0.1620	0.1986	0.2133	0.2554*	0.2687*	0.2515
	(0.1330)	(0.1281)	(0.1512)	(0.1506)	(0.1555)	(0.1680)
$Physical_{t-1}$	0.0239	0.0266	0.0382	0.0307	0.0190	0.0325
	(0.0324)	(0.0381)	(0.0521)	(0.0476)	(0.0434)	(0.0474)
2016y	–0.0241***	–0.0128	–0.0043	0.0012	–0.0068	–0.0003
	(0.0113)	(0.0082)	(0.0066)	(0.0083)	(0.0065)	(0.0049)
2017y	–0.0316*	–0.0081	0.0072	0.0150	–0.0046	0.0114
	(0.0183)	(0.0119)	(0.0092)	(0.0120)	(0.0133)	(0.0081)

Notes: *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. One period lag is applied to each regressor. 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 3 Random effects estimates with lagged regressors (continued)

Variable	*Total DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*
2018y	–0.0407*	–0.0053	0.0144	0.0253	–0.0021	0.0199
	(0.0249)	(0.0156)	(0.0132)	(0.0183)	(0.0183)	(0.0129)
2019y	–0.0507	–0.0015	0.0185	0.0356	0.0008	0.0281
	(0.6378)	(0.0192)	(0.0179)	(0.0247)	(0.0235)	(0.0179)
Constant	2.0562***	3.0738***	2.8486***	3.1434***	2.8934***	3.1073***
	(0.6380)	(0.4985)	(0.5080)	(0.6301)	(0.5589)	(0.5814)
N	110	110	110	110	110	110
R^2	0.3896	0.3312	0.3646	0.2958	0.4281	0.2988
R^2 within	0.6245	0.6088	0.5848	0.5650	0.5801	0.5680
R^2 between	0.3953	0.3497	0.3730	0.3093	0.4391	0.3104
Wald chi^2	38.54***	42.04***	36.18***	39.90***	35.58***	29.07***
sigma_u	0.4147	0.4341	0.4233	0.4473	0.3645	0.4551
sigma_e	0.0207	0.0211	0.0218	0.0223	0.0218	0.0228
Rho	0.9975	0.9976	0.9974	0.9975	0.9964	0.9975

Notes: *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. One period lag is applied to each regressor. 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 4 Panel fixed effect estimates with IVs and lagged regressors

Instruments	*Correlation coefficients*		*IV coefficients*					
	Labour productivity	*DESI*	*DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*
Age	–0.0242	–0.1056	0.0031	0.0013***	–0.0038	0.1247	–0.0123	0.0009
			(0.2326)	(0.0946)	(0.2816)	(1.1135)	(0.9181)	(0.0680)
Graduates in STEM (%)	0.6216***	0.8117***	–0.3674	0.1204	–0.1348	0.1345*	0.1826	–0.0767
			(1.9956)	(0.5552)	(0.6634)	(0.0739)	(0.8549)	(0.3810)
Employment rate of tertiary graduates (%)	0.0240	0.5747***	–1.6497	–0.5791	0.6760***	0.1345*	–27.1029	–0.3989
			(1.0828)	(0.3333)	(0.2316)	(0.0739)	(481.503)	(0.2183)
Household with internet (%)	0.6028***	0.8591***	–0.0170	–0.0078	0.1832	0.1345*	–0.0519	–0.0124
			(0.1861)	(0.0850)	(1.9426)	(0.0739)	(0.5817)	(0.1357)
Total unemployment rate	0.0013	–0.4557***	2.1142	1.4192	–3.2558	1.5633	–0.7877	0.2800**
			(1.4255)	(1.5559)	(4.3382)	(1.3320)	(0.5550)	(0.1248)

Notes (*) 22 European countries analysed in the years 2014–2019. All the variables are in logarithmic scale. All variables have been transformed in natural logarithm. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$.

Source: Authors' elaboration on European Commission (2020)

Table 5 Panel fixed effect estimates with total unemployment rate as IV

Variable	*DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*
DESI	2.1142					
	(1.4255)					
DESI1		1.4192				
		(1.5559)				
DESI2			–3.2558			
			(4.3382)			
DESI3				1.5633		
				(1.3320)		
DESI4					–0.7877	
					(0.5550)	
DESI5						0.2800**
						(0.1248)
Employees with tertiary education$_{t-1}$	–0.3353	–0.5633	1.3596	–0.2678	0.3407	0.3108**
	(0.4767)	(1.0075)	(1.4590)	(0.5508)	(0.2114)	(0.1329)
Physical capital$_{t-1}$	0.0788	0.0760	0.2680	0.1303	0.2837***	0.2010***
	(0.1024)	(0.1687)	(0.1862)	(0.1044)	(0.1056)	(0.0500)
year_2015	–0.1272	–0.1584	0.0852	–0.0804	0.0654	–0.0080
	(0.0927)	(0.1845)	(0.1086)	(0.0783)	(0.0444)	(0.0134)
year_2016	–0.2418	–0.2655	0.1184	–0.1039	0.1532	–0.0298
	(0.1702)	(0.3025)	(0.1504)	(0.0991)	(0.1035)	(0.0213)

Notes: *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 5 Panel fixed effect estimates with total unemployment rate as IV (continued)

Variable	*DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*
year_2017	–0.3363	–0.3452	0.1677	–0.1612	0.2190	–0.0413
	(0.2398)	(0.3996)	(0.2040)	(0.1550)	(0.1435)	(0.0300)
year_2018	–0.4377	–0.4118	0.2696	–0.2264	0.2793	–0.0560
	(0.3131)	(0.4808)	(0.3290)	(0.2166)	(0.1807)	(0.0397)
year_2019	–0.5424	–0.5179	0.3235	–0.2944	0.3084	–0.0731
	(0.3888)	(0.6053)	(0.3905)	(0.2807)	(0.1960)	(0.0503)
Constant	–2.5121	2.8616**	7.3533	2.2485*	4.6244***	2.6631***
	(3.9042)	(1.1821)	(5.7188)	(1.1857)	(1.2457)	(0.5144)
N	132	132	132	132	132	132
R^2	0.3142	0.0240	0.1338	0.1607	0.3222	0.2488
R^2 within						0.2886
R^2 between	0.3165	0.0239	0.1391	0.1643	0.3546	0.2520
Wald chi^2	711,772***	269,215***	182,251***	445,743***	651,680***	1.63e+06***
sigma_u	0.4283	0.5251	0.8977	0.4753	0.6421	0.4488
sigma_e	0.0546	0.0888	0.1079	0.0690	0.0571	0.0361
Rho	0.9840	0.9722	0.9858	0.9794	0.9922	0.9936

Notes: *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Furthermore, given the way this variable is calculated, it also allows us to take into account the current level of digitalisation reached in each country in these years. The corresponding model is reported in the Appendix (Table 9). Results highlight that Ireland, Denmark, Italy, and France have the highest potential in labour productivity due to digitalisation when controlling for human and fixed capital. All the other Central and Nordic countries follow in this rank, while at the bottom of the rank, we find the poorest economies of Eastern Europe, followed by Iberian countries and Greece. Note that the coefficients can be interpreted in terms of elasticities and are, therefore strictly comparable with each other. They show that the effect of digitalisation in Ireland, Denmark, Italy, and France is more than double that of all the Eastern European countries and Portugal.

4.3 Robustness checks

Tables 3, 4 and 5 are alternative specifications of Models 3 in Table 2 estimated as robustness checks (equation (3)). Through Tables 3 and 4, we try to account for possible endogeneity. This latter may occur because there could be an issue of reverse causality between labour productivity and digitalisation since the level of digitalisation might in turn be affected by that of labour productivity. Indeed, high labour productivity can boost the process of digitalisation. As already mentioned in the methodology section, we follow two methods to control for endogeneity. The first one consists of regressing labour productivity on the lagged, rather than the current levels of digitalisation (Table 3), as represented in equation (7). The second one involves the use of IVs. (Table 4), as explained in equations (5) and (6) above. Finally, in Table 5, we test the stability of the results by assuming a different measure of labour productivity, proxied by the GDP per hour worked.

4.3.1 Using lagged variables

Table 3 confirms the previous results for the control variables and the DESI indices, but the fixed capital loses its significance mainly. The coefficients of DESI are also very similar to the previous ones, confirming that the relationship with labour productivity is strong and robust to possible bias due to reverse causality.

4.3.2 The IV approach

The second way of controlling for endogeneity consists of using an instrument for digitalisation, strongly correlated with digitalisation, the possible endogenous regressor (relevant condition), but not with labour productivity (so-called exclusion restriction). The question arises because digitalisation could be endogenous, that is it may reflect the effect of other omitted factors influencing both productivity and digitalisation.

We experiment with a number of IVs (Table 4). Most of the indicators initially selected because of their strong possible correlation with digitalisation were also correlated with labour productivity. This is the case of the share of graduates in STEM fields and the share of households with an internet connection, which measures the ability of the population to take advantage of digitalisation. The mean age level of the population (Age) has been selected under the hypothesis that the younger the population, the higher their propensity towards digitalisation, but its correlation with digitalisation appears weak. The only indicators which have been found able to satisfy the relevance condition and scarcely correlated with LP were the share of tertiary educated and more (ISCED 5-8) who have found a job from 1 to 3 years after graduation (employment rate of tertiary graduates) and TUR. We chose the Employment rate of tertiary graduates under the hypothesis that a labour market can exploit the highly educated labour force is more inclined to digitalisation. This variable shows a high correlation with DESI (0.5745), but a practically non-existent correlation with labour productivity (0.024). However, it is strongly correlated with the HC, already included in the model, and the test based on the introduction of residuals of regression of DESI on the IV in the main model estimation failed. Conversely, TUR, which proxies the countries' general economic condition, not only satisfies the exclusion restriction, but yields a non-statistically significant coefficient for the residuals of the estimate of the DESI indicator on the independent variables plus the IV (Becker, 2016; Stock, 2015).

For the sake of brevity, in Table 4, we report only, for each of the IV variables, the correlations with labour productivity and the DESI index and the regression coefficients for DESI and its pillars in the model instrumented through each of them. The estimate of the equation (5) above is provided in Table 5. When included in the main equation, the coefficient of the residuals of the regression of DESI on TUR is 0.007 with a p-value of 0.881. Therefore, TUR is an instrument which satisfies both the conditions required.

However, when we consider the model with TUR, the only instrument respecting both the conditions for IV, the coefficients for DESI and its pillars lose their significance. This may indicate that digitalisation does not represent itself the main driver of labour productivity growth. It could be itself the effect of other factors, such as the tendency to innovate and the ability to enhance the complementary production factors, such as the human capital and skills of the workforce.

Table 6 Random effects panel estimates

Variable	*Model 1 DESI*	*Model 2 DESI1*	*Model 3 DESI2*	*Model 4 DESI3*	*Model 5 DESI4*	*Model 6 DESI5*
DESI	0.1839					
	(0.1610)					
DESI1		0.0613				
		(0.0584)				
DESI2			–0.0187			
			(0.1374)			
DESI3				–0.0083		
				(0.0925)		
DESI4					0.1945***	
					(0.0802)	

Notes: Determinants of GDP per hours worked. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$.

Source: Authors' elaboration on European Commission (2020)

Table 6 Random effects panel estimates (continued)

Variable	*Model 1 DESI*	*Model 2 DESI1*	*Model 3 DESI2*	*Model 4 DESI3*	*Model 5 DESI4*	*Model 6 DESI5*
DESI5						–0.0133
						(0.0644)
Employees with tertiary education	0.2222**	0.2574***	0.2972***	0.2932***	0.2511**	0.2926***
	(0.1090)	(0.0962)	(0.1136)	(0.1071)	(0.1146)	(0.1074)
Physical capital	0.1980***	0.2050***	0.2104***	0.2100***	0.1822***	0.2092***
	(0.0554)	(0.0550)	(0.0599)	(0.0591)	(0.0498)	(0.0578)
year_2015	–0.0175*	–0.0133*	–0.0056	–0.0056	–0.0195**	–0.0054
	(0.0101)	(0.0074)	(0.0094)	(0.0103)	(0.0086)	(0.0085)
year_2016	–0.0434**	–0.0306**	–0.0216**	–0.0216**	–0.0564***	–0.0204***
	(0.0188)	(0.0124)	(0.0085)	(0.0101)	(0.0169)	(0.0075)
year_2017	–0.0612**	–0.0472***	–0.0305***	–0.0303**	–0.0789***	–0.0286***
	(0.0257)	(0.0169)	(0.0108)	(0.0153)	(0.0244)	(0.0101)
year_2018	–0.0764**	–0.0565***	–0.0359**	–0.0359*	–0.0974***	–0.0565***
	(0.0336)	(0.0198)	(0.0144)	(0.0201)	(0.0309)	(0.0142)
year_2019	–0.0920**	–0.0674***	–0.0417***	–0.0415*	–0.1085***	–0.0385**
	(0.0436)	(0.0266)	(0.0152)	(0.0243)	(0.0350)	(0.0193)
constant	3.4147***	3.8407***	3.8927***	3.8769***	3.6199***	3.8880***
	(0.7311)	(0.4387)	(0.4664)	(0.4227)	(0.4185)	(0.4075)
N	132	132	132	132	132	132
R^2	0.3916	0.3797	0.3714	0.3755	0.5203	0.3765
R^2 within	0.2085	0.2065	0.1943	0.1932	0.2683	0.1949
R^2 between	0.3951	0.3837	0.3753	0.3794	0.5251	0.3806
Wald chi^2	92.35***	103.80***	76.12***	79.29***	89.00***	93.66***
sigma_u	0.2099	0.2118	0.2118	0.2121	0.1781	0.2119
sigma_e	0.0303	0.0303	0.0303	0.0306	0.0291	0.0305
rho	0.9796	0.9799	0.9796	0.9797	0.9740	0.9796

Notes: Determinants of GDP per hours worked. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses. All variables have been transformed in natural logarithm. *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$.

Source: Authors' elaboration on European Commission (2020)

4.3.3 Changing the measure of labour productivity

As a further step, we provide an alternative measure of labour productivity: the GDP per hour worked (Table 6). While the coefficients for human capital and fixed capital remain positive and significant, some DESI coefficients lose their significance because of the weaker correlation between the DESI components and this measure of labour productivity compared to that used in the previous estimates. However, the results are globally consistent with the previous ones.

5 Discussion and hypotheses testing

The results of our analysis show that digitalisation has a relevant role in explaining the variations in labour productivity. However, when we decompose the overall measure of productivity, measured by the DESI index, in its components and test the effect of each of them on labour productivity, we find that a significant role in labour productivity is exerted by the human capital (DESI2) and the interconnection (DESI4) components. This finding widely confirms our H1 hypothesis, based on the assumption that digitalisation itself is not sufficient to boost economic growth. The integration of digital technologies and the level of human capital are indeed determinants to explain the cross-country differences in the levels of digitalisation and the changes occurred in the time period analysed.

6 Conclusions

In this paper, we analysed the effect of digitalisation on labour productivity from 2014 to 2019, just before the outbreak of the pandemic emergency. The 23 EU countries analysed show very different levels of labour productivity and digitalisation. While in the Nordic countries, a virtuous circle of economic growth, high productivity and high levels of digitalisation emerges, for Southern countries, Greece and Italy in particular, characterised by decades of low economic growth, low labour productivity growth, high levels of unemployment and public debt, the opposite is true. Moreover, Eastern countries still exhibit a gap in the level of development and high rates of economic growth.

The econometric analysis shows that digitalisation exerts a strong effect on labour productivity and, in addition, that the effect is greater in countries where the process of digitalisation is more advanced, like Denmark and Sweden (the country effects are, respectively, 0.35 and 0.32 – see Figure 3 and Table 8 in the Appendix). The effect of digitalisation is also important in such countries as Ireland (0.40), showing the highest levels of labour productivity in the last years, and Italy (0.34), which has shown a significant decrease in economic and labour productivity growth in the last decades. Very low, the effect of digitalisation for Eastern countries, such as Latvia and Lithuania, where it is less than 0.04.

Our analysis also highlights the important role of human capital as a factor of labour productivity growth and, therefore, indirectly in taking advantage of the digital revolution. The regression coefficients for the variable measuring the share of labour force with tertiary education are statistically significant in most cases.

These results are confirmed when the covariates are lagged of one year: DESI and human capital still exert an important impact on labour productivity, while fixed capital formation loses its statistical significance. This suggests that our findings are robust to issues of reverse causality of labour productivity on digitalisation.

In our IV approach to exogenise digitalisation, our results are only partially confirmed. When we use as an IV the TUR, the only one which satisfies both the relevance and exclusion restriction, the coefficients for DESI and all its pillars lose their statistical significance, suggesting that, probably, the effect on labour productivity is not directly due to digitalisation, but to other factors able to enhance the effect of digitalisation, such as investment in R&D, innovation and efficient use of human capital.

Overall, our study suggests that already in the years of digitalisation, the expected positive effects on labour productivity have overcome the negative ones, and digitalisation is affecting labour productivity. This suggests that the COVID emergency might reduce the gaps in labour productivity among EU countries in the years to come. In fact, the pandemic has dramatically reduced the gap in the digitalisation process across EU countries. This is good news for those worried about the divide among EU countries between Centre-North, on the one hand, and East and South, on the other. Of course, we cannot expect that closing the gap in digitalisation will also close the gap in labour productivity, but at least it should be able to reduce it in the near future. This will necessarily be the testing hypothesis for future studies on the impact of digitalisation.

The EU policymakers and national governments of EU member states may draw important policy implications from our study, which are particularly important in view of the programmes to be decided on how to spend – for instance – the resources of the next generation fund. First, investing in the digitalisation of production, including the public sector, may generate labour productivity gains not only in the long but also in the short run. Moreover, small and medium-sized enterprises, which represent the backbone of the production structure of South and East European countries, should be supported in the process of digitalisation. They represent an important asset for the lagging regions if they exploit digitalisation well. Digitalisation is an advantage for small and medium-sized enterprises since it reduces the cost of accessing world markets and bring the specificity of small and medium-sized firms to the attention of the global markets.

However, the results of the model based on the IVs show that digitalisation alone is not able to produce significant effects on labour productivity, but in order to increase labour productivity and, therefore, boost economic growth, it is necessary to create the conditions for enhancing the advantages from digitalisation, first of all investing in high education. Hence, the focus of Europe 2030 on investment in human capital is well placed and applies especially in South and East European countries. The Next Generation Fund should support the development of R&D and higher education in these countries to get the best of the investment in digitalisation.

7 Limitations and future research

This paper has some limitations, which can be summarised as follows. First of all, in our paper, we consider the selection of labour productivity as a ratio between GDP and the number of employees in each country. In addition, we provide a different measure of labour productivity – the GDP per hour worked – which produced similar conclusions. Nevertheless, different equally possible (and potentially more comprehensive) performance measures can be involved. Second, the choice of IVs – although sufficiently supported by authors – may not be exogenous entirely. Furthermore, the analysis is based on the 2014–2019 years for 23 European countries, but the time series could consider more recent data.

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Notes

1 Descriptive statistics suggested to drop from the analysis Luxembourg because of its recognised role of outlier in terms of GDP and economic growth.

2 Brexit has not been considered because in the period analyses UK was part of EU.

3 The DESI 2018 report is available at https://ec.europa.eu/digital-single-market/en/news/digital-economy-and-society-index-2018-report.

4 To get valid estimates in the Hausman test, we used the Stata option 'sigmamore', which allows us to correct for possible not positive definite variance in small samples using an efficient estimator (Green, 2018). In some cases, the Hausman test rejects the null hypothesis of absence of correlation between residuals and regressors, but the coefficients estimates are very similar between the two model specifications (random effects and fixed effects).

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Appendix

Table 7 Correlation matrix

Variable	*DESI*	*DESI1*	*DESI2*	*DESI3*	*DESI4*	*DESI5*	*Labour productivity*	*GDP per hours worked*	*Employees with tertiary education*	*Physical capital*	*Population dens.*	*Total unempl. rate*	*Share of elderly population.*	*Employed in manuf.*	*Innovation*
DESI	1														
DESI1	0.883***	1													
DESI2	0.876***	0.669***	1												
DESI3	0.934***	0.812***	0.899***	1											
DESI4	0.803***	0.615***	0.637***	0.655***	1										
DESI5	0.819***	0.674***	0.595***	0.695***	0.571***	1									
Labour productivity	0.562***	0.390***	0.561***	0.461***	0.677***	0.374***	1								
GDP per hours worked	0.495***	0.326***	0.483***	0.357***	0.645***	0.332***	0.923***	1							
Employees with tertiary ed.	0.679***	0.438***	0.648***	0.640***	0.589***	0.644***	0.550***	0.544***	1						
Physical capital	0.465***	0.435***	0.450***	0.399 ***	0.311***	0.347***	0.131	0.379	0.223***	1					
Population density	–0.068	0.086	–0.166*	–0.084	0.121	–0.230***	0.251***	0.230	–0.165*	–0.196**	1				
Total unemployment rate	–0.456***	–0.557***	–0.434***	–0.480***	–0.253***	–0.217**	0.001	–0.055	–0.025	–0.505***	–0.226***	1			
Share of elderly population	0.085	0.144*	0.001	0.106	–0.036	0.167**	0.006	–0.259***	–0.150	–0.419***	–0.078	0.058	1		
Employed in manufacturing %	–.0323***	–0.180**	–0.268***	–0.317***	–0.392***	–0.0290***	–0.644***	–0.500***	–0.615***	0.281***	–0.156*	–0.361***	–0.088	1	
Innovation	0.169**	0.133	0.246***	0.133	0.231***	0.009	0.009	0.259***	0.025	0.076	0.390***	–0.234***	0.018	0.166**	1

Note: (*) All variables have been transformed in natural logarithm. *** p < 0.01; ** p < 0.05; *p < 0.1.

Source: Authors' elaboration on European Commission (2020)

Table 8 Panel estimates of the determinants of labour productivity

Variable	*Total DESI*			*1 Connectivity*			*2 Human capital*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
DESI	0.3819*	0.3524	0.2909*						
	(0.2041)	(0.2143)	(0.1633)						
DESI1				0.1222	0.1080	0.0911			
				(0.0809)	(0.0812)	(0.0683)			
DESI2							0.2638*	0.2323	0.2058
							(0.1365)	(0.1475)	(0.1387)
Employees with tertiary education	0.1079	0.2177			0.1435	0.2502*		0.1334	0.2394
	(0.1379)	(0.1446)			(0.1180)	(0.1326)		(0.1340)	(0.1514)
Physical capital		0.1685***				0.1759***			0.1774***
		(0.0373)				(0.0406)			(0.0463)
2015y	–0.0072	–0.0074	–0.0107	0.0040	0.0028	–0.0028	0.0119	0.0100	0.0030
	(0.0095)	(0.0097)	(0.0093)	(0.0072)	(0.0074)	(0.0080)	(0.0109)	(0.0110)	(0.0087)
2016y	–0.0230	–0.0237	–0.0255	0.0007	–0.0022	–0.0086	0.0151	0.0109	0.0021
	(0.0220)	(0.0220)	(0.0190)	(0.0132)	(0.0134)	(0.0143)	(0.0124)	(0.0126)	(0.0104)
2017y	–0.0252	–0.0262	–0.0308	0.0105	0.0060	–0.0054	0.0292*	0.0231	0.0085
	(0.0311)	(0.0313)	(0.0265)	(0.0173)	(0.0177)	(0.0185)	(0.0166)	(0.0170)	(0.0150)
2018y	–0.0315	–0.0328	–0.0384	0.0184	0.0122	–0.0027	0.0356*	0.0282	0.0099
	(0.0413)	(0.0414)	(0.0345)	(0.0209)	(0.0215)	(0.0217)	(0.0209)	(0.0217)	(0.0197)
2019y	–0.0376	–0.0377	–0.0463	0.0233	0.0177	–0.0024	0.0466*	0.0392	0.0145
	(0.0513)	(0.0517)	(0.0436)	(0.0258)	(0.0260)	(0.0274)	(0.0242)	(0.0248)	(0.0222)

Notes Fixed effects. Legend: *** p < 0.01; ** p < 0.05; *p < 0.1. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses.
(**) Hausman test is based on the comparison between the models with fixed effects reported in this Table A2 and the corresponding random effects models in Table 3. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 8 Panel estimates of the determinants of labour productivity (continued)

Variable	*Total DESI*			*1 Connectivity*			*2 Human capital*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
_cons	2.5632***	2.2917***	2.4022***	3.6932***	3.2200***	3.1655***	3.3429***	2.9480***	2.9230***
	(0.7592)	(0.8030)	(0.7782)	(0.1908)	(0.4364)	(0.5167)	(0.3234)	(0.4908)	(0.5588)
N	132	132	132	132	132	132	132	132	132
R^2 overall	0.3475	0.3823	0.3262	0.1145	0.3048	0.2691	0.2873	0.3577	0.3091
R^2 within	0.5480	0.5525	0.6322	0.5227	0.5307	0.6186	0.5248	0.5316	0.6213
R^2 between	0.3725	0.3978	0.3300	0.2288	0.3559	0.2768	0.3189	0.3766	0.3129
F	6.08***	5.45***	16.73***	6.35***	6.24***	18.68***	6.56***	5.97***	15.10***
sigma_u	0.4664	0.4551	0.4475	0.4987	0.4790	0.4648	0.4764	0.4618	0.4512
sigma_e	0.0285	0.0285	0.0260	0.0293	0.0292	0.0264	0.0292	0.0291	0.0263
rho	0.9963	0.9961	0.9967	0.9966	0.9963	0.9968	0.9962	0.9960	0.9966
Hausman test(**)									
Chi^2	6.18***	5.52	5.69	4.73**	6.43**	5.47	5.26**	5.40*	4.94

Notes Fixed effects. Legend: *** p < 0.01; ** p < 0.05; *p < 0.1. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses.
(**) Hausman test is based on the comparison between the models with fixed effects reported in this Table A2 and the corresponding random effects models in Table 3. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 8 Panel estimates of the determinants of labour productivity (continued)

Variable	3 Use of internet services			4 Integration of digital technology			5 Digital public services		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
DESI3	0.0157*	–0.0177	–0.0382						
	(0.1513)	(0.1329)	(0.1283						
DESI4				0.1312*	0.1325*	0.0983			
				(0.0774)	(0.0777)	(0.0660)			
DESI5							0.0164	0.0161	0.0233
							(0.0628)	(0.0624)	(0.0607)
Employees with tertiary education		0.2114	0.3200**		0.2087	0.3016*		0.2049	0.3064*
		(0.1334)	(0.1482)		(0.1451)	(0.1635)		(0.1466)	(0.1696)
Physical capital		0.1841***				0.1702***			0.1843***
		(0.0472)				(0.0420)			(0.0440)
2015y	0.0192**	0.0168*	0.0100	0.0100	0.0054	0.0007	0.0194**	0.0149	0.0065
	(0.0093)	(0.0091)	(0.0099)	(0.0085)	(0.0091)	(0.0090)	(0.0088)	(0.0092)	(0.0062)
2016y	0.0264**	0.0204*	0.0118	0.0030	–0.0061	–0.0090	0.0256**	0.0169	0.0058
	(0.0107)	(0.0116)	(0.0133)	(0.0142)	(0.0152)	(0.0162)	(0.0104)	(0.0101)	(0.0065)
2017y	0.0447***	0.0364**	0.0223	0.0121	–0.0010	–0.0072	0.0435***	0.0310**	0.0130
	(0.0166)	(0.0177)	(0.0198)	(0.0204)	(0.0220)	(0.0233)	(0.0148)	(0.0137)	(0.0095)
2018y	0.0597***	0.0493**	0.0315	0.0187	0.0017	–0.0064	0.0580***	0.0418**	0.0185
	(0.0231)	(0.0239)	(0.0266)	(0.0254)	(0.0278)	(0.0286)	(0.0204)	(0.0185)	(0.0143)
2019y	0.0742**	0.0646**	0.0409	0.0298	0.0119	–0.0015	0.0719***	0.0549**	0.0241
	(0.0298)	(0.0291)	(0.0326)	(0.0286)	(0.0307)	(0.0313)	(0.0261)	(0.0228)	(0.0189)
_cons	3.9413***	3.2582***	3.2093***	3.7372***	2.9998***	3.0069***	3.9387***	3.2176***	3.1428***
	(0.2845)	(0.5513)	(0.6548)	(0.1408)	(0.5341)	(0.6072)	(0.1231)	(0.5013)	(0.5821)

Notes Fixed effects. Legend: *** $p < 0.01$; ** $p < 0.05$; *$p < 0.1$. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses.
(**) Hausman test is based on the comparison between the models with fixed effects reported in this Table A2 and the corresponding random effects models in Table 3. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 8 Panel estimates of the determinants of labour productivity (continued)

Variable	*3 Use of internet services*			*4 Integration of digital technology*			*5 Digital public services*		
	Model 1	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
N	132	132	132	132	132	132	132	132	132
R^2	0.0125	0.2615	0.2493	0.3931	0.4529	0.3615	0.2745	0.0136	0.2598
R^2 within	0.4875	0.5049	0.6014	0.5186	0.5366	0.6173	0.5058	0.4885	0.6027
R^2 between	0.2313	0.2937	0.2547	0.5275	0.4759	0.3679	0.3039	0.1673	0.2644
F	6.70***	7.56***	14.58***	18.68***	5.90***	13.20***	5.32***	5.28***	18.99***
sigma_u	0.5072	0.4800	0.4661	0.4804	0.4514	0.4458	0.4777	0.5071	0.4628
sigma_e	0.0303	0.0300	0.0270	0.0294	0.0290	0.0265	0.0300	0.0303	0.0270
rho	0.9964	0.9961	0.9966	0.9963	0.9959	0.9965	0.9961	0.9964	0.9966
Hausman test (**)									
Chi^2	5.50**	5.46*	4.25	15.13***	11.66***	11.41***	4.49	3.74*	3.14

Notes Fixed effects. Legend: *** p < 0.01; ** p < 0.05; *p < 0.1. (*) 22 European countries analysed in the years 2014–2019. Robust standard errors in parentheses.
(**) Hausman test is based on the comparison between the models with fixed effects reported in this Table A2 and the corresponding random effects models in Table 3. All variables have been transformed in natural logarithm.

Source: Authors' elaboration on European Commission (2020)

Table 9 Random effects estimates with interactions between country dummies and DESI. (**)

	Model 1(*)		*Model 1(*)*
Employees with tertiary education	0.1402 (0.1286)	DESI_LV	0.0317 (0.0544)
Physical capital	0.0680 (0.0485)	DESI_NL	0.3179*** (0.0558)
DESI_AT	0.3218*** (0.0530)	DESI_PL	0.0580 (0.0569)
DESI_BE	0.3228***(0.0595)	DESI_PT	0.1674*** (0.0438)
DESI_CZ	0.1299***(0.0446)	DESI_SE	0.3256*** (0.0559)
DESI_DE	0.3034*** (0.0500)	DESI_SI	0.1669*** (0.0539)
DESI_DK	0.3541*** (0.0609)	DESI_SK	0.1091*** (0.0461)
DESI_EE	0.0620 (0.0567)	DESI_UK	0.2791*** (0.0561)
DESI_EL	0.2448*** (0.0521)	Constant	2.7356*** (0.3135)
DESI_ES	0.2439*** (0.0584)	N	110
DESI_FI	0.2995*** (0.0582)	R^2	0.9963
DESI_FR	0.3331*** (0.0572)	R^2 within	0.3923
DESI_HU	0.0629 (0.0442)	R^2 between	>0.9999
DESI_IE	0.4010*** (0.0652)	Wald chi^2	28,673.55***
DESI_IT	0.3394*** (0.0431)	sigma_u	0
DESI_LT	0.0397*** (0.0593)	sigma_e	0.0127
		Rho	0

Notes: *** p<.01; ** p<.05; *p<.1.
(*) All variables have been transformed in a natural logarithm.
(**)Austria – AT; Belgium – BE; the Czech Republic – CZ; Denmark – DK; Estonia - EE; Finland - FI; France – FR; Germany – DE; Greece – EL; Hungary – HU; Ireland - IE; Italy – IT; Latvia – LV; Lithuania – LT; Luxembourg – LU; the Netherlands – NL; Poland – PL; Portugal – PT; Slovakia – SK; Slovenia – SI; Spain – ES; Sweden – SE; the United Kingdom – UK.

Source: Authors' elaboration on European Commission (2020)