

 Bennett School of Public Policy

Digitisation and productivity in the transport sector



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Abstract

Digitisation makes possible both increased productivity and improved energy efficiency in the transport sector, yet the sector has contributed to the productivity growth slowdown since the mid-2000s. This paper investigates the impact of investment in information and communication technology (ICT) capital on productivity and energy efficiency in the transport sectors of 20 Organisation for Economic Co-operation and Development (OECD) countries over the period 1995 – 2019. We find that greater ICT investment significantly boosts productivity across all measures, and particularly energy productivity. An increase in the ICT capital share in total capital from 10% to 11% boosts labour productivity level by about 1%, and energy productivity level by almost 1.5%. Investment in hardware drives productivity, while software investment plays a dominant role in energy productivity gains. However, these impacts were stronger before 2008. Our findings highlight the importance of continuous ICT investment, complementary human capital, and policy frameworks that encourage digital transformation in the transport sector.

1 Introduction

The widespread slowdown in productivity growth since around 2008 (Figure 1) among the advanced economies has been intensively studied. It is considered a puzzle because it has coincided with continuing or accelerated progress in digital technologies. One of the primary drivers of productivity growth is technological innovation and adoption (e.g., Aboal and Tacsir (2018); Brynjolfsson et al. (2019); Liu and Saam (2022); Banday and Erdem (2024)). The US economy, exceptionally, experienced an increase in productivity growth (Inklaar et al., 2005; Dahl et al., 2011; Cardona et al., 2013). One potential explanation for the divergence between the US and European economies is strong American investment into ICTs (Van Ark et al., 2008; Bloom et al., 2012; Biagi, 2013; Cardona et al., 2013; Mohnen et al., 2019). In particular, sectors that are ICT intensive account for most of the observed rise in US productivity (Dahl et al., 2011; Ceccobelli et al., 2012; Cardona et al., 2013; Acharya, 2016).

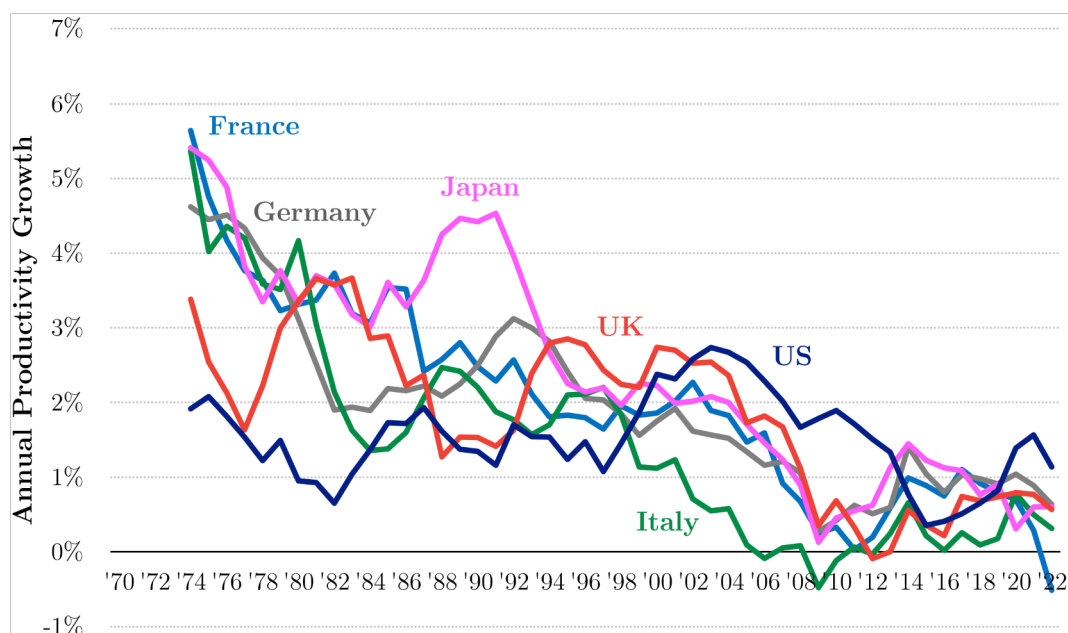


Figure 1: Growth of productivity (output per hour worked) in major economies, 1970 – 2022. Lines represent a five-year moving average (OECD, 2024).

ICTs include computing equipment (e.g., laptops, tablets), communication devices (e.g., networks, smartphones), software, data storage, and network infrastructure, as well as more recent technologies, such as artificial intelligence (AI), blockchain, cloud computing, internet of things, or edge computing. These technologies allow for the potential simplification of complex tasks, bringing greater efficiency, faster decision-making, lower transaction costs, and increased market competition (Litan and Rivlin, 2001; Aboal and Tacsir, 2018; Lahouel et al., 2021; Banday and Erdem, 2024). For example, according to Gal et al. (2019), a 10-percentage point (p.p.) increase in adoption of cloud computing across a sector leads to a 3.5% increase in productivity of an average European firm after five years. Furthermore, ICTs as general-purpose technologies spur further complementary innovations across the economy (Ceccobelli et al., 2012; Jung et al., 2013; Arendt and Grabowski, 2017; Elstner et al., 2022; Schwark and Tryphonides, 2025). However, ICTs

also require complementary investments in worker skills, and organisational expertise (Timmer et al., 2010; Díaz-Chao et al., 2015).

In this context we consider the transport sector,¹ which is an important input into other sectors of the economy and plays a key part in global supply chains. Evidence for the US from the late 1990s attributed much of the surge in productivity then to ICT-driven improvements in logistics in domestic and global supply chains (Lewis et al., 2001). However, sectoral decompositions indicate that the transport sector has contributed substantially to the post-2008 productivity slowdown (Coyle and Mei, 2023). It is also one of the least digitised sectors in the economy. Only about 64% of European Union (EU) firms in the transport sector use advanced digital technologies, the lowest percentage of all industries, except for the tourism (61%) and construction (52%) sectors (EIB, 2023). Digitisation could not only increase productivity, but also help with other challenges faced by the transport sector, particularly climate change (Leviäkangas, 2016; Mandys and Taneja, 2024). The transport sector represented over 23% of global greenhouse gas (GHG) emissions in 2022, second only to electricity and heat generation (IEA, 2024). In developed countries the transport sector is in fact the biggest contributor to GHG emissions, at 28% in the US and 26% in the EU (Department for Transport, 2023; EPA, 2024). Greater digitisation has shown the potential to reduce overall energy use, and therefore lead to lower GHG emissions (Bastida et al., 2019; Haben et al., 2021; Taneja and Mandys, 2024). Consequently, ICT adoption in the transport sector could contribute to both swifter productivity growth and reaching net-zero emissions by 2050.

There is limited literature on technology and productivity in the transport sector. Our contribution in this paper is to estimate the impact of digitisation on labour productivity and Total Factor Productivity (TFP) in the transport sector across 20 OECD countries from 1995 to 2019. We also examine how greater adoption of ICTs influences energy productivity in the sector. We construct a panel dataset from several sources, covering 20 OECD countries for the period 1995–2019. We also examine how the impact of ICTs in the sector varies across countries. To the best of our knowledge, our paper is the first to examine this key sector using several different productivity measures and more recent data.

We find that higher ICT capital investments significantly boost TFP, labour productivity, and energy productivity in the transport sector. An increase of ICT capital share in total capital from 10% to 11% raises labour productivity level by 1% and TFP by 0.1%, while the impact on energy productivity level is 1.5%. Disaggregated estimates reveal that hardware drives most of the gains in labour productivity and TFP, while software investment drives improvements in energy productivity. We identify 2009 as a structural break, after which the positive impact of ICT capital decreases in size. We also show that high-productivity and low-transport-intensity countries in particular benefit from ICT investments. Counterfactual analyses show that if ICT investment (growth in ICT share) was larger by 1% since 1995, the levels of labour and energy productivity would be 4 p.p. and 6 p.p. higher by 2019, respectively. These findings highlight the importance of continuing ICT investment for persistent productivity and energy saving effects.

¹ We construct the transport sector from five subsectors: manufacture of transport equipment, land transport, water transport, air transport, and warehousing and storage.

2 Context

There was considerable investment in ICTs before the financial crisis, with the average share of ICT capital in total capital doubling from 4.5% to almost 9% on average across the Group of 7 (G7) economies (Figure 2). However, over the decade after the financial crisis, the ICT share increased considerably more slowly. This slower pace of investment occurred despite the implementation of many policies to promote the uptake of digital technologies over this period. For example, the e-Japan Strategy was implemented in 2001 with subsequent updates; Germany introduced the *Breitbandstrategie* in 2009, bringing large public and private investments in internet infrastructure. A similar policy was adopted by the US in 2010 – the National Broadband Plan, and by France in 2013 – the *Plan France Très Haut Débit*. Similarly, the EU implemented several policies and strategies to increase and harmonise the uptake of digital technologies across Europe.

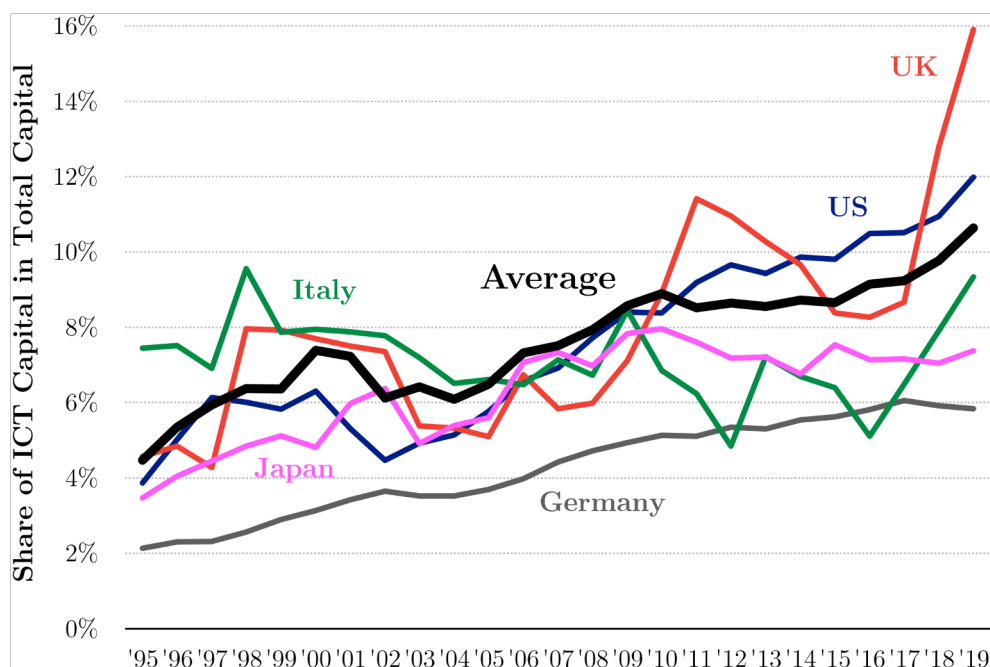


Figure 2: Growth of the share of ICT capital in total capital in major economies, 1995–2019 (authors' own work).

There is by now a rich literature estimating the impact of ICT investment on productivity and economic growth. Researchers generally found a positive impact of ICTs in the 1990s (e.g., Brynjolfsson and Hitt (1996); Lehr and Lichtenberg (1999); Sichel (2001)). Oulton (2002), focusing on the UK between 1989 and 1998, found that ICT has a positive and increasing impact on economic growth, contributing about a fifth of overall GDP growth. Similarly, Becchetti et al. (2003) explored the effect of ICT investment on productivity in Italian firms (1995 – 1997), concluding that communication devices contribute to the creation of new products and process, but it is software and human capital that raise labour productivity.

Several EU and non-EU countries were analysed by [Van Ark and Piatkowski \(2004\)](#) during the 1990s, using growth accounting. The results suggested that ICTs had a comparable impact on productivity growth in both country groups, and this was mainly driven by the manufacturing industries. A comparison between EU countries and the United States (US) was done by each of [Inklaar et al. \(2005\)](#), [Matteucci et al. \(2005\)](#), and [Timmer and Van Ark \(2005\)](#). All three papers concluded that ICT investments had a considerably stronger impact on productivity in the US in the 1990s, compared to the EU. [Timmer and Van Ark \(2005\)](#) concluded that the US lead in productivity growth over the EU was primarily caused by stronger ICT capital deepening and ICT-goods production.

Focusing on the impact of disaggregated ICT capital, [Papaioannou and Dimelis \(2007\)](#) found a significant effect only for hardware and communication devices, not for software. Similarly, [Spiezia \(2013\)](#) found that ICT investments add between 0.4% and 1% extra value-added growth, with computing equipment providing the largest contribution. Analysing the impact of disaggregated ICTs in the Netherlands, [Borowiecki et al. \(2021\)](#) discovered that hardware investments have a strong positive impact on productivity, but software investments benefit particularly low-productivity firms.

While most authors found that digitisation has a significant positive effect on productivity, as is also confirmed by the literature reviews of [Cardona et al. \(2013\)](#) and [Biagi \(2013\)](#), several papers have found a partially negative impact for specific periods. For example, [Pohjola \(1998\)](#) found a generally negative relationship between productivity and ICT investments in the US in the 1980s and early 90s ([Kenny, 2003](#)). A similar conclusion was reached by [Van Ark and Inklaar \(2006\)](#), finding a negative effect of ICT investment on TFP growth during the 1980s, both in Europe and the US. Nevertheless, the authors also found that this is a temporary impact, and the effect of ICT returns to being positive after several years. A potential explanation of this finding may be the investments into human and knowledge capital, that have immediate costs but delayed results. The same conclusion was also reached by [Liao et al. \(2016\)](#) and [Kallal et al. \(2021\)](#).

Turning to the transport sector specifically, there are few studies. A positive impact of software on labour productivity in the transport sector was found by [Vu and Hartley \(2022\)](#). Looking at the impact of digitisation in the Finnish transport sector, [Leviäkangas \(2016\)](#) found only a weak positive correlation between ICTs and productivity.

The literature on energy productivity is also relatively sparse. [Honma and Hu \(2009\)](#) use 1993 – 2003 data for Japan to compute a novel total-factor energy productivity change index. The results showed an annual 0.2% rise in total-factor energy efficiency over the period examined. More recently, [Parker and Liddle \(2017\)](#) examined the dynamics of energy productivity across 61 OECD countries, between 1980 and 2009. While results differed across country groups, more advanced technology and greater investment contributed to higher energy productivity. The impact of ICTs on green TFP was analysed by [Wang and Guo \(2023\)](#). By applying a Chinese panel dataset from 2008–2019 to a spatial Durbin model, the authors confirmed that ICTs can promote local green TFP, but may have a negative effect on surrounding cities. Similarly, using the data from G7 economies between 1990 and 2020, [Ullah et al. \(2023\)](#) demonstrate that environmental ICT innovations may contribute towards energy transition and productivity. The relationship between ICT, productivity, and CO₂ emissions was analysed by [Lahouel et al. \(2021\)](#). The results indicated

that ICT investments can not only promote economic growth, but also reduce emissions ([Haben et al., 2021](#); [Taneja and Mandys, 2022, 2024](#)).

To the best of our knowledge, we are the first to analyse the impact of various ICT investments on the transport sector, using several different measures of productivity and energy productivity.

3 Data

We constructed a panel dataset from four different sources: the latest data from EU KLEMS², the Groningen Growth and Development Centre productivity database, the International Energy Agency (IEA) energy prices data, and the IEA extended world energy balances. We construct key variables, creating a panel dataset for 5 transport subsectors, 25 years (1995–2019), and 20 OECD countries. We also collected supplementary data from the OECD, the World Bank, and the US Bureau of Economic Analysis, for control variables. We take advantage of the panel structure of the multi-country and sector dataset, allowing us to control for country, sector, and time-specific unobserved fixed effects. We are able to explore the effect of ICTs on productivity within transport sub-sectors separately from any changes in market or firm structures. While all our countries are members of OECD, their ICT adoption levels are unlikely to be similar ([Krutova et al., 2022](#); [Banday and Erdem, 2024](#)). As seen in [Table 1](#), some countries, such as Sweden, Denmark, or Finland, are significantly more digitised than others such as Italy or France ([Biagi, 2013](#); [European Commission, 2024](#)). We would expect the impact of digitisation may vary across different countries.

The transport sector is composed of five subsectors: vehicle manufacturing (which includes manufacture of motor vehicles, trailers, semi-trailers, and other transport equipment), land transport (including rail transport, road transport, and transport via pipelines), water transport (including sea and coastal transport, and inland water transport), air transport (including passenger and freight air transport, and space transport), and warehousing (includes support activities, storage, and cargo handling).

The dataset covers 20 OECD countries, namely Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Japan, Latvia, Luxembourg, Netherlands, Portugal, Romania, Slovakia, Spain, Sweden, UK, and the US. In terms of variables, the dataset includes different measures of productivity, ICT capital, national accounts data, human capital, trade and openness, and others such as infrastructure, research and development (R&D), and energy use and prices.

² EU KLEMS is an industry level international dataset. EU KLEMS stands for EU level analysis of capital (K), labour (L), energy (E), materials (M), and service (S) inputs.

Table 1: Rankings of European Union countries by extent of digitisation, 2024 ([European Commission, 2024](#)).

Country	ICT graduates	High-speed internet subscription	SMEs with basic digital intensity	Use of AI	Use of cloud computing	Digital public services	Average
Sweden	7	3	2	10	3	4	4.8
Denmark	9	6	5	1	2	9	5.3
Finland	4	20	1	2	1	5	5.5
Luxembourg	2	7	14	3	19	3	8.0
Netherlands	19	10	3	5	5	8	8.3
Belgium	23	9	6	4	9	11	10.3
Spain	15	2	11	11	23	10	12.0
Germany	10	21	9	7	13	18	13.0
Hungary	5	5	18	24	14	20	14.3
Austria	13	23	13	9	16	14	14.7
Portugal	24	4	17	14	20	12	15.2
Latvia	12	11	23	22	22	6	16.0
Italy	26	13	10	19	6	23	16.2
Czech Republic	11	24	22	16	17	16	17.7
Romania	6	1	27	27	26	27	19.0
France	21	16	19	17	24	21	19.7
Slovakia	18	22	25	15	21	22	20.5

Note: The numbers represent the ranking of each country for each particular category out of the 27 member countries of the European Union. The final column is a simple average of the six digitisation columns.

The primary source is the latest release of the EU-KLEMS productivity database, specifically the EU-KLEMS & INTANProd 2025 Release, which contains key information about the inputs and outputs of different countries and sectors, for the period 1995–2021 ([Bontadini et al., 2023](#)). Within EU-KLEMS, we extract data from the national accounts, the capital accounts, and the growth accounts. The accounts provide information on variables such as gross output, value added, intermediate inputs, labour compensation, number of employees, hourly wage, and factor prices. The accounts also include information on ICT capital services, and their disaggregation into computing equipment, communication devices, and software. These capital variables represent the different measures of digitisation. Furthermore, we also take additional variables from EU-KLEMS including non-ICT capital services, measures of R&D capital, as well as transport equipment. Furthermore, a variable labelling each country-sector combination is constructed, controlling for country and sector fixed effects, while a “year” variable controls the time fixed effects. The dependent, independent, and control variables are also converted into natural logarithms before the regression analysis. Further detail on data construction and descriptive statistics is given in the [Appendix](#).

We estimate two measures of productivity and two measures of energy productivity: labour productivity (gross value added per employee), TFP (using the method of [Levinsohn and Petrin](#)

(2003)), energy productivity (gross value added per unit of energy cost), and the Malmquist energy productivity index, estimated using data envelopment analysis. All the productivity variables are transformed into an index, where the base year is 1995. Figure 3 portrays the four measures of productivity and energy productivity in the transport sector, between 1995 and 2019. All four productivity measures have been increasing throughout the period examined; nevertheless, the slowdown after the 2008 financial crisis is evident. Labour and energy productivity grew by about 3.6% per year respectively, from 1995 until the financial crisis. However, from 2008 to 2019, the annual growth was 1.2% for labour productivity and 2.6% for energy productivity. TFP and the Malmquist energy productivity index show a similar pattern.

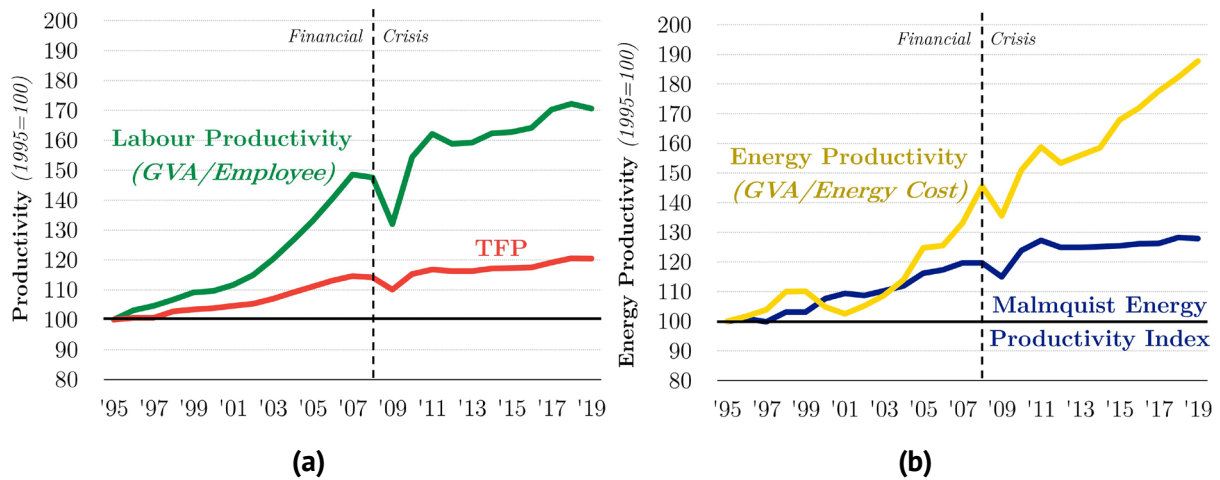


Figure 3: (a) Overall productivity, and (b) energy productivity in the transport sector, 20 OECD countries, 1995–2019 (authors' own work).

We then estimate the impact of ICTs on the different measures of productivity using a logarithmic weighted panel fixed effects model. We also identify a time structural break in the data to examine the impact of ICTs over time. We distinguished countries by productivity levels, and by transport intensity levels. Furthermore, we conducted several counterfactual tests to identify the potential ICT impact on productivity if ICT investments had been higher or lower over the past decades. Lastly, we also perform a series of robustness checks (including for endogeneity using system generalised method of moments (GMM)), shown in the Appendix.

The key independent variable is the ICT capital share, in total and disaggregated into computing equipment, communication devices, and software. We define this as the share of ICT capital in total capital, where total capital is the sum of ICT capital and non-ICT capital. The disaggregated ICT variables are constructed in a similar manner.

A range of factors are controlled for in our estimates, including human capital variables, such as the share of high-skilled workers and the share of females in the workforce. The share of high-skilled workers is defined as the share of the workforce that has tertiary education, similarly as in Audretsch and Belitski (2020). A greater share of highly skilled workers may positively impact productivity, due to the greater ability of the workers (Cette et al., 2022; Banday and Erdem, 2024). The share of females may act as a proxy for labour market flexibility or average management quality, for example. The levels of transparency and restrictiveness for Foreign Direct Investment (FDI) are included as well. The transparency indicator reflects the perception

of the degree of corruption in each country and year. The countries are divided into three groups, from lowest transparency (value of 1) to highest transparency (value of 3). The FDI restrictiveness variable measures the strictness of a country's FDI rules on a scale of 0 to 1, looking at foreign equity restrictions, discriminatory screening, restrictions on key foreign personnel, and operational restrictions. There is evidence that higher transparency and lower FDI restrictiveness may contribute to productivity growth (Del Mar Salinas-Jiménez and Salinas-Jiménez, 2007; Beverelli et al., 2017). These control variables are expected to have a significant impact on productivity, both intuitively and based on past literature. For example, importance of education and human capital was pointed out by Cette et al. (2022) and Banday and Erdem (2024). Similarly, previous research found significant results for trade (e.g., Solarin (2016)), as well as R&D capital (e.g., Cette et al. (2017)).

We further aimed to capture the effect of exports, infrastructure, transport equipment, and R&D capital. The export variable is defined as the share of exports in GDP, while transport equipment and R&D capital are measured in per capita terms. We expect these factors to have a positive impact on productivity, where the importance of R&D capital was confirmed by several previous studies (Cette et al., 2017; Pieri et al., 2018). Greater trade openness brings new expertise, increased competition, and encourages firms to adopt modern technologies (Solarin, 2016; Banday and Erdem, 2024). The infrastructure variable is defined as the total length of land³ infrastructure (motorways and railways) per thousand km², for each country. While intuitively positive, the impact of infrastructure on productivity is mixed in the prior literature (Deng, 2013).

In addition, we also include the impact of energy by controlling for energy prices. The energy prices are calculated from electricity and non-electric energy prices, weighted by the energy use of each energy type. For electricity prices, the total industrial sector prices are used, while for non-electric energy prices, the following steps are taken. For oil price, the high sulphur oil price is used, and if this is not available in the data, the low sulphur or light oil prices are used. Similarly, for gas price, natural gas is used, and replaced by liquefied petroleum (LP) gas if needed. Auto diesel price is used for petroleum, and replaced by various types of gasoline if needed. And lastly, steam coal price is used for coal, and replaced by coking coal if needed. A weighted average energy price is then calculated from these individual energy prices, weighted by each energy type's consumption.

4 Method

Labour productivity is defined as a simple ratio of total value added in real terms to the total number of employees in each country-sector:

$$LP_{it} = \frac{VA_{it}^{Real}}{E_{it}} \quad (1)$$

³ Infrastructure for water transport (length of waterways) and air transport (number of commercial airports) was also considered. However, these were not included in the estimations, as their variability throughout the years was negligible, preventing any meaningful analysis.

where LP_{it} is labour productivity of country-sector i in year t , VA_{it}^{Real} is real value added, and E_{it} is the number of employees.

For TFP, we follow the approach of [Levinsohn and Petrin \(2003\)](#), which addresses the simultaneity problem, i.e., the correlation between inputs and unobservable productivity shocks. Compared to e.g., [Olley and Pakes \(1992\)](#) who rely on the use of investment data, [Levinsohn and Petrin \(2003\)](#) instead use the data for intermediate inputs. The aim is to avoid the empirical problem of zeroes present in investment data, taking advantage of intermediate inputs not being a state variable and being proxy for productivity shocks ([Audretsch and Belitski, 2020](#)). We define the base productivity function as:

$$Y_{it} = A_{it}f(L_{it}, C_{it}, K_{it}, M_{it}), \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T \quad (2)$$

where Y_{it} is the gross output of country-sector i in the year t , A_{it} is the level of technology (TFP), L_{it} represents labour, C_{it} is ICT capital, K_{it} is non-ICT capital, M_{it} are intermediate inputs (i.e., materials), N is the total number of country-sector combinations, and T is the total number of years.

We assume that labour and intermediate inputs adjust freely to shocks, while capital is a quasi-fixed (state) input. In logarithmic form:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_c c_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it} \quad (3)$$

Above, ω_{it} and ε_{it} are errors, with ω_{it} being a state variable (affecting input decisions) and ε_{it} being an i.i.d. variable (no impact on input decisions). We assume that after a productivity shock, intermediate inputs m_{it} are adjusted immediately, based on the demand function:

$$m_{it} = m_{it}(\omega_{it}, c_{it}, k_{it}) \quad (4)$$

It is also assumed that the levels of capital c_{it} and k_{it} are decided at time $t - 1$, and that the function m_{it} is monotonic in ω_{it} . Due to the monotonicity, we can invert equation 4:

$$\omega_{it} = \omega_{it}(m_{it}, c_{it}, k_{it}) \quad (5)$$

Substituting into equation 3, our model becomes:

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \varphi_{it}(m_{it}, c_{it}, k_{it}) + \varepsilon_{it} \\ \varphi_{it}(m_{it}, c_{it}, k_{it}) &= \beta_0 + \beta_c c_{it} + \beta_k k_{it} + \omega_{it}(m_{it}, c_{it}, k_{it}) \end{aligned} \quad (6)$$

where the expression φ_{it} can be treated as a control that accounts for productivity shocks.

Following [Levinsohn and Petrin \(2003\)](#), equation 6 can then be estimated in two stages. First, we use a non-parametric approach to obtain an estimate of β_l . The expression φ_{it} is typically approximated using a low-order polynomial in m_{it} , c_{it} , and k_{it} , with equation 6 estimated by regressing output on labour and the polynomials. Second, a moment-based estimation is used to get the remaining parameters. If it is assumed that ω_{it} follows a first-order Markov process and that c_{it} and k_{it} do not adjust immediately to productivity shocks defined as:

$$\xi_{it} = \omega_{it} - E[\omega_{it}|\omega_{it-1}] \quad (7)$$

then we can define output without labour contribution as:

$$\begin{aligned} y_{it}^* &= \beta_0 + \beta_c c_{it} + \beta_k k_{it} + \beta_m m_{it} + E[\omega_{it}|\omega_{it-1}] + \varepsilon_{it}^* \\ \varepsilon_{it}^* &= \xi_{it} + \varepsilon_{it} \end{aligned} \quad (8)$$

Assuming $E[m_{it-1}\varepsilon_{it}^*] = 0$, the remaining parameters can be identified. Therefore, this two-stage semi-parametric approach yields consistent estimates of the production function coefficients and allows recovery of TFP by taking the difference between observed output and the fitted contributions of labour, ICT capital, and non-ICT capital.

The third productivity variable, energy productivity, is defined as the ratio between real value added and real energy compensation (energy price and consumption):

$$EP_{it} = \frac{VA_{it}}{EC_{it} \cdot EP_{it}} \quad (9)$$

Where EP_{it} is energy productivity of country-sector i in year t , VA_{it} is real value added, EC_{it} is total energy consumption, and EP_{it} is total energy price. Total energy consumption is calculated by adding the usage of all energy types, i.e., electricity, oil, gas, petroleum, coal, and other. Similarly, total energy price is constructed as the weighted average of individual energy prices, weighted by each energy's use. Therefore, the energy productivity variable measures how much value added (in 2017 \$) each unit of energy value provides.

Lastly, for the calculation of the fourth productivity variable, the Malmquist energy productivity index, we use non-parametric data envelopment analysis (DEA (e.g., [Zhou et al. \(2012\)](#) and [Zheng et al. \(2020\)](#))). The DEA method uses the data on input and output quantities, and creates a piecewise linear surface over the data points ([Coelli and Rao, 2005](#)). Compared to the parametric stochastic frontier approach, the DEA method does not need functional specification of the technology, or specific assumptions about the distribution of the inefficiency terms ([Haider et al., 2021](#)). The Malmquist index measures the change in energy productivity of a country-sector between two time periods, by comparing its distance to a production efficiency frontier (maximum potential) in each period. The method assumes that the base production frontier has constant returns to scale ([Rehman and Nunziante, 2023](#)), while focusing on minimising inputs for given outputs. Furthermore, the approach accounts for changes in efficiency (i.e., how each country-sector moves towards the maximum potential frontier), as well as for technical changes (i.e., shifts of the frontier due to technological shocks). Under constant returns to scale, the technology set is defined as:

$$T_t = \{(x, e, y) | x \geq X_t \lambda, e \geq E_t \lambda, y \leq Y_t \lambda, \lambda \geq 0\} \quad (10)$$

where T_t is the technology set, X_t are the non-energy inputs, such as labour, ICT capital, and non-ICT capital, over all country-sectors in year t , E_t is the energy input, Y_t is the output, and λ is an intensity vector.

Measuring the distance from the frontier, the input-oriented distance function is:

$$D_t(x_{it}, e_{it}, y_{it}) = \min_{\theta, \lambda} \theta \quad \text{s.t.} \quad \begin{cases} X_t \lambda \leq \theta x_{it} \\ E_t \lambda \leq \theta e_{it} \\ Y_t \lambda \geq y_{it} \\ \lambda \geq 0 \end{cases} \quad (11)$$

The distance function D_t finds the smallest combination θ of inputs (x, e) that produces the output y . Consequently, a value of $D_t < 1$ suggests that a country-sector could reduce its inputs by $1 - D_t$ and still produce the same output.

We then define the Malmquist energy productivity index as:

$$M_{it} = \frac{D_t(x_{it+1}, e_{it+1}, y_{it+1})}{D_t(x_{it}, e_{it}, y_{it})} \cdot \sqrt{\frac{D_t(x_{it+1}, e_{it+1}, y_{it+1})}{D_{t+1}(x_{it+1}, e_{it+1}, y_{it+1})} \cdot \frac{D_t(x_{it}, e_{it}, y_{it})}{D_{t+1}(x_{it}, e_{it}, y_{it})}} \quad (12)$$

where M_{it} is the Malmquist index between the year t and $t + 1$, the first fraction represents efficiency change and the expression within the square root is the technical change.

The efficiency change measures how far each country-sector is from the maximum production frontier, while the technical change measures how the frontier itself shifts due to changes in technology. A Malmquist index that is greater than one signifies productivity growth, and value below one indicates productivity decline.

With the four dependent variables defined, we move on to estimate the impact of ICT capital and other control variables on productivity in the transport sector. We use a panel fixed effects model, in order to account for the unobserved country-sector fixed effects (time-invariant heterogeneity) and time fixed effects (common shocks and trends). The regressions are weighted based on the gross output of each country-sector in each year, in order to account for the varying sizes of each country and transport subsector. The variables are also transformed into natural logarithms. For aggregated ICT capital, our base panel fixed effects model is:

$$\ln Y_{it} = \beta_0 + \beta_C \ln C_{it} + \sum_{k=1}^K \beta_k \ln X_{kit} + \mu_i + \tau_t + \epsilon_{it} \quad (13)$$

where Y_{it} is one of the four measures of productivity, C_{it} is ICT capital, X_{kit} represents the different control variables, μ_i are the country-sector fixed effects, τ_t are the year fixed effects, ϵ_{it} is the error term, β_C is the ICT capital coefficient, β_k are the coefficients of the control variables, and K is the total number of control variables.

Similarly, the model for the disaggregated ICT capital then takes the form:

$$\ln Y_{it} = \beta_0 + \beta_H \ln H_{it} + \beta_N \ln N_{it} + \beta_S \ln S_{it} + \sum_{k=1}^K \beta_k \ln X_{kit} + \mu_i + \tau_t + \epsilon_{it} \quad (14)$$

where H_{it} are computing equipment (i.e., hardware), N_{it} is communication (network) devices, and S_{it} is software.

In addition to estimating the base model for aggregated and disaggregated capital, we also analyse whether the impact of digitisation changes over time. We employ the novel method of [Ditzen et al. \(2025\)](#) to identify multiple structural breaks in our panel dataset. The method is able to identify structural breaks in panel data with interactive fixed effects, estimate the number of breaks, and their location. Applying this method, we identify a single structural break in our dataset, in 2009. We therefore split our sample into a pre-crisis period (1995 – 2008) and a post-crisis period (2009 – 2019), and apply equation 13 to each of the subsamples, to quantify the impact of ICTs on different types of productivity before and after the structural break point.

We use the same approach to analyse the impact of digitisation on productivity for countries with different productivity levels and different transport intensity levels. In the case of productivity levels, we split the sample into low productivity and high productivity countries, based on their labour productivity and energy productivity levels. Similarly, for transport intensity, we split the sample into low and high transport intensity countries, where transport intensity represents the value added of each country's transport sector as a share of total value added.

Lastly, we test for the potential endogeneity of ICT capital, i.e., where ICT capital may be correlated with the residuals. We test this by applying the efficient two-step system GMM panel data estimator ([Arellano and Bover, 1995](#); [Blundell and Bond, 1998](#)), similarly as e.g., [Rehman and Nunziante \(2023\)](#). Our baseline system GMM estimation is:

$$\ln Y_{it} = \beta_0 + \beta_Y \ln Y_{it-1} + \beta_C \ln C_{it} + \sum_{k=1}^K \beta_k \ln X_{kit} + \mu_i + \tau_t + \epsilon_{it} \quad (15)$$

where Y_{it-1} is the lagged measure of one of the four measures of productivity.

The method is particularly useful for panel datasets which have a relatively low number of time periods compared to cross sections ([Roodman, 2009](#)). The greater number of available instruments can lead to greater efficiency of the estimates ([Dimelis and Papaioannou, 2010](#)). We use lagged levels of all the control variables, with a lag of two years or greater as instruments, and collapse the matrix of the instruments to prevent overfitting ([Acharya, 2016](#)). We also report several diagnostic tests for the validity of the system GMM estimations. This includes the Hansen J test, which tests whether the set of instruments used is valid, i.e., uncorrelated with the error term, as well as the first and second-order serial correlations in the difference residuals, testing if the level-lagged instruments are not endogenous themselves. Robustness test results are given in the [Appendix](#).

5 Results

5.1 Impact of ICTs on productivity

We first present the baseline results labour productivity ([Table 2](#)) and TFP ([Table 3](#)). As the dependent and independent variables are in logarithms, the results are interpretable as percentages. For both aggregated and disaggregated ICTs, we report four different model

specifications, each controlling for a more complete set of independent variables. While model 1 only includes the ICT share variable, as well as the country-sector and year unobservable fixed effects, model 4 contains all control variables. The fact that our results are generally consistent across the various model specifications provides some evidence of the robustness of our findings. We focus on Model 4.

Table 2: Effect of digitisation on labour productivity

Variables	Digitisation and Labour Productivity							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Ln ICT share	0.179*** (0.010)		0.080*** (0.011)		0.081*** (0.011)		0.104*** (0.016)	
Ln Computing share		0.088*** (0.011)		0.080*** (0.010)		0.071*** (0.010)		0.088*** (0.015)
Ln Comm. share		-0.053*** (0.009)		-0.043*** (0.008)		-0.044*** (0.008)		-0.049*** (0.010)
Ln Software share		0.131*** (0.013)		0.046*** (0.012)		0.052*** (0.012)		0.063*** (0.017)
Ln High-skill share			0.062* (0.034)	0.082** (0.036)	0.036 (0.036)	0.059 (0.037)	0.122** (0.050)	0.135*** (0.052)
Ln Female share			0.294*** (0.045)	0.337*** (0.046)	0.326*** (0.046)	0.365*** (0.048)	0.280*** (0.064)	0.312*** (0.065)
Transparency level ¹			0.084** (0.035)	0.066* (0.036)	0.084** (0.036)	0.067* (0.037)	0.113** (0.048)	0.095** (0.049)
Ln FDI restrictiveness			-0.039 (0.028)	-0.088*** (0.029)	-0.018 (0.028)	-0.067** (0.030)	-0.029 (0.037)	-0.104*** (0.040)
Ln Exports GDP share			0.543*** (0.034)	0.507*** (0.034)	0.478*** (0.036)	0.461*** (0.037)	0.256*** (0.049)	0.282*** (0.048)
Ln Land infrastructure					0.421*** (0.098)	0.302*** (0.103)	0.148 (0.127)	0.015 (0.130)
Ln Transport equip.					0.030*** (0.009)	0.028*** (0.010)	0.041*** (0.012)	0.027** (0.013)
Ln R&D capital							0.007 (0.011)	0.035*** (0.011)
Ln Energy prices							0.138*** (0.022)	0.120*** (0.023)
Countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.147	0.145	0.329	0.354	0.339	0.361	0.425	0.441
Observations	1,819	1,657	1,806	1,650	1,749	1,609	1,059	1,017

Note: Panel fixed effects regression for finding the effect of aggregated and disaggregated ICT capital on labour productivity. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

As [Table 2](#) and [Table 3](#) show, the share of ICT capital in total capital is positive and significant for both measures, but its impact on labour productivity is an order of magnitude larger than for TFP. Specifically, a rise in the ICT capital share from 10% to 11% would boost labour productivity level by 1%, but TFP by only 0.1%. A possible explanation for the difference in scale is the labour-augmenting nature of ICTs in the transport sector. Many transport subsectors have high labour intensity, and ICT improvements (e.g., automated scheduling, fleet tracking, maintenance alerts, etc.) directly increase labour productivity by capital deepening, automating routine tasks. On the other hand, improving overall system efficiency, such as optimisation of logistics over the entire network, can take longer to come into effect. The control variables show similar coefficient signs for both labour productivity and TFP.

Table 3: Effect of digitisation on total factor productivity

Variables	Digitisation and Total Factor Productivity							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Ln ICT share	0.058*** (0.005)		0.010** (0.005)		0.011** (0.005)		0.012* (0.007)	
Ln Computing share		0.014*** (0.005)		0.013*** (0.004)		0.011** (0.004)		0.023*** (0.006)
Ln Comm. share		-0.011*** (0.004)		-0.012*** (0.003)		-0.012*** (0.003)		-0.017*** (0.004)
Ln Software share		0.054*** (0.005)		0.010** (0.005)		0.013** (0.005)		0.012* (0.007)
Ln High-skill share			0.085*** (0.015)	0.086*** (0.015)	0.080*** (0.015)	0.082*** (0.016)	0.080*** (0.021)	0.084*** (0.022)
Ln Female share			0.147*** (0.019)	0.153*** (0.020)	0.154*** (0.020)	0.162*** (0.021)	0.139*** (0.027)	0.146*** (0.027)
Transparency level ¹			0.017 (0.015)	0.013 (0.015)	0.018 (0.015)	0.015 (0.016)	0.024 (0.020)	0.020 (0.020)
Ln FDI restrictiveness			-0.032*** (0.012)	-0.044*** (0.012)	-0.025** (0.012)	-0.037*** (0.013)	-0.027* (0.015)	-0.051*** (0.017)
Ln Exports GDP share			0.202*** (0.014)	0.190*** (0.015)	0.188*** (0.016)	0.178*** (0.016)	0.131*** (0.020)	0.123*** (0.020)
Ln Land infrastructure					0.097** (0.041)	0.071* (0.043)	0.021 (0.053)	-0.021 (0.054)
Ln Transport equip.					0.005 (0.004)	0.007 (0.004)	0.004 (0.005)	0.002 (0.005)
Ln R&D capital							0.015*** (0.005)	0.022*** (0.005)
Ln Energy prices							0.049*** (0.009)	0.041*** (0.010)
Countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.092	0.088	0.328	0.338	0.330	0.340	0.378	0.394
Observations	1,611	1,516	1,607	1,512	1,560	1,474	1,011	982

Note: Panel fixed effects regression for finding the effect of aggregated and disaggregated ICT capital on total factor productivity. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

The tables also show the impact of the disaggregated digital technologies; computing equipment and software have a significant positive effect, stronger for labour productivity compared to TFP. The larger impact on productivity comes from computing equipment (i.e., hardware) rather than software, where a 1% increase in computing and software capital share boosts labour productivity level by about 0.09% and 0.06%, respectively.

An unexpected result can be seen for communication devices capital, having a significant negative impact on both labour productivity and TFP. One interpretation of this result is as a reflection of the role of centralized decision-making, consistent with the framework proposed by [Garicano \(2000\)](#). With the expansion of information technologies (computing, software), information becomes cheaper to acquire, enabling lower-level workers to make better decisions without having to rely on their managers, i.e., decentralisation ([Garicano, 2000](#); [Garicano and Rossi-Hansberg, 2015](#)). This may lead to faster decision-making, fewer bottlenecks, reduced burdens on managers, and greater efficiency, contributing to productivity gains. On the other hand, communication technologies make communication cheaper, allowing workers to consult with their managers more frequently, i.e., they facilitate centralisation ([Bloom et al., 2014](#); [Garicano and Rossi-Hansberg, 2015](#)). This may improve coordination and reduce errors, but also

cause slower decision-making, increased bureaucracy, and more micromanagement. Consequently, communication technology may have a negative effect on productivity if it leads to more reliance on centralised decision-making.

Table 4: Effect of digitisation on energy productivity

Variables	Digitisation and Energy Productivity							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Ln ICT share	0.239*** (0.013)		0.135*** (0.013)		0.138*** (0.014)		0.148*** (0.017)	
Ln Computing share		0.090*** (0.014)		0.091*** (0.013)		0.088*** (0.014)		0.085*** (0.017)
Ln Comm. share		-0.029*** (0.011)		-0.025*** (0.010)		-0.026*** (0.010)		-0.022* (0.011)
Ln Software share		0.177*** (0.016)		0.081*** (0.015)		0.086*** (0.016)		0.115*** (0.018)
Ln High-skill share			0.045 (0.044)	0.071 (0.046)	0.027 (0.045)	0.058 (0.048)	0.059 (0.056)	0.069 (0.057)
Ln Female share			0.404*** (0.057)	0.458*** (0.059)	0.433*** (0.059)	0.475*** (0.060)	0.418*** (0.070)	0.439*** (0.071)
Transparency level ¹			-0.011 (0.046)	-0.022 (0.047)	-0.012 (0.048)	-0.024 (0.049)	0.049 (0.054)	0.039 (0.054)
Ln FDI restrictiveness			-0.062* (0.035)	-0.106*** (0.037)	-0.054 (0.036)	-0.097** (0.038)	-0.012 (0.041)	-0.064 (0.044)
Ln Exports GDP share			0.490*** (0.041)	0.488*** (0.041)	0.444*** (0.045)	0.469*** (0.044)	0.248*** (0.054)	0.285*** (0.053)
Ln Land infrastructure					0.191 (0.118)	0.082 (0.124)	0.131 (0.141)	0.024 (0.143)
Ln Transport equip.					0.026** (0.012)	0.012 (0.013)	0.034*** (0.013)	0.013 (0.014)
Ln R&D capital							0.007 (0.012)	0.034*** (0.013)
Ln Energy prices							0.143*** (0.024)	0.127*** (0.025)
Countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.210	0.183	0.348	0.365	0.349	0.364	0.425	0.437
Observations	1,423	1,325	1,416	1,322	1,374	1,286	1,034	1,005

Note: Panel fixed effects regression for finding the effect of aggregated and disaggregated ICT capital on energy productivity. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

In terms of control variables, as expected, a greater share of highly skilled workers in the sector is correlated with higher productivity. Similarly, a larger share of female workers has a strongly significant effect on productivity for both productivity measures. Countries that are more open and export a greater share of goods and services experience higher productivity, as do countries that are more transparent and less restrictive for FDI. Energy prices are positively correlated with both productivity measures.

The impact of aggregated and disaggregated digital technologies on energy productivity and the Malmquist energy productivity index can be seen in [Table 4](#) and [Table 5](#), respectively. The share of ICT capital in total capital has a strong, positive, and significant effect on both energy productivity and the Malmquist index, similarly as in [Parker and Liddle \(2017\)](#) and [Ullah et al. \(2023\)](#). Specifically, an increase of ICT capital share from 10% to 11% would boost energy productivity level by almost 1.5%, and the Malmquist index by about 0.7%. The pattern of results is similar to those for the other two productivity measures.

Table 5: Effect of digitisation on the Malmquist energy productivity index

Variables	Digitisation and the Malmquist Energy Productivity Index							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
Ln ICT share	0.137*** (0.006)		0.089*** (0.007)		0.064*** (0.007)		0.065*** (0.008)	
Ln Computing share		0.020*** (0.007)		0.023*** (0.007)		0.027*** (0.007)		0.023*** (0.008)
Ln Comm. share		0.006 (0.006)		0.004 (0.006)		0.004 (0.005)		0.002 (0.006)
Ln Software share		0.112*** (0.009)		0.054*** (0.008)		0.020** (0.008)		0.029*** (0.010)
Ln High-skill share			0.059*** (0.020)	0.059*** (0.022)	0.069*** (0.020)	0.077*** (0.022)	0.058** (0.024)	0.059** (0.025)
Ln Female share			0.220*** (0.027)	0.245*** (0.029)	0.201*** (0.027)	0.218*** (0.028)	0.163*** (0.032)	0.173*** (0.033)
Transparency level ¹			0.004 (0.021)	-0.001 (0.022)	-0.003 (0.021)	-0.008 (0.021)	0.020 (0.023)	0.015 (0.024)
Ln FDI restrictiveness			-0.019 (0.016)	-0.026 (0.018)	-0.012 (0.016)	-0.017 (0.017)	0.001 (0.018)	-0.003 (0.020)
Ln Exports GDP share			0.176*** (0.021)	0.226*** (0.021)	0.228*** (0.022)	0.278*** (0.022)	0.169*** (0.025)	0.211*** (0.026)
Ln Land infrastructure					0.056 (0.051)	0.050 (0.054)	0.058 (0.060)	0.042 (0.063)
Ln Transport equip.					0.020*** (0.005)	0.033*** (0.006)	0.019*** (0.006)	0.030*** (0.007)
Ln R&D capital							0.025*** (0.007)	0.030*** (0.007)
Ln Energy prices							0.054*** (0.012)	0.060*** (0.013)
Countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.285	0.196	0.405	0.381	0.419	0.407	0.465	0.450
Observations	1,224	1,144	1,224	1,144	1,185	1,110	927	898

Note: Panel fixed effects regression for finding the effect of aggregated and disaggregated ICT capital on the Malmquist energy productivity index. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

5.2 Temporal dynamics and cross-sectional heterogeneity

We next examine whether the positive impact that digitisation has on productivity and energy productivity changes over time. As described, we find that there is a single time structural break in our dataset, in 2009. We thus split our full sample into two subsamples, 1995 to 2008, and 2009 to 2019. The results are shown in in [Table 6](#).

Table 6: Effect of digitisation on productivity and energy productivity across time

Variables	Digitisation, Productivity, and Time Structural Break							
	Labour Prod.		TFP		Energy Prod.		Malmquist	
	95-08	09-19	95-08	09-19	95-08	09-19	95-08	09-19
Ln ICT share	0.146*** (0.019)	0.060*** (0.022)	0.034*** (0.008)	0.006 (0.008)	0.098*** (0.023)	0.081*** (0.031)	0.058*** (0.011)	0.031*** (0.010)
Ln High-skill share	0.148** (0.066)	0.112 (0.091)	0.059** (0.026)	0.087** (0.034)	-0.108 (0.079)	0.144 (0.127)	-0.003 (0.033)	0.111** (0.043)
Ln Female share	0.297*** (0.072)	0.076 (0.082)	0.168*** (0.028)	0.039 (0.031)	0.116 (0.085)	0.443*** (0.115)	0.222*** (0.037)	-0.003 (0.042)
Transparency level ¹	-0.074 (0.052)	0.188*** (0.062)	-0.022 (0.021)	0.040* (0.023)	-0.052 (0.062)	0.216** (0.089)	-0.028 (0.026)	0.032 (0.029)
Ln FDI restrictiveness	-0.160 (0.138)	-0.330** (0.139)	-0.059 (0.055)	-0.112** (0.050)	-0.608*** (0.165)	-0.039 (0.195)	0.149** (0.072)	-0.135** (0.064)
Ln Exports GDP share	0.240*** (0.051)	0.283*** (0.077)	0.117*** (0.020)	0.110*** (0.028)	0.317*** (0.061)	0.207* (0.108)	0.176*** (0.028)	0.181*** (0.039)
Ln Land infrastructure	0.338* (0.204)	0.585* (0.337)	0.103 (0.081)	0.220* (0.123)	-0.190 (0.244)	1.060** (0.473)	0.345*** (0.103)	0.125 (0.156)
Ln Transport equip.	0.037* (0.020)	0.008 (0.011)	0.003 (0.008)	-0.004 (0.004)	-0.010 (0.024)	0.031** (0.015)	0.004 (0.011)	0.027*** (0.005)
Ln R&D capital	0.005 (0.012)	-0.027 (0.016)	0.009* (0.005)	-0.004 (0.006)	0.011 (0.014)	0.007 (0.023)	0.008 (0.008)	-0.035*** (0.009)
Ln Energy prices	0.139*** (0.023)	0.009 (0.041)	0.052*** (0.009)	-0.013 (0.015)	0.112*** (0.027)	0.057 (0.057)	0.069*** (0.014)	-0.007 (0.024)
Countries	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.470	0.169	0.434	0.185	0.303	0.166	0.435	0.285
Observations	578	481	574	437	571	463	529	398

Note: Panel fixed effects regression for finding the effect of ICT capital on productivity and energy productivity across time. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The impact of digitisation on both productivity and energy productivity is consistently positive throughout but becomes considerably weaker after the financial crisis, for all measures of productivity. A similar finding was also reported by e.g., [Polák \(2017\)](#) and [Mollins and St-Amant \(2019\)](#). Up to 2008, an increase in ICT capital share from 10% to 11% would raise labour productivity and TFP by about 1.5% and 0.3%, respectively. Post-2008 the impact on TFP disappears, while the effect on labour productivity falls to only 0.6%. A similar, albeit smaller, decline can be observed for energy productivity and the Malmquist index. This result is consistent with other work showing that the transport sector contributed notably to the aggregate productivity growth slowdown.

The impact of ICTs on productivity for countries at different average productivity levels can be seen in [Table 7](#) and [Table 8](#), respectively. We split our sample into low productivity and high productivity OECD countries, based on their labour productivity and energy productivity levels.⁴ Do countries benefit more - or less - from digitisation as they get more productive?

⁴ The high transport productivity level countries in our sample are: Austria, Belgium, Czech Republic, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Spain, Sweden, UK, and US.

Table 7: Effect of digitisation on productivity across productivity levels

Variables	Digitisation Impact Across Productivity Levels			
	Labour Productivity		TFP	
	Low Prod.	High Prod.	Low Prod.	High Prod.
Ln ICT share	0.022 (0.021)	0.126*** (0.020)	0.005 (0.008)	0.014* (0.008)
Ln High-skill share	-0.361*** (0.120)	0.168*** (0.058)	-0.104** (0.049)	0.094*** (0.025)
Ln Female share	0.130 (0.138)	0.252*** (0.074)	0.138** (0.059)	0.137*** (0.031)
Transparency level ¹	0.410*** (0.115)	0.081 (0.056)	0.163*** (0.045)	0.008 (0.024)
Ln FDI restrictiveness	-0.024 (0.075)	0.027 (0.044)	0.008 (0.029)	-0.024 (0.019)
Ln Exports GDP share	0.364*** (0.066)	0.339*** (0.070)	0.161*** (0.026)	0.137*** (0.030)
Ln Land infrastructure	0.802*** (0.217)	0.103 (0.176)	0.169** (0.084)	-0.020 (0.075)
Ln Transport equip.	-0.055* (0.028)	0.038*** (0.013)	-0.042*** (0.011)	0.007 (0.006)
Ln R&D capital	0.011 (0.031)	0.028** (0.013)	0.028** (0.013)	0.017*** (0.005)
Ln Energy prices	-0.083* (0.045)	0.145*** (0.027)	0.003 (0.017)	0.051*** (0.011)
Countries	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes
R-squared	0.434	0.465	0.573	0.365
Observations	325	734	277	734

Note: Panel fixed effects regression for finding the effect of ICT capital on productivity across productivity levels. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

Our results suggest that ICT investments have a larger positive effect in more productive economies, across all four of our measures of productivity. As such, digitisation generally boosts productivity, but this effect appears to be stronger as productivity increases (similarly as in e.g., [Deng et al. \(2022\)](#) and [Lei et al. \(2024\)](#)). For less productive countries, ICTs have only a small impact on productivity and energy productivity. However, for the more productive nations, ICTs have a positive, and significant effect on all productivity measures. In [Table 7](#), an increase of ICT capital share from 10% to 11% in highly productive countries would boost labour productivity by 1.3% and TFP by 0.14%. Similarly in [Table 8](#), after a rise of ICT share from 10% to 11% in high productivity countries, energy productivity would increase by about 1.9% and the Malmquist index by 0.8%. Specifically, the Malmquist energy productivity index indicates that the positive effect of ICT capital is approximately three times greater in high productivity countries than in low productivity ones. This suggests that more productive countries can take better advantage of digitisation within the transport sector to further improve their overall productivity.

Table 8: Effect of digitisation on energy productivity across energy productivity levels

Variables	Digitisation Impact Across Energy Productivity Levels			
	Energy Productivity		Malmquist Index	
	Low Prod.	High Prod.	Low Prod.	High Prod.
Ln ICT share	0.002 (0.025)	0.188*** (0.022)	0.025** (0.013)	0.080*** (0.010)
Ln High-skill share	-0.079 (0.141)	0.073 (0.063)	-0.257*** (0.075)	0.088*** (0.027)
Ln Female share	0.270* (0.162)	0.383*** (0.080)	0.248*** (0.091)	0.124*** (0.035)
Transparency level ¹	0.391*** (0.147)	0.012 (0.061)	0.165** (0.068)	0.009 (0.026)
Ln FDI restrictiveness	0.092 (0.089)	0.039 (0.048)	0.011 (0.042)	0.014 (0.021)
Ln Exports GDP share	0.224*** (0.079)	0.421*** (0.077)	0.198*** (0.039)	0.184*** (0.035)
Ln Land infrastructure	0.545** (0.264)	0.166 (0.191)	0.306** (0.125)	0.036 (0.081)
Ln Transport equip.	-0.086*** (0.033)	0.028* (0.015)	-0.066*** (0.016)	-0.019*** (0.006)
Ln R&D capital	0.048 (0.037)	0.022 (0.014)	0.061*** (0.019)	0.028*** (0.007)
Ln Energy prices	0.042 (0.053)	0.107*** (0.029)	-0.040 (0.029)	0.048*** (0.014)
Countries	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes
R-squared	0.357	0.479	0.509	0.490
Observations	300	734	243	684

Note: Panel fixed effects regression for finding the effect of ICT capital on energy productivity across energy productivity levels. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

Various factors might contribute to this finding. High productivity economies can benefit more from wide network spillover effects, well established institutions, and easier access to finance and investments, allowing for the funding of even large-scale ICT projects. More productive nations may have better collaboration between firms, government institutions, and universities, bringing easier sharing of data and best practices. These institutional clusters may amplify the marginal returns of ICT investments. Similarly, better regulatory environments focusing on data protection and competition policy can reduce risk and promote widespread diffusion of ICTs, while better access to funding makes adoption easier.

Table 9: Effect of digitisation on productivity across transport intensity levels

Variables	Digitisation Impact Across Transport Intensity ² (Prod.)			
	Labour Productivity		TFP	
	Low Intensity	High Intensity	Low Intensity	High Intensity
Ln ICT share	0.144*** (0.018)	0.050* (0.028)	0.022*** (0.008)	0.009 (0.012)
Ln High-skill share	0.171*** (0.054)	0.281* (0.154)	0.093*** (0.023)	0.158** (0.064)
Ln Female share	0.249*** (0.067)	0.372 (0.233)	0.122*** (0.029)	0.265*** (0.098)
Transparency level ¹	0.094 (0.062)	0.002 (0.069)	0.025 (0.026)	-0.001 (0.029)
Ln FDI restrictiveness	0.008 (0.043)	0.057 (0.080)	-0.027 (0.018)	0.022 (0.034)
Ln Exports GDP share	0.214*** (0.051)	0.940*** (0.241)	0.124*** (0.022)	0.327*** (0.101)
Ln Land infrastructure	-0.016 (0.158)	-0.259 (0.189)	-0.028 (0.066)	-0.122 (0.079)
Ln Transport equip.	0.045*** (0.012)	-0.056 (0.041)	0.007 (0.005)	-0.031* (0.017)
Ln R&D capital	-0.016 (0.012)	0.114*** (0.028)	0.005 (0.005)	0.058*** (0.012)
Ln Energy prices	0.110*** (0.023)	0.264*** (0.091)	0.038*** (0.010)	0.088** (0.038)
Countries	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes
R-squared	0.427	0.666	0.365	0.676
Observations	894	165	862	149

Note: Panel fixed effects regression for finding the effect of ICT capital on productivity across transport intensity levels. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

² Transport intensity represents the value added share of each country's transport sector in overall total value added.

We also examine the impact that digitisation has on productivity across different transport intensity levels. We define transport intensity as the value-added share of each country's transport sector in their overall total value added. The countries in our sample are then split into lower transport intensity and higher transport intensity countries. The impact of ICTs on general productivity and energy productivity can be seen in [Table 9](#) and [Table 10](#), respectively.

The impact of ICTs across transport intensities can be seen to be positive in general but they appear to boost the productivity measures considerably more in countries that are less transport intensive. For example, an increase in the ICT share from 10% to 11% will boost labour productivity by about 0.5% for high transport intensity countries, but 1.4% for low transport intensity economies. Similarly for the Malmquist index, the impact would be again about 0.5% for high intensity nations, but over 0.8% for low intensity economies.

Table 10: Effect of digitisation on energy productivity across transport intensity levels

Variables	Digitisation Impact Across Transport Intensity ² (En. Prod.)			
	Energy Productivity		Malmquist Index	
	Low Intensity	High Intensity	Low Intensity	High Intensity
Ln ICT share	0.193*** (0.019)	0.041 (0.043)	0.084*** (0.010)	0.046*** (0.015)
Ln High-skill share	0.115** (0.057)	0.328 (0.236)	0.090*** (0.025)	0.128 (0.083)
Ln Female share	0.352*** (0.071)	0.868** (0.361)	0.124*** (0.033)	0.439*** (0.127)
Transparency level ¹	0.002 (0.065)	0.104 (0.107)	0.026 (0.028)	-0.030 (0.038)
Ln FDI restrictiveness	-0.031 (0.046)	0.112 (0.123)	0.005 (0.020)	0.017 (0.044)
Ln Exports GDP share	0.219*** (0.054)	0.475 (0.374)	0.157*** (0.026)	0.304** (0.132)
Ln Land infrastructure	-0.098 (0.166)	-0.144 (0.290)	0.002 (0.073)	-0.136 (0.102)
Ln Transport equip.	0.047*** (0.013)	-0.135** (0.064)	-0.016*** (0.006)	-0.047** (0.023)
Ln R&D capital	-0.027** (0.012)	0.140*** (0.043)	0.002 (0.007)	0.088*** (0.015)
Ln Energy prices	0.103*** (0.024)	0.257* (0.141)	0.032** (0.013)	0.117** (0.050)
Countries	Yes	Yes	Yes	Yes
Sectors	Yes	Yes	Yes	Yes
Years	Yes	Yes	Yes	Yes
R-squared	0.461	0.497	0.480	0.683
Observations	894	140	787	140

Note: Panel fixed effects regression for finding the effect of ICT capital on energy productivity across transport intensity levels. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

¹ Transparency level refers to the perceived level of corruption in each country. Countries are divided into three groups, from lowest transparency (1) to highest transparency (3).

² Transport intensity represents the value added share of each country's transport sector in overall total value added.

5.3 Counterfactual analyses

Finally, we can illustrate how productivity and energy productivity levels and growth would differ in the counterfactual worlds of higher or lower ICT investment. The fall in labour productivity and energy productivity due to ICT capital share being 1 p.p. lower can be seen in [Figure 4](#). This can be seen to immediately reduce labour productivity by about 1.8% in 1995 with the impact getting cumulatively larger to reach 2.7% by 2019. It would reduce energy productivity by about 2.5% initially, with the decline reaching almost 3.8% by 2019.

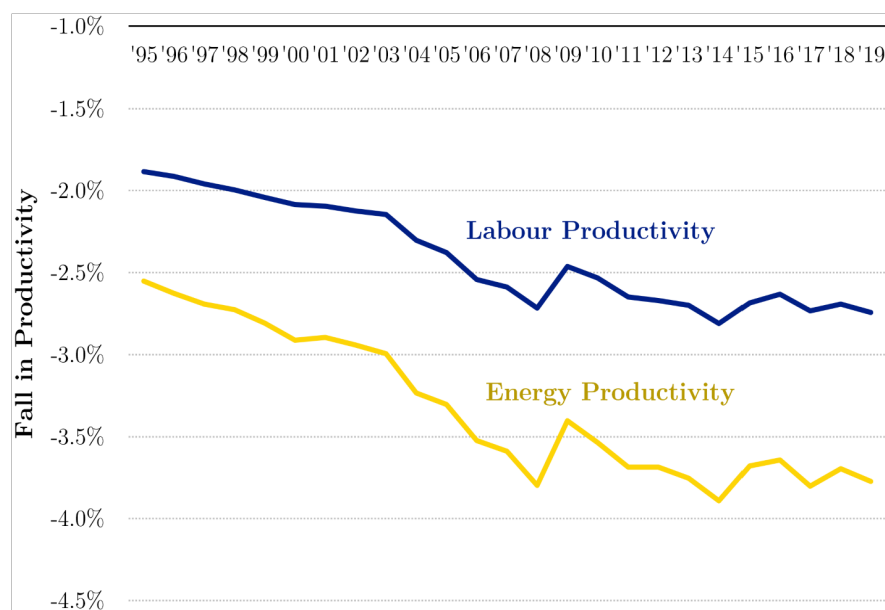


Figure 4: Percentage fall in productivity due to reduction of ICT share in total capital by 1 p.p. (authors' own work).

A similar but opposite scenario can be seen in Figure 5. Had the ICT investments been continuously 1% larger since 1995, the labour productivity level would be a cumulative 4 p.p. higher by 2019, and the energy productivity level would be higher by 6 p.p. by 2019.

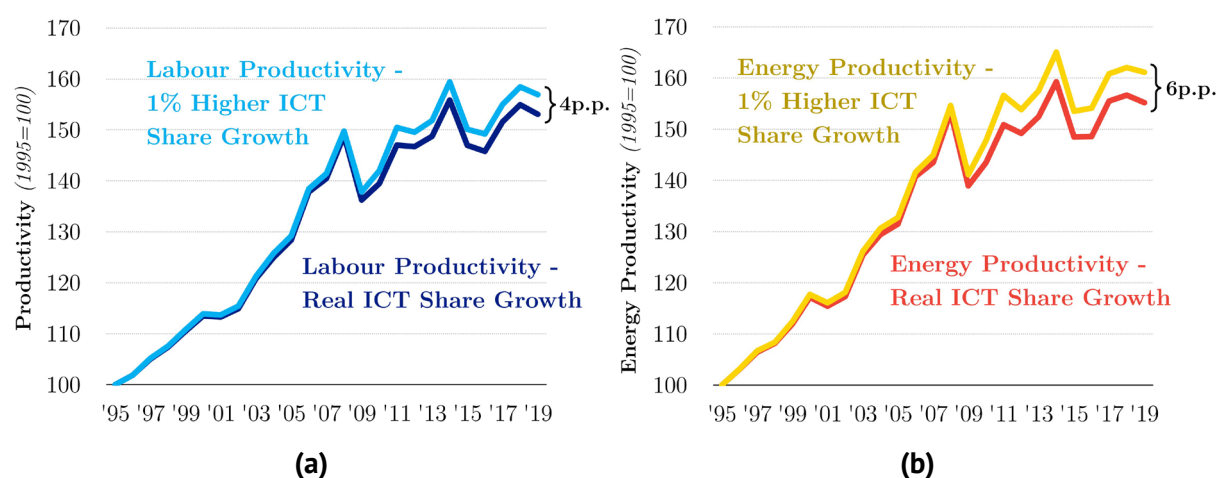


Figure 5: Productivity development if the annual growth of ICT share was 1% higher, for (a) overall productivity, and (b) energy productivity (authors' own work).

6 Conclusion

The transport sector is currently one of the least digital-intensive, with some of the largest GHG emissions. The sector has also made a notable contribution to the post-2008 slowdown in productivity growth. The potential for greater adoption of ICTs to increase productivity and reduce energy use, leading to lower GHG emissions, is clear. Despite the importance of the sector

for wider economic activity, including global supply chains, there has been a notable absence of analysis of its productivity trends and the impact of digitisation in the existing literature.

This paper helps fill the gap. We found that a higher ICT capital share has a positive, robust, and economically (as well as statistically) significant impact on all measures of productivity used – although with a much stronger impact on labour productivity and energy productivity than on TFP. These results reflect the role of ICTs in both raising output per worker, and particularly strong impact in reducing energy intensity, but to a lesser degree in shifting the production frontier. Computing hardware investments drive the majority of improvements in labour productivity and TFP, while software investments account for the majority of gains in energy productivity, perhaps as this allows for real-time optimisation of fuel and electricity use.

The impact of digitisation on the sector was considerably larger in 1995 – 2008 than in 2009 – 2019, echoing the wider productivity slowdown. Our counterfactual analyses illustrate the power of compounding: sustaining ICT investment at 1% above its actual path would have raised the sector's labour productivity by 4 p.p. and energy productivity by about 6 p.p. by 2019, compared with the actual levels.

In general, our findings demonstrate that investment in digital technology is crucial for driving both productivity and energy efficiency in the transport sector. Governments in OECD countries should therefore focus on creating long-term ICT investment frameworks that would promote and ensure continuous and predictable investments into digitisation. National ICT policies rarely highlight transport, but it is an important input into other sectors and so productivity improvements in the sector can have spillover and complementary effects elsewhere. For example, transport policies could be aligned with broader “smart city” initiatives, to ensure interoperability with new traffic management systems, logistics, and smart energy grids. Given that we found the impact of digital investments is particularly strong for energy productivity, transport policies should specifically target energy-saving digital technologies, to not only boost productivity, but also contribute to efficiency and the targets of net-zero emissions by 2050. Integrating grants and rebates, along with carbon pricing and fuel taxes, into ICT adoption programs can increase the incentive to adopt ICTs that are also energy focused.

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Appendix

A.1 Detail on the data construction

All of the EU-KLEMS variable units are in nominal terms and in national currency of each country. Therefore, in order to be directly comparable to each other, it is necessary to transform the variables into real terms and a common currency. Within our dataset, we use the 2017 US dollar. To transform the data from nominal to real terms and a common currency, we use the latest data (2023) from the GGDC Productivity Level Database (Inklaar et al., 2024). The database contains information on purchasing power parities (PPPs) for different countries and sectors. Following similar approach to Schulte et al. (2016), we construct conversion factors from the PPP data, which allow us to create variables in real terms.

We estimate the conversion factors as:

$$\phi_{xist} = \left(\frac{PI_{xis2017}}{PI_{xist}} \right) \cdot \left(\frac{1}{PPP_{is2017}} \right) \quad (A1)$$

where ϕ_{xist} is the conversion factor for variable x , country i , transport subsector s , and year t , PI_{xist} is the price index of variable x , country i , transport subsector s , and year t from the EU-KLEMS data, and PPP_{is2017} is the total PPP value for country i and sector s in year 2017.

After calculating the conversion factors from equation A1, the variables in real terms are calculated as:

$$x_{ist}^{2017\$} = \phi_{xist} \cdot x_{ist}^{Nominal} \quad (A2)$$

where $x_{ist}^{2017\$}$ is the converted variable in real 2017 US dollars.

The variables related to energy are taken from the International Energy Agency databases. In particular, industrial electric and non-electric energy prices for different countries over time are taken from the IEA Energy Prices database (IEA, 2025a). Furthermore, the data on the detailed industrial electricity and non-electric energy consumption for different countries over time comes from the IEA World Energy Balances database (IEA, 2025b). Within our energy price and consumption data, we identify six separate energy sources, including electricity, crude oil, gas, petroleum products, coal, and others (e.g., heat, biofuel, waste). The energy prices are again converted in order to be denominated in real 2017 US dollars, while energy consumption is converted to be in US dollars per kilotonnes of oil equivalent (\$/ktoe).

Furthermore, a range of control variables is taken from additional online sources. We take the variable measuring the level of transparency for each country from the Transparency International dataset (Transparency International, 2025), while the measure of the restrictiveness for foreign direct investment (FDI) is taken from the OECD database (OECD, 2025). The data on transport infrastructure is collected from the United Nations Economic Commission for Europe statistical database (UNECE, 2025). The trade variables, such as exports of goods and services as a share of GDP, are taken from the World Bank (World Bank, 2025), along with the data for total

population of each country over time, allowing for the calculation of per capita variables. Furthermore, the human capital variables, such as the share of high skilled workers and females by country and sector, are collected from the International Labour Organisation and the Eurostat, respectively (ILOSTAT, 2025; Eurostat, 2025). In the case of missing data for several variables, data from national databases (e.g., US Bureau of Labor Statistics) is also introduced.

A.2 Descriptive statistics

Table A1 reports the descriptive statistics for the key variables of our dataset over the entire period examined. In general, there are considerable differences between the lowest and highest percentiles. The average transport subsector has a gross output of \$50.5 billion, and employs about 230,000 persons. However, typically the output is between \$2.3 billion and \$26 billion, while the number of employees ranges between 11,000 and 175,000. The median level of ICT capital in the transport subsectors is \$38 million, with the largest part coming from software (\$21 million), and smaller parts from computing equipment (\$8 million) and communication devices (\$5 million). Nevertheless, ICT capital represents a small share of total capital, as the median level of non-ICT capital is \$762 million. Therefore, the median share of ICT capital in total capital is 5.9%.

Table A1: Descriptive statistics of the key variables

Variable	Obs.	Mean	Min	25 th p.	50 th p.	75 th p.	Max
Value added (<i>mil. 2017 \$</i>)	1,875	18,977	1	718	2,714	8,540	322,589
Gross output (<i>mil. 2017 \$</i>)	1,875	50,495	47	2,313	8,110	26,041	1,039,794
Intermediate inputs (<i>mil. 2017 \$</i>)	1,875	32,214	2	1,567	5,069	21,828	722,234
No. of employees (<i>thousands</i>)	1,875	233	0.2	11	47	175	2,845
Employee cost (<i>mil. 2017 \$</i>)	1,814	12,304	6	481	1,702	5,073	194,275
ICT capital (<i>mil. 2017 \$</i>)	1,875	393	0	10	38	182	9,700
ICT - Computing (<i>mil. 2017 \$</i>)	1,875	66	0	1	8	46	1,659
ICT - Communications (<i>mil. 2017 \$</i>)	1,875	79	0	1	5	39	2,707
ICT - Software (<i>mil. 2017 \$</i>)	1,875	241	0	5	21	103	7,333
Non-ICT capital (<i>mil. 2017 \$</i>)	1,869	4,762	0	178	762	2,955	76,017
ICT capital share in total capital (%)	1,875	12.7	0.0	2.9	5.9	10.2	100.0
ICT - Computing share (%)	1,875	14.2	0.0	0.5	1.2	3.4	100.0
ICT - Communications share (%)	1,875	13.3	0.0	0.2	0.9	2.7	100.0
ICT - Software share (%)	1,875	9.2	0.0	1.4	3.1	6.5	100.0
High-skill workers (%)	1,875	20.6	2.2	10.6	16.5	28.4	93.3
Female workers (%)	1,875	22.9	0.0	14.5	20.7	30.3	62.5
Transparency level ¹	1,875	2.5	1	2	3	3	3
FDI restrictiveness	1,875	0.26	0.08	0.12	0.20	0.31	1.00
Exports share in GDP (%)	1,875	43.4	8.8	27.1	40.3	54.1	206.4
Land infrastructure (<i>km per th. km²</i>)	1,875	1,264	153	436	955	1,778	5,175
Transport equip. per capita (<i>2017 \$</i>)	1,875	28.2	0.0	1.6	8.2	26.6	865.6
R&D per capita (<i>2017 \$</i>)	1,578	19.6	0.0	0.0	0.2	3.3	437.6
Energy price (<i>th. \$/ktoe</i>)	1,536	955	0	625	932	1,269	2,233
Energy use (<i>ktoe</i>)	1,875	11,240	0	36	169	2,857	566,911
Electricity price (<i>th. \$/ktoe</i>)	1,750	1,105	0	720	1,077	1,518	2,768
Electricity use (<i>ktoe</i>)	1,875	210	0	0	6	94	5,175
Non-electricity price (<i>th. \$/ktoe</i>)	1,536	834	0	453	739	1,212	2,140
Non-electricity use (<i>ktoe</i>)	1,875	11,029	0	14	113	1,644	565,855

Note: The unit *ktoe* represents kilotonnes of oil equivalent.

Furthermore, the median transport subsector has 16.5% share of high-skilled workers, with 20.7% of workers being female, a low perception of corruption and low restrictiveness for FDI (0.2 out

of 1.0), and a total of 955 km of land infrastructure per 1,000 km². In terms of exports as a share of GDP, these range between 27.1% and 54.1%, while median per capita transport equipment and R&D are at \$8.20 and \$0.20, respectively. Looking at energy variables, the median transport subsector uses 169 ktOE of energy annually, and pays a price of \$932,000 per ktOE of energy used.

A.3 Robustness checks

We conduct a series of robustness checks that test any potential issues in our data and methodology and strengthen the confidence in our findings. One of the key possible issues addressed is the potential endogeneity of ICT capital, where ICT capital may be correlated with the residuals. We test this potential issue by applying a two-step system GMM panel data estimator with the lagged levels of all control variables used as instruments, as in e.g., [Cardona et al. \(2013\)](#). Applying this approach to the base model of this paper, the results can be seen in [Table A2](#) for all four measures of productivity, i.e., labour productivity, TFP, energy productivity, and the Malmquist energy productivity index.

Table A2: System GMM results – effect of digitisation on labour and energy productivity

Variables	Digitisation and Productivity – System GMM			
	Lab. Prod.	TFP	En. Prod.	Malmquist
Lag Productivity	0.930*** (0.015)	0.854*** (0.036)	0.786*** (0.019)	0.709*** (0.024)
Ln ICT share	0.083*** (0.010)	0.022*** (0.003)	0.081*** (0.015)	0.059*** (0.007)
Ln High-skill share	-0.021*** (0.008)	0.011* (0.006)	-0.035** (0.014)	0.005 (0.008)
Ln Female share	0.036*** (0.007)	0.025*** (0.006)	0.113*** (0.015)	0.012 (0.015)
Transparency level ¹	-0.059*** (0.010)	-0.033*** (0.005)	-0.003 (0.018)	-0.058*** (0.015)
Ln FDI restrictiveness	-0.008 (0.006)	-0.005 (0.003)	-0.015 (0.011)	-0.030*** (0.011)
Ln Exports GDP share	0.019** (0.008)	0.015** (0.006)	0.049*** (0.013)	-0.009 (0.011)
Ln Land infrastructure	0.003 (0.005)	0.004 (0.003)	-0.004 (0.008)	0.015 (0.011)
Ln Transport equip.	0.008*** (0.002)	0.004** (0.002)	0.004 (0.005)	0.007*** (0.002)
Ln R&D capital	0.002** (0.001)	0.003** (0.001)	0.010*** (0.003)	0.010** (0.004)
Ln Energy prices	-0.030*** (0.007)	-0.010*** (0.002)	-0.021** (0.009)	-0.015*** (0.004)
Observations	1,020	972	995	891
Number of instruments	56	56	56	56
Hansen test	0.498	0.706	0.617	0.796
AR(1) in first diff z	0.00***	0.01***	0.01***	0.00***
AR(2) in first diff z	0.06	0.68	0.08	0.10

Note: System GMM regression for finding the effect of ICT capital on productivity and energy productivity. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

The system GMM estimation includes a measure of the productivity lag; as expected this variable is strongly positive and very significant for all measures of productivity, as past productivity is correlated with future productivity. Looking at our key independent variable – the ICT capital, the coefficients remain positive and strongly statistically significant for all productivity measures, suggesting that ICTs boost both general and energy productivity, confirming our earlier findings.

For general productivity, the GMM coefficient of labour productivity is slightly smaller compared to panel fixed effects, while the TFP coefficient is slightly larger. Nevertheless, the results confirm our previous finding that digitisation boosts labour productivity more than TFP. Similar is the case for energy productivity, where the coefficients are slightly smaller compared to panel fixed effects, but the stronger effect on energy productivity compared to the Malmquist index is maintained. These are comparable findings to e.g., [Tambe and Hitt \(2012\)](#) who found GMM estimates to be about 10% lower compared to unadjusted estimates. Examining the diagnostic tests for the validity of the system GMM, the Hansen J-test fails to reject the null hypothesis that the instrument set is valid for all productivity measures. This suggests that the instrumental variables are uncorrelated with the error term. Similarly, the AR(1) and AR(2) tests indicate a correctly specified model. All coefficients for AR(1) are significant, while all AR(2) coefficients are insignificant, showing that the instruments are valid and the moment conditions are correctly specified. Therefore, the system GMM results are consistent with the main results, and it can thus be concluded that our findings are robust to the potential endogeneity of ICT capital.

Apart from the test for endogeneity, we conduct several other robustness checks. First, we test for the stationarity of our panel dataset for all four measures of productivity, using the Levin-Lin-Chu test, the Im-Pesaran-Shin test, and the Fisher test. As all of the tests for all productivity variables are significant, we conclude that our panels are in fact stationary ([Table A3](#)).

Table A3: Results of the tests for stationarity of the panel dataset

Variable	Levin-Lin-Chu Test	Im-Pesaran-Shin Test	Fisher Test	Interpretation
Labour productivity	-6.66***	-4.18***	-3.33***	Passed – panels are stationary.
TFP	-8.41***	-5.24***	-2.98***	Passed – panels are stationary.
Energy productivity	-14.44***	-4.85***	-2.96***	Passed – panels are stationary.
Malmquist index	-5.62***	-4.91***	-5.70***	Passed – panels are stationary.
ICT capital share	-7.09***	-5.92***	-12.47***	Passed – panels are stationary.

Note: The numbers are test statistics. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, we conduct the Pesaran test of cross-sectional independence, checking whether residuals across cross-sectional units are uncorrelated. As the coefficients for all four productivity measures are insignificant, we find no cross-sectional dependence in our data ([Table A4](#)).

Table A4: Results of the test for panel cross-sectional dependence

Variable	Pesaran Test of Cross-sectional Independence	Interpretation
Labour productivity	1.026	Passed – no cross-sectional dependence.
TFP	1.847*	Passed – no cross-sectional dependence.
Energy productivity	0.287	Passed – no cross-sectional dependence.
Malmquist index	0.946	Passed – no cross-sectional dependence.

Note: The numbers are test statistics. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, we estimate several Granger causality tests for the four productivity measures, to check whether ICT capital Granger-causes productivity and/or vice versa. The results of the tests indicate that ICT capital share Granger-causes productivity, but not vice versa. This is true for all

productivity measures, suggesting that causality flows more from ICT capital towards productivity, rather than in the opposite direction (Table A5).

Table A5: Results of the Granger causality tests

Variable	ICT Share Granger-Causing Productivity	Productivity Granger-Causing ICT Share	Interpretation
Labour productivity	2.80***	1.70*	ICT Granger-causes productivity, but likely not vice versa.
TFP	3.23***	0.98	ICT Granger-causes productivity, but not vice versa.
Energy productivity	3.19***	1.43	ICT Granger-causes productivity, but not vice versa.
Malmquist index	6.39***	1.59	ICT Granger-causes productivity, but not vice versa.

Note: The numbers are test statistics. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Fourth, we run multicollinearity tests, to check whether our independent variables are not linear functions of each other. The tests estimate a variance inflation factor (VIF) for each variable, with a value of below ten typically signifying an acceptable level. Our highest variable has a VIF of 4.7, and the mean VIF value is at 2.4; therefore, we conclude that there is no multicollinearity present in our estimations (Table A6).

Table A6: Results of the test for multicollinearity

Five Variables with Largest VIF	VIF Value	Interpretation
1. Ln High-skill workers share	4.65	Passed – no multicollinearity.
2. Ln Exports share in GDP	4.57	Passed – no multicollinearity.
3. Ln FDI restrictiveness	3.66	Passed – no multicollinearity.
4. Ln Research & Development	2.07	Passed – no multicollinearity.
5. Ln Land infrastructure	1.94	Passed – no multicollinearity.

Note: The numbers represent the test statistics. The model used is a baseline WLS estimation with all independent and control variables. The mean VIF value is 2.43.

And fifth, we conduct the Ramsey RESET test for omitted variable bias, as well as the model specification error test (link test). As both of the tests are insignificant, we conclude that our model is indeed correctly specified (Table A7).

Table A7: Results of the omitted variable bias and model specification error tests

Variable	Ramsey RESET Test	Specification Link Test	Interpretation
Labour productivity	0.07	0.89	Passed – model is correctly specified.
TFP	0.26	0.67	Passed – model is correctly specified.
Energy productivity	1.45	0.24	Passed – model is correctly specified.
Malmquist index	1.03	0.13	Passed – model is correctly specified.

Note: The numbers represent the test statistic for the Ramsey test and P-values for the Link test. The model used is a baseline WLS estimation with all independent and control variables. Significance levels are: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.



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