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Digital Intensity and Labour Productivity in the European Union: Between-Country, Within-Country and Within-Sector

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Abstract: The European Union's Digital Decade programme aims for more than 90% of small and medium-sized enterprises to reach at least basic digital intensity by 2030, assuming that digitalisation raises productivity. Yet studies comparing EU countries disagree on whether more digitally intensive economies are more productive once their development level is considered. This study investigates how two indicators of enterprise digitalization, the percentage of enterprises achieving at least basic digital intensity and the percentage engaging in online sales, are associated with labour productivity.. The association is examined between countries, within countries over time, and between sectors within the same country and year, using Eurostat data for the EU-27 over 2015–2024. The results show that countries with more digitally intensive enterprises are more productive, but this association disappears once economic development is controlled. Within the same country, more digitally intensive sectors are significantly more productive. However, increases in digital intensity over time are not followed by measurable productivity gains. Digital intensity is therefore a marker of productive economies and sectors rather than a demonstrated short-run driver of productivity growth, and adoption targets should be accompanied by support for skills, management and complementary investment.

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1. Introduction

Labour productivity growth in Europe has slowed for more than a decade, and the slowdown has widened the gap with global peers while deepening territorial disparities within the Union (Chrysanthakopoulos et al., 2026). The gap with the United States and China has become central

to the EU competitiveness debate (Rodríguez-Pose & Dijkstra, 2026). European policy has responded by placing enterprise digitalisation at the centre of its competitiveness agenda. The Digital Decade Policy Programme 2030 sets the target that "more than 90 % of Union SMEs reach at least a basic level of digital intensity" by 2030 (Decision (EU) 2022/2481, Art. 4(1)(3)(b)). Eurostat reports that 59% of EU enterprises had reached that level in 2023 (Eurostat, 2024). The policy logic is straightforward: firms that adopt more digital technologies should produce more value per worker. Yet it remains unclear whether economies and sectors with more digitally intensive enterprises actually achieve higher labour productivity, because firm-level and country-level studies reach different conclusions.

Theory gives reasons to expect both large and small returns. Information technology raises output when it is combined with organisational change, new work practices and managerial capability (Brynjolfsson & Hitt, 2000; Bloom et al., 2012). Without those complements, adoption can absorb resources without visible gains. General-purpose technologies also require intangible investment that measured output does not capture at first, so measured productivity may fall before it rises, following a J-curve (Brynjolfsson et al., 2021). Composition effects add a further layer. When only high-capability firms gain from adoption, substantial micro-level change can coexist with negligible aggregate gains (Han, 2026). Growth-accounting evidence for 32 OECD countries shows that neutral technical change contributed little to output growth over 1994–2019, consistent with a productivity paradox (Feder, 2026; see also Acemoglu et al., 2014).

The empirical record mirrors this ambiguity, and it divides along the level of analysis. Firm-level studies in Europe mostly report positive associations. Finnish service firms with higher DII scores have higher value added and labour productivity (Kuosmanen et al., 2026). German and Dutch firms that analyse big data from several sources are more productive (Andres et al., 2025). Portuguese early adopters of cloud computing outperform later adopters (Alexandre et al., 2026). Italian firms receiving Transition 4.0 funding show about 7% higher total factor productivity (Palma & Scotti, 2026). Country-level evidence is weaker and more contested. In an EU-27 panel for 2017–2022, within-country changes in DESI digital integration are not associated with enterprise productivity, and most cross-country differences are attributable to GDP per capita (Aleca & Mihai, 2026). In a cross-section of the 27 member states, the positive correlations between AI adoption, digital skills and productivity vanish once development level is controlled (Kavele, 2026). Other EU panels report positive effects on SME value added (Dvoulety et al., 2026) and on productivity in light manufacturing (Cheng & Rasool, 2026).

Three features of the existing aggregate evidence limit what it can establish. First, most EU studies measure digitalisation with the Digital Economy and Society Index (DESI), a composite that mixes household, government and business dimensions. The enterprise-only Digital Intensity Index is used mainly as a predictor of AI adoption (Boghian, 2026) or at firm level (Kuosmanen et al., 2026). Moreover, the DII exists in four versions whose composition changes between survey years, and Eurostat warns that comparability over time may be limited (Eurostat, 2026). Second, country-level designs struggle to separate digitalisation from general economic development, which drives both. Third, EU panels contain only 27 country clusters, yet none of the reviewed abstracts reports inference designed for so few clusters.

This study asks whether higher enterprise digital intensity, measured as the share of enterprises that reach at least a basic level on the Eurostat Digital Intensity Index (DII), is associated with

higher labour productivity, measured as value added per person employed, in the EU-27. The association is examined at three levels: between countries, within countries over time, and between sectors within the same country and year. The study addresses four research questions. RQ1 asks whether digital intensity is positively associated with labour productivity. RQ2 asks whether the association persists after controlling for macroeconomic conditions, capital investment and fixed effects. RQ3 asks whether it differs by enterprise size class or sector. RQ4 asks whether it appears with a time lag or is nonlinear. The corresponding hypotheses H1–H4 are developed in Section 2.

The study makes three contributions. First, it measures digitalisation with an indicator that refers only to enterprises, the DII, and matches it with productivity data for exactly the same business sectors, whereas most EU studies use the broader DESI composite, which also covers households and public services. Second, it compares sectors within the same country and year. This comparison removes differences in national development level, institutions, prices and business cycles by construction, and it has not been used in the EU literature to address the confounding documented by Aleca and Mihai (2026) and Kavele (2026). Third, it uses statistical inference designed for a sample of only 27 countries and reports all pre-specified results, including null results. Because the data are aggregated and the study does not rely on a natural experiment, the results describe associations rather than causal effects, and they apply to countries and sectors rather than to individual firms.

The article proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data, the treatment of DII versions and the econometric designs. Section 4 reports the results. Section 5 discusses them, and Section 6 concludes with the implications, limitations and directions for future research.

2. Literature review and theoretical framework

2.1 Measuring enterprise digital intensity

Aggregate studies of the EU mostly rely on the DESI composite or its sub-indices (Aleca & Mihai, 2026; Dvoulety et al., 2026; Ghazy et al., 2022; Sofrankova et al., 2025). DESI is useful for benchmarking, but its dimensions mix connectivity, citizens' skills, public services and business integration. The Eurostat Digital Intensity Index is narrower. It counts how many of 12 digital technologies and practices an enterprise uses and classifies enterprises as very low (0–3), low (4–6), high (7–9) or very high (10–12) intensity (Eurostat, 2026). The DII is built from the ICT usage survey, which covers enterprises with ten or more persons employed in the non-financial business economy, from manufacturing to administrative and support services (NACE sections C to N, excluding financial and insurance activities in section K). Its composition changes between survey years, so levels are not strictly comparable over time (Eurostat, 2026). Firm-level indicators built from the same survey reveal strong regional and sectoral heterogeneity in digital readiness (Crespi et al., 2026). Eurostat ICT-usage indicators have also been linked to aggregate outcomes. Data-analytics capability and AI adoption bundles are positively associated with value added per SME across member states, with GDP per capita controlled (Csiszár, 2026). A data envelopment analysis that uses the share of SMEs with high DII as an input finds that the economic effect of digitalisation is larger for large enterprises than for SMEs (Kyshakevych et al., 2024). The e-commerce share and the share of turnover from e-sales also vary strongly with enterprise size (Soava et al., 2022), and ICT development is

positively correlated with GDP across the EU-27 (Magoutas et al., 2024). At country level, the DII is a strong predictor of AI adoption (Boghian, 2026), but apart from efficiency rankings (Kyshakevych et al., 2024), the reviewed literature has not related it to aggregate labour productivity.

2.2 Labour productivity, intangible capital and complementarities

Labour productivity depends on capital deepening, skills and intangible assets as well as on technology. In 14 EU member states and the UK over 1995–2019, productivity growth in services is driven by intangibles other than R&D, including software, organisational capital and training, while goods-producing sectors benefit most from non-ICT tangible capital (Roth & Mitra, 2025). The returns to a given technology depend on these complements. AI adopters in Canada combine adoption with R&D, cloud computing, data analytics and ICT training, and their productivity premium may not be attributable to AI alone (Li & Liu, 2026). Productivity gains from industrial robots are strongly moderated by management practices (Hu & Li, 2026). Big-data analytics is associated with productivity only when it spans several data sources (Andres et al., 2025), and its gains are amplified by human capital (Alexandre et al., 2026). Firms need relevant digital skills to turn technology investments into productivity gains (Massini et al., 2026), and the effects of advanced digital technologies depend on whether they are adopted in bundles and used for market creation (Chun & Shin, 2025). Returns also differ by technology: among Chinese listed firms, AI has the strongest association with TFP, while cloud computing and blockchain show no significant effect (Song et al., 2026). Digital skills relate positively to productivity in EU country-sector data, though their mediating role is limited (Rabadán-Pérez & Muñoz-Céspedes, 2026).

2.3 Theoretical perspectives

Four perspectives frame the expected relationship. In a production-function view, digital technologies act as a form of capital and as a shifter of total factor productivity, so adoption should raise output per worker. The resource-based view holds that technology yields an advantage only when it is combined with scarce, firm-specific capabilities (Herrero et al., 2026). The complementary-assets perspective adds that information technology pays off through organisational transformation and management quality (Brynjolfsson & Hitt, 2000; Bloom et al., 2012), and reviews of the empirical literature report positive but heterogeneous returns to ICT (Cardona et al., 2013). Finally, the productivity J-curve argues that intangible investments accompanying general-purpose technologies cause measured productivity to be understated early and overstated later (Brynjolfsson et al., 2021). Recent evidence suggests that the productivity paradox can also be distributional or conditional. Mean innovation effects on productivity can be negative even when the typical firm records neutral or positive returns (Hameed et al., 2026). The Solow paradox persists in Chinese manufacturing sub-sectors that depend heavily on factor inputs (Zhu et al., 2025), and in Vietnam it appears for computerisation in large firms but depends on human capital (Nguyen & Be, 2025). Together these perspectives predict a positive association in levels between digitally mature and productive units, but weak or delayed associations between changes in adoption and changes in productivity.

2.4 Empirical evidence: firm, sector and country level

Firm-level European evidence is mostly positive. Firm DII scores are associated with higher value added and labour productivity in Finland, with the strongest links among top performers

(Kuosmanen et al., 2026). Digitalisation is associated with sales and productivity in Spanish science parks, where basic technologies show more robust effects than advanced ones (Herrero et al., 2026). Digitalisation is linked to turnover growth among European SMEs (Corrocher & Mancusi, 2026). Among SMEs in Central and Eastern Europe, the performance effects of digitalisation depend on initial performance and structural context (Noja et al., 2026). The only quasi-experimental EU estimate concerns a policy instrument: Transition 4.0 funding is associated with 7% higher TFP in Italian firms (Palma & Scotti, 2026). Among large European listed firms, digital transformation is positively associated with firm performance (Khelil et al., 2026), and indices of digital capability correlate positively with performance in the European food sector (Marczewska et al., 2026). Not all European evidence is positive: advanced digital maturity in Dutch hospitals shows no significant association with financial, operational or workforce performance after correction for multiple testing (Remus et al., 2026). Outside Europe, firm-level panels report productivity gains from digital transformation (Kulkova & Zhang, 2026; Li, Yue, et al., 2026), from IT investment (Baxamusa & Jalal, 2025) and from industrial robots, where a 10% increase in robot quantity is associated with 0.23% higher TFP (Chen & Tang, 2026).

Sector-level and country-level evidence in the EU is mixed. A TWFE panel of 21 EU countries and eight light-manufacturing subsectors finds that a one-unit increase in a composite digitalisation index is associated with about 0.43% higher productivity, with diminishing returns (Cheng & Rasool, 2026). In construction, AI adoption shows a small negative association with productivity, consistent with adjustment costs (Bocean et al., 2026). In the financial sectors of Central Europe and the Baltic states, ICT use is associated with higher productivity but lower employment (Tóth et al., 2025). At country level, positive dynamic effects of DESI on SME value added (Dvoulety et al., 2026), of digital skills and cloud adoption on labour productivity (Aleca & Mihai, 2025) and of ICT specialist employment on productivity (Firtescu et al., 2026) contrast with null within-country effects of DESI integration (Aleca & Mihai, 2026). Further EU-27 panels associate digital adoption with higher resource productivity over 2015–2024, with human capital the most robust determinant (Hurduzeu et al., 2026), link digitalisation to growth with threshold effects (Polishchuk et al., 2026), and find that ICT graduates and digital skills raise GDP per capita (Sîrghi et al., 2026). Yet development level absorbs the cross-sectional association in several studies (Aleca & Mihai, 2026; Kavele, 2026; Zegrean et al., 2025), and in post-2004 member states DESI technology integration is associated with higher unemployment after a lag, consistent with short-term adjustment (Schmutzer et al., 2026).

Evidence from outside the EU shows the same mix of positive average effects and strong conditionality. Across 176 economies, a one-unit increase in the ICT Development Index is associated with 0.43% higher service productivity, with stronger effects in high-income countries (Wagan & Sidra, 2025), and robot adoption raises TFP growth across 52 economies (Matsuki, 2026). In Gulf economies, however, digitalisation is negatively related to productivity (Ben Tahar & Ben Slimane, 2026), and a meta-analysis of 85 robot studies finds at best small effects and strong publication bias (Schneider, 2026). Institutional quality shapes the speed and spread of diffusion itself (Labhard et al., 2026), and R&D effects on productivity appear only after three to six years (Postula et al., 2026).

2.5 Synthesis, research gap and hypotheses

The literature points to a level-of-analysis puzzle. Firm-level studies mostly find positive associations, while country panels find that the association is absorbed by development level or disappears within countries over time. Three gaps follow. Aggregate studies rarely use an enterprise-only measure aligned with the productivity statistics. They have not exploited variation across sectors within a country-year, which holds development level fixed by construction. They do not report inference suited to 27 clusters. Figure 1 summarises the framework.

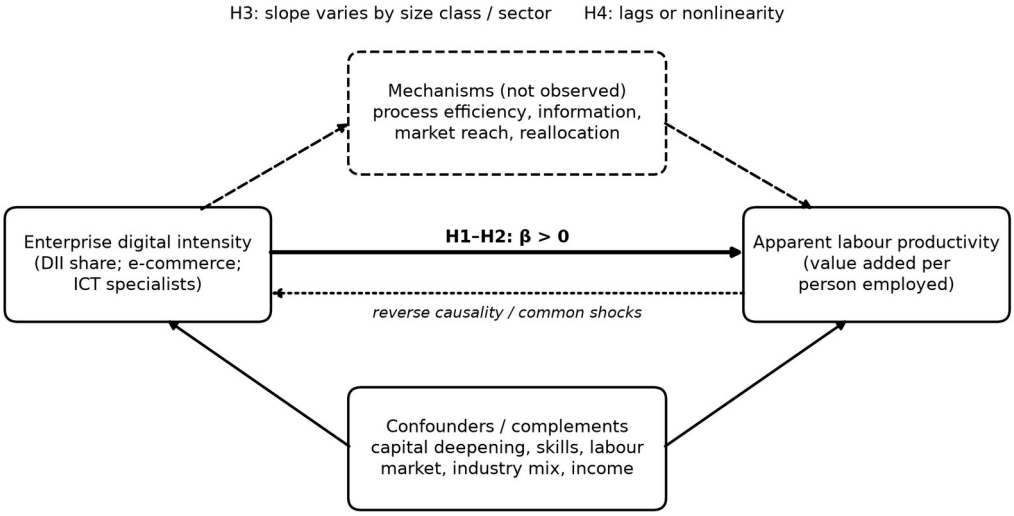


Figure 1. Conceptual framework. Enterprise digital intensity is hypothesised to relate to labour productivity (H1–H2) through unobserved mechanisms: process efficiency, information, market reach and reallocation. Capital deepening, skills, labour-market conditions, industry mix and income act as confounders or complements, and reverse causality or common shocks may run from productivity to adoption. H3 concerns heterogeneity by size class and sector; H4 concerns lags and nonlinearity. Bold arrow: tested association; dashed box and arrows: unobserved mechanisms; dotted arrow: reverse causality or common shocks; plain arrows: confounding paths.

Drawing on the production-function view, the complementary-assets perspective and the J-curve argument reviewed above, the study tests four hypotheses.

H1: Higher enterprise digital intensity is associated with higher labour productivity.

H2: The association remains after controlling for observed confounders and for country and year fixed effects.

H3: The association differs by enterprise size class and by sector.

H4: The association appears with a time lag or it is nonlinear.

3. Data and methodology

3.1 Data sources and scope

All data are public Eurostat tables downloaded through the SDMX API on 2 November 2026. Every download is logged with its table code and timestamp, and the full pipeline is

reproducible from a single script (Appendix E). The unit of observation is the EU-27 member state and year (2015–2024), and for the sector design the country × sector × year cell. Digital intensity comes from the Community survey on ICT usage and e-commerce in enterprises (tables isoc_e_dii for the business economy and isoc_e_diin2 for NACE sectors). Labour productivity comes from Structural Business Statistics: sbs_na_sca_r2 for 2012–2020 (Regulation (EC) No 295/2008) and sbs_ovw_act for 2021 onwards (European Business Statistics Regulation (EU) 2019/2152). Prices, hours worked, investment and capital stocks come from the national accounts (nama_10_a10, nama_10_a10_e, nama_10_an6, nama_10_nfa_st) and purchasing power parities from prc_ppp_ind. Controls come from the labour force survey (une_rt_a, edat_lfse_03) and nama_10_pc. The two sources differ in activity coverage, so the productivity aggregate is aligned with the ICT survey. The ICT survey covers eleven sections of the business economy: manufacturing (NACE section C); electricity and gas supply (D); water supply and waste management (E); construction (F); wholesale and retail trade (G); transport and storage (H); accommodation and food services (I); information and communication (J); real estate (L); professional, scientific and technical activities (M); and administrative and support services (N). Financial and insurance activities (K) are not covered. Value added and persons employed are therefore summed over these same eleven sections, so that productivity and digital intensity refer to the same part of the economy. A country-year aggregate is formed only when all eleven sections are reported; confidential cells are never imputed. The aggregate closely tracks Eurostat's official business-economy series, which also includes mining and quarrying (section B), with a correlation of 0.9999 and a median ratio of 0.998.

3.2 Variables

Outcome. Apparent labour productivity is value added at factor cost per person employed, in thousands of euros. Three versions are used. Nominal productivity (lp_nom) is used for between-country comparisons. Real productivity (lp_real) is converted to national currency, deflated with a business-economy gross value added deflator (2015 = 1, the ratio of current-price to chain-linked value added over NACE B–E, F, G–I, J, L and M–N) and converted back to euros at 2015 exchange rates; it is used for within-country designs. Productivity in purchasing power standards (lp_pps) is a robustness check. Exchange rates are implied by the national accounts as the ratio of national-currency to euro current-price value added. National-accounts gross value added per hour worked (sections B–E, F, G–I, J and M–N) provides an hours-based alternative.

Digital intensity. The DII counts how many of 12 digital technologies and practices an enterprise uses (Appendix B). The main predictor (dii_basic) is the percentage of enterprises with ten or more persons employed that reach at least a basic level, that is, 100 minus the share with very low intensity. The share with high or very high intensity (dii_high) is an alternative. The DII exists in four versions with different technology sets: v1 (2015–2019, annual), v2 (2018 and 2020), v3 (2021, 2023, 2025) and v4 (2022, 2024). Levels are therefore not strictly comparable across versions (Eurostat, 2026). In 2018, the only year published in two versions, the v1 and v2 means differ (57.3% versus 50.9%) but the country rankings are almost identical ($r = 0.96$). The design responds to this in three ways. Cross-sectional comparisons use year fixed effects, so only within-year differences matter. The within-country design standardises the DII within each year (dii_basic_z), so it measures a country's position in the EU distribution. A

version-consistent alternative, the share of enterprises with e-commerce sales (ecom_sell), has been collected on a stable definition since 2012.

Timing. E-commerce and ICT-specialist indicators collected in survey year t refer to calendar year t−1 (Eurostat metadata, ESMS section 5), so they are re-dated to t−1. DII items refer mostly to the survey year and are not re-dated.

Controls. The unemployment rate captures cyclical slack and labour-market tightness. The share of 25–64-year-olds with tertiary education proxies human capital. The manufacturing share of business-economy value added captures structural composition. Gross investment in tangible goods per person employed (SBS) proxies capital deepening. Round-two specifications add gross fixed capital formation in ICT equipment and in intellectual-property products as shares of GDP, and the net stock of ICT equipment and software per hour worked. Real GDP per capita is used only as a robustness check, because it shares value added with the outcome and is likely to be partly a result of productivity. Table 1 reports descriptive statistics.

Table 1. Descriptive statistics, EU-27 country-years, 2015–2024

Variable	N	Mean	SD	Min	Median	Max	Within-country SD
Labour productivity, nominal (k EUR)	259	51.12	32.95	11.91	40.52	207.01	7.91
Labour productivity, real (k EUR 2015)	259	46.53	30.78	11.91	35.96	196.37	4.83
Labour productivity (k PPS)	259	51.11	23.28	12.62	47.32	176.72	7.14
DII at least basic (% enterprises)	270	61.61	14.33	23.47	62.04	92.76	6.76
DII high or very high (%)	268	25.58	12.07	4.74	23.44	62.23	6.57
E-commerce sales (% enterprises)	269	22.98	7.93	7.42	21.87	43.03	3.74
ICT specialists employed (% enterprises)	189	21.42	5.52	9.88	20.11	35.27	2.38
Investment per person (k EUR)	244	9.88	5.72	2.35	7.95	49.62	2.56
Unemployment rate (%)	270	7.09	3.67	2.00	6.30	25.00	1.86
Tertiary attainment (%)	270	34.89	8.90	17.20	34.85	56.60	2.90
Manufacturing share of VA (%)	262	26.88	7.91	9.04	25.60	50.21	1.37

Note: Within-country SD is the standard deviation after removing country means. E-commerce and ICT specialists are re-dated to the reference year. Source: Eurostat; author's calculations.

3.3 Sample

Of 270 possible country-years, all have DII data. Eleven lack a complete SBS aggregate because at least one section is confidential (Finland 2020, Ireland 2018 and 2024, Malta 2015–2021 and Romania 2017), leaving 259 observations for the main models. Fifteen further observations lack investment data (Cyprus 2016–2024, Ireland 2020–2022 and Malta 2022–2024), so models with investment use 244 observations from 26 countries. The e-commerce panel covers 2012–2024 (336 observations). The sector panel has 2,235 country × sector × year cells for ten sectors (C, D–E combined, F, G, H, I, J, L, M and N; sectors L and M are covered only from 2021) and 27 countries. The size-class panel has 632 country × size × year cells for enterprises with 10–49, 50–249 and 250 or more persons employed. Its sectors are C, F, G, H, I, J, M and N, the sections for which SBS size-class data are available.

3.4 Empirical designs

The four designs isolate different sources of variation. Design A compares countries within the same year:

$$\ln LP_{ct} = \alpha + \beta\, DII_{ct} + X_{ct}^{'}\gamma + \tau_t + \varepsilon_{ct} \quad (1)$$

where c indexes countries, t years, X the controls and τ year fixed effects. Models A1 to A3 add controls and investment in turn. With a log outcome and the DII in percentage points, 100β is the approximate percentage difference in productivity per percentage point of enterprises with at least basic intensity.

Design B adds country fixed effects μ and uses the within-year standardised DII, so β is identified from changes in a country's relative position over time:

$$\ln LP_{ct}^{real} = \beta\, z(DII)_{ct} + X_{ct}^{'}\gamma + \mu_c + \tau_t + \varepsilon_{ct} \quad (2)$$

Design C has the same structure with the version-consistent e-commerce share, over 2012–2024, including one- and two-year lags.

Design S, the co-primary design added by the protocol amendment, compares sectors within the same country and year:

$$\ln LP_{cst} = \beta\, DII_{cst} + \delta_{ct} + \lambda_{st} + \varepsilon_{cst} \quad (3)$$

where s indexes sectors. Country × year effects δ absorb everything that varies at national level in a given year: development level, institutions, price levels, exchange rates, business cycles and the national DII version. Sector × year effects λ absorb EU-wide sector shocks and sector-specific changes in DII composition. Model S1 therefore asks whether, within a country-year, sectors where more enterprises are digitally active have higher productivity than the EU-wide pattern for those sectors would predict. Model S2 adds country × sector fixed effects and so uses only changes within a country-sector over time. Models SE1 and SE2 repeat S1 and S2 with the sector e-commerce share. The size-class panel applies the same logic with country × year and size × year fixed effects (model Z1), and estimates between-country slopes by size class.

3.5 Inference

There are only 27 clusters, and conventional cluster-robust standard errors over-reject with few clusters. All models report CR1 standard errors clustered by country with critical values from the t distribution with G − 1 degrees of freedom. The main p-values come from a wild cluster restricted bootstrap with Webb six-point weights (Webb, 2023), using 9,999 replications and a fixed seed; the bootstrap is designed for settings with few clusters. The implementation was checked against standard software for both OLS and weighted least squares, and a simulation under the null rejected at 5.3% at the nominal 5% level. Bootstrap p-values and t-based confidence intervals can occasionally disagree near the 5% threshold; where they do, this is noted.

3.6 Protocol and robustness

The analysis protocol (variable definitions, designs, controls and robustness checks) was written before estimation. One amendment, also written before the corresponding models were run, promoted Design S to a co-primary design and added investment in ICT and intellectual property, capital stocks, an hours-based outcome and employment weighting after the literature review identified development level as the main confounder. All pre-specified results are reported regardless of sign or significance. The robustness battery includes: excluding Ireland and Luxembourg; separating the two SBS regimes (2015–2020 and 2021–2024) and the DII versions; a balanced panel; excluding 2020; dropping observations with Cook's distance above 4/N; employment weighting; the high-intensity measure; alternative outcomes; country-specific linear trends in Designs B and C; and leave-one-country-out and leave-one-sector-out re-estimation. A quadratic in the DII and one- and two-year lags test H4. The study is associational: none of the designs rules out reverse causality or unobserved factors that vary within country-years across sectors.

4. Results

4.1 Descriptive patterns

The share of enterprises with at least basic digital intensity averages 61.6% across country-years but ranges from 23.5% to 92.8% (Table 1). Most of this variation is between countries: the within-country standard deviation is 6.8 points, against an overall standard deviation of 14.3. Productivity is even more dispersed between countries. Nominal productivity ranges from 11.9 to 207.0 thousand euros per person employed, but its within-country standard deviation is only 7.9 thousand euros, and 4.8 thousand in real terms. Figure 2 shows that DII levels shift at the version breaks, which is why the within-country design uses the standardised measure. Median real productivity also rises sharply between 2020 and 2021, the year SBS moved to the new regulation. Part of that jump may therefore reflect the methodological break, and the robustness checks split the sample at 2021 for this reason. Figure 3 shows the 2024 cross-section: countries with more digitally active enterprises are clearly more productive.

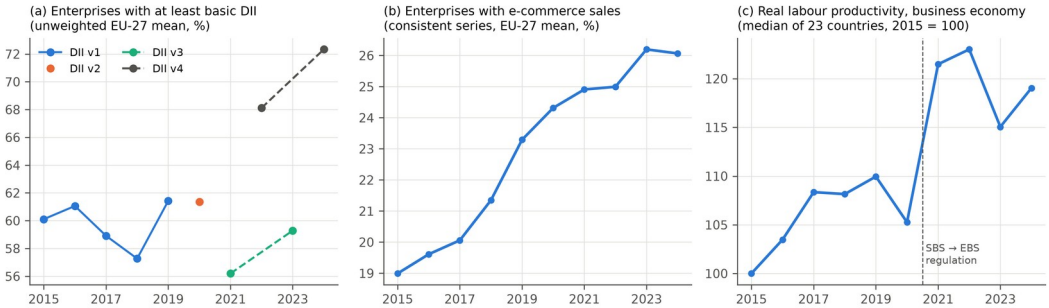


Figure 2. (a) Share of enterprises with at least basic digital intensity, by DII version (unweighted EU-27 mean; dashed lines connect the alternating v3 and v4 years). (b) Share of enterprises with e-commerce sales (consistent series). (c) Real business-economy labour productivity (median of 23 countries with complete data, 2015 = 100); the dashed line marks the change from the SBS to the EBS regulation in 2021. Source: Eurostat; author's calculations.

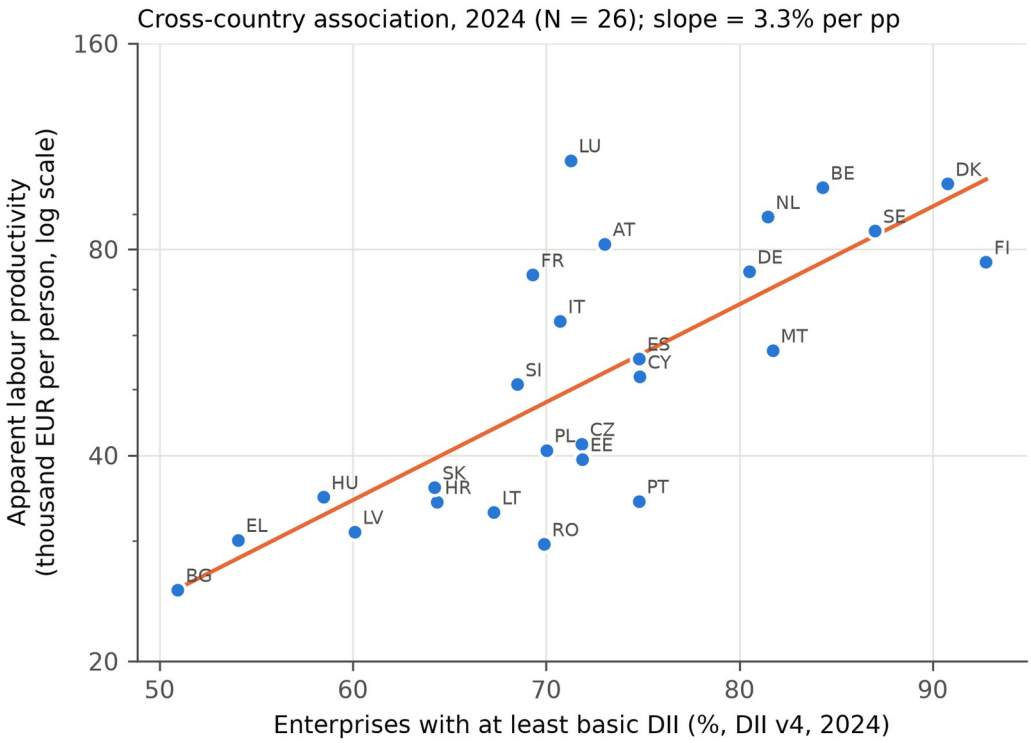


Figure 3. Share of enterprises with at least basic digital intensity and nominal labour productivity (log scale), EU member states, 2024. Source: Eurostat; author's calculations.

4.2 Between-country association (Design A)

Table 2 reports the main estimates. Without controls, one additional percentage point of enterprises with at least basic intensity is associated with 3.0% higher nominal labour productivity (A1: 0.0303, 95% CI 0.0244 to 0.0362, bootstrap $p < 0.001$). Adding unemployment, tertiary attainment and the manufacturing share reduces the coefficient to 2.2% (A2: 0.0219, CI 0.0123 to 0.0315, $p = 0.002$). Adding investment per person reduces it further, to 1.1% (A3: 0.0112, CI 0.0042 to 0.0182, $p = 0.010$, 26 countries). The association is present in every year. The year-by-year A2 coefficients range from 0.0171 (2023) to 0.0273 (2024), all with $p < 0.02$, and they show no visible discontinuity at the version breaks (Appendix C). A one-year lag of the DII gives a similar estimate (0.0207, $p = 0.003$).

Table 2. Main estimates: ln labour productivity on digital measures

Model	Design and variation	Predictor	Coef.	95% CI	p (WCR)	N	G	Within R^2
A1	Between countries, year FE	DII basic (pp)	0.0303	0.0244, 0.0362	<0.001	259	27	0.497
A2	+ controls	DII basic (pp)	0.0219	0.0123, 0.0315	0.002	259	27	0.594
A3	+ investment	DII basic (pp)	0.0112	0.0042, 0.0182	0.010	244	26	0.808
B1	Within country, TWFE	DII basic (z)	0.0165	−0.0186, 0.0517	0.339	259	27	0.010
B2	+ controls	DII basic (z)	0.0194	−0.0160, 0.0548	0.288	259	27	0.074
B3	+ investment	DII basic (z)	0.0109	−0.0257, 0.0475	0.586	244	26	0.080

Model	Design and variation	Predictor	Coef.	95% CI	p (WCR)	N	G	Within R^2
C1	Within country, TWFE	E-commerce (pp)	0.0070	0.0011, 0.0129	0.043	336	27	0.091
C2	+ controls	E-commerce (pp)	0.0058	−0.0001, 0.0117	0.076	336	27	0.161
C3	+ investment	E-commerce (pp)	0.0053	−0.0010, 0.0115	0.154	319	26	0.135
S1	Within country-year, across sectors	DII basic (pp)	0.0075	0.0033, 0.0117	<0.001	2,235	27	0.050
S2	+ country × sector FE	DII basic (pp)	0.0010	−0.0001, 0.0021	0.042	2,235	27	0.002
SE1	Within country-year, across sectors	E-commerce (pp)	0.0050	0.0012, 0.0088	0.014	2,712	27	0.017
SE2	+ country × sector FE	E-commerce (pp)	−0.0010	−0.0036, 0.0016	0.412	2,712	27	0.001

Note: Outcome is ln nominal labour productivity in A and S, ln real labour productivity in B and C. Controls: unemployment rate, tertiary attainment and manufacturing share; investment is ln gross tangible investment per person employed. S models include country × year and sector × year FE. CIs use CR1 standard errors clustered by country with t(G − 1) critical values; p-values come from a wild cluster restricted bootstrap (Webb weights, 9,999 replications). For S2 the bootstrap p-value (0.042) and the t-based CI (which includes zero) disagree. Within R^2 is computed after partialling out the fixed effects.

The between-country association survives every robustness check but one (Table 3). Leaving out each country in turn gives coefficients between 0.0193 and 0.0252, all with $p < 0.001$. Excluding Ireland and Luxembourg raises the estimate to 0.0269. It is similar in the old and new SBS regimes (0.0220 and 0.0215), with the high-intensity measure (0.0224) and with productivity in PPS (0.0134, $p = 0.027$). The estimate is also robust to the round-two confounders: adding ICT and intellectual-property investment gives 0.0203 ($p = 0.001$); productivity per hour worked gives 0.0115 ($p = 0.014$); employment weighting gives 0.0229 ($p = 0.028$); and all three together give 0.0127 ($p = 0.004$). The one exception matters. Adding ln real GDP per capita reduces the coefficient to 0.0020 (CI −0.0039 to 0.0079, $p = 0.67$). This replicates the pattern found with DESI measures (Aleca & Mihai, 2026; Kavele, 2026). Because GDP per capita is partly an outcome of productivity, this check is not decisive, but it shows that the cross-country association cannot be separated from development level in country data alone.

Table 3. Robustness of the between-country (A2) and within-country (B2, C2) estimates

Check	A2 coef. (p)	B2 coef. (p)	C2 coef. (p)
Baseline	0.0219 (0.002)	0.0194 (0.288)	0.0058 (0.076)
Excluding IE, LU	0.0269 (<0.001)	0.0086 (0.613)	0.0052 (0.149)
Old SBS regime only	0.0220 (0.004)	0.0008 (0.954)	0.0045 (0.090)
New SBS regime only (2021–2024)	0.0215 (0.002)	−0.0033 (0.712)	0.0024 (0.401)
Balanced panel	0.0277 (<0.001)	0.0138 (0.516)	0.0066 (0.091)
Excluding 2020	0.0217 (0.002)	0.0207 (0.235)	0.0057 (0.087)
Dropping Cook's D > 4/N	0.0245 (<0.001)	0.0175 (0.167)	0.0063 (0.010)
+ ln real GDP per capita	0.0020 (0.665)	0.0100 (0.323)	0.0033 (0.052)
Country-specific trends	–	0.0029 (0.765)	0.0021 (0.410)
+ ICT and IPP investment (% GDP)	0.0203 (0.001)	0.0198 (0.304)	0.0058 (0.081)
+ ICT and software capital per hour (G = 15)	0.0206 (0.046)	0.0008 (0.979)	0.0096 (0.028)
Outcome: NA GVA per hour worked	0.0115 (0.014)	0.0134 (0.384)	0.0029 (0.195)
Employment-weighted	0.0229 (0.028)	0.0056 (0.680)	0.0040 (0.146)

Check	A2 coef. (p)	B2 coef. (p)	C2 coef. (p)
Per hour + ICT/IPP + weighted	0.0127 (0.004)	0.0044 (0.613)	0.0017 (0.525)
One-year lag of predictor	0.0207 (0.003)	0.0165 (0.186)	0.0060 (0.033)
Two-year lag of predictor	–	–	0.0062 (0.015)

Note: p-values from the wild cluster restricted bootstrap. The old SBS regime covers 2015–2020 for A2 and B2 and 2012–2020 for C2. Leave-one-country-out ranges and the remaining checks are in Appendix C.

4.3 Within-country association over time (Designs B and C)

Within countries, changes in relative digital intensity are not detectably associated with changes in real productivity. A one-standard-deviation rise in a country's DII position is associated with 1.9% higher productivity in B2, but the confidence interval is wide (−1.6% to 5.5%, p = 0.29). None of the 17 variants of Design B reaches the 10% level; the smallest p-value is 0.17. The round-two variants are also insignificant. The version-consistent e-commerce measure gives a weaker but similar result. In C1 an extra percentage point of enterprises selling online is associated with 0.70% higher real productivity (p = 0.043). With controls the estimate is 0.58% (C2, p = 0.076), and with investment 0.53% (C3, p = 0.154). Lagged e-commerce shares are more precisely estimated: 0.60% for a one-year lag (p = 0.033) and 0.62% for a two-year lag (p = 0.015). The e-commerce association is fragile, however. In the contemporaneous specification (C2) it disappears with country-specific trends (0.0021, p = 0.41), with the national-accounts outcome (0.0019, p = 0.33), with nominal productivity (0.0031, p = 0.58) and when hours, investment and weighting are combined (0.0017, p = 0.53). With ICT and software capital per hour, available for only 15 countries, the estimate is 0.0096 (p = 0.028). The share of enterprises employing ICT specialists gives 0.0055 (p = 0.113). Figure 4 summarises the contrast between designs.

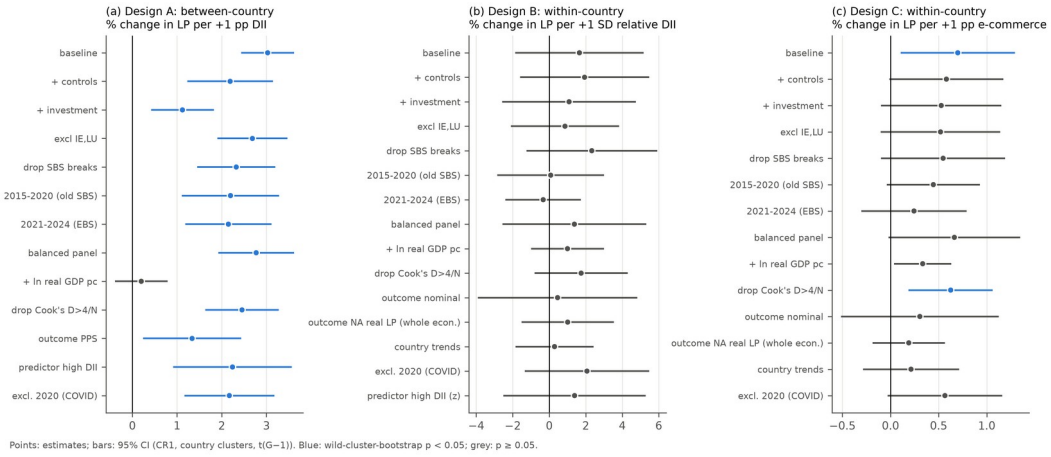


Figure 4. Coefficients and 95% confidence intervals for the between-country (A) and within-country (B, C) designs and their main robustness variants. Units differ by design (A: per pp DII; B: per SD; C: per pp e-commerce).

4.4 Within country-year, across sectors (Design S)

Design S holds the country-year fixed. Within the same country and year, sectors in which one more percentage point of enterprises reaches basic digital intensity have 0.75% higher productivity than the EU-wide pattern for those sectors would predict (S1: 0.0075, CI 0.0033 to 0.0117, p < 0.001). The coefficient is about one-third of the between-country estimate. This suggests that a substantial part of the country-level association reflects national factors, but a

sizeable association remains after they are absorbed. The S1 estimate is stable (Table 4, Figure 5). Leaving out each country in turn gives estimates between 0.0059 and 0.0079, and leaving out each sector between 0.0054 and 0.0083, all with $p < 0.05$. The estimate is similar in the DII v1 years (0.0085) and the v3/v4 years (0.0066, $p = 0.004$). It is also similar with employment weights (0.0085), with sector investment as a control (0.0070), with the high-intensity measure (0.0066), excluding Ireland and Luxembourg (0.0063), excluding the atypical sectors L and D–E (0.0090), and with clustering by country × sector (268 clusters). The version-consistent e-commerce measure gives the same picture (SE1: 0.0050, CI 0.0012 to 0.0088, $p = 0.014$).

Table 4. Design S: robustness of the within-country-year sector estimate (S1)

Variant	Coef.	95% CI	p (WCR)	N
S1 baseline	0.0075	0.0033, 0.0117	<0.001	2,235
Excluding IE, LU	0.0063	0.0036, 0.0089	<0.001	2,068
Excluding sectors L, D–E	0.0090	0.0035, 0.0144	<0.001	1,917
Balanced sector set (excluding L, M)	0.0084	0.0034, 0.0134	<0.001	2,039
2015–2020 (old SBS; DII v1, v2)	0.0082	0.0040, 0.0124	<0.001	1,207
DII v1 years only (2015–2019)	0.0085	0.0044, 0.0126	<0.001	1,008
2021–2024 (EBS; DII v3, v4)	0.0066	0.0018, 0.0114	0.004	1,028
Employment-weighted	0.0085	0.0038, 0.0131	<0.001	2,235
+ ln investment per person	0.0070	0.0024, 0.0116	<0.001	2,215
Predictor: high DII	0.0066	0.0026, 0.0107	0.002	2,109
Dropping Cook's D > 4/N	0.0068	0.0045, 0.0091	<0.001	2,104
Clustering by country × sector (G = 268)	0.0075	0.0039, 0.0110	<0.001	2,235
Leave one country out (range)	0.0059 to 0.0079	–	all < 0.05*	–
Leave one sector out (range)	0.0054 to 0.0083	–	all < 0.05*	–

Note: All models include country × year and sector × year FE; outcome ln nominal sector labour productivity. *CR1 t-test p-values (bootstrap not run for the leave-one-out loops).

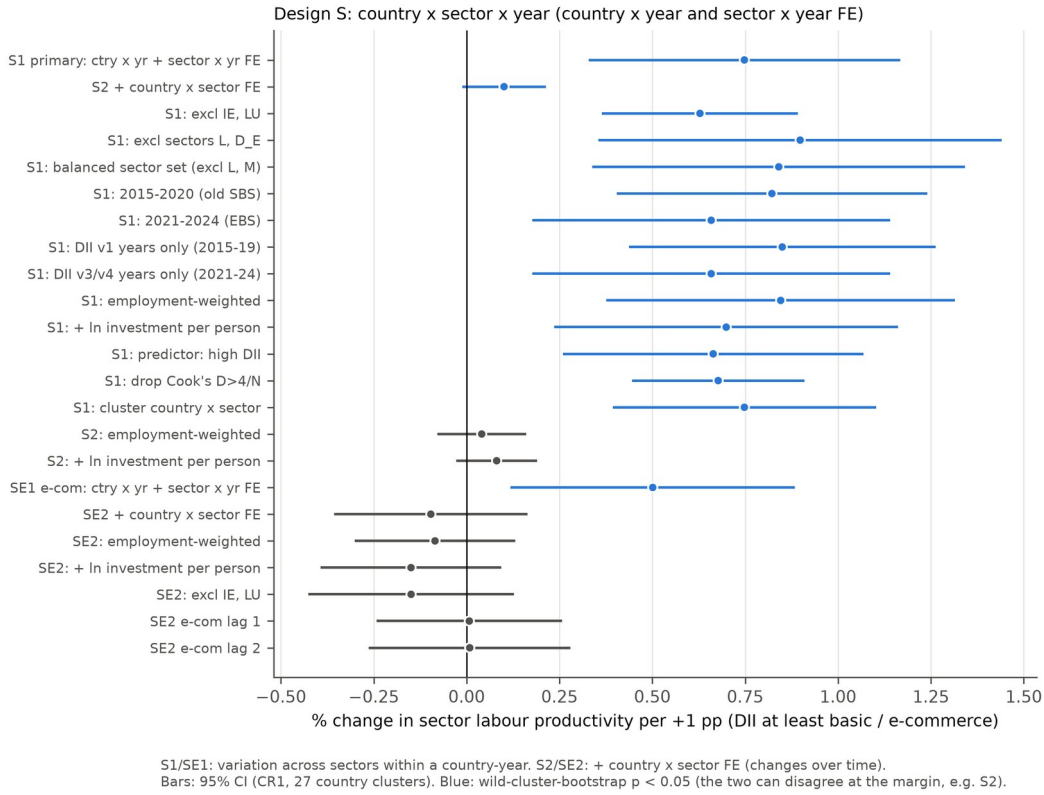


Figure 5. Design S: within-country-year sector estimates (S1, SE1), within-country-sector estimates (S2, SE2) and robustness variants, with 95% confidence intervals. Where the t-based interval and the wild bootstrap p-value disagree (S2), both are reported in Table 2.

When country × sector fixed effects are added, the association almost vanishes. In S2 the coefficient falls to 0.0010. Its bootstrap p-value is 0.042, but the t-based interval includes zero, and the estimate loses significance with employment weights ($p = 0.445$) and with investment ($p = 0.088$). With e-commerce, the within-country-sector estimate is −0.0010 (SE2, $p = 0.41$), and the one- and two-year lags are close to zero ($p = 0.95$). The within-country-year association is therefore a level association between sectors, not a link between changes over time.

4.5 Heterogeneity by sector and enterprise size (H3)

Between-country slopes estimated separately for each sector are positive and significant in all ten sectors (Table 5). They are largest in information and communication (J: 3.67% per point), manufacturing (C: 3.33%) and professional, scientific and technical activities (M: 3.21%), and smallest in accommodation and food services (I: 1.99%). Within country-years, the association is weaker in service sectors than in manufacturing, utilities and construction (interaction −0.0030, $p = 0.053$), although the difference is only marginally significant. By enterprise size, the between-country slope rises from 2.55% for small enterprises (10–49 persons employed) to 2.99% for medium-sized enterprises and 3.34% for large enterprises (250 or more). Within country-years, however, size classes with higher digital intensity are not more productive than the EU-wide size pattern predicts (Z1: −0.0005, $p = 0.83$). With small enterprises as the reference, the within-country-year association is weaker for large enterprises (interaction −0.0073, $p = 0.008$). Size therefore moderates the between-country gradient, but within country-years digital intensity adds little information beyond size itself.

Table 5. Heterogeneity: between-country slopes by sector and size class (year FE)

Group	Coef. (per pp DII)	95% CI	p (WCR)	N
C Manufacturing	0.0333	0.0229, 0.0437	<0.001	257
D–E Utilities	0.0232	0.0160, 0.0305	<0.001	228
F Construction	0.0236	0.0184, 0.0287	<0.001	264
G Trade	0.0227	0.0163, 0.0292	<0.001	267
H Transport	0.0237	0.0130, 0.0343	<0.001	248
I Accommodation and food	0.0199	0.0106, 0.0291	0.006	249
J Information and communication	0.0367	0.0203, 0.0531	0.003	259
L Real estate (2021–2024)	0.0233	0.0143, 0.0324	<0.001	90
M Professional services (2021–2024)	0.0321	0.0248, 0.0394	<0.001	106
N Administrative services	0.0227	0.0130, 0.0325	<0.001	267
Size 10–49	0.0255	0.0205, 0.0305	<0.001	230
Size 50–249	0.0299	0.0243, 0.0354	<0.001	206
Size 250+	0.0334	0.0220, 0.0448	0.002	196

Note: Each row is a separate regression of ln nominal labour productivity on the DII with year FE, without controls. Size-class models cover sections C, F, G, H, I, J, M and N.

4.6 Lags and nonlinearity (H4)

There is no evidence of nonlinearity. Adding a squared DII term to A2 gives a quadratic coefficient of −0.007 per 100 squared points ($p = 0.74$), and the linear term is unchanged (0.0218). Lagged predictors behave like contemporaneous ones in the between-country design and are not significant in Design B. The only lag evidence is the positive one- and two-year e-commerce lags in Design C. Their contemporaneous counterpart is fragile (Section 4.3), and within country-sectors the lags are zero (SE2).

5. Discussion

5.1 Where the association lives

The four designs give a consistent answer once they are read as answers to different questions. In levels, digital intensity and productivity are strongly related. Countries with more digitally active enterprises are more productive (H1 supported), and the relationship survives standard controls, investment in ICT and intellectual property, hours-based outcomes and employment weighting. It does not survive control for real GDP per capita. Within the same country and year, sectors with more digitally active enterprises are also more productive, by about 0.75% per percentage point. This estimate does not depend on national development level, institutions, prices or the DII version, because all of these are absorbed by the country × year effects. Over time, by contrast, neither the standardised DII nor the e-commerce share moves detectably with productivity within countries or within country-sectors. H2 is therefore supported in the cross-sectional sense, within country-years, but not in the longitudinal sense.

This pattern helps reconcile the two strands of the literature reviewed in Section 2. Firm-level studies find that digitally intensive firms are more productive (Kuosmanen et al., 2026; Herrero et al., 2026; Andres et al., 2025). Country panels find that the association disappears with development controls or within countries (Aleca & Mihai, 2026; Kavele, 2026; Zegrean et al., 2025). Our results suggest that both are right. The association is a feature of levels: digital intensity marks productive units, and this holds even among sectors of the same economy. It is not, at least in a decade of aggregate data, a feature of short-run changes.

5.2 Explaining the pattern: delayed returns, selection or shared capabilities

Three interpretations are consistent with this pattern, and the data cannot fully separate them. First, the J-curve view (Brynjolfsson et al., 2021) implies that adoption is accompanied by intangible investment whose returns arrive later, so changes in adoption should be weakly related to measured productivity in the short run. The fragile positive e-commerce lags in Design C point in this direction, but the contemporaneous e-commerce association does not survive country trends or alternative outcomes, and the within-sector lags are zero. Regional evidence also shows that the effects of ICT and software differ between early and mature phases of the technology life cycle, so aggregate estimates can mask opposing phase-specific dynamics (Jaccoud et al., 2026). Second, selection and reverse causality: more productive firms and sectors can afford to adopt more technologies, and they have more to gain from them. A level association would then reflect who adopts rather than what adoption does. Third, common capabilities: management quality, skills and organisational capital raise both adoption and productivity (Bloom et al., 2012; Brynjolfsson & Hitt, 2000). This view fits the evidence that returns depend on complements (Li & Liu, 2026; Hu & Li, 2026; Alexandre et al., 2026). On this view, the DII would act as a marker of capabilities rather than as their cause.

Two results lean against a simple causal reading. If digital adoption raised productivity strongly and quickly, within-unit changes would show it. With ten years and sizeable changes in adoption, Designs B, C, S2 and SE2 should have some power, yet their estimates are small or imprecise, and in SE2 negative. In addition, the between-country association is absorbed by GDP per capita, which is consistent with digital intensity and productivity both reflecting the general level of development. Neither result rules out causal effects that are small, slow or heterogeneous, and the power of within-country designs is limited by low within-country variation in measured productivity (Table 1).

5.3 Heterogeneity

The between-country gradient is steepest in information and communication, manufacturing and professional services, where digital technologies are central to the production process, and flattest in accommodation and food services. This is consistent with the complementarity view, since sectors with more intangible-intensive production can make more use of digital tools (Roth & Mitra, 2025). The gradient also rises with enterprise size, which fits the firm-level finding that gains concentrate among top performers (Kuosmanen et al., 2026) and with the larger economic effect of digitalisation reported for large enterprises (Kyshakevych et al., 2024). Within country-years, however, size explains productivity differences without help from the DII, and the services interaction is only marginal. H3 therefore receives partial support: heterogeneity is clear in the between-country slopes but weak within country-years.

5.4 Nonlinearity and timing

The absence of a quadratic term suggests that, at the aggregate level and within the observed range, there is no threshold above which returns to digitalisation rise or fall. This differs from the diminishing returns reported for light manufacturing (Cheng & Rasool, 2026) and from the inverted U-shaped relationship between the diversity of digital deployment and capacity utilisation in Chinese manufacturing firms (Li, Su, et al., 2026). The difference may reflect sector coverage and the use of a share of adopters rather than a composite intensity index. H4 is

not supported for nonlinearity, and support for lags is weak: it appears only for country-level e-commerce and not within country-sectors.

6. Conclusion

6.1 Main findings

Does digitalization improve business productivity in the EU? Using public Eurostat data for 2015–2024 and four complementary designs, this study finds that the answer depends on which comparison is made. Across countries, each additional percentage point of enterprises with at least basic digital intensity is associated with about 2.2% higher labor productivity, but this association cannot be separated from development level. Within the same country and year, sectors with more digitally active enterprises are about 0.75% more productive per percentage point, a result that is robust across years, versions, sectors, countries and specifications. Within countries and country-sectors over time, changes in digital intensity are not detectably associated with changes in productivity.

Digital intensity is therefore a reliable marker of productive economies and sectors, but there is no evidence that short-run increases in adoption raise aggregate productivity. The results are consistent with delayed returns, with selection, or with shared capabilities behind both adoption and productivity. Separating these explanations will require longer series on a consistent measure and firm-level data on adoption and its complements. Until then, policy targets based on adoption shares should be judged by the productivity they deliver, not only by the number of enterprises that reach them.

6.2 Implications for policy

The Digital Decade programme aims for more than 90% of EU SMEs to reach at least a basic level of digital intensity by 2030 (Decision (EU) 2022/2481, Art. 4(1)(3)(b)). In 2023, 59% of EU enterprises had reached that level (Eurostat, 2024). The results support the indicator as a marker of productive structures: in every year and every sector, more digitally intensive economies and sectors are more productive. They do not show that raising the share of adopters will, by itself, raise productivity in the short run. Within countries, changes in the share of adopters over 2015–2024 were not detectably followed by productivity gains. Policy that counts adopters therefore risks measuring the means rather than the outcome. Two practical implications follow. First, programmes that fund technology adoption could be paired with support for the complements on which returns depend, such as management practices, skills and organisational change (Bloom et al., 2012; Li & Liu, 2026). This is consistent with the large TFP gains associated with Italy's Transition 4.0 programme, which funded investment rather than counting adopters (Palma & Scotti, 2026). Second, monitoring could track productivity and intangible investment alongside adoption shares, so that progress toward the 2030 target can be judged by its economic results.

6.3 Implications for managers

The association between digital intensity and productivity is strongest in sectors where digital tools are central to production (information and communication, manufacturing and professional services) and in larger enterprises. Adoption alone is unlikely to close a productivity gap, because the gains documented in firm-level studies depend on data

capabilities, skills and complementary investment (Andres et al., 2025; Alexandre et al., 2026). Firms may therefore benefit more from building capabilities around a few technologies than from adding technologies to their count.

6.4 Implications for statistics and research

The frequent changes in the DII's composition make it difficult to use for monitoring change over time, which is exactly what the 2030 target requires. Publishing a version-consistent core index, or bridging tables for overlapping years, would make longitudinal analysis more reliable. Researchers using country panels of the EU should report small-cluster inference, and should test whether associations hold within country-years as well as between countries.

6.5 Limitations and future research

The study has several limitations. First, the design is associational. None of the designs identifies a causal effect. Reverse causality and unobserved capabilities can explain the level associations, and the within-country-year sector design removes national confounders but not sector-specific ones that vary across countries. Second, digital intensity is measured imperfectly. The DII changes composition between versions, so its levels are not comparable over time. Standardising within years preserves rankings but discards changes in the EU-wide level, and the version-consistent e-commerce measure captures only one dimension of digitalisation. Only three of the 12 items are common to all versions (Appendix B), and one of them is e-commerce sales, so the DII and the e-commerce measure are not fully independent. Third, apparent labour productivity per person employed does not adjust for hours, capital or the quality of inputs. The SBS series has a methodological break in 2021, and real productivity relies on a business-economy deflator that is not sector-specific. The hours-based national-accounts outcome partly addresses the first point, and the regime-split checks address the second. More generally, productivity measurement remains oriented towards manufacturing, while services and digital activities now dominate value added (Fisher, 2025).

Fourth, the data are aggregated. Country and sector shares say nothing about which firms adopt or how intensively they use each technology, and they cannot distinguish productivity gains within firms from reallocation between firms. Linked firm-level data would be needed for that. Fifth, power and the time span are limited. With 27 countries and ten years, and limited within-country variation in measured productivity, the within-country designs can detect only moderately large effects. Small or slow effects cannot be ruled out, and the J-curve view in particular predicts effects beyond the observation window. Sixth, eleven country-years are missing because of confidential cells, and recent SBS years may be revised. Future research could address these limitations with linked firm-level data on adoption and complementary investment, longer series on a consistent digital measure, and policy changes that shift adoption for reasons unrelated to productivity, which would allow causal effects to be identified.

Appendices

Appendix A. Data sources and variable construction

Variable	Eurostat table	Construction
Value added, persons employed, gross investment	sbs_na_sca_r2 (≤2020), sbs_ovw_act (≥2021)	Sum over NACE C, D, E, F, G, H, I, J, L, M, N; only when all 11 sections are reported

Variable	Eurostat table	Construction
Labour productivity, nominal	as above	Value added / persons employed, thousand EUR
Labour productivity, real	+ nama_10_a10	Nominal LP × exchange rate / business-economy GVA deflator (2015 = 1) / 2015 exchange rate
Labour productivity, PPS	+ prc_ppp_ind	Nominal LP × exchange rate / PPP (national currency per PPS)
GVA per hour worked	nama_10_a10, nama_10_a10_e	Chain-linked (2015) or PPS GVA over B–E, F, G–I, J, M–N / hours worked
DII at least basic	isoc_e_dii, isoc_e_diin2	100 − % enterprises with very low DII (version-specific indicator codes)
DII high or very high	as above	% high + % very high
DII standardised	as above	Within-year z-score across EU-27
E-commerce sales	isoc_ec_eseln2 (E_AESELL)	% enterprises; re-dated to t−1
ICT specialists	isoc_ske_itspen2 (E_ITSP2)	% enterprises employing ICT specialists; re-dated to t−1
Unemployment rate	une_rt_a	% of labour force
Tertiary attainment	edat_lfse_03	% of population aged 25–64 with ISCED 5–8
Manufacturing share	SBS	Section C value added / aggregate value added, %
ICT and IPP investment	nama_10_an6	GFCF in ICT equipment and intellectual-property products, % GDP
ICT and software capital	nama_10_nfa_st	Net stock of ICT equipment and software (B–E, F, G–I, J, M–N) per hour worked
Real GDP per capita	nama_10_pc	Chain-linked euros per capita

Non-positive investment values (nine cells) are set to missing. All tables were downloaded on 2 November 2026; the download log records the URL and timestamp of each file.

Appendix B. DII versions

Version	Survey years	Comparability
v1	2015–2019 (annual; Eurostat flags breaks in 2016–2019)	12 technologies; composition changes between years
v2	2018, 2020	Different technology set; 2018 overlap with v1 (mean 50.9% vs 57.3%; country ranks r = 0.96)
v3	2021, 2023, 2025	Different technology set; used for 2021 and 2023
v4	2022, 2024	Different technology set; used for 2022 and 2024

The index gives one point for each of 12 conditions, and enterprises are grouped as very low (0–3 points), low (4–6), high (7–9) or very high (10–12). The components below are summarised from Eurostat's annex "Digital Intensity Index (DII) composition overview 2015–2025" (Eurostat, 2026). Only three items are common in substance to every year: more than 50% of persons employed have internet access for business purposes (2015–2019 wording: used computers with internet access); the fastest fixed internet connection is at least 30 Mb/s; and e-commerce sales account for at least 1% of turnover. The other nine items change between versions and, in v1, also between years.

Version (years used)	Items 4–12 (summary)
v1 (2015–2019)	Web sales >1% of turnover with B2C >10% of web sales; >20% of persons employed with mobile internet devices; website features; website; social media use; ICT specialists; then a rotating set across years: supply-chain information sharing, paid internet advertising, ERP, CRM, e-invoices, medium-high cloud services, ICT-security awareness, ≥3 ICT-security measures, social media for ≥2 purposes, e-commerce sales to other EU countries
v2 (2018, 2020)	Big data analysis; mobile internet devices; website features; website; 3D printing; ICT specialists; industrial or service robots; medium-high cloud services; e-invoices
v3 (2021, 2023, 2025)	Web sales with B2C share; cloud computing services; sophisticated or intermediate cloud services; ≥2 social media; any social media; IoT (2021) or data analytics by own staff or provider (2023, 2025); any AI technology; ERP; CRM (2025 replaces one cloud item with having a website)
v4 (2022, 2024)	Documented ICT-security measures; staff awareness of ICT-security obligations; ≥3 ICT-security measures; ICT training for staff; ICT specialists; industrial or service robots (2022) or any AI technology (2024); remote access to e-mail and documents; remote meetings

Note: Items 1–3 are listed in the text. The "at least basic" share used in this study equals 100 minus the very-low share; Eurostat publishes it directly (E_DI3_GELO, E_DI4_GELO) only from 2021. v3 emphasises cloud, AI and business software, and v4 emphasises ICT security and remote work, which helps explain why levels shift between alternating years (Figure 2).

Appendix C. Additional robustness results

Year-by-year between-country estimates (A2 specification, ln nominal LP on DII basic).

Year	Version	N	Coef. without controls	Coef. with controls	95% CI (with controls)	p
2015	v1	26	0.0366	0.0269	0.0123, 0.0414	0.001
2016	v1	26	0.0304	0.0194	0.0038, 0.0349	0.017
2017	v1	25	0.0327	0.0236	0.0065, 0.0408	0.009
2018	v1	25	0.0268	0.0255	0.0116, 0.0393	0.001
2019	v1	26	0.0291	0.0213	0.0098, 0.0328	0.001
2020	v2	25	0.0330	0.0235	0.0125, 0.0345	<0.001
2021	v3	26	0.0282	0.0209	0.0099, 0.0318	0.001
2022	v4	27	0.0347	0.0265	0.0145, 0.0384	<0.001
2023	v3	27	0.0247	0.0171	0.0058, 0.0284	0.005
2024	v4	26	0.0330	0.0273	0.0175, 0.0370	<0.001

Note: Separate OLS cross-section for each year; heteroskedasticity-robust (HC1) standard errors with t(N − 1) critical values. Controls as in A2.

Leave-one-country-out. A2: 0.0193 to 0.0252, all $p < 0.001$. B2: 0.0124 to 0.0329, p from 0.015 to 0.40. C2: 0.0033 to 0.0069, p from 0.019 to 0.16. S1: 0.0059 to 0.0079; leave-one-sector-out 0.0054 to 0.0083; all $p < 0.05$ (CR1 p-values).

Other checks. Dropping SBS observations flagged as breaks: A2 0.0232 ($p < 0.001$), B2 0.0233 ($p = 0.19$), C2 0.0055 ($p = 0.14$). The high-intensity standardised DII in B2: 0.0139 ($p = 0.51$). The raw DII in percentage points with country and year FE: 0.0015 ($p = 0.22$). Between-country slope of e-commerce with controls: 0.0240 ($p = 0.085$). Between-country slope of ICT specialists: 0.0333 ($p = 0.10$). Size-class panel with country × size FE (within country-size over time, Z2): 0.0011 ($p = 0.42$).

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