Twin Transition and Productivity Growth

Why intangible capital matters

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Date:
August 2026

The Productivity Institute
Working Paper No.80

Key words
green tasks; digital skills; productivity; twin transition

JEL codes
O44, P18, Q00, Q01, Q20, Q43, Q50

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Acknowledgements
This research is supported by The Productivity Institute at The University of Manchester, as part of the project "Investment and skills for the twin transition: the future of produc tivity growth in the UK, US and the EU - (cod. R130703)". The authors gratefully acknowledge the financial support provided, which made this study possible. We also thank the OECD-Italian Ministry of Economy and Finance joint project on fostering multilateral cooperation for structural reforms and economic development, on whose work our methodology partly builds.

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Suggested citation

E. Gallo, C. Jona-Lasinio, I. Smiderle (2026) *Twin Transition and Productivity Growth: why intangible capital matters*. Working Paper No. 80, The Productivity Institute.

The Productivity Institute is an organisation that works across academia, business and policy to better understand, measure and enable productivity across the UK. It is funded by the Economic and Social Research Council (grant number ES/V002740/1).

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Abstract

This paper examines how the twin transition – the simultaneous shift toward greener and more digital production – affects labour productivity growth at the industry level across 16 OECD countries over 2004-2020. We estimate an augmented production function incorporating measures of green task intensity, digital skill intensity, and intangible capital stocks, and test the productivity effect of the twin transition through a composite Twin Transition Index. Our findings suggest that digital skill intensity independently raises productivity growth while green task intensity, considered in isolation, yields no significant effect. The composite index, however, generates positive and significant productivity gains especially when it is complemented by intangible capital and in particular intangible assets not included in national accounts.

1 Introduction

The global economy is undergoing two simultaneous and profound structural transformations: the digital transition and the green (or net-zero) transition, collectively referred to as the twin transition. These shifts are reshaping business operations, altering production inputs, and redefining the institutional and social environment in which firms operate, ultimately influencing productivity growth. While each transition presents distinct challenges and opportunities, their combined effect on economic performance remains an area of active exploration. The digital transition has driven advancements in automation, artificial intelligence, and data-driven decision-making, leading to increased efficiency and economic gains, whereas the green transition is necessary for achieving environmental sustainability and reducing carbon emissions, but may concomitantly provide opportunities for technological progress: both these transitions are calling for massive investments in R&D and are reshaping the labour market, driving a surge in demand for digital and green skills. Undoubtedly, this theme has been at the core of policy debates and directives: both in programmatic speeches and policy documents (Kovacic et al., 2024; Gao, 2025), and in recovery funds in response to the COVID-19 crisis. Notably, within the framework of the NextGenerationEU (European Commission, 2020), each European National Recovery and Resilience Plan (NRRP) is expected to allocate at least 37% of the related funds to climate objectives and 20% to digital objectives (European Commission, 2026).

As necessary as they may be, there is no consensus on how these two transitions interact. Because they affect a wide range of outcomes – from investment decisions to labour-market adjustments – their coexistence may entail both trade-offs and synergies. As Aloisi (2025) suggests, the green transition is goal-oriented, largely driven by public policies and efforts aimed at achieving environmental targets through regulatory and financial incentives. In contrast, the digital transition is primarily market-driven, focusing on efficiency and innovation, with public intervention playing a supplementary role in fostering R&D investments with positive spillover effects. Despite these distinctions, the digital transition holds the potential to accelerate the green transformation by enabling more efficient production processes and reducing the costs of clean technologies.

From a labour market perspective, jobs with high green and digital intensity tend to be associated to higher wages (Bontadini et al., 2025). At the same time, these transformations may lead to job displacement, as in the case of automation of mechanical tasks through robotics (Acemoglu and Restrepo, 2020) and the decline of so-called brown jobs in high-emission industries (Causa et al., 2024b). Furthermore, the long-term impact of the widespread adoption and continuous advancement of artificial intelligence remains uncertain, whereas its increasing energy requirements are putting pressure on water-stressed areas of the planet and are calling for more intensive investment efforts in energy efficiency (Li et al., 2025). In this context of rapid change and unpredictability, informative metrics and analysis are essential to effectively capture and analyse both the digital and green transitions. This is why we investigate the extent to which the two transitions, individually and jointly, are affecting productivity dynamics. Further, we try to disentangle the channels trough which these transformations can affect the production process. As it is widely recognised the role of digitalisation as an enabler of the green transition: digital technologies can improve production efficiency, reduce energy consumption, and, when combined with the appropriate skills, support the development of innovative, greener products (Gagliardi et al., 2016).

Human capital accumulation may prove fundamental to reap the benefits of both transitions, but also to offset negative, unforeseen or unintended consequences of rapid technological advancements and adjustment to climate change. For instance, Consoli et al. (2016) showed that green jobs typically require highly educated and skilled workers, entailing that this kind of employment is less likely to suffer from displacement due to advancements in technologies and automation. In a recent study on EU and US firms exploiting the EIB Survey, Veugelers et al. (2023) find that firms that couples investments to tackle climate change and to adopt advanced technologies are more likely to be leading innovators in their sectors. These firms have also better management practises and tend to invest more on employment training: interestingly, across all surveyed firms the principal constrain to investment is the availability of staff with the right skills-set, suggesting that the synergies between investments and the human capital component are primary drivers of a successful adaptation of firms to the changing environment. Indeed, the effects of investment in digital and green technologies on productivity may crucially hinge on the complementary investment in the skills required to exploit efficiently these technologies. Pisu et al. (2021) point to sluggish digital technology adoption and slow economic growth as being partly driven by the challenges of investing in intangible assets, particularly the skills necessary for digital transformation. Similarly, a successful transition to a zero-carbon economy requires the diffusion of jobs with green skills and tasks, encompassing competencies and practises essential for developing and implementing sustainable technologies (Consoli et al., 2016; Chen et al., 2020; Causa et al., 2024c). Despite the established importance of these sets of skills and these investment efforts, empirical research quantifying their combined effect on productivity remains scarce. A significant obstacle in this respect is the dearth of standardized definitions and metrics to capture the evolving features of the business environment: this is especially the case for those factors affecting the production inputs. We leverage on recent developments on estimates of key metrics of the twin transitions: new measures of green capital stock and investment and new sectoral level estimates on the prevalence of green tasks and digital skills in the workforce developed in Bontadini et al. (2025) and Smiderle et al. (2026). We will evaluate their individual and joint impacts on industry productivity growth across the UK, the US, and a sample of European economies in the period 2008-2020.

Our empirical analysis is conducted at the industry level and contributes to a more comprehensive understanding of the linkages between the digital and net-zero transitions, leveraging novel data on greenness of occupations and digital skills, and assess their productivity effects in synergy with both tangible and intangible capital. Then we estimate a standard production function augmented with occupational-based measures of greenness and digital skills intensities to measure their direct impact on labour productivity. Afterward, we also test the extent to which the two transitions interact to contribute to productivity growth, by fostering innovation, efficiency improvements and creating new market opportunities.

The paper proceeds as follows. Section 2 reviews the existing literature on the twin transition, productivity dynamics, the measurement of green investment as well as of green tasks and digital skills. Section 3 describes our data sources and presents metrics for green capital stocks, green task, and digital skills intensities. Section 4 outlines our empirical strategy, while section 5 presents the empirical results, detailing how we estimate a standard production function augmented with green tasks and digital skills intensities at the industry level to quantify their contributions to productivity growth. Section 6 concludes and discusses policy implications.

2 Background literature

This section reviews the existing literature on the possible linkages between the twin transition and productivity (subsection 2.1) as captured by measures of green tasks and digital skills (subsection 2.2).

2.1 Twin Transition

Determining the extent to which digital transformation and the net-zero transition interact is a complex task. The trajectory of this shift is shaped not only by technology but also by a wide array of factors, including evolving social norms and the need of a just transition. The impact of digitalisation on labour productivity has been extensively examined (Gal et al., 2019) and also the attention to the green transition, relatively more recent, propelled a great research interest across multiple dimensions, spanning from economic growth, public debt, employment, income distribution, competitiveness, inflation, to energy prices (Erbach and Höflmayr, 2022). Additionally, traditional economic perspectives often frame low-carbon transitions as costly for productivity such environmental shifts can generate moderate but widespread productivity gains, driven by technological learning and induced investment (Mercure et al., 2025). An historical perspective on how the twin transition may unfold is provided by Fouquet and Hippe (2022): they study the evolution of both information and energy transitions in the last 200 years. The energy transition – *i.e.* the shift toward decarbonisation and improved energy efficiency – risks lagging behind digitalisation. This imbalance partly reflects incentives: much of the value of decarbonisation accrues as avoided social costs, whereas the ICT transition generates more appropriable private returns. The green economy is, however, highly heterogeneous in this respect: its most dynamic segments, e.g. solar, batteries, and electric vehicles, are increasingly driven by private returns, although scaling them up typically requires public intervention to overcome market and coordination failures. This underscores the need to foster synergies between the two transitions. The digital transition has reshaped production processes, raising resource efficiency and enabling cleaner energy supply at lower costs, and it is unsurprising that much of the twin transition literature focuses on deploying digital technologies in support of decarbonisation targets. A prominent channel is energy efficiency: ICT drives efficiency gains not only within production but across the distribution chain. Smart grids optimise real-time energy flows and reduce waste (Knell, 2024), digital technologies accelerate electric vehicle adoption (Castellacci and Santoalha, 2025), and more broadly, digitalisation improves access to and efficient use of renewables, supporting productivity growth and economic resilience (Aldieri et al., 2021).

Innovation is a key propeller of productivity growth and a suitable channel to investigate the dual transition dynamics: as digitalisation fosters research capabilities and accelerates the development and diffusion of clean technologies, it acts as a catalyst for innovative environmental solutions (Gagliardi et al., 2016). Around 20% of climate-related inventions incorporate digital technology with ICT sectors and workers playing a key role in developing low-carbon technologies (Amoroso et al., 2021) and the evidence related to twin-transition patents is increasing. Here, the green dimension is not to be considered ancillary to the digital technological counterpart: Damioli et al. (2025) maintain that the green scientific orientation of specific regions is one of the most important predictor and incubator of twin innovations, provided also a base of digital knowledge. Indeed, Fazio et al. (2025) show the need to support primarily ICT innovation to foster twin-innovation, alongside with evidence of the clustering of twin-innovation. While they still represent a small fraction of the total number of inventions, twin-transition patents more saw more than a doubling from 2005 to 2017, with a high variation across countries (Aklilu et al., 2025). Moreover, low carbon patents have a higher share citation of digital patents with respect to high carbon ones, suggesting that green patents have benefitted more from digital advancements with respect of grey ones: this could point to higher digital spillovers benefit for cleaner technologies (Calvino et al., 2025). Lately, interesting evidence using using Italian firms level data suggest that AI is having a prominent role in driving eco-innovation (Montresor and Vezzani, 2023).

Synergies are not the only dimensions of the interplay between the digital and green transformations: sound evidence is needed also on its trade-offs, particularly related to the goal of decreasing GHG-emissions. On one hand, the decarbonization of the economy is increasingly mediated by ICT applications: adopting a macroeconomic perspective, Haldar and Sethi (2022) found that when proxying ICT technologies with mobile-subscriptions in emerging countries, the interaction with renewable energy leads to significant reductions in CO2 emissions. Also the relationship between innovation and internet-use (as additional ICT proxy) has emission-decreasing effects. Zhang and Du (2025) findings from China show that emission reduction effects are particularly pronounced in less developed regions. However, several studies warn that efficiency gains from digital adoption can increase total demand and absolute energy use, leading to rebound effects that could undermine the benefits of the green transition (Huang and Lin, 2025). Indeed, the demand and use of energy from all sources is increasing (IEA, 2025), especially for cooling and data centres, and emissions are consequently still on the rise world-wide. Calvino et al. (2025) propose a framework to study how the latest phases of the digital transitions (emergence and diffusions of GPTs) influence the quantity and quality of the energy consumed in the economy. Identifying multiple channels, they acknowledge that the direction of the effect of digitalisation on net-zero transition is theoretically undetermined: for instance, machines are made more productive, increasing the use of capital, an input more energy-intensive with respect to labour. While in their set-up the capital is complementary with the energy component, our framework allows to estimate also the impact of a qualitative change in the labour component along both the digital and green dimensions.

At the micro level, emerging research highlights how firms are adapting to the twin transition and provide evidence on the implications this has for productivity and competitiveness. Veugelers et al. (2023) find that EU and US firms combining climate and advanced technology investments are more likely to be sector-leading innovators.[1] These firms also show stronger management and invest more in employee training. Moreover, evidence from Ferri et al. (2023) shows that Italian firms receiving funding through the National Recovery and Resilience Plan (NRRP) are significantly increasing their engagement with the twin transition, both in terms of the scale and scope of investment, resulting in enhanced firm performance. Finally, Kesidou et al. (2025) show that digitally advanced UK SMEs are more likely to adopt net zero innovations, highlighting strong complementarities between digitalization and environmental goals.

However, scaling up from the firm perspective, empirical estimates of how these transitions co-move in the aggregate economy are lacking and the macroeconomic evidence that couples the digital and green dimensions of the productivity dynamics, without subordinating one dimension to the other, is scarcer. The most common approach involves the use as outcome variable of the environmentally adjusted multifactor productivity

[1] See also Kalantzis et al. (2026) for related evidence on the digital and green transitions using the same EIB Investment Survey data.

(Mante et al., 2023), a measure of productivity that along with standard inputs incorporates environmental factors such as resource use and undesirable outputs (like pollution and carbon emissions).

Studying the impact of the twin transition on productivity is not immediate: Geels et al. (2021) argue the need to adopt an integrated, systemic approach that captures complex and dynamic changes beyond traditional analyses. In this context, our study contributes by offering novel insights into the twin transition, with the aim of encouraging further research that embraces this systemic and multidimensional perspective. Empirical macroeconomic evidence of the impact of the twin transition intended as dual force of different but interacting structural shifts is fundamentally lacking, especially due to a dearth of harmonised data. Our study thus proposes a new perspective on the literature on twin transition impact on productivity: we will consider the digital and the green transition in a parallel, non-hierarchical fashion where neither transition is merely a mediator for the other or in a relationship of *enabler-enabled*. Exploring how digitalization and the green transitions contribute to labour productivity in a macroeconomic setting with novel estimates, will yield insights on how to build a policy framework able to integrate the various measures commanded by the two different natures of these transitions. (Santarius et al., 2023).

2.2 Skills and Tasks for the Twin Transitions

In our framework, workforce skills and tasks enter as labour-augmenting features in the process of production, where we measure the extent to which improvements in the digital skills or the quality of tasks (i.e. *greenness of tasks*) may translate into higher productivity growth. Skills are one of the main drivers of productivity, increasing the human capital of workers, actively fostering innovations in all domains, but also contributing to the wide-scale adaptation to revolutionary transitions, in particular the fast-paced technological progress and climate change. Rincon-Aznar et al. (2015) survey growth accounting and econometric evidence on skills and UK productivity, reporting that labour composition has contributed on average 15-20% to labour productivity growth in recent decades.

Channels through which the skills set of the workforce may enhance productivity include their role in igniting innovation and ensuring technology diffusion and adoption by firms (Leiponen, 2005). Early evidence of the complementarities of skilled labour to the information technologies revolution can be found in Bresnahan et al. (2002), where the authors propose a framework in which IT capital stock, skilled labour and reorganizational practises are mutually self-reinforcing in shaping the labour demand and firm productivity. O'Mahony et al. (2022) found that these complementarities have reversed after the financial crisis, uncovering evidence of capital-skills substitutions. Understanding conditions under which technological progress is labour-saving or labour-augmenting remains a fundamental topic of investigations.

2.2.1 Measuring labour quality

The measurement of human capital has traditionally relied on enrollment rates and educational attainment, whereby formal education served as primary indicator of skills (Romer, 1990; Barro, 1991; Levine and Renelt, 1992). To capture broader sources of workforce skills, Mason et al. (2012) constructed a measure that accounts for both certified education-related skills and uncertified skills, acquired through on-the-job training or employment-based learning, confirming the positive impact of human capital on average labour productivity. Hanushek and Kimko (2000) paved the way to the use of international standardised tests ad a measure of cognitive skills, especially related to the areas of mathematics and science.

Beginning in the early 2000s, economic research introduced task-based approaches to better understand the labour market effects of computerization and technological change. A seminal contribution in this domain is the work of Autor et al. (2003), who distinguish between routine and non-routine tasks to demonstrate how computerization substitutes for routine cognitive and manual tasks, while complementing abstract, problem-solving, and interpersonal activities. Building on this foundation, Acemoglu and Autor (2011) further formalize the task-based approach into a model that incorporates endogenous assignment of tasks to factors of production. This model accounts for changes in the wage distribution, particularly in realtion to job polarization[2], for the rapid advent of labour-saving technologies and the interplay between domestic and foreign labour supply. Empirical evidence is further provided by Autor and Handel (2013), who use detailed task data linked to individual worker characteristics to quantify the task content of jobs and better understand the distributional consequences of technological change. An interesting recent development on the measure of skills is the increasing use of online job vacancies to capture at high frequence changes in the labour market demand of skills (Romanko and O'Mahony, 2022). This method could be relevant also to study twin transitions' dynamics in the evolution of required skills, simultaneously informing on the extent of skills shortages, an issue that, as previously mentioned, plays a fundamental role in hindering investments (Veugelers et al., 2023). Data-collection efforts in this direction are starting to appear (e.g. Gotti et al. 2024). Finally, occupation-based metrics of skills are available by statistical and governmental bodies: this is the case of the Occupational Information Network (O*NET) Resource Center, of the US Department of Labour, that provides updated information of work characteristics linking to the US Standard Occupational Classification (SOC) system, and of the European framework that characterises Skills, Competences, Qualifications and Occupations (ESCO, European Commission) and

[2]Phenomenon whereby the wage distribution and the employment composition in the labour market is concentrating at the extremes (high and low-skills level) and reducing at the medium-skill level.

is tight to the International Standard Classification of Occupations (ISCO).

2.2.2 Digital Skills and Green Tasks

On the bases of the literature highlighted above, we will resort to different measures of labour force quality, acknowledging that the digital and green transitions might have a variety of mechanisms in impacting productivity growth through the labour input and thus require different metrics. We employ occupational-based measures, referring to a task-based measure to gauge the extent of jobs related with the transitions to net-zero technologies, whereas we rely on a skill-based measure to estimate the prevalence of digital-enabled or enhanced occupations. This approach has been used among others by Vona et al. (2018), Scholl et al. (2023), Causa et al. (2024c) in the characterisation of green employment and green skills and by Lennon et al. (2023) to uncover digital skills. Building on this research, Bontadini et al. (2025) couple digital and green labour metrics and compute their diffusion within sectors. One of the key contribution of their paper is the production of an international database that allow comparability of measures for different countries and sectors of G7 countries. Being simultaneously interested in the net-zero and digital transitions, we rely on their occupational-metrics in the revised and expanded version of Smiderle et al. (2026).

Green Tasks. The diffusion of 'new work', intended as bundle of activities emerged in response to new technologies and information, has been implemented by Lin (2011) as measure of changes in the organization of production responding to the introduction of new technologies. The identification of existing and new occupations, as well as of the associated skills and tasks, is at the base of the data collecting effort of the aforementioned Occupational Information Network (O*NET) Resource Center. Despite it initially contributed mainly to the studying of computerisation and digital transition (see discussion below), the task-based approach has been fruitfully applied in recent years to examine the characteristics of jobs emerging from the green transition. A pioneering project in this direction is the O*NET "Green Task Development Project" (Dierdorff et al., 2011), which mapped green tasks of new and existing occupations related to the green transition, including *green new and emerging occupations*, and *green enhanced occupations*, intended as those whose content underwent a significant change in response to the green transition.

An expanding body of literature has focused on identifying the prevalence and characteristics of *green jobs* following this *task-based* approach (e.g. Consoli et al. 2016; Vona et al. 2018; Valero et al. 2021; Causa et al. 2024a; Bontadini et al. 2025). This occupational-based method is described by Valero et al. (2021) as a bottom-up approach, whereby jobs are classified based on their task content at the most granular occupational level. This contrasts with top-down approaches, which designate entire industries or sectors as green, overlooking the role of occupation-specific green characteristics in traditionally high-emission sectors. These occupational-based measure have been used as cornerstone for the investigation of characteristics of *green jobs* and consequences of their diffusion. Consoli et al. (2016) inspect the qualitative differences between green occupations and similar occupations classified as non-green, using specific descriptors from the O*NET dictionary of occupations, among which the level of education, training and experience requested. They consider also the incidence of tasks of different natures (e.g. manual, abstract, routine, cognitive tasks), finding an overall higher intensity of human capital in green jobs with respect of peers non green jobs, declined in the various forms mentioned above. Building on the same O*NET database, Vona et al. (2018) construct measures of *green tasks intensity*, as the share of green specific tasks over total tasks in an occupation, and define *green skills* as those more strongly associated with green occupations, ultimately evaluating the net employment effects and shortage of green skills supply in response to a more stringent environmental regulation. In turn, Causa et al. (2024a) use the green tasks measure developed by Vona et al. (2018) to identify *green jobs* and examine labour market dynamics of the green transition in Europe from 2009 to 2019. Their research finds that the shares of green and high-polluting jobs have remained stable, indicating a slow shift toward greener employment. The distribution of green and "brown" jobs varies across demographic and social characteristics: women are under-represented in both, green jobs tend to require higher education, while high-polluting jobs are more common in rural areas and among those with lower education. Causa et al. (2024c) focuses on transition to and from high-polluting jobs, green jobs and non-employment. Their results reinforce the evidence on the heterogeneous effect of structural drivers on the workforce, highlighting the relevant role that place-based policies could have in preventing or mitigating the short and long-term negative labour market effects of the net-zero transition. The use of occupational-based measures of greenness to investigate productivity outcomes is rather novel: an exception can be found in Scholl et al. (2023) whose results show that, in a sample of Portuguese firms, more productive firms typically employ more workers in green jobs with respect of brown jobs. [3]

While investigating green skills or green jobs might be optimal to uncover the dynamics of job creation, job displacement or skills mismatches associated with the policies seeking to foster the green transition (e.g. Popp et al. (2021), Causa et al. (2024c)), we rely on the share of green tasks in each occupation to characterise the impact of *green labour* on productivity, as introduced in Vona et al. (2018). Firstly, this measure

[3] A caveat worth mentioning is that occupation-based measures of greenness aggregate activities that differ widely in their technological content and productivity-growth potential (e.g. ranging from land restoration to electrotechnology engineering). To the extent that low-productivity-growth activities dilute the signal from innovative green segments, estimated average returns to green tasks will understate the contribution of the latter.

of *greenness* is more adequate to capture the actual state of green employment of the economy, as it pertains to the carrying out of activities aimed *specifically* at supporting or enabling the net-zero transition, in contrast to *green skills* that are also used in non-green occupations, albeit with different intensities. Secondly, we build on the data effort of Scholl et al. (2023), Causa et al. (2024a) and, in particular, Bontadini et al. (2025) and Smiderle et al. (2026) that provides detailed and comparable sectoral level estimates for many countries and years. Finally, this approach entails a higher level of granularity in green estimates with respect to metrics based on green employment: we avoid arbitrary thresholds used to define a job *green* or *non-green*, providing rather than a dichotomous division, a spectrum of *greenness* by computing the share of *green tasks*, ensuring the highest level of detail in depicting the labour force composition.

Digital Skills. If the literature on *green skills* has been gaining momentum in recent years, the attention to digital skills has been considerably higher over the last decades. Not only this is attributable to the earlier interest to the digitalisation process with respect to climate changes concerns, but digital capabilities are seen as key enabler of technological changes, fostering technology diffusion and adoption. It is mainly through this channel that we can expect digital skills to have impact on productivity (Brynjolfsson et al., 2021). Despite their importance, the diffusion of digital skills remains slow and uneven across countries and sectors, hindering productivity growth and exacerbating existing labor market inequalities (Andrews et al., 2018; Gal et al., 2019). Investigating the prevalence of these skills may be useful to shed light on drivers of the labour productivity divergence between firms at the global frontier and so-called laggard firms Andrews et al. (2016). This is illustrated by Berlingieri et al. (2025) show that least productive firms face slower catch-up in digital- and skill-intensive industries, especially in presence of skill mismatches, further deepening the productivity divide. Accurately capturing the digital skill requirements of occupations is thus essential for understanding the dynamics of technological adoption and its labour market and productivity implications. Traditional task-based approaches have offered valuable insights into how the computerisation of the economy has reshaped the labour market and what consequences this has brought in terms of job displacement and opportunities (Autor and Handel, 2013; Michaels et al., 2014). One of the most valuable attempt to assess the landscape of skills in a cross-country perspective is the OECD Programme for the International Assessment of Adult Competencies (PIAAC), which collects survey-based information on "adult's proficiency in key information-processing skills" (OECD). Since PIAAC also provides data on the frequency and type of tasks performed in working activities, Grundke et al. (2017) construct tasks-based indicators of skills using exploratory factor analysis. They found that the ICT skills indicator shows a persistent positive association with both labour productivity and participation in global value chain at the industry level[4]. Calvino et al. (2018) exploit the number of ICT specialists employed in each sector as digital-related human-capital input in production, as part of an effort to structure a taxonomy for several dimensions of the digital transformation.

Notwithstanding these important results, task-based approaches often fall short in capturing the complexity and heterogeneity of digital-intensive occupations. In response, Lennon et al. (2023) propose a novel skill-based indicator derived from occupational classifications, which is shown to perform significantly better in identifying technology-intensive roles than approaches focusing solely on white-collar or routine tasks. They identify digital skills that are coupled with the most detailed occupational level of the ESCO framework. These skills are retrieved firstly from key groups of skills referring to the digital domain (containing words as "ict", "computer", "digital") and secondly selecting through text analysis key descriptive terms that have a comparative advantage in identifying these digital skills. The result is 1151 *digital skills* that allow the characterisation of the digital requirements of each ESCO occupational code computing the share of digital skills over the total number of skills (Bontadini et al., 2025). As mentioned in Section 2.2.1, one of the most promising method to uncover the skill demand and trends in latest years is through the study of online job advertisement data. Exploring the unstructured and structured job data through machine learning and natural language processing tools is becoming a powerful tool also to measure jobs and skills mismatch or alignment (Romanko and O'Mahony, 2022; Khaouja et al., 2021). Sostero and Tolan (2022) exploited this method to trace the evolution and trends in demand for digital skills in the United Kingdom, providing evidence of different wage premia on the basis of specific digital skills required. This and other research contributions (see Acemoglu and Restrepo (2020) for US and Squicciarini and Nachtigall (2021) for cross-country evidence) speak to the way Artificial Intelligence in particular is reshaping the labour market.

One challenge in using information from online job markets is that such data may not be fully representative. Not all job vacancies are published online, often due to specific reasons such as confidentiality, the excessive time and effort required by online recruiting compared to other mechanisms, or the firm's reliance on alternative hiring sources. Additionally, online job postings have evolved significantly in recent years, whereas survey-based measures have been consistently available over a much longer period. In this context, a classification-based approach (e.g. based on O*NET or ISCO frameworks) combined with employment data from labour force surveys strikes a good balance between the need to achieve a comprehensive industrial coverage of the economy and to follow labour market evolution in the years 2008-2020.

[4]Also Management and Communication skills and Readiness to Learn are positively associated with these two outcome variables.

2.2.3 Interactions and complementarities

The impact of digital skills and green tasks on productivity growth can be best understood when studied in combination with other inputs and different types of competencies or human capital features. First, "foundation" skills such as literacy and numeracy proficiency are prerequisites for "development of the skills demanded in the digital economy" (OECD, 2016, p. 11).

Other important human capital factors hindering the adoption of digital technologies include the availability of managerial skills in firms (Bugamelli and Pagano, 2004). A cross-country analysis by Andrews et al. (2018) show the concurrent role of poor managerial quality and lack of ICT skills in curbing technology adoption and diffusion. The necessity of complementary intangible investment to harness the benefits of new technologies and digitalisation progress is well established in the literature (Brynjolfsson et al., 2021; Gal et al., 2019); however, also thanks to the availability of new data on intangibles assets (Corrado et al., 2022; Bontadini et al., 2023), recent research further clarify the role of investment in intangibles in bridging productivity growth and income gaps, ensuring firm-level efficiency gains from digital adoption (Nicoletti et al., 2020; Corrado et al., 2021; Pisu et al., 2021). Calvino et al. (2022) use a sample of Italian firms to prove that both top executives and middle management skills not only spurs adoption but also increases the returns to technology and workers skills, enhancing their complementarity.

Research efforts are still needed to understand the channels through which digitalisation is not only enabled but in turn influences innovation and skill dynamics: in this context Ciarli et al. (2021) propose a co-evolutionary framework to assess how digital technologies and firm innovation practices interact with and shape the development of workforce skills over time.

3 Descriptive evidences

The dataset used in this paper covers 16 OECD countries for the period 2004-2020.[5] It encompasses annual data on green task and digital skill intensities, gross fixed capital formation, hours worked, and labor productivity.

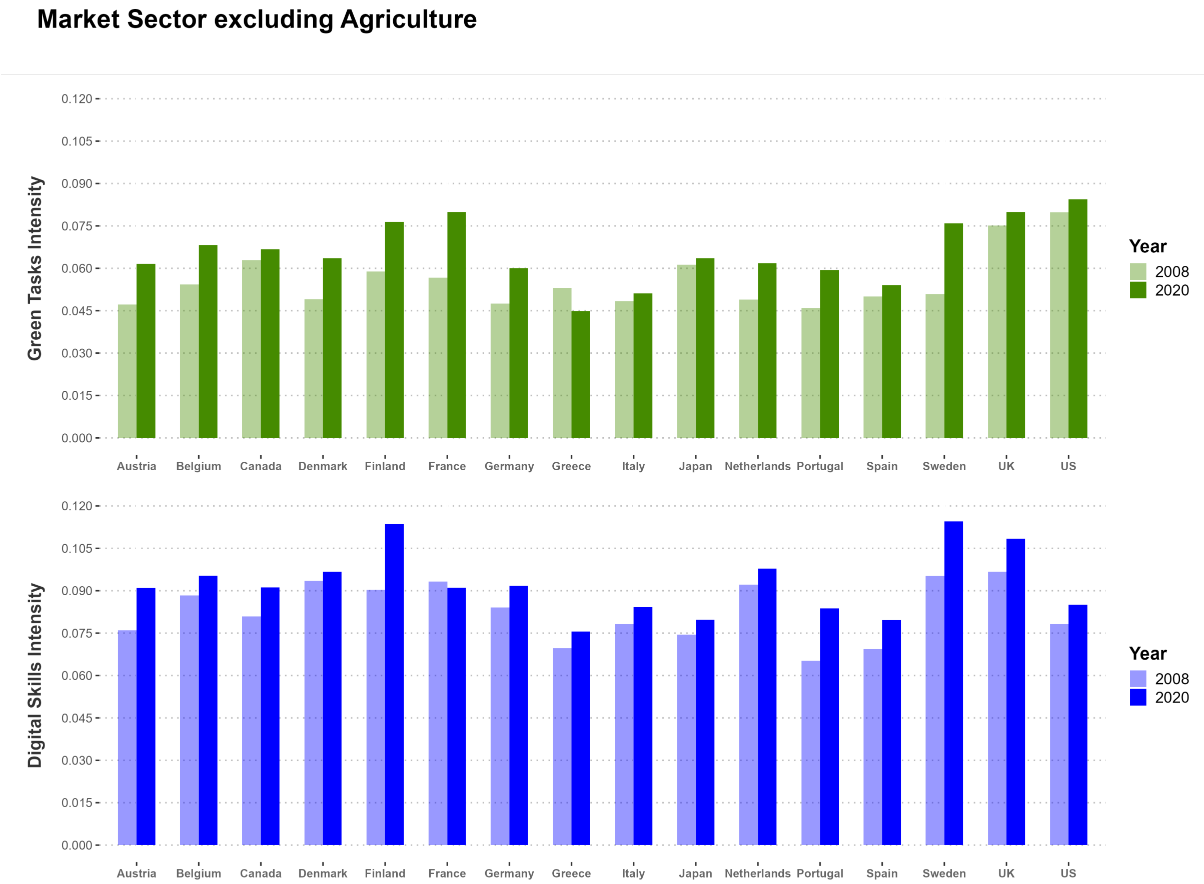
3.1 Green and Digital Intensities

We begin by examining the composition of the workforce across the sample countries, comparing the extent of digital skill intensity and green task intensity at the beginning and end of the time span. The data in Figure 1 show widespread but heterogeneous increases

[5]The database covers all G7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) plus Austria, Belgium, Denmark, Finland, Greece, Netherlands, Portugal, Spain, and Sweden.

in both green and digital intensity across countries.[6] Panel A reports the changes of the average number of green tasks carried out by workers between 2020 and 2008 showing that green tasks accounted for between 4,5% (Greece) to 8,5% (United States) of total tasks, with stark increases in Finland, France and Sweden over the sample period. At the same time, digital intensities look relatively higher than the corresponding green intensities, but with a slower growth rate over the time span (Panel B). Notice that the digital indicator captures the reallocation of employment across occupations considering varying degrees of digital intensity, but not changes in digital skill requirements within a given occupation. As new technologies are integrated into production, one would expect both an upgrading of digital skills relative to other skill types within occupations and a structural shift toward more digitally intensive roles. Our results suggest that the second mechanism had a positive but modest impact across the sample, with the notable exception of countries such as Finland and Sweden where the shift is more pronounced. A potential concern is that the final year of the sample coincides with the COVID-19 pandemic, which may distort the estimates; however, results remain robust when 2019 is used as the endpoint.

[6] Notice that in the following sections we rely on market sector industry data (excluding agriculture) and that descriptive analysis for the total economy is available in the Appendix

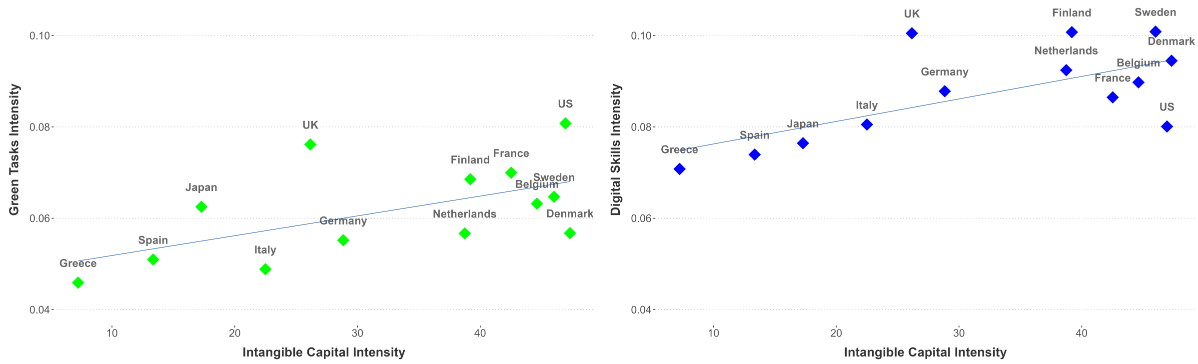


NOTE: The graphs report the green task intensity (upper panel) and digital skills intensity (lower panel) in 13 OECD countries in 2008 and 2020. Values for each country are computed averaging the intensities across market sectors weighting for the employment in each sector. Sectors included correspond to the following ISIC 1-D codes: B, C, F, G, H, I, J, K, M, N. Values for UK in 2008 are substituted with values from 2009, due to classificational changes in the survey data. Estimates for Germany in 2020 are substituted with values from 2019 due to due to missing LFS data. Authors' elaboration of data from Smiderle et al. (2026).

Figure 1: Green and Digital Intensities in 2008 and 2020

3.2 Complementarities

The first step of our descriptive analysis examines the relationships between workforce characteristics – as captured by the green and digital intensity indicators – and intangible capital, with a view to identifying potential complementarities and their joint implications for productivity. Figure 2 displays the cross-correlations between intangible capital intensity and both green task and digital skill intensity. Intangible capital intensity is positively correlated with both measures across countries. To assess the robustness of these patterns over timing, we also estimated lagged specifications; the results are consistent with the contemporaneous correlations reported here.



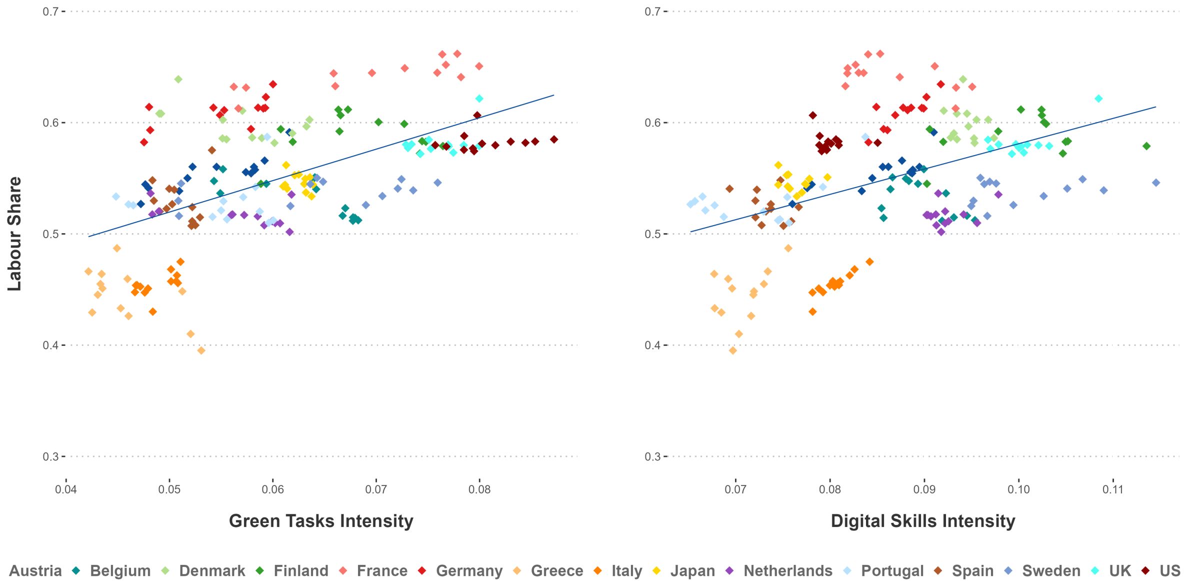
NOTE: The graphs report the cross-correlation between green task intensity and digital skills intensity and intangible capital intensity in 13 OECD countries from 2008 to 2020. Intangibles stock measures are expressed in PPP-adjusted U.S. dollars per hour worked. Values for each country are annual and are computed averaging the intensities across market sectors weighting for the employment in each sector. The blue line represents the linear prediction computed on the underlying two dimensional dataset. Sectors included correspond to the following ISIC 1-D codes: B, C, F, G, H, I, J, K, M, N. Estimates for intangible and ICT capital intensity for Portugal are not available. Authors' elaboration of data from Smiderle et al. (2026) and EUKLEMS-INTANProd database.

Figure 2: Cross-correlations between green and digital intensities and intangible capital intensity

Understanding the productivity implications of the twin green and digital transitions also requires looking into the dynamics of the labour share has evolved in relation to workforce composition. For this purpose, we compute the labour share for each country-sector-year as the ratio of employee compensation to value added and study sector- and country-specific dynamics widely acknowledged to be over a long-run decline at the aggregate level(Karabarbounis and Neiman, 2014).

Figure 3 plots labour shares (measured using EUKLEMS&INTANProd data) against our two indicators of twin-transition exposure – green tasks intensity (left panel) and digital skills intensity (right panel) – across country-years. Both panels show a positive cross-sectional relation: economies characterised by a higher incidence of green tasks and digital skills in their occupational structure also tend to allocate a larger share of value added to labour. Although omitted here for brevity, the labour share and both intensity indicators exhibit upward trends over time, so that the cross-sectional pattern is reinforced rather than offset by the within-country dynamics. More striking, however, is the substantial cross-country heterogeneity underlying the aggregate fit. Southern European economies – Italy, Spain, Portugal, and Greece – cluster in the lower-left quadrant of both plots, and are particularly distinctive in the digital skills panel, where comparatively low skill intensity coincides with comparatively low labour compensation shares. Continental and Northern European economies occupy the upper-right region, while the United States displays intermediate intensity levels paired with labour shares below those of most European peers at comparable intensity, consistent with its well-documented institutional configuration. These patterns point to two descriptive regularities. First, production structures in which labour input receives a larger share of value added also tend to score higher on our indicators of green and digital transitions, suggesting that labour-intensive configurations may be more receptive to, or better aligned with, the new task content and skill demands that these transitions entail. Second, the slope and dispersion of the labour share-intensity relationship differ markedly across country groupings, implying that the distributive implications of the twin transition are mediated by national institutional and structural context rather than following mechanically from exposure alone. Taken together, these patterns are suggestive of a productivity-distribution nexus in which the twin transition is not mechanically associated with a compression of the labour share. Economies whose production structures rely more intensively on green tasks and digital skills tend, on average, to allocate a larger share of value added to labour – a pattern at odds with a narrative in which technological upgrading systematically erodes labour's position.

Figure 3: Cross-correlations between green and digital intensities and labour shares



NOTE: The graphs report the cross-correlation between green task intensity (first row) and digital skills intensity (second row) and the labour sharen in 13 OECD countries from 2008 to 2020. Labour shares are calculated as the ratio of employee compensation to value added in each sector-year-country cell, based on EUKLEMS-IntanProd data (unadjusted labour shares). Values for each country are annual and are computed averaging the intensities across market sectors weighting for the employment in each sector. The blue line represents the linear prediction computed on the underlying two dimensional dataset. Sectors included correspond to the following ISIC 1-D codes: B, C, F, G, H, I, J, K, M, N. Authors' elaboration of data from Smiderle et al. (2026) and EUKLEMS-INTANProd database.

Table 1 reports the descriptive statistics of the variables used in the econometric analysis in the next sections. In the subsequent analysis, we restrict the sample along three dimensions to ensure that productivity dynamics are comparable across units and that the asset-level decomposition of capital is well defined. First, we focus on the nonagricultural market sector, excluding mining and quarrying (B). Mining and utilities are dropped because their productivity is largely driven by resource prices and regulated tariffs rather than firm-level input choices. Second, we exclude Canada and Portugal for data availability reasons, as the data in EUKLEMS&INTANProd are either absent or only reports total gross fixed capital formation, without the asset-level breakdown. Finally, we set 2019 as the end year of the sample, dropping 2020 to avoid having the COVID-19 shock as the last observation.

Table 1: Descriptive Statistics

	N	Mean	SD	Min	Max
$\Delta \ln LP$	1,728	0.007	0.047	-0.373	0.356
$\Delta \ln K^{\text{Tang}}$	1,750	0.000	0.045	-0.309	0.263
$\Delta \ln K^{\text{Intang}}$	1,558	0.019	0.051	-0.223	0.767
$\Delta \ln K^{\text{NatAcc}}$	1,739	0.030	0.089	-0.636	1.085
$\Delta \ln K^{\text{NonNatAcc}}$	1,651	0.014	0.044	-0.303	0.263
ln Green_int	1,750	-3.041	0.698	-5.879	-1.820
ln Digital_int	1,750	-2.564	0.686	-4.408	-0.869
Twin Index	1,750	-0.000	1.177	-4.375	1.871

Sample: 9 NACE sectors, we exclude Canada and Portugal because of data availability, and year 2020. Capital stocks and labour productivity are log first-differences normalised by hours worked. Green and digital intensity are in logs. Twin Index is a PCA composite of ln Green_int and ln Digital_int.

4 Empirical Strategy

To investigate the impact of the twin transition (green and digital) on labour productivity growth, we adopt a production function framework augmented with intangible assets and measures of green task and digital skill intensities. Therefore the empirical strategy proceeds in three steps: we first estimate a baseline augmented production function, then assess the direct and interactive effects of green and digital intensity on productivity, and finally we address potential endogeneity biases using instrumental variable (IV) and Generalised Method of Moments (GMM) estimators.

4.1 The Baseline Augmented Production Framework

The benchmark framework draws on the augmented production function developed by (Corrado et al., 2017), which decomposes capital deepening into its tangible and intangible components. The baseline specification is as follows:

$$\Delta \ln LP_{i,c,t} = \alpha + \beta_1 \Delta \ln K^{\text{Tang}}_{i,c,t} + \beta_2 \Delta \ln K^{\text{Intang}}_{i,c,t} + \mu_c + \tau_t + \varepsilon_{i,c,t} \tag{1}$$

where:

- $\Delta \ln LP_{i,c,t}$ is the growth rate of labour productivity for sector i, in country c, at time t.

- $\Delta \ln K^{\text{Tang}}_{i,c,t}$ and $\Delta \ln K^{\text{Intang}}_{i,c,t}$ are the growth rates of non-residential tangible capital and intangible capital per hour worked, respectively.

- μ_c and τ_t are country and year fixed effects to absorb unobserved macroeconomic shocks and time-invariant structural differences.

- $\varepsilon_{i,c,t}$ is the idiosyncratic error term.

4.2 Testing the Productivity Impact of the Twin Transition: the role of Intangible Capital

To empirically capture the structural shift associated with the simultaneous unfolding of both green and digital transitions, we construct a synthetic index of the twin transition (Twin Index), resorting to the Principal Component Analysis (PCA) and applaying it to the two log-transformed occupational intensity measures introduced above – $\ln \text{Green\_int}$ and $\ln \text{Digital\_int}$. The Twin Index is defined as the first principal component, which by construction maximises the explained common variance between the two series:

$$\text{Twin Index} = \omega_1 \, z_{Green} + \omega_2 \, z_{Digital} \tag{2}$$

where z_{Green} and $z_{Digital}$ are the standardized values of green task and digital skill intensity, respectively, and ω_1, ω_2 are the factor loadings determined endogenously to maximise explained variance. We retain components with eigenvalue greater than one (Kaiser criterion), which in practice yields a single component, confirming that the two intensity measures share a strong common factor.

We adopt this PCA-based index rather than entering the two regressors separately for two reasons. First, the index captures the *complementarity* between the two transitions: sectors that simultaneously advance along the green and digital dimensions are expected to realise larger productivity gains than the sum of independent effects would imply, and the first principal component isolates precisely this joint variation. Second, $\ln \text{Green\_int}$ and $\ln \text{Digital\_int}$ are substantially correlated ($r > 0.6$), so including both as separate regressors risks inflating standard errors; collapsing them into a single index mitigates this multicollinearity while preserving the informational content of both series.

Additionally, a central hypothesis of this framework is that the productivity dividends of the twin transition are conditional upon complementary investments in intangible assets, such as organizational capital, R&D, and workforce training (Corrado et al., 2022).

To test these assumptions, we estimate the following specification:

$$\Delta \ln LP_{i,c,t} = \cdots + \gamma \text{Twin Index}_{i,c,t-k} + \theta(\text{Twin Index}_{i,c,t-k} \times \Delta \ln K^{\text{J}}_{i,c,t}) + \mu_c + \tau_t + \varepsilon_{i,c,t} \quad (3)$$

In equation (3), K^{J} is a vector of different types of capital stock, i.e. total intangibles (K^{Intang}), National Accounts intangibles (K^{NatAcc}), Non-National Accounts intangibles ($K^{\text{NonNatAcc}}$), and tangible assets (K^{Tang}). We test different specifications to evaluate the possible complementarities across different capital categories. The twin transition index enters with a lag (e.g., $t-1$, $t-2$), to account for the possible delayed productivity returns of technological adoption processes.[7]

4.2.1 Identification Strategy and Endogeneity

The estimation of productivity equations suffers from inherent endogeneity issues, particularly the simultaneity of input selection and output realization. This can lead to biased estimates if capital accumulation and technology adoption decisions are correlated with unobserved productivity shocks (Gallo et al., 2025). To mitigate these concerns and ensure causal identification, we employ two complementary empirical strategies. The first relies on panel instrumental variables, where endogenous capital inputs are instrumented using their own lags – specifically the $t-1$ and $t-2$ values of tangible and intangible capital growth – alongside lags of selected sub-components, including R&D expenditure and investment in traditional machinery.[8] The second strategy adopts a two-step system GMM estimator with orthogonal deviations, which further exploits the internal moment conditions available in a dynamic panel setting. Capital deepening variables and interaction terms are treated as endogenous and instrumented through lags of the level variables, a procedure that limits instrument proliferation while preserving the validity of the moment conditions. [9]

5 Empirical Results

5.1 Baseline Estimates and the Twin Transition

Table 2 presents the baseline estimates of the augmented production function model, to assess the contribution of tangible and intangible capital deepening and the twin transition on labor productivity growth. Across all specifications, the coefficients for tangible

[7]For further justification, see Gallo et al. (2025).

[8]This approach exploits the temporal structure of the panel to isolate exogenous variation in capital accumulation that is plausibly orthogonal to contemporaneous productivity shocks

[9]It is worth noting that lag-based instruments address the simultaneity of input choices but cannot fully rule out that some sectors might self-select into both digital and green upgrading. The inclusion of intangible capital may mitigates this concern, but our estimates are best read as robust conditional associations rather than definitive causal effects.

($\Delta \ln K^{\text{Tang}}$) and intangible ($\Delta \ln K^{\text{Intang}}$) capital growth are positive and statistically significant at the 1% level, and in line with the existing literature (Roth and Thum, 2013; Corrado et al., 2017, 2021).

Columns (2) through (4) examine the independent and interactive effects of the green and digital transitions, measured via the greeness of occupational tasks and the intensity of digital skills.

When estimated independently (Column 2), digital skill intensity is positively and statistically significant correlated with labor productivity growth. By contrast, green task intensity coefficient is statistically insignificant, as is the interaction term between green task intensity and digital skills in Column (3). This likely reflects the distinct nature of these occupational shifts, as well as our different approach to measuring the green and digital indicators; whilst we focus on intensity of the task for the former, the latter index better reflects digital upskilling of the workforce. Alongside, while digital skills directly enhance operational efficiency, green tasks likely involve different resource management. These tasks, while necessary for sustainability, may not yield short-term productivity returns by themselves.[10]

The economic impact of the twin transition is characterized by a fundamental divergence in the functional roles of digital skills and green tasks. Digital skills operate as a *general-purpose technology* (GPT) multiplier, directly augmenting labor productivity by reducing information costs and enhancing operational activities. In contrast, green task intensity represents a *structural redirection* of human capital toward environmental mitigation and resource management. While digital competencies typically yield immediate efficiency gains, green task intensity may initially impose a "productivity penalty" as labor is diverted from marketable output toward abatement activities. Consequently, the productivity dividends of the green shift are often delayed. While digital integration acts as the necessary catalyst to offset the short-term costs of environmental restructuring and unlock long-term sustainable growth.

Then to capture the broader structural shift in occupational composition, Columns (5) through (7) test the composite Twin Transition Index. The Twin Index shows a positive and significant effect on productivity growth, both contemporaneously and with a lag. These results suggest that digital capabilities provide the technical framework for firms to convert green regulatory constraints into operational advantages. By leveraging data and automation, digitalization allows firms to internalize environmental requirements. This interpretation is empirically supported by the positive and statistically significant coefficient of the *Twin Transition Index* in Column (5). Furthermore, the stability of this result

[10] A further structural asymmetry reinforces this divergence: digital infrastructure is largely additive, layering onto existing capital, whereas green energy must displace incumbent fossil-based networks, confronting sunk costs, stranded assets, and political-economy barriers. Short-run measured returns to green tasks can therefore be depressed for reasons independent of the skills themselves, particularly in a sample period that largely predates the inflection point in solar, wind, and battery costs.

is supported by the GMM estimator in Column (7) confirming that the synergy between digital and green intensities yield a robust productivity dividend, even after addressing for potential endogeneity. In this sense, digital capabilities may raise the returns to green tasks both by concentrating green activity in its more technology-intensive segments and by enabling the monitoring, optimisation, and coordination that green processes require to translate into efficiency gains

Table 2: Regression Results for Labor Productivity Growth

VARIABLES	(1) $\Delta \ln LP$	(2) $\Delta \ln LP$	(3) $\Delta \ln LP$	(4) $\Delta \ln LP$	(5) $\Delta \ln LP$	(6) $\Delta \ln LP$	(7) $\Delta \ln LP$
$\Delta \ln K^{\text{Tang}}$	0.178***	0.180***	0.181***	0.146***	0.164***	0.133***	0.070
	(5.984)	(6.093)	(6.124)	(4.619)	(5.560)	(4.353)	(1.183)
$\Delta \ln K^{\text{Intang}}$	0.143***	0.140***	0.142***	0.139***	0.145***	0.151***	0.145*
	(5.658)	(5.617)	(5.703)	(5.323)	(5.798)	(5.926)	(1.689)
ln Green_int		-0.002	0.009				
		(-0.959)	(1.067)				
ln Digital_int		0.012***	0.022***				
		(6.901)	(2.734)				
Twin Index					0.005***		0.005***
					(5.209)		(4.600)
ln Green_int × ln Digital_int			0.003				
			(1.296)				
ln Green_int$_{t-1}$				0.007			
				(0.716)			
ln Digital_int$_{t-1}$				0.017*			
				(1.933)			
ln Green_int$_{t-2}$ × ln Digital_int$_{t-2}$				0.002			
				(0.769)			
Twin Index$_{t-1}$						0.005***	
						(5.262)	
Observations	1,536	1,536	1,536	1,314	1,536	1,425	1,200
Number of Sectors ($i \times c$)	111	111	111	111	111	111	101
Estimator	GLS	GLS	GLS	GLS	GLS	GLS	GMM
Country & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

z-statistics in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5.2 Intangible capital and the twin transition

While Table 2 examines the individual effects of green tasks and digital upskilling – as well as their joint impact via the Twin Transition Index – Table 3 investigates their impact on productivity growth when accounting for the complementary investments in both tangible and intangible assets.

Specifically, Column (1) of Table 3 tests the interaction between the Twin Index and aggregate intangible capital.

The interaction term is positive and statistically significant, suggesting that the impact of intangible capital on productivity is conditional upon a sector's progress in the twin transition (Figure 4). Specifically, the marginal effects show that for sectors at the lower end of the *Twin Index* (e.g., the 10th percentile), intangible capital deepening does not significantly influence productivity growth. In contrast, for sectors in the upper part of the distribution, the marginal returns to intangible assets increase substantially. This suggests that adapting the occupational structure requires concurrent investments in knowledge and organizational assets. Conversely, results in Column (2) indicate that the complementarity between the *Twin Index* and tangible capital is positive but lacks statistical significance.

Figure 4: Marginal effect – Twin transition index and intangible capital growth

To specify the nature of the synergies between our Twin Index and intangible assets, Columns (3) through (7) decompose intangible capital growth into National Accounts (NatAcc: e.g., R&D, software, databases) and Non-National Accounts (NonNatAcc: e.g., organizational capital, structural redesign, branding).[11]

As expected, the direct effects of both sub-components are positive and significant (Corrado et al., 2017). However, their interactions with the twin transition index is rather different. In particular, the interaction between the lagged Twin Index and National Accounts intangibles growth is not statistically significant, both with one (Column 3) and two lags (Columns 5 and 6). Conversely, the interaction between the Twin Index and the growth rate of Non-National Accounts intangibles is positive and significant when a two-period lag is applied. This delayed effect suggests that transitioning to a workforce with

[11] For asset definitions and further discussion, see Bontadini et al. (2023).

Table 3: Regression Results: The Twin Transition and Sub-components of Intangible Capital

VARIABLES	(1) $\Delta \ln LP$	(2) $\Delta \ln LP$	(3) $\Delta \ln LP$	(4) $\Delta \ln LP$	(5) $\Delta \ln LP$	(6) $\Delta \ln LP$	(7) $\Delta \ln LP$
$\Delta \ln K^{\text{Tang}}$	0.159***	0.124***	0.097***	0.104***	0.096***	0.056	0.103***
	(5.403)	(4.240)	(3.202)	(3.395)	(3.020)	(1.060)	(3.254)
$\Delta \ln K^{\text{Intang}}$	0.158***						
	(6.257)						
$\Delta \ln K^{\text{NatAcc}}$		0.040***	0.047***	0.037***	0.048***	0.062***	0.043***
		(3.215)	(3.218)	(2.909)	(3.176)	(3.206)	(3.227)
$\Delta \ln K^{\text{NonNatAcc}}$		0.187***	0.194***	0.199***	0.183***	0.123*	0.189***
		(6.176)	(6.295)	(6.426)	(5.759)	(1.666)	(5.943)
Twin Index	0.004***	0.005***					
	(4.372)	(5.517)					
Twin Index$_{t-1}$			0.005***	0.005***			
			(5.065)	(5.258)			
Twin Index$_{t-2}$					0.005***	0.006***	0.005***
					(4.771)	(4.571)	(4.852)
Twin Index $\times \Delta \ln K^{\text{Intang}}$	0.068***						
	(3.126)						
Twin Index $\times \Delta \ln K^{\text{Tang}}$		0.015					
		(0.795)					
Twin Index$_{t-1} \times \Delta \ln K^{\text{NatAcc}}$			0.016				
			(1.577)				
Twin Index$_{t-1} \times \Delta \ln K^{\text{NonNatAcc}}$				0.031			
				(1.636)			
Twin Index$_{t-2} \times \Delta \ln K^{\text{NatAcc}}$					0.011	0.021	
					(1.062)	(1.386)	
Twin Index$_{t-2} \times \Delta \ln K^{\text{NonNatAcc}}$							0.044**
							(2.217)
Observations	1,536	1,651	1,534	1,534	1,417	1,200	1,417
Number of Sectors ($i \times c$)	111	117	117	117	117	101	117
Estimator	GLS	GLS	GLS	GLS	GLS	GMM	GLS
Country & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

high digital skills to perform green tasks requires structural shifts and the reorganization of managerial practices, with productivity returns materializing only with lags. In this sense, although our framework measures short-run, industry-level productivity returns rather than innovation potential, the lagged complementarity between the Twin Index and non-National Accounts intangibles captures part of the dynamic adjustment through which transition investments translate into productivity gains.

6 Conclusion

This paper examined how the simultaneous unfolding of the green and digital transitions shapes labour productivity dynamics across advanced economies. Drawing on an industry-level dataset for 16 OECD countries over 2004–2020 (Smiderle et al., 2026), we combine measures of green task intensity and digital skill intensity with harmonised accounts of tangible and intangible capital from EUKLEMS&INTANProd.

The descriptive analysis reveals widespread increases in both green task and digital skill intensities across the market sector. Countries with higher intangible capital intensity tend to score higher on both dimensions, suggesting structural complementarities between the two transitions (Santoalha et al., 2021; Faggian et al., 2025), a finding further supported by the positive association between green and digital intensities and labour shares in knowledge-intensive service industries.

The econometric analysis (estimation sample: 2008–2019) delivers two main findings. First, digital skill intensity has a positive and significant impact on productivity growth when estimated independently, whereas green task intensity does not. This divergence suggests that digital capabilities offer a direct efficiency channel, while green occupational shifts involve structural adjustments whose productivity returns are harder to detect. The composite Twin Transition Index, however, demonstrates a robust and positive effect on productivity across specifications and lag structures, indicating that it is the joint advancement along both dimensions – not either in isolation – that unlocks productivity gains. Second, these gains are conditional upon concurrent investment in intangible capital: the interaction between the Twin Transition Index and aggregate intangibles is positive and significant, with marginal effects increasing at higher levels of the index. No such pattern is observed for tangible assets. Decomposing intangible assets further suggests that this synergy is primarily driven by non-National Accounts assets, including organisational capital, design, branding, and managerial practices.

These findings carry clear policy implications. Since productivity gains emerge from the joint advancement of the green and digital transitions, rather than from either in isolation, implies that green occupational shifts deliver measurable efficiency gains when embedded in a conducive technological environment. Integrated policy design is therefore essential: green investment programmes should systematically pair investment targets with digital capability building, and policymakers should resist siloed approaches by, for instance, conditioning access to green subsidies on complementary digital upskilling or aligning training programmes with the twin demand of net-zero and technology-intensive occupations. These results should not be read as evidence that green skills or green investment are unimportant, nor as implying that policymakers should prioritise digital over green investment. Rather, three considerations suggest that our estimates may understate the productivity contribution of frontier green tasks, especially over longer horizons. First, occupation-based green metrics aggregate heterogeneous activities, ranging from land restoration to electrotechnology engineering, so productivity gains in more innovative green segments may be diluted by activities characterised by slower productivity growth. Second, our sample captures an earlier phase of the energy transition, when several key technologies were still diffusing and moving down their learning curves. Third, green capital often requires the replacement of incumbent fossil-based systems and must therefore confront sunk costs, stranded assets, and system-level adjustment frictions, whereas digital capital may more readily augment existing production processes. These asymmetries may depress short-run returns for reasons unrelated to the underlying value of green skills. Our findings therefore point less to a hierarchy between digital and green investment than to the importance of complementarities: the productivity dividends of the green transition are more likely to materialise when green occupational shifts are combined with digital capabilities and intangible investment. The implication is an integrated, rather than sequenced, policy agenda. In this respect, the role of intangible capital deserves particular attention. Since productivity gains from the twin transition are conditional on intangible investment, emerging with a two-year lag, programmes fostering intangible capital formation should be positioned as integral components of twin transition strategies rather than ancillary measures. The delayed nature of these returns also implies that policy evaluation frameworks must adopt sufficiently long time horizons, avoiding premature withdrawal of support before structural adjustments translate into observable productivity gains.

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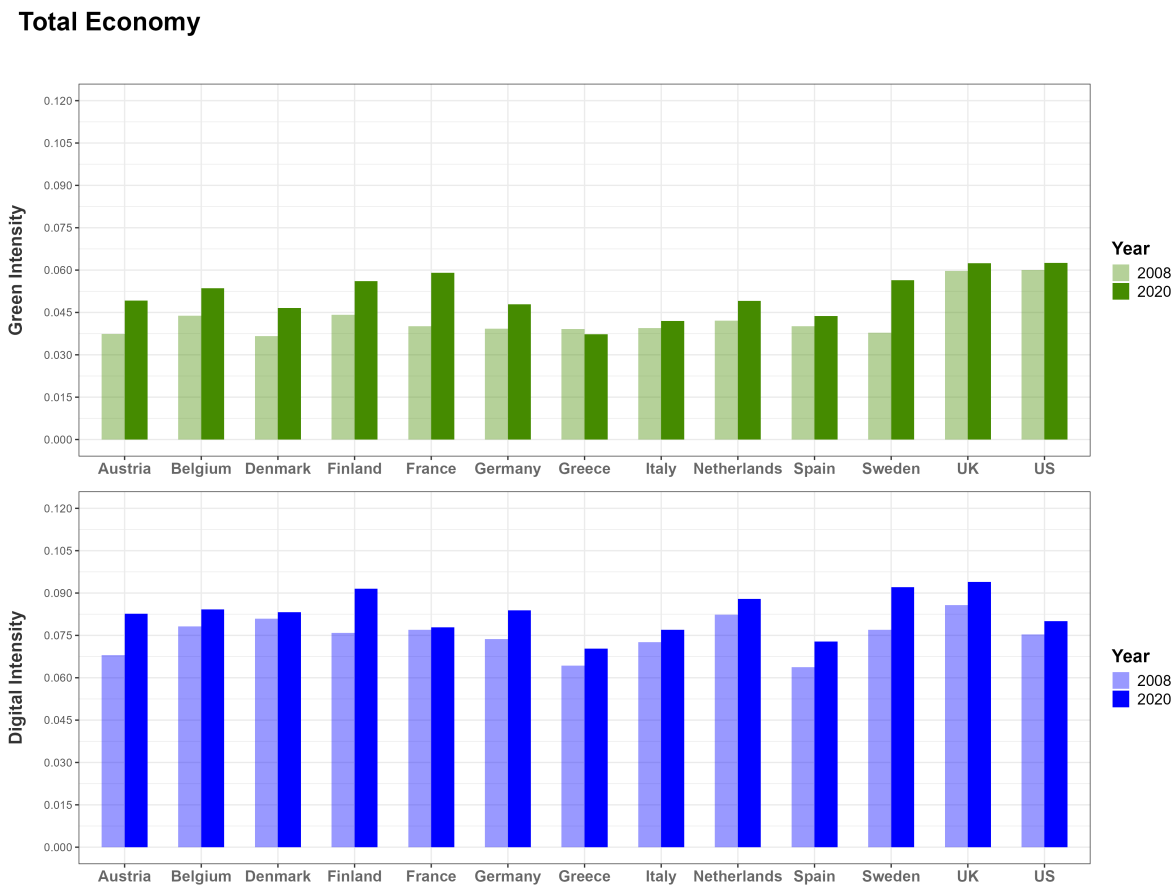
Appendix



NOTE: The graphs report the green task intensity (upper panel) and digital skills intensity (lower panel) in 13 OECD countries in 2008 and 2020. Values for each country are computed averaging the intensities across market sectors weighting for the employment in each sector. Metrics are computed across all sectors of the economy. Values for UK in 2008 are substituted with values from 2009, due to classificational changes in the survey data. Estimates for Germany in 2020 are substituted with values from 2019 due to due to missing LFS data.

Figure 5: Green and Digital Intensities in 2008 and 2020 (All sectors)