Capturing Green and Digital Intensities: Key Metrics for Monitoring the Twin Transition

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Date:
March 2026

The Productivity Institute
Working Paper No. 069

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Key words
Twin transition, digital skills, green tasks

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 productivity growth in the UK, US and the EU - (cod. R130703)". The authors gratefully acknowledge the financial support provided, which made this study possible. The methodology adopted in this work builds on the work conducted within the OECD – Italian Ministry of Economy and Finance joint project on fostering multilateral cooperation for structural reforms and economic development.

Suggested citation

I. Smiderle, F. Bontadini, F. Filippucci, E. Gallo, C. Jona-Lasinio, G. Nicoletti, A. Saia (2026) *Capturing Green and Digital Intensities: Key Metrics for Monitoring the Twin Transition*. Working Paper No. 069, 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

The Twin Transition, i.e. the simultaneous shift towards digitalisation and zero-carbon economies, is reshaping labour markets, requiring a better understanding of the intersection between digital skills and "green" occupations. This paper presents a novel, harmonized dataset to analyse the Twin Transition and its impact on labour markets across 30 OECD countries. To quantify these dimensions, we compute two standardized indicators: 1) a green intensity index measured using a task-based approach from the O*NET database, representing the share of green-specific tasks per occupation; 2) a digital intensity indicator estimated using a skill-based index from the ESCO database, and defined as the ratio of essential digital skills to total occupational skills required for an occupation. We first attach these indicators to every occupation used in the labour force surveys, then we aggregate them using employment weights to get estimates at the industry and country level. We document the numerous crosswalks between different classifications implemented to ensure cross-country comparability. Empirical results reveal a strong positive correlation between greenness and digitalisation, though significant heterogeneity exists across industries and countries. This dataset offers insights into one of the most significant labour market transformations of our time and provides a critical foundation for future research investigating the impact and the policy implications associated with the unfolding of the Twin Transition.

Summary

Introduction

The digital transformation and the transition to zero-carbon technologies are reshaping economies and societies in profound ways. Digital technologies offer both a vast potential for enhancing living standards as well as possible new ways of managing and supporting zero-carbon objectives. As green and digital technologies enable new productive processes, workforce skills play a crucial role in determining economies' capacity to adapt to the so-called "Twin Transition".

Early evidence shows that green and digital technologies have the potential to be mutually reinforcing: investments in these areas not only drives digital advancement but also accelerates the transition to a more sustainable future and are associated with productivity gains (Veugelers et al., 2023; Gallo et al., 2025). The challenges and opportunities triggered by these structural changes demand a workforce with new skills and expertise. However, slow digital technology take up and disappointing growth effects are partly due to difficulties and delays in implementing complementary investments in intangibles, especially the skills needed for efficient use of digital technologies (Gal et al., 2019). Therefore, digital skills can be considered as a key requirement to embrace digital technologies (Nicoletti et al., 2020; Corrado et al., 2021; Pisu et al., 2021).

As for green skills and jobs, an emerging literature has also started to investigate their diffusion and their role in fostering sustainable economic growth, adopting green technologies and supporting the green transition (Causa et al., 2024c; Valero et al., 2021; Consoli et al., 2016, Chen et a. 2020).

Despite the expected increase in demand for green and digital skills and their importance for the twin transition, evidence on their prevalence across industries and countries is scant. Furthermore, recent studies highlight the crucial need for even more granular statistics on the twin transition, as the green transformation in particular is poised to be a place-based phenomenon, where socio-

economic factors might shape the long-term outcome of this transformative change (Barbero et al., 2025; Rodríguez-Pose and Bartalucci, 2024).
To understand the evolving nature of the labour market in the context of the Twin Transition we thus need to answer some critical questions:

- How are green tasks and digital competencies changing the skills landscape?
- Are these shifts occurring uniformly across countries and industries?
- Do green and digital competences play a complementary role or do they substitute each other?

Addressing these questions requires robust and comparable indicators for in-depth analysis at both national and sectoral levels. To date, no such effort has been undertaken. This is largely due to the absence of a universally accepted framework in the literature for defining and measuring key green variables, including green investment and green occupations. It is also the result of the heavy reliance on national classification systems in workforce statistics, which makes meaningful cross-country comparison especially difficult.

The purpose of this methodological paper is to build new standardised metrics of green and digital intensity of the labour force, characterising green tasks and digital skills across occupations. By addressing this gap, we aim to provide a foundation for more comprehensive and comparable metrics to evaluate the Twin Transition's impacts on the labour force, enabling meaningful cross-country and cross-sectoral analyses.

In the first part of this paper, we will define the *greenness* of jobs and the *digital intensity* of occupations and provide standardized indicators accordingly. To define the greenness of an occupation, we build on a growing body of literature that focuses on characterizing green jobs based on their task content, i.e. specific activities performed to fulfil job functions (Consoli et al., 2016; Vona et al., 2018; Causa et al., 2024a; Tyros et al., 2023). Task-based indicators are widely adopted in the literature on technology and employment (Autor and Dorn, 2009; Michaels et al., 2014), as investigating the task content of an occupations helps shed light on specific characteristics and skills needed for the digital transition. In the context of green employment, Valero et al. (2021) adopt a 'bottom-up approach', i.e. a method for defining green jobs starting from detailed information at the occupation level. Unlike sector-based classifications that consider all occupations within green industries as green ('top-down approaches'), the task-based approach allows to identify green jobs also within high-emission or 'non-green' sectors, thus providing a more accurate representation of the workforce composition. In addition, evaluating green tasks is a first step for a finer characterization of the greenness of jobs as on this basis it is possible to generate a continuous indicator capturing the degree of greenness for each occupation. These measures are based on the US O*NET database that provides the number of green tasks implemented in each occupation relative to the total number of tasks. We define this metrics as the *green tasks intensity* of an occupation.

Next, we quantify the extent to which an occupation involves digital competencies and skills. Resorting to the work by Lennon et al. (2023), we measure the requirement of digital competences for each occupation, using their novel skill-based indicator. We privilege a skill-based indicator in the digital domain as it is shown by Lennon et al. (2023) to perform comparatively better at describing highly digitalised and complex occupations with respect of task-based metrics.

Then, we build a panel dataset comprehensive of digital and green intensities by industry for the 30 OECD countries, over the years 20011-2022, with extended coverage for selected countries. To this end, we leverage on multiple surveys to map occupational metrics into industries by looking at the composition of the labour force in each sector and every year.

In the first two sections, we present the definitions and data sources to generate the greenness and digitalisation indicators. In the third section, we illustrate the methodology to map these indicators to multiple occupational classification systems. Exploiting labour force surveys, we then compute the green and digital intensity of sectors of their economies, translating each indicator in terms of the International Standard Industrial Classification of All Economic Activities (ISIC). Due to the specificity of the classifications for each area, this section illustrates separately the approach adopted to cross classify digital and green indicators for European Countries, the US and the UK. We subsequently present some descriptives concerning the development of the digital and green intensities over time and across sectors and countries. The concluding section discusses policy considerations informed by the study's findings.

1. Green Tasks Intensity: Sources and Indicators

Despite extensive research on the topic, there is no universally adopted methodology on how to measure the 'greenness' of an occupation, namely the main features that make a specific job relevant and necessary for transitioning to an environmentally sustainable economy. We follow Vona et al. (2018) and School et al. (2023), considering the tasks content of an occupation to characterize its greenness profile assuming that it captures the variety of activities performed to achieve green goals. Importantly, their methodology relies on the Occupational Information Network (O*NET) data of the U.S. Department of Labor's Employment and Training Administration (ETA). The O*NET project[1] is one of the most extensive and systematic attempts to characterize the evolving profile of the labour force, providing a set of specific tasks for each occupation. Within "the Green Task Development Project", they engaged in a comprehensive assessment of the occupations relevant to the green economy and they documented the *tasks* that contribute to "*reducing the use of fossil*

[1] See at the following link: https://www.onetcenter.org/database.html#individual-files

fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy" (Dierdorff et al., 2011, p.3). In particular, '*green occupations'* are classified as: 1) Green *new and emerging occupations*, all tasks of which are labelled as green; 2) *Green enhanced occupations*, namely the occupations for which the green transition implies a substantial change of the main tasks[2]. Once defined these two groups, the O*NET categorization is linked to the Standard Occupational Classification (US SOC) system, the national classification system for occupations in the United States, thus making the mapping of O*NET detailed data to SOC codes straightforward. The harmonized SOC-O*NET database provides as a result information about the green tasks at a very granular level (SOC 8-digit).

Building on this information, we define a *greenness index based on* the metrics developed by Vona et al. (2018), School et al. (2023) and Causa et al. (2024b). We capture the greenness (green intensity) of an individual occupation by the share of green specific tasks over the total number of specific tasks of each occupation, as firstly used by Vona et al. (2018).

$$Greenness\ of\ occupation\ K = \frac{\#green\ specific\ tasks_k}{\#total\ specific\ tasks_k}$$

This is a continuous index, ranging between 0 and 1 providing more nuanced information than a binary indicator that dichotomously divides the pool of occupations between *green* and *non-green*.

To construct our green task intensity, we download task-level data on occupations listed by O*NET. Since data on occupational features (i.e. frequency, relevance or type of tasks) are periodically revised, we use the latest data-release per each year from 2011 to 2019 (Martin and Monahan, ONS, 2022)[3]. For years prior to 2011 we assume that the green tasks of occupations are the same as in 2011; similarly, we extend 2019 green intensities to later years.

Then as O*NET provides a more granular classification compared to the US SOC, and multiple O*NET codes may be attached to a unique SOC it is necessary to make some assumptions. Some O*NET-SOC do not have an assessment of green tasks: when this is the case, we rely on the average of green task intensity of subcategories, if available, or we conservatively assign 0 green task intensity[4]. The last step is to aggregate each SOC-O*NET 8-digit code green intensity indicator to the SOC 6-digit level[5].

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[2] More information is available at https://www.onetcenter.org/reports/GreenTask.html

[3] Green tasks statements tasks of O*NET-SOC occupation are labelled as green only from 2011 to 2019.

[4] Under the assumption that occupations most relevant to the green transition are object of O*NET monitoring. For more information on the O*NET-SOC framework, see https://www.onetcenter.org/dl_files/Taxonomy2010_Summary.pdf.

[5] We average across the nested O*NET-SOC 8-digit. We can only operate a simple average, since we do not have U.S. employment data available at such granular level. Implicitly, we are assuming that the workers in the SOC 6-digit are distributed uniformly within SOC 8-digit occupational codes (School et al., 2023). This should not imperil the precision of our indicator: Vona et al. (2018) suggest that variation lies more fundamentally at the SOC 6-digit level (School et al., 2023).

2. Digital Skills Intensity: Sources and Indicators

To fully understand the drivers of the Twin Transition, we consider the digitalisation competencies required in each job, as a complementary aspect of greenness of occupations. We then define an indicator of digital intensity of occupations as the share of skills essential to deal with digital technologies (*digital skills*) over total skills required in an occupation. Indeed, the use of digital competencies extends beyond digital tasks. Many jobs entail digital skills and knowledge in ways that may not be immediately apparent. Therefore, to limit the possible underestimation of the digital intensity we follow the approach by Lennon et al. (2023) defining new indices that look at the skills required in each occupation as listed in the European Skills, Competences, Qualifications and Occupations (ESCO).

The adoption of the ESCO framework has some advantages. Firstly, it provides a granular breakdown of each occupation, outlining both essential and optional tasks[6]. This level of detail allows for a more nuanced understanding of the skills and knowledge required for each role. Additionally, ESCO's higher-level occupational groupings align with the International Standard Classification of Occupations 2008 (ISCO-08), ensuring consistency and comparability with international data. Although we rely on a specific version of the ESCO database, it is regularly updated. This is particularly important in the rapidly evolving digital landscape, where new technologies and skills emerge constantly.

Therefore, we construct a digital indicator at the 5-digit ESCO level as the ratio between the essential digital tasks and all the essential tasks mapped to an occupation in the ESCO dictionaries.

$$Digital\ intensity\ of\ occupation\ K = \frac{\#essential\ digital\ skills_k}{\#total\ essential\ skills_k}$$

The categorization of skills as *digital* or *non-digital* by Lennon et al. (2023) involves three main steps.

1. In the first step, they isolate ESCO skills groups that contain the terms “computer”, “ict” and “digital” and classify as *digital* all the related competencies.
2. The second step of the process involves the use of Natural Language Processing tools: the authors perform a text analysis of *labels* and *descriptions* of all the skills in the ESCO database and retrieve some key words. They analyse which of these key words are more predictive of the previously defined digital skills, identifying 20 words that better qualify digital skills.

[6] In the ESCO framework, each occupation is associated with two sets of skills: (1) skills *essential* to perform that job, and (2) skills that are *optional*. Lennon et al. (2023) conduct several tests to determine which set better captures occupational characteristics and suggest relying exclusively on essential skills, as including optional ones would introduce excessive arbitrariness and weaken consistency across occupations. For additional information, see https://esco.ec.europa.eu/en/classification/occupation_main.

3. In the last step all skills containing these selected keywords are added to those already labelled as digital, if not previously comprised, for a total of 1151 digital skills.

Then as our analysis is conducted at the 4-digit ISCO classification, we aggregate the ESCO data accordingly. Specifically, we compute the average digital intensity at 5-digit ESCO codes that maps to a 4-digit ISCO code. While this indicator offers valuable insights into the digitalisation of the labour market and its shifting composition, it does have limitations. Notably, it does not capture the dynamic nature of digital skills, which evolve rapidly over time *within occupations*. Despite this limitation, the indicator provides a crucial foundation for understanding current trends in digitalisation *across occupations*. We will further refine this approach by adapting it to other occupational classification systems, as detailed below.

3. Construction of the Dataset

Since the primary objective of this project is to develop a harmonized dataset that profiles multiple countries over several years, it is necessary to provide comparable information on the level of greenness and digitalisation of their workforce. To achieve this goal, we adopt a two-step approach:

1. *National Adaptation.* First, we map our green and digital intensities indicators to the national occupational classifications commonly used in labour market surveys to ensure that our set of indicators is relevant and usable within specific country contexts.
2. *Industry-Level Analysis***.** Second, we use the International Standard Industrial Classification of All Economic Activities (ISIC) to generate estimates of green and digital intensities for various industries across all countries in our sample. This will provide valuable insights into the sectoral distribution of green tasks and digital skills and its potential impact on economic performance.

As our green intensity is expressed in terms of the US SOC classification, in the 2010 revision, whereas the digital intensity of the occupations is based on the European Skills, Competences, Qualifications and Occupations framework (ESCO, version 1.1.0), our first outcome is to provide both green and digital indicators at the level of ISCO, SOC US and SOC UK[7] occupational classifications.

There are several layers of crosswalks that must be performed. The next step of the process involves transposing our data into the ISCO and SOC US classifications. Then, for European countries, the US and the UK, we produce industry level indicators resorting to the ISCO and the UK SOC classifications respectively.

[7] The Standard Occupational Classification of the United Kingdom.

A key challenge in this project is the complexity of mapping occupations across different classification systems. The ‘crosswalking’ process is often complicated by multiple correspondences, where a single occupation in one system corresponds to multiple occupations in another (Scholl et al. 2023). This requires careful consideration of distributional and weighting assumptions to ensure accurate comparisons.

The challenge is further compounded by two factors. First, occupational classifications are regularly updated to reflect changes in the economy, requiring cross walking not only between different systems but also across multiple versions of the same system over time. Second, data sources often adopt diverse occupational coding practices. While some surveys rely on standardized national systems, others use aggregated categories or even ad-hoc classifications, further complicating the harmonization process. Similarly, these observations hold when transposing the estimates of industry of all countries in the International Standard Classification System (ISIC).

To address these concerns, we are required to make some assumptions, which we explicit below.

1. To exploit our classification-based indicators, we assume that *the same occupation across all countries and all sectors is characterized by identical digital skills intensity and the same level of green tasks intensity.* While this assumption allows for international comparisons, it is important to acknowledge potential variations in how specific occupations are performed across different contexts.
2. When transferring indicators from classification system A to classification system B, a single code in one system may correspond to multiple codes in the other. In these cases, we typically assume that employment is uniformly distributed across the mapped categories. As a result, the (digital or green) intensity assigned to an occupation *X* in system B is calculated as the simple average of the indicators for all system-A codes that map to occupation *X*.

Starting from occupational-level measures, the intermediate result of our process is a measure of **green & digital intensities for each occupational code**. The next step is to compute the green and digital intensities for each sector by taking the weighted average of the occupation-level indicators within each industry, where the weights correspond to the number of workers employed in each occupation. The resulting sectoral measures represent therefore the average green and digital intensity of an occupation in that industry. Finally, we map the sectoral intensities from the national classification onto the international framework to obtain a harmonised dataset. To illustrate the process, we present two charts below. The following section provides a detailed and technical explanation of the entire crosswalking procedure, structured by geographical area.

Figure 1 – Summary Crosswalk: Green Intensity

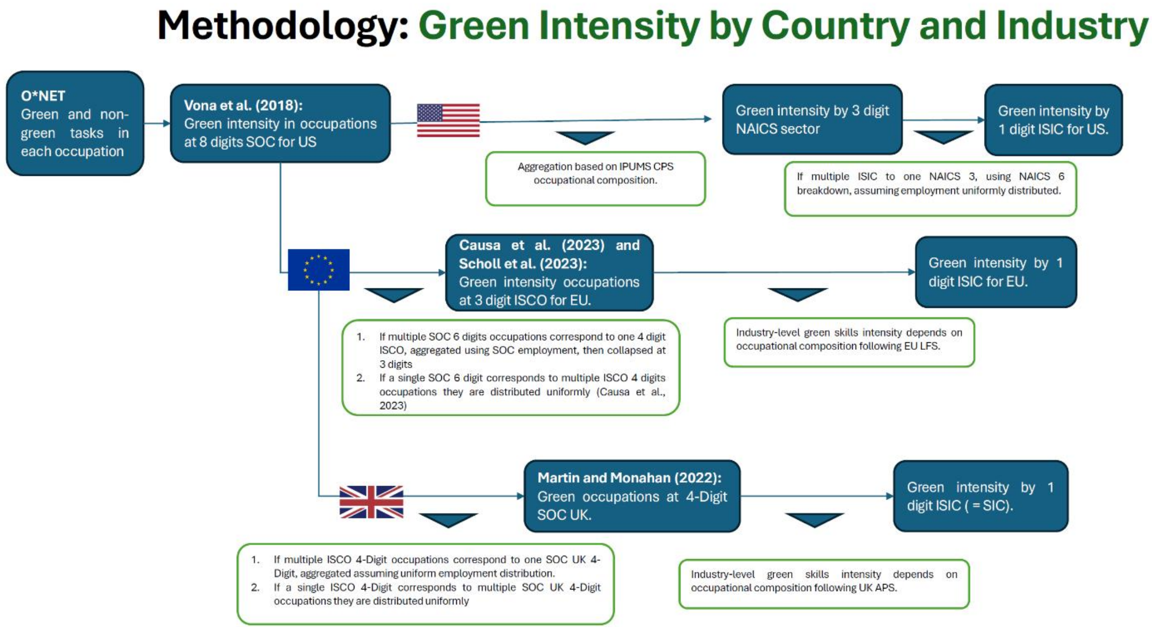
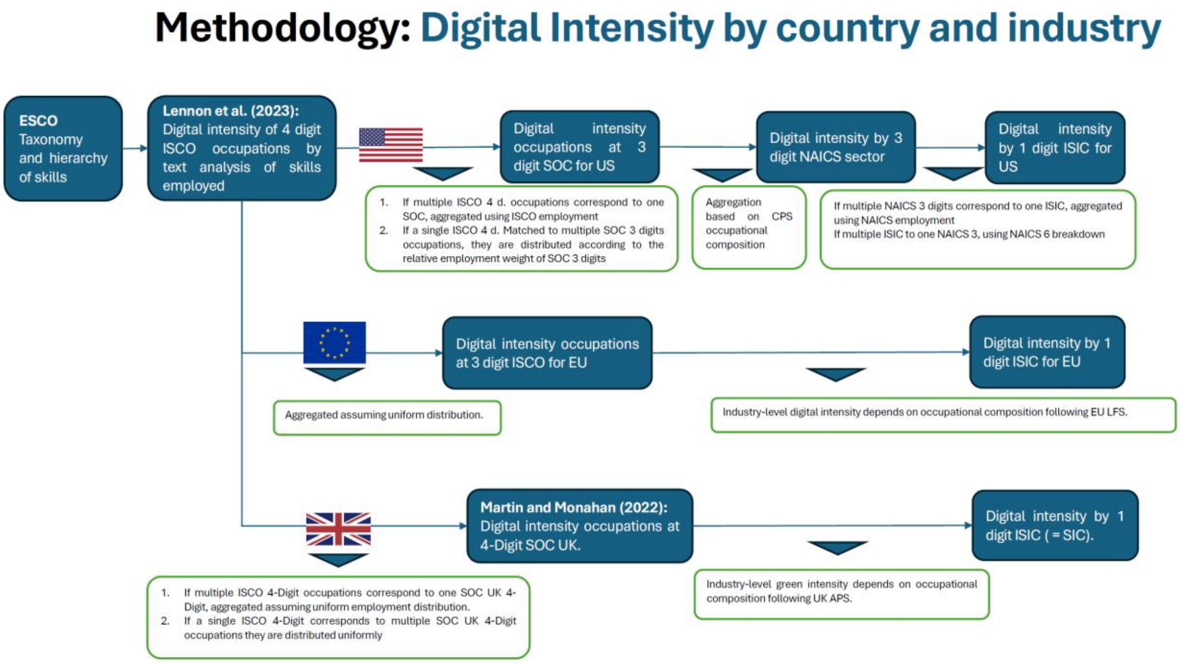


Figure 2 – Summary Crosswalk: Digital Intensity



European Countries

The primary data source for European economies is the EU Labour Force Survey (EU LFS) that supplies micro-data on labour market activity, employment and related characteristics of the working population (Eurostat, 2024). It provides standardized statistics of EU Member States and other European countries. We gather information for the period 2003-2022 for the following European countries: Austria, Belgium, Bulgaria, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Luxembourg, Latvia, Netherlands, Norway, Poland, Portugal, Romania, Sweden, Slovenia, Slovakia. The EU LFS details occupational information by ISCO codes, aggregated at the 3-digit level.

Digital Skills Intensity. We obtain digital indicators at the ISCO 3-digit level as a simple average of the underlying ISCO 4-digit Codes, since employments weights at the 4-digit level are not publicly available. No further conversion is required because the EU LFS occupation variable is codified in terms of ISCO classification: we can easily incorporate the indicator in the European dataset.

Green Tasks Intensity. Conversely, to apply the greenness index at the European level, we must transpose this indicator from the SOC US classification to the ISCO-08 taxonomy. To map them onto the ISCO framework, we employ the official correspondence table between 2010 US SOC System and the International Standard Classification of Occupations in its 2008 revision (ISCO-08), provided by the U.S. Bureau of Labor Statistics (BLS).

To address multiple mappings, we use publicly available employment statistics at the 6-digit 2010 US SOC level. Following Scholl et al. (2023), we calculate average employment over 2016–2018. These SOC employment figures are then merged with the corresponding SOC occupations in the crosswalk. Using multi-year average employment weights allows us to account for multiple mappings while reflecting a more realistic employment structure and avoiding distortions from single-year composition effects. We rely solely on US employment weights, as EU employment statistics are not publicly available at a comparable level of detail.

When a US SOC Code is mapped to multiple ISCO Codes, we equally apportion the SOC employment to the mapped ISCO Codes. Our assumption is therefore that the employment of each SOC Code is uniformly distributed in the mapped ISCO Codes. Consequently, if an ISCO Code is associated with multiple SOC Codes, we will take an average of the greenness of these SOC occupations, weighted by the employment allocated to each couple.

The procedure presented above enabled us to crosswalk from the 6-digit SOC Codes to the 4-digit ISCO Codes. Since the EU-LFS reports occupations at the 3-digit ISCO level, the corresponding greenness indicator is finally calculated as the average greenness intensity of the underlying 4-digit occupations.

Industry level indicators. The industry classification in the EU LFS refers to the European Classification of Economic Activities (NACE Rev.2) that is uniquely mapped to ISIC. Therefore, we take an average of the green and digital intensities across workers in each industry and year, accounting for their sample weight, and obtain industry level green and digital intensities at the ISIC 1-digit level. This green and digital intensity estimates cover every sector of the European economy, spanning each year from 2011 to 2022.

Other levels of crosswalks. The ISCO-08 framework is implemented in the EU-LFS starting from 2011, therefore, to expand our analysis further back in time, we adapted our indicators to the ISCO-88 classification, used in the EU-LFS until 2010. This involved cross walking from the 2008 ISCO codes to the 1988 ISCO codes, assuming uniformly distributed employment. This means that we calculated the digital and green intensity for each 1988 code, by averaging those of the corresponding 2008 codes. It is important to note that while cross walking to earlier classifications like ISCO-88 allows for a broader historical analysis, it also introduces potential inaccuracies. The further back in time our analysis extends, the less reliable our indicators may become. This is because occupational classifications are periodically updated to reflect changes in the labour market. For example, the shift from ISCO-88 to ISCO-08 involved removing obsolete occupations and incorporating new ones, particularly those driven by advancements in information and communication technology. Furthermore, prior to 2007, the EU-LFS employed the more aggregated NACE Rev. 1.1 classification, but meaningful comparisons over time are still possible at the country level.

United States

Our indicators for the United States are based on the IPUMS CPS (Integrated Public Use Microdata Series, Current Population Survey) database providing detailed microdata from the U.S. Census Bureau's monthly household surveys (Flood et al., 2025). These data offer comprehensive insights into the social, economic, and demographic dynamics of the United States over time; for our analysis we rely on the Annual Social and Economic (ASEC) supplement[8].

Data for the United States span the period from 2003 to 2024, including more than 1.8 million observations. As described below, we employ multiple crosswalks to ensure our estimates of green and digital intensities are comparable across different industries and countries.

Digital Skills Intensity. The first crosswalk implemented in this section allows us to transpose the digital intensity from the ISCO 4-D to the US SOC 6-D level, assuming a uniform distribution of employment in multiple mappings. We employ the same correspondence table used for the inverse

[8] More information at https://cps.ipums.org/cps/samples.shtml

crosswalk[9]. Thereafter, US SOC-level indicators are transposed to the Census Classification of Occupations, where we again assume uniform distribution of employment in dealing with multiple mappings.

Green Tasks Intensity. To compute greenness indicators for occupations at the Census Classification level, we rely on the same process used for digital indicators, starting this time from the SOC 6-D occupational codes, mapping them to the US Census Bureau occupational codes.

Industry level indicators. In a similar fashion to the occupational variables, the IPUMS CPS also lists the industry variables according to a specific Census classification. The steps of the crosswalk involve the transposition of the Census industrial variable to the North American Industry Classification System[10] (NAICS) of 2017. We follow the crosswalk provided in IPUMS USA to attach a NAICS 3-digit code to each Census industrial code.

Subsequently, we compute the green and digital indicators by industry averaging the intensities for all workers in each NAICS 3-digit industry. The last step in ensuring comparability with estimates from other countries is to translate the indicators by industry to the ISIC Rev. 4 framework, using the relevant correspondence table[11].

Using survey data, we assign intensity estimates from the NAICS 3-digit level to the more granular NAICS 6-digit codes. To do this, we distribute employment uniformly across the 6-digit codes within each 3-digit category. This approach allows for a more precise and nuanced mapping between the two classification systems, reducing the distortion that can arise from multiple mappings at coarser levels of the classification. Therefore, when a NAICS 6-D code is mapped to multiple ISIC 1-D, we divide equally the employment attributed to that NAICS 6-D among the ISIC 1-D codes. We finally compute the industrial level indicators at the ISIC 1-D level, based on occupational composition from the NACE 6-D codes.

Other levels of crosswalks. Both industrial and occupational classifications were revised over time; this requires the use of intermediate Census crosswalks following the same principles outlined above to ensure the most adequate mapping of the codes throughout years.

United Kingdom

Our source of microdata for the United Kingdom is the Annual Population Survey, which builds on two waves of the Quarterly Labour Force Survey UK and on annual local boost surveys (Office for

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[9] Correspondence table provided by provided by the U.S. Bureau of Labor Statistics (BLS). Available at the link https://www.bls.gov/soc/soccrosswalks.htm

[10] https://www.census.gov/naics/?68967

[11] Concordance tables are available at the link https://www.census.gov/naics/?68967.

National Statistics, 2023). The APS provides key information on labour supply at the local level for the period from 2004 to 2023. Occupational information of the respondents is collected through the UK Standard Occupational Classification (SOC UK here after). As there are no direct correspondence tables from the O*NET-SOC classification to the UK framework, we draw on the work of Martin and Monahan (2022) to transpose digital and green indicators from the ISCO system: the authors devised a correspondence table for both UK SOC 2000 and UK SOC 2010.

Digital and Green Intensity. We transpose our occupational-level indicators from the ISCO 4-D level to the UK SOC 4-D level. If a UK SOC 4-D code is mapped to multiple ISCO codes, we take an arithmetic average of the intensities at the ISCO level, as described in previous sections. The APS occupational variable is coded in terms of UK SOC 3-digit, therefore we collapse the 4-digit indicators to merge them with the survey data. The process is the same as that described for obtaining indicators at the ISCO 4-D level as presented in the previous section (see European Countries Section).

Industry level indicators. Starting in 2009, the APS implemented the UK Standard Industrial Classification of economic activities (SIC) 2007[12], whose higher aggregation level maps uniquely to ISIC 1-D Rev. 4 framework. Consequently, we obtain the indicators of green and digital intensities by industry averaging those of the occupations based on employment shares.

Other levels of crosswalks. The UK SOC changed a second time in our sample period in 2020, and the APS implemented this revised version to codify occupations from 2021-2023. Since there are no publicly available correspondence tables from ISCO-08 to UK SOC 2020, we build one retracing the methodological steps outlined in Martin and Monahan (2022). First, we download the latest coding index for UK SOC 2020[13], used by data collectors as a mapping guide between ISCO-08 and UK SOC frameworks. To transform this coding index into a conversion table, Martin and Monahan (2022) suggest employing the so-called *truncated proportional conversion*: this method filters out unique or rare ISCO-08 and SOC 2010 code pairings, while ensuring that all SOC 2010 codes have associated ISCO-08 codes.[14] We obtain in this way a similar conversion table for the newest version of the classification and transpose indicators from 4-digit ISCO-08 codes to 4-digit UK SOC 2020 codes, completing the characterization of the UK labour force represented in the APS.

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12 https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007

13 https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume2codingrulesandconventions

14 In detail: the weight ("proportion") of each ISCO-SOC mapping is how many times it appears relative to total number of mappings for a given ISCO code. We also drop pairs that have a weight in the proportional weight of less than 2, and pairs that appear only twice and have a weight of less than 5% (Martin and Monahan, 2022).

Complete dataset

In the previous sections, we outlined the methodology for constructing the indices of green and digital intensities by industry for European countries, the US and the UK.

Our analysis involved a three-step process to quantify the digital and green *content* of occupations within industries across different countries:

1. *Indicators of digitalisation and greenness of occupations.* We began by assigning a 'digital intensity' and a 'green intensity' score to each occupational code. Digital intensity represents the level of digital skills required for that occupation, while green intensity reflects the percentage of tasks considered relevant for the green transition.
2. *Industry-Level Aggregation.* Using worker-level data from various surveys, we grouped individuals by industry. We then calculated the average digital and green intensity for each industry, weighting each occupation by its employment share within that industry.
3. *Harmonization and Cross-Country Comparison.* To ensure comparability across countries, we standardized the industry classifications. We converted industry-specific codes from national surveys to the International Standard Industrial Classification (ISIC), creating a harmonized dataset of digital and green intensities at the industry level for cross-country analysis.

4. Findings and Descriptives

In this section, we present estimates of digital skills intensity and green tasks intensity at both the sectoral and country levels. Our indicators provide the most reliable measurements starting from 2011[15], with data extending up to 2022 for European countries, and to 2023 and 2024 for the UK and the US, respectively.

Figure 3 shows our estimates of green tasks intensity across countries over time: while most countries experienced an increase from 2011 to 2022, growth rates were modest, and levels of green task intensity range from 3.7% in Greece to 6.7% in Lithuania in the latest year. Only 5 countries report a green tasks intensity higher than 6% (United Kingdom, Latvia, United States, Estonia and Lithuania). Our greenness estimates are lower compared to other studies (Causa et al., 2024b; Valero et al., 2021): this is primarily due to our granular, task-based approach, as an occupation's contribution to the greenness of the economy depends only on the extent to which it involves green tasks. However, the sluggish dynamics of green employment over the span of more than 10 years

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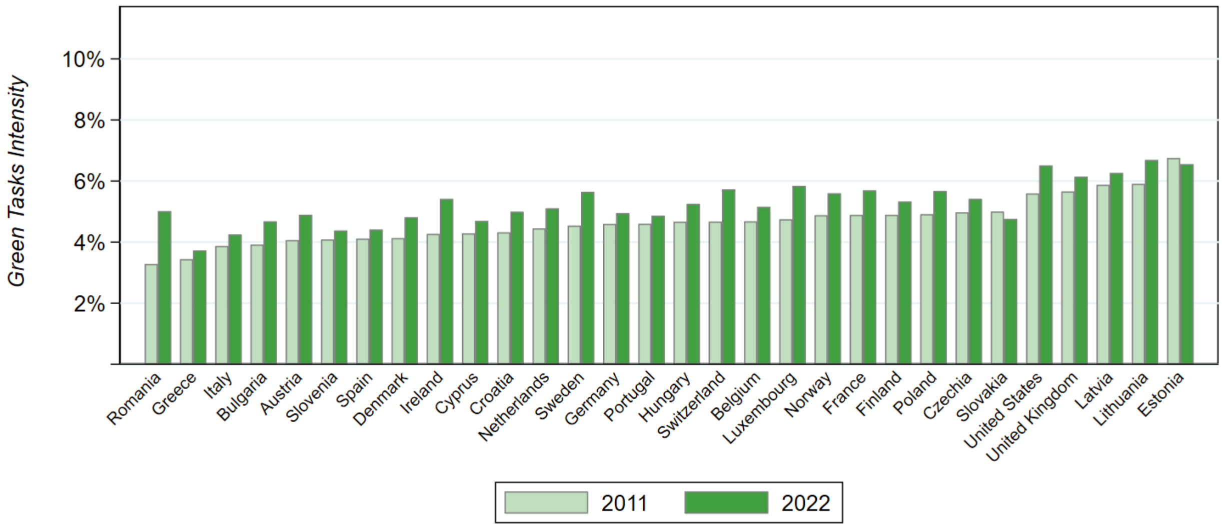
[15] The shift from ISCO-88 to ISCO-08 framework entailed a disruption in occupational statistics in the European countries.

is in line with previous findings in studies based on O*NET data (Causa et al., 2024b). Martin and Monahan (2022) found that in the UK in 2019, approximately 7% to 8% of total working hours were allocated to green tasks. Our estimates yield a slightly lower but comparable 6% green task intensity.

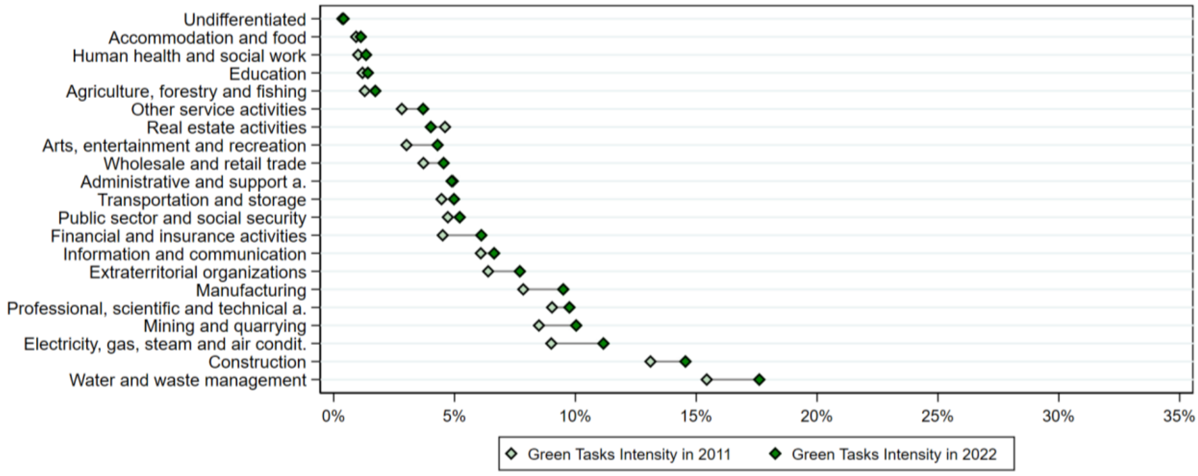
Figure 3 – Green Tasks Intensity Across Countries in 2011 and 2022



The displayed values correspond to employment weighted averages for 2011 and 2022.
Data sources: EU - Labour Force Survey for European Countries, Annual Population Survey for the UK, and IPUMS CPS for the US.

These country-level statistics mask substantial industrial heterogeneity: in Figure 4 we report the dynamics of greenness by ISIC industries from 2011 to 2022. On average in our sample, green tasks intensity is higher in sectors like Water and Waste Management, Construction, and Energy and Mining and Quarrying. The fact that these are high-emitting industries underscores the importance of using occupational-level indicators to investigate the greenness profile of the labour force rather than sector-level *'umbrella'* definitions (Valero et al., 2021; Causa et al., 2024c). The shift towards higher green employment is more pronounced in key industries such as Financial and Insurance Activities, for their potential to redirect capital and funding to renewable energy and sustainable initiatives, and Manufacturing, that employ from 10% to 20% of the total workforce across the sample countries.

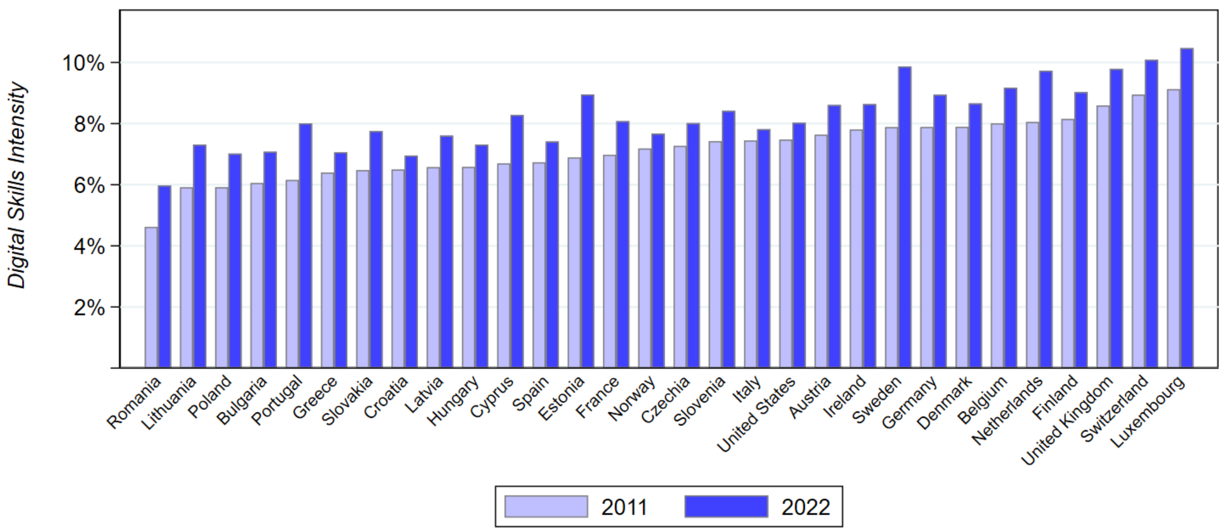
Figure 4 – Green Tasks Intensity Across Industries in 2011 and 2022



The displayed values correspond to employment weighted averages for 2011 and 2022.
Data sources: EU - Labour Force Survey for European Countries, Annual Population Survey for the UK, and IPUMS CPS for the US.

Turning to the digitalisation of the economies in the sample, we see a more substantial and rapid increase of digital skills intensity: in 2022 Luxembourg, Switzerland, and Sweden lead at nearly 10%, while Romania, Poland, Bulgaria and Croatia display the lowest share of digital skills. Due to the time-invariant nature of our digital indicator, we cannot investigate how much the digital skills of the same occupation evolved over time, although this might be an important channel of the digital transition. However, our digital skills intensity indicators are designed to capture structural shifts towards occupations with high digitalisation requirements: our results suggest that a gradual and modest shift in the composition of occupations occurred across these countries in 11 years.

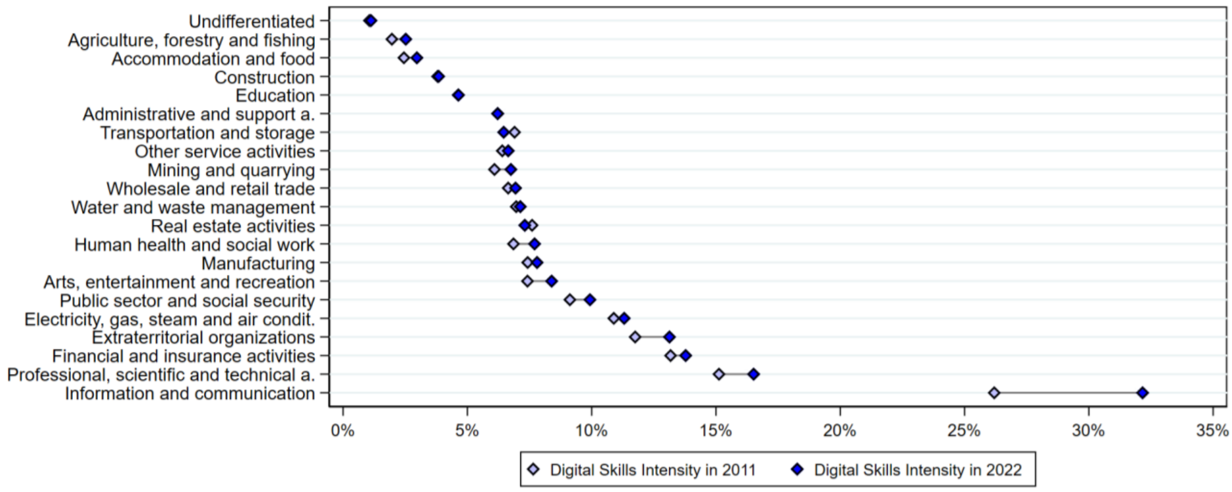
Figure 5 – Digital Skills Intensity Across Countries in 2011 and 2022



The displayed values correspond to employment weighted averages for 2011 and 2022.
Data sources: EU - Labour Force Survey for European Countries, Annual Population Survey for the UK, and IPUMS CPS for the US.

The industrial-level analysis helps shed light on the driving forces of the modest increase of the digital skills intensity in our sample: the surge in digitalisation is predominantly driven by the *ICT* sector, rising by 7 percentage points over the decade. A relevant shift occurred also in the *Professional, Scientific and Technical Activities* industry, whereas the remaining sectors were relatively stagnant.

Figure 6 – Digital Skills Intensity Across Industries in 2011 and 2022



The displayed values correspond to employment weighted averages for 2011 and 2022.
Data sources: EU - Labour Force Survey for European Countries, Annual Population Survey for the UK, and IPUMS CPS for the US.

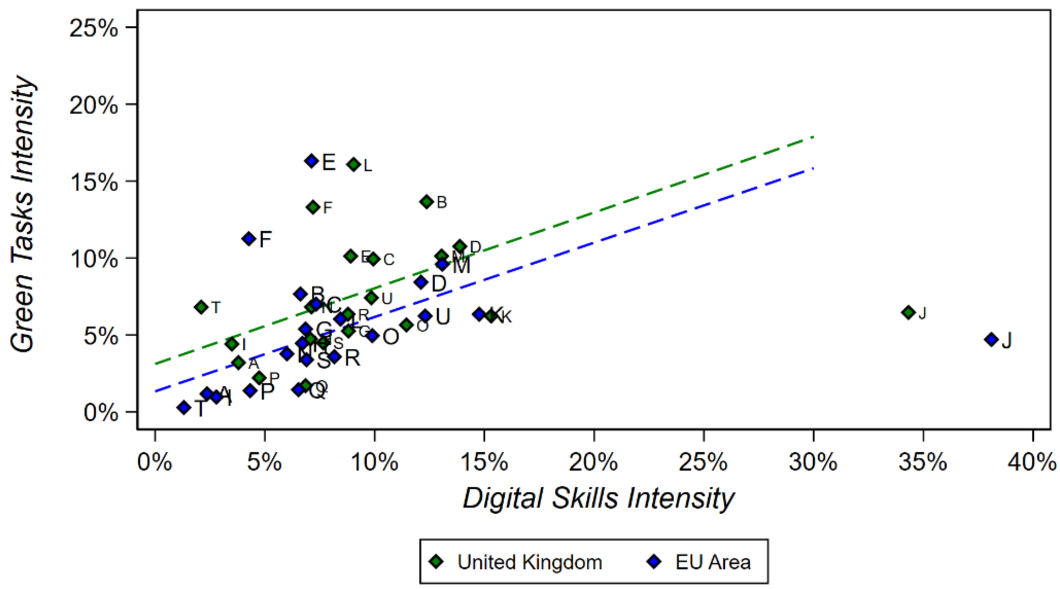
We have thus far constructed and evaluated separately our indicators of green tasks intensity and digital skills intensity, each differing in nature and methodology. However, a comprehensive assessment of the Twin Transition requires a joint analysis of these indicators. We consider three separate geographical areas in this section: the UK, the US and the EU. Figure 7 compares the green and digital indicators for the three areas in 2022. The industrial breakdown is at the 1-D level[16].

A strong positive correlation emerges between greenness and digitalisation across occupations. While the UK demonstrates a stronger green task intensity on average, the correlation between green tasks and digital skills, indicated by the slope of the fit line, is similar to that observed in European countries. Most UK industries, excluding the *Information and Communication* (J) sector, exhibit greater digital skill intensity than their European counterparts and generally show higher green task intensity as well. Notably, the *Professional, scientific and technical activities* (M) sector

[16] Legend for the industrial taxonomy ISIC Rev. 4 at the 1 Digit level: *A: Agriculture, forestry and fishing; B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air cond. supply; E: Water supply; sewerage, waste management and remediation activities; F: Construction; G: Wholesale and retail trade; repair of motor vehicles and motorcycles; H: Transportation and storage; I: Accommodation and food service activities; J: Information and communication K: Financial and insurance activities; L: Real estate activities; M: Professional, scientific and technical activities; N: Administrative and support service activities; O: Public administration and defence; compulsory social security; P: Education; Q: Human health and social work activities; R: Arts, entertainment and recreation; S: Other service activities; T: Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use; U – Activities of Extraterritorial Organizations and Bodies.*

presents remarkably similar metrics for both areas. This industry's fusion of high digital skill requirements with significant green task content underscores its critical role in advancing technological innovation and sustainability.

Figure 7 – Digital & Green Intensities Across Industries[17] in 2022 in UK and EU Area

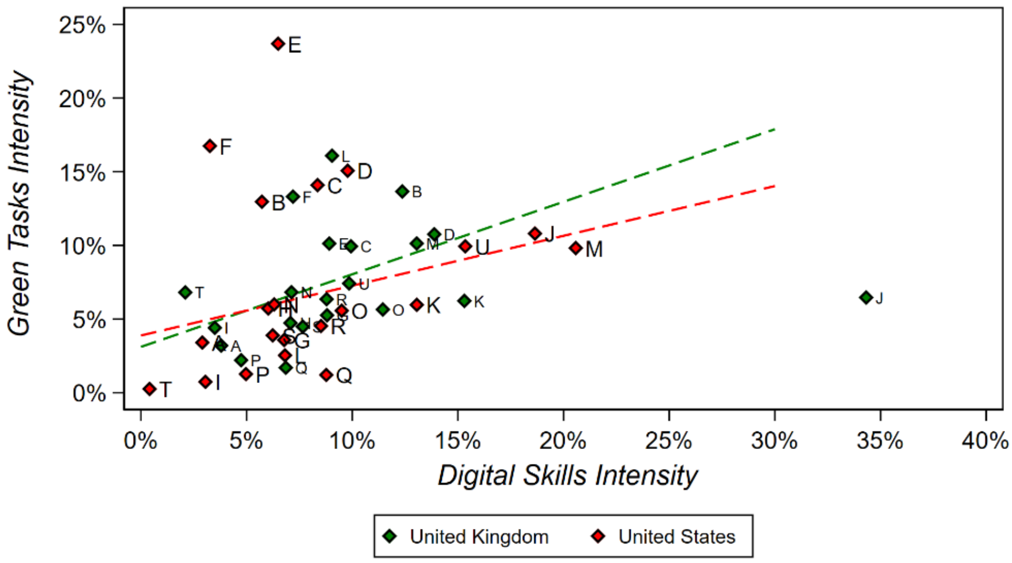


Notes: The graph displays Green Tasks and Digital Skills Intensities across industries of the United Kingdom and the EU Area in year 2022. The dashed green and red lines represent the linear prediction plot based on the underlying data of respectively the United Kingdom and the EU Area in 2022, excluding outlier industries (E & J).

A comparison with the USA reveals a different picture regarding the greenness and digitalisation of occupations. The US economy exhibits a weaker correlation between green tasks and digital skills and its industries fall into three main clusters. The first comprises natural resource-intensive sectors with high greenness but low digital intensity (e.g., *Manufacturing*, *Construction*, respectively sector C and F). The second group contains just two industries, *Information and Communication* (J) and *Professional, Scientific & Technical Activities* (M), with moderate green intensity but high digitalisation. The third and largest cluster, which includes the majority of employment, reports low green task intensity across a range of digital skill levels. This pattern closely resembles that of the UK.

[17] Fit lines in the graphs are computed with the exclusion of *Water supply; sewerage, waste management and remediation activities* (industry E) and *Information and communication* (industry J), outliers respectively for green tasks intensity and digital skills intensity.

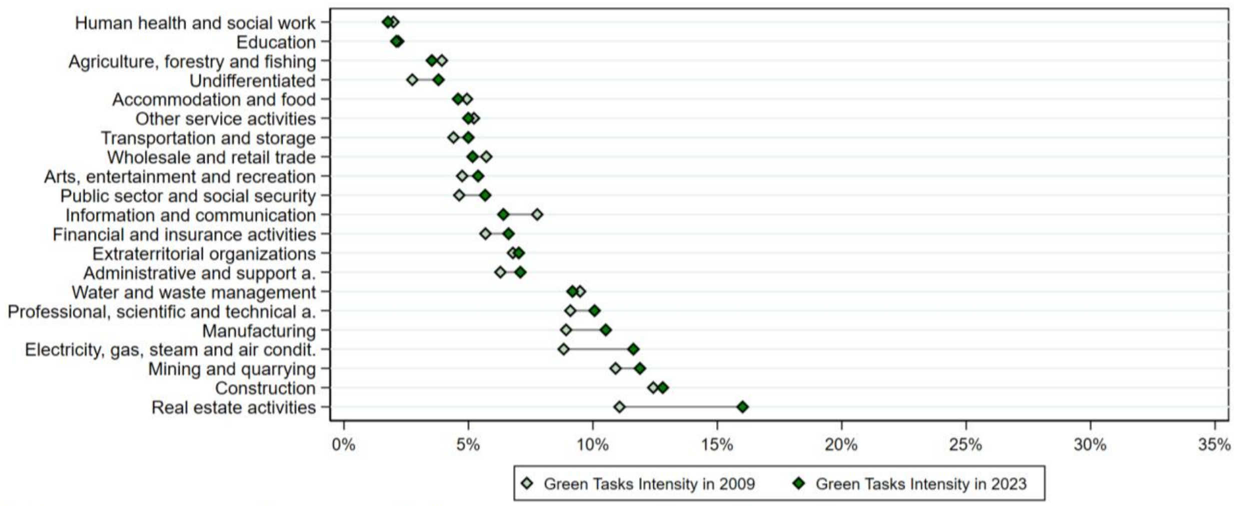
Figure 8 – Digital & Green Intensities Across Industries in 2022 in UK and USA



Notes: The graph displays Green Tasks and Digital Skills Intensities across industries of the United Kingdom and the United State in year 2022. The dashed green and red lines represent the linear prediction plot based on the underlying data of respectively the United Kingdom and the United States in 2022, excluding outlier industries (E & J).

To address the sample heterogeneity, our analysis now focuses on the dynamics of greenness within UK industries. By leveraging crosswalking procedures and the Annual Population Survey, we constructed a data series spanning from 2009 to 2023. While the UK began with a relatively high greenness value in 2011 (Figure 3), Figure 9 illustrates that overall growth has been modest. This limited growth has primarily occurred in sectors that already had high green task intensity.

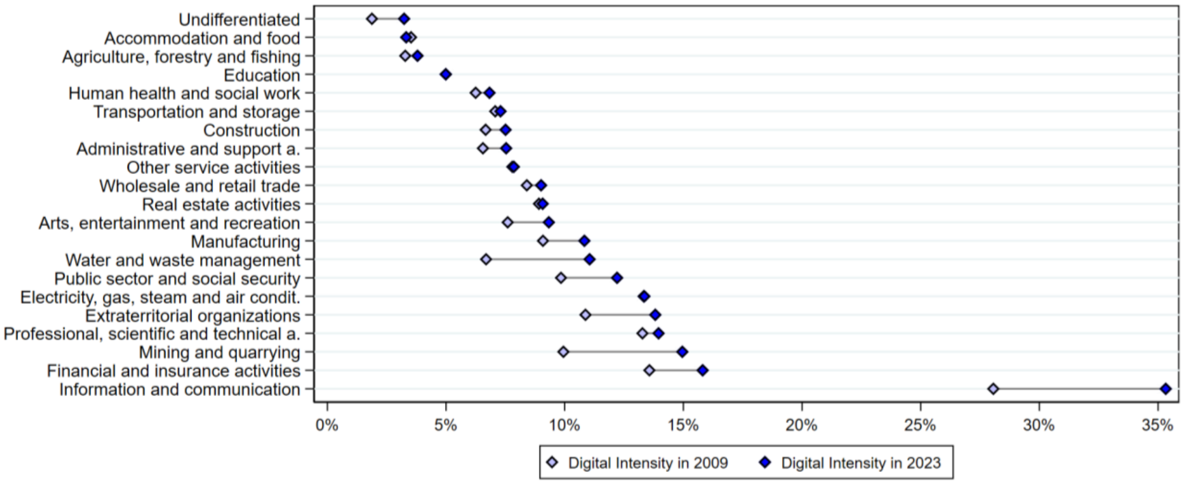
Figure 9 – Focus UK: Green Intensities Across Industries in 2009 and 2023



The displayed values correspond to employment weighted averages for the UK in 2009 and 2023. Data source: Annual Population Survey for the UK.

While growth in green task intensity has been moderate, it is accompanied by a substantial rise in digital skills, predictably driven by the *Information and Communication* sector (Figure 10). Notably, a significant part of this digitalisation is happening within traditionally 'green' sectors like *Water and* *waste management*. This pattern suggests the Twin Transition is a two-way process: it involves not only greening digital industries but also leveraging technology to boost the dynamism and adaptability of established green sectors.

Figure 10 – Focus UK: Digital Skills Intensity Across Industries in 2009 and 2023

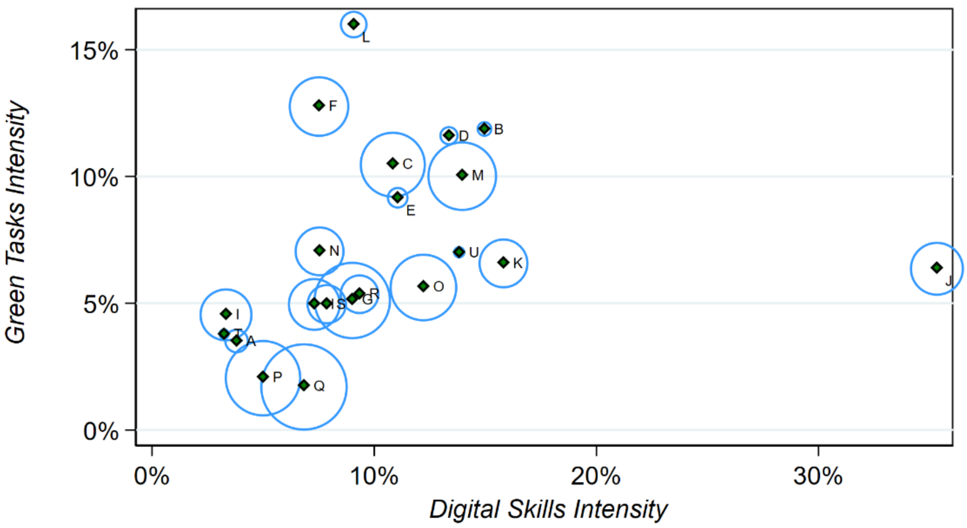


The displayed values correspond to employment weighted averages for the UK in 2009 and 2023. Data source: Annual Population Survey for the UK.

Across the sampled countries, the Professional, Scientific, and Technical Activities sector (M) plays a central role in advancing the Twin Transition because it combines the digital and the green dimensions into highly skilled jobs, an auspicable foundation for an equitable dual transition.

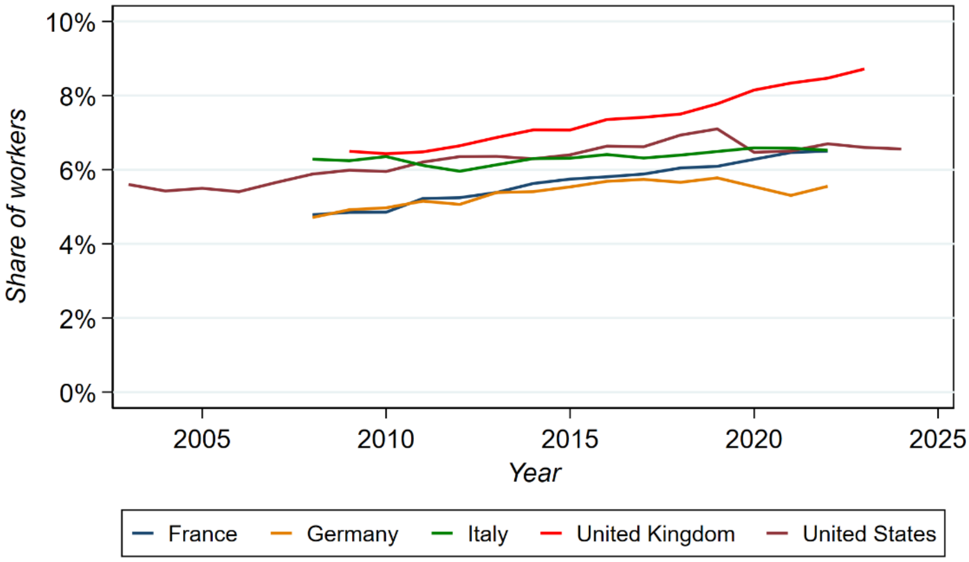
The UK exemplifies this trend. While the UK's average skill intensity has been stable, it shows a sustained increase in employment within this professional sector (Figures 11 and 12). This demonstrates a significant structural shift in its labour force that is less evident elsewhere, positioning the UK as a leader in building a more skilled, sustainable, and growing economy.

Figure 11 – Focus UK: Digital & Green Intensities with Industry Employment in 2023



Notes: The graph displays Green Tasks and Digital Skills Intensities across UK industries in year 2023.
The width of blue circles corresponds to relative employment in that sector.

Figure 12 – Dynamics of the Employment Share in Professional, Scientific and Technical Activities



Notes: The graph displays the evolution of the share of workers employed in *Professional, scientific and technical activities* in selected countries. Data sources: EU LFS for France, Germany and Italy, APS for the UK, and IPUMS CPS for the US.

5. Discussion and Conclusions

We dedicate this last section to discuss the characteristics of the dataset at hand, drawing some conclusions. We constructed a harmonized dataset to provide a comparable, long-term resource to inform structural labour market trends and how the "Twin Transition" is reshaping the labour force. Our standardised metrics consist of classification-based indicators of green and digital intensities at both the occupational and industry levels.

As a result, they can be applied to any data source including information on specific occupational codes, according to most used classification systems. We provided occupation-level data to investigate cross-national labour-market comparisons, but the potential applications of this dataset are many and include the possibility of applying the estimates to more granular data, e.g. at the regional level.

The dataset has been constructed using several necessary assumptions that are worth recalling from previous sections. First, each occupation is assumed to have the same characteristics across countries, thereby implicitly ignoring national differences that may still be relevant for the Twin Transition. Our estimates should thus be considered as reflecting structural tendencies across occupations rather than precise national-level impacts. Second, in our framework the green intensity measure strictly depends on the task content of each occupation. This is a powerful approach to characterise the profile of an occupation. However, as the concept of "green" is multidimensional, future research needs to focus on a more holistic approach to better capture the green dimension, integrating emission-based or skilled-based metrics to better represent the greening of the workforce. Finally, a key limitation that applies to our dataset is that the digital intensity metrics are static: future versions of this dataset will explore how to embed the dynamic nature of digital skills, potentially providing time-varying indicators that would also allow to capture the impact of AI on the composition of the labour force. By combining employment-based metrics with information on workers' educational backgrounds, and making use of the survey's micro-level detail, these indicators can be substantially improved. In addition, future analysis could explore alternative aggregation approaches, such as using value added rather than employment shares.

Exploiting this novel dataset, we explored the dynamics of digitalisation and greening of the labour force over the past decade. Although deeper analysis is warranted, our data suggest that digital and green skill intensities are not yet at the stage of boosting the Twin Transition.

The indicators described above are a first attempt to capture the green and digital intensity dynamics of the labour market and they need to be considered as a first experiment in this direction. However, our estimates reveal substantial heterogeneity across countries for the green and digital intensities. Future work will build on this novel empirical foundation to further develop methods for capturing ongoing changes in the labour market and to improve our understanding of the double structural change induced by the twin transition.

References

Autor, D., & Dorn, D. (2009). This Job Is 'Getting Old': Measuring Changes in Job Opportunities Using Occupational Age Structure. *American Economic Review*, *99*(2), 45–51. https://doi.org/10.1257/aer.99.2.45

Barbero, J., A. Collado, L., Rodríguez-Crespo, E., & Santos, A. M. (2025). The twin transition in the European Union: Assessing regional patterns of EU-funded investments. *European Planning Studies*, *33*(10), 1801–1821. https://doi.org/10.1080/09654313.2025.2528882

Causa, O., Nguyen, M., & Soldani, E. (2024a). *A new measurement approach for identifying high-polluting jobs across European countries* (OECD Economics Department Working Papers No. 1795; OECD Economics Department Working Papers, Vol. 1795). https://doi.org/10.1787/f5127e4c-en

Causa, O., Nguyen, M., & Soldani, E. (2024b). *Lost in the green transition? Measurement and stylized facts* (OECD Economics Department Working Papers No. 1796; OECD Economics Department Working Papers, Vol. 1796). https://doi.org/10.1787/dce1d5fe-en

Causa, O., Soldani, E., Nguyen, M., & Tanaka, T. (2024c). Labour markets transitions in the greening economy: Structural drivers and the role of policies. *OECD Economics Department Working Papers*, Article 1803. https://ideas.repec.org//p/oec/ecoaaa/1803-en.html

Chen, Z., Marin, G., Popp, D., & Vona, F. (2020). Green Stimulus in a Post-pandemic Recovery: The Role of Skills for a Resilient Recovery. *Environmental & Resource Economics*, *76*(4), 901–911. https://doi.org/10.1007/s10640-020-00464-7

Consoli, D., Marin, G., Marzucchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, *45*(5), 1046–1060. https://doi.org/10.1016/j.respol.2016.02.007

Corrado, C., Criscuolo, C., Haskel, J., Himbert, A., & Jona-Lasinio, C. (2021). *New evidence on intangibles, diffusion and productivity* (OECD Science, Technology and Industry Working Papers No. 2021/10; OECD Science, Technology and Industry Working Papers, Vol. 2021/10). https://doi.org/10.1787/de0378f3-en

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Rivkin, D., & Lewis, P. (2011). *Greening of the World of Work: Implications for O*NET®-SOC and New and Emerging Occupations*. https://www.onetcenter.org/dl_files/Green.pdf

Eurostat. (2024). *EU Labour Force Survey (EU-LFS)* [Data set]. European Commission. https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, J. R., Backman, D., Breton, E., Cooper, G., Rivera Drew, J. A., Richards, S., Van Riper, D., & Williams, K. C. W. (2025). *IPUMS CPS* (Version 13.0) [Data set]. IPUMS. https://doi.org/10.18128/D030.V13.0

Gal, P., Nicoletti, G., Renault, T., Sorbe, S., & Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail – Firm-level empirical evidence from EU countries. *OECD Economics Department Working Papers*. https://www.oecd.org/en/publications/digitalisation-and-productivity-in-search-of-the-holy-grail-firm-level-empirical-evidence-from-eu-countries_5080f4b6-en.html

Gallo, E., Jona-Lasinio, C., & Samoncini, B. (2025). Green Investment and Productivity Dynamics. *Review of Income and Wealth*, *71*(3), e70024. https://doi.org/10.1111/roiw.70024

Lennon, C., Zilian, L. S., & Zilian, S. S. (2023). Digitalisation of occupations—Developing an indicator based on digital skill requirements. *PLOS ONE*, *18*(1), e0278281. https://doi.org/10.1371/journal.pone.0278281

Martin, J., & Monahan, E. (2022, March). *Developing a method for measuring time spent on green tasks—Office for National Statistics*. Office for National Statistics. https://www.ons.gov.uk/economy/environmentalaccounts/articles/developingamethodformeasuringtimespentongreentasks/march2022

Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *The Review of Economics and Statistics*, *96*(1), 60–77. https://doi.org/10.1162/REST_a_00366

Nicoletti, G., von Rueden, C., & Andrews, D. (2020). Digital technology diffusion: A matter of capabilities, incentives or both? *European Economic Review*, *128*, 103513. https://doi.org/10.1016/j.euroecorev.2020.103513

Office for National Statistics. (2023). *Annual Population Survey* (6th release) [Data series]. UK Data Service. https://doi.org/10.5255/UKDA-Series-200002

Pisu, M., von Rueden, C., Hwang, H., & Nicoletti, G. (2021). *Spurring growth and closing gaps through digitalisation in a post-COVID world: Policies to LIFT all boats* (OECD Economic Policy Papers No. 30; OECD Economic Policy Papers, Vol. 30). https://doi.org/10.1787/b9622a7a-en

Rodríguez-Pose, A., & Bartalucci, F. (2024). The green transition and its potential territorial discontents. *Cambridge Journal of Regions, Economy and Society*, *17*(2), 339–358. https://doi.org/10.1093/cjres/rsad039

Scholl, N., Turban, S., & Gal, P. (2023). The green side of productivity. *OECD Productivity Working Papers*. https://www.oecd.org/en/publications/the-green-side-of-productivity_a363530f-en.html

Tyros, S., D. Andrews, & de Serres, A. (2023). *Doing green things: Skills, reallocation, and the green transition. OECD Economics Department Working Papers.* https://www.oecd.org/en/publications/doing-green-things-skills-reallocation-and-the-green-transition_286a5007-en.html

Valero, A., Draca, M., Li, J., Muller, S., Nguyen-Tien, V., & Riom, C. (2021). Are ‘green’ jobs good jobs? *CEP Reports*, Article 39. https://ideas.repec.org//p/cep/cepsps/39.html

Veugelers, R., Faivre, C., Rückert, D., & Weiss, C. T. (2023). The Green and Digital Twin Transition: EU vs US Firms. *Intereconomics*. https://www.intereconomics.eu/contents/year/2023/number/1/article/the-green-and-digital-twin-transition-eu-vs-us-firms.html

Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). Environmental Regulation and Green Skills: An Empirical Exploration. *Journal of the Association of Environmental and Resource Economists*, *5*(4), 713–753. https://doi.org/10.1086/698859