The Labour Flow Network of Green and Digital Firms: the Cases of Emilia-Romagna and Veneto

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Abstract: This paper examines the network of labour inflows characterising manufacturing firms engaged in the twin transition (digital and green) in Emilia-Romagna and Veneto. Using a unique dataset that combines administrative records and survey data, we construct and compare occupational networks for four types of firms, namely *Digital*, *Green*, *Green and Digital*, and *Non-Green and Non-Digital*. Network analysis reveals that *Green* and *Digital* firms exhibit denser, more interconnected, and more diversified labour inflows, suggesting higher skill intensity and multidisciplinary requirements. We also show that the average job-relatedness of *Green and Digital* firms is always higher than that of *Non-Green and Non-Digital* firms. These findings underscore the variety of workforce needs in the transition, highlighting the importance of adaptive recruitment strategies and interdisciplinary education.

Keywords: circular innovation, digital technology, labour flow network.
JEL classification: J24; Q55; R11.

1. Introduction

The envisioned transformation of economies and societies, driven by the combined adoption of digital technologies and the introduction of environ-

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mental innovations (also referred to as eco-innovations), lies at the core of the European political agenda (European Commission, 2020, 2022). According to this agenda, the joint role of green innovations and digital technologies in fostering a systemic transformation that encompasses industries, culture, science, technology, markets, and user practices is commonly referred to as the *Twin Transition* (hereafter, TT) (Muench *et al.*, 2022). Although the two technological paradigms differ significantly and are often promoted by distinct actors (Aloisi, 2025), their potential complementarities, particularly the enabling role of digital technologies (DTs) in fostering environmental innovations (EIs), are increasingly recognized as fundamental to achieving sustainable and inclusive growth (Montresor, Vezzani, 2023). A particularly noteworthy synergy concerns the role of digital technologies (DTs) in mitigating environmental impacts (Diodato *et al.*, 2023), including their contribution to reducing the carbon footprint (Rehman *et al.*, 2023) and facilitating the implementation of circular economy innovations (CEIs) within manufacturing firms (Rosa *et al.*, 2020). CEIs, in turn, can help reduce the environmental footprint of digital technologies themselves by enhancing energy efficiency and promoting material recovery throughout their entire life cycle, particularly in relation to critical and rare minerals (Muench *et al.*, 2022).

Within the TT framework, the adoption of digital technologies and the development of environmental innovations have been specifically analysed with respect to their impacts on labour demand and employment dynamics (**Santoalha** *et al.*, **2023**). This perspective is crucial, given the strong occupational dimension of the green transition, which involves not only shifts across sectors but also across occupations, with significant implications at the local level and for related upstream and downstream industries (Vandeplas *et al.*, 2022).

A critical aspect of firms' ability to benefit from the technological transition lies in their capacity to meet the evolving skill demands it entails. In this context, three primary channels of skill acquisition can be identified. The first involves hiring young workers entering the labour market, particularly graduates from degree programs emphasising sustainability-related content (Cattani *et al.*, **2025a o b???**). The second involves the reskilling of existing employees through structured training interventions, either off-the-job or on-the-job (Pedota *et al.*, 2023). The third consists of the recruitment of new employees with external expertise, thereby expanding the firm's knowledge base without undermining its absorptive capacity (Li *et al.*, 2024).

Focusing on this third channel of skill acquisition, the present study operationalises the occupational dynamics associated with the TT at firm-level by investigating the network structure of the workflows characterizing four types of manufacturing firms, classified according to their engagement with the TT: 1) static firms («neither green nor digital»), 2) firms adopting or investing in DTs («digital»), 3) firms introducing CEIs («green»), and 4) firms actively involved in both dimensions of the TT («green and digital»).

The territorial focus of the analysis is on two Italian regions, Emilia-Romagna and Veneto, for which a rich dataset is available. These regions represent two significant cases of engagement with the TT, not only because of their substantial contribution to national value added (jointly accounting for 20.7% in 2022) (ISTAT, 2023), but also due to their medium-to-high levels of green and digital technological as well as scientific specialisation (Benecchi *et al.*, 2023; Cicerone *et al.*, 2023; Lotti, Nobile, 2025; Damioli *et al.*, 2025). Moreover, the same regions showed a highly dynamic performance concerning circular economy-related outcomes (Silvestri *et al.*, 2020).

The central research question is as follows: «How do occupational inflows connect one to each other across firms with differing levels of engagement in the TT?». More specifically: «Do the occupational networks of TT, digital, and green firms exhibit greater variety than those of static firms?». Answering these questions is important to understand whether companies that adopt CEI are characterised, *ex ante*, by a diversified flow of incoming skills or not. If this were the case, it could provide a possible answer to the difficulties that (Italian) companies are complaining about in recruiting workers with the levels and types of skills appropriate to the tasks required by this type of activity (Cedefop, **2023a o b???**; EntreComp4Transition, 2025). The analysis builds on two main assumptions. The first is that workers accumulate a portfolio of skills throughout their careers; these skills vary by occupation and not only facilitate labour market mobility but also enable firms, industries, and regions to adapt and evolve (**Whittle, Kogler, 2019**). The second is that green and digital technologies, as well as the jobs and firms associated with them, are more complex and more intensive in knowledge and human capital than other technologies or occupations (Consoli *et al.*, 2016; Barbieri *et al.*, 2020; Martinelli *et al.*, 2021). This suggests that the underlying structure of skills and competencies required is also more diversified.

The empirical analysis is based on a unique dataset combining firm-level survey data (2020-2022) with employee-employer administrative records (2008-2020) for manufacturing firms in the Italian regions of Emilia-Romagna and Veneto. Using these data, we compare the previous occupations of job changers (i.e., workers entering the firms surveyed) with their current occupational roles, constructing an occupational network for each group of firms. The main results show that TT firms exhibit denser, more interconnected, and more diverse labour flow networks than static firms, which in turn demonstrates more complex networks than static firms when we adopt a strict definition of TT firms.

The remainder of the paper is structured as follows: Section 2 reviews the conceptual background; Section 3 describes the dataset; Section 4 details the network analysis and discusses the results; Section 5 offers concluding remarks.

2. Related literature and conceptual background

It is increasingly common to describe the profound transformations currently unfolding, and expected to intensify soon, in our economies as the result of the TT: the simultaneous digital and environmental transitions. In this framework, both agendas are viewed as mutually reinforcing, with digital innovations facilitating greener solutions and environmental imperatives shaping the direction of technological progress (Damioli *et al.*, 2025; **Fazio** *et al.*, **2024**; Cicerone *et al.*, 2023). In an ideal scenario, this synergy can effectively realise the following: digital tools and systems can unlock innovative business models, equip workers with new skills, boost productivity, and deliver cleantech solutions that accelerate environmental goals. In practice, however, the push for digitalisation and the shift toward net zero emissions can also pull in different directions: digital technologies can be highly energy-demanding, rely on scarce materials, and generate waste (**Fazio** *et al.*, **2024**). This dual nature has fuelled extensive debate over whether digitalisation advances or hinders the green transition, with scholars also emphasising the role of spatial heterogeneity in shaping outcomes (Damioli *et al.*, 2025; **Fazio** *et al.*, **2024**; Cicerone *et al.*, 2023; Montresor, Vezzani, 2023; **Damioli** *et al.*, **2023**). Against this backdrop, the present study focuses on the specific implications for the circular economy. The circular economy represents indeed one of the most prominent strategies within the environmental transition. Within the broader environmental agenda, the circular economy stands out as a strategy whose complexity makes it particularly dependent on digital innovation. Its inherently decentralised and systemic nature relies on interconnected networks of firms, sectors, and regions engaged in resource loops, reverse logistics, and product-life extension strategies. These arrangements require intensive coordination across often unrelated value chains (Chioatto *et al.*, 2025; Bourdin, Torre, 2025; Chauhan *et al.*, 2022). Recent studies (e.g., Bocken *et al.*, 2016) highlight the enabling role of digital technologies, such as IoT, data analytics, and blockchain, in supporting this coordination by enhancing traceability, monitoring product lifecycles, and enabling platform-based collaboration.

In the face of such advancements, the TT has clear global implications for labour markets, particularly concerning the emergence of new skills and novel (re)combinations of existing skills required to perform new tasks and manage evolving technologies. On the other hand, the rapidly changing landscape of skills and employment in the context of the TT suggests not only a shift in skill combinations but also a pressing need for significant policy interventions to ensure a just transition for displaced workers. Digitalisation renews concerns about technological unemployment and its impacts on vulnerable segments of the population. Increased resource efficiency may reduce labour demand, and moreover, the adoption of innovation-driven circular economy strategies could necessitate the previous recruitment of specialised, highly qualified workers, potentially displacing lower-skilled employees (Buyukyazici, Quatraro, 2025). These concerns have been emphasised by the International Labour Organization (ILO, 2016), which highlights the importance of policies that guarantee adequate support and training opportunities for workers in declining sectors. Similarly, initiatives under the European Green Deal (European Commission, 2019) have prioritised upskilling efforts in green and digital sectors to promote fairness in the transition. Recently, Cedefop (2023a, 2023b) also underlines the role of inclusive vocational training and reskilling programs in preparing the workforce for the demands of the TT.

While the two transitions are unfolding simultaneously, much of the existing research on the skills required for these transformations focuses on either the green or the digital transition in isolation. On the green side, studies such as Vona *et al.* (2015, 2018), Burger *et al.* (2019), Beducci *et al.* (2024), Buyukyazici and Quatraro (2025) explore the labour market impacts and skill profiles associated with the green transition. The academic literature remains however particularly limited when it comes to the skill and knowledge composition required to support the circular economy. Research on the digital transition includes contributions by **Zeike *et al.* (2019)**, Audrin *et al.* (2024), and Flores *et al.* (2020). Only a few studies explicitly address the TT as a combined phenomenon (e.g., Trevisan *et al.*, 2024).

Despite widespread acknowledgment of the skill gaps arising from the TT, challenges remain in clearly defining, measuring, and analysing the new or recombined skills required for firms to adopt circular economy-oriented solutions and innovations. The existing literature, both theoretical and empirical, tends to examine the impacts of digitalisation and automation on skills, tasks, and occupations (e.g., **Acemoglu, Restrepo, 2018**, **2020**), or the implications of green technologies (e.g., Vona *et al.*, 2018; **Marin *et al.*, 2019**; Pianta, Lucchese, 2020; Marin, Vona, 2023), while largely neglecting their joint effects. Among these, **Acemoglu and Restrepo (2020)** argue that digitalisation has contributed to labour market polarisation: high-skill jobs expand while middle-skill jobs decline due to the automation of routine tasks, particularly in clerical, administrative, and manufacturing roles. This has led to a bifurcated employment structure, with growth concentrated in both high-wage, cognitively intensive jobs and low-wage, non-routine manual occupations, and a corresponding erosion of middle-income employment. On the green side, Vona *et al.* (2018) note that while the green transition generates demand for specialised green skills, it also risks exacerbating labour shortages in traditional sectors where skills are not easily transferable or where re-skilling is particularly challenging. Similarly, Burger *et al.* (2019) emphasise that circular economy innovations (CEIs) typically require a heterogeneous skill set comprising both cognitive and non-cognitive skills.

Another recent study investigates the skill requirements of the circular economy in Italy (Buyukyazici, Quatraro, 2025). Using data from the INAPP-ISTAT Sample Survey on Professions (ICP) and the Italian Labour

Force Survey (ILFS), the study develops a bottom-up, data-driven method to identify key and complementary skills in core and enabling circular industries, using skill-relatedness and complexity measures. The findings highlight that core circular industries rely on less complex, manual skills suitable for low-skilled worker transitions, while enabling circular industries require more knowledge-intensive skills. Regional analysis shows that low-income areas may specialise in core circular industries with the right policy support. Overall, effective coordination between core and enabling circular industries is essential to advancing the circular economy.

Pianta and Lucchese (2020), in their discussion of the European Green Deal, argue for the necessity of higher skills in response to changing technologies and production systems, framed within a broader call for active industrial policy and a just transition. However, the green transition literature tends to concentrate on profiling green jobs and their spatial distribution, paying limited attention to the underlying role of human capital. For instance, early empirical evidence indicates that green job holders tend to deploy more advanced cognitive and interpersonal skills than their non-green counterparts (Barbieri, Consoli, 2019), and that green jobs are typically high-skilled and regionally concentrated (Vona *et al.*, 2019).

A regional perspective offers further insights into the dynamics of skill demand. Eco-innovation often relies on the recombination of locally embedded knowledge bases (Montresor, Quatraro, 2020), suggesting that regions specialising in green technologies will increasingly require highly qualified labour from diverse backgrounds to promote cross-sectoral knowledge spillovers (Pinate *et al.*, 2024). This is supported by findings that regional diversification across unrelated sectors fosters green employment growth by exploiting skill complementarities (Barbieri, Consoli, 2019). Preliminary evidence also suggests that firms advancing along the TT path may benefit from diversified employment flows, akin to Jacobs-type externalities, particularly in urban areas where firms are better positioned to use digital technologies to develop environmental innovations (**Cattani *et al.*, 2023**).

Regarding contributions that explicitly examine both green and digital transitions, albeit often separately, Trevisan *et al.* (2024) provide a notable example. Conducting a systematic literature review, the authors explore the skills required for the integrated implementation of the TT within the manufacturing sector. They identify 40 essential skills, categorised into three broad dimensions: resilience skills, digital technology skills, and specialised/technical skills. Their findings may offer a foundational framework for interpreting the empirical results presented in this paper.

Although far from exhaustive, this brief literature review highlights two significant gaps in the literature. First, it identifies *Green* and *Digital* firms using direct information on the activities carried out and the innovations introduced, rather than analysing their patents. Second, all the studies look at the consequences of the green or digital transition on skill requirements for firms and industries; that is, they examine what skills are required and/or used in firms and sectors that are already classified as circular or digital. No study, instead, considers which job profiles contribute to determining *ex ante* the propensity of firms or sectors to adopt digital or circular economy-related technologies. In other words, this means looking at the (network of) job profiles that are needed to adopt new products or processes inspired by circular economy principles. Our main research questions are as follows: how do occupational inflows interconnect firms with different levels of engagement in TT? Do the occupational spaces of TT-oriented, digital, and circular firms display greater diversity compared to firms that do not commit to digital and circular innovation? Since green and digital technologies are more complex and knowledge-intensive than other types (Barbieri *et al.*, 2020), as well as green jobs are more human capital-intensive than other types (Consoli *et al.*, 2016), we expect to find that firms engaged in the TT have a more diversified and skill-intensive network of incoming workflows compared to firms that do not commit into digital and circular economy-related processes and technologies. This paper seeks to answer these questions by leveraging micro-level administrative and survey data for two Italian regions, Emilia-Romagna and Veneto, as detailed in the next section.

3. Empirical analysis

The empirical analysis relies on a novel dataset that integrates information from three distinct sources. Two of these sources consist of administrative data derived from mandatory reporting systems, which record information on hirings, contract changes, and separations for most of the workforce employed in the Emilia-Romagna and Veneto regions of Italy from 2008 to 2020. The third source is a survey of manufacturing enterprises operating in Emilia-Romagna and Veneto, from which data on circular economy innovations and the adoption of, or investment in, digital technologies between 2020 and 2022 are extracted.

The economic profiles of Emilia-Romagna and Veneto are marked by their substantial contributions to Italy's overall economy, as reflected in their Gross Domestic Product (GDP) at constant market prices. In 2023, Emilia-Romagna's GDP was approximately € 180 billion, while Veneto's was slightly higher at around € 185 billion, underscoring their status as key economic hubs within the country (**ISTAT, 2025**). Labour market indicators further emphasise the relative economic strength of both regions. In 2024, the employment rate reached 70.3% in Emilia-Romagna (corresponding to 2,233,000 employed individuals) and 70.2% in Veneto (2,230,000 employed), both significantly above the national average of 62.2%. These figures point to a robust labour market and high labour force participation in both territories. Correspondingly, unemployment rates remain comparatively low, at

4.3% in Emilia-Romagna and 3% in Veneto, indicating favourable labour market conditions (Regione Emilia-Romagna, 2025; Regione Veneto, 2025). In terms of income levels, the average annual wage per worker in 2023 was estimated at approximately € 27,080 in Emilia-Romagna and € 29,000 in Veneto, compared to a national average of € 24,830 (**INPS, 2023**). These figures reflect the regions' productive capacities, as well as the presence of diversified and competitive economic structures, particularly in the industrial and service sectors. Notably, both regions exceed the national average in terms of digital development according to the regional adaptation of the DESI Index proposed by Benecchi *et al.* (2023). Emilia-Romagna ranks second and Veneto ninth out of 21 regions. With respect to Emilia-Romagna, recent literature has also found a significant correlation between the adoption of Industry 4.0 technologies and a relatively higher demand for advanced skills (cognitive, technical, soft, in particular) over basic skills (Antonietti *et al.*, 2022). Similarly, in terms of the adoption of green technologies, as measured by patent applications, it has been observed that most provinces in Emilia-Romagna and Veneto are relatively specialised in green technologies, in terms of the share of green patents (Lotti, Nobile, 2025) and the number of different environmental technologies associated with regional patenting activity (Cicerone *et al.*, 2023). The empirical analysis offers a descriptive picture of the structure and composition of labour inflows in Emilia-Romagna and Veneto manufacturing firms between 2014 and 2020. Through the network analysis, we will see whether, and to what extent, compared to firms that did not innovate or invest in circular/digital technologies, firms involved in the TT are characterised by a denser, more diversified network of incoming workflows.

3.1. Data: building the SILVER

Information on workers and occupations was collected from two administrative data sources: the *Sistema Informativo Lavoro Emilia-Romagna* (SIL-ER) and the *Sistema Informativo Lavoro Veneto* (SIL-V)[1]. The integration of these two databases forms what we refer to as SILVER. These datasets fall under the category of Linked Employer-Employee Data (LEED). SIL-ER and SIL-V are based on mandatory reporting that employers must submit for each hiring, contract extension, transformation, and termination. This reporting underpins the construction of employee labour flow data.

Each labour contract, instead, is identified through the fiscal codes of both the employer and the employee. Key variables in the dataset include

[1] The release of data followed the conclusion of an agreement between the Department of Economics and Management «Marco Fanno», University of Padova, and, respectively, ART-ER for Emilia-Romagna and Veneto Lavoro for Veneto. The data are protected by privacy and confidentiality constraints and may not be disseminated publicly.

the start, transformation, and end dates of employment contracts; the type of employment contract; the sector classification of the firm; and the occupational code of the worker.

3.2. Survey on circular innovation

The survey was carried out as a deliverable of the *GRINS – Growing Resilient, INclusive, and Sustainable project*. This initiative falls under Extended Partnership Theme 9, *Economic and Financial Sustainability of Systems and Territories*, within Spoke 5, *Innovation-Ecosystems for the Circular Economy*, as part of Italy's National Recovery and Resilience Plan (PNRR). Specifically, it aligns with Mission 4, *Education and Research* – Component 2, *From Research to Business* – Investment 1.3, funded by the European Union through NextGenerationEU.

The survey was conducted between October and November 2023 with the support of Izi S.p.A. Data collection employed a mixed-method approach using CATI (Computer-Assisted Telephone Interviewing) and CAWI (Computer-Assisted Web Interviewing) techniques. Firms completed a structured questionnaire referring to the three years from 2020 to 2022. The initial population of active firms was drawn from the Chambers of Commerce and stratified by company size (based on number of employees), sector (using the two-digit ATECO classification), and geographic location within the two target regions. From an initial pool of 19,534 firms, a final sample of 1,549 firms was obtained, corresponding to a response rate of approximately 8%.

The questionnaire comprises four main sections: 1) firm characteristics, 2) innovation and investments, 3) Circular economy, and 4) COVID-19 impact and firms' recovery strategies. The first section gathers general firm-level information, including geographical location, year of establishment, size, sector classification, membership in industrial groups, districts, or supply chains, composition of management, R&D employment, turnover, and the adoption of certifications (e.g., ISO 9001, ISO 14001, ISO 45001, SA 8000).

The second section focuses on assessing firms' innovation activities. It differentiates among product, process, and organizational innovations implemented during the three-year reference period, and collects information on the main obstacles encountered as well as the support received. Firms are also asked to report their investment capacity in research and development (R&D) and patent-related activities during this timeframe. In addition, this section investigates the adoption of digital technologies over the same period, including the Internet of Things (IoT), robotics, big data/analytics, augmented reality/virtual reality/metaverse, cybersecurity, artificial intelligence, 3D printing, and cloud storage.

The third section specifically explores circular economy practices between 2020 and 2022. Using the European Commission's (2016) Flash Eurobarometer taxonomy, the circular innovations investigated include: *a*) reduc-

Table 1: Summary statistics: firm characteristics

	Obs	Mean	Std. Dev.	Min	Max	ER	Veneto
Number of employees 2020	1,549	383.796	2.261.656	0	8130	3.397.516	4.151.381
Age	1,549	3.081.924	1.957.011	0	168	29.33	31.88
Group	1,549	.1446094	.3518202	0	1	.1490683	.1414365
Supply chain	1,549	.1439638	.3511664	0	1	.1475155	.1414365
District	1,549	.0755326	.2643341	0	1	.0698758	.079558
Exporting firm	1,549	.4964493	.5001489	0	1	.4347826	.5403315
Female manager	1,549	.3854099	.4868492	0	1	.3618012	.4022099
Young manager (<35 years old)	1,549	.1581666	.3650149	0	1	.1506211	.1635359
Main market: local	1,549	.2796772	.3536703	0	1	.3271584	.2458895
Main market: regional	1,549	.2388961	.2857404	0	1	.2485248	.2320442
Main market: national	1,549	.2890316	.2910208	0	1	.2673137	.3044862
Main market: international	1,549	.1923951	.2770759	0	1	.1570031	.2175801
Innovation and R&D							
Product innovation	1,549	.3511943	.4774977	0	1	.310559	.3801105
Process Innovation	1,549	.3602324	.4802228	0	1	.3338509	.3790055
Organizational innovation	1,549	.3182699	.4659553	0	1	.2981366	.3325967
Patents (dummy)	1,549	.0742414	.2622481	0	1	.0667702	.079558
Nr. patents	1,549	2.652174	3.564059	0	25	2.302326	2.861111
Investments R&D	1,549	.227889	.4196061	0	1	.2298137	.2265193
%Turnover to R&D (2020-2022)	1,549	.0634844	.0748182	.01	.55	.0654505	.062065
Digital Technologies							
Introduction of digital technologies	1,549	.4009038	.4902398	0	1	.3649068	.4265193
N. of digital innovation technologies	1,549	.5571336	.8038159	0	5	.5574534	.5569061
Internet of Things	1,549	.0877986	.2830931	0	1	.1024845	.0773481
Robotics	1,549	.1200775	.3251571	0	1	.1149068	.1237569
Big Data/Analytics	1,549	.0393802	.1945607	0	1	.0357143	.041989
Augmented Reality/Virtual Reality/Metaverse	1,549	.0051646	.0717026	0	1	.0046584	.0055249
Cybersecurity	1,549	.0484183	.2147179	0	1	.0559006	.0430939
Artificial Intelligence	1,549	.0058102	.0760275	0	1	.007764	.0044199
3D Printing	1,549	.0477728	.2133539	0	1	.0450311	.0497238
Cloud Storage	1,549	.0438993	.2049372	0	1	.0403727	.0464088
Circular innovation and green R&D							
Investments on green R&D (only firms investing in R&D)	353	.4164306	.4936664	0	1	.3445946	.4682927
Nr. green patents (only patenting firms)	115	.3391304	1.115.182	0	10	.1860465	.4305556
Circular economy innovation	1,549	.3227889	.4676937	0	1	.2686335	.361326
Reducing water usage	1,549	.0400258	.1960831	0	1	.0326087	.0453039
Reducing raw material usage	1,549	.1768883	.3816974	0	1	.1459627	.198895

Table 1: (*continue*)

	Obs	Mean	Std. Dev.	Min	Max	ER	Veneto
Changing design to reduce material consumption	1,549	.0858618	.2802504	0	1	.060559	.1038674
Using renewable energy	1,549	.1129761	.3166658	0	1	.0931677	.1270718
Reducing electrical energy consumption	1,549	.0961911	.2949483	0	1	.0900621	.1005525
Design changes to increase product durability	1,549	.0639122	.2446755	0	1	.0590062	.0674033
Design changes to facilitate disassembly of components	1,549	.0277598	.1643371	0	1	.0326087	.0243094
Design changes to improve product reparability	1,549	.0529374	.2239808	0	1	.0434783	.0596685
Design changes to enhance product recyclability	1,549	.0606843	.2388274	0	1	.0434783	.0729282
Replacing environmentally harmful materials with sustainable alternatives	1,549	.0768238	.2663976	0	1	.0559006	.0917127
Reducing waste generation per unit of output	1,549	.0903809	.2868193	0	1	.0822981	.0961326
Reusing waste within the firm's production process	1,549	.062621	.2423584	0	1	.0496894	.0718232
Delivering waste to other firms to be used as inputs in their production processes	1,549	.0697224	.2547608	0	1	.0512422	.0828729

Source: ???:

ing water usage; *b*) reducing raw material usage; *c*) redesigning products to reduce material consumption; *d*) using renewable energy sources; *e*) reducing electricity consumption; *f*) design changes to increase product durability; *g*) design changes to facilitate component disassembly; *h*) design changes to improve product reparability; *i*) design changes to enhance recyclability; *l*) replacing environmentally harmful materials with sustainable alternatives; *m*) reducing waste generation per unit of output; *n*) reusing waste within the firm's production process; and *o*) transferring waste to other firms to be used as inputs in their production processes. This section also investigates the drivers of circular innovation, considering both market-based and non-market instruments, as well as the main financial instruments used to support circular innovation initiatives.

The final section examines the impact of the COVID-19 pandemic on firms, including its effects on turnover, innovation and green innovation investments, training activities, and the main strategies employed to overcome the economic shock. The final dataset consists of 1,549 manufacturing firms, 644 (41.6%) of which are from Emilia-Romagna and the remaining 905 (58.4%) from Veneto, and for which a total number of 429,012 labour contracts are available, 36% of which involving workers in Emilia-Romagna and 64% involving workers operating in Veneto. Table 1 shows the summary statistics of the surveyed firms. Interestingly, the share of firms using circular and/or digital technologies is significantly higher than emerged in previous research based on patent data (Basilico *et al.*, 2024). The use of survey data, indeed, can also capture non-patented innovations, which are quite common among CEIs.

We observe that firms operating in Veneto are, on average, larger, older, more frequently located in industrial districts, more prone to export and to serve international markets, more intensive in female and young management, more (circular) innovative and patent-intensive, and more frequently adopting digital technology, although less prone to adopt AI, IoT, and cybersecurity software. On the other hand, firms located in Emilia-Romagna are, on average, more inclined to participate in supply chains, more organised into business groups, and more oriented to the regional market. However, for seven out of thirteen types of circular innovation, firms in Emilia-Romagna state more frequently than those in the Veneto region that they have already introduced them before 2020 (for more details on the structure of the survey, see Antonietti, Luzzago, 2025).

3.3. Workflow construction

To construct our network of labour flows, we begin by merging data from the SILVER dataset with the Survey on the Circular Economy, using the Italian tax code as the key variable. This allows us to associate and trace the corresponding mass of labour flows for each surveyed firm between 2008 and 2020. For both regions under analysis, we further classify firms into four groups based on their engagement with digital technologies and circular economy innovations.

To define these groups, we calculated the median values for the number of Industry 4.0 technologies adopted (1) and the number of circular innovations introduced (3) between 2020 and 2022. The first group consists of firms that are neither digital nor green (*No Digital and No Green*), that is, static firms which, during the 2020-2022 period, adopted no digital technologies and introduced no circular innovations. The second group (*Digital*) includes firms that adopted more than one Industry 4.0 technology but introduced fewer than three circular innovations. The third group (*Green*) represents the opposite case: firms that adopted fewer than one Industry 4.0 technology but introduced more than three circular innovations. Finally, the fourth group (*Green and Digital*) comprises firms that exceed the median values for both the number of Industry 4.0 technologies adopted and the number of circular innovations introduced.

For each group of firms in both regions, we analyse the corresponding networks of labour flows, using three-digit occupational codes (*Codici Profes-*

Table 2: Number of firms and working contracts by group and region*

Region		No-no	Digital	Green	G&D	Tot
Emilia-Romagna	firms	371	142	39	45	597
	Working contracts	8.898	6.530	3.178	2.832	21.438
Veneto	firms	458	185	76	112	831
	Working contracts	17.648	7.080	3.390	8.920	37.038

Note: * The results were also calculated considering the entire set of firms, divided into groups based on the presence or absence of technology adoption or circular innovations.
Source: ???.

sionali – CP2011). Our objective is to identify which occupations are most central within these networks and to determine whether there are notable differences in the density and heterogeneity of labour flows across the four groups, particularly between the *No Green and No Digital* group and the *Green and Digital* (*G&D*) group. To this end, the first step is to define an appropriate time frame for the analysis of labour flows. Beginning in 2008 would result in an excessively long observation period, potentially including flows that are too distant in time from the period of interest. Conversely, a time frame that is too short might fail to capture relevant transitions in a worker's career. Therefore, we adopt a six-year window, from 2014 to 2020, representing half of the available years in the SILVER dataset. This approach allows us to examine the incoming labour flows characterising the four types of firms by constructing their respective networks and deriving synthetic indicators of density, connectivity, and variety.

At this point, the main question is how to identify the workflows relevant to our investigation. Given that, over six years, everyone may have held several jobs before entering a contract with a firm in the survey in 2020-2022, the key point is to understand which starting point to select in an employee's work history. A first approach might be to consider, for each employee, the entire work history before entering a labour contract with a surveyed firm. However, a glance at the data shows us frequent job changes that are often inconsistent in terms of occupational codes and, therefore, the relative skills acquired. For this reason, we decided to consider the most frequent job code (i.e. the mode) during the 2014-2020 period, with the idea that it is related to the competences and skills that were most, or most frequently, developed by each worker before joining one of the four groups of firms. Table 2 shows the number of firms and labour flows (i.e., labour contracts) for each group of firms in both regions[2].

[2] The labour flows in Table 2 are built considering only those workers characterised by two employment relationships. Some workers had only one employment relationship, but this is not relevant for our analysis, as it does not generate flows by moving between two occupational codes.

4. Network analysis

The next step involves conducting a network analysis of the labour flows characterising the four groups of firms and their respective occupation spaces. This exercise is particularly valuable as it enables us to assess whether firms that are partially (*Digital* or *Green*) or fully (*G&D*) engaged in the twin transition exhibit a different structure of incoming workflows and a different occupation space compared to firms that are less engaged in the twin transition. The analysis of incoming workflows enables a better understanding of variations in their heterogeneity, whereas the representation of occupational spaces offers insights into the occupational profiles most closely aligned with the existing labour force structure within each group.

4.1. Incoming workflows

First, we present the main tools and metrics we developed for the analysis of the incoming workflows.

We first define the network structure (Wasserman, Faust, 1994) of all the labour flows, taking the three-digit CPs as nodes and the workflows among CPs to define the links. More precisely, we define directed and unweighted networks, where g denotes the firm group and r represents the region, Emilia-Romagna or Veneto[3]. The fundamental components of each graph are the nodes V_i and the edges E_{ij}, where i and j correspond to different occupational codes (CP) at the three-digit level[4]. Each node thus represents a specific occupational code i, while the edge is a binary variable equal to 1 if a worker's transition from occupation i to occupation j is observed, and 0 otherwise. As we consider directed networks, the adjacency matrices are asymmetric, such that $E_{ij} \neq E_{ji}$.

The next step is to examine whether *Green* and *Digital* firms require, before committing to digital and green innovation, a denser and more diversified occupational set. We compare the workflow network of *No Green and No Digital* group with those of the other three groups of firms. A simple comparison of network measures across graphs may appear viable; however, such comparisons are complicated by the fact that the workflow datasets underlying each group vary significantly in size. For example, in the Veneto region, the *No Green and No Digital* group comprises 17,648 working contracts and generates 8,824 edges, whereas the *Digital* group includes 7,080 working contracts and 3,540 edges. When making the adjacency

[3] In the formulas that follow, the subscripts r and g are omitted for simplicity, as they are applicable throughout the analysis.

[4] Italian occupational codes (*Codici Professionali* – CP) are based on the International Standard Classification of Occupations (ISCO) and refer to standardised classifications of jobs and professions, used to categorise workers based on their tasks and skills. For further information, see ISTAT (2013).

matrix binary to represent unweighted flows, we should expect that the *No Green and No Digital* group, having nearly four times as many edges, would naturally exhibit a higher number of occupational code combinations. An alternative approach would be to normalise network measures by group size. However, this strategy is also problematic, given that we are dealing with binary (unweighted) networks. Normalisation fails to account for the fact that, as networks become denser, the likelihood of generating new unique edges for each additional workflow diminishes. Consequently, normalising by size may introduce bias, leading to an underestimation of the network characteristics for larger groups.

To address this issue and enable a meaningful comparison, we chose to equalise the size of the *No Green and No Digital* group networks to match those of the *Digital*, *Green*, and *G&D* groups, respectively. This procedure is applied separately for each region, beginning with Emilia-Romagna and then replicated for Veneto. Specifically, we extract the list of edges from the *No Green and No Digital* group and truncate it at a threshold k, which corresponds to the number of edges in the comparison group (e.g., *Digital*, *Green*, or *G&D*). To avoid bias in edge selection, we generate 5,000 random samples of k edges directly from the original workflow dataset, thereby creating 5,000 synthetic networks that reflect the underlying structure of the *No Green and No Digital* group. For each of these networks, we compute the relevant network measures and test for statistically significant differences between the groups. More in detail, let us consider a network indicator m that we wish to test. We compare the distribution of the synthetic values of m, derived from the 5,000 randomly generated networks of the *No Green and No Digital* group, with the observed value of m from the actual network of the comparison group. For each comparison, we compute the probability $p_i = f_i/5000$, where f_i is the number of times the synthetic value of m exceeds the observed value from the actual graph. If p_i is less than 5%, we interpret this as evidence that the network measure m extracted from the actual group is significantly higher than that of the *No Green and No Digital* group, at the 5% significance level (Milo *et al.*, 2002)[5]. We focus on three metrics that capture the global density and connectedness of the workflow network, the indegree connectedness of each node of the network, and the heterogeneity of links that we reformulate in terms of related and unrelated variety.

[5] When randomising the lists of edges, we retain transitions in which the occupational code remains unchanged (e.g., from CP 121 to CP 121). These self-loops capture cases where a worker obtains a new employment contract without changing occupation. Consequently, part of the observed variation in our centrality measures may stem from the presence of such transitions, which do not entail actual occupational mobility.

4.1.1. Network density

We start by considering *density*, a global measure computed as the ratio of the number of links and the number of total possible links in a network (Wasserman, Faust, 1994; Jackson, 2008), as in Equation [1]:

$$density = \frac{\sum_i \sum_j E_{ij}}{n(n-1)} \text{ for all } j \neq i \qquad [1]$$

where i and j are three-digit occupational codes (CP). A higher value reveals that the observed network is more connected relative to the maximum number of possible connections. In our context, density can take two meanings. It can be a measure of overall connectedness, where a higher density implies that a larger proportion of all possible connections between occupations are realised through actual worker transitions. Second, it can be conceived as a measure of labour mobility diversity: a higher density might indicate that workers are transitioning between a wider variety of occupations, suggesting a more diversified and flexible employment structure. Comparing the density of the *No Green and No Digital* group versus the *Digital*, *Green*, and *G&D* groups could help assess whether firms that are planning to engage in digital or green transitions require *ex ante* more occupational diversity, as indicated by more numerous or varied transitions between job types.

4.1.2. Normalised indegree centrality

We now turn to local measures of node centrality in our workflow networks. Specifically, we are interested in counting the jobs performed by employees who then worked, with job i, in our sample companies (*Green*, *Digital*, *G&D*, and *No Green and No Digital*) between 2020 and 2022. One such measure is, for example, the *normalized indegree centrality* (Wasserman, Faust, 1994), which counts how many different occupations (i.e., CP) «feed into» occupation i through observed labour flows over the whole number of possible links. In other words, the indegree allows counting how many inflows from different occupational codes, for each specific occupational code of surveyed firms, where observed. In the context of firms engaged in digital or green innovation, higher indegree connectedness may indicate that these firms require job roles that are fed by a more diverse set of prior experiences, pointing to greater skill variety or multidisciplinary integration. In Figure 1, we consider the example of node (CP) 422 «Customer reception and information clerks» (**colour: light blue**). Figure 1 (left graph) shows that the *degree* of node 422 is equal to 14, which can be computed as in Equation [2]:

$$degree_i = \sum_j E_{ji} + E_{ij} \text{ for all } j \neq i \qquad [2]$$

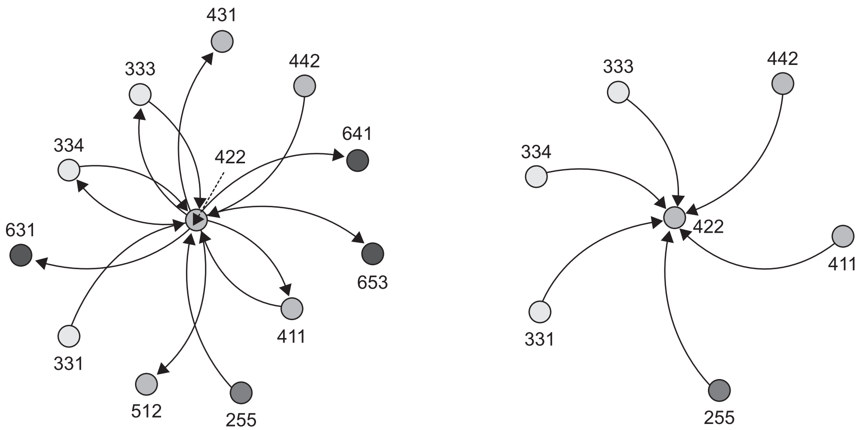

Figure 1: Indegree connectedness of occupation 422.
Source: ???.

where the first element of Equation [2] counts the incoming edges for node i in region r, while the second counts the outgoing edges. In our specific case, we are interested in the incoming edges and look specifically at the *indegree* measure defined as:

$$indegree_i = \sum_j E_{ji} \text{ for all } j \neq i \qquad [3]$$

The indegree for node 422 is 6, as shown in Figure 1 (right graph). An increase in the indegree for node 422 would mean that workers with CP 422 employed in a surveyed firm in 2020-2022 come from a higher number of previous occupations and therefore have a more varied job experience.

By normalising the indegree using all the possible edges of a graph, we obtain the *normalised indegree* of node i, as follows:

$$norm-indegree\ centrality_i = \frac{\sum_j E_{ji}}{n-1} \text{ for all } j \neq i \qquad [4]$$

where $n - 1$ is the maximum number of incoming edges a node can have (excluding self-loops).

Following the same methodology used in Section 4.1 for density, we compare the normalised indegree of each node in the synthetic *No Green and No Digital* network with the normalised indegree of each node of the *Digital*, *Green*, and *G&D* groups in both regions.

4.1.3. Within and between occupation variety

The final step involves identifying which types of occupations are more strongly associated with each node within each group, relative to the baseline *No Green and No Digital* group. To this end, we adopt an approach analogous to that used in the computation of relatedness or related and unrelated variety indicators based on real inter-industry labour flows (Boschma *et al.*, 2014; Neffke *et al.*, 2017; Farinha *et al.*, 2019; Hane-Weijman *et al.*, 2022) but adapted to our data. First, we employ a weighted representation of our workflow networks: instead of using binary edges, we define links based on the actual number of workflows among occupations. Accounting for the diversity of incoming workflows complements our previous binary analysis, allowing us not only to assess whether *Digital*, *Green*, and *G&D* firms exhibit a more connected network, but also to capture the heterogeneity of these incoming flows. For each three-digit occupational code (CP) observed in the surveyed firms, we distinguish between two types of incoming workflows: those originating from the same one-digit CP, used to compute *within-occupation* variety, and those originating from different one-digit CPs, used to calculate *between-occupation* variety. For example, for the job code 422 in Figure 3, within-occupation variety captures the distribution of the incoming (three-digit) workflows within the one-digit code 4, while between-occupation variety captures the distribution of all the (three-digit) workflows outside the one-digit code 4.

The degree of both within and between variety is calculated using the Shannon entropy index $\sum_{j=1}^{J} p_j log_2\left(\frac{1}{p_j}\right)$, which captures how evenly the shares of three-digit occupations p_j ($j = 1 \ldots J$) are distributed within each node's sub-network. A higher value of the within-occupation variety index indicates that incoming workflows are evenly distributed among multiple three-digit occupations within the same one-digit CP. Conversely, a lower value suggests that incoming workflows are concentrated in a limited number of such occupations. Similarly, a higher value of the between-occupation variety index implies that, on average, a given node *i* is connected to a more evenly distributed set of three-digit CPs external to its one-digit occupational group. Finally, we aggregate these values across all CPs within each firm group to obtain overall measures of within and between occupation variety. These aggregated values are then compared to those of the synthetic baseline group, *No Green and No Digital*.

4.2. Labour force structure and relatedness

We complement our analysis of worker inflows by focusing exclusively on employed workers in *No Green and No Digital*, *Digital*, *Green*, and *G&D*

Table 3: Number of workers hired by firms by group and region since 2014

Region		No-no	Digital	Green	G&D	Tot
Emilia-Romagna	workers	8.830	7.245	3.746	2.774	22.595
Veneto	workers	16.023	5.911	2.777	7.336	32.047

Source: ???.

firms. This approach shifts the focus from workers' professional backgrounds to their actual roles within these firms, allowing us to compute the average relatedness across the four groups and thus provide a more comprehensive picture of the current structure of the labour force. To this end, we first construct occupation spaces for the *No Green and No Digital*, *Digital*, *Green*, and *G&D* groups in both regions. Specifically, we build an $n \times M$ matrix for each group in each region, where each element M_{fo} represents the number of workers with occupational code o who have established a working contract with firm f after 2014. Table 3 reports the number of workers by group and region.

We compute the Revealed Comparative Advantage matrix (Balassa, 1965), where the element RCA_{fo} is defined as in Equation [5]:

$$RCA_{fo} = \frac{M_{fo} \big/ \sum_o^m M_{fo}}{\sum_f^n M_{fo} \big/ \sum_f^n M_{fo}} \qquad [5]$$

In this specific context, the RCA shows the most relevant occupations for each firm's labour force composition. Following Hidalgo *et al.* (2007), we compute the matrix representing the occupation space as follows:

$$\phi_{oo'} = \min\left\{P(RCA|RCA_{o'}), P(RCA_{o'}|RCA_{o'}) \text{ for all } o \neq o' \right. \qquad [6]$$

In Equation [6], each element $\phi_{oo'}$ refers to the proximity between two occupations; therefore, the matrix ϕ represents the structure of the occupation space of each group in each region.

For each firm, we calculate the corresponding relatedness density to identify which occupations are more coherent with its current labour force structure. The relatedness density of firm f to occupation o is defined in Equation [7]:

$$RD_{fo} = \frac{\sum_o^m \phi_{oo'} M_{fo'}}{\sum_o^m \phi_{oo'}} \cdot 100 \text{ for all } o \neq o' \qquad [7]$$

Finally, we compute the average relatedness, $RD_f = \frac{\sum_o^m RD_{fo}}{n}$, which represents the average degree of relatedness of each firm to its labour force structure. We then compare the average relatedness across the four groups by taking the mean of RD_f within each group, in order to assess whether there are significant differences in group means across regions.

5. Results

In Section 5.1, we present the results obtained from the analysis of incoming workflows, while Section 5.2 reports the findings on relatedness and the ANOVA results concerning the labour force structures of the groups in both Emilia-Romagna and Veneto.

5.1. Incoming workflows

Figures 2 and 3 illustrate the workflow networks for the four groups of firms in Emilia-Romagna and Veneto, respectively. The graphs are visualised using the ForceAtlas2 layout algorithm, which tends to position nodes with higher degree centrality closer to the centre of the network.

Node colours are determined by the first digit of the occupational code: warmer **colours** (e.g., r**ed, orange, yellow**) represent higher-skilled professions (e.g., one-digit CP 1, 2, and 3), while **cooler colours** (e.g., **blue, green, dark green**) indicate lower-skilled professions (e.g., one-digit CP 6, 7, and 8). In Figure 2, which refers to Emilia-Romagna, we observe a clear clustering of nodes based on skill level. High-skilled occupations tend to group, as do low-skilled ones, forming visually distinct clusters. Additionally, a key feature emerging from the networks is the greater degree centrality of low-skilled occupations, which consistently occupy more central positions across all four graphs.

In Figure 3, which presents the networks for the Veneto region, we again observe a clustering of nodes based on skill levels, with warm- and cool-coloured nodes forming distinct groups. Notably, nodes corresponding to lower-skilled occupations (**blue, green, and dark green**) tend to occupy more central positions in terms of connectedness, thus showing a higher degree of centrality. We also observe that, in *G&D* (and *Digital*) firms, the **yellow and red nodes** (corresponding to the most highly qualified occupations) are, on average, larger and positioned closer to the centre than those in the benchmark *No Green and No Digital* firms. We now consider a set of different metrics to better highlight some specific features of the networks shown in Figures 2 and 3. Table 4 reports the results related to network density. The values of p_i indicate the probability that the density of each group's workflow network is lower than that of the synthetic *No Green and No Digital* benchmark network.

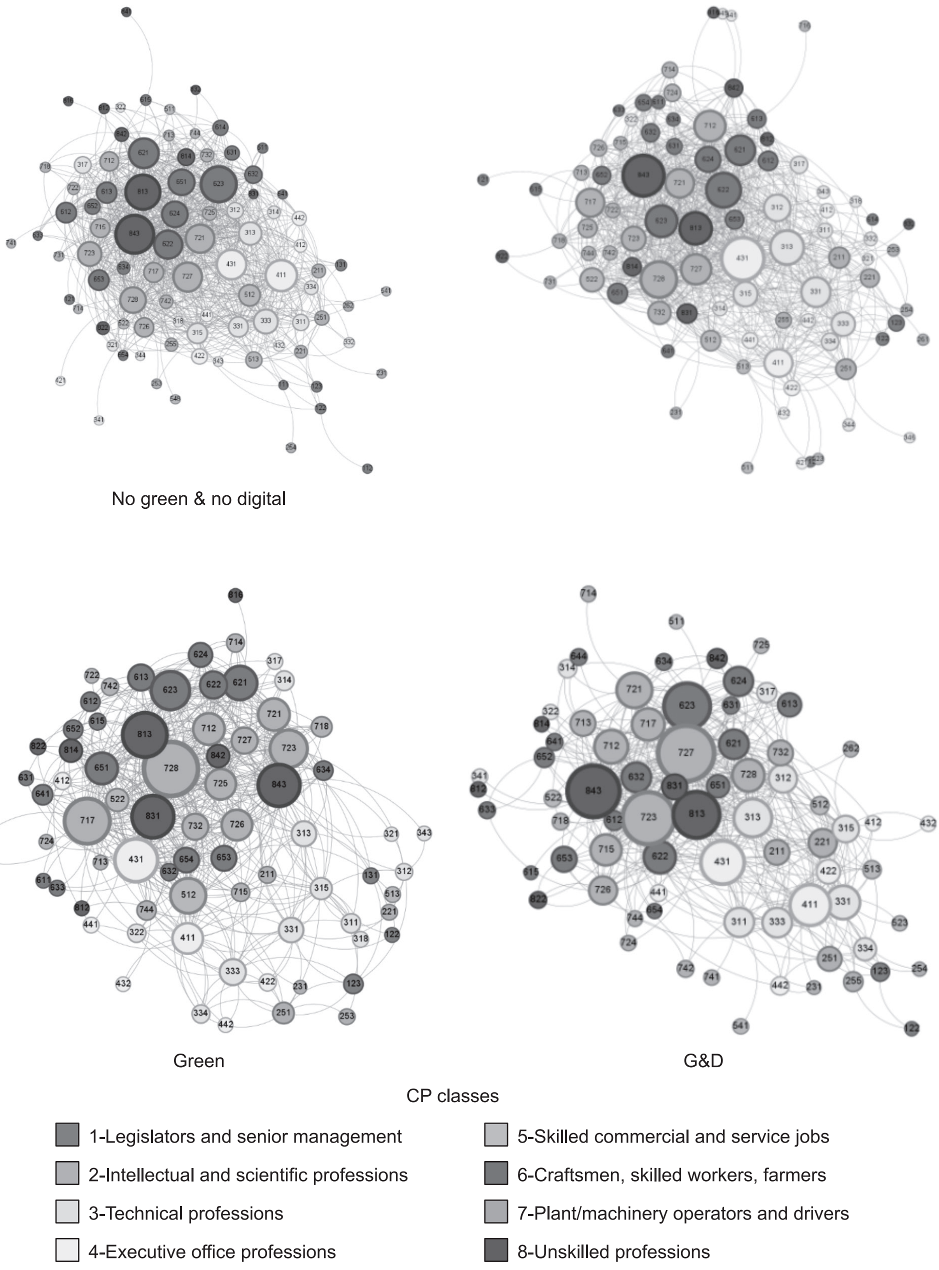

Figure 2: Workflow network of Emilia-Romagna.
Source: ???.

In both regions, the workflow networks of *Green* and *G&D* firms are significantly denser than those of the benchmark group (*No Green and No Digital*). The probability that the density of a synthetic *No Green and No*

Figure 3: Workflow network of Veneto.
Source: ???.

Digital network exceeds that of the *Digital*, *Green*, or *G&D* networks is close to zero. The only exception is the *Digital* group in Emilia-Romagna, where the probability rises to around 2%, still providing strong evidence that this group's network is denser than that of the *No Green and No Digital* firms.

Table 4: Network density comparison

	Emilia-Romagna		Veneto	
Group	*Density*	*p*	*Density*	*p*
Digital	0.0496	0.0000	0.0544	0.0000
Green	0.0322	0.0000	0.0349	0.0000
G&D	0.0299	0.0242	0.0618	0.0000

Source: ???.

These results suggest that firms specifically engaged in CEIs, those adopting digital technologies, or those combining digital and green innovations, exhibit more connected and diversified networks of labour flows compared to firms not involved in either of these transitions.

As previously noted, density is a global measure; therefore, to further enrich our analysis, we examine *normalised indegree centrality* to explore how connections within our groups' networks differ when focusing on specific occupations. The results are presented in Figures 4 and **Table 5**. In Figure 4, for each region, the columns correspond to the three firm groups (*Digital*, *Green*, and *G&D*), while each row corresponds to a three-digit occupational code. White cells represent CPs for which no labour flows are observed in either of the two groups under comparison, making the comparison meaningless, or CPs for which p_i lies between 0.05 and 0.95. **Blue** and **red** cells, instead, identify CPs whose normalised indegree is compared with that derived from the synthetic randomised network of the *No Green and No Digital* group. **Blue cells** indicate cases where $p_i > 0.95$, that is, where the normalised indegree in the synthetic group is higher than in the observed group, whereas **red cells** denote cases where $p_i < 0.05$, meaning that the normalised indegree in the synthetic group is lower than that observed in the empirical network.

Table 5 summarises the results by counting, by one-digit occupational code and firm group, the number of times in which p_i is lower than 5% (**red cells**, left number) compared to the number of times in which p_i is higher than 95% (**blue cells**, right number). Interestingly, we observe that *Digital* and *G&D* firms display a higher share of **red cells** in both regions for technical and professional occupations (CP code 3). In both Emilia-Romagna and Veneto, plant operators (CP code 7) in *Digital*, *Green*, and *G&D* firms exhibit a **red-to-blue cell** ratio greater than one. Conversely, for CP code 2 (intellectual and scientific professionals), a higher share of **red cells** is observed only in the *Digital* group in Emilia-Romagna.

It is also noteworthy that, in Veneto, there is a greater-than-one share of **red** cells among skilled occupations related to service and commercial activities. On average, for both the *Digital* and *G&D* groups, the number of **red** cells exceeds that of **blue** cells, indicating that their workflow networks are denser and more diversified than those of *No Green and No Digital* firms.

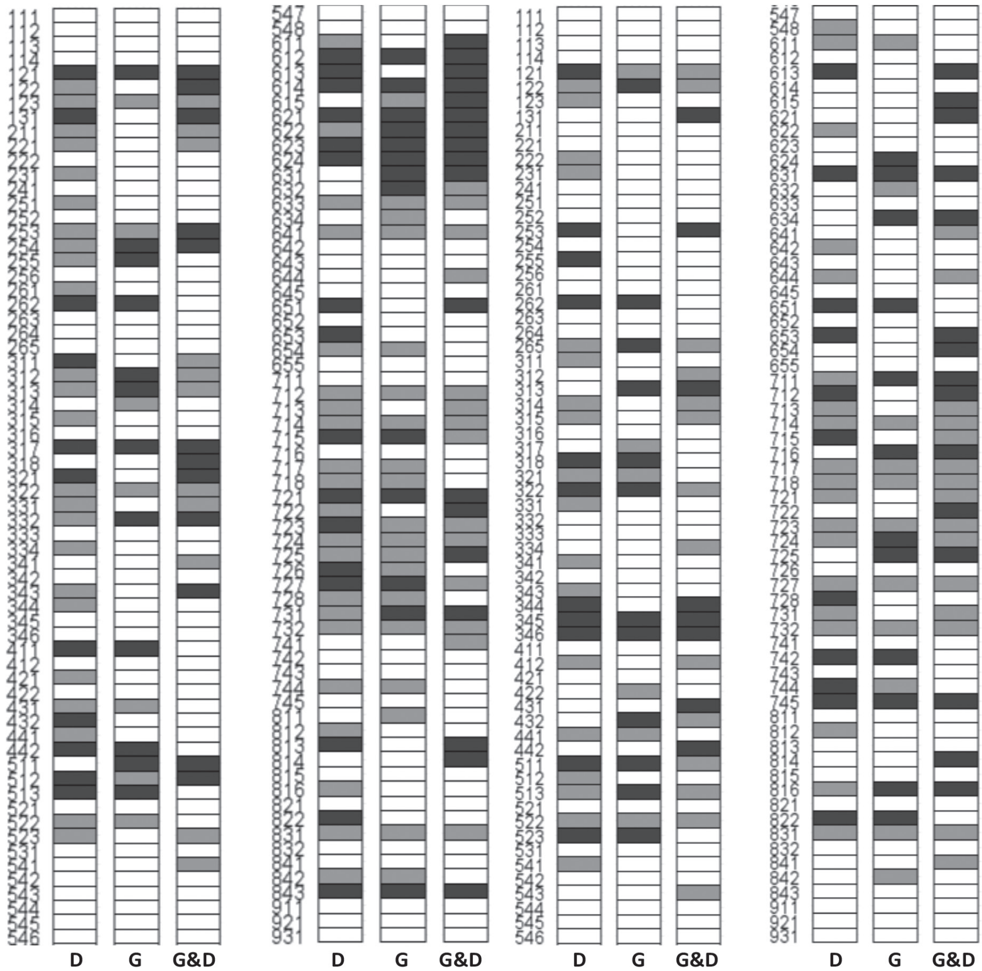

Figure 4: Comparison of indegree connectedness across three-digit occupations.
Source: ???.

To conclude our analysis of incoming workflows, we also examine the within- and between-occupation variety in the weighted networks, to assess whether *Digital*, *Green*, and *G&D* firms exhibit more heterogeneous incoming workflows than static firms. Table 6 reports the results of this comparison.

We find that, with few exceptions, both forms of variety are significantly greater in *Green*, *Digital*, and *G&D* firms than in the synthetic *No Digital and No Green* group. This reinforces the notion that firms planning to adopt digital technologies and/or introduce new products or processes aligned with circular economy principles require a diversified portfolio of jobs and underlying skills. Our findings indicate that this heterogeneity is pronounced not only

Table 5: No. of cases where $p_i < 0.05$ (<u>red cells</u>)/ No. Of cases where it is higher than $p_i < 0.95$ (<u>blue cells</u>)

	Emilia-Romagna			Veneto		
CP	D	G	G&D	D	G	G&D
1 – Managers, entrepreneurs	2/2	1/1	1/3	2/1	1/1	2/1
2 – Intellectual, scientific professionals	**8/1**	1/3	2/2	3/3	0/2	1/1
3 – Technical professionals	**9/3**	2/4	**6/5**	**7/5**	2/5	**5/4**
4 – Executive professionals in office works	3/3	1/2	0/0	2/0	2/1	2/2
5 – Skilled professions in commerce and services	2/2	2/2	2/2	**5/2**	1/3	**4/0**
6 – Craftsmen, farmers	5/8	5/8	4/11	4/4	2/4	2/7
7 – Plant operators	**12/5**	**11/4**	**9/4**	**11/6**	**7/6**	**11/6**
8 – Unskilled professions in commerce and services	4/3	3/1	1/3	3/1	2/2	2/2
9 – Armed forces	0	0	0	0	0	0

Source: ???.

Table 6: Within-occupation and between-occupation variety

Emilia-Romagna	*Within*	*p*	*Between*	*p*
Digital	61.9025	0.0000	151.0671	0.0000
Green	43.6116	0.0012	114.1303	0.0000
G&D	40.7299	0.2578	108.2931	0.0074
Veneto	*Within*	*p*	*Between*	*p*
Digital	75.5773	0.6012	162.793	0.0000
Green	52.3334	0.0000	122.2606	0.0000
G&D	83.0031	0.0030	175.5097	0.0000

Source: ???.

within the distributions of occupations sharing the same first-digit code but also across different first-digit codes, suggesting that variation in professional backgrounds may encompass occupations that are relatively distant in terms of professional classification. The implication is that companies wishing to adopt digital technologies and introduce circular innovations need a more diversified and diverse set of skills and professional profiles, demonstrating the multidisciplinary nature of the knowledge domains underpinning TT.

5.2. Relatedness and ANOVA on labour force structure

Finally, we conclude our analysis looking at the labour force structure of the *No Green and No Digital*, *Digital*, *Green*, and *G&D* firms for which we

Table 7: Average Relatedness density by group and region

	Emilia-Romagna	Veneto
Group	*Av. Relatedness density*	*Av. Relatedness density*
No-no	8.9914	8.8914
Digital	11.9063	11.3036
Green	14.9474	13.1036
G&D	13.4577	13.4166

Source: ???.

Table 8: Analysis of variance between firms' groups by region

Regions	Source of variation	df	Sum of squares	Mean square	F	p-value
Emilia-Romagna	Firm's groups	3	1.939.349	646.450	13.932	0.000
	Residuals	500	23.200.434	46.401		
Veneto	Firm's groups	3	2.445.815	815.272	18.925	0.000
	Residuals	716	3.0843.829	43.078		

Source: ???.

have computed the average relatedness of each group in each region[6]. The results are shown in Table 7.

In both regions, the benchmark group, *No Green and No Digital*, has a lower average relatedness than the other groups. In Emilia-Romagna, the group with the highest average relatedness is the *Green* one, while in Veneto, it is the *G&D* one.

To be sure that the differences in average relatedness between groups are statistically significant, we perform an analysis of variance (ANOVA). The results are presented in Table 8.

For both Emilia-Romagna and Veneto, the results of the ANOVA show that the difference in the groups' average relatedness density is significant at the 1% level.

We further assess the significance of pairwise differences in the average relatedness of each group using the Tukey HSD test[7]. The results, presented

[6] The results of the average relatedness density were also calculated considering individual 1-digit occupational codes, yielding similar outcomes.

[7] The Tukey HSD (Honestly Significant Difference) test is a post-hoc analysis used after ANOVA to identify which pairs of group means differ significantly while controlling for Type I error. It compares all possible pairs of means using a single value of the studentised range statistic, providing confidence intervals for the differences and indicating which differences are statistically significant.

Table 9: Tukey HSD – Emilia-Romagna

Comparison	Mean difference	Conf. low	Conf. high	p-value
2-1	2.915	1.092	4.738	0.0002
3-1	5.956	2.639	9.273	0.0000
4-1	4.466	1.654	7.278	0.0003
3-2	3.041	-0.454	6.536	0.1130
4-2	1.551	-1.468	4.571	0.5480
4-3	-1.490	-5.588	2.609	0.7850

Source: ???.

Table 10: Tukey HSD – Veneto

Comparison	Mean difference	Conf. low	Conf. high	p-value
2-1	2.412	0.842	3.982	0.0005
3-1	4.212	2.027	6.398	0.0000
4-1	4.525	2.647	6.403	0.0000
3-2	1.800	-0.595	4.194	0.2140
4-2	2.113	-0.005	4.230	0.0507
4-3	0.313	-2.294	2.920	0.9900

Source: ???.

in Table 9 for Emilia-Romagna and Table 10 for Veneto, indicate that the lower average relatedness observed in the *No Green and No Digital* group is statistically significant at the 1% level when compared with all other groups. No additional significant differences emerge in the pairwise comparisons for Emilia-Romagna, whereas in Veneto, a significant difference is observed between the *Digital* and *G&D* groups at the 90% confidence level.

6. Conclusions

This paper has analysed the workflow networks characterising firms oriented towards adopting digital technologies and/or introducing circular economy innovations (CEIs), which are typically considered part of the green components of the twin transition (TT). These innovations are valued not only for their potential to decouple manufacturing processes from material resource use but also for their role in mitigating the environmental footprint of digital technologies. The aim is to investigate whether firms engaged in the twin transition exhibit, prior to adoption, a more diversified workflow structure, oriented towards skill-intensive occupational profiles and a broader range of incoming occupations. In doing so, we want to test whether, as suggested by the literature on green jobs (Vona *et al.*, 2019) and green patents (Barbieri *et al.*, 2020), the twin transition is, on average, associated with more coherent or diversified incoming occupational profiles for firms (Burger *et al.*, 2019; Buyukyazici, Quatraro, 2025).

To do this, we combine two types of data sources: administrative data based on mandatory reporting from the *Sistema Informativo Lavoro* Emilia-Romagna and Veneto, and survey data on manufacturing firms operating in the same two regions between 2020 and 2022.

After constructing the inflows for four distinct types of firms, namely *No Green and No Digital*, *Digital*, *Green*, and *Green and Digital* (*G&D*), by adopting a network analysis approach we calculated three global and local indicators that gave us indications of the density of the network of flows, the amount of contacts that each occupation in 2020-2022 had in the previous six years (2014-2020), and the variety of these occupations. Comparing these indicators against a randomised network concerning the reference sample of *No Green and No Digital* firms, we found that those partially or jointly involved with digital technologies and/or circular innovations are indeed characterised by a denser, more interconnected, and diverse network of labour flows. Our main contribution to the literature, therefore, lies in providing evidence that the increasing complexity of occupational profiles required by the TT is reflected in a more diversified profile of workers entering the firm from the external labour market.

These results bring important managerial and policy implications. From a policy perspective, this evidence can be interpreted in two ways. First, it provides an empirical basis for understanding why firms engaged in, or preparing for, the TT, often face significant challenges in identifying suitable professional profiles. Engaging with a denser and more interconnected network of incoming workers plausibly entails greater time and effort for recruitment processes. This finding aligns with recent evidence indicating that firms must implement extended screening procedures to navigate the growing supply of green skills (Cattani *et al.*, **2025a o b???**). It also helps explain why these firms allocate substantial resources to employee training, aiming to align incoming skill sets with those required in practice at local level, as already suggested in response to the diffusion of digital technologies in the manufacturing industry (e.g., Capello, Lenzi, 2022). Second, the study raises important questions about how human capital is developed by educational institutions, including schools, universities, and vocational training centres. If the development, introduction, and adoption of circular and digital technologies require a highly diversified mix of occupational profiles and competences, then multidisciplinary training pathways, integrating both environmental and digital knowledge, should be prioritised over narrowly focused programmes. Finally, our results emphasise the fundamental importance of human capital for the technological transition, showing that its implementation requires more complex recruitment strategies and may therefore expose firms to skill mismatches and rising training costs. Consequently, the technological transition calls for the coordination of diverse and often unrelated actors across firms, educational institutions, and local governments.

The main limitations of this study concern the exclusion of certain categories of workers from the dataset. First, the SILVER does not include workers hired before 2008 who continuously remained in the same plant until 2020 without any change in qualification or contractual status. This may lead to an overestimation of the relative weight of workflows within firms' workforces. Second, the SILVER dataset covers only workers employed in manufacturing firms, excluding inflows from the tertiary sector and potentially underestimating the occupational variety of such inflows. Third, the spatial restriction to Emilia-Romagna and Veneto implies that our findings primarily reflect workflows in the manufacturing industries in which these regions are specialised, compared to other Italian regions. Finally, we acknowledge a limitation of the survey methodology, as respondents may overestimate or underestimate their innovative performance due to a limited understanding of the theoretical framework underlying the questions.

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