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The relationship between green and digital skill supply and industrial dynamics

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Abstract

We contribute to the literature on the green, digital and twin transitions by providing novel evidence on their implications for industrial dynamics. In particular, we investigate whether the local supply of skills in the green, digital and twin domains is related to firm entry and exit at the NUTS3 level in Italy. We exploit a recently created dataset on the near-universe of Italian university programme descriptions to capture the skills provided through higher education. We find that the supply of green, digital and twin skills enhances opportunities for firm entry. We rule out the possibility that this effect simply reflects the supply of high-skilled labour in general. The supply of green skills may induce higher industrial renewal, being it also correlated with higher exit rates.

Keywords: skill supply; university graduates; industrial dynamics; local economic performance

JEL codes: O33, Q55, J24, R11

1 Introduction

Over the last decades European countries have experienced a profound technological transformation driven by advances in automation, robotization, digitalization, and, more recently, the diffusion of artificial intelligence (AI) technologies (Guarascio et al., 2025; Foster-McGregor et al., 2021; Burlina and Montresor, 2022). This transformation has been accompanied by an urgent call for action on climate change and environmental sustainability (OECD, 2025). The duality of technological advancements in the digital domain and the "greening" of the economy is commonly referred to as twin, that is digital and green, transition.

The capacity to effectively pursue a twin transition strategy relates to (i.e. impacts and depends on) the capabilities of the labour force. Recent studies have examined the employment effects of the twin transition (Leibrecht et al., 2023) documenting heterogeneous impact across firms, sectors, regions, and individuals (European Commission, 2022). Both researchers and policy-makers show a unanimous agreement on the importance of human capital and *skills*, especially from a regional perspective, for successfully adopting emerging technologies and facilitating a green transformation of the economies (Guarascio et al., 2025; OECD, 2023). However, according to the Report on the European Year of Skills (2025)[1], many firms, in particular small and medium-sized enterprises, face a shortage of qualified workers. These trends highlight the need to understand how the availability of specific groups of skills impacts regional economic development paths, in particular those aligned with the twin transition.

Although the positive role of skills and human capital in general for innovation, productivity, and economic performance of regions is well-established in the literature (Faggian and McCann, 2006; Faggian et al., 2019; Lee et al., 2010), much less is known about the local supply of skills, especially for domains closely connected to the twin transition. Existing studies typically investigate the twin transition from a country or sectoral perspective (Leibrecht et al., 2023; Foster-McGregor et al., 2021; Acemoglu and Restrepo, 2022; Card and DiNardo, 2002), often focusing on the demand side, e.g. transition-induced changes in employment and skill demand. As a result, evidence on skill supply in relation to the transition remains scarce. This is calling for a better understanding of the territorial distribution of skills, especially digital and green skills, and their role in local economic performance.

Identifying appropriate proxies for skill supply is a challenging task, especially at lower levels of territorial disaggregation. In this sense, researchers often rely on "indirect" indicators of regional human capital endowments, such as the share of people with tertiary education or composite indicators of universities' performance (Marrocu

[1] Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52025DC0583 (Last accessed January 2026)

et al., 2022; Schubert and Kroll, 2016; Kantor and Whalley, 2014). Despite their computational efficiency, such metrics lack granularity in grasping specific types of skills acquired through academic programs, thereby limiting the analysis and mapping of domain-specific skills.

The aim of this paper is to analyse the relationship between the local supply of green and digital skills and industrial dynamics in Italy. We focus on the skills of university graduates in the green, digital, and twin domains, and investigate how their supply affects firm creation and exit at the provincial (NUTS 3) level. We exploit a dataset that uses detailed records of tertiary education programmes in Italy and links them to the European Skills, Competences and Occupations (ESCO) database to construct a "direct" measure of skill supply (Barbieri et al., 2026). This measure allows us to overcome the limitations of "indirect" human capital indicators and to provide a more comprehensive and domain-specific assessment of skill supply at the provincial level.

Our results point to a nuanced and non-trivial role of skill supply in shaping local industrial dynamics. Focusing on degree programmes in the top 25% of the national distribution by skill orientation, we find that the supply of digital, green and twin skills is positively associated with firm entry. These effects are robust to the inclusion of a rich set of province-level controls and suggest that highly specialised competences aligned with the twin transition foster entrepreneurial activity at the local level. At the same time, entry effects are heterogeneous across skill domains. While digital skills appear to stimulate firm creation without significantly relating to firm survival, green skills are associated with higher exit rates, pointing to a more pronounced turnover process. This pattern suggests that green-oriented local economies may experience faster industrial renewal, characterised by both higher firm entry and higher firm exit. By contrast, the absence of a significant exit effect for digital and twin skills indicates more stable entrepreneurial dynamics in these domains. We seek to corroborate our evidence through a placebo test and confirm that the above mentioned evidences are peculiar of green, digital and twin skills instead of high-skills in general.

The contribution of this paper is twofold. First, we contribute to the nascent literature that leverages granular data on university programme descriptions (e.g. Han et al., 2023; Javadian Sabet et al., 2024). Exploiting a recent dataset for the Italian context (REF), we show that these data can provide useful information on skill supply and thus on its effects. REF's data originates from skills descriptions coming from the Skills, Competences, Qualifications and Occupations (ESCO) classification. This ensures that the indicators used in our paper are not only suitable for the case of Italy, but could be compared to other European contexts, whenever analysts are in the position to access representative data on university programmes and the number of graduates. Second, we offer novel empirical evidence on the role of directly measured skill supply for local industrial dynamics (Valero and Van Reenen, 2019). By identifying university programmes predominantly targeting the supply of green and digital skills, we investigate how they relate to firm creation and exit at province level. Our analysis contributes to the emerging literature on twin transition and provides important insights into its supply-side determinants.

The remainder of the paper is structured as follows. Section 2 builds theoretical framework by reviewing relevant literature on skills, regional development, and digital and green transition. Section 3 describes the data sources and methodology. Section 4 reports the results, and the last section concludes.

2 Literature review

Given the aim of this paper, in this section we outline two interrelated streams of research. The first avenue of research explores human capital accumulation and upgrade through universities and its contribution to regional economic development. The second stream of research explores the relation between green and digital transitions, occupations and skills.

2.1 Human capital and regional economic performance

To set the stage, over the past decades, the EU labour market has undergone a structural shift marked by rising demand for high- and low-skilled jobs accompanied by a simultaneous weaker demand for jobs in the middle of the distribution (Eurofound, 2020). This phenomenon, observed in many developed countries and known as labour market polarization (Jaimovich and Siu, 2020; Autor and Dorn, 2013), has been initially explained by the skill-biased technological change hypothesis (Acemoglu, 2002; Card and DiNardo, 2002). More recently, however, the shrinking share of mid-paid jobs - which also require performance of repetitive tasks - has been attributed to the routine-biased technological change (Goos et al., 2014).

A positive effect of skills and human capital on regional development is a well-established finding in the literature (Faggian et al., 2019). In their seminal paper, Acemoglu and Dell (2010) demonstrate that within-country differences in terms of income inequality are to a large extent explained by differences in the local human capital endowment. Some existing contributions find positive spillover effects of skill supply from universities to local economies (e.g., Kantor and Whalley, 2014). Moreover, an increase in skill supply is shown to drive the demand of local labour markets for higher skills (Carneiro et al., 2022). Other studies highlight a positive role of universities in fostering regional economic growth (Agasisti and Bertoletti, 2022; Agasisti et al., 2019; Valero and Van Reenen, 2019) and enhancing productivity (Marrocu et al., 2022; Buendía Azorín and del Mar Sánchez de la Vega, 2015). In addition, Schubert and Kroll (2016) find that universities also play a role in reducing the local unemployment rate. At the same time, universities themselves operate in an increasingly more competitive (and internationalised) environment, aiming to attract students by introducing new programmes and withdrawing others (Hewitt-Dundas and Roper, 2018).

Although many empirical studies examine the role of universities in regional economic development, they rely on "indirect" proxies for human capital and skills. In particular, some papers reviewed in this subsection use the number of universities in the region as a proxy of local human capital and estimate its contribution to the regional GDP (Agasisti and Bertoletti, 2022; Valero and Van Reenen, 2019). Other studies consider efficiency metrics of universities and analyze their impact on the regional GDP. More specifically, Agasisti et al. (2019) construct a composite index based on three pillars to capture university efficiency: the number of graduates, academic publications, and spin-offs. Similarly, Schubert and Kroll (2016) consider different demand- and supply-side indicators of universities' performance, such as, for instance, the number of students, staff, graduates, publications, third-party funding etc., to study the impact of higher education institutions on the local GDP and labour market. Kantor and Whalley (2014) use university expenditures to investigate knowledge spillover effect from universities to local economies. A more general measure of local human capital is applied by Marrocu et al. (2022) and Buendía Azorín and del Mar Sánchez de la Vega (2015) who rely on the share of people with a tertiary education over the total population in the region. Regarding skill supply, Carneiro et al. (2022) use the data on new regional college openings to estimate the impact of increased skill supply.

Within this line of research, several studies scrutinize more closely the relation between knowledge, skills, innovation and economic growth. For instance, Faggian and McCann (2006) demonstrate a positive association between university graduates' migration and regional innovation activities. Furthermore, other authors explore the role of universities and graduates' knowledge for industrial dynamics and entrepreneurship. Carlsson et al. (2009) highlight the contribution of university-generated knowledge to the creation of new firms, university spin-offs, and entrepreneurial activities, ultimately driving economic growth. Similarly, Beine et al. (2024) establish a causal link between foreign graduates and start-ups' creation. Other related contributions emphasize the role of knowledge spillovers and spatial proximity in explaining industrial dynamics (see Frenken et al. (2014) for a survey of studies on firms' entry, survival and exit in the context of spatial clustering of industries). Audretsch et al. (2005) show that new technology-intense and knowledge-based firms tend to locate in proximity to universities. This phenomenon is often attributed to knowledge spillovers, which enhance firms' innovation activities (Audretsch et al., 2011). At the firm level, Bonaccorsi et al.

(2024) point to a positive impact from the university graduates for economic performance of firms located in the neighborhood, highlighting again the effect of spatial proximity.

To sum up, existing research commonly acknowledges the fundamental function of universities related to knowledge creation, spillovers, and human capital formation. The positive impact of universities on regional economic performance typically captures level effects for local GDP associated with knowledge accumulation and human capital formation (Agasisti and Bertoletti, 2022; Agasisti et al., 2019). The impact on industrial dynamics shows a different mechanism, in which universities are essential actors enabling regions' transformation and adaptation to technological change (Brekke, 2020; Cassia et al., 2008). However, what remain underexplored is the role of local skill supply for entrepreneurial activities in the region. To the best of our knowledge, a "direct" domain-specific indicator of skill supply, especially at regional or local level, has not been developed yet. This is a knowledge gap which we intend to address, paying particular attention to the territorial unfolding of the green and digital transitions (Faggian et al., 2024).

2.2 Digital and green transition, occupations and skills

The ongoing green and digital transition, also known as twin transition, is transforming occupations and labour market structures, having important implications at the national, regional, firm and individual levels. In this context, the availability of skills becomes crucial.

When considering digital and green occupations, it is important to highlight the differences between these two domains. In particular, the adoption of green technologies - and the enabled growth in green employment - is connected to regulatory framework and environmental policy goals, rather than by "pure" market incentives and profit-oriented behaviour of firms (Vona et al., 2018; Consoli et al., 2016; UNEP, 2011; Jaffe et al., 2003). This specificity of green transformation and related occupations distinguishes them from digital technologies - and occupations requiring digital skills - which are primarily driven by market forces and competition among firms. In fact, Massini et al. (2022) show that improved processes/methods and expansion of goods/services range are among the main reasons why firms adopt advanced digital technologies in the UK.

Environmental regulation seems to have important implications on employment outcomes (Vona et al., 2018). In fact green occupations often require higher non-routine analytical skills and human capital characteristics (Consoli et al., 2016), and are predominantely high-skilled jobs (Vona et al., 2019).[2] Moreover, as suggested by

[2]It should be noted, however, that the discussed empirical exercises performed by Vona et al.

Vona et al. (2019), green occupations are often spatially concentrated. This finding is particularly striking from a regional perspective as some regions tend to lag behind in meeting the requirements of the greening economy. Therefore, stricter environmental regulations and geographical concentration of green jobs and corresponding skills can exacerbate existing territorial disparities, making left behind territories even more vulnerable (Rodríguez-Pose and Bartalucci, 2023).

As for the second domain, i.e. digital one, the role of digital technologies is frequently investigated from technology adoption perspective. Recently, researchers have established a micro-level approach to examine the relationship between technology adoption, automation and robotization on worker flows (Bachmann et al., 2024), and perceived work quality and job meaningfulness (Nikolova et al., 2024). The interplay between institutional factors, such as employee representation, and adoption of advanced technologies and automation risk has been explored at firm (Belloc et al., 2023) and individual (Belloc et al., 2022) levels. Other contributions focused on the impact of Artificial Intelligence (AI) on employment, occupational tasks and wages. By doing so, Lane and Saint-Martin (2021); Agrawal et al. (2019); Arntz et al. (2017) reported low (country-level) unemployment risks associated with the adoption of AI.

By taking a slightly different perspective, Ciarli et al. (2021) developed a conceptual framework of co-evolution between digital technologies, innovation and skills formation. The findings show that continuous skill adjustment will be required to keep up with rapidly changing technologies. Moreover, similarly to spatial effects of green transformation, digital transition can also exacerbate existing territorial divide due to spatial concentration of digital jobs and resulting higher wage inequality Ciarli et al. (2021).

To the best of our knowledge, the work by Prytkova et al. (2024) is (one of) the first attempt to estimate employment effects of technology exposure across European regions. By considering a broader set of emerging digital technologies (i.e., beyond the AI), the authors find heterogeneous impact of such technologies on the overall employment, and high- and low-skilled occupations. In fact, exposure to new technologies can affect workers unequally, offering potential gains for high-skilled and augmented threats for middle-skilled occupations, resulting in greater job polarization (Prytkova et al., 2024; Lane and Saint-Martin, 2021).

Taken together, the demand-driven impact of technological transformation has been widely explored in the literature (Card and DiNardo, 2002; Goos et al., 2014; Ace-

(2019), Vona et al. (2018) and Consoli et al. (2016) rely on the Occupational Information Network (O*NET) - a classification of occupations, knowledge and skill profiles relevant for the US labour market. However, its applicability to the European labour market context might not be straightforward. For instance, based on ESCO classifications, green jobs are not so markedly high-skilled in the EU context (Landini et al., 2025). Moreover, studies in this field focus on the determinants of green skill demand and green skill shortages due to further greening of the economy, largely overlooking the role of green skill supply.

moglu and Restrepo, 2022). The literature has disentangled the effects of technology adoption on workers, skill demand, firms and employment. However, the complementary perspective, namely the role of skill supply for technological transition, has been largely overlooked. This gap is particularly evident in the case of green and digital skills supply, where evidence remains scarce, especially at lower levels of geographical disaggregation.

Considering the complexities of human capital measurement and the established indirect approach to model skills, our understanding of local skill supply remains limited. This is especially pronounced for green and digital domains, which are central for twin transition. Therefore, this is calling for a better understanding of the territorial distribution of skill supply and scrutinizing their role for local economic development, an aspect that is central in our analysis.

3 Data and methods

3.1 Data

For our analysis we created the harmonized dataset with a province-year structure (i.e., NUTS 3 level[3]) and covers the period from 2018 to 2023, based on data availability.

Our aim in this paper is to estimate the relationship between the supply of green and digital skills and industry dynamics at the province level. We therefore identify firms' entry and exit rates as our dependent variables. We retrieve the annual information on industrial dynamics from the InfoCamere - based on the archives of the Italian Chambers of Commerce - which provides the number of active, newly registered and closed (failed) enterprises of all legal forms. Following the usual approach in the literature (e.g. Audretsch and Fritsch, 1994; Barbieri and Rizzo, 2023) we calculate the entry rate as the ratio between newly created firms in year t to the total number of registered firms in $t-1$ for each province. Similarly, the exit rate is computed as the ratio of closed firms in year t to the total number of registered firms in $t-1$.

Our main variables of interest are green, digital and twin skill supply. Data on skill supply are sourced from the Scheda Unica Annuale (SUA), a mandatory document that every Italian university must submit annually to the Ministry of Universities and Research for each degree programme offered. The SUA provides a standardized account of educational objectives, curricular content, resources, and student services, and is used both for accreditation and quality assurance purposes and as a public

[3]There are 107 provinces in Italy. However, for some of them the variables of interest were not available: in particular, the entry and exit rates are missing for Sud Sardegna (ITG2H) and Barletta-Andria-Trani (ITF48). Moreover, the data on graduates' skills constructed based on SUA were not available for Verbano-Cusio-Ossola (ITC14), Crotone (ITF62), Vibo Valentia (ITF64), Massa-Carrara (ITI11), Pistoia (ITI13) and Grosseto (ITI1A).

information source. We collected all SUA records from 2013 to 2022 and merged with official administrative data on first-year enrollments, achieving coverage of more than 95% of accredited programmes in Italy over the period (see Barbieri et al., 2026). To capture the skill provided by the different programmes, the analysis relies on the ESCO (European Skills, Competences and Occupations) database, which contains almost 14,000 skill entries in Italian, each with a structured textual description.

The next step involved linking course descriptions to ESCO skills by constructing a similarity matrix measuring the degree of alignment between each programme and each skill. The approach consists of segmenting programme texts into short overlapping windows and computing their semantic similarity with ESCO skill descriptions using advanced natural language processing techniques. This yields a high-dimensional representation of each programme's skill profile, allowing systematic comparisons across institutions and over time. The detailed methodology is described in Barbieri et al. (2026).

The resulting skill provision matrix was then employed to map "green" and "digital" programmes in Italy. This was done by calculating, for each degree programme, the average similarity score with the sets of green skills and digital skills identified in the ESCO database. In other words, each programme was assigned a measure of green and digital content based on the mean similarity score across all skills within the respective green and digital skill collections. For what concern the twin skill supply measure we rely on the intersection of the green and digital skills, and replicated the same exercise based on this subsample of skills [4]. Using these scores, we classified a programme as green, digital or twin if it ranked within the top-25% nationally for green, digital and twin content in a given year. We then constructed our variable capturing the supply of skills by considering the number of graduates from bachelor or master courses from the top-25% degree programmes in each province, based on the province in which the degree is taught.

Finally, we also add some control variables to our estimates. First, we need to consider the "general" provision of skill in a province. To this aim we add the number of graduates, net of those getting a degree from courses that are reflected in the focal variable of each specification - i.e. green, digital and twin (or language in the additional placebo estimates, see below). This helps us to isolate the contribution of green and digital skill supply. Then, to account for differences in local economic structure in the light of structural transformation (Duarte and Restuccia, 2010; Jorgenson and Timmer, 2011), we add the share of service sectors in the province's value added. Empirical studies show that tangible and intangible capital belong to the determinants of industrial dynamics. Higher capital intensity might represent higher entry barriers

[4] In a robusntess check we will calcilate as a placebo the language skills supply, and in that case we make use of the language skills collection provided by ESCO

for new firms, while it can reduce the probability of firms' exit (Nyström, 2007). Hence, we control for the province-level stock of fixed and intangible capital. The information on firm-level fixed assets and intangible assets was retrieved from the AIDA database, provided by the Bureau van Dijk. AIDA offers comprehensive data, including the balance sheet data and profit-and-loss reports, for a large sample of companies in Italy operating across various economic sectors. Historical series are available for up to ten years[5] These firm-level balance-sheet data on fixed and intangible assets from AIDA were aggregated to the province level. Then these values were deflated to obtain real province-level measures of fixed and intangible assets. Descriptive statistics is reported in Table 1.[6]

3.2 Methods

The empirical strategy relies on panel-data models exploiting the province-year structure of the dataset described above. To estimate the relationship between local skill supply and provincial economic dynamics, we employ fixed-effects (FE) specifications of the following general form:

$$Y_{pt} = \beta_1 \ln \text{Skills}^g{}_{p(t-1)} + \mathbf{X}_{p(t-1)}\gamma + \mu_p + \tau_t + \varepsilon_{pt} \tag{1}$$

where Y_{pt} denotes, alternatively, the entry rate, exit rate, in province p and year t. The variable $\ln \text{Skills}^g{}_{p(t-1)}$ capture the annual flow of graduates where g represent the number of students in either green-, digital- or twin-intensive degree programmes located in province p (based on the SUA–ESCO skill-matching procedure described in Section 3.1). The vector $\mathbf{X}_{p(t-1)}$ includes a set of time-varying controls that account for the economic structure of each province (share of value added attributable to service), the stock of tangible and intangible assets, and the flow of graduates coming from courses that are not reflected in the focal skill domain of each specification. We lag our explanatory variables by one year as we expect that a higher local skill supply might require some time to be materialised in updated local industrial dynamics. Province fixed effects μ_p control for all time-invariant characteristics-including geography, industrial history, and long-run institutional quality, while year fixed effects τ_t absorb national shocks common to all provinces.

[5] In our case, AIDA data are available for the period 2014–2023. However, we restrict the analysis to the shorter time span 2018–2023 in order to ensure consistency with the graduates' skill supply data derived from the SUA. Specifically, degree programmes in our sample differ in length, including two-year, three-year, and five-year programmes. To correctly link each cohort of graduates to the full set of courses attended during their programme of study, we must observe the entire duration of the longest programmes. Since the SUA data start in 2013, complete information for all graduates is therefore only available from 2018 onwards, which determines the starting year of our analysis.

[6] All independent variables that are not expressed as shares (i.e. share of value added attributable to service sectors) are used in their log-transformed version in the econometric analysis.

4 Results

This section presents the empirical results on the relationship between local skill supply and industrial dynamics at the province level. We first discuss firm entry, and then turn to firm exit. All specifications include province and year fixed effects, and progressively account for local economic structure and capital endowments.

Tables 2, 3 and 4 report the estimates for firm entry rates associated with the local supply of digital, green and twin skills, respectively, measured through graduates from top-quartile degree programmes. Table 2 shows that the supply of digital skills is positively associated with firm entry. While the coefficient on digital skill supply is not statistically significant in the first specification, it becomes positive and significant once controlling for the economic structure and capital endowment. The magnitude of the effect is stable across specifications and suggests that provinces hosting a larger number of highly digital-oriented degree programmes experience higher rates of firm creation. Importantly, the coefficient on the net number of graduates from non-digital programmes remains not significant, indicating that the observed relationship is specific to digital skills rather than reflecting a general expansion in tertiary education.

Results for green skills, reported in Table 3, display a similar pattern. The coefficient on green skill supply is positive and statistically significant across all specifications, with a magnitude comparable with that of the coefficients of digital skills. This evidence suggests that the availability of green skills triggers industrial dynamics and in particular the creation of new firms.

Table 4 focuses on twin skills, defined as degree programmes that exhibit digital and green content jointly. Once again, the results show a positive and statistically significant association between twin skill supply and firm entry across all specifications. The magnitude of the coefficient is comparable to those estimated separately for digital and green skills.

Tables 5, 6 and 7 investigate the relationship between skill supply and firm exit rates, allowing us to assess whether the entry-enhancing effects documented above are accompanied by changes in firms' survival. Table 5 reports the estimates for digital skills. Across all specifications, the coefficient on digital skill supply is positive but not statistically significant. This suggests that, while digital skills appear to foster firm entry, they do not systematically increase or reduce the likelihood of firm exit at the province level. Hence, digital skill provision does not seem to be associated with heightened competitive pressure leading to firm displacement, nor with increased fragility of newly created firms.

A different pattern emerges for green skills in Table 6. The coefficient on green skill supply is positive and statistically significant across all specifications, indicating that provinces with a stronger concentration of highly green-oriented degree programmes also experience higher firm exit rates. At the same time, the coefficient on the net number of graduates from non-green programmes is negative and significant, suggesting that exit dynamics are specifically related to green skill provision rather than to general human capital accumulation. This finding points to an unfavourable risk–reward profile associated with green-oriented skills and industrial activities, potentially reflecting the novelty, regulatory uncertainty, and technological complexity characterising the green transition.

Finally, Table 7 presents the results for twin skills. The coefficient on twin skill supply is positive but not statistically significant, while the net number of graduates from non-twin programmes is negatively associated with firm exit in some specifications. Overall, the exit dynamics associated with twin skills appear closer to those observed for digital skills than for green ones. This suggests that combining green competences with digital capabilities may mitigate some of the risks associated with green-oriented activities, possibly by enhancing firms' adaptability and capacity to cope with technological and regulatory challenges.

Taken together, the results for top-quartile programmes highlight a nuanced role of skill supply in shaping local industrial dynamics. While digital, green and twin skills are all associated with higher firm entry, only green skills exhibit a robust positive relationship with firm exit. This asymmetry suggests that green-oriented regions may experience faster industrial renewal, characterised by both higher firm creation and higher firm turnover. By contrast, digital and twin skills appear to support firm entry without significantly increasing exit, pointing to more sustainable entrepreneurial dynamics.[7]

4.1 Robustness checks

To assess whether our main results are driven by a general effect of high-skilled graduates rather than by domain-specific competences related to the twin transition, we conduct a placebo analysis using language-oriented degree programmes. Language skills provide a suitable falsification test because, while they reflect advanced and transferable competences acquired in higher education, they are not directly related to either digitalisation or environmental sustainability. Therefore, any significant effect associated with language-oriented programmes would suggest that our main results capture a generic graduate supply effect rather than skills specific to the twin transition.

Tables 8 and 9 report the estimates for firm entry and exit rates associated with the local supply of graduates from language degrees in the top 25% of the national

[7]In a series of unreported regressions we explore the possible relation between green and digital skill supply, on the one hand, and labor productivity and innovation (both patenting and adoption of firm practices) on the other hand. Overall, the emerging evidence does not point to systematic and clear-cut relations.

skill distribution. In contrast to the results for green, digital and twin skills, we do not find robust evidence of a significant association between language skill supply and firm entry. The coefficient on language skills is small and statistically insignificant across all specifications, suggesting that the positive entry effects documented above are not driven by a generic expansion in tertiary-educated labour supply.

Similarly, the results for firm exit do not point to a systematic role of language skills in shaping exit dynamics. While the coefficient on language skill supply is positive, it is not statistically significant once controls are introduced. These findings indicate that language-oriented competences do not exhibit the same relationship with industrial dynamics as green and digital skills.

Overall, the placebo analysis strengthens the interpretation of our main results by showing that the estimated effects are not attributable to a broad high-skill channel, but rather to the domain-specific nature of green, digital and twin skills. This supports the view that skills aligned with the twin transition play a distinct role in shaping local industrial entry and exit dynamics.

As a further robustness check we also replicate our analysis with the top 10% green, digital and twin courses from each province and year. Results are reported in the Appendix in Tables A1, A2 and A3 for entry, and in Tables A4, A5 and A6 for exit. This batch of robustness checks reveals no significant effects on firm exit and exit. Reading this latter piece of evidence on highly focused programmes, together with our baseline results, leads us to contend that a certain degree of interdisciplinarity - linking green, digital and twin competences to broader domains and fields of applications - is an important catalyst of the entry dynamics we observed above.

5 Conclusions

The greening and the digitalisation of the economies intertwine with labour in a complex fashion. Large part of the academic and public debate focuses on the way in which said transformations are going to impact on the skills demanded, the tasks performed by workers and the risk that these dynamics may entail on the employment and on job quality (Landini et al., 2025; Vona et al., 2018; Acemoglu and Restrepo, 2018; Nikolova et al., 2024; Nurski and Hoffmann, 2022). Successful green and digital transitions, and the implications these may have on economic and industrial development, depend critically on the availability and supply of appropriate skills. On these matters, the available insights are more limited, due also to data constraint in accessing reliable and systematic information on relevant competences and their provision. With the aim of providing a contribution in this direction our analysis has focused on the extent to which the availability of green, digital and twin skills associate with regional industrial dynamics. We sought to understand whether skills provided by universities in the fields of environmental sustainability and digitalisation allow for the entry and survival of firms. In this sense, we provided evidence on whether the provision of adequate skills determines a renewal of the firms in a region.

Leveraging original data (created by Barbieri et al. (2026)) representing the near-universe of Italian university programmes and natural language process techniques, jointly with the definition of green and digital skills by ESCO, we created indicators of supply of graduates possessing relevant skills in the twin transition domains. Our results support the idea green and digital skill provision can indeed trigger industrial dynamics via entry of firms, especially when considering skills provided by non-narrow courses - that is not overfocused on green and/or digital competences. We also observed a higher risk of firm exit associated with green skill provision. We postulate that this may be associated with the novelty and complexity characteristics of the green transition. Our results, based on a placebo analysis focused on language skills and the control of non-focal (i.e. green or digital) competences seem to exclude the possibility that we are capturing a general high-skill supply effect. In addition, we also observe that the combination of green and digital skills into twin competences associates, like their originating components, with higher entry. In terms of exit, twin skills appear to be closer to the digital component which exerts to significant effect.

While exploratory in its nature, due to the absence of a purely exogenous variation that can be exploited, we believe our results yield relevant implications for policy. At the outset, our analysis appears to support the delivery of green- and digital-targeted, yet not overfocused, programmes that may act as fundamental drivers of industrial dynamics aligned with the challenges of the twin transition. Our results suggest that rather than specific courses, interdisciplinarity may foster twin-aligned industrial dynamics. We hope that future research can shed light on the skills that may fruitfully complement the green and digital ones. On this matter a recent study have put forward the notion of green-, digital-, and twin-enabling skills (Martinelli et al., 2025). We believe this is a useful starting point. Second, the higher exit of firms associated to green skills should be looked at with high attention by the decision maker, in that it may request targeting competences that can smooth the risks associated with the green transition on both firms adopting environmentally sustainable practices and their competitors alike. Notwithstanding, the exit process related to green competences should be carefully considered. An evolutionary lens may consider this process as further reinforcing the industrial renewal, to the extent to which firms exiting the market are those that are unable to produce and deliver green products or services. Unfortunately, the data at end do not allow us to distinguish firms by their uptake of green practices and strategies. We hope that our analysis can pave the way for future research on how skill provision can become an integral part of industrial policies targeting the twin transition. To achieve this goal the possibility to rely on more structured data, which can be accessed by a wide range of analysts and decision makers seem to be necessary. Relatedly, a continuous monitoring and mapping of the relevant skills is advisable, given the ongoing nature and thus needs of the twin transition.

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Table 1: Descriptive statistics

	Obs	Mean	Std. Dev.	Min	Max
Dependent variables					
Entry rate	494	0.05	0.01	0.03	0.08
Exit rate	494	0.06	0.01	0.03	0.15
Local skill supply					
Digital (top 25 %)	494	772.30	1835.34	0	14712
Green (top 25 %)	494	590.88	1249.17	0	8265
Twin (top 25 %)	494	626.20	1460.53	0	11967
Control variables					
Graduates, net digital top 25	494	2481.06	5402.31	0	39742
Graduates, net green top 25	494	2662.48	5917.03	0	42116
Graduates, net twin top 25	494	2627.16	5759.78	0	41769
Service share	494	0.71	0.08	0.54	0.88
Fixed assets	494	84564.01	259994.1	530.92	2386298
Intangibles	494	31265.31	141425.6	123.99	2085039

Note: fixed assets and intangibles were deflated and are reported in thousands of euros.

Table 2: Firm entry and digital skill supply (top 25 %)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Digital top 25_{t-1}	4.93e-04	4.86e-04	5.23e-04*	5.30e-04*	5.34e-04*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net D_{t-1}		0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Service share_{t-1}			0.034***	0.034***	0.034***
			(0.012)	(0.012)	(0.012)
Fixed assets_{t-1}				-0.002	-0.003
				(0.006)	(0.006)
Intangibles_{t-1}					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.578	0.582	0.588	0.588	0.588

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 3: Firm entry and green skill supply (top 25%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Green top 25_{t-1}	6.60e-04**	6.05e-04*	5.66e-04*	5.64e-04*	5.64e-04*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net G_{t-1}		0.002***	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
Service $share_{t-1}$			0.034***	0.034***	0.034***
			(0.012)	(0.012)	(0.012)
Fixed $assets_{t-1}$				-0.002	-0.002
				(0.006)	(0.006)
$Intangibles_{t-1}$					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.579	0.590	0.596	0.596	0.596

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 4: Firm entry and twin skill supply (top 25%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Twin top 25_{t-1}	6.52e-04**	6.07e-04**	5.92e-04**	5.81e-04**	5.82e-04**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net T_{t-1}		6.72e-04	7.80e-04	8.44e-04	8.38e-04
		(0.001)	(0.001)	(0.001)	(0.001)
Service $share_{t-1}$			0.034***	0.0336***	0.0338***
			(0.012)	(0.012)	(0.012)
Fixed $assets_{t-1}$				-0.002	-0.003
				(0.006)	(0.006)
$Intangibles_{t-1}$					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.582	0.583	0.588	0.589	0.589

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 5: Firm exit and digital skill supply (top 25%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Digital top 25_{t-1}	1.80e-04	1.80e-04	1.97e-04	3.06e-04	3.04e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net D_{t-1}		0.000	0.000	-0.000	-0.000
		(0.001)	(0.001)	(0.001)	(0.001)
Service share_{t-1}			0.015	0.009	0.009
			(0.056)	(0.054)	(0.055)
Fixed assets_{t-1}				-0.036***	-0.036***
				(0.010)	(0.010)
Intangibles_{t-1}					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.253	0.254	0.254	0.268	0.268

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 6: Firm exit and green skill supply (top 25%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Green top 25_{t-1}	7.99e-04*	9.13e-04*	9.07e-04*	8.67e-04*	8.68e-04*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Graduates, net G_{t-1}		-0.003**	-0.003**	-0.003**	-0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
Service $share_{t-1}$			0.006	-0.002	-0.002
			(0.057)	(0.055)	(0.055)
Fixed $assets_{t-1}$				-0.036***	-0.036***
				(0.010)	(0.010)
$Intangibles_{t-1}$					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.255	0.262	0.262	0.276	0.276

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 7: Firm exit and twin skill supply (top 25%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Twin top 25_{t-1}	2.64e-04	4.71e-04	4.67e-04	3.14e-04	3.13e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net T_{t-1}		-3.12e-03**	-3.09e-03**	-2.17e-03	-2.17e-03
		(0.002)	(0.002)	(0.002)	(0.002)
Service share_{t-1}			8.83e-03	3.59e-03	3.41e-03
			(0.056)	(0.054)	(0.055)
Fixed assets_{t-1}				-0.034***	-0.034***
				(0.010)	(0.010)
Intangibles_{t-1}					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.254	0.257	0.257	0.269	0.269

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 8: Firm entry and language skill supply (top 25%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Language top 25_{t-1}	7.14e-05	1.60e-04	1.76e-04	1.65e-04	1.65e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net L_{t-1}		8.23e-04	8.51e-04	8.48e-04	8.45e-04
		(0.001)	(0.001)	(0.001)	(0.001)
Service share_{t-1}			0.034***	0.034***	0.034***
			(0.012)	(0.012)	(0.012)
Fixed assets_{t-1}				-0.002	-0.002
				(0.006)	(0.006)
Intangibles_{t-1}					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.572	0.576	0.582	0.582	0.583

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table 9: Firm exit and language skill supply (top 25%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Language top 25_{t-1}	5.13e-04	4.27e-04	4.34e-04	2.27e-04	2.27e-04
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Graduates, net L_{t-1}		-7.96e-04	-7.84e-04	-8.39e-04	-8.36e-04
		(0.001)	(0.001)	(0.001)	(0.001)
Service $share_{t-1}$			0.015	0.007	0.007
			(0.056)	(0.055)	(0.055)
Fixed $assets_{t-1}$				-0.035^{***}	-0.035^{***}
				(0.010)	(0.010)
$Intangibles_{t-1}$					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.254	0.255	0.255	0.268	0.268

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Appendix A: Supplementary Tables

Table A1: Firm entry and digital skill supply (top 10%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Digital top 10_{t-1}	2.03e-04	1.04e-04	1.13e-04	1.08e-04	1.08e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net D_{t-1}		0.003***	0.003***	0.003***	0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
Service $share_{t-1}$			0.038***	0.037***	0.037***
			(0.012)	(0.012)	(0.012)
Fixed $assets_{t-1}$				-0.003	-0.003
				(0.006)	(0.006)
$Intangibles_{t-1}$					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.573	0.588	0.595	0.595	0.595

Notes: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table A2: Firm entry and green skill supply (top 10%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Green top 10_{t-1}	2.80e-04	2.64e-04	2.66e-04	2.69e-04	2.68e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net G_{t-1}		0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Service $share_{t-1}$			0.034^{***}	0.034^{***}	0.034^{***}
			(0.012)	(0.012)	(0.012)
Fixed $assets_{t-1}$				-0.003	-0.003
				(0.006)	(0.006)
$Intangibles_{t-1}$					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.574	0.578	0.583	0.584	0.584

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table A3: Firm entry and twin skill supply (top 10%)

	(1) Entry rate	(2) Entry rate	(3) Entry rate	(4) Entry rate	(5) Entry rate
Twin top 10_{t-1}	-9.61e-06	-4.92e-05	-2.81e-05	-1.50e-05	-1.53e-05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net T_{t-1}		2.42e-03***	2.48e-03***	2.47e-03***	2.46e-03***
		(0.001)	(0.001)	(0.001)	(0.001)
Service share_{t-1}			3.54e-02***	3.51e-02***	3.52e-02***
			(0.012)	(0.012)	(0.012)
Fixed assets_{t-1}				-0.002	-0.002
				(0.006)	(0.006)
Intangibles_{t-1}					0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.572	0.585	0.591	0.591	0.591

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table A4: Firm exit and digital skill supply (top 10%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Digital top 10_{t-1}	3.23e-04	4.28e-04	4.31e-04	3.58e-04	3.59e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net D_{t-1}		-0.003	-0.003	-0.003	-0.003
		(0.002)	(0.002)	(0.002)	(0.002)
Service share_{t-1}			0.011	0.004	0.004
			(0.055)	(0.053)	(0.053)
Fixed assets_{t-1}				-0.035***	-0.035***
				(0.010)	(0.010)
Intangibles_{t-1}					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.254	0.256	0.256	0.269	0.269

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table A5: Firm exit and green skill supply (top 10 %)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Green top 10_{t-1}	-3.77e-04	-3.46e-04	-3.45e-04	-3.13e-04	-3.12e-04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Graduates, net G_{t-1}		-0.002	-0.002	-0.001	-0.001
		(0.001)	(0.001)	(0.001)	(0.001)
Service share_{t-1}			0.013	0.006	0.006
			(0.055)	(0.054)	(0.054)
Fixed assets_{t-1}				-0.035***	-0.035***
				(0.010)	(0.010)
Intangibles_{t-1}					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.254	0.256	0.256	0.268	0.268

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.

Table A6: Firm exit and twin skill supply (top 10%)

	(1) Exit rate	(2) Exit rate	(3) Exit rate	(4) Exit rate	(5) Exit rate
Twin top 10_{t-1}	1.61e-04	1.89e-04	1.97e-04	4.77e-04	4.77e-04
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Graduates, net T_{t-1}		-1.67e-03	-1.65e-03	-1.86e-03	-1.86e-03
		(0.002)	(0.002)	(0.002)	(0.002)
Service share$_{t-1}$			1.36e-02	6.57e-03	6.44e-03
			(0.055)	(0.053)	(0.053)
Fixed assets$_{t-1}$				-0.037***	-0.037***
				(0.010)	(0.010)
Intangibles$_{t-1}$					-0.000
					(0.001)
Province FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	494	494	494	494	494
R^2	0.253	0.254	0.254	0.269	0.269

Notes: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Clustered (at NUTS 3 level) standard errors in parentheses. Within R^2 is reported.