Regional Capability Change Within Occupations: Evidence from Italian ICT Labour Demand

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Abstract

Most regional analyses capture labour-market transformation through industries, occupations, or human-capital endowments. We add a demand-side perspective by examining how employers' skill requirements evolve within occupations. Using Lightcast online job advertisements for ICT professionals in five major Italian regional labour markets, we estimate posting-level skill intensity through a multilevel Item Response Theory model and decompose its 2021–2024 change into within- and between-occupation components. Skill intensity declines across all regions and most provinces, driven mainly by changes in requested skill bundles within occupations. Regional capabilities therefore evolve not only through occupational recomposition, but also through changing requirements within existing jobs.

Keywords: Skill intensity, Online job postings, Item response theory, Shift-share decomposition, Regional capabilities, ICT.

1 Introduction

Recent work in regional studies has increasingly emphasised that regional economic development depends not only on economic structures and educational endowments, but also on the place-based capabilities embedded in local labour markets. From this perspective, workers' skills matter not simply as individual attributes, but as components of a broader regional capability base shaping adaptation, development and structural change (Boschma, 2017; Corradini et al., 2023; Hidalgo, 2023). Recent contributions have therefore begun to treat workplace skills and local labour-market structures as more direct indicators of regional capabilities and of their transformation over time (Buyukyazici et al., 2024).

The growing availability of digital trace data has considerably expanded the empirical possibilities for studying skills and labour-market change. Online Job Advertisements (OJAs), in particular, provide detailed evidence on how employers formulate and update their skill requirements, making them an increasingly important source in the economic literature on labour demand and technological change (Deming and Kahn, 2018; Deming and Noray, 2020; Modestino et al., 2020; Acemoglu et al., 2022; Goldfarb et al., 2023). Their principal advantage is that they provide a more direct measure of employers' stated skill requirements than approaches that infer them from educational attainment (Glaeser et al., 2014), occupational categories or labour mobility (Neffke and Henning, 2013). This feature is particularly promising for regional analysis because it makes it possible to observe how skill requirements vary across places and evolve over time, thereby connecting the analysis of labour demand with debates in Evolutionary Economic Geography (EEG) on regional capabilities and structural transformation. A small but growing literature has already begun to exploit this potential in the study of regional skill demand (Giambona et al., 2024; Henning et al., 2025).

However, regional labour-market transformation is still often analysed through changes in occupational or industrial composition (Neffke et al., 2011; Deegan et al., 2024). Such approaches implicitly treat occupations as relatively stable bundles of tasks and competences. Yet technological and organisational change may alter the skills required within an occupation even when its title and employment share remain unchanged. Occupation-based measures may therefore overlook an important dimension of regional capability transformation: the reconfiguration of skill bundles inside existing jobs.

This paper addresses this issue by examining how the skill content of labour demand for Information and Communication Technologies (ICT) professionals evolved across five major Italian regional ICT labour markets and their provinces between 2021 and 2024. ICT occupations provide a particularly relevant setting because they are central to regional digital upgrading and because changes in requested skill bundles are especially visible in this occupational domain (Giambona et al., 2024;

Kahlawi et al., 2024). The main research questions are twofold. First, how did the skill requirements of ICT vacancies change across regions and provinces during this period? Second, did the observed change result primarily from shifts in the occupational composition of vacancies or from changes in skill requirements within occupations?

Our analysis addresses these questions by constructing a posting-level measure of skill requirements, which we define as skill intensity, using a multilevel Item Response Theory (IRT) model. Each OJA is treated as a bundle of requested skills, and the latent trait captures the underlying level of skill requirements embodied in the complete bundle rather than simply the number of skills listed. Skills contribute differently to the index according to their estimated difficulty and discrimination parameters. The model accounts for grouped heterogeneity across regions (NUTS-2), provinces (NUTS-3) and occupations (ESCO-4 digit, v.1.1.1, corresponding to the fourth level of ISCO-08[1]) while estimating a common latent dimension. Posting-level scores are subsequently aggregated to obtain model-based territorial averages across NUTS-2 and NUTS-3 territories. We subsequently apply a symmetric shift-share decomposition to distinguish the component of change associated with occupational recomposition from the component associated with changing skill intensity within occupations.

The paper makes two distinct contributions. First, it contributes to the regional capabilities literature by showing that capability transformation can occur through changes in the skill content of existing occupations, rather than only through industrial diversification or occupational recomposition. Empirically, it demonstrates that recent changes in ICT skill demand across the principal Italian regional labour markets were driven predominantly by within-occupation transformations. This finding suggests that occupation-based indicators may overlook an important dimension of local labour-market change. Second, the paper develops a demand-side, posting-level measure of skill requirements that accounts for the composition of requested skill bundles and identifies the skills that are most informative in distinguishing job ads with higher and lower levels of skill intensity. The measure can also be aggregated at the regional and provincial levels, enabling territorial and temporal comparisons across different segments of the labour market.

The remainder of the paper is organised as follows. Section 2 discusses the skills as regional capabilities and the role of changing labour demand in regional transformation. Section 3 describes the data and empirical setting. Section 4 presents the measurement strategy and shift-share

[1] ESCO stands for European Skills, Competences, and Occupations, a classification that identifies and categorises skills, competences, qualifications and occupations relevant for the European labour market and education and training (European Commission, 2019). Occupations are organised hierarchically and the top four levels are mapped to those of the International Standard Classification of Occupations ISCO-08.

decomposition. Section 5 reports the results and robustness analyses. Section 6 discusses their interpretation and some policy implications while Section 7 concludes.

2. Regional capabilities and changing labour demand

2.1 Skills as regional capabilities: the role of OJAs

Recent literature in EEG has consistently shown that regional development is path dependent: new growth paths tend to build on capabilities already present within regions rather than emerging from scratch (Boschma, 2017; Corradini et al., 2021; Hidalgo, 2023; Chen et al., 2025). This idea informs both the *relatedness* literature and the *Smart Specialisation* agenda, which emphasise that new regional trajectories depend on pre-existing capabilities and on their recombination over time.

Within this broad framework, recent contributions have argued that workplace skills should be treated not simply as individual worker attributes, but as territorially embedded capabilities that shape regional transformation (Buyukyazici, 2024; Buyukyazici and Quatraro, 2025; Buyukyazici and Coll-Martínez, 2026). However, much of this literature still approaches skills primarily from the supply side. Koo (2005), for instance, examines regional economic characteristics and prospects through the types of jobs performed by local workers. Glaeser et al. (2014) use education as a proxy for skills and show that human capital contributes to regional change through entrepreneurship, labour demand, and productivity growth. Neffke and Henning (2013) infer the role of skills from labour mobility across industries, using worker flows as a proxy for skill relatedness. Buyukyazici et al. (2024), in turn, rely on workers' subjective evaluations of tasks and skill profiles to derive measures of skill intensity and, subsequently, of skill relatedness and complexity. These approaches are clearly valuable, but they do not directly observe the skills that firms require in vacancies across occupations and industries. They may therefore be less able to capture rapid changes in the content of employer demand. More generally, such measures may themselves be shaped by changes in economic structure and local labour market dynamics (Henning et al., 2025). For this reason, a more direct perspective on the demand side of skills is needed.

A demand side perspective is especially valuable because it offers a direct view of the skills that firms require in local labour markets, rather than inferring them from education, workforce composition, or worker mobility. In this respect, OJAs are particularly useful. Recent economic research has increasingly used online job-posting data to analyse labour demand, especially in the US context. A seminal contribution in this literature is Deming and Kahn (2018), who show that cognitive and social skills observed in job postings are associated with higher wages across firms and labour markets. Deming and Noray (2020), using a near universe of postings, show that the earnings premium of STEM graduates in computer-intensive fields declines rapidly over time as skill requirements change.

Modestino et al. (2020) further show that skill and education requirements increased during the Great Recession. Together, these studies highlight the value of OJAs as a direct and dynamic source for analysing labour demand and changing skill requirements. Evidence for Italy is more recent and still limited, but it is growing. Colombo and Marcato (2023) use posting data to study labour-market concentration, while Giambona et al. (2024) and Kahlawi et al. (2024) use OJAs to analyse regional skill demand and ICT-related labour-market structures in Italy.

The use of OJAs has therefore started to show its analytical potential, although it remains less developed within the literature on regional capabilities. An important contribution in this direction is Henning et al. (2025), who use job-postings data to study job skill relatedness and local skill coherence, showing how vacancy-level information can enrich the analysis of regional labour-market structures. Building on this perspective, our paper shifts attention from the mapping of local skill structures to the evolution of skill requirements over time, examining how territorial ICT labour demand changes across Italian regions and provinces. In this sense, OJAs provide not only a more direct measure of employers' skill requirements, but also a useful way to observe how these requirements evolve alongside broader processes of technological and labour-market change. This perspective opens the door to a second key issue, namely how technological change is reflected in the changing skill content of occupations and in the transformation of local labour markets over time.

2.2 Skill change and local labour-market transformation

Technological change may reshape labour markets not only through the emergence of new occupations or the decline of existing ones, but also through changes in the skill requirements attached to jobs (Autor et al., 2003; Atalay et al., 2020; Freeman et al., 2020). Occupations should therefore not be seen as fixed bundles of competences. Even when occupational titles remain the same, the level and combination of requested skills may evolve over time. Understanding local labour-market transformation thus requires attention not only to occupational composition, but also to how skill requirements change within occupations. This point is especially relevant in ICT labour markets (Castellacci et al., 2020). In these contexts, where the tasks and the requested skills are highly related to digital and technological change, labour demand may be altered both through occupational recomposition and through within-occupation adjustments in requested skill bundles.

The economic literature has long examined the effects of technological change on labour-market outcomes. Early contributions analysed how computerisation affected workers' skills and wages (Krueger, 1993; Autor et al., 1998), while subsequent research extended this perspective to employment dynamics, task reallocation and routinisation (Autor et al., 2003; Goos and Manning, 2007; Goos et al., 2014). More recently, this debate has also been brought closer to regional and local labour market analysis. In regional science and EEG, technological change has increasingly been linked to place-based capabilities, the evolution of local labour-market structures, and the uneven ability of regions to adapt and transform over time (Boschma et al., 2017; Castellacci et al., 2020; Elekes et al., 2023; Capello et al., 2025). From this perspective, technological change matters because it reshapes the skill requirements that underpin regional transformation. OJA-level data make these changes directly observable across occupations, places and time, providing a more fine-grained view than measures based solely on education, occupational structures or worker mobility (Henning et al., 2025).

These considerations suggest that the transformation of regional labour demand should be examined along two distinct margins. Changes in average skill requirements may result from occupational recomposition, when the relative demand for more- and less-skill requiring occupations changes, or from transformations within occupational categories, when employers modify the blundle of skills advertised for vacancies classified within the same occupation. The analytical distinction between compositional and within-occupation change is well established in the task-based labour literature, which separates changes arising from shifts in employment across occupational categories from changes in task content within those categories (Freeman et al., 2020; Fernández-Macías et al., 2023). We extend this logic to regional advertised labour demand by distinguishing changes in the occupational composition of job postings from changes in the skill bundles of postings classified within the same occupation. This regional application makes it possible to assess whether local capability transformation occurs primarily through a changing mix of occupations or through the reconfiguration of skill demand within occupational categories. Section 4.2 presents the empirical strategy used to distinguish these two components.

3. Data and empirical setting

This study uses OJAs data provided by Lightcast, a private labour-market analytics company specialising in the collection and harmonisation of job postings. The dataset contains detailed information for each advertisement, including the date of publication, employer, the employer's economic activity, occupation, geographic location, educational and experience requirements, employment and contract characteristics, and the skills requested by employers. Lightcast collects postings from online sources and processes their textual content using machine-learning and natural-language-processing techniques. It also applies cleaning and harmonisation procedures, including the removal of duplicate and non-genuine postings, the identification of inactive advertisements, and the classification of occupations and skills according to standardised taxonomies.

Even if OJAs are harmonized from Lightcast to proxy vacancies, they do not provide a complete census for them. Not all vacancies are advertised online, and employers' propensity to use online recruitment channels varies across occupations, industries and territories (Fabo & Kureková, 2022). The data therefore measure employers' observed online recruitment demand, rather than the total number of job openings. Nevertheless, their detailed, timely and consistently harmonised information makes them particularly suitable for analysing the characteristics of labour demand and changes in employers' skill requirements. Previous research shows that OJAS provide a reliable basis for comparing relative patterns and changes across occupations, industries, regions and periods, even when they do not fully represent the level of total vacancies (Deming & Kahn, 2018; Hershbein & Kahn, 2018; Modestino et al., 2020)

For the purposes of this paper, we use Italian Lightcast data covering the period from 2021 to 2024. We focus on ICT professionals, defined as the ESCO four-digit occupational subgroups belonging to major group 25 (*Information and Communication Technology Professionals*). These occupations are particularly suitable for the analysis because their job advertisements tend to provide detailed information on the technical skills, technologies and tools requested by employers. ICT professionals are therefore especially suitable for analysing changes in employer skill demand using posting data, since they are more likely to be selected based on skills, compared to technicians (Deming and Kahn, 2018). They also constitute a relevant empirical setting for examining technological transformation because their task and skill content is directly affected by changes in digital technologies and new production methods.

[PLACE FIGURE 1 AROUND HERE]

Figure 1 reports the regional distribution of ICT professional postings in the Lightcast dataset. The largest share is observed in Lombardia, which accounts for 32.5% of postings, followed by Emilia-Romagna and Lazio, with 13.2% and 13.1%, respectively. Together with Veneto and Piemonte, these five regions account for approximately 77% of the ICT professional postings observed in the dataset. The empirical analysis is restricted to these five regions because the paper aims to examine territorial variation at the provincial level. The restriction is motivated by sample-size considerations. In several other regions, the number of ICT postings becomes very small once observations are disaggregated simultaneously by province, occupation and year. These sparse cells would produce unstable estimates of provincial skill requirements and limit meaningful comparisons across territories. Concentrating on the regions with the largest volumes of ICT postings therefore allows us to retain a finer geographical resolution while maintaining adequate empirical support for province-level analysis. A deeper discussion on the choice of the five selected regions can be found in the Appendix A.

The skill set is restricted to technical and occupation-specific skills associated with the technological content of ICT work. Transversal and social skills are excluded because they capture transversal attributes that are relevant across occupations but are conceptually distinct from the technical specialisation of an ICT vacancy. Including them would combine technical skill requirements with broader cognitive and interpersonal worker attributes. Their exclusion does not imply that these skills are unimportant or unaffected by technological change; rather, their evolution lies outside the construct examined in this paper. Accordingly, throughout the analysis, the skill requirements refer to the technical and occupation-specific skill bundle requested in ICT vacancies.

Finally, to exclude extremely rare items that provide limited information for model estimation, we retain only skills appearing in at least 1% of the pooled estimation sample. The same set of skills is used across all years to ensure temporal comparability. The resulting estimation sample comprises 298,577 online job advertisements and 174 skills, distributed across 5 regions, 41 provinces and 4 years.

4. Research design and measurement strategy

4.1 Multilevel IRT model

IRT is a probabilistic framework widely used to measure latent traits through categorical items, including both dichotomic and ordered polytomous responses (Samejima, 1969; De Ayala, 2009). This methodology was originally developed to analyse students' performance in multi-item tests by modelling the probability of selecting a specific response category using a logistic function. These probabilities depend on parameters related to both individual characteristics and item properties.

In the context of the ICT Italian labour market, and focusing on the demand side captured by OJAs, we define $k = 1, \dots, K$ as the set of OJAs, while the items $X_{ik} = X_{1k}, \dots, X_{Nk}$ are interpreted as the skills requested in the postings. Therefore, X_{ki} is defined as a dichotomic variable categorized as, $X_{ki} = 1$ if the OJA k requests the skill i, and $X_{ki} = 0$ otherwise. Accordingly, θ_k is the skill intensity, and can be interpreted as a measure of the latent skill requirements for each OJA k.

Each job posting is associated with a province and an occupation. Provinces are nested within regions, while occupations are observed across multiple provinces and regions. The latent-score specification therefore includes region-, province- and occupation-specific random effects to account for grouped heterogeneity in job postings skill bundles. We estimate the following multilevel IRT model (Chalmers, 2012, 2015):

$$\Pr(X_{ki} = 1 \mid \theta_k, a_i, b_i) = \frac{\exp[a_i(\theta_k - b_i)]}{1 + \exp[a_i(\theta_k - b_i)]}.$$

In this model, θ_k is given by:

$$\theta_k = \mu + v_{r(k)} + \gamma_{p(k)} + u_{g(k)} + \varepsilon_k,$$

with random effects:

$$v_r \sim \mathcal{N}(0, \sigma_{\text{reg}}^2), \qquad r = 1, \dots, R,$$

$$\gamma_p \sim \mathcal{N}(0, \sigma_{\text{prov}}^2), \qquad p = 1, \dots, P,$$

$$u_g \sim \mathcal{N}(0, \sigma_{\text{occ}}^2), \qquad g = 1, \dots, G,$$

$$\varepsilon_k \sim \mathcal{N}(0,1).$$

v_r is the region-specific random effect, γ_p is the province-specific random effect, u_g is the occupation-specific random effect, and ε_k includes the residual posting-level heterogeneity not captured by the geographical and occupational random effects. From this model the two item parameters a_i and b_i for each skill are estimated[2]. The latent trait θ_k is then estimated using the Expected a Posteriori (EAP) method, a Bayesian scoring approach that, in this application, falls within the Empirical Bayes (EB) framework[3]. The $\hat{\theta}_k$ estimates of the latent trait provide an advertisement-level measure of skill intensity. However, as is common with latent variable models, the original scale of $\hat{\theta}_k$ is not directly interpretable in substantive units. In particular, the sign and magnitude of the estimated scores only indicate the relative position of each OJA on the latent skill-intensity scale. To facilitate interpretation, the estimated latent scores are therefore linearly rescaled into a skill-intensity index I_k with mean 100 and standard deviation 10. Specifically, the index is defined as:

$$\hat{I}_k = 100 + 10\frac{\hat{\theta}_k - \bar{\theta}_k}{\sigma_k},$$

where $\bar{\theta}_k$ is the pooled sample mean, while σ_k is the pooled standard deviation[4].

From an interpretation point of view, $\hat{I}_k$ the skill intensity, can be understood as the level of skill requirements for each OJA k. Each skill i is characterised by two item parameters a_i and b_i. The discrimination parameter a_i measures how strongly the skill differentiates between OJAs with lower and higher levels of skill intensity, while b_i identifies the level of $\hat{\theta}_k$ at which the probability of

[2] To estimate the model, we use the R package mirt. Estimation is performed via the Metropolis–Hastings Robbins–Monro (MH-RM) algorithm, which is the standard approach for this class of models in the literature.

[3] More information on these models can be found in Chalmers (2012) and Chalmers (2015).

[4] Since the index is obtained from estimated EAP scores, we denote it by $\hat{I}_k$. In the empirical analysis and in the decomposition, hats are omitted for notational simplicity

requiring that skill equals 0.50. Skills with both high difficulty and high discrimination are therefore especially informative: they are more likely to appear in high-skill-intensity advertisements and, when present, they contribute strongly to distinguishing these advertisements from less skill-intensive ones. A straightforward way to measure the skill content of an OJA would be to simply count the number of skills it contains. However, a raw skill count implicitly assigns the same weight to all skills, regardless of their rarity, specificity, or capacity to distinguish between more and less skill-intensive vacancies. This can be problematic when comparing job postings that list the same number of skills but differ substantially in the nature of the requested skill bundle. For instance, an advertisement requiring Microsoft Word, Microsoft Excel, office administration, and data entry has the same raw skill count as an advertisement requiring JavaScript frameworks, MySQL, user-interface design, and web programming. Yet the latter arguably reflects a more specialised and technically demanding profile. The skill intensity measure proposed in this paper addresses this limitation by relying on an IRT framework, which infers a latent level of skill requirements from the observed combination of skills in each advertisement. In this framework, skills contribute differently to the latent score according to their estimated difficulty and discrimination parameters.

Skill intensity is therefore defined as *the latent level of skill requirements embodied in an OJA, inferred from the combination of requested skills and weighted by the difficulty and discriminating power of those skills within the labour market for ICT professionals*. Territorial measures of skill intensity can then be derived by averaging OJA-level skill intensity within each territory. We denote these averages as $\bar{I}_p$ for provinces and $\bar{I}_r$ for regions. A territory with higher skill intensity is one in which ICT professional vacancies require, on average, more demanding skill bundles.

4.2 The shift-share decomposition of the skill intensity change

The previous section defines skill intensity as a posting-level measure of the skill requirements embodied in each OJA. Once this measure is aggregated at the territorial level, changes in average skill intensity over time may arise through two analytically distinct channels. First, a province may experience a change in the occupational composition of ICT labour demand. For example, the share of vacancies for relatively high skill-intensive ICT occupations may decline, while the share of vacancies for less skill-intensive ICT occupations may increase. In this case, average territorial skill intensity would change even if the skill requirements attached to each occupation remained constant. Second, average skill intensity may change because the skill content of vacancies changes within occupations. In this case, the same ICT occupations are advertised with different bundles of requested skills over time.

To distinguish between these two channels, we decompose the observed change in average skill intensity using a shift-share decomposition. This approach follows the logic used in recent task-based studies of labour-market change, where aggregate changes are separated into changes due to shifts in employment or job composition and changes due to transformations in the content of work within jobs (Freeman et al., 2020; Fernández-Macías et al., 2023). In our setting, the decomposition allows us to distinguish between changes at the extensive margin of ICT labour demand, namely changes in the occupational composition of vacancies, and changes at the intensive margin, namely changes in the skill intensity of vacancies within the same occupations. Formally, $\bar{I}_{opt}$ is the average skill intensity in occupation o, province p, year t for each province p. Therefore, $\bar{I}_{pt}$ can be written as:

$$\bar{I}_{pt} = \sum_{o} s_{opt}\ \bar{I}_{opt},$$

where s_{opt} represent share of OJAs in occupation o in province p, year t. Then, the change in $\bar{I}_{pt}$ from 2021 to 2024 is:

$$\Delta\bar{I}_{p} = \bar{I}_{p,2024} - \bar{I}_{p,2021}.$$

After some algebra[5], this can be decomposed into:

$$\Delta\bar{I}_{p} = B_p + W_p,$$

Where:

$$B_p = \sum_{o} (s_{op,2024} - s_{op,2021}) \frac{\bar{I}_{op,2021} + \bar{I}_{op,2024}}{2}$$

and

$$W_p = \sum_{o} (\bar{I}_{op,2024} - \bar{I}_{op,2021}) \frac{s_{op,2021} + s_{op,2024}}{2}.$$

The term B_p is the between-occupation component. It captures the part of the change in provincial skill intensity associated with changes in the occupational composition of ICT vacancies. It is positive when the province shifts towards occupations with higher average skill intensity and negative when it shifts towards occupations with lower average skill intensity. The term W_p is the within-occupation component. It captures the part of the change associated with changes in skill intensity within occupations. It is positive when the same ICT occupations are advertised with more skill-intensive

[5] The complete derivation shift share symmetric decomposition is available in the Appendix B.

bundles of requirements in 2024 than in 2021, and negative when they are advertised with less skill-intensive bundles.

5.Results

5.1 Regional and provincial patterns of ICT skill intensity in Italy

The regional and provincial skill intensity estimates are reported in Table 1, together with their rankings, while Table C2 in Appendix C reports the full set of provincial estimates. Since the index is rescaled so that the pooled average skill intensity equals 100, the estimates can be interpreted not only in terms of rankings, but also in terms of their relative distance from the overall mean. Moreover, because the differences among many of the upper-ranked regions and provinces are small, the rankings positions should not be interpreted as a precise hierarchy.

[PLACE TABLE 1 AROUND HERE]

First, regional and provincial patterns are closely aligned. At the regional level, Lazio and Lombardia display the highest estimated average skill intensity. This pattern is associated with the relatively high estimates observed for Roma and Milano. These provinces also account for the largest shares of OJAs, suggesting that, in the Italian ICT labour market, the largest local labour markets are also among the most skill intensive. The provincial estimates also identify several smaller labour markets, including Piacenza, Varese, Biella and Lodi, with average values close to those of the major metropolitan hubs. The results nevertheless suggest that relatively high-intensity ICT skill bundles are not observed exclusively in the largest metropolitan labour markets. One possible explanation is that specialised manufacturing and service systems generate concentrated demand for particular technical profiles in some smaller provinces[6]. These cases suggest that advanced ICT labour demand in Italy is not confined to the largest metropolitan areas but may also emerge in smaller provinces where digital skills are embedded in specific local industrial and service specializations.

Second, territorial differences in skill intensity are not extremely large. This is expected, as territorial values are obtained by aggregating skill-intensity scores across individual OJAs. Nevertheless, a substantial variation remains. The highest provincial values are slightly above 100, whereas the lowest value is close to 94, almost 6 index points below the imposed mean. Thus, the top province does not stand far above the overall ICT labour-demand average. Rather, the main territorial

[6] Examples include Zucchetti in Lodi, Leonardo and Elmec Informatica in Varese, Sella Group and Centrico in Biella, and the mechatronics, industrial automation and logistics specializations of Piacenza.

difference is concentrated in the lower tail of the distribution, where some provinces display substantially less skill-intensive ICT job postings profiles. The gap between the highest- and lowest-ranked province is 7 index points, corresponding to 0.7 pooled OJA-level standard deviations. This indicates a visible degree of territorial differentiation. Interestingly, differences are more pronounced when skill intensity is aggregated by occupation ($\bar{I}_o$) as shown in Table 2. Web and multimedia developers display the highest average skill intensity, with an index value of 107, followed by software developers, with a value of 105.5. More generally, coding- and software-related occupations appear to be among the most skill-intensive groups within the ICT professional labour market. The gap across occupations is sizeable: the difference between the highest- and lowest-ranked occupation is around 16 index points, corresponding to 1.6 pooled OJA-level standard deviations. This occupational heterogeneity motivates the decomposition analysis. Since occupations differ substantially in their average skill intensity, changes in the occupational composition of ICT labour demand could, in principle, affect aggregate territorial skill intensity, even if skill requirements within occupations remained unchanged. Whether this compositional channel is empirically relevant is assessed in the decomposition in the next section.

[PLACE TABLE 2 AROUND HERE]

Considering the skills side, estimated difficulty (b_i) and discrimination (a_i) item parameters are available in Table 3. Skills that score highly on both dimensions are therefore particularly informative for identifying vacancies located at the upper end of the skill intensity distribution. In our estimates, these skills are mainly related to web development, programming languages, query languages, and software-development activities. This suggests that coding- and development-related competences play a central role in structuring the estimated skill-intensity dimension of ICT labour demand[7].

[PLACE TABLE 3 AROUND HERE]

[7] However, these parameters should not be interpreted simply as measures of the overall market importance of each skill, since highly difficult skills may be relatively rare. Rather, they identify the skills that are most informative in distinguishing highly skill-requiring ICT vacancies from less skill-requiring ones. For instance, "using a computer" is highly difficult but not highly discriminating, likely because it is rarely stated explicitly in ICT vacancies, where it is usually taken for granted.

Figures 2 and 3 show the evolution of regional and provincial skill intensity, respectively. All five regions experience a decline between 2021 and 2024, with an average reduction of approximately 4 index points. The decrease is largest in Lazio, at almost 5 points, and smallest in Piemonte, at just over 3 points. The decline is observed in every year, except for a slight increase in Emilia-Romagna between 2023 and 2024. The broad regional hierarchy remains stable, with Lazio and Lombardia displaying the highest values and Veneto the lowest, while Emilia-Romagna and Piemonte remain close and change relative position over time. By 2024, all regional estimates lie below the pooled-sample benchmark of 100.

[PLACE FIGURE 2 AROUND HERE]

A similar pattern emerges for Roma, Milano, Bologna, and Torino. All four provinces record a marked decline, averaging slightly more than 4 index points between 2021 and 2024. The reduction is close to 5 points in Roma and Milano and smaller in Bologna and Torino. As a result, the initial gap between the four provinces narrows substantially, and their estimates converge to a very similar level by 2024. Overall, the evidence points to a widespread decline in skill intensity, accompanied by a compression of territorial differences among the leading ICT labour markets. This motivates the decomposition analysis, which assesses whether the decline is driven by changes in occupational composition or by changes in skill intensity within occupations.

[PLACE FIGURE 3 AROUND HERE]

5.2 Within- and between-occupation sources of change

Results from the shift-share decomposition are reported in Figure 4. The figure shows the two components of the change in skill intensity for the 15 provinces with the highest average level of skill intensity, ordered from the smallest to the largest decline. The red bars report the between-occupation component, B_p, which captures the part of the change associated with shifts in the occupational composition of ICT vacancies. The blue bars report the within-occupation component, W_p, which captures the part of the change associated with variation in skill intensity within occupations. The sum of the two components corresponds to the total change in provincial skill intensity. Full decomposition results for all provinces are reported in Table C3 in Appendix C, where the largest component of the change is highlighted in bold.

The decomposition shows that the decline in skill intensity is mainly driven by within-occupation changes rather than by shifts in the occupational composition of ICT labour demand. Among the 15 provinces displayed in Figure 4, the within-occupation component is larger than the between-occupation component in most cases. This means that, in most of the provinces considered, the decrease in average skill intensity is associated more with changes in skill intensity within occupations than with changes in the occupational mix of ICT vacancies.

[PLACE FIGURE 4 AROUND HERE]

This pattern is particularly visible in the largest and most important ICT labour markets. In Milan, the total decline in skill intensity is around -4.82 points, of which -3.52 points are due to the within-occupation component and -1.30 points to the composition component. Similarly, in Rome, the total decline is around -5.29 points, with a within-occupation component of -3.34 and a composition component of -1.95. The same pattern emerges in Turin and Bologna: in Turin, the within component accounts for around -2.00 points of a total decline of -2.68, while in Bologna it accounts for around -2.51 points of a total decline of -3.45. These results are important because Milan, Rome, Turin, and Bologna are not only among the most skill-intensive provinces, but also among the main ICT labour-market hubs in the country.

Table C3 in the Appendix C confirms that this pattern is not limited to the provinces shown in Figure 4. For most provinces (70%), the decline in skill intensity is dominated by the within-occupation component. At the same time, the decomposition also reveals some territorial heterogeneity. In a few provinces, such as Biella and Pavia, the composition effect is larger in magnitude than the within-occupation effect, indicating that changes in the occupational mix played a more important role in explaining the decline. In other cases, the two components are closer in magnitude, as in Novara and Piacenza, where both occupational recomposition and within-occupation changes contributed substantially to the overall decrease.

5.3 Robustness analyses

This section examines two potential concerns of the measurement strategy. First, we assess whether the decline in skill intensity simply reflects a reduction in the number of skills listed in each advertisement. Second, we assess the sensitivity of the results to the temporal stability of the IRT item parameters.

A raw skill count and the IRT-based index capture related but distinct dimensions of labour demand. A skill count assigns equal weight to every requested skill, whereas the IRT measure accounts for differences in the estimated difficulty and discrimination of individual skills and therefore captures the weighted composition of the complete skill bundle. Tables C4–C6 in Appendix C report the evolution of average skill counts by region, by the largest provinces in terms of OJA volume, and by occupation. The skill-count results do not reproduce the systematic decline observed in skill intensity. At the aggregate level, the average number of requested skills increases slightly, from 21.15 in 2021 to 21.27 in 2024. Territorial patterns are more heterogeneous: counts decline in Lazio and Emilia-Romagna, remain virtually unchanged in Veneto, and increase in Lombardia and Piemonte. Among the four largest provincial ICT labour markets, they slightly decline in Roma and Bologna but increase in Milano and Torino. At the occupational level, six of the nine groups record a higher average count in 2024 than in 2021. In particular, counts increase among applications programmers and remain broadly stable among software developers and web and multimedia developers, even though these coding-related occupations experience substantial declines in IRT-based skill intensity[8]. The decline in skill intensity therefore cannot be explained by employers listing fewer skills; rather, it reflects changes in the composition and estimated contribution of the requested skills to the latent dimension. Second, we assess the temporal stability of the item parameters. The baseline multilevel IRT model constrains the difficulty and discrimination parameters to remain constant over 2021–2024. We therefore re-estimate the model separately by year and qualitatively compare the highest-ranking items. Because separately estimated IRT models do not necessarily share the same scale, we do not interpret differences in the absolute magnitude of annual item parameters, however annual results can still be used to identify unusual parameter behaviour. Results are reported in Tables C7–C10. Most of the skills identified as highly difficult or discriminating in the pooled model also appear among the leading items in the annual estimates, suggesting broad stability. The main exception is 2023, when a few skills display unusually large parameter values. We therefore re-estimate the pooled model excluding 2023. As shown in Figure C1 and Figure C2, the decline in skill intensity between 2021 and 2024 remains evident across all five regions and the main provincial ICT labour markets, although its magnitude and some territorial rankings change. The main result is therefore not driven by the anomalous 2023 estimates, and the assumption of constant item parameters estimates during the whole period is reasonable.

6. Discussion

The central finding of the analysis is that the decline in ICT skill intensity was driven predominantly by changes within occupations rather than by changes in the occupational composition of vacancies. In other words, the transformation of ICT labour demand occurred mainly through changes in the

[8] See Table C11 in Appendix C, which will be discussed later.

skill bundles requested for existing occupations, rather than through a shift in the types of occupations demanded by employers. This decline should not be interpreted simply as employers requesting fewer skills or as evidence of a generalised de-skilling of ICT workers. The complementary analysis of raw skill counts shows no comparable systematic decline: the average number of skills listed per advertisement remains broadly stable over the period. The reduction in skill intensity therefore appears to reflect changes in the composition of requested skill bundles and in the contribution of particular skills to the estimated latent dimension, rather than a uniform shortening of job postings requirements.

Several mechanisms may contribute to this pattern. Among the others, one possible interesting interpretation concerns the growing role of Artificial Intelligence (AI) and related forms of software automation in reorganising the task and skill content of work. The economic literature increasingly conceptualises AI as a technology that changes the allocation of tasks between workers and machines within occupations (Acemoglu and Restrepo, 2019). Consistent with this perspective, evidence from online vacancies suggests that establishments exposed to AI modify both their occupational composition and the skill requirements attached to continuing occupations (Acemoglu et al., 2022). Green (2024), using Lightcast data from ten OECD countries, similarly finds that greater establishment-level AI exposure is associated with declining demand for several established digital skills, including programming, scripting languages, Python, SQL and database-management competences.

The occupation-level results in our study are consistent with this interpretation. Table C11 in the Appendix C shows that the average skill intensity declines across all nine ICT occupational groups, indicating that the aggregate pattern is not confined to a single occupation. The largest reductions are observed among database designers and administrators, web and multimedia developers, software developers and applications programmers. These occupations are closely associated with several of the skills that are particularly informative in structuring the estimated skill-intensity dimension, including programming, web development, query languages and SQL. The pattern is therefore compatible with Green's (2024) evidence that AI exposure may reduce the explicit demand for some established digital competences. Nevertheless, the present analysis does not observe firm-level AI adoption and cannot identify AI as the cause of the decline. Future research could examine this mechanism directly by linking vacancy-level skill changes to measures of firm or regional AI exposure and adoption.

Transformation may therefore occur through changes in the skills requested within existing occupations. Consequently, analyses based solely on industries, occupations, or qualifications may overlook an important dimension of regional change. This finding has important policy implications and is closely connected to the framework proposed by Corradini et al. (2023), particularly its emphasis on the dynamic identification of evolving skill needs and on systemic coordination among the institutions responsible for skills policy and regional development. Regional skills strategies and labour-market observatories commonly assess labour-market change, skill needs, and mismatches using indicators such as occupational employment, qualifications, and sectoral composition. Our results indicate that these indicators may remain relatively stable even as employers modify the combinations of technical skills requested within the same occupational categories. Policymakers should therefore complement occupation-based forecasts with the repeated monitoring of vacancy-level (or online job postings) skill combinations, validated, where possible, against employer surveys and data on realised hiring. OJAs are particularly valuable for this purpose because they provide timely and geographically detailed information on employers' stated requirements. However, their coverage varies across regions, sectors, and occupations. Vacancy-based indicators should therefore be benchmarked against employer surveys, public employment-service records, and other official labour-market data sources (Deming and Kahn, 2018; Fabo and Kureková, 2022; Vermeulen and Gutierrez Amaros, 2024).

7 Conclusion

This paper examines how employers' stated skill requirements for ICT professionals evolved across five Italian regions and their provinces between 2021 and 2024. To capture these requirements, we use online job postings data and construct a posting-level measure of skill intensity using a multilevel IRT model and aggregate it at the regional and provincial levels. We then apply a symmetric shift-share decomposition to distinguish changes associated with occupational recomposition from changes occurring within occupations.

The results reveal a widespread decline in skill intensity across all five regions and most of the provinces analysed. The decomposition shows that the within-occupation component dominates the between-occupation component in the large majority of provinces, including the principal ICT labour-market hubs of Milano, Roma, Bologna and Torino. The transformation of ICT labour demand therefore occurred mainly through changes in the skill bundles requested within existing occupations rather than through shifts in the types of occupations demanded by employers. Moreover, the complementary analysis of raw skill counts indicates that this pattern cannot be explained simply by employers listing fewer skills. It instead reflects changes in the composition of requested technical skill bundles.

As other papers, also this paper entails some limitations. First, the study focuses on the five regions with the largest observed volumes of ICT postings in the Lightcast data, and its findings should not be generalised automatically to regions with smaller or structurally different labour markets. Second, OJAs capture employers' stated requirements in advertised vacancies rather than the complete universe of online and non-online vacancies, realised hiring outcomes or the skills ultimately used after recruitment. Lastly, the analysis is restricted to ICT professionals and cannot be directly extended to the labour market as a whole, even if the ICT professional are a crucial segment of the contemporary labour market. However, despite these limitations, the paper provides a novel demand-side perspective on regional labour-market transformation. By combining job posting-level information on skill requirements with a model-based measure of skill intensity and a shift-share decomposition, it shows that regional capabilities can evolve even when the occupational structure of labour demand remains relatively stable. Analyses based only on industries, occupations or qualifications may therefore overlook an important dimension of regional change. Regional labour markets evolve not only when the types of jobs demanded by employers change, but also when employers redefine what workers are expected to know and do within those jobs. Observing this within-occupation margin provides a more complete account of how regional capabilities adapt to technological change.

Disclosure statement

The authors report there are no competing interests to declare.

Data Disclaimer

This article reflects solely the results and opinions of the authors and does not necessarily represent the position of Lightcast, which shall not be held liable for its content.

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Tables

Table 1: Regional and Provincial ranking in territorial skill intensity.

Rank	Region	$\bar{I}_r$	Rank	Province	$\bar{I}_p$
1	Lazio	100.943	1	Roma	101.320
2	Lombardia	100.278	2	Milano	101.195
3	Emilia-Romagna	99.781	3	Bologna	100.701
4	Piemonte	99.662	4	Torino	100.539
5	Veneto	98.681	5	Piacenza	100.326
			6	Varese	100.133
			7	Biella	99.992
			8	Lodi	99.805
			9	Modena	99.616
			10	Parma	99.551
			11	Reggio nell'Emilia	99.451
			12	Padova	99.365
			13	Rimini	99.319
			14	Treviso	99.307
			15	Brescia	99.171

Notes: Out of 41 provinces Table 1 shows the top 15. Full table can be found in Appendix C. *Sources*: Authors elaboration on Lightcast Corp. data 2021-2024.

Table 2: Occupational ranking considering average skill intensity by occupation.

Rank	ESCO level 4 Occupations	n	$\bar{I}_o$
1	Web and multimedia developers	32282	107.1609
2	Software developers	62121	105.4868
3	Applications programmers	42289	100.6909
4	Database designers and administrators	14794	98.04649
5	Systems analysts	77381	97.90326
6	Systems administrators	19059	95.93163
7	Computer network professionals	7511	95.53385
8	Database and network professionals not elsewhere classified	22185	95.01487
9	Software and applications developers and analysts not elsewhere classified	20955	91.00927

Source: Authors elaboration on Lightcast Corp. data 2021-2024.

Table 3: Discrimination and difficulty parameter estimates.

Rank	Skill	b_i	Rank	Skill	a_i
1	Create the front-end design of a website	6.396	1	Create the front-end design of a website	4.862
2	Computer programming	5.740	2	Using Mark-up languages	4.356
3	Knowledge of SQL language	4.984	3	Knowledge of JavaScript framework	4.232
4	Using query languages	4.699	4	Developing Software projects	4.067
5	Knowledge of PHP language	4.645	5	Using query languages	3.679
6	Using mark-up languages	4.320	6	Knowledge of PHP language	3.654
7	Knowledge of Java language	3.891	7	Creating a user interface	3.533
8	Knowledge of Unified Modelling Language	3.712	8	Knowledge of CSS language	3.389
9	Knowledge of CSS language	3.400	9	Knowledge of SQL language	2.833
10	Using a computer	3.241	10	Knowledge of the std. WWW Consortium	2.779
11	Web programming	3.090	11	Knowledge of Unified Modelling Language	2.668
12	Creating a user interface	2.403	12	Knowledge of MySQL	2.622
13	Database knowledge	2.141	13	Knowledge of Apache Maven	2.476
14	Handling a database	2.093	14	Knowledge of JavaScript language	2.426
15	Knowledge of JavaScript framework	1.974	15	Web programming	2.381

Notes: Estimates of all the 174 skills are available upon request. *Source*: Authors elaboration on Lightcast Corp. data 2021-2024.

Figures

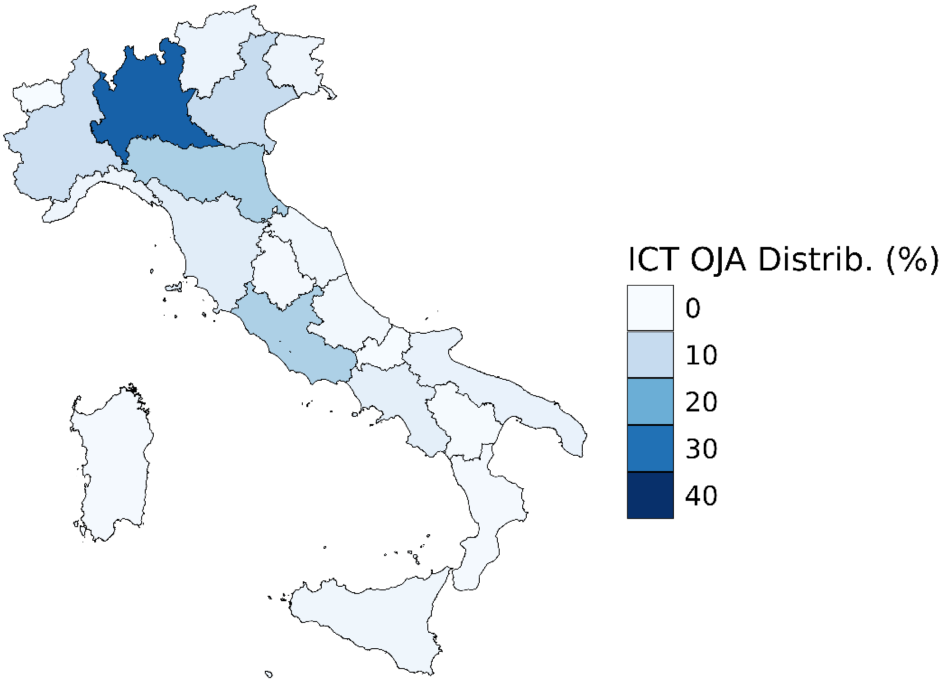

Figure 1: Percentage distribution of ICT OJAs in the Italian regions. *Source*: Lightcast Corp. 2021-2024.

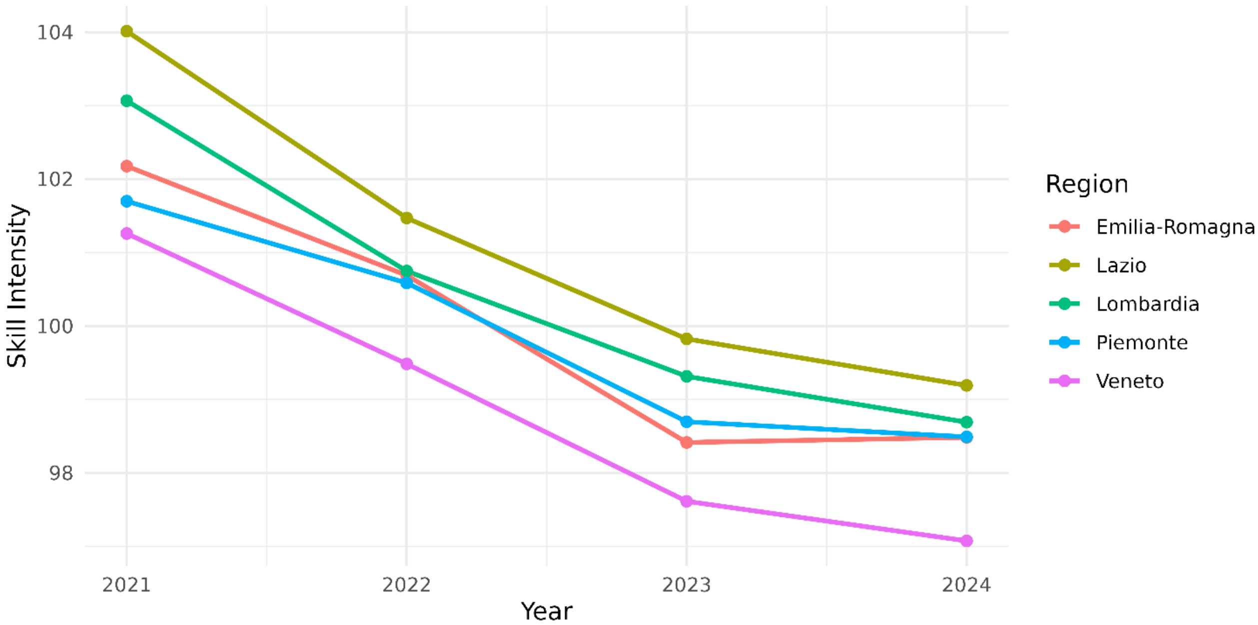

Figure 2: Evolution of regional skill intensity from 2021 to 2024. *Source*: Authors elaboration on Lightcast Corp. data 2021-2024.

Figure 3: Evolution of provincial skill intensity from 2021 to 2024 (considering the top 4 provinces). *Source*: Authors elaboration on Lightcast Corp. data 2021-2024.

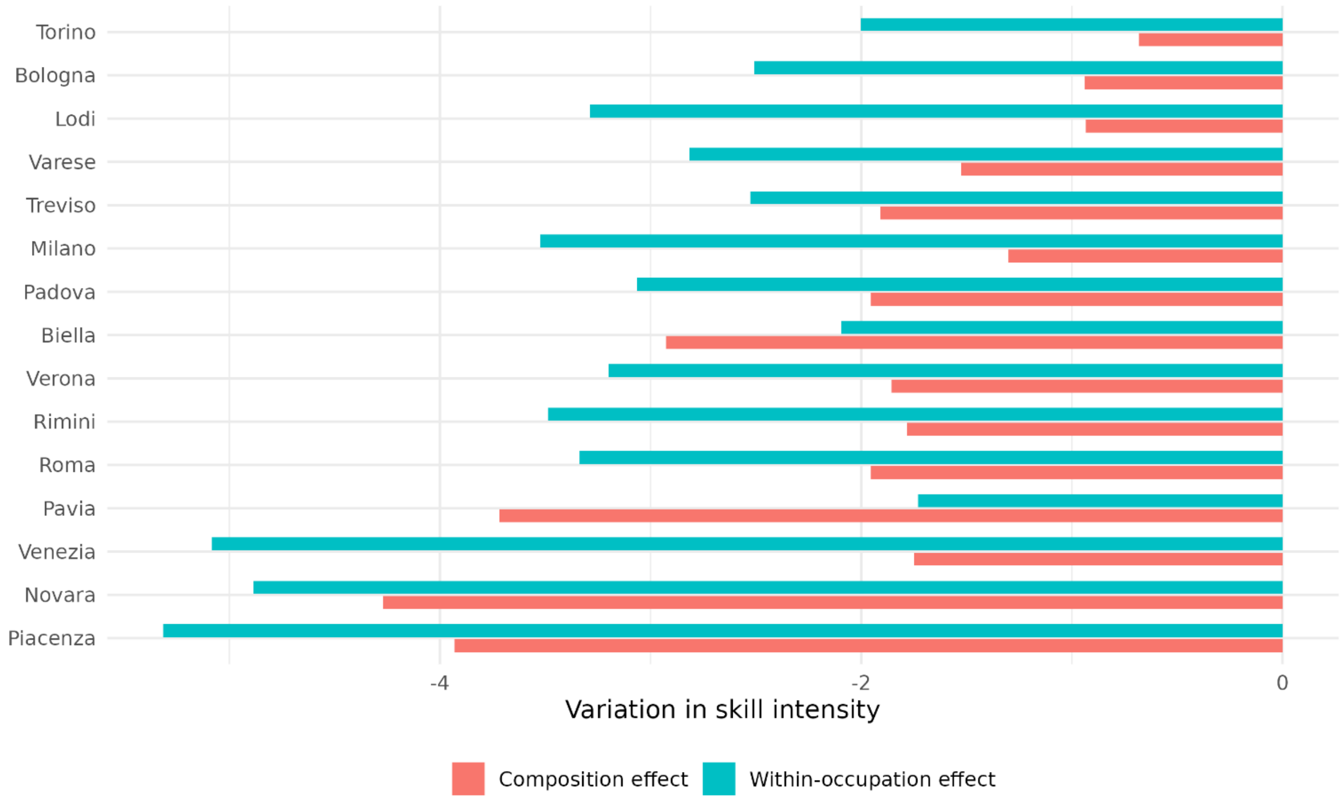

Figure 4: Shift-share decomposition of the provincial skill intensity change in within occupation effect and composition effect. *Source*: Authors elaboration on Lightcast Corp. data 2021-2024.

Figure List

Appendix A

The restriction of the analysis to five regions is primarily motivated by the territorial distribution of the data. These regions account for the largest concentrations of OJAs for ICT professionals and therefore provide sufficiently large samples for analyses at the provincial level. At the same time, the restriction does not result in a sample of economically homogeneous regions. This appendix documents the substantial differences among the selected regions in terms of innovation performance, productive structure, and the relative presence of ICT specialists.

We compare regions using the Regional Innovation Scoreboard (European Commission, 2023) data. Regarding the innovation performance we consider the RII (Regional Innovation Index). This index is the composite indicator used to summarise regional innovation performance. In the 2023 edition, it is calculated as the unweighted average of the normalised scores of 21 innovation indicators available at the regional level and is subsequently adjusted through a country-specific correction factor to ensure consistency with the corresponding national results of the European Innovation Scoreboard. In the summary regional rankings, performance is expressed relative to the EU average, set equal to 100. So, the RII values in the table are expressed relative to the EU average. The productive structure is evaluated using manufacturing, services and public administration employment shares on the total employment of the region. While the ICT specialist Index shows the presence of ICT specialist compared to the Italian average, where Italian level as the benchmark (Italy = 100). Higher (lower) values mean that there are more (less) ICT specialist then the Italian average. As shown in Table A1, in the 2023 four of the five selected regions are considered moderate innovators when compared to the EU benchmark (RII between 70 and 100), but perform above the Italian average, while Emilia Romagna is a strong Innovator (RII>100). The five regions differ in the economic structures in which ICT labour demand is embedded. Lazio is predominantly service-oriented, with a high share of employement in Public Administration, whereas Piemonte, Veneto and Emilia-Romagna have comparatively manufacturing-intensive employment structures; Lombardia combines a large service economy with a substantial manufacturing base, as well. Moreover, the selected regions differ markedly in the relative presence of ICT specialists. Values range from 64 in Veneto and 85 in Emilia-Romagna to 102 in Piemonte, 146 in Lombardia and 230 in Lazio.

Although the selected regions are therefore not statistically representative of Italy as a whole, they form a heterogeneous set of major regional markets for advertised ICT labour demand. Their differences allow us to assess whether changes in ICT skill intensity are shared across regional economies with distinct innovation profiles, productive structures, and levels of ICT specialisation.

Table A1: Selected statistics from the 2023 Regional Innovation Scoreboard.

	RII	Manufacturing (%)	Services (%)	Public Administration (%)	ICT specialists Index
Italy	90.3	18.6	64.4	5.3	100
Piemonte	95.4	24.0	60.9	4.0	102
Lombardy	97.4	24.4	64.2	2.6	146
Veneto	97.9	27.4	59.3	3.5	64
Emilia-Romagna	101.2	25.3	60.3	3.7	85
Lazio	97.6	8.0	73.5	9.1	230

Notes: Manufacturing, services, and public administration are expressed as shares of total employment. *Source*: Regional Innovation Scoreboard (European Commision, 2023).

Appendix B

Symmetric shift-share decomposition of skill intensity change

This appendix provides the formal derivation of the shift-share decomposition used in Section 4.3. The objective is to decompose the change in average provincial skill intensity into a between-occupation component and a within-occupation component.

Let $\bar{I}_{opt}$ denote the average skill intensity of vacancies belonging to occupation o, province p, and year t. This quantity is obtained by averaging the estimated vacancy-level skill intensity scores $\hat{I}_i$ across all OJAs i in occupation o, province p, and year t:

$$\bar{I}_{opt} = \frac{1}{N_{opt}} \sum_{i \in (o,p,t)} \hat{I}_i,$$

where N_{opt} is the number of OJAs in occupation o, province p, and year t.

Let s_{opt} denote the share of vacancies in province p and year t accounted for by occupation o:

$$s_{opt} = \frac{N_{opt}}{N_{pt}},$$

where N_{pt} is the total number of ICT OJAs in province p and year t. Average skill intensity in province p and year t can therefore be written as the weighted average of occupation-specific skill intensity:

$$\bar{I}_{pt} = \sum_{o \in O} s_{opt} \bar{I}_{opt}.$$

Let 2021 be the initial year and 2024 the final year. For each occupation-province cell, define:

$$\Delta s_{op} = s_{op,2024} - s_{op,2021},$$

and

$$\Delta \bar{I}_{op} = \bar{I}_{op,2024} - \bar{I}_{op,2021}.$$

The total change in provincial skill intensity is:

$$\Delta \bar{I}_p = \sum_{o \in O} s_{op,2024} \bar{I}_{op,2024} - \sum_{o \in O} s_{op,2021} \bar{I}_{op,2021}.$$

Using the definitions above, the final-year values can be written as:

$$s_{op,2024} = s_{op,2021} + \Delta s_{op},$$

and

$$\bar{I}_{op,2024} = \bar{I}_{op,2021} + \Delta \bar{I}_{op}.$$

Substituting these expressions into the total change gives:

$$\Delta\bar{I}_p = \sum_{o \in O} \left(s_{op,2021} + \Delta s_{op}\right)\left(\bar{I}_{op,2021} + \Delta\bar{I}_{op}\right) - \sum_{o \in O} s_{op,2021}\,\bar{I}_{op,2021}.$$

Expanding the product yields:

$$\sum_{o \in O} \left(s_{op,2021} + \Delta s_{op}\right)\left(\bar{I}_{op,2021} + \Delta\bar{I}_{op}\right)$$
$$= \sum_{o \in O} s_{op,2021}\,\bar{I}_{op,2021} + \sum_{o \in O} \bar{I}_{op,2021}\,\Delta s_{op} + \sum_{o \in O} s_{op,2021}\,\Delta\bar{I}_{op} + \sum_{o \in O} \Delta\, s_{op}\Delta\bar{I}_{op}.$$

Subtracting the initial-year term from both sides cancels out $\sum_{o \in O} s_{op,2021}\,\bar{I}_{op,2021}$. Therefore:

$$\Delta\bar{I}_p = \sum_{o \in O} \bar{I}_{op,2021}\,\Delta s_{op} + \sum_{o \in O} s_{op,2021}\,\Delta\bar{I}_{op} + \sum_{o \in O} \Delta\, s_{op}\Delta\bar{I}_{op}.$$

This expression separates the total change into three elements. The first term is the pure between-occupation effect, because it captures the contribution of changing occupational shares while holding occupation-specific skill intensity fixed at the 2021 level. The second term is the pure within-occupation effect, because it captures the contribution of changing occupation-specific skill intensity while holding occupational shares fixed at the 2021 level. The third term is an interaction term, because it captures the fact that occupational shares and occupation-specific skill intensity may change simultaneously. A three-term decomposition is exact, but the interaction term is not straightforward to interpret substantively. Assigning the whole interaction term to either the between-occupation component or the within-occupation component would make the result depend on an arbitrary choice. We therefore use a symmetric two-component decomposition, in which the interaction term is divided equally between the two margins.

The reported between-occupation component is the first component with half of the interaction term added:

$$B_p = \sum_{o \in O} \bar{I}_{op,2021}\,\Delta s_{op} + \frac{1}{2}\sum_{o \in O} \Delta\, s_{op}\Delta\bar{I}_{op}$$

The reported within-occupation component is the second component with half of the interaction term added:

$$W_p = \sum_{o \in O} s_{op,2021}\,\Delta\bar{I}_{op} + \frac{1}{2}\sum_{o \in O} \Delta\, s_{op}\Delta\bar{I}_{op}.$$

The two-component decomposition is therefore exact. Its advantage is that it preserves a clear distinction between changes due to occupational recomposition and changes due to within-occupation skill intensity, while avoiding the arbitrary allocation of the interaction term to only one side of the decomposition

Appendix C

Table C1: Occupations ranking by skill count.

Rank	ESCO level 4 Occupations	Share (%)	Skill count
1	Software developers	20.0	26.4
2	Web and multimedia developers	12.7	24.5
3	Applications programmers	14.2	19.9
4	Systems analysts	24.7	19.6
5	Database and network professionals not elsewhere classified	7.2	19.5
6	Computer network professionals	2.4	18.6
7	Database designers and administrators	5.2	17.9
8	Systems administrators	6.8	17.3
9	Software and applications developers and analysts not elsewhere classified	6.8	17

Note: Skill count refers to the average skill count by occupation. Share refers to the share (expressed with percentages) of OJA for each occupation of the total number of OJA in the ICT professional's sector. *Source*: authors' elaboration on Lightcast Corp. data from 2021-2024 on OJA across ICT professionals.

Table C2: Provincial ranking in territorial skill intensity.

Rank	Province	$\bar{I}_p$
1	Roma	101.320
2	Milano	101.195
3	Bologna	100.701
4	Torino	100.539
5	Piacenza	100.326
6	Varese	100.133
7	Biella	99.992
8	Lodi	99.805
9	Modena	99.616
10	Parma	99.551
11	Reggio nell'Emilia	99.451
12	Padova	99.365
13	Rimini	99.319
14	Treviso	99.307
15	Brescia	99.171
16	Verona	99.122
17	Como	98.987
18	Forlì-Cesena	98.980
19	Monza e della Brianza	98.958
20	Cremona	98.789
21	Pavia	98.777
22	Rieti	98.727
23	Belluno	98.492
24	Bergamo	98.234
25	Venezia	98.066
26	Vercelli	97.981
27	Novara	97.943
28	Ravenna	97.680
29	Viterbo	97.526
30	Mantova	97.389
31	Alessandria	97.335
32	Vicenza	97.034
33	Ferrara	97.022
34	Latina	96.840
35	Cuneo	96.526
36	Lecco	95.907
37	Rovigo	95.901
38	Sondrio	95.668
39	Frosinone	95.433
40	Asti	95.002
41	Verbano-Cusio-Ossola	94.790

Source: authors elaboration on the estimation sample derived by Lightcast Corp. data 2021-2024.

Table C3: Shift-share decomposition of provincial skill intensity change.

Province	Total change ($\Delta\bar{I}_p$)	Composition effect (B_p)	Within effect (W_p)
Alessandria	-1.3886	**-1.6898**	0.3012
Asti	-1.7526	2.3427	**-4.0953**
Belluno	-0.5641	-0.1754	**-0.3887**
Bergamo	-1.5485	**-1.0572**	-0.4913
Biella	-5.0215	**-2.9263**	-2.0952
Bologna	-3.4458	-0.9374	**-2.5084**
Brescia	-1.3317	**-0.8565**	-0.4752
Como	-5.0105	-1.4479	**-3.5626**
Cremona	-1.8836	-0.2342	**-1.6494**
Cuneo	-1.7048	-0.6025	**-1.1023**
Ferrara	-4.6803	-0.6512	**-4.0292**
Forlì-Cesena	-4.6948	-2.3021	**-2.3927**
Frosinone	-1.6630	**-2.3593**	0.6962
Latina	-5.9952	-2.2553	**-3.7399**
Lecco	-2.2438	**-2.0506**	-0.1933
Lodi	-4.2208	-0.9345	**-3.2863**
Mantova	-0.4915	**-0.4154**	-0.0761
Milano	-4.8228	-1.3005	**-3.5222**
Modena	-3.9625	-1.5824	**-2.3801**
Monza e della Brianza	-3.5202	-1.0589	**-2.4613**
Novara	-9.1524	-4.2682	**-4.8842**
Padova	-5.0205	-1.9543	**-3.0662**
Parma	-2.5604	-0.4980	**-2.0625**
Pavia	-5.4483	**-3.7185**	-1.7298
Piacenza	-9.2440	-3.9307	**-5.3133**
Ravenna	-3.0108	-0.7160	**-2.2948**
Reggio nell’Emilia	-1.4081	**-0.9258**	-0.4823
Rimini	-5.2690	-1.7817	**-3.4873**
Roma	-5.2914	-1.9534	**-3.3380**
Rovigo	-3.4668	-1.1797	**-2.2870**
Sondrio	-0.1715	**-0.1715**	0.0000
Torino	-2.6812	-0.6801	**-2.0011**
Treviso	-4.4358	-1.9089	**-2.5269**
Varese	-4.3408	-1.5253	**-2.8155**
Venezia	-6.8319	-1.7484	**-5.0834**
Verbano-Cusio-Ossola	-8.1960	**-8.1960**	0.0000
Vercelli	-5.4480	-2.0302	**-3.4177**
Verona	-5.0544	-1.8555	**-3.1989**
Vicenza	-2.9796	-0.9415	**-2.0381**
Viterbo	3.4127	**2.9148**	0.4979

Notes: In bold is highlighted the largest component. Rieti province is missing, since we could not compute the $\bar{I}_p$ due to the low number of OJA in certain occupations (<20). *Source*: authors elaboration on Lightcast Corp. data in 2021 and 2024.

Table C4: Average skill count in job ads by regions.

Region	2021	2022	2023	2024	% change
Emilia-Romagna	20.4895	20.7837	19.4968	20.1853	-0.01485
Lazio	22.3983	22.0712	21.3808	21.6621	-0.03287
Lombardia	21.6035	21.5991	21.5503	21.9608	0.01654
Piemonte	19.2846	21.4330	20.7725	21.2071	0.09969
Veneto	20.2709	20.4082	19.9588	20.2443	-0.00131

Notes: The last column show the percentage change from 2021 to 2024. *Source*: authors elaboration on Lightcast Corp. data in 2021 and 2024.

Table C5: Average skill count in job ads in the most skill intense provinces.

	2021	2022	2023	2024	% change
Bologna	22.6655	22.4507	21.4121	21.8054	-0.0379
Milano	22.9757	22.4829	22.3672	23.3717	0.0172
Roma	22.8312	22.3073	21.6665	21.9451	-0.0388
Torino	20.1732	22.3373	21.8207	22.1822	0.0996

Notes: The last column show the percentage change from 2021 to 2024. *Source*: authors elaboration on Lightcast Corp. data in 2021 and 2024.

Table C6: Average skill count in job ads in the most skill intense occupations.

	2021	2022	2023	2024	% change
Applications programmers	19.2207	20.4874	19.6725	19.8149	0.0309
Computer network professionals	17.6625	19.2400	18.4564	19.6731	0.1138
Database and network professionals n.e.c	19.5424	20.1404	20.3093	20.3542	0.0415
Database designers and administrators	18.8537	19.2517	19.0568	17.9116	-0.0500
Software and applications developers and analysts n.e.c	15.9322	17.2143	16.8570	17.0433	0.0697
Software developers	26.1083	25.4011	25.4810	25.9814	-0.0049
Systems administrators	17.4347	18.0191	16.7632	17.8859	0.0259
Systems analysts	18.2569	19.5291	20.1151	20.8970	0.1446
Web and multimedia developers	25.2826	24.3285	23.8635	25.1399	-0.0056

Notes: The last column show the percentage change from 2021 to 2024. N.e.c stands for “not elsewhere classified”. *Source*: authors elaboration on Lightcast Corp. data in 2021 and 2024.

Table C7: Top 15 item parameter estimates for the year 2021.

Skill	b_i	skill	a_i
Create the front-end design of a website	6.8991	Create the front-end design of a website	4.1108
Computer programming	6.7074	Using mark-up languages	3.8744
Using mark-up languages	5.4351	Knowledge of JavaScript framework	3.2641
Knowledge of SQL language	4.8877	Developing Software projects	3.2370
Knowledge of CSS language	4.2021	Knowledge of CSS language	2.7845
Web programming	3.8914	Creating a user interface	2.5088
Knowledge of Java language	3.8869	Knowledge of SQL language	2.4293
Knowledge of Unified Modelling Language	3.6309	Knowledge of JavaScript language	2.4071
Using query languages	3.4346	Using query languages	2.3744
Knowledge of PHP language	3.4102	Knowledge of PHP language	2.3640
Using a computer	2.9348	Knowledge of Unified Modelling Language	2.3517
Using object-oriented programming	2.3500	Computer programming	2.2883
Knowledge of JavaScript language	2.2685	Web programming	2.1476
Database knowledge	2.2072	Knowledge of Java language	2.1288
Handling a database	1.7865	Knowledge of the std. WWW Consortium	2.0803

Source: authors' elaboration on Lightcast Corp. data from the estimation sample considering year 2021.

Table C8: Top 15 Item parameter estimates for the year 2022.

Skill	b_i	Skill	a_i
Computer programming	7.1283	Create the front-end design of a website	3.5540
Create the front-end design of a website	6.9638	Using mark-up languages	3.4025
Knowledge of SQL language	5.6488	Knowledge of JavaScript framework	3.1275
Using mark-up languages	5.4421	Developing Software projects	2.9796
Using query languages	4.9792	Creating a user interface	2.7852
Knowledge of PHP language	4.9406	Using query languages	2.6876
Knowledge of Java language	4.6459	Knowledge of PHP language	2.6784
Knowledge of Unified Modelling Language	4.4235	Knowledge of CSS language	2.4950
Knowledge of CSS language	4.0294	Knowledge of Apache Maven	2.2593
Web programming	3.6576	Knowledge of SQL language	2.2517
Using a computer	3.3709	Knowledge of the std. WWW Consortium	2.2197
Creating a user interface	3.1937	Knowledge of Unified Modelling Language	2.0818
Knowledge of JavaScript framework	2.5936	Knowledge of JavaScript language	2.0467
Using object-oriented programming	2.4131	Knowledge of MySQL	2.0266
Handling a database	2.2598	Computer programming	2.0139

Source: authors' elaboration on Lightcast Corp. data from the estimation sample considering year 2022.

Table C9: Top 15 item parameter estimates for the year 2023.

Skill	b_i	skill	a_i
Using query languages	16.7416	Using query languages	10.1770
Knowledge of PHP language	16.2555	Knowledge of PHP language	9.9056
Create the front-end design of a website	11.3068	Create the front-end design of a website	7.2519
Computer programming	5.8431	Knowledge of MySQL	3.2673
Knowledge of SQL language	5.0183	Knowledge of JavaScript framework	3.1613
Using a computer	3.9099	Developing Software projects	3.0897
Knowledge of Unified Modelling Language	3.5674	Using mark-up languages	2.5492
Knowledge of Java language	3.4879	Knowledge of Apache Maven	2.4292
gestire database	2.8107	Knowledge of CSS language	2.4257
Knowledge of MySQL	2.7955	Knowledge of NoSQL	2.3886
Database knowledge	2.4878	Knowledge of SQL language	2.3856
principi del lavoro di gruppo	2.3091	Creating a user interface	2.3717
utilizzare microsoft office	2.2568	Knowledge of Apache Tomcat	2.2446
Web programming	2.1171	Knowledge of the std. WWW Consortium	2.2436
utilizzare i fogli elettronici	2.1159	Knowledge of Unified Modelling Language	2.1641

Source: authors' elaboration on Lightcast Corp. data from the estimation sample considering year 2023.

Table C10: Top 15 item parameter estimates for the year 2024.

Skill	b_i	skill	a_i
Create the front-end design of a website	7.2712	Using mark-up languages	4.5104
Using query languages	6.6400	Knowledge of CSS language	4.2050
Knowledge of PHP language	6.5630	Creating a user interface	4.1582
Using mark-up languages	6.5512	Create the front-end design of a website	3.8965
Knowledge of SQL language	6.1596	Knowledge of JavaScript framework	3.5097
Knowledge of CSS language	6.1147	Using query languages	3.3926
Creating a user interface	5.9871	Knowledge of PHP language	3.3719
Computer programming	5.7236	Developing Software projects	3.2799
Knowledge of Unified Modelling Language	4.8982	Knowledge of the std. WWW Consortium	2.4788
Knowledge of Java language	4.7564	Knowledge of SQL language	2.4624
Using a computer	4.4309	Knowledge of Unified Modelling Language	2.3783
Web programming	3.8578	Web programming	2.2188
Knowledge of JavaScript framework	3.4421	Knowledge of MySQL	2.1709
Handling a database	3.2952	Knowledge of C++	2.0846
Knowing groupwork’s principles	3.1459	Knowledge of Java language	1.9435

Source: authors’ elaboration on Lightcast Corp. data from the estimation sample considering year 2024.

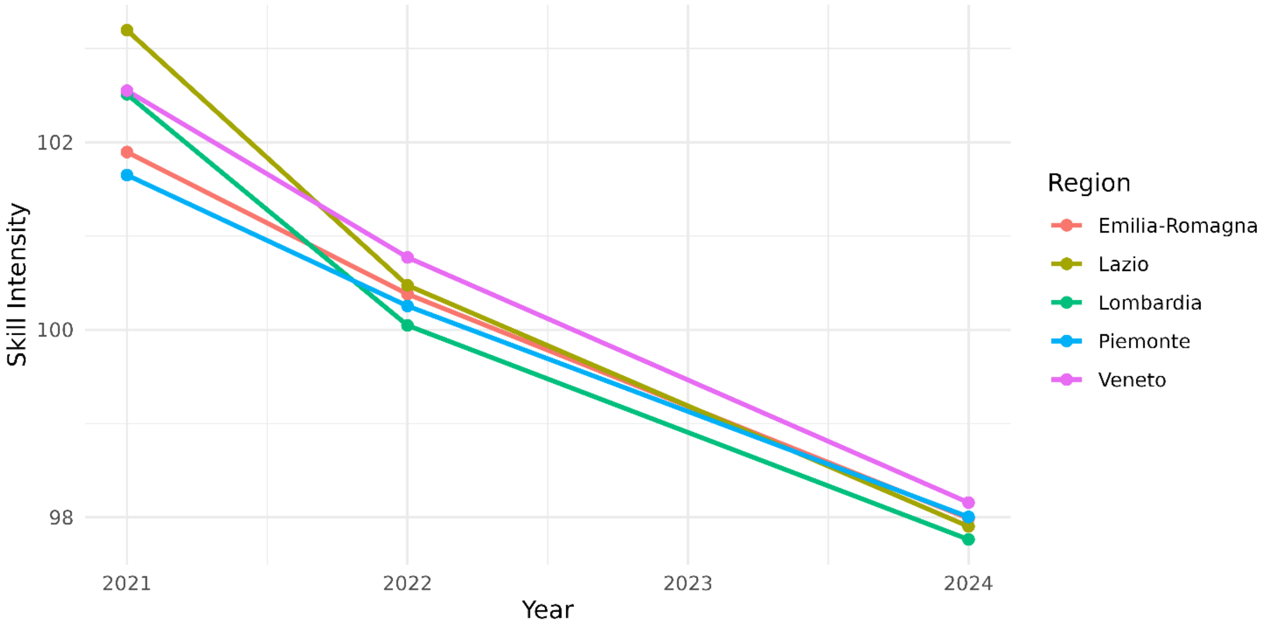

Figure C1: Evolution of regional skill intensity from 2021 to 2024, excluding 2023.

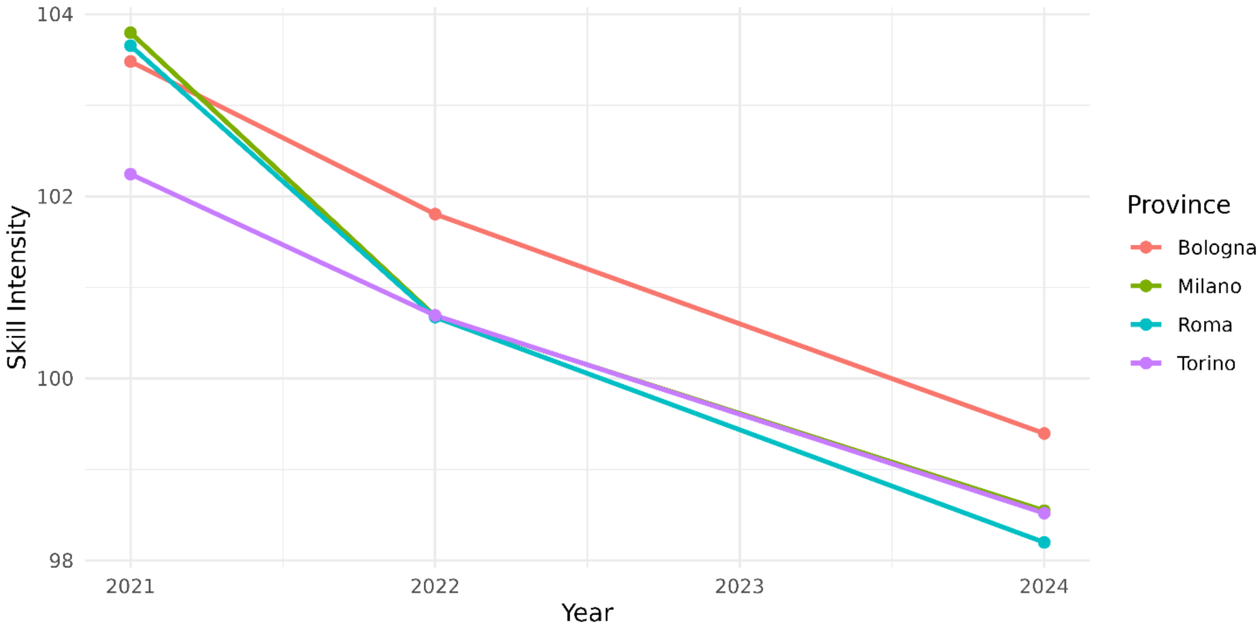

Figure C2: Evolution of provincial skill intensity from 2021 to 2024 (considering the top 4 provinces), excluding 2023.

Table C11: Skill intensity changes within ICT occupations.

	n_{2021}	$\bar{I}_{o,2021}$	n_{2024}	$\bar{I}_{o,2024}$	$\Delta\bar{I}_o$
Database designers and administrators	2904	100.582	3415	95.972	-4.61
Web and multimedia developers	8368	109.929	5919	105.693	-4.236
Software developers	12607	108.11	12712	104.313	-3.797
Applications programmers	9617	102.451	10038	99.047	-3.404
Database and network professionals n.e.c.	2987	96.714	6188	94.233	-2.481
Systems administrators	3849	97.345	4933	94.944	-2.4
Software and applications developers and analysts n.e.c	3037	92.542	5560	90.171	-2.371
Computer network professionals	1505	96.166	1955	95.046	-1.12
Systems analysts	10965	98.742	20570	97.718	-1.024

Notes: n.e.c stands for "not elsewhere classified". n_t represent the number of OJA for occupation o in the selected year *Source*: authors elaboration on Lightcast data 2021-2024.