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Skill demand and labour market concentration: evidence from Italian vacancies

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Abstract

Purpose – The authors provide a novel interpretation of the relationship between skill demand and labour market concentration based on the training rationale.

Design/methodology/approach – The authors use a novel data set on Italian online job vacancies during 2013–2018 to analyse the relationship between labour market concentration and employers' skill demand. The authors construct measures of market concentration and skill intensity in the local labour market. The authors regress the measures of skill demand on market concentration, controlling for sector, occupations and other features of the labour market. The authors also use the Hausman–Nevo instrument for market concentration.

Findings – The authors show that employers in a highly concentrated labour market demand competencies associated with the ability of workers to learn faster (e.g. social skills) rather than actual knowledge. They also require less experience but higher education. These results are consistent with the hypothesis that employers in more concentrated labour markets are more prone to train their employees. Instead of looking for workers who already have job-specific skills, they look for workers who can acquire them faster and efficiently. The authors provide a theoretical framework within which to analyse these aspects as well as providing a test for the relevant hypotheses.

Practical implications – In addition to cross-countries differences in labour market regulations, the authors' findings suggest that policy authorities should consider the local labour market structure when studying workforce development programmes aimed at bridging the skill gap of displaced workers. Moreover, the authors show that market concentration can have relevant implications for human resource (HR) managers by affecting their recruitment behaviour through the demand for skills. In fact, concentrated markets tend to favour firms' collusion and anti-competitive behaviour that could strongly affect HR management practices.

Originality/value – The authors' paper innovates on the literature in a number of ways. First, the authors provide evidence of local labour market concentration in Italy. Second, the authors provide evidence of skill demand at the local level using a detailed skill taxonomy that goes beyond the classical distinction between high and low skills. Third, and most importantly, the authors provide evidence of the relationship between skill demand and labour market concentration. By analysing detailed skills and competencies, the authors take one step beyond understanding the features of labour demand in monopsonistic markets.

Keywords Local labour market, Concentration, Skill demand, Training

Paper type Research paper

1. Introduction

In recent years a great deal of emphasis has been placed on the rise in market concentration (Covarrubias *et al.*, 2019; Grullon *et al.*, 2019). Increasing concentration is a general phenomenon that can have relevant macroeconomic consequences such as the fall in the labour share (Autor

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et al., 2020; De Loecker *et al.*, 2020) and the stagnation of aggregate investment (Gutiérrez and Philippon, 2017). In the labour market concentration translates into firms' monopsony power which is often associated with lower wages (larger markdowns), inefficient labour allocation and consequent welfare losses (Marinescu *et al.*, 2021; Azar *et al.*, 2020a; Schubert *et al.*, 2020; Berger *et al.*, 2022; Jarosch *et al.*, 2019; Benmelech *et al.*, 2022).

Another prominent phenomenon observed in labour markets is the change in skill requirement with the increasing relevance and emphasis placed on cognitive and social skills (Modestino, 2020; Clemens *et al.*, 2020; Ziegler, 2020; Burke *et al.*, 2019; Kuhn *et al.*, 2018; Deming and Kahn, 2018; Deming, 2017; Beaudry *et al.*, 2016). The literature has mostly associated changes in skill requirements with globalisation and technical progress. Yet, little is known about whether and to what extent local labour market concentration *per se* affects skill demand. In this paper, we address this question using a unique dataset of Italian Online Job Advertisements (OJAs), which provide granular information on the demand for skills and competencies for detailed occupations and the local labour market.

We show that employers in a highly concentrated labour market demand competencies associated with the ability of workers to learn faster (e.g. social skills) rather than actual knowledge. They also require less experience but higher education. These results are consistent with the hypothesis that employers in more concentrated labour markets are more prone to train their employees. Instead of looking for workers who already have job-specific skills, they look for workers who can acquire them faster and more efficiently. Our findings, thus, highlight the importance of tailoring active labour market policies to the specificity of each local labour market.

Our paper innovates on the literature in a number of ways. First, we provide evidence of local labour market concentration in Italy. As stressed below, the literature so far has been focused on the USA whilst less evidence so far has been collected on labour market concentration in Europe. Second, we provide evidence of skills demand at the local level using a detailed skill taxonomy that goes beyond the classical distinction between high and low skills. Third, and most importantly, we provide evidence of the relationship between skill demand and labour market concentration. To the best of our knowledge a similar issue has been explored only by Modestino (2020), who, however, focuses exclusively on the level of education and experience demanded. By analysing detailed skills and competencies we take one step beyond in understanding the features of labour demand in monopsonistic markets.

Our results have clear implications for human resource (HR) management practices. In fact, concentrated markets tend to favour firms' collusion and anti-competitive behaviour that could strongly affect HR management practices. Given the increase in concentration documented above, the problem is so severe that in the U.S. Department of Justice/Antitrust Division and Federal Trade Commission (2016), have issued specific guidance for HR professionals in concentrated markets. In this paper, we provide a new angle to analyse this issue by showing that recruitment behaviour and the demand for skills differ in monopsonistic markets.

We interpret the relationship between labour market concentration and skill demand through the lens of a monopsonistic model with employer-provided training. To provide the intuition, assume that two sets of skills characterise workers: one more challenging to learn (e.g. soft skills) and the other easier to teach and learn, such as standard technical competencies (e.g. specific software). Assume that those two sets of skills are equally important for production. However, the second set of skills, being easier to be taught, can be provided to the workers through on-the-job training more efficiently (i.e. at a lower cost). Therefore, a firm's training decision impacts the demand for skills as some are more "trainable" than others. Suppose firms with higher market power face higher recruitment costs. In that case, they are also more likely to invest in training, providing internally trainable skills whilst looking on the market for untrainable skills. Therefore firms will look for skills that are relatively difficult to be taught or that help new workers acquire new competencies fast and effectively.

The remainder of the paper is structured as follows. Section 2 illustrates the literature most closely related to the paper; section 3 develops a simple theoretical setting that conveys the main testable hypothesis; section 4 presents the data and the methodology; section 5 illustrates the results and provides some robustness checks; finally section 6 concludes. The appendix presents the full derivation of the model, further results with IV estimator, detailed descriptive statistics and an analysis of the representativeness of OJAs.

2. Related literature

Our paper is related to two major strands of the literature. The first is the analysis of labour market concentration and its effects on firms' training decisions. There is strong evidence of increasing concentration in USA labour market (Hershbein *et al.*, 2021; Azar *et al.*, 2020a; Berger *et al.*, 2022), and there is also growing evidence of the same effect in Europe (in addition to our paper and Marcato (2021) for Italy, see Marinescu *et al.* (2021) for France and Bighelli *et al.* (2021) for Europe). The literature shows that stronger monopsony power allows firms to extract large rents from workers' productivity [1]. So long as on-the-job training increases workers' performance, it is more likely to be provided by firms with considerable market power. Empirically the link between market structure and firms' training decisions is well documented. For example, Brunello and Gambarotto (2007), Brunello and De Paola (2008), Harhoff and Kane (1997) find a negative and significant effect of labour market competition on firms' decision to train [2].

The second strand of the literature is the analysis of skill demand. Since the seminal paper by Autor *et al.* (2003) the "task approach" has been used to analyse the changing structure of labour demand in industrialised countries [3]. One of the difficulties with this approach is to have a granular measure of tasks and skills for occupations. Recently a new impulse to this literature has been provided by the availability of detailed data from OJAs. Such data has been used mainly in the USA (Azar *et al.*, 2020b; Deming and Kahn, 2018; Hershbein and Kahn, 2018; Modestino *et al.*, 2016; Modestino, 2020) whilst little information is available in Europe with the exception of Colombo *et al.* (2019) for Italy and Adrjan and Lydon (2019) for Ireland. Our paper contributes to this literature by providing detailed evidence of skill needs in the Italian local labour market. The analysis of OJAs has a number of advantages for extracting information about skills. First, it follows a bottom-up approach that is entirely data-driven. The initial data collected contains all the information that individual firms post on the web. This large amount of data is subsequently filtered and processed using appropriate techniques to obtain the required information. In this way, the tools help to categorise a pre-existing information set, but they do not pre-classify the information itself (as generally done in surveys). This is particularly useful for the identification of soft skills and certain occupation-specific skills that surveys often ignore. In our data, we are able to identify more than 250 specific skills that can be subsequently grouped into different macro categories following a standard taxonomy.

3. Theoretical framework

Although the main focus of our paper is empirical, to guide the empirical analysis, we present a theoretical setting that can deliver simple testable predictions. In this section, we discuss the main implications and the intuition of the model. The detailed derivations are reported in the Appendix. Our model encompasses two different approaches. First, we present a generalised monopsonistic model (section 3.1) that shows how market concentration affects firms' recruitment decisions. Second, we nest the first model in a standard task model (section 3.2) where firms can choose between trainable and untrainable labour inputs.

3.1 Generalised monopsonistic model

Following Manning (2006), we consider a monopsonistic model where firms compete for workers, but where, in order to set their level of employment N, they must pay both a direct and an indirect cost. The direct cost per worker is the wage W, whereas the indirect cost, $I(N)$, can be thought of as the recruiting cost necessary to substitute the exogenously separated workers with new recruits. We assume that this recruiting cost is increasing with the share of employment working in the firm, therefore, aggregating at the market level, a higher level of concentration leads to higher recruiting costs. The rationale is that the larger the share of workers working for a firm in a market, the more difficult it becomes to find a good match amongst potential recruits. Alternatively, one can think of a framework as in Berger *et al.* (2022) where workers have an idiosyncratic preference or specific bundle of competencies for a workplace, therefore the larger the share of employees working in a firm, the costlier it becomes to convince the remaining workers to work in that workplace because they are those with the lowest idiosyncratic preference or the lack of necessary competencies [4]. For our purposes the key element is that it is the employment share to drive an increase in hiring costs, rather than the absolute number of employees [5].

To maintain the model simple, we are excluding factors such as the possibility for workers to move across markets as well as the entry or exit of new workers or firms. Our results will go through even incorporating these elements so long as the basic features of the monopsonistic model are preserved [6]. Empirically the evidence on workers' mobility in Italy is mixed, depending also on the geographical unit considered.

In this setting, a firm chooses N to maximise profits which are given by:

$$\pi = \max_{N} \Upsilon(N) - \underbrace{[I(N) + W]N}_{C(W,N)} \tag{1}$$

In equation (1) the level of employment N affects the cost function $C(W, N)$ both through its direct cost (through wages) and through its indirect cost ($I(N)$). The latter effect operates through local labour market concentration: the larger the firm the larger its share in the local market, the more concentrated the market is.

The first order condition of equation (1) is the following

$$MP_N = \left(1 + \frac{\partial C(W,N)}{\partial N}\frac{N}{C}\right)C(W,N) = (1 + e(N))C(W,N) \tag{2}$$

where MP_N is the marginal productivity of labour and $e(N)$ is the inverse labour supply elasticity which depends on the employment share. As stated above we assume that the inverse labour supply elasticity is increasing with the level of employment, $C'_N > 0$ and $C''_{NN} \geq 0$, which implies that it becomes increasingly costly to recruit workers [7].

Building on this result, we will proxy the increase in labour market concentration with an increase in the indirect cost of labour through an increase in the employment share, keeping unchanged the level of employment and thus the direct cost.

The assumption that firms can just adjust their labour force and not their wages is specific for a country with high wage rigidities and collective contracts, like Italy. Although the incentive to reduce wages from the reduction in labour market competition, the downward wage rigidity forbids them this channel, pushing them to intervene through the labour demand one [8].

3.2 Production function

We embed the approach outlined above in a canonical model of human capital with different tasks and factor-augmenting technology (Acemoglu, 2002; Autor *et al.*, 2003; Acemoglu and Autor, 2011). Consider an economy where labour is the only input, divided in two distinct categories: "trainable" and "untrainable". The competencies in the trainable category can be quickly learnt through on-the-job training — for example, standard technical skills. Instead, the "untrainable" category includes those competencies that are difficult to learn because they are linked to character or attitude. Some straightforward examples are competencies like leadership, problem-solving and social skills. The two groups of skills are both needed for production. Thus, they are complements and not substitutes [9].

Assume that the production function is a Cobb-Douglas function nested in a constant elasticity of substitution (CES) function:

$$\Upsilon = \left[\left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} + \mathcal{U}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} \tag{3}$$

where T is the trainable labour component, $\mathcal{U}$ is the untrainable one, A is the amount of training provided and $\theta \in [0, \infty)$ is the elasticity of substitution between trainable and untrainable labour inputs. Given that the two skill groups are complements, $0 < \theta < 1$. As an additional simplification, we assume that training can only improve the productivity of the "trainable" labour component [10].

3.3 Equilibrium and empirical predictions

There is a training cost τ linear in the amount of training. Both inputs belong to the same market which follows the structure described in section 3.1. Both inputs have the same direct cost W and indirect cost $I(N)$, which depends on the total amount of labour inputs used $N = T + \mathcal{U}$ [11]. Thus, the profit maximisation problem can be written as:

$$\max_{A,T,\mathcal{U}} \left[\left(A^{\alpha} T^{1-\alpha} \right)^{\frac{\theta-1}{\theta}} + \mathcal{U}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} - \tau A - C(W, N)N \tag{4}$$

where A is the amount of on-the-job training provided. Taking into account that T and $\mathcal{U}$ labour inputs have the same increasing cost due to the indirect cost, an employer decides the optimal bundle of untrainable and trainable skills and the total amount of training provided to the latter.

Our primary objective is to examine the impact of employment concentration on employers' preferences for trainable and untrainable labour components. Assume that a rise in employment concentration increases the indirect cost of both inputs. Given the possibility to improve the productivity of one of the inputs through training, the optimal bundle relies not only on their relative cost and productivity but also on the ability to substitute the trainable input with training expenditures. Therefore, as input costs increase due to a rise in market concentration, measured by the Herfindahl–Hirschman Index (HHI), which represents the cumulative sum of squared employment shares of each firm within a local labour market, this alternative to substitute the training input with training becomes increasingly more financially advantageous [12].

Proposition 1. *Consider a general monopsonistic model where employers face an increasing labour cost function and can choose a bundle of trainable and untrainable labour input as well as the amount of on-the-job training. The ratio between trainable and untrainable inputs decreases with the level of concentration. Formally,*

$$\frac{\partial \left(T^{*} / \mathcal{U}^{*} \right)}{\partial HHI} < 0$$

Therefore employers facing a concentrated labour market are more likely to demand relatively more untrainable competencies. As the concentration rises, the inverse labour supply becomes steeper, increasing the marginal cost of the labour inputs; given that the two inputs are complements, an employer will find it more profitable to divert part of the investment from the trainable input to the untrainable one, substituting the former with an increase in the training investment. Indeed, as a corollary, it can be shown that this simple model also predicts an increase in training spending following an increase in employment concentration.

4. Data and measures

4.1 Sources

The source of the vacancy data is Wollybi, [13] a project that collects online vacancies in Italy from job portals since February 2013. For internal data consistency, we concentrate on the years from 2015 to 2018, and we select only primary sources, neglecting secondary sources such as aggregators (e.g. websites that re-post vacancies retrieved from other websites) [14]. Each vacancy includes detailed information such as location, industry, education and skill requirements [15].

To measure the level of concentration across local labour markets, we exploit the Italian ORBIS dataset, AIDA, by Bureau van Dijk, from 2015 to 2018. This dataset contains the full balance sheets and income statements of Italian firms. Similar data have been used in recent research, see for example Gopinath *et al.* (2017).

One potential drawback of online vacancies is that they capture only vacancies posted on the Internet and may not be representative of the universe of vacancies. Online vacancies have been used by other papers and have been found fairly representative of the universe of job openings (Hershbein and Kahn, 2018; Modestino, 2020). In the appendix we provide a detailed assessment of the representativeness of online data; however, it is worth mentioning that our paper focuses on the skill distribution within occupation across markets characterised by different degrees of concentration, therefore any bias that online vacancies may have is likely to be greatly weakened.

We restrict the analysis only to those vacancies that report both the province and 2-digit NACE industry code, this leads to a final sample of 553,132 vacancies, distributed over 4 years, 106 provinces, 380 occupation codes and 73 industry codes. In addition to the skill content, OJA contains information about the level of education (ISCED) and the level of experience required (expressed in years). Tables A9 and A10 show the summary statistics of this final sample.

4.2 Skill classification

To allow comparability with other papers of the literature we have used the skill taxonomy of O*NET, developed by the Bureau of Labour Statistics [16]. Skills extracted from OJA are classified into the finest level of the O*NET taxonomy which is organised into three hierarchical levels. We used the finest level as the building block to construct two classifications. The first is the broadest O*NET level composed of the following categories: *Knowledge*, *Skills*, *Abilities*, *Work Activities* and *Work Styles* [17]. The broad classification available in O*NET however does not lend itself to a clear interpretation as there are subtle differences between what is classified as skill and what is classified as, say, ability or work activity. For example “mathematical reasoning” is classified as an ability under the category of “cognitive abilities”; on the other hand “use of mathematics to solve problems” is classified as a skill under the category of “basic skills”. Moreover “developing and building teams” is considered as a work activity under the category of “interacting with others” whilst “persuasion” and “coordination” are considered as skills (social skills). Starting from the finest level we have therefore constructed a different skill classification composed of the following groups *Cognitive*, *Social*, *Digital*, *Hard (technical)*, *Organisational* skills. We did not regroup items of the *Knowledge* category leaving them separate as we believe that these refer to a set of principles and facts applying in general domains which can be easily linked to the educational system [18]. Table 1 lists the competency classifications and the corresponding description of each category.

4.3 Measuring skill intensity

Once extracted the information from vacancies and mapped into a skill taxonomy, the final challenge pertains to the creation of measures of intensity of a given skill (or category of skills). Measuring the intensity with which a job vacancy demands each skill is challenging. To address this issue, we define two different measures: a binary and a continuous measure, the *term frequency–inverse document frequency* (TF-IDF), which is similar to the local-quotient measure used by Alabdulkareem *et al.* (2018). On the one hand, the binary measure provides a more straightforward interpretation of the results. However, on the other hand, it fails to measure how much a particular skill is essential for that specific vacancy compared to the other vacancies in the same occupation.

The binary measure describes whether a vacancy demands at least one skill of that category. In contrast, the TF-IDF documents how important a particular skill is for a vacancy relative to the importance of that skill in the vacancy's occupation.

For a skill category j in vacancy i for occupation o, the *term frequency* (tf_{ijo}) is the share of skills of category j demanded. The *inverse document frequency* (idf_{ijo}) is the log of the share of vacancies in occupation o demanding at least a competency of the category j. Formally, the TF-IDF is computed as:

$$tf\text{-}idf_{ijo} = \frac{S_{ijo}}{\sum_j S_{ijo}} \log\left(\frac{\sum_j V_{oj}}{V_{oj}}\right)$$

where S_{ijo} is the number of skills demanded in vacancy i of category j in occupation o; and V_{jo} is the number of vacancies in occupation o demanding a competency of category j.

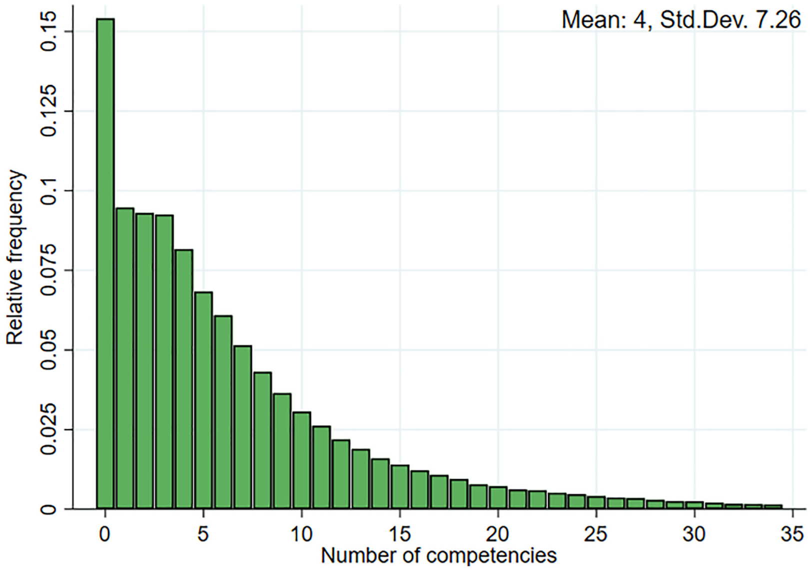
The TF-IDF is a standard measure in the literature of information retrieval, [19] and is our preferred measure as it gives more importance to occupation-specific skills rather than to general skills. Indeed, skill categories that are unimportant for a vacancy will have a low TF-IDF score because the tf_{ijo} will be low. On the other hand, very common skill categories will instead have a low TF-IDF score because that category will be demanded in most of the vacancies in that occupation; thus, the idf_{ijo} will be very low. On the opposite, specific skills in high demand for a given occupation will be characterised by a high TF-IDF score.

Group	Description
GROUP I	*(based on first level O*NET classification)*
Knowledge	Organized sets of principles and facts applying in general domains
Skills	Developed capacities that facilitate learning or the more rapid acquisition of knowledge
Abilities	Enduring attributes of the individual that influence performance
Work activities	General types of job behaviours occurring on multiple jobs
Work styles	Personal characteristics that can affect how well someone performs a job
GROUP II	*(Own classification based on finest skill categorisation)*
Cognitive	Cognitive abilities, complex problem-solving skills and mental processes
Social	Interacting with others, persuasion, negotiation and teamwork
Digital	Software and technology
Hard Skills	Technical skills, tools and work output
Organisational	System skills and resource management skills

Note(s): The classification of the first group is based on the O*NET pillars classification, for more detail see O*NET webpage. The categories of the second group follows our own classification based on detailed level skills

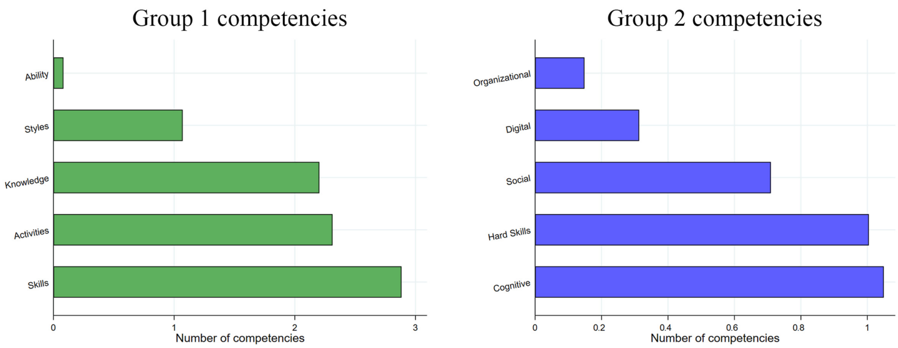
Table 1. Description of the competencies groups

Figure 1 shows the distribution of the number of skills demanded for each job ad. We can see that almost half of the vacancies demand less than 5 skills. Figure 2 displays the average number of skills demanded by each group. The categories *Skill*, *Activity* and *Knowledge* are the most requested with an average of more than two competencies belonging to these categories per job ad. Tables A13 and A14 report the correlation matrices between the different categories for the two different intensity measures.



Note(s): Distribution of the competencies demanded, where the competencies are defined as the finest level of the O*NET taxonomy
Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure 1. Distribution of number of competencies per job ad



(a) **(b)**

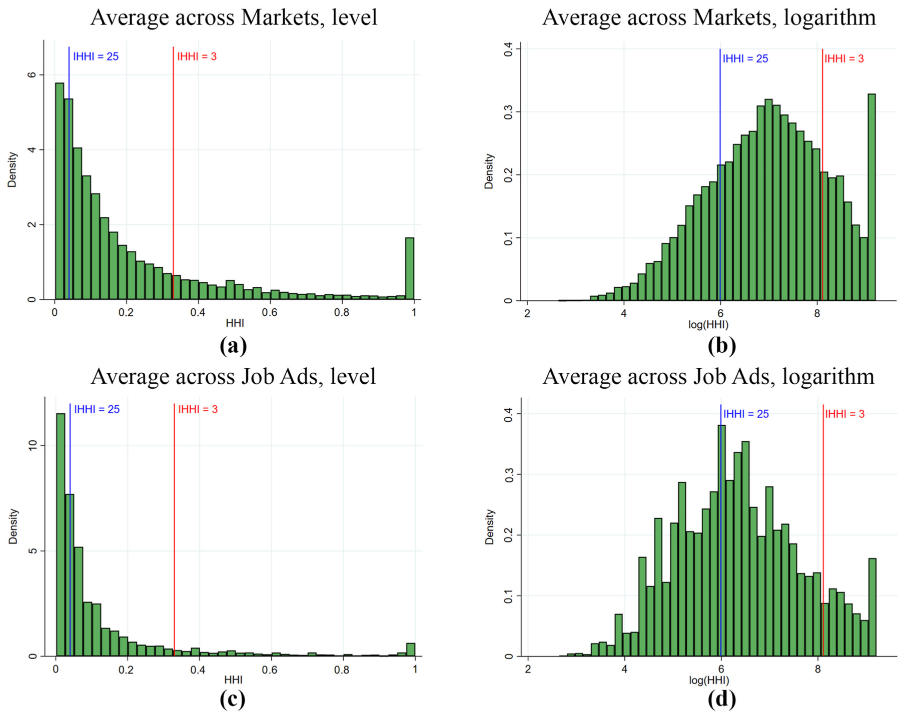
Note(s): Average number of distinct competencies demanded per skill category, where the competencies are defined as the finest level of the O*NET taxonomy
Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure 2. Average number of competencies by type per job ad

4.4 Measuring labour market concentration

Following the literature, we define a local labour market as the combination between a province, [20] an industry/sector and a year.

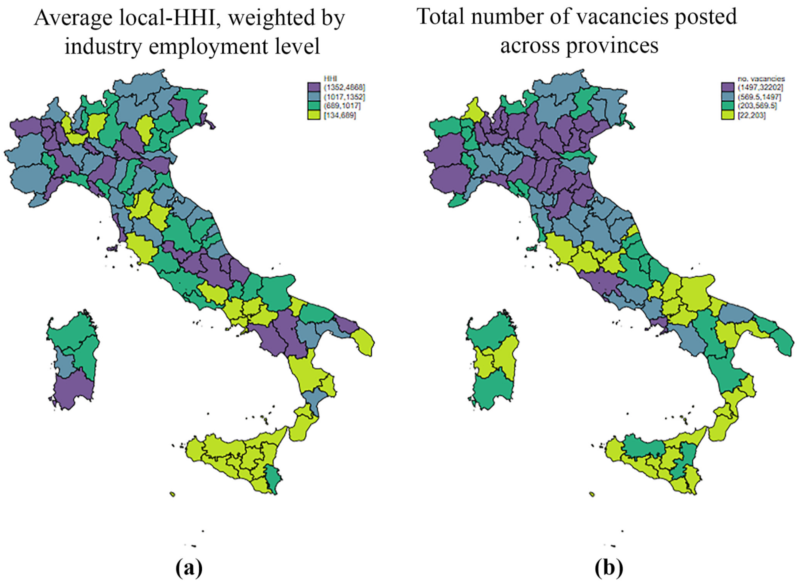
As a measure of concentration, we use the HHI, defined as the sum of squares of each firm's employment shares in a local labour market. Figure 3 shows the logarithmic distribution of the HHI at the local labour market level, unweighted or weighted for the number of vacancies posted. The average local labour market is moderately concentrated, with a mode around log(HHI) = 7, equivalent to an HHI of 0.11 or an Inverse Herfindahl–Hirschman Index (IHHI) of 9.2 [21]. The IHHI can be interpreted as the number of equal-sized firms that will induce the same observed HHI [22]. However, the average job vacancy is posted in a low-concentrated market with a mode around log(HHI) = 6. As also observable in Figure 4, which plots the maps of the average HHI and the number of vacancies posted at the province level, employers in less concentrated markets post more job vacancies [23].



Note(s): The HHI is computed at the local labour market level, which is define as a combination of Province, Ateco 2-digit, and year. The two graphs in the top of the figure are calculated taking the average across local labour market. The two graphs in the bottom of the figure are calculated taking the average across job ads. The logarithm are taken on the HHI multiplied by 10'000. The IHHI defines the Inverse Herfindahl-Hirschman Index, which can be interpreted as the number of equally sized firms that will obtain the same HHI. For illustrative purposes we report the level of concentration associated with the presence of 3 (red line) and 25 (blue line) equally sized firms in the market

Source(s): Authors' calculations on AIDA data 2015-2018

Figure 3.
Employment concentration in the Italian local labour markets (2015–2018)



Note(s): Figure (a) shows the average HHI computed at the local labour market level, which is define as a combination of Province, Ateco 2-digit, and year. These measures are aggregated at the provincial level, weighted by the number of employees in each industry (2digit Ateco). Figure (b) shows the total number of vacancies posted for each province across 2018

Source(s): Authors' calculations on AIDA and WollyBi data of 2018

Figure 4. Employment concentration and number of vacancies across Italian provinces (2018)

4.5 Empirical strategy

For our empirical specification, we regress the two measures of skill demand at the vacancy level on the log-HHI index of the local labour market where the vacancy was posted, formally

$$Y_{i,pst} = \alpha_p + \alpha_s + \alpha_t + \alpha_o + \beta \log(HHI_{pst}) + \varepsilon_{i,pst}$$

where i denotes the vacancy, p is the province, s is the industry sector, t is the year and $\log(HHI_{pst})$ is the log of the HHI index for the local labour market (pst). Y is one of the two different competency demand measures, previously described. The α defines the year-, industry-, province- and occupation-fixed effects [24].

This empirical specification aims to understand whether differences in the concentration level are associated with differences in the demand for competencies. Controlling for the fixed effects, we want to pick up the difference in skill demand associated with the difference in the concentration level and not pick up province- or occupation-wide differences.

The specification outlined above has been enriched with a number of possible controls and augmented with an IV estimator. Section 5.5 describes them in detail.

5. Results

5.1 Effect of labour market concentration on experience and education

In a well-known paper Modestino (2020) show that, in the USA, following an increase in the supply of workers, employers' requirements in terms of education and experience increase, denoting some form of opportunistic upskilling. This effect should be similar considering firms with stronger monopsony power.

Therefore we start by analysing the effect of labour market concentration on experience and education. Table 2 reports the estimates of labour market concentration on whether a vacancy requires less than 1 year of experience (*No Exp. required*), the years of experience demanded (*Experience*), [25] whether it requires a university degree (*Graduate*) and the total number of skills demanded. Overall labour market concentration is negatively correlated with experience and positively with the level of education. Specifically, one standard deviation increase in the labour market concentration increases the probability that the vacancy does not require any experience by 5.6%, i.e. an increase of 1% point [26]. The same change in HHI decreases the amount of experience required by 6% points, or 2.2%, which amounts to almost 25 days less of experience required. Furthermore, labour market concentration is positively correlated with the probability that the job ad requires a university degree.

Overall, our results suggest a different interpretation than Modestino (2020). We observe in fact that an increase in local labour market concentration reduces the experience required, but, at the same time, it increases the demand for graduate workers. These results are in line with the training hypothesis. If employers in a more concentrated labour market are more prone to training new workers, they do not demand that workers already possess job experience; instead, they look for workers who can acquire and learn new competencies fast and efficiently, as signalled by their education level [27].

Finally, considering the skill variable, we do find evidence of an “upskilling” effect but it is somewhat different from the standard interpretation, in our case an increase in labour market concentration leads to an increase in the number of skills required. However, so far we have not analysed the type and nature of the skills required. The next section deals with these issues.

5.2 Market concentration and skill demand

For reasons of space we report in the text the results of the TF-IDF measure whilst we leave the tables related to the binary measure in the Appendix. We start with the broad O*NET classification of the competencies set, Tables 3 and A11 report the results for the ordinary least squares estimations of the TF-IDF and binary intensity measure, respectively. Each

	No competencies per ad	No exp. required	Experience	Graduate
log(HHI)	0.0503***	0.0085***	−0.0507***	0.0062***
	(0.0102)	(0.0010)	(0.0073)	(0.0007)
Year FE	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓
MDV	6.557	0.197	2.971	0.246
mean(HHI*10k)	1,319	1,213	1,213	1,319
R^2	0.500	0.078	0.092	0.238
N	553,030	375,122	375,122	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables (1) *No. competencies per ad*, (2) *No Exp. required*, (3) *Experience* and (4) *Graduate* which define (1) the number of competencies demanded in the vacancy, if the vacancy demands (2) less than 1 year of experience, (3) the midpoint-approximation years of experience demanded and (4) a bachelor's degree. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3) and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table 2. OLS estimates of labour market concentration on No. skills, experience and education

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009*	−0.0009*	−0.0003	0.0008*	0.0008
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3) and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table 3. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure

table includes five different categories of skill/competency as dependent variable: Skill, Knowledge, Ability, (Work) Activity and (Work) Style [28]. Overall Knowledge is negatively correlated with labour market concentration whilst work styles activities and skills are positively correlated although the results are sharper when considering the TF-IDF measure.

Note that the Knowledge pillar consists in the "organised set of principles and facts", whereas the Skills pillar defines "developed capacities to facilitate learning" and Work Activities are "general types of job behaviours occurring on multiple jobs" [29]. These results are in line with the training rationale. Employers in more concentrated markets are more willing to provide on-the-job training, so they are more interested in workers that are able to learn faster rather than workers who already possess knowledge. Knowledge pertains to competencies that are strongly connected with formal training and can be taught by the firm internally. On the contrary, working attitudes such as being a quick learner or being good at interacting with others are less easily trainable and are acquired by the firm on the market through hiring.

To give a clearer sense of these results, Figures 5 and A5 plot the estimated coefficient for all the different competencies and for the two different intensity measures. Regarding the magnitude of the coefficients, a standard deviation rise in the labour market concentration decreases the Knowledge TF-IDF score by around 1.5%. The same increase in local labour market concentration, *ceteris paribus*, leads to an increase of Skill TF-IDF score by around 1.1%. Therefore, a rise in the HHI decreases the importance of Knowledge competencies and increases that of Skill competencies compared to their usual relevance for that occupation.

To better explore these issues we regrouped skills and competencies into a classification that allows us to shed more light on what type of skills are requested in concentrated markets. Tables 4 and A12 report the results [30]. Social and hard skills are positively related to labour market concentration using both intensity measures. On the other hand, cognitive, digital and organisational skills are negatively correlated with labour market concentration using the TF-IDF measure whilst the results are less sharp with the binary intensity measure.

Results presented so far fit with the training rationale. Higher concentration in the labour market lead firms to demand fewer trainable competencies (e.g. the knowledge pillar) and more that are un-trainable (e.g. social skills) [31]. However there some results are not completely in line. For example, following the training hypothesis, we would expect cognitive skills to be positively correlated with market concentration whilst our results show that the relationship is negative for the TF-IDF measure and null for the binary measure.

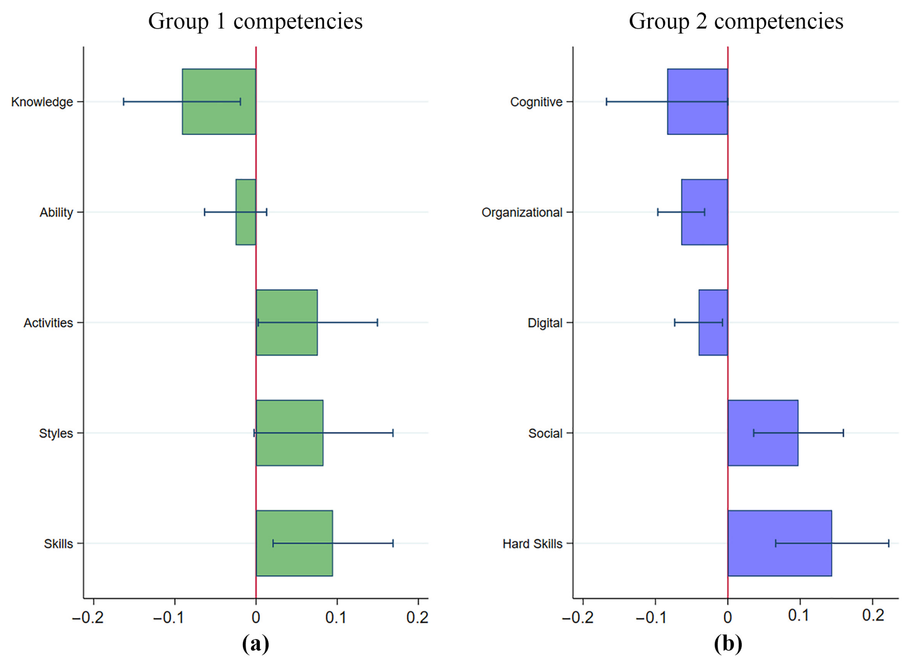


Figure 5.
Ordinary least squares (OLS) coefficients plots of labour concentration on competencies demand (TF-IDF measure)

Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Table 4.
OLS estimates of labour market concentration on skill/ competency demand (group 2), TF-IDF measure

	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI)	−0.0008*	0.0014***	−0.0006***	0.0010**	−0.0004*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.035	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

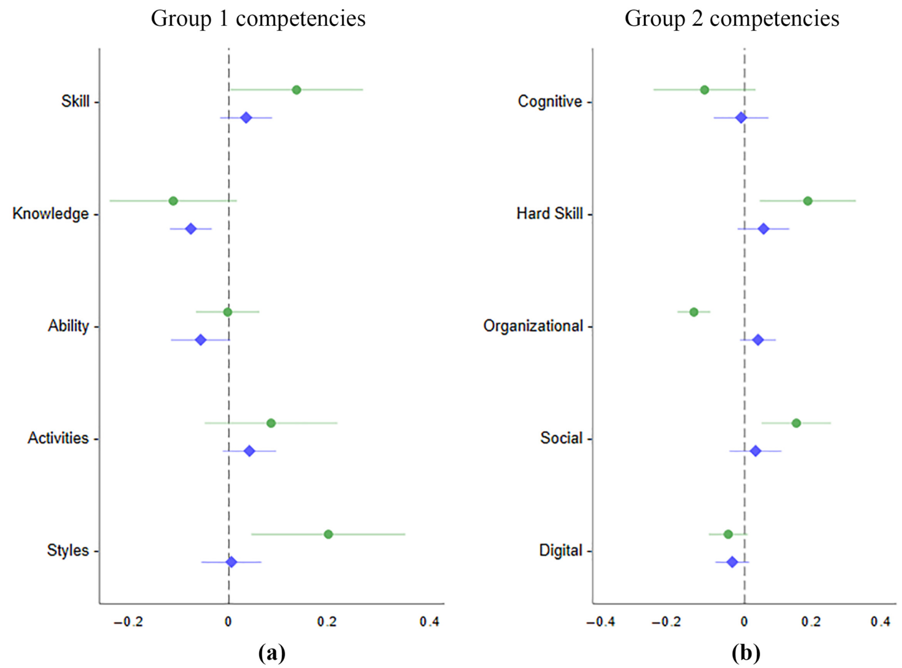
Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3) and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

5.3 Skill demand heterogeneity across occupations

To shed light on these issues we have analysed separately different classes of occupation. Following the ISCO classification, we divided occupations into high- and medium/low-skill occupations. Specifically, those occupations with the 1-digit ISCO code between 1 and 3 are high-skill occupations, whereas the occupations with codes between 4 and 9 are low/medium occupations [32]. We, therefore, estimate separately the effect on high and medium/low occupations [33]. Figures 6 and A6 show the heterogeneous effect of local labour market concentration on the demand for skills [34]. Two results emerge. First, the binary measure delivers sharper differences, this is expected as it does not weigh skills by their relative importance. Second, it emerges a clear difference between high and medium-low-skill occupations.

Compared with medium-low skill occupations, employers posting vacancies in high-skill occupations in highly concentrated labour markets increase the relative demands for Cognitive skills and reduce the demand for Knowledge. On the contrary, for low-skill occupations Hard and Social skills become relatively more important. Given the different nature of the tasks performed in each occupation class, employees in high-skill occupations are required to perform more complex tasks and duties than employees in low occupations. Also, organisational skills are positively correlated with market concentration for high skills occupations whilst they are negatively correlated with low-skill ones.



Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure 6. Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (TF-IDF measure)

As stressed above, results for the binary measure are sharper than those of the TF-IDF measure, especially for some skills such as cognitive and digital. This can be partly explained by the increased generalised diffusion of these competencies. In a more concentrated labour market is more common to require such competencies: it is in fact more frequent that advertisements contain at least one of these skills (binary measure). At the same time, these competencies are becoming increasingly required in all vacancies. This reduces their relative weight in the TF-IDF measure. We know that labour market concentration is also associated with an increase in the number of skills (Table 2). Splitting these estimates by occupation (Table 5) shows that this effect is driven by high-skill occupations. Thus labour market concentration is associated with an increase in the number of competencies in high-skill occupations. In addition, cognitive and digital skills are increasing but also becoming more general. This explains why the effect on the TF-IDF measure becomes zero or even negative.

5.4 Alternative measure of skill intensity: effective use

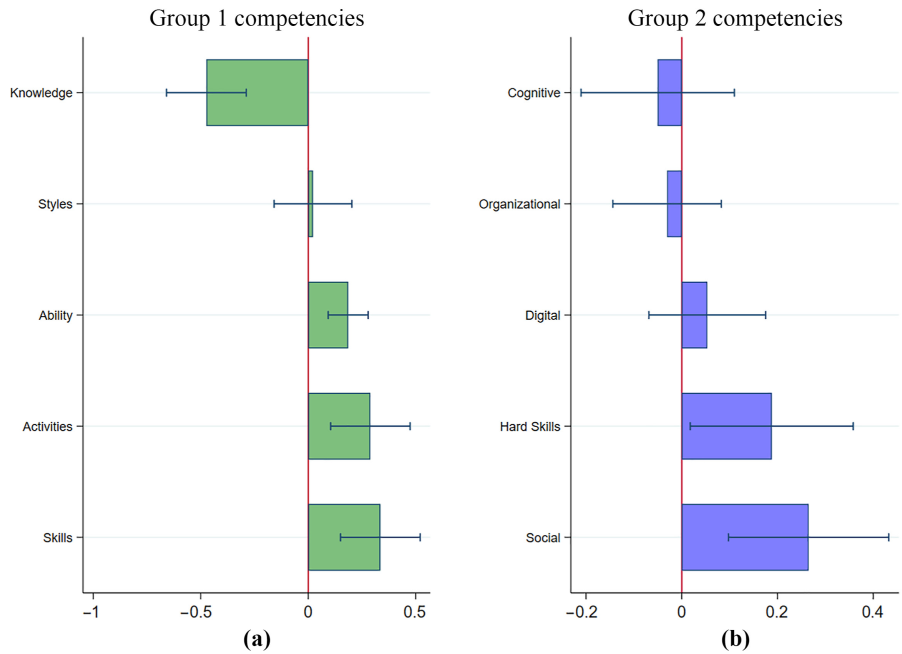
The previous paragraph shows that there is not an ideal approach to measure skill intensity as there is always a tension between skills that are in high demand in general and skills that are in high demand because are occupation specific. A possible way to reconcile the different approaches is to rely on the *effective-use* measure described in Alabdulkareem *et al.* (2018). The intuition is simple starting from the TF-IDF measure, or more precisely a variant of it, it is possible to identify a threshold that defines the average demand for skill within an occupation. The *effective use* is a dichotomous measure that takes the value of 1 if that particular skill is demanded more than the average and 0 otherwise.

Figures 7 and 8 displays the estimates following the same methodology described in Section 4.5. The *effective-use* measure shows clearer differences between high and low-skill occupations which reinforce the interpretation provided so far. Compared with low-skill occupations, employers posting vacancies in high-skill occupations in highly concentrated labour markets increase the relative demands for Cognitive skills and reduce the demand for Knowledge. Moreover, digital skills are positively correlated with labour market concentration for high-skill occupations, whilst they are negatively correlated for medium-low skill occupations.

Table 5.
OLS estimates of labour market concentration on No. skills, experience and education, separated by occupation-skill level

	No competencies per ad		Experience		Graduate	
	Low	High	Low	High	Low	High
log(HHI)	−0.0118	0.1214***	−0.0414***	−0.0601***	0.0047***	0.0076***
	(0.0078)	(0.0193)	(0.0093)	(0.0114)	(0.0008)	(0.0013)
Year FE	✓	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓	✓
MDV	3.409	9.643	2.655	3.287	0.111	0.378
mean(HHI*10k)	1,298	1,340	1,177	1,249	1,298	1,340
R^2	0.311	0.409	0.114	0.064	0.115	0.183
N	273,788	279,239	187,282	187,839	273,788	279,239

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs separated fr high and low skill occupations using as dependent variables (1) *No. competencies per ad*, (2) *Experience* and (3) *Graduate* which define (1) the number of competencies demanded in the vacancy, (2) the midpoint-approximation years of experience demanded and if the vacancy demands (3) at least a bachelor's degree. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3) and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

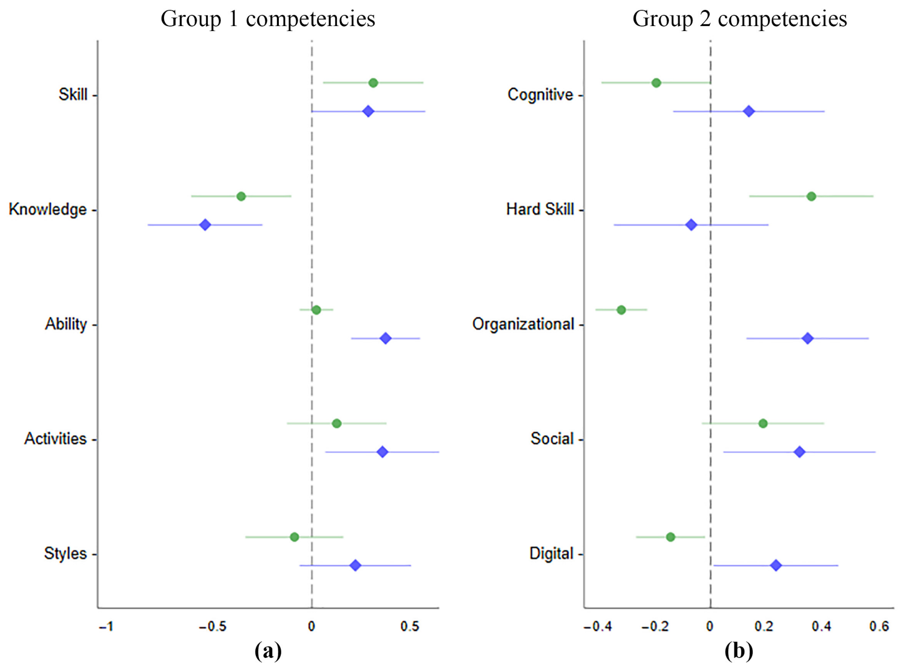


Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the effective-use score for that particular skill category, variable described in Section 5.4. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure 7. OLS coefficients plots of labour concentration on competencies demand (effective-use measure)

Overall these results support the training rationale as they can be explained in terms of different training requirements of high and low-skill occupations. Presumably, new hires in high-skill occupations need to learn in-depth and complex competencies, which are difficult to be taught through mentoring or assistance from senior colleagues, instead, these competencies require formal teaching as in-class courses. For example, the type of organisational skills that are needed for high-skill occupations are generally managerial skills that can be acquired in graduate studies. Hence firms in more concentrated markets tend to demand more of these skills alongside a higher level of education. Table 5 shows that labour market concentration increases the level of education and the share of graduates and this effect is higher for high-skill occupations. On the other hand, new hires in low-skill occupations, performing simpler duties and tasks, can learn by being assisted and guided by an experienced colleague. Thus, having good social and hard skills can particularly help recruits in low-skill occupations to learn the required competencies. Whilst in high-skill occupations, where workers are more likely to be trained through more formal training activities, cognitive abilities become particularly important to enable the workers to learn and acquire new knowledge. Finally, it is important to stress that several cognitive skills, being often general, are less likely to be explicitly mentioned for high-skill occupations as they are subsumed by the higher level of education. This can explain the low significance of the coefficient for high-skill occupations.



Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the effective-use score of that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure 8.
OLS Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (effective-use measure)

5.5 Robustness

Although our results are robust to different specifications and include several controls for sectors/occupations etc. we acknowledge that they do not settle the issue of possible unobserved heterogeneity/endogeneity. In order to address this issue we have performed several robustness checks. First, we have controlled for the average firm size in the local labour market (larger firms may demand different skills); second we have controlled for the level of unemployment in the local labour market (unemployment may be correlated with concentration). Third, given the significant correlation between the different skills, we have controlled for the other skills in each specification. Fourth, we have estimated a more rigourous model using year times province, year times industry and year times occupation-fixed effects to control for potential province, industry and occupation-specific shocks. Fifth, we have implemented an IV estimator using the Hausman–Nevo instrument. Our findings are robust to all these different specifications/controls. The detailed results are available in the appendix.

6. Discussion and conclusion

By exploiting Italian OJAs, this paper shows that labour market concentration increases both the overall amount of competencies requested and its composition. Employers in a highly concentrated labour market demand competencies associated with the ability of workers to learn faster (e.g. Social competencies) rather than actual knowledge. They also require less experience but higher education. These results align with the training rationale: employers in highly concentrated labour markets are more likely to provide training to their employees. Thus, they are relatively less interested in job-specific knowledge and competencies but more in attitudes and skills that allow them to learn faster. We also observe heterogeneity in skill demand across high and low-skill occupations. In high-skill occupations due to the level of complexity of the knowledge required, training is more likely to be provided in a more formal way, e.g. through in-class courses. In contrast, for low-occupation jobs training can be provided through on-the-job cross-training with other employees.

Our results lend themselves to a number of policy implications. First, labour market policies need to be designed considering also the structure of the labour market as it heavily affects firms' hiring decisions. Second, policies should be centred on reducing the skill mismatch that involves not only displaced workers but also new entrants. From this point of view labour market policies are intertwined with education ones. Third, the rising importance of soft skills calls for a thorough analysis of their origin. Soft skills in fact have an innate, idiosyncratic component, but also a component that depends on the parental and social background. Given that education is not the main channel of transmission of social skills, these can be a mechanism for the transmission of inequality of opportunities. Finally, our paper has implications HR practices and policies. Generally, the literature and policymakers focused on the fact that market concentration tend to favour anti-competitive behaviour in HR practices. Firms in fact could collude for setting limits to employees' salaries (wage fixing arrangements), or they could agree not to solicit other company's employees ("no poaching" agreements). Very little research has been done on the effect of market concentration on the type and quality of potential hires. By informing on how market concentration affects firms' recruitment behaviour this paper can provide policymakers with different angle to tackle this issue. Further research on this is certainly needed.

Notes

1. See, amongst others, Acemoglu and Pischke (1998), Stevens (1994), Manning (2003, 2021), Sokolova and Sorensen (2021).
2. See also Bratti *et al.* (2021), Marcato (2021) for similar analysis.
3. See Acemoglu and Autor (2011) for a review.
4. Labour costs can rise with firms' employment share also for matching frictions as in Burdett and Mortensen (1998).
5. As an example, consider a firm that employs ten workers in a market with thousands of workers as opposed to the same firm in a small market with few dozens of workers. In the former, the firm is a minor actor, in the latter it is a dominant player.
6. For a recent literature review on monopsonistic wage setting models see Card (2022).
7. In the Appendix, we provide the solution for a simple case when the cost function is linear both in wages and employment share.
8. On the wage rigidity in Italy, see for example (Belloc *et al.*, 2019; Boeri *et al.*, 2021). In France, which has a similar framework to Italy, Bassanini *et al.* (2020) and Marinescu *et al.* (2021) found a limited effect of concentration on wages, while a strong effect on the number of hirings, supporting our idea that in a labour market characterized by high wage rigidity, the employers intervene more through their labour demand rather than their wages.
9. This distinction of competencies between trainable and untrainable is a convenient simplification. One could easily extend it to a world with a continuum of different groups of competencies, each one with a different cost to be taught.

10. An extension of our framework to include a factor-augmenting technology also for the untrainable component would leave the qualitative empirical implication unaffected if the untrainable-augmenting technology has a lower return to scale or a higher cost. To simplify the computation, we also assume constant return to scale between the trainable and the untrainable labour component, however, all the results of interest hold with any function ($A^{\alpha}T^{\beta}$).

11. This framework could be extended to include separate markets for each of the inputs. However, this extension goes beyond the scope of this paper because the intuition would be less sharp as we would need to take into account relative prices between different inputs. Indeed, the empirical predictions will remain qualitatively unaffected if an increase in concentration will lead to a rise in both indirect input costs. Besides in Italy, the existence of national collective contracts substantially reduces the extent of wage differentiation.

12. See Appendix for further details.

13. See www.wollybi.com. This source is now part of the products of Burning Glass Europe, the European division of Burning Glass Technology.

14. The sources are all private as the website of the Italian Public Employment Service at present contains too few vacancies and is rarely updated.

15. For recent applications and more details on extraction and classification of information from OJAs see Colombo *et al.* (2019).

16. www.onetonline.org

17. The O*NET taxonomy includes also the following broad categories: work context and interests. We excluded the items falling into these categories as they are not useful for our analysis.

18. Our classification is analogous to a coarser version of the one adopted by Deming and Kahn (2018).

19. See Baeza-Yates and Ribeiro-Neto (2011) for a reference.

20. A province in Italy is equivalent to a NUTS-3 European level classification of regions. Nuts-1 define countries, Nuts-2 regions within countries, Nuts-3 define portions of regions (provinces). The literature sometimes uses commuting zones as an alternative geographical measure, as it is expected to offer a more accurate representation of local labour markets compared to administrative borders such as the NUTS classification. However, due to data limitations, we are unable to replicate the results by adopting this alternative geographical measure.

21. Note that as a standard procedure, we have taken the log of the HHI multiplied by 10,000, this is to avoid having negative numbers. To have a sense of these numbers notice that, according to the guidelines of the U.S. Department of Justice/Federal Trade Commission (2010), a value of HHI above 1500 is "moderately concentrated", and above 2,500 is "highly concentrated".

22. For example, an IHHI of 10 implies that the market has the same HHI that a market consisting of 10 firms with the same number of employees would have.

23. For presentation purposes in Figure 4 the HHI is weighted by the number of employees to avoid over-representation of small markets.

24. The occupation is defined at the 4-digit ISCO level.

25. Required experience is reported in ranges, therefore we use the midpoint of these ranges to create a variable measuring the years of experience. Some vacancies have missing information on the year of experience, we opted to drop these vacancies; including them does not change the results. For details, see Table A9.

26. Note that for a lin-log model: $\delta = (mean(HHI) + sd(HHI))/mean(HHI)$; $(\widehat{\beta} * \log(1+\delta)) * 100 = \Delta$. Where Δ is the estimated change in percentage points due to an increase of 1 standard deviation of the independent variable.

27. It is worth underlining how education does provide not only knowledge and information but also provides a method of study and helps develop problem-solving skills. It teaches how to learn

complex and abstract concepts. Considering a signalling model à la Spence (1973), education can also signal the worker's innate abilities to potential recruiters.

28. The results are also graphically represented in the appendix with residualized binscatter plots in Figure A7.
29. In particular, it consists of Mental processes and Interacting with others, see ONET webpage
30. The results are also graphically represented in the appendix with residualized binscatter plots in Figure A8.
31. The Italian National Institute of Statistics (Istat, 2017) has shown that training programs are mostly directed towards technical and operational skills. Similar results can be observed from other data sources, such as the Adult Education Survey (AES) and Survey of Income and Program Participation (SIPP).
32. For more details on the classification, see the International Labor Office website.
33. The adoption of a separate regression approach allowed us to accommodate the varying impacts of control variables on the high or low-skill occupation groups. As an alternative approach, we also conducted an analysis using an interaction strategy, which assumes that the fixed effects exert identical effects on both groups. Despite the differences in these approaches, the results obtained are consistent and robust. Table A19 reports the results.
34. Additional results can be found in Tables A15 and A18.
35. Remember that the inverse labour supply elasticity is driven by the level of employment share, as an increase in the employment share increases the indirect cost of hiring/retaining workers.

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Appendix 1
Detailed model solution
This section provides detailed derivations of the mathematical formulae that appear in the main text, section 3.

Firm's problem
In addition to the level of trainable (T) and untrainable ($\mathcal{U}$) competence the workforce should have, the firm chooses also the amount of training (A) to provide to its workforce. This leads to the following maximisation problem,

$$\Upsilon = \max_{A,T,\mathcal{U}} \left[\left(A^{\alpha} T^{1-\alpha}\right)^{\frac{\theta-1}{\theta}} + \mathcal{U}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}} - \tau A - C(W,N)N$$

$$\text{s.t.} \quad N = T + \mathcal{U}$$

The first order conditions lead to

$$\Upsilon^{-1}\left(A^{\alpha}T^{1-\alpha}\right)^{\frac{-1}{\theta}} A^{\alpha}A^{-1}T^{1-\alpha}(\alpha) = \tau \tag{5}$$

$$\Upsilon^{-1}\left(A^{\alpha}T^{1-\alpha}\right)^{\frac{\theta-1}{\theta}} T^{-1}(1-\alpha) = (1+e(N))C(W,N) \tag{6}$$

$$\Upsilon^{-1}\mathcal{U}^{-\frac{1}{\theta}} = (1+e(N))C(W,N) \tag{7}$$

Dividing 5 over 6,

$$A = \frac{\alpha}{1-\alpha}\frac{(1+e(N))C(W,N)}{\tau}T$$

Then substituting it into 6

$$\Upsilon^{-1}\left[\left(\frac{\alpha}{1-\alpha}\right)^{\alpha}\left(\frac{(1+e(N))C(W,N)}{\tau}\right)^{\alpha} T^{\alpha}T^{1-\alpha}\right]^{\frac{\theta-1}{\theta}} T^{-1}(1-\alpha) = (1+e(N))C(W,N)$$

Divide this on 7

$$\frac{T}{\mathcal{U}} = \left[\frac{\alpha}{1-\alpha}\right]^{\alpha(\theta-1)}\left[\frac{(1+e(N))C(W,N)}{\tau}\right]^{\alpha(\theta-1)}(1-\alpha)^{\theta}$$

Considering a rise of the HHI that increases the average employment share for each labour input keeping the level of input unchanged. One can think of the closure of some of the competing firms reducing the number of the competitors in a local labour market. Assume this HHI rise affects the two inputs market at the same way, i.e. it increases the inverse labour supply elasticity for both the trainable and untrainable inputs of the same amount [35].

$$\frac{\partial T/\mathcal{U}}{\partial HHI} \propto \frac{\alpha(\theta-1)}{\tau}\left[\frac{(1+e(N))C(W,N)}{\tau}\right]^{\alpha(\theta-1)-1}\frac{\partial}{\partial N}(1+e(N)C(W,N))$$

Since

$$e(N) = \frac{\partial C}{\partial N}\frac{N}{C} \quad \Rightarrow (1+e(N))C = C_N'N + C > 0$$

$$\frac{\partial}{\partial N}(1+e(N)C(W,N)) = \left(C_{NN}''N + 2C_N'\right) > 0$$

Because $C_N' > 0$, $C_{NN}'' \geq 0$, and $\theta < 1$

$$\frac{\partial T/u}{\partial HHI} < 0$$

Simple case with linear cost function in employment share

To provide a better understanding on the link between employment share and the HHI concentration measure, let's consider a linear cost function as follow:

$$C(W, N) = \frac{N}{\mathbf{N}} + W$$

where $\mathbf{N}$ is the total employment in the market. Therefore, the average optimal share of trainable and untrainable inputs $\left(\frac{\overline{T}}{\overline{u}}\right)$ is:

$$\frac{\overline{T}}{\overline{u}} = \left[\frac{\alpha}{1-\alpha}\right]^{\alpha(\theta-1)} \left[\frac{\left(1+e\left(\overline{N}\right)\right)C\left(W, \overline{N}\right)}{\tau}\right]^{\alpha(\theta-1)} (1-\alpha)^{\theta}$$

where, given the assumed function of $C(W, N)$, we can re-write $(1+e(\overline{N}))C(W, \overline{N})$ as

$$\left(1+e\left(\overline{N}\right)\right)C\left(W, \overline{N}\right) = C\left(W, \overline{N}\right) + \frac{\partial C\left(W, \overline{N}\right)}{\partial \overline{N}}\overline{N} = 2\frac{\overline{N}}{\mathbf{N}} + W$$

Given that $\overline{N}$ is the average employment in the market, it can be also written as $\sum_i s_i N_i$, where $s_i = N_i/\mathbf{N}$ is the share of employment employed by employer i

$$\left(1+e\left(\overline{N}\right)\right)C\left(W, \overline{N}\right) = \frac{1}{\mathbf{N}^2}\sum_i s_i^2 + W = \frac{HHI}{\mathbf{N}^2} + W$$

Therefore, we can rewrite the average optimal share of trainable and untrainable inputs as:

$$\frac{\overline{T}}{\overline{u}} = \left[\frac{\alpha}{\tau(1-\alpha)}\right]^{\alpha(\theta-1)} \left[\frac{HHI}{\mathbf{N}^2} + W\right]^{\alpha(\theta-1)} (1-\alpha)^{\theta}$$

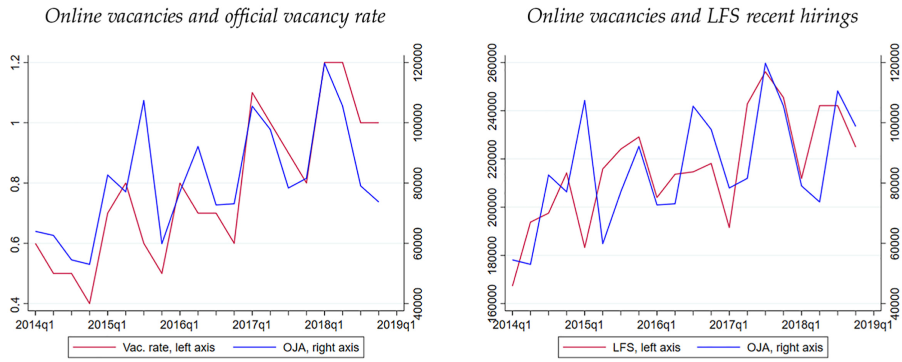
Which leads to the following condition:

$$\frac{\partial \overline{T}/\overline{u}}{\partial HHI} \propto \frac{\alpha(\theta-1)}{\mathbf{N}^2}\left[\frac{HHI}{\mathbf{N}^2} + W\right]^{\alpha(\theta-1)-1} < 0$$

Appendix 2

Representativeness of online vacancy data data

As mentioned in the text a potential drawback of OJAs is that they may offer a biased representation of the entire universe of vacancies opening in a given country/region. Indeed Lovaglio *et al.* (2020) using time series decomposition and cointegration analyses, show that OJAs and official vacancies present similar time series properties, suggesting stocks of web job vacancies are reliable indicators of the true stocks of job vacancies. With the exception of the above-mentioned paper assessing the representativeness of OJAs for the specific case of Italy is not easy as the natural benchmark - official vacancy statistics - is not available. The Italian Statistical Office (Istat) in fact, publishes only the vacancy rate while the number of vacancies is kept confidential. To overcome this issue we have constructed two simple indicators. The first analyses the evolution over time (by quarter) from 2014 to 2019 of OJAs and of the vacancy rate which, albeit on a different scale, tallies very closely the number of vacancies posted. The second is derived from Labour Force Statistics (LFS). Using microdata from LFS we have identified positions filled in the last 3 months as a proxy of the number of vacancies. As vacancies signal positions open but not yet filled we have compared the LFS indicator with the lagged measure of OJAs. Also in this case we expect the scale of the two variables to be different while their time evolution to be similar. Figure A1 shows that in both cases OJAs tally quite closely the evolution over time of both the vacancy rate and of recent hires (LFS) confirming that OJAs are a reliable indicator of the number of job openings in Italy.



(a) (b)

Figure A1. Online vacancies and official statistics

Note(s): LFS data refer to recent hirings (those who found a job in the last 3 months)

Source(s): Authors' calculations Istat and WollyBi data of 2014-2018

Appendix 3

Further issues of endogeneity

We acknowledge that the correlation between labour market concentration and the demand for skills could emerge only because they each reflect the same exogenous determinants. Although the fixed effect estimates are reassuring, they do not settle the matter and endogeneity concerns remain.

An alternative explanation for the estimates could be that firms in a more concentrated labour market are larger on average, and larger firms may demand more or different types of skills than smaller firms. Unfortunately, we do not have information on the size of the firm posting vacancies, but to address this concern we control for the average firm size in each specific local labour market. Tables A1 and A2 show the results when controlling for the average firm size in a local labour market. The estimates are robust to controlling for the market average firm size suggesting that the estimates are associated with changes in the market structure rather than the firm size.

Another potential bias might emerge if firms behave differently in their hiring decisions according to the level of unemployment, which in turn could change the number of competencies demanded by the employers. Thus, if the unemployment rate correlates with the concentration level, this can bias the estimates obtained in section 5. For example, Bilal (2021) observes that employers can have different time opportunity costs to find a new worker depending on their productivity, and thus behave differently according to the level of unemployment. Productive firms are less willing to spend much time for searching potential candidates, while less productive firms have less incentive to accelerate the hiring procedure. To account for the possible effect of the unemployment rate, Tables A3 and A4 include a control for the level of unemployment in the local labour market, confirming the main findings.

Finally, although our time horizon is short, another possible threat to the fixed effect estimates is the occurrence of market-specific shocks affecting concentration and skill demand. As an illustration, a local negative economic conjecture in a local labour market could drive firms to default and mass workers layoffs. Given the higher labour supply, this will likely increase concentration and the demand for skills. On the other hand, the fast growth of a productive firm could also lead to an increase in concentration, as this firm will hire a larger share of the workers in that local labour market. Still, simultaneously growing

Table A1. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure; controlling for the log of the market average firm employment size

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0007*	−0.0010***	−0.0002	0.0006	0.0014***
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0005)
log(avg. no. workers)	0.0007*	0.0003	−0.0000	0.0004	−0.0020***
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A2. OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure; controlling for the log of the market average firm employment size

	Cognitive	HardSkills	Organizat	Social	Digital
log(HHI)	−0.0012***	0.0011**	−0.0008***	0.0011***	−0.0004**
	(0.0005)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
log(avg. no. workers)	0.0013***	0.0013***	0.0005**	−0.0003	0.0001
	(0.0005)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.035	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

fast, the firm could reduce the demand for skills to speed up the recruiting process. To further address this issue and provide more robust results, we estimate a more rigorous model using year times province, year times industry, and year times occupation fixed effects to control for potential province-, industry-, and occupation-specific shocks. The results are displayed in Tables A5 and A6. Moreover, we also adopt an instrumental variable approach. In particular, using a Hausman-Nevo instrument (Hausman, 1996; Nevo, 2001), we exclusively consider variations to the local labour market concentration level arising from national shocks rather than local shocks. Specifically, we instrument the HHI for each province-industry-year combination with the average of the log of the inverse of the number of employers for the same industry and year in the other provinces.

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009*	−0.0009*	−0.0003	0.0008*	0.0008
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
unemploym	0.0006	0.0003	0.0004*	0.0008*	0.0008*
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A3. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure; controlling for unemployment rate

	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI)	−0.0008*	0.0014***	−0.0006***	0.0010**	−0.0004*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
unemploym	0.0002	0.0004	−0.0001	0.0002	0.0003*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.035	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A4. OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure; controlling for unemployment rate

$$\text{Instrument}(HHI)_{pst} = \frac{1}{M-1}\sum_{m \neq p} \log\left(\frac{1}{N_{mst}}\right)$$

where M is the number of provinces, N_{mst} is the number of employers in province m, industry s and year t. Conceptually, this approach provides variations in local concentration that are driven by national-level changes and not by local-specific determinants. A similar strategy was already applied in a similar context by Marinescu *et al.* (2021), Azar *et al.* (2020a), and Qiu and Sojourner (2019).

The IV approach consists in instrumenting the changes in the potential endogenous variable for a specific location with the changes of a determinant of this endogenous variable in other locations. In our

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0008**	−0.0010***	−0.0002	0.0006	0.0008*
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0004)
Year × Prov	✓	✓	✓	✓	✓
Year × Ind	✓	✓	✓	✓	✓
Year × ISCO4	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.141	0.148	0.021	0.132	0.124
N	552,960	552,960	552,960	552,960	552,960

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A5. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure; with time-variant fixed effects

	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI)	−0.0009**	0.0013***	−0.0006***	0.0010***	−0.0005***
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
Year × Prov	✓	✓	✓	✓	✓
Year × Ind	✓	✓	✓	✓	✓
Year × ISCO4	✓	✓	✓	✓	✓
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.041	0.088	0.066	0.097	0.058
N	552,960	552,960	552,960	552,960	552,960

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A6. OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure; with time-variant fixed effects

framework, we instrument the HHI of a market (combination of province, industry, and year) with the average of the logarithm of the inverse of the number of employers across the other markets of the same industry and in the same year.

Figure A2 plots the estimated coefficients for all the different competencies for the TF-IDF intensity measure, while Tables A7 and A8 show the regression results. The Two-Stage-Least-Squares (TSLS) results are also in line with the results obtained with the ordinary least squares (OLS) specifications. Specifically, both the negative impact of labour market concentration on knowledge and the positive effect on Social skills persist. Moreover, as is often the case, the IV estimates tend to be larger in magnitude than the OLS estimates. This may reflect either a reduction in the associated attenuation bias or a larger local average treatment effect. Nonetheless, there is no evidence that the OLS estimates were upward biased.

We acknowledge that our IV strategy is far from perfect as it relies on the strong assumption that national shocks affect differently the demand for skills only through changes in the concentration level. Therefore, the IV estimates do not clear completely the concerns on endogeneity, and the results should therefore be taken with caution.

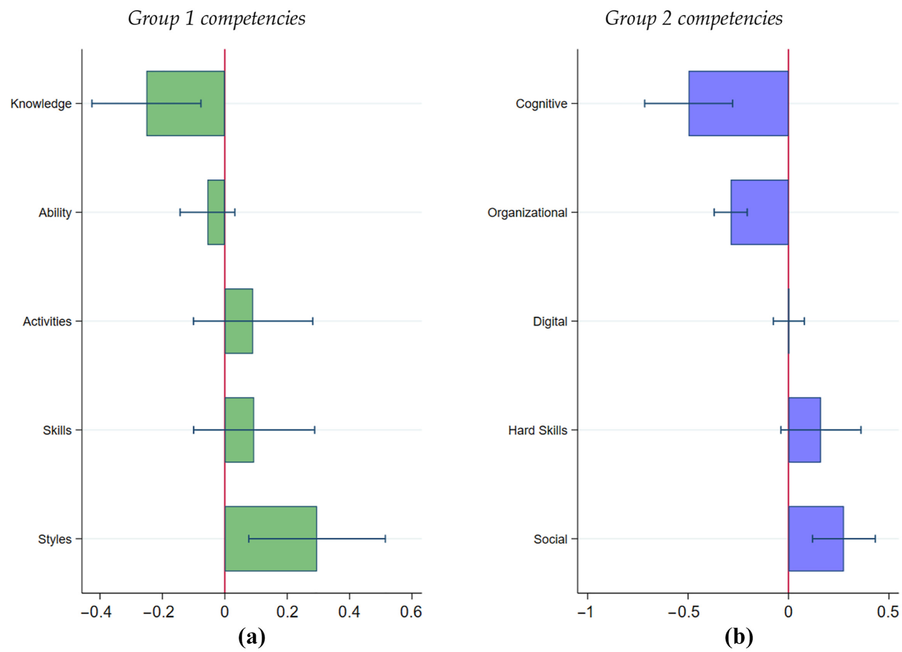


Figure A2.
TSLS coefficients plots of labour concentration on competencies demand (TF-IDF measure)

Note(s): The Figure plots the TSLS coefficient in percentage points and 95% confidence interval of log. HHI on the tf-idf score of that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0009	−0.0025**	−0.0006	0.0009	0.0030**
	(0.0009)	(0.0008)	(0.0005)	(0.0009)	(0.0010)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.078	0.306	0.008	0.302	0.154
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
F	111,822	111,822	111,822	111,822	111,822
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the TSLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A7.
TSLS estimates of labour market concentration on vacancy competencies demand (TF-IDF measure)

	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI)	−0.0050***	0.0016	−0.0029***	0.0028***	0.0000
	(0.0010)	(0.0010)	(0.0004)	(0.0008)	(0.0005)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.097	0.121	0.015	0.122	0.023
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
F	111,822	111,822	111,822	111,822	111,822
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the TSLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A8. TSLS estimates of labour market concentration on vacancy competencies demand (TF-IDF measure)

Finally as the correlation matrix shows a significant correlation between the different skills, we controlled for the other skills in each specification. This is done in Tables A20-A22.

Appendix 4
Descriptive statistics and additional results

	N	mean	sd	p25	median	p75
HHI	553,132	0.132	0.201	0.0219	0.0538	0.136
HHI*10k	553,132	1319.215	2011.002	219	538	1,364
log(HHI*10k)	553,132	6.355	1.293	5.39	6.29	7.22
No. skills per ad	553,132	6.557	7.266	2	4	9
Education index [1,8]	553,132	4.461	1.164	4	4	5
Primary	553,132	0.021	0.145	0	0	0
Lower secondary	553,132	0.000	0.014	0	0	0
Post-secondary	553,132	0.037	0.189	0	0	0
Short-cycle tertiary	553,132	0.691	0.462	0	1	1
Upper secondary	553,132	0.005	0.068	0	0	0
Bachelor or equivalent	553,132	0.188	0.391	0	0	0
Master or equivalent	553,132	0.050	0.217	0	0	0
Doctoral or equivalent	553,132	0.008	0.091	0	0	0
Experience index [1,8]	375,182	3.662	1.769	3	4	4
No experience	375,182	0.153	0.360	0	0	0
<= 1 year	375,182	0.043	0.204	0	0	0
(1–2] years	375,182	0.246	0.431	0	0	0
(2–4] years	375,182	0.371	0.483	0	0	1
(4–6] years	375,182	0.078	0.267	0	0	0
(6–8] years	375,182	0.013	0.115	0	0	0
(8–10] years	375,182	0.029	0.167	0	0	0
>10 years	375,182	0.066	0.248	0	0	0

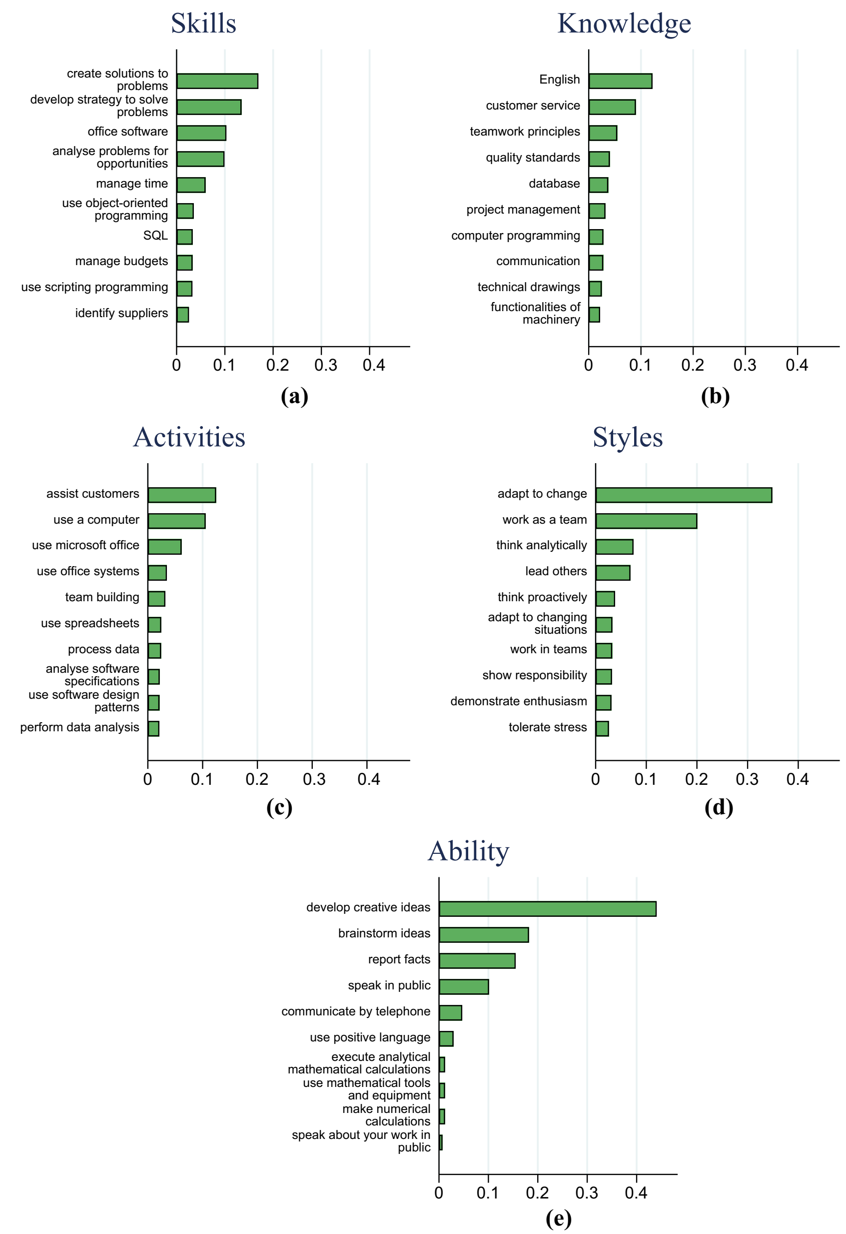
Source(s): Authors' calculations on AIDA and Wollybi data of 2015–2018

Table A9. Summary statistics

GROUP I	N	mean	sd	p25	median	p75
Skills						
Binary	553,132	0.332	0.471	0	0	1
TF-IDF	553,132	0.099	0.191	0	0.0358	0.119
Knowledge						
Binary	553,132	0.705	0.456	0	1	1
TF-IDF	553,132	0.082	0.180	0	0.0215	0.0868
Ability						
Binary	553,132	0.070	0.256	0	0	0
TF-IDF	553,132	0.017	0.108	0	0	0
Activities						
Binary	553,132	0.676	0.468	0	1	1
TF-IDF	553,132	0.094	0.190	0	0.0303	0.104
Work style						
Binary	553,132	0.515	0.500	0	1	1
TF-IDF	553,132	0.103	0.219	0	0.0151	0.111
GROUP II	N	mean	sd	p25	median	p75
Cognitive						
Binary	553,132	0.353	0.478	0	0	1
TF-IDF	553,132	0.076	0.213	0	0	0.063
Hard-skills						
Binary	553,132	0.414	0.493	0	0	1
TF-IDF	553,132	0.089	0.205	0	0	0.086
Organizational						
Binary	553,132	0.122	0.327	0	0	0
TF-IDF	553,132	0.022	0.090	0	0	0
Social						
Binary	553,132	0.457	0.498	0	0	1
TF-IDF	553,132	0.060	0.163	0	0	0.057
Digital						
Binary	553,132	0.173	0.378	0	0	0
TF-IDF	553,132	0.024	0.095	0	0	0

Source(s): Authors' calculations on AIDA and Wollybi data of 2015–2018

Table A10.
Summary statistics, skill/competency classification



Note(s): Each figure shows the top 10 finest competencies and their distribution for each specific broader competency classification
Source(s): Authors' calculation based on Wollybi data 2015-2018 period

Figure A3.
Description top 10 competencies for group 1

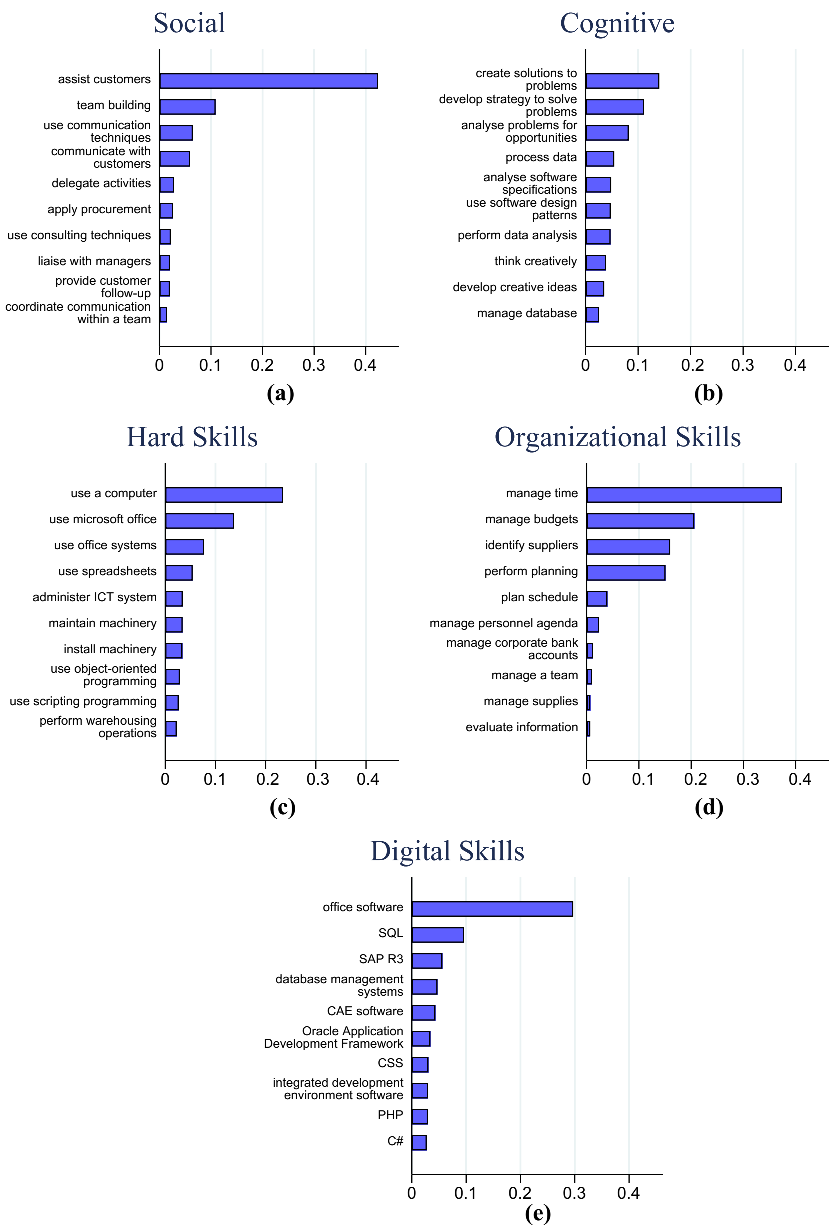


Figure A4.
Description top 10 competencies for group 2

Note(s): Each figure shows the top 10 finest competencies and their distribution for each specific broader competency classification
Source(s): Authors' calculation based on Wollybi data 2015-2018 period

	Skill	Knowledge	Ability	Activities	Styles
log(HHI)	0.0005	−0.0036***	0.0019***	0.0020*	0.0003
	(0.0008)	(0.0007)	(0.0005)	(0.0008)	(0.0009)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.332	0.705	0.070	0.676	0.515
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.312	0.371	0.145	0.344	0.199
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary intensity measure of the broader skill classification (group 1). The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A11. OLS estimates of labour market concentration on skill/competency demand (group 1), binary measure

	Cognitive	Hard skills	Organizational	Social	Digital
log(HHI)	0.0001	0.0037***	−0.0006	0.0029***	0.0007
	(0.0008)	(0.0008)	(0.0006)	(0.0008)	(0.0006)
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.353	0.414	0.122	0.457	0.173
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.323	0.279	0.215	0.387	0.361
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary measure of the finer skill classification (group 2). The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A12. OLS estimates of labour market concentration on skill/competency demand (group 2), binary measure

(a) Binary measure

	Skills	Knowledge	Ability	Activities	Styles
Skills	1				
Knowledge	0.316	1			
Ability	0.238	0.142	1		
Activities	0.374	0.443	0.170	1	
Styles	0.344	0.404	0.159	0.293	1

(b) TF-IDF measure

	Skills	Knowledge	Ability	Activities	Styles
Skills	1				
Knowledge	0.194	1			
Ability	0.0759	0.00602	1		
Activities	0.937	0.187	0.0629	1	
Styles	−0.0361	0.0386	−0.0223	−0.0728	1

Note(s): The tables report the correlation matrix between the demand for the different competency categories
Source(s): Authors' calculation based on Wollybi data 2015–2018 period

Table A13. Correlation matrix between group 1 skill types

(a) Binary measure

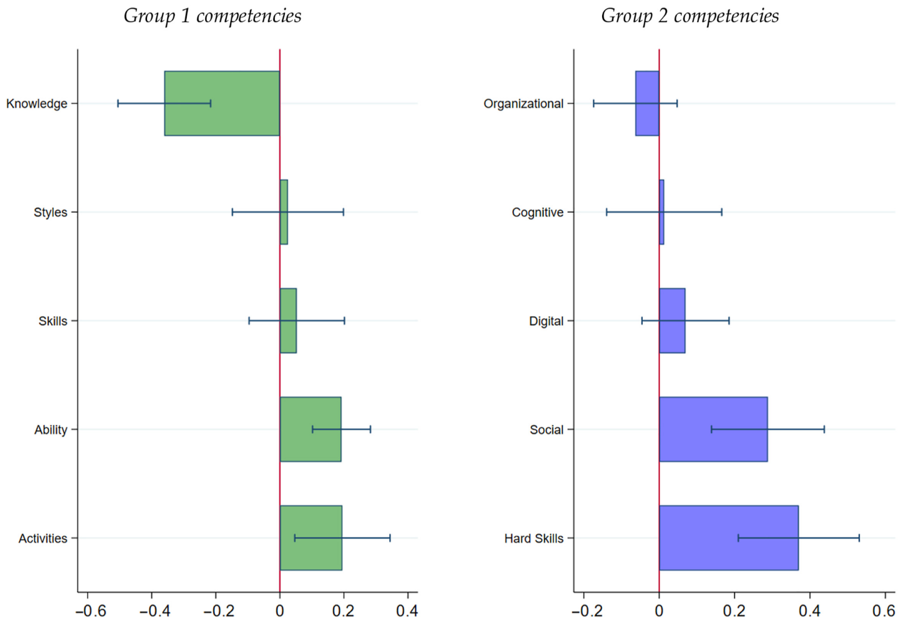
	Cognitive	Hard skills	Organizat	Social	Digital
Cognitive	1				
Hard skills	0.318	1			
Organizat	0.231	0.296	1		
Social	0.267	0.194	0.172	1	
Digital	0.381	0.415	0.110	0.206	1

(b) TF-IDF measure

	Cognitive	Hard skills	Organizat	Social	Digital
Cognitive	1				
Hard skills	−0.0345	1			
Organizat	0.0604	0.0442	1		
Social	−0.0248	−0.0377	−0.0119	1	
Digital	0.0246	0.0677	−0.0151	−0.0359	1

Note(s): The tables report the correlation matrix between the demand for the different competency categories
Source(s): Authors' calculation based on Wollybi data 2015–2018 period

Table A14. Correlation matrix between group 2 skill types



(a) **(b)**

Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the probability that a vacancy is demanding that particular skill category. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure A5. Coefficients plots of labour concentration on competencies demand (binary measure)

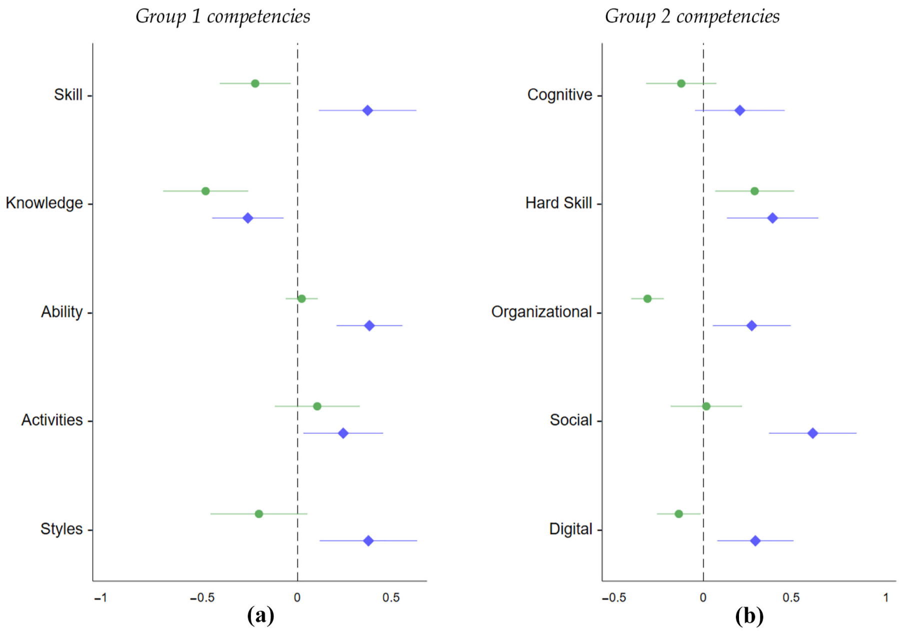
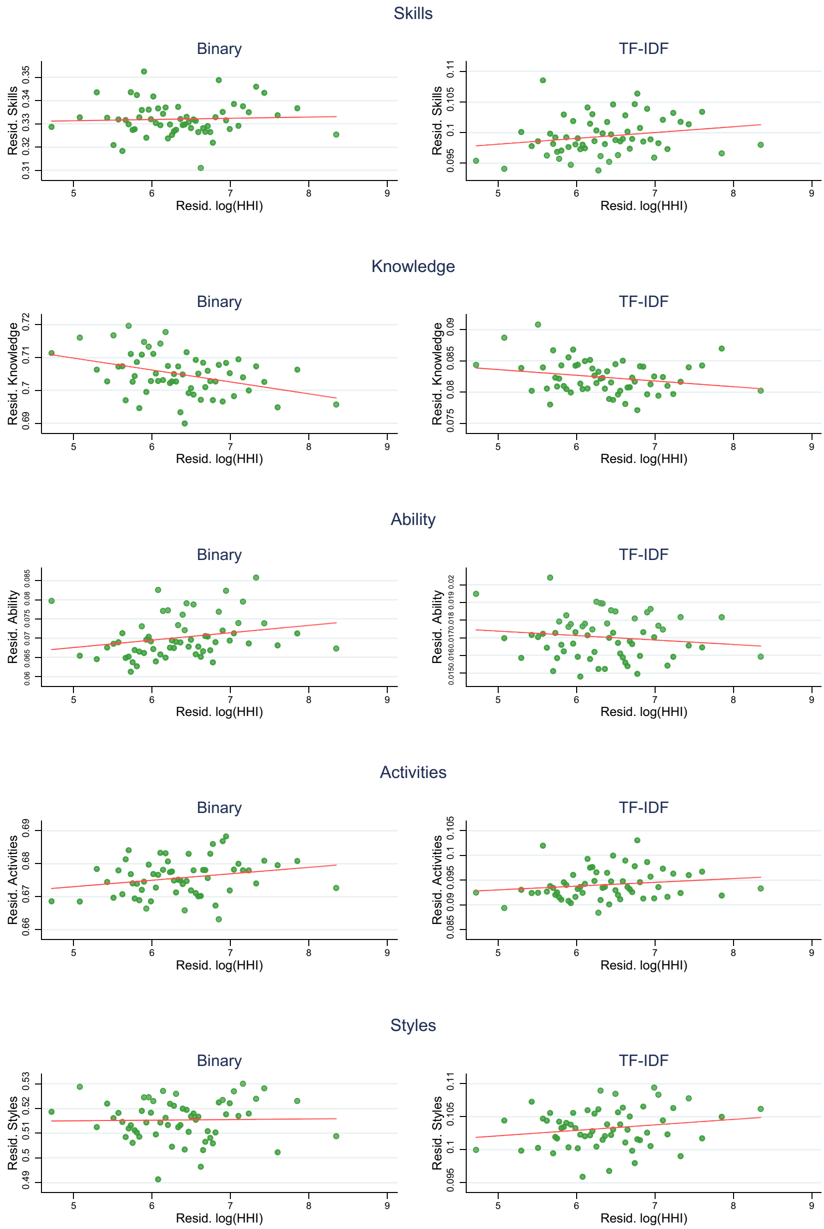


Figure A6.
Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (binary measure)

Note(s): The Figure plots the OLS coefficient in percentage points and 95% confidence interval of log. HHI on the probability that a vacancy is demanding that particular skill category, separated for high and low skill occupations. The green circles shows the estimates for low-skill occupations, while the blue diamonds the estimates for high-skill occupations. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects

Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018



Note(s): The residuals are computed using as regressors occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects
Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

Figure A7.
Binned scatter plot of labour concentration on demand for the competencies in group 1

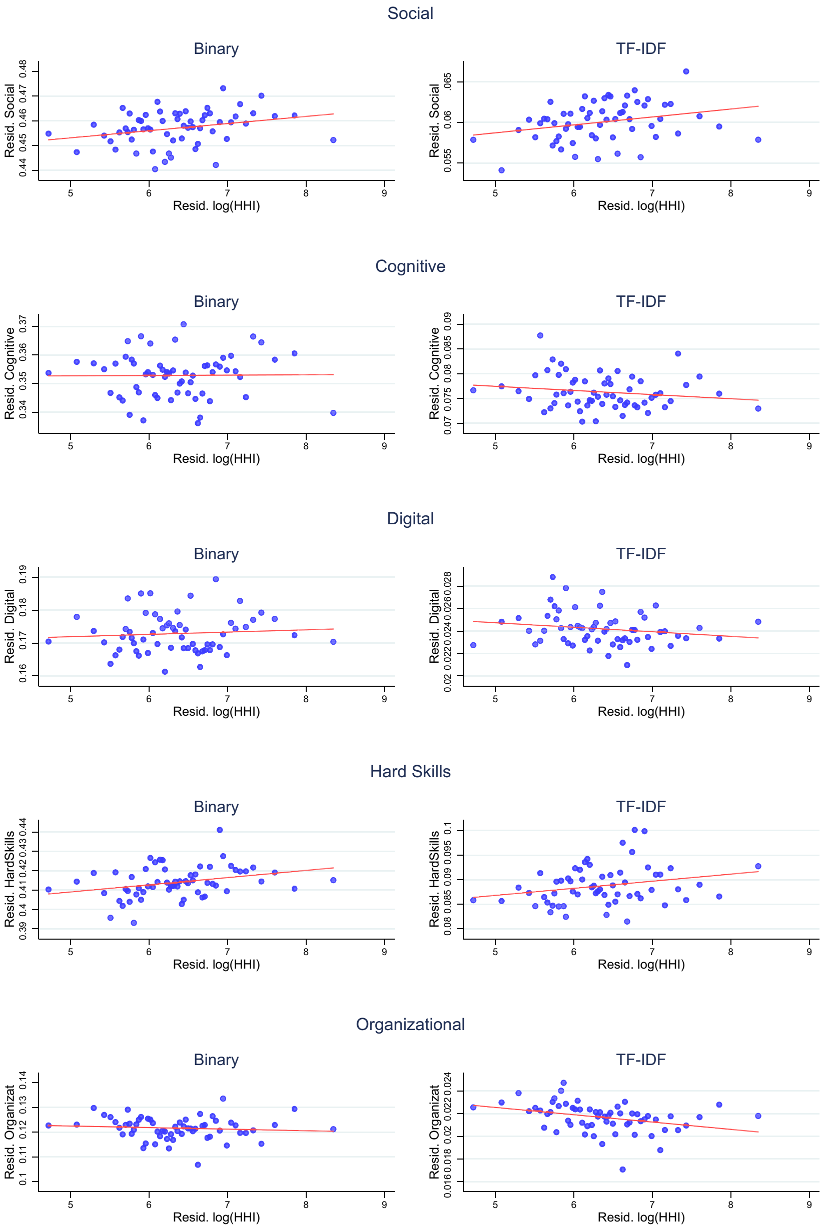


Figure A8.
Binned scatter plot of labour concentration on demand for the competencies in group 2

Note(s): The residuals are computed using as regressors occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects
Source(s): Authors' calculations on AIDA and WollyBi data of 2015-2018

	Skill	Knowledge	Ability	Activities	Styles
GROUP 1, *Binary measure: High-skill occupations*					
log(HHI)	0.0036**	−0.0026**	0.0037***	0.0023*	0.0036**
	(0.0013)	(0.0009)	(0.0009)	(0.0010)	(0.0013)
MDV	0.519	0.851	0.115	0.798	0.636
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.230	0.184	0.136	0.201	0.168
N	279,239	279,239	279,239	279,239	279,239
GROUP 1, *Binary measure: Low-skill occupations*					
log(HHI)	−0.0022*	−0.0047***	0.0002	0.0010	−0.0020
	(0.0009)	(0.0011)	(0.0004)	(0.0011)	(0.0012)
MDV	0.142	0.555	0.024	0.550	0.392
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.092	0.358	0.053	0.361	0.136
N	273,788	273,788	273,788	273,788	273,788

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary measure of the broader skill classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A15. OLS estimates of labour market concentration on skill/competency demand (group 1), Binary measure across high and low skill occupations

	Cognitive	Hard skills	Organizational	Social	Digital
GROUP 2, *Binary measure: High-skill occupations*					
log(HHI)	0.0020	0.0038**	0.0026*	0.0060***	0.0028**
	(0.0013)	(0.0013)	(0.0011)	(0.0012)	(0.0011)
MDV	0.540	0.550	0.211	0.532	0.287
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.258	0.222	0.163	0.293	0.348
N	279,239	279,239	279,239	279,239	279,239
GROUP 2, *Binary measure: Low-skill occupations*					
log(HHI)	−0.0012	0.0028**	−0.0031***	0.0002	−0.0013*
	(0.0010)	(0.0011)	(0.0004)	(0.0010)	(0.0006)
MDV	0.162	0.275	0.030	0.381	0.056
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.096	0.220	0.093	0.462	0.107
N	273,788	273,788	273,788	273,788	273,788

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary measure of the finer skill classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A16. OLS estimates of labour market concentration on skill/competency demand (group 2), Binary measure across high and low skill occupations

Table A17. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure across high and low skill occupations

	Skills	Knowledge	Ability	Activities	Styles
GROUP 1, *TF-IDF measure: High-skill occupations*					
log(HHI)	0.0003	−0.0007***	−0.0005	0.0004	0.0001
	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
MDV	0.073	0.052	0.022	0.067	0.065
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.319	0.290	0.019	0.267	0.122
N	279,239	279,239	279,239	279,239	279,239
GROUP 1, *TF-IDF measure: Low-skill occupations*					
log(HHI)	0.0013	−0.0011	−0.0000	0.0008	0.0019*
	(0.0007)	(0.0007)	(0.0003)	(0.0007)	(0.0008)
MDV	0.127	0.114	0.012	0.122	0.142
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.079	0.093	0.014	0.076	0.086
N	273,788	273,788	273,788	273,788	273,788

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader classification (group 1) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A18. OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure across high and low skill occupations

	Cognitive	Hard skills	Organizat	Social	Digital
GROUP 2, *TF-IDF measure: High-skill occupations*					
log(HHI)	−0.0001	0.0005	0.0004	0.0003	−0.0004
	(0.0004)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
MDV	0.073	0.070	0.031	0.050	0.029
mean(HHI*10k)	1,340	1,340	1,340	1,340	1,340
R^2	0.071	0.099	0.055	0.069	0.050
N	279,239	279,239	279,239	279,239	279,239
GROUP 2, *TF-IDF measure: Low-skill occupations*					
log(HHI)	−0.0011	0.0018**	−0.0014***	0.0015**	−0.0005
	(0.0007)	(0.0007)	(0.0002)	(0.0005)	(0.0002)
MDV	0.079	0.108	0.012	0.070	0.019
mean(HHI*10k)	1,298	1,298	1,298	1,298	1,298
R^2	0.027	0.065	0.048	0.098	0.055
N	273,788	273,788	273,788	273,788	273,788

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Group 1	Skill	Knowledge	Ability	Activities	Styles
log(HHI) × Low-skill	−0.0001	−0.0015***	−0.0005**	−0.0002	0.0000
	(0.0005)	(0.0005)	(0.0002)	(0.0005)	(0.0006)
log(HHI) × High-skill	0.0021***	−0.0002	0.0000	0.0018***	0.0017***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0004)
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.133	0.140	0.017	0.124	0.112
N	553,030	553,030	553,030	553,030	553,030
	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI) × Low-skill	−0.0023***	0.0014***	−0.0011***	0.0007*	−0.0005**
	(0.0005)	(0.0005)	(0.0002)	(0.0004)	(0.0002)
log(HHI) × High-skill	0.0007*	0.0014***	−0.0001	0.0012***	−0.0003*
	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0002)
MDV	0.076	0.089	0.022	0.060	0.024
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.036	0.078	0.061	0.090	0.054
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer classification (group 2) described in section 4. The independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. All the regressions include year, province, industry, and occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A19. OLS estimates of labour market concentration on skill/competency demand, TF-IDF measure interacted by high and low skill occupations

	No competencies per ad	No exp. required	Experience	Graduate
log(HHI)	0.0535***	0.0085***	−0.0499***	0.0064***
	(0.0099)	(0.0010)	(0.0073)	(0.0007)
Cognitive	3.1241***	−0.0123***	0.1458***	0.0638***
	(0.0414)	(0.0028)	(0.0190)	(0.0022)
Hard skills	2.9036***	−0.0020	0.2017***	0.0197***
	(0.0313)	(0.0031)	(0.0193)	(0.0021)
Organizat	6.0033***	−0.0223***	1.0279***	0.1591***
	(0.1488)	(0.0067)	(0.0528)	(0.0069)
Social	0.9009***	0.0060	0.1025***	−0.0152***
	(0.0285)	(0.0042)	(0.0285)	(0.0027)
Digital	4.4561***	−0.0163**	0.1965***	0.0581***
	(0.1082)	(0.0065)	(0.0431)	(0.0058)
Year FE	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓
MDV	6.557	0.197	2.971	0.246
mean(HHI*10k)	1,319	1,213	1,213	1,319
R^2	0.523	0.078	0.093	0.241
N	553,030	375,122	375,122	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables (1) *No. competencies per ad*, (2) *No Exp. required*, (3) *Experience*, and (4) *Graduate* which define (1) the number of competencies demanded in the vacancy, if the vacancy demands (2) less than 1 year of experience, (3) the midpoint-approximation years of experience demanded, and (4) a bachelor's degree. The independent variables are the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level; and the TF-IDF measure for all the group 1 competency groups. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A20. OLS estimates of labour market concentration on No. skills, experience, and education

	Skills	Knowledge	Ability	Activities	Styles
log(HHI)	0.0002	−0.0008**	−0.0003	−0.0001	0.0009**
	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0004)
Skills		−0.1357***	−0.0082***	0.9112***	−0.0770***
		(0.0032)	(0.0011)	(0.0048)	(0.0035)
Knowledge	−0.0267***		−0.0133***	0.0051***	−0.0304***
	(0.0006)		(0.0006)	(0.0006)	(0.0023)
Ability	−0.0039***	−0.0320***		0.0009*	−0.0269***
	(0.0005)	(0.0009)		(0.0005)	(0.0014)
Activities	0.9022***	0.0254***	0.0019*		−0.0915***
	(0.0015)	(0.0031)	(0.0010)		(0.0033)
Styles	−0.0100***	−0.0201***	−0.0074***	−0.0120***	
	(0.0006)	(0.0015)	(0.0005)	(0.0004)	
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.851	0.153	0.017	0.849	0.130
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the broader skill classification (group 1) described in section 4. The main independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. The regressions are further control for the demand of all the other competencied, measured with the TF-IDF measure. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A21. OLS estimates of labour market concentration on skill/competency demand (group 1), TF-IDF measure

	Cognitive	Hard skills	Organizat	Social	Digital
log(HHI)	0.0002	−0.0008**	−0.0003	−0.0001	0.0009**
	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0004)
Skills		−0.1357***	−0.0082***	0.9112***	−0.0770***
		(0.0032)	(0.0011)	(0.0048)	(0.0035)
Knowledge	−0.0267***		−0.0133***	0.0051***	−0.0304***
	(0.0006)		(0.0006)	(0.0006)	(0.0023)
Ability	−0.0039***	−0.0320***		0.0009*	−0.0269***
	(0.0005)	(0.0009)		(0.0005)	(0.0014)
Activities	0.9022***	0.0254***	0.0019*		−0.0915***
	(0.0015)	(0.0031)	(0.0010)		(0.0033)
Styles	−0.0100***	−0.0201***	−0.0074***	−0.0120***	
	(0.0006)	(0.0015)	(0.0005)	(0.0004)	
Year FE	✓	✓	✓	✓	✓
Prov. FE	✓	✓	✓	✓	✓
Ind. FE	✓	✓	✓	✓	✓
ISCO4 FE	✓	✓	✓	✓	✓
MDV	0.099	0.082	0.017	0.094	0.103
mean(HHI*10k)	1,319	1,319	1,319	1,319	1,319
R^2	0.851	0.153	0.017	0.849	0.130
N	553,030	553,030	553,030	553,030	553,030

Note(s): Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the TF-IDF intensity measure of the finer skill classification (group 2) described in section 4. The main independent variable is the log of the employment HHI, measured at the industry (2-digit ATECO code), province (NUTS-3), and year level. The regressions are further control for the demand of all the other competencied, measured with the TF-IDF measure. All the regressions also include occupation (ISCO 4-dig) fixed effects. Robust standard errors in parentheses ***p < 0.01, **p < 0.05, *p < 0.1
Source(s): Authors' calculation on AIDA and Wollybi data in 2015–2018 period

Table A22. OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure, controlling for the competency demand for the other groups