Skill Demand and Labour Market Concentration: Evidence from Italian Vacancies*

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Abstract

This paper analyses the relationship between labour market concentration and employers' skill demand. Using a novel data set on Italian online job vacancies during 2013-2018 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 efficiently.

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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 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; Arnold, 2020; Schubert et al., 2020; Berger et al., 2019; Jarosch et al., 2019; Benmelech et al., 2018).

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 et al., 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 to globalization 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 which provide granular information on the demand for skills and competencies for detailed occupations and 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 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 US while less evidence so far has been collected on labour market concentration in Europe. Second we provide evidence of skills demand at 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 et al. (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 HR management practices as they show that the recruitment behaviour and the demand for skills differ in monopsonistic markets.[1]

Our explanation of the relationship between labour market concentration and skill demand is therefore based on a training rationale. To provide the intuition, assume that workers are characterised by two sets of skills: one more challenging to learn (e.g., soft skills) and the other easier to teach and learn, such as standard technical competencies (e.g. a 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, firm's training decision impacts on the demand for skills as some are more "trainable" than others. If firms with higher market power face higher recruitment costs, they are also more likely to invest in training, providing internally trainable skills while looking on the market for un-trainable 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

[1] Indeed the US Antitrust Guidance for Human Resource Professionals DOJ (2016) has been issued to draw attention to the effect that labour market concentration and anticompetitive practices affecting human resources.

closely related with 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 describes the empirical strategy; section 6 illustrates the results, section 7 provides some robustness checks, finally section 8 concludes.

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 US labour market (Hershbein et al., 2021; Azar et al., 2020a; Berger et al., 2019), and there is also a 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.[2] 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 decision is well documented. For example, Rzepka and Tamm (2016); 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.[3]

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. According to this approach the fundamental units of production are job tasks, which are then combined to produce output. Tasks in turn can be performed by capital, foreign or domestic labour, and by different types of labour; in equilibrium

[2]See, among others, Acemoglu and Pischke (1998,9); Stevens (1994); Manning (2003); Moen and Rosén (2004); Manning (2021); Sokolova and Sorensen (2021)

[3]See also Bratti et al. (2021); Marcato (2021); Starr (2019); Muehlemann and Wolter (2011); Picchio and Van Ours (2011) for similar analysis.

the assignment of factors to tasks is determined by comparative advantages.[4] The task approach has been successfully used to investigate how and to what extent technological progress and globalization (outsourcing and offshoring) change labour demand, however when coming to skill demand the analysis has been limited to the distinction between high and low skills or between routine and non routine tasks. The reason lies in the difficulty of measuring tasks and the skills associated with them. One approach has focused on occupational job descriptor databases such as the U.S. Dictionary of Occupational Titles; however the infrequent updates of such data-sets made them useful only for low frequency long run analysis (see Lin (2011) and Deming (2017)). Other approaches are based on surveys such as the IAB/BIBB in Germany, the UK skill survey or the STAMP survey in the US. The limit of surveys however is that they are top-down tools which need to be designed first and subsequently implemented. For this reason, due also to the burden on the respondent, questions about skills are restricted to a general pre-defined list. Recently a new impulse to this literature has been provided by the availability of detailed data from Online Job Advertisements. These can provide information about detailed skill requirements for each occupation. Such data has been used mainly in the US (Azar et al., 2020b; Deming and Kahn, 2018; Hershbein and Kahn, 2018; Modestino et al., 2016, 2020) while 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 online job advertisements has a number of advantages for the 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 categorize 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 in different macro categories following a

[4]See Acemoglu and Autor (2011) for a review.

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 is able to 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 monoposnistic 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 as the recruiting cost necessary to substitute the exogeneously 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, higher level of concentration leads to higher recruiting costs. The rationale is that the larger is the share of workers working for a firm in a market, the more difficult it becomes to find a good match among potential recruits. Alternatively, one can think that workers have idiosyncratic preference or specific bundle of competencies for a workplace, therefore the larger is 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. The crucial aspect is that employment share drives an increase in hiring costs, rather than the absolute number of employees.[5]

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

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

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

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

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

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.[6]

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

[5]For a clarifying example, employing ten workers in a very populated market with thousands of workers is different than employing the same number of workers in a small market with dozen employees. In the former, the ten employees firm is a minor actor, while it is a dominant one in the latter. For a more structured framework on how employment share impacts labour supply elasticity and, in turn, hiring costs, see Berger et al. (2019).

[6]In the Appendix, we provide the solution for a simple case when the cost function is linear both in wages and employment share.

to reduce wages from the reduction in labour market competition, the downward wage rigidity forbid them this channel, pushing them to intervene through the labour demand one.[7]

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 "un-trainable". The competencies in the trainable category can be quickly learned 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 the production. Thus, they are complements and not substitutes.[8]

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

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

where T is the trainable labour component, 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

[7] On the wage rigidity in Italy, see for example (Belloc et al., 2019; Boeri et al., 2021). In France, which has a similar framework of Italy, Bassanini et al. (2020) and Marinescu et al. (2021) found a limited effect of concentration on wages, while a strong effects on the number of hirings, supporting our idea that in labour market characterized by high wage rigidity, the employers intervene more through their labour demand rather than their wages.

[8] 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.

component.[9]

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 $N = T + U$.[10] Thus, the profit maximization problem can be written as:

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

where A is the amount of on-the-job training provided. Taking into account that T and 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 main goal is to understand how employment concentration affects employers' demand of trainable vs untrainable labour component. Assume that a rise in employment concentration increases the indirect cost of both inputs. Given the possibility of improving the productivity of one of the inputs through training, the optimal bundle of factors will depend not only on their relative cost and productivity but also on the ability to substitute the trainable input with training. This option becomes increasingly more profitable as the input costs increase following a rise in market concentration.

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-*

[9] 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 training and the training labour component, however all the results of interest hold with any function ($A^{\alpha}T^{\beta}$).

[10] 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.

job training. The ratio between trainable and untrainable inputs decreases with the level of concentration. Formally,

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

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,[11] 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).[12] Each vacancy includes detailed information such as location, industry, education, and skill requirements.[13]

To measure the level of concentration across local labour markets, we exploit the Italian ORBIS dataset, AIDA (Analisi Informatizzata Delle Aziende), by Bureau van Dijk, from 2013 to 2018.

[11]See www.wollybi.com. This source is now part of product of Burning Glass Europe, the European division of Burning Glass Technology.

[12]The sources are all private as the website of the Italian PES at present contains too few vacancies and is rarely updated.

[13]For recent applications and more details on extraction and classification of information from online job advertisements see Colombo et al. (2019).

This dataset contains the full balance sheets and income statements of Italian firms. Similar data have been used in recent research, see for example Kalemli-Ozcan et al. (2015) and 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 et al., 2020). Regarding in particular the Italian case Lovaglio et al. (2020) show that online vacancies display the same time series behaviour of vacancies obtained from official statistics, both overall and at sectoral level. In the appendix we provide a more detailed assessment of the representativeness of online data. Moreover 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.

4.2 Skill classification

A major research challenge pertains the classification of terms extracted from web vacancies into specific taxonomies. While this is easy for occupations, sectors, regions and education as there are well known benchmark taxonomies (respectively ISCO, NACE, NUTS, ISCED), the same does not hold for skills as there is not a standard taxonomy to be used as benchmark. In this work we have used the taxonomy contained in O*NET, developed by the Bureau of labour Statistics.[14] This allows comparability with other papers in the literature most of which follow the O*NET taxonomy. 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 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*.[15] The broad

[14] www.onetonline.org

[15] 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.

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" while "persuasion" and "coordination" are considered as skills (social skills). Starting from the fines level we have therefore constructed a different skill classification composed of the following groups *Cognitive*, *Social*, *Digital*, *Hard (technical)*, *Organizational* skills. We did not regroup items of the *Knowledge* category leaving them separate as we believe that the these refer to set of principles and facts applying in generals domains which can be easily linked to the educational system. 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 it into a skill taxonomy the final challenge pertains the creation of measures of intensity of a given skill (or category of skills). Given these categorizations, we define the intensity of the demand for each category with two different measures: a binary and our preferred measure the *term frequency–inverse document frequency* (tf-idf), which is similar to the local-quotient measure used by Alabdulkareem et al. (2018). The binary measure describes whether a vacancy demands at least one skill of that category. In contrast, the *term frequency-inverse document frequency* (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[16] and is our preferred measure as it gives more important 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.

Figure 3 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 4 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 A1 and A2 report the correlation matrices between the different categories for the two different intensity measures.

4.4 Measuring labour Market Concentration

Following the literature, we define a local labour market as the combination between a province,[17] an industry/sector, and a year. As measure of concentration we use the Herfindahl-Hirschman Index (HHI), defined as the sum of squares of each firm's employment shares in a local labour market. Figure 1 shows the logarithmic distribution of the HHI at the local labour market level. We find that the average local labour market is moderately concentrated, with a mode around

[16] See Baeza-Yates and Ribeiro-Neto (2011) for a reference.

[17] 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).

log(HHI) = 7, equivalent to an HHI of 0.11 or an Inverse Herfindahl-Hirschman Index (IHHI) of 9.2.[18] The Inverse Herfindahl-Hirschman Index (IHHI) can be interpreted as the number of equal-sized firms that will induce the same observed HHI.[19]

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 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 measure, previously described. The α defines the year, industry, province, and occupation fixed effects.[20]

Although our time horizon is short, a possible threat to identify the skill demand effect in our OLS regression is the possible existence of a time-varying market-specific variable that we do not control for, correlated both with the HHI and the skill demand. To further address this issue and provide more robust results, in section 7 we use the so-called Hausman-Nevo instrument (see Hausman (1996) and Nevo (2001)). 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

[18]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 number notice that, according to the guidelines of the US Department of Justice DOJ/FTC (2010), a value of HHI above 1500 is "moderately concentrated", and above 2500 is "highly concentrated".

[19]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.

[20]The occupation is defined at the 4-digit ISCO level.

industry and year in the other provinces.

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

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).

6 Results

We restrict the analysis only to those vacancies that report both the province and 2-digit ATECO 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. Tables 2 and 3 show the summary statistics of this final sample.

6.1 Effect of labour Market Concentration on Experience and Education

In a well known paper Modestino et al. (2020) show that, in the US, 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 4 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*),[21] whether is required a university degree (*Graduate*), and the total number of skills demanded. Overall labour market concentration is negatively related 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 percentage point.[22] The same change in HHI decreases the amount of experience required by 6 percentage points, or 2.2 percent, 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 support a different interpretation to Modestino et al. (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 signaled by their education level.[23]

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 sections deals with these issues.

[21] 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 2.

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

[23] 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 signaling model à la Spence (1973), education can also signal the worker's innate abilities to potential recruiters.

6.2 Market concentration and skill demand

We start with the broad O*NET classification of the competencies set, Tables 5 and 6 report the results for the ordinary least squares estimations of the binary and tf-idf intensity measure, respectively. Each table includes five different categories of skill/competency as dependent variable: Skill, Knowledge, Ability, (Work) Activity, and (Work) Style.[24] Overall Knowledge is negatively correlated with labour market concentration while 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 "organized set of principles and facts", whereas Skills pillar defines "developed capacities to facilitate learning", and Work Activities are "general types of job behaviors occurring on multiple jobs."[25] 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 competences 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 7 and 8 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.

In order to better explore these issues we regrouped skills and competencies into a classification

[24] The results are also graphically represented with residualized binscatter plots in figure 5.

[25] In particular, it consists of Mental processes and Interacting with others, see ONET webpage

that allows to shed more light on what type of skills are requested in concentrated markets. Tables 7 and 8 report the results.[26] Social and hard skills are positively related with 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 while the results are less sharp with the binary intensity measure.

Results presented so far fit with the training rationale. Higher concentration in labour market lead firms to demand less competences that are trainable (e.g. the knowledge pillar) and more that are un-trainable (e.g social skills). However there some results are note completely in line. For example following the training hypothesis we would expect cognitive skills to be positively correlated with market concentration while our results show that the relationship is negative for the tf-idf measure and null for the binary measure.

6.3 Skill Demand Heterogeneity across Occupations

In order to shed light into 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.[27] We therefore estimate separately the effect on high and medium/low occupations. Figures 9 and 10 show the heterogeneous effect of local labour market concentration on the demand for skills. Two results emerge. First the binary measure delivers sharper differences, this is expected as it does not weight 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 occupation Hard and Social

[26]The results are also graphically represented with residualized binscatter plots in figure 6.
[27]For more details on the classification, see ILO website.

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 organizational skills are positively correlated with market concentration for high skills occupations while they are negatively correlated for low skill ones.

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 competences. In more concentrated labour market is more common to require such competences: it is in fact more frequent that advertisements contain at least one of these skills (binary measure). At the same time these competences 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 4). Splitting these estimates by occupation (table 9) shows that this effect is driven by high skill occupations. Thus labour market concentration is associated with an increase in the number of competences 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.

6.4 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 define 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.

Figure 11 displays the estimates following the same methodology described in Section 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 while they are negatively correlated for medium-low skill occupations.

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 competences require formal teaching as in-class courses. For example the type of organizational skills that are needed for high skill occupations are generally managerial skills which can be acquired in graduate studies. Hence firms in more concentrated markets tend to demand more of these skills alongside with a higher level of education. Table 9 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 from an experienced colleague. Thus, having good social and hard skill can particularly help recruits in low-skill occupations to learn the required competencies. While 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.

7 Additional Robustness Checks

Although, as explained in section 5, results are robust to different specifications and definitions, we present some additional robustness checks. First, we present the results of an instrumental variable approach. Second, we introduce additional controls to account for local labour market conditions.

7.1 Instrumental variable approach

As explained in section 5 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 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. We acknowledge that our IV strategy is far from perfect as it relies on the time variation of the skill intensity measure neglecting the variability cross province. These results should therefore be taken with caution.

Figure 13 plots the estimated coefficients for all the different competencies for the tf-idf intensity measure. With IV estimates, the magnitude of the impact of labour market concentration on competencies demand appears to be greater. The TSLS results are also in line with the results obtained with the OLS specifications. Specifically, the negative impact of labour market concentration on Knowledge persists, as well as the positive effect on Social skills.

7.2 Controlling for unemployment level

A possible 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 6. 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 low productive firms have less incentive to accelerate the hiring procedure. To account for the possible effect of the unemployment rate, tables 12 and 13 include a control for the level of unemployment in the local labour market, confirming the main findings.

8 Discussion and Conclusion

What are the effects of local labour market concentration on the skills and competencies demanded by employers? By exploiting Italian Online Job Advertisements, we showed that labour market concentration increases the overall amount of competencies requested, in line with the upskilling phenomenon observed in the literature. However, more interestingly, we observed that not only the number of competencies demanded changes, but also its composition. We show that 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. Specifically, the negative effect of concentration on knowledge competencies is driven by high skill occupation, while the positive impact on Social competencies is driven by low and medium skill ones. Also this is in line with the training hypothesis. In high skill occupation 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.

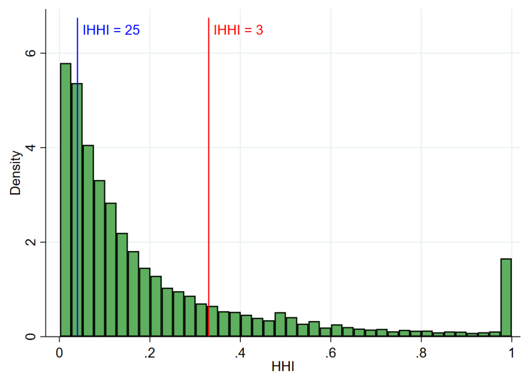
Unfortunately, we do not have data on how the training is carried out; therefore, this question is left for future research.

Overall our findings suggest that policy authorities should consider the local labour market structure when studying workforce development programs aimed at bridging the skill gap of displaced workers. Our results have clear implications for HR management practices as they show that the recruitment behaviour and the demand for skills differ in monopsonistic markets and should be taken into consideration when designing policies aimed at mitigating anticompetitive practices affecting human resources.

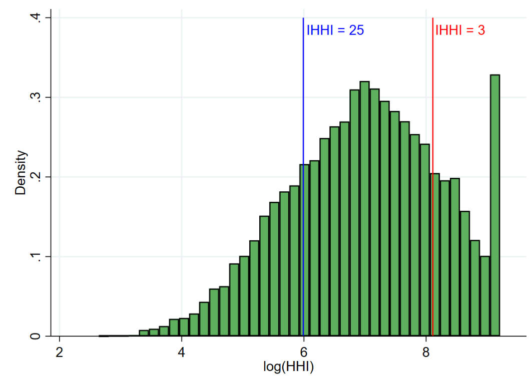
List of Figures

Figure 1: Employment concentration in the Italian local labour markets (2015-2018)

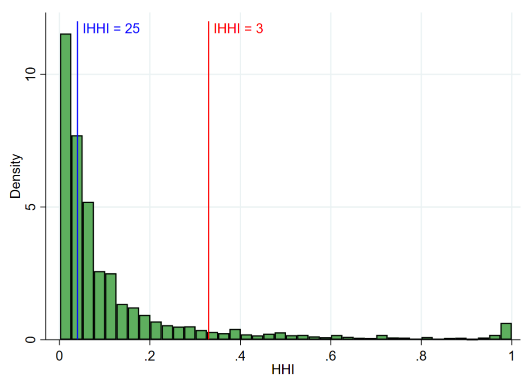
(a) *Average across Markets, level*



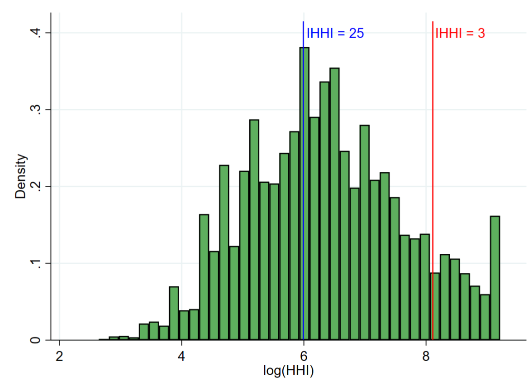
(b) *Average across Markets, logarithm*



(c) *Average across Job Ads, level*



(d) *Average across Job Ads, logarithm*

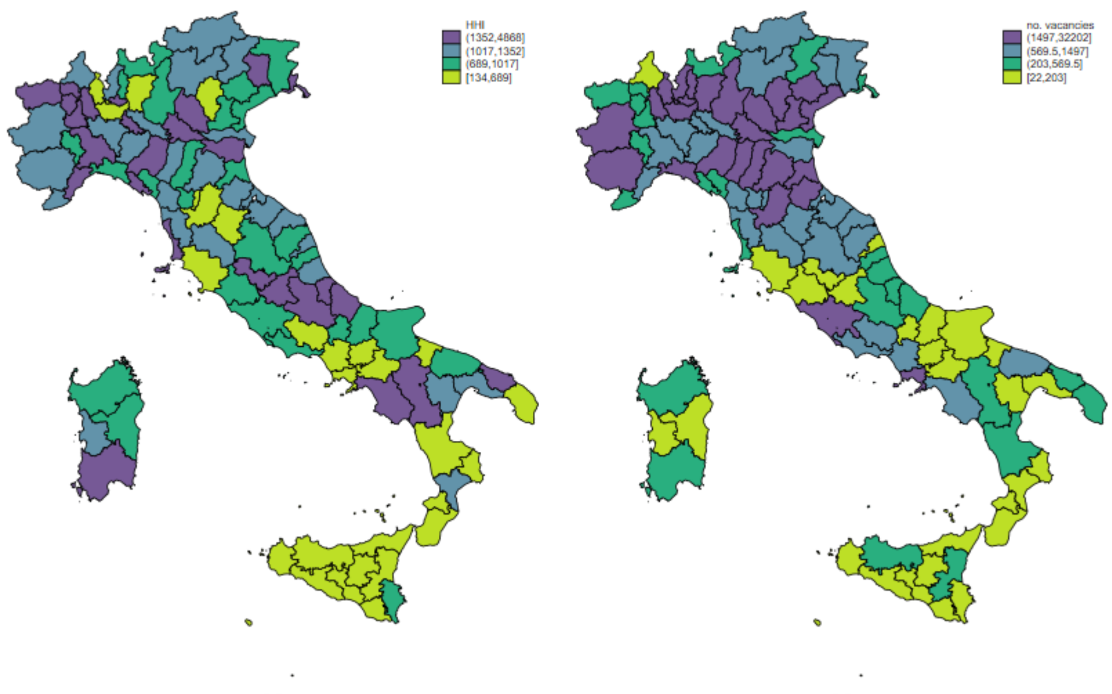


Authors' calculations on AIDA data 2015-2018. The HHI is computed at the local labour market level, which is define as a combination of Province, Ateco 2-digit, and year. The two graphs in the top of the figure are calculated taking the average across local labour market. The two graphs in the bottom 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.

Figure 2: Employment concentration and number of vacancies across Italian provinces (2018)

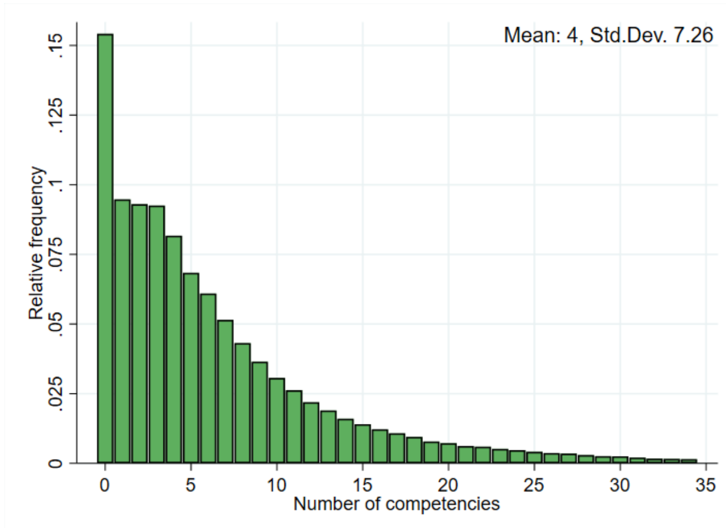
(a) *Average local-HHI, weighted by industry employment level*

(b) *Total number of vacancies posted across provinces*



Authors' calculations on AIDA and WollyBi data of 2018. 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.

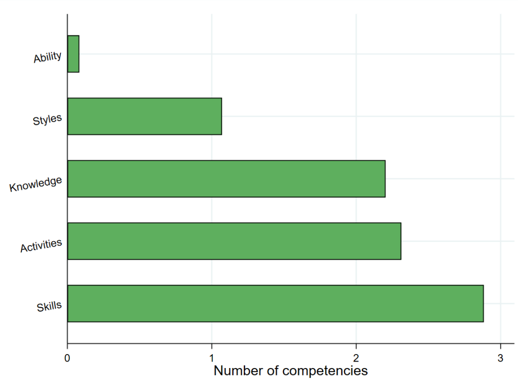
Figure 3: Distribution of number of competencies per job ad



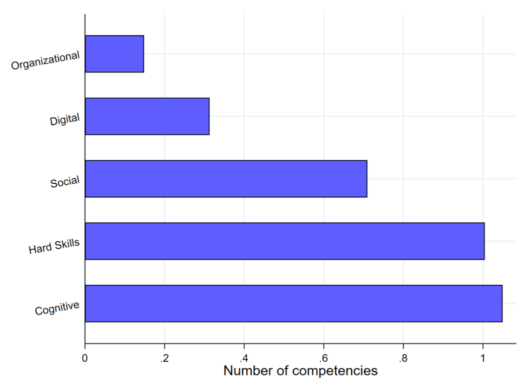
Authors' calculations on AIDA and WollyBi data of 2015-2018. Distribution of the competencies demanded, where the competencies are defined as the finest level of the O*NET taxonomy.

Figure 4: Average number of competencies by type per job ad

(a) *Group 1 competencies*

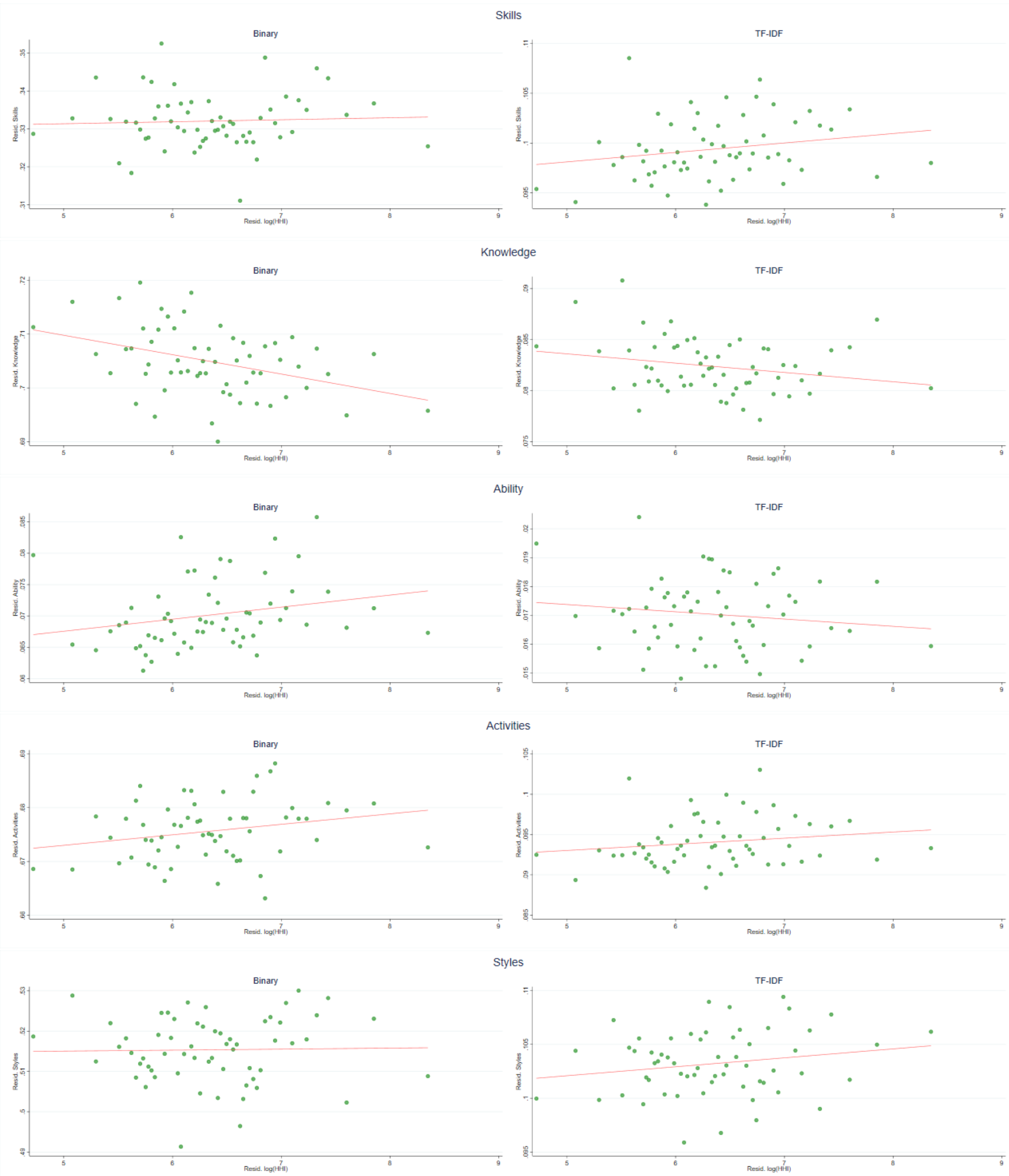


(b) *Group 2 competencies*



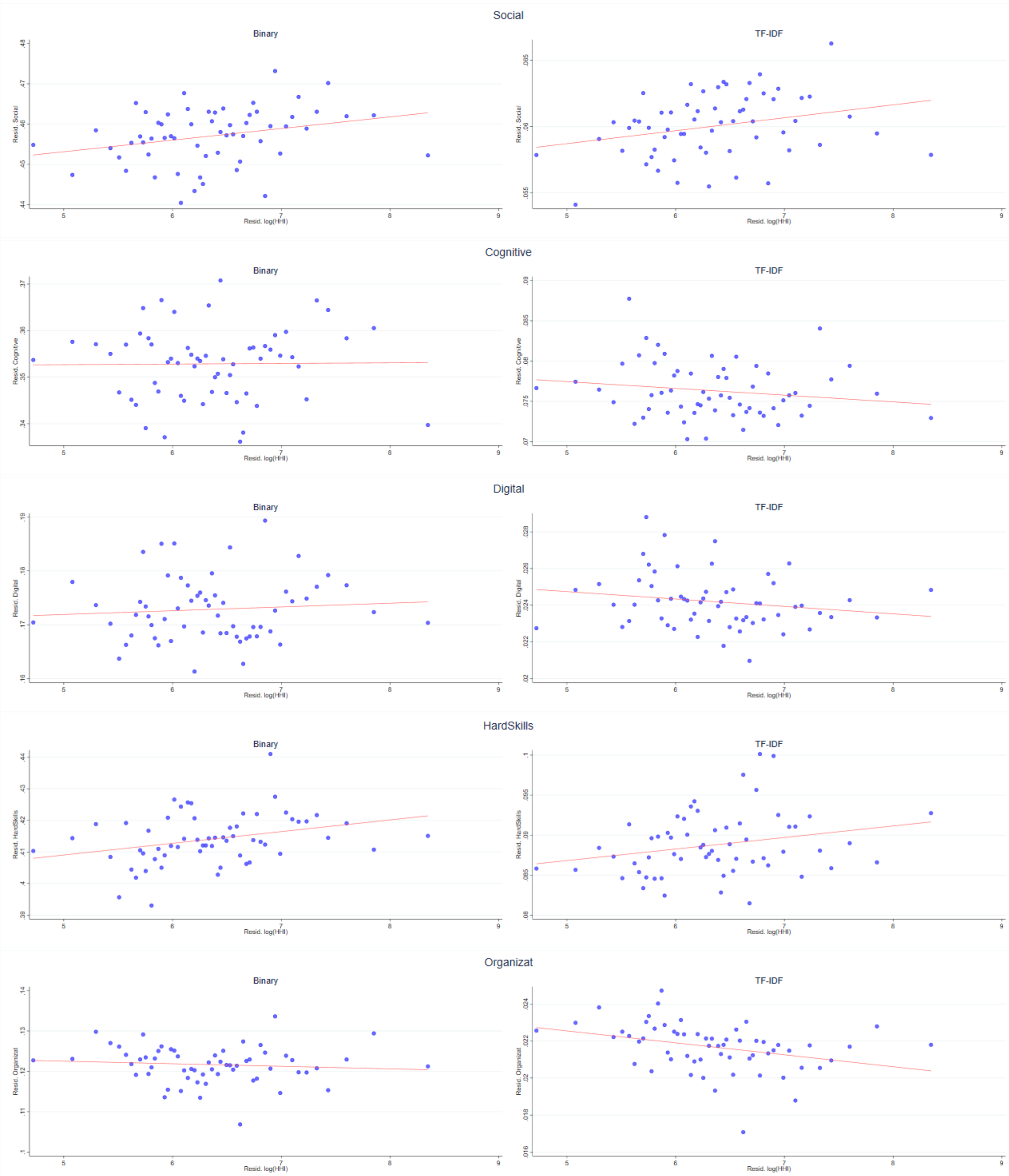
Authors' calculations on AIDA and WollyBi data of 2015-2018. Average number of distinct competencies demanded per skill category, where the competencies are defined as the finest level of the O*NET taxonomy.

Figure 5: Binned scatter plot of labour concentration on demand for the competencies in group 1



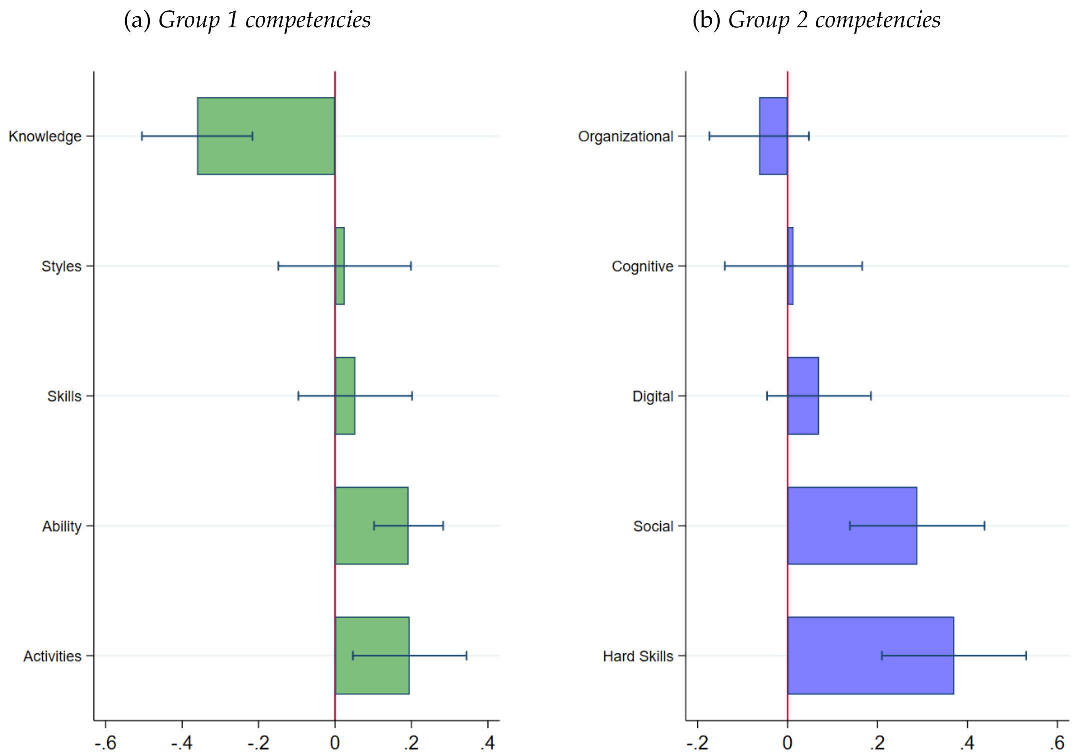
Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The residuals are computed using as regressors occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

Figure 6: Binned scatter plot of labour concentration on demand for the competencies in group 2



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

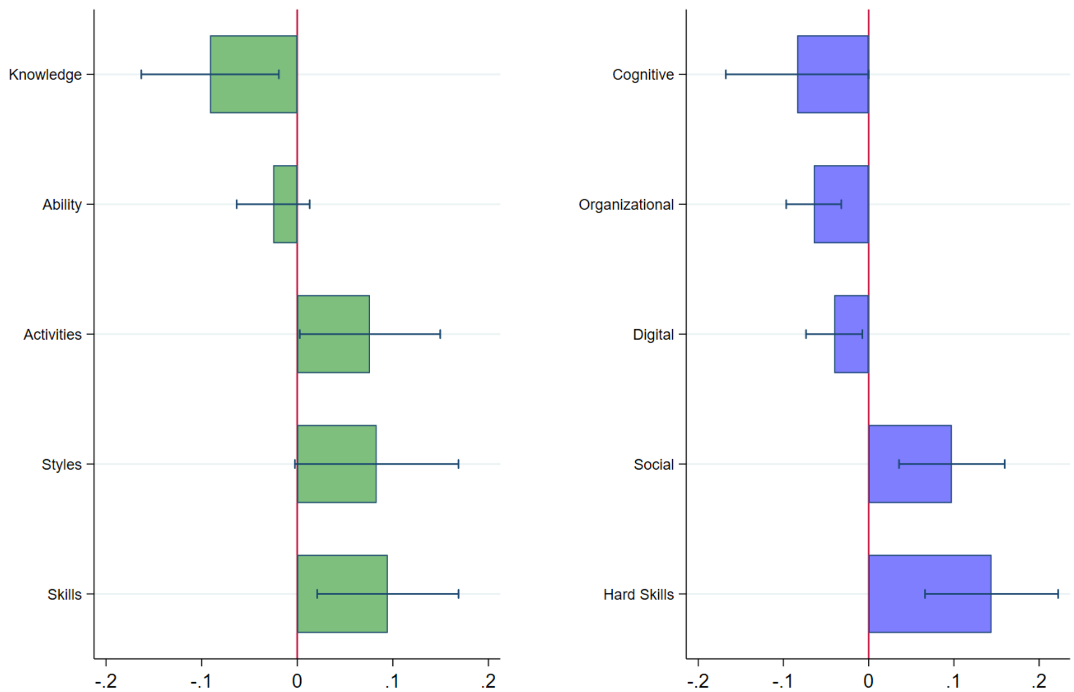
Figure 7: Coefficients plots of labour concentration on competencies demand (binary measure)



Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The Figure plots the OLS coefficient 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.

Figure 8: OLS coefficients plots of labour concentration on competencies demand (TF-IDF measure)

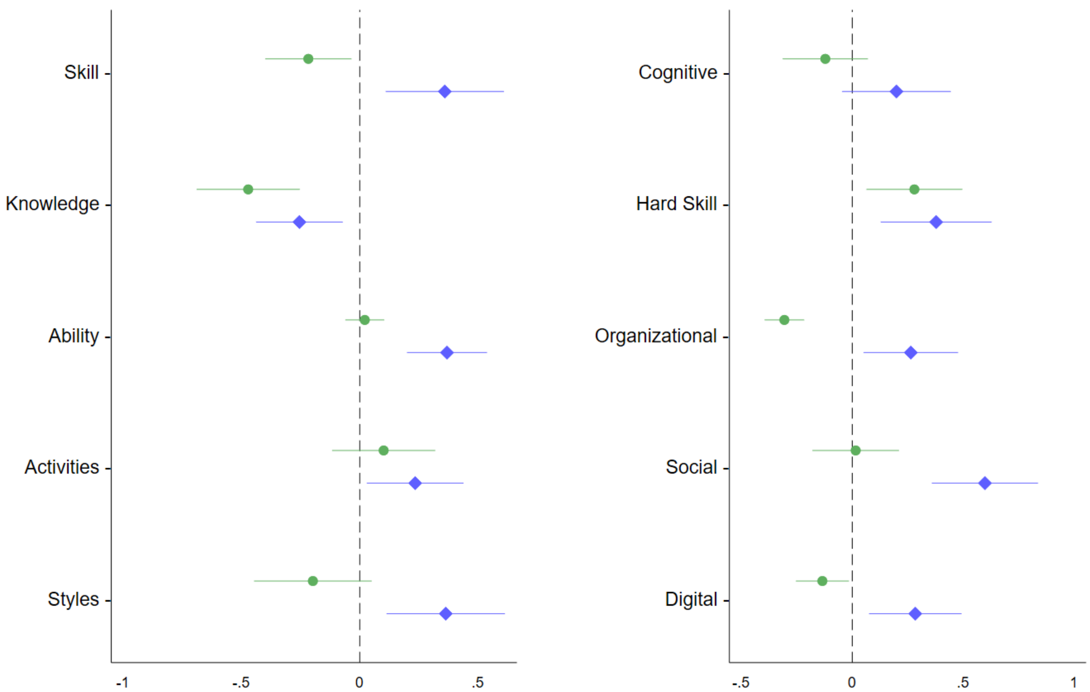
(a) *Group 1 competencies* (b) *Group 2 competencies*



Authors' calculations on AIDA and WollyBi data of 2015-2018. Note: The Figure plots the OLS coefficient 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.

Figure 9: Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (binary measure)

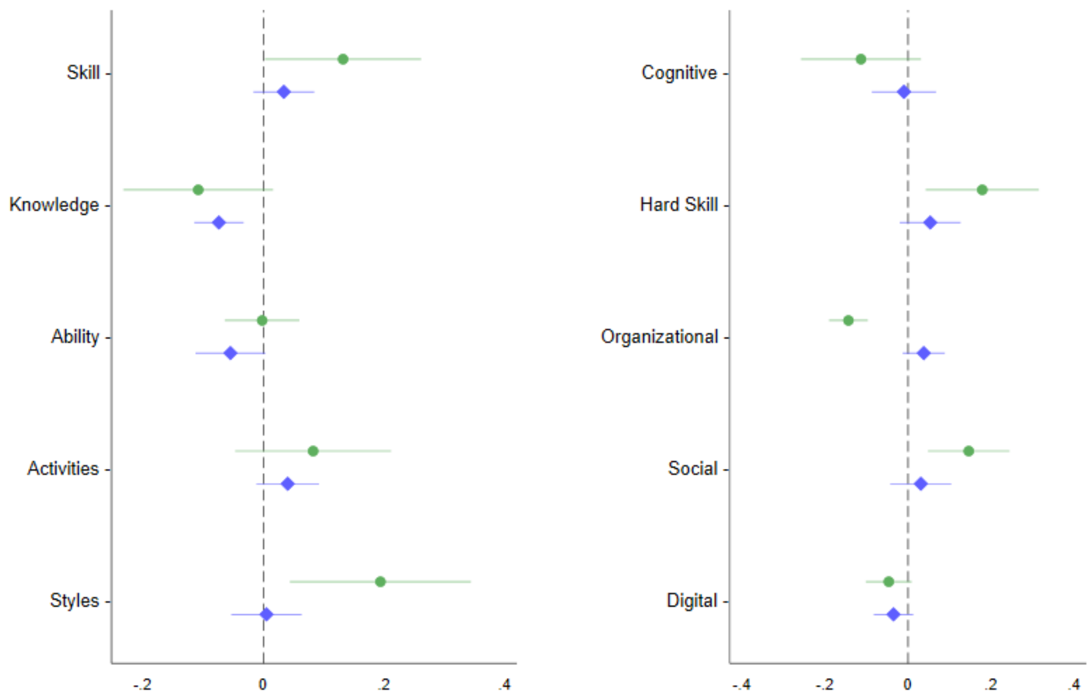
(a) *Group 1 competencies* (b) *Group 2 competencies*



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient 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.

Figure 10: Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (tf-idf measure)

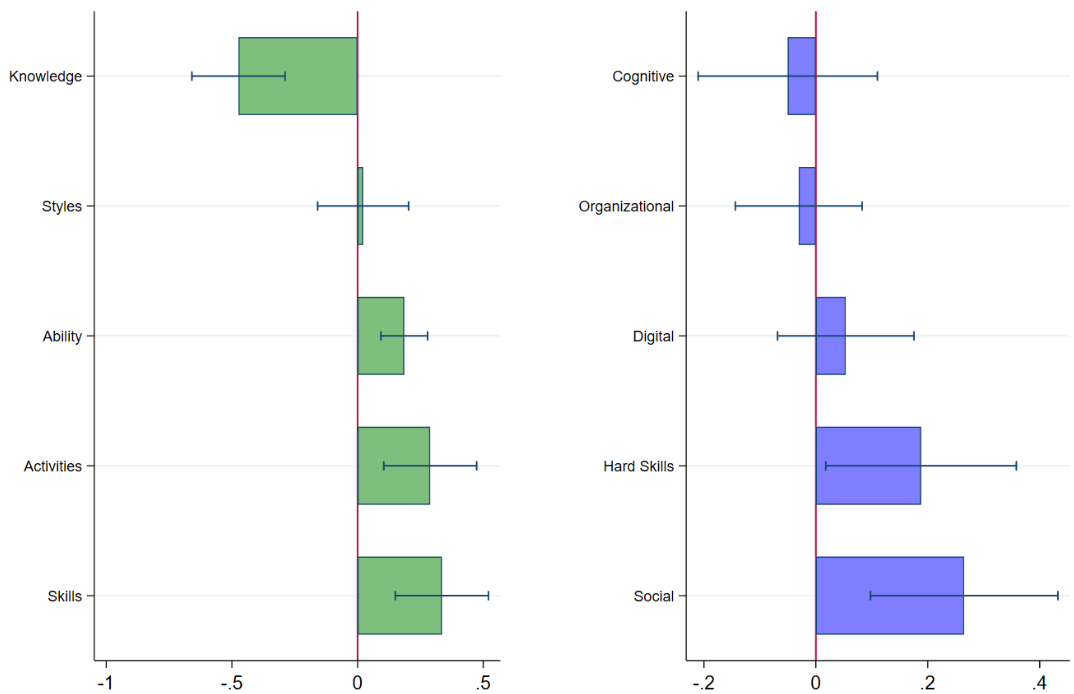
(a) *Group 1 competencies* (b) *Group 2 competencies*



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient 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.

Figure 11: OLS coefficients plots of labour concentration on competencies demand (effective-use measure)

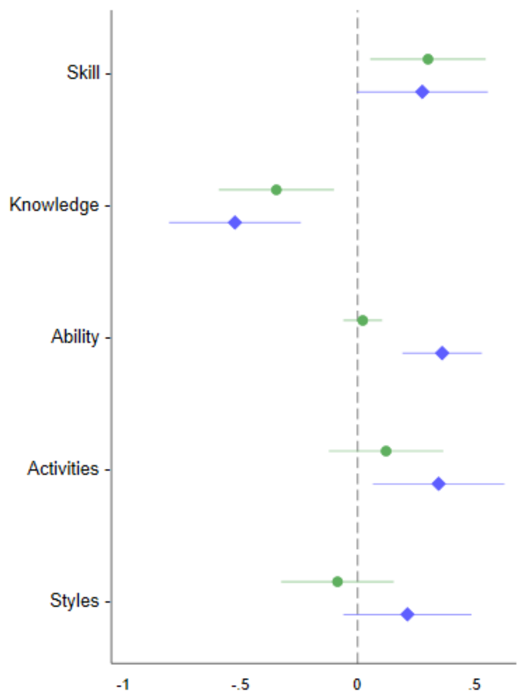
(a) *Group 1 competencies* (b) *Group 2 competencies*



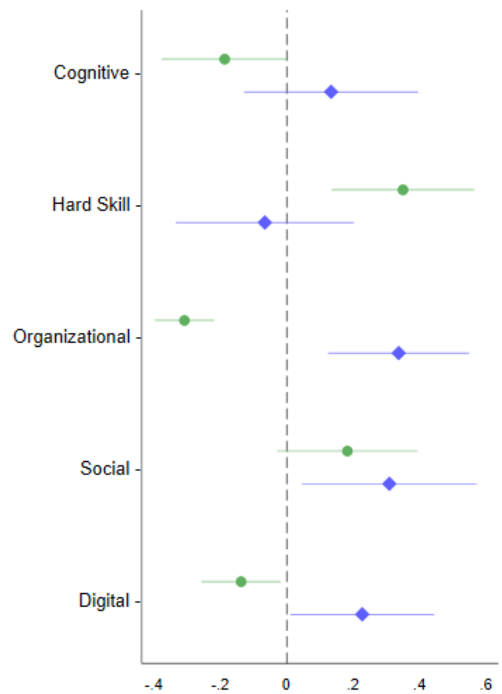
Authors' calculations on AIDA and WollyBi data of2015-2018. The Figure plots the OLS coefficient and 95% confidence interval of log. HHI on the effective-use score for that particular skill category, variable described in Section 6.4. Regressions also include occupation (ISCO 4-dig), province (NUTS-3), industry sector (Ateco 2-digit), and year fixed effects.

Figure 12: OLS Coefficients plots of labour concentration on competencies demand by high- or low-occupation skill (effective-use measure)

(a) *Group 1 competencies*

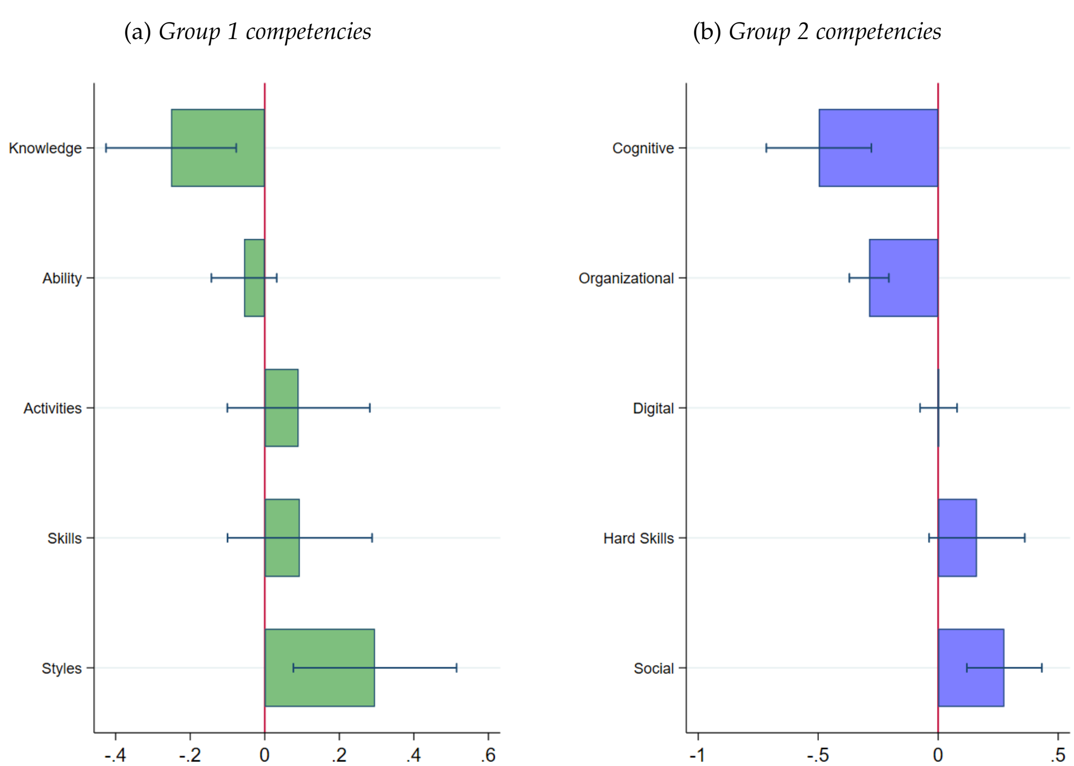


(b) *Group 2 competencies*



Authors' calculations on AIDA and WollyBi data of 2015-2018. The Figure plots the OLS coefficient 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.

Figure 13: TSLS coefficients plots of labour concentration on competencies demand (TF-IDF measure)



Authors' calculations on AIDA and WollyBi data of2015-2018. The Figure plots the TSLS coefficient 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.

List of Tables

Table 1: Description of the competencies groups

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 behaviors 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 categorization)*
Cognitive	Cognitive Abilities, Complex Problem Solving Skills, Mental Processes
Social	Interacting with others
Digital	Software and Technology
Hard Skills	Technical skills, Tools, Work output
Organizational	System skills, Resource Management Skills

Note: 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 2: Summary statistics

	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

Table 3: Summary statistics, skill/competency classification

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	0.0625
Hard-Skills						
Binary	553,132	0.414	0.493	0	0	1
TF-IDF	553,132	0.089	0.205	0	0	0.0862
Organizational						
Binary	553,132	0.122	0.327	0	0	0
TF-IDF	553,132	0.022	0.090	0	0	0
Digital						
Binary	553,132	0.173	0.378	0	0	0
TF-IDF	553,132	0.024	0.095	0	0	0

Table 4: OLS estimates of labour market concentration on No. skills, experience, and education

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table 5: OLS estimates of labour market concentration on skill/competency demand (group 1), binary measure.

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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) 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

Table 6: OLS estimates of labour market concentration on skill/competency demand (group 1), tf-idf measure.

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table 7: OLS estimates of labour market concentration on skill/competency demand (group 2), 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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: Each observation consists in a vacancy. This table reports the OLS regression outputs using as dependent variables the binary 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

Table 8: OLS estimates of labour market concentration on skill/competency demand (group 2), tf-idf measure.

	Cognitive	HardSkills	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table 9: 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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: TSLS estimates of labour market concentration on vacancy competencies demand (tf-idf measure)

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.
Note: 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

Table 11: TSLS estimates of labour market concentration on vacancy competencies demand (tf-idf measure)

	Cognitive	HardSkills	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.
Note: 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

Table 12: OLS estimates of labour market concentration on skill/competency demand (group 1), tf-idf measure; controlling for unemployment rate.

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table 13: OLS estimates of labour market concentration on skill/competency demand (group 2), tf-idf measure; controlling for unemployment rate.

	Cognitive	HardSkills	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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Appendix I: detailed model solution

This section provides detailed derivations of mathematical formulae that appear in the main text, section 3.

Firm's problem

In addition to the level of trainable (T) and untrainable (U) competence the workforce should have, the firm choose also the amount of training (A) to provide to her workforce. This leads to the following maximization problem,

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

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

The first order conditions lead to

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

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

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

Dividing 5 over 6,

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

Then substituting it into 6

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

Divide this on 7

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

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.[28]

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

Since

$$\begin{aligned}e(N)=\frac{\partial C}{\partial N}\frac{N}{C}\quad&\Rightarrow(1+e(N))C=C'_{N}N+C>0\\ \frac{\partial}{\partial N}(1+e(N)C(W,N))&=(C''_{NN}N+2C'_{N})>0\end{aligned}$$

Because $C'_N>0$, $C''_{NN}\geq 0$, and $\theta<1$

$$\frac{\partial^{T}/_{U}}{\partial HHI}<0$$

[28]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.

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 ($\frac{\overline{T}}{\overline{U}}$) is:

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

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

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

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

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

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:

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

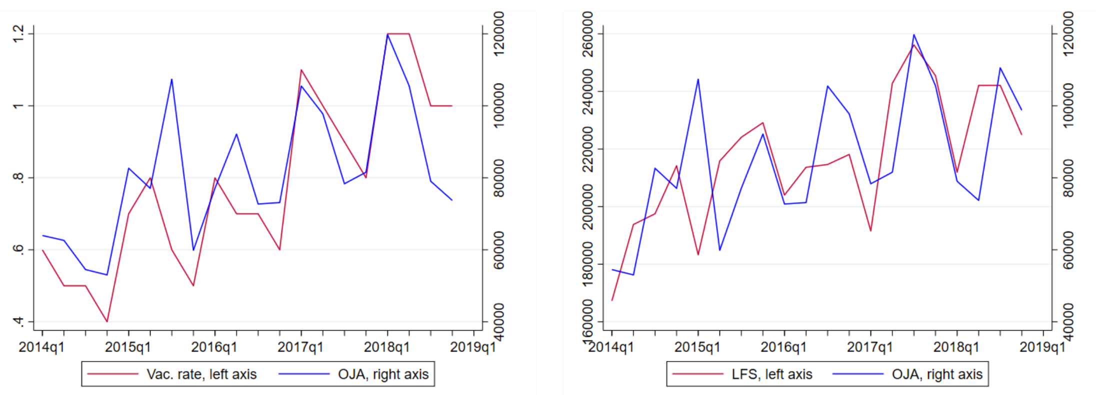
Appendix II. Representativeness of online vacancy data data

As mentioned in the text a potential drawback of Omline Job Advertisements (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 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. In order 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. 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.

Figure A1: Online vacancies and official statistics

(a) *Online vacancies and official vacancy rate*

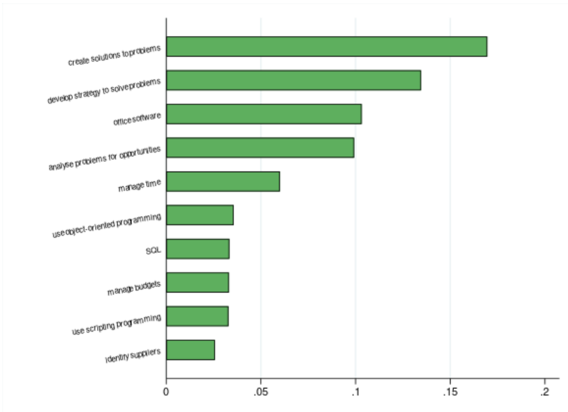
(b) *Online vacancies and LFS recent hirings*



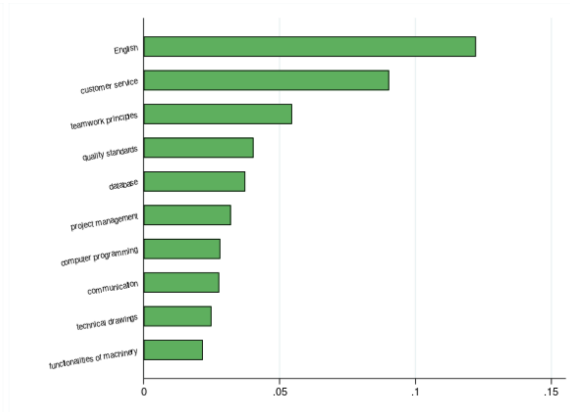
Authors' calculations Istat and WollyBi data of 2014-2018. LFS data refer to recent hirings (those who found a job in the last 3 months).

Figure A2: Description top10 competencies for group 1

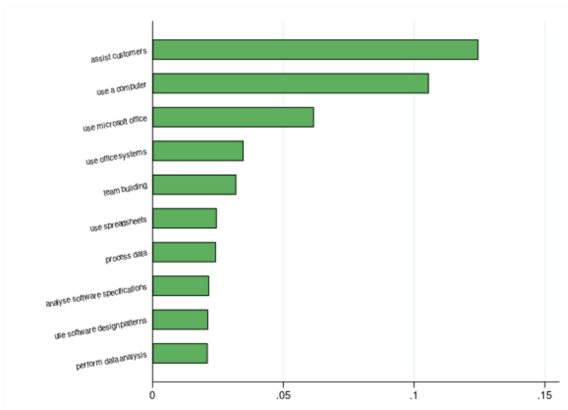
(a) Skills



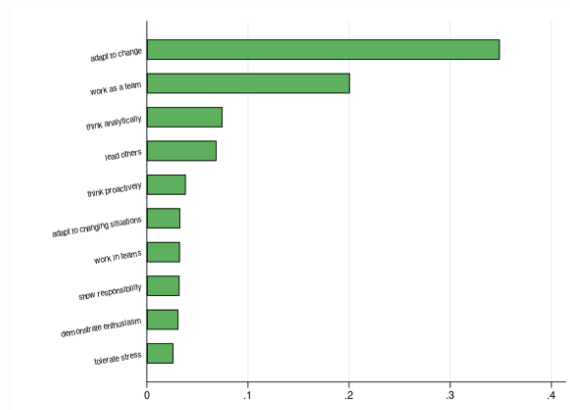
(b) Knowledge



(c) Activities



(d) Styles



(e) Ability

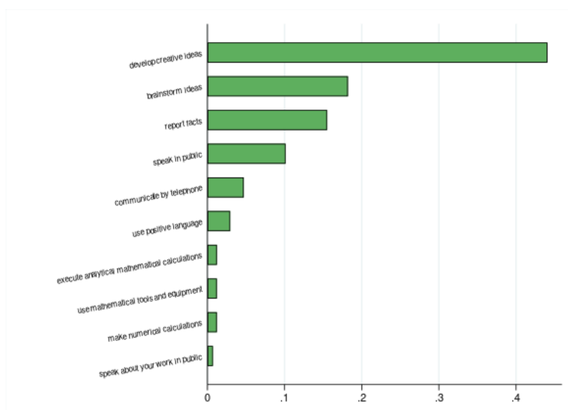
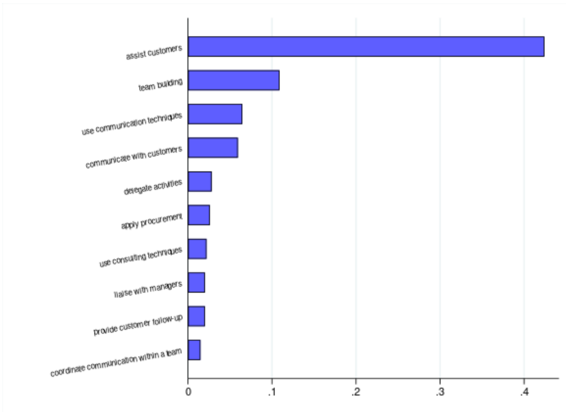
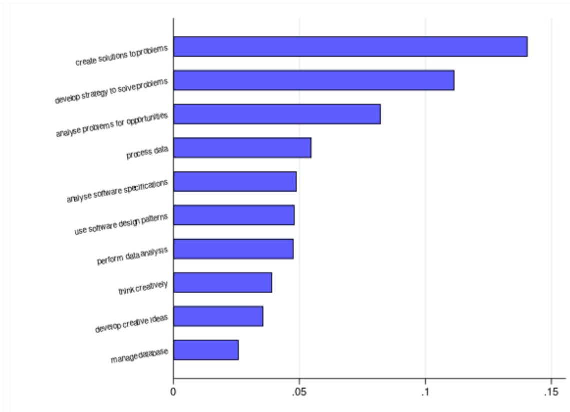


Figure A3: Description top10 competencies for group 2

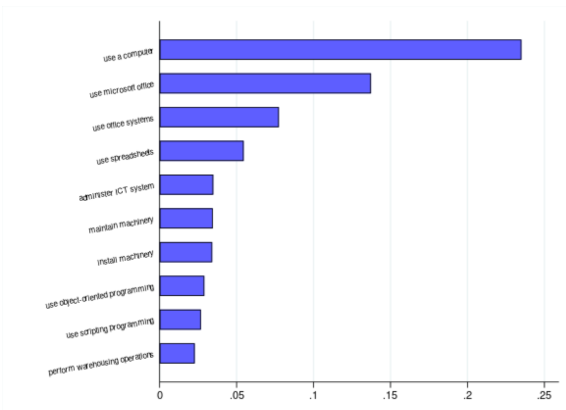
(a) Social



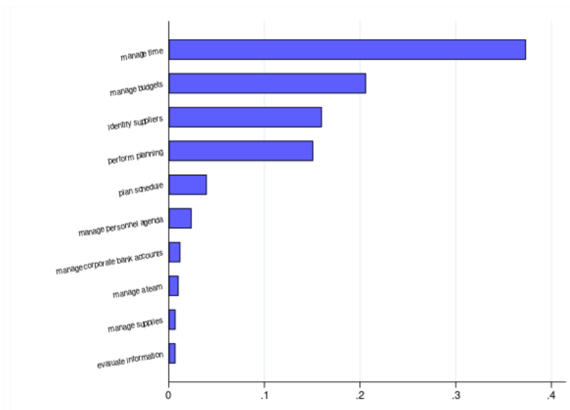
(b) Cognitive



(c) Hard Skills



(d) Organizational Skills



(e) Digital Skills

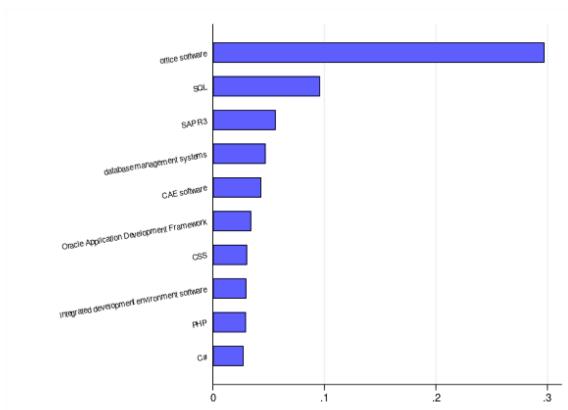


Table A1: Correlation matrix between group 1 skill types

(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

Table A2: Correlation matrix between group 2 skill types

(a) Binary measure

	Cognitive	HardSkills	Organizat	Social	Digital
Cognitive	1				
HardSkills	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	HardSkills	Organizat	Social	Digital
Cognitive	1				
HardSkills	-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

Table A3: OLS estimates of labour market concentration on skill/competency demand (group 1), Binary measure across high and low skill occupations.

	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table A4: OLS estimates of labour market concentration on skill/competency demand (group 2), 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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table A5: 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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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

Table A6: OLS estimates of labour market concentration on skill/competency demand (group 2), TF-IDF measure across high and low skill occupations.

	Cognitive	HardSkills	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

Source: Authors' calculation on AIDA and Wollybi data in 2015-2018 period.

Note: 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 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$