Demand for Skills and Wage Inequality*

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Abstract

This paper studies the relationship between wage inequality and skill demand and its connection to worker and firm heterogeneity. Combining linked employer-employee data from Italy with aggregate-level information on detailed skill requirements extracted from online job vacancies, we first study the relationship between wages and the demand for cognitive and social skills across labor markets defined by province, sector, and occupation. We find a strong and positive correlation between wages and the demand for cognitive and social skills, which is pronounced when both skills are required jointly for the same job position highlighting their complementarity. We then estimate the worker- and firm-pay components of the wage process through an AKM model and investigate their relationship with skill demand at the labor market level. Our analysis suggests that in markets in which firms demand more frequently both cognitive and social skills, higher wages are driven by worker effects, reflecting the higher market value of a combined skill set, rather than by firm pay policies. In contrast, in markets where firms predominantly demand either cognitive or social skills, higher wages are associated with higher firm effects, indicating larger firm pay premiums for specialized workers, despite the lower market value of specialized skills. These results highlight the role of worker and firm heterogeneity as mechanisms through which variations in skill demand influence overall wage inequality.

Keywords: Skill demand, wage differentials, inequality, returns to skills, unobserved heterogeneity

JEL Codes: J24, J31, J63

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1 Introduction

The rise in wage inequality observed in many advanced economies over the past few decades has been the focus of extensive research. One prominent line of inquiry has examined the impact of changes in the returns to skills, induced by technological and organizational advances, on wage inequality (Autor et al., 2003, 2006, 2008, Autor and Dorn, 2013, Goos and Manning, 2007, Goos et al., 2009, 2014, Acemoglu and Autor, 2011). This literature has focused on shifts in skill demand, wages, and employment for different groups of workers (e.g., by occupation and education), considering a market-level determination of skill pricing, with little emphasis on individual worker and firm heterogeneity. Concurrently, another branch of literature, stemming from the seminal work by Abowd et al. (1999, AKM hereafter), has examined how worker and firm heterogeneity contribute to wage dispersion (Card et al., 2013, 2016, 2018, Song et al., 2019). These studies typically model wages as a log-linear additive function of two components: one capturing unobserved variation in individual worker qualities, and the other firm compensation policies, without considering whether different returns to skills arise for workers of various types within diverse firms.

This paper aims to explore the mechanisms through which disparities in skill demand influence wage inequality, specifically examining how variations in skill returns reflect differences in individual and firm pay structures. In doing so, it aims to bridge the aforementioned two distinct yet interrelated strands of literature. Our analysis begins by examining the relationship between wages and skill demand across labor markets to uncover the overall returns to different skill types and their influence on wage dispersion. We then investigate how the relationship between wage and skill demand is shaped by individual worker qualities and firm compensation policies. More precisely, we characterize the returns to skills in terms of worker pay (reflective of market-determined skill prices) and firm-specific pay premiums (indicative of firms' compensation policies), and assess their respective roles in the determination of overall skill returns.

Our empirical study is based on a dataset covering the period from 2014 to 2019, combining two distinct data sources. The first source is a comprehensive matched employer-employee dataset for Italy, which includes detailed records on wages, occupations, number of workdays, types of contract, along with various demographic characteristics of workers and attributes of firms. The second source is a dataset that encompasses the near-universe of online job vacancies posted in Italy during the specified period. From this, we use detailed information about the skill requirements specified by employers in their job postings, such as cognitive, social, management, and computer skills, as well as more standard education and experience requirements.

In the first part of our analysis, using the methodology of Deming and Kahn (2018), we regress the logarithm of average wages on average skill requirements at the province-sector-occupation level, focusing on cognitive and social skills and their complementarity, reflected by their joint demand within the same job. This emphasis is motivated by the importance of these skills in the discussions of how technological change influences wage inequality. Our model specification includes fixed effects for province, sector, and occupation, which account for unobserved variation across each of these dimensions. To further account for systematic variation in skill composition across labor markets, we include a rich set of controls at the cell level, such as other skill requirements reported in job postings as well as a wide range socio-demographic and labor market characteristics.

Our findings reveal a significant and positive relationship between wages and the demand for cognitive and social skills, suggesting that variations in the demand for these skills strongly predicts wage dispersion, even after controlling for several other factors. Furthermore, we show that these positive returns are particularly pronounced in jobs requiring both cognitive and social skills, implying a wage premium attributed to the complementary nature of cognitive and social skills at the job level. These findings align with recent studies emphasizing the growing importance of social skills in the labor market and their complementarity with cognitive skills (Borghans et al., 2014; Deming, 2017; Deming and Kahn, 2018; Weinberger, 2014), extending this evidence beyond the US context.[1]

In the second part of our analysis, we build upon the previous framework to further examine the returns to skills separately in terms of worker and firm pay. The model used in the first part of the analysis to estimate the overall returns to skills conflates the wage premiums accruing to individuals due to market-level skill valuations with those stemming from varying compensation policies across different firms. While a portion of the wage returns associated with a specific skill originates from its market valuation, independent of firm compensation policies, there is an additional part where workers benefit from firm-specific pay premiums, which may differ based on their skill set.[2] For example, a specific skill (or a combination of skills) might increase the productivity of a worker across a range of tasks that could be performed at firms of various types, which is reflected by its market price. At the same time, how a particular firm might value the same skill set might vary, influenced

[1]Furthermore, our findings relate to the rapidly growing research that uses data from online job postings to estimate the wage returns to specific skills (e.g., Alekseeva et al., 2021; Atalay et al., 2024; Chaturvedi et al., 2024; Deming and Kahn, 2018; Deming and Noray, 2020) as well as to personality traits (Brenčič and McGee, 2024).

[2]Previous research has explored various explanations for firm pay differentials, including rent-sharing (Van Reenen, 1996; Card et al., 2018), productivity differences (Barth et al., 2016; Dunne et al., 2004; Faggio et al., 2010), and the role of compensating wage differentials and job amenities valuation (Dupuy and Galichon, 2022; Mas and Pallais, 2017; Lavetti and Schmutte, 2018; Sorkin, 2018).

by factors such as the centrality of these skills to the firm's production process and their degree of complementarity with the firm's overall technology, potentially leading to variation in firm compensation.

To shed light on these two mechanisms through which skill demand influences wages, we adopt a two-step empirical approach. First, we leverage matched employer-employee data to estimate the worker and firm components of the wage structure by fitting an AKM model on the largest set of firms connected through worker mobility. Second, we calculate the average of the estimated worker and firm effects within each province-sector-occupation labor market cell. We then analyze the relationship of these averages with the cell-level average skill requirements, employing the same analytical framework as in the first part of the paper.[3,4]

In terms of worker pay, we find that labor markets with a higher joint demand for cognitive and social skills are associated with higher market-level returns, as measured by the cell average of estimated worker effects. On the contrary, markets with a greater demand for cognitive skills alone are associated with slightly lower worker pay, suggesting that these skills, when required alone, attract marginally lower market returns. However, our analysis does not reveal a significant relationship between markets with a higher demand for solely social skills and the worker-related wage component. With regard to firm compensation, we find that labor markets with a higher joint demand for cognitive and social skills are associated with lower firm pay. Conversely, we find that markets with a higher demand for either cognitive or social skills in isolation are associated with higher firm pay.

This set of findings suggests that the observed positive wage premiums, associated with jobs demanding both cognitive and social skills, predominantly arise from worker-related effects. This emphasizes the increased market valuation of these skills when they are combined. In contrast, it appears that higher-paying firms tend to reward positions that require specialization in either cognitive or social skills individually, rather than rewarding the complementary nature of these skills. This pattern is consistent with a setting in which high-paying firms have more complex structures involving several specialized workers. These

[3]Similar approaches fitting an AKM model to disentangle worker and firm effects, and later using the obtained estimates as dependent variables to investigate their relationship with given variables of interest are featured, for example, in Macis and Schivardi (2016, firm export activity) and Engbom et al. (2023, firm productivity).

[4]This approach to cell-level aggregation stems from the absence of firm identifiers in our job posting data, precluding the possibility of a firm-level analysis. By way of comparison, Deming and Kahn (2018) observe firm identifiers in a subsample of their online job posting data. However, they have no wage information on individual workers. Their firm-level wage measure is computed as the weighted average of market-level mean wages (coming from OES survey data), using firm posting shares across cells. In a further analysis, they regress this measure on skill demand to investigate firm-level skill returns. Nevertheless, such analysis does not allow disentangling skill returns in terms of worker- and firm-specific wage components, since it cannot control for unobserved worker heterogeneity.

workers are likely to reap higher firm pay premiums, reflecting their central role in the firm's production process. Instead, firms at the lower end of the job ladder, which are often less productive, may operate with leaner structures, employing fewer but more generalist workers receiving lower firm pay.

Our analysis contributes to a deeper understanding of the mechanisms driving the relationship between skill demand and wage inequality, by illustrating how distinguishing between firm-specific premiums and broader market valuation for given skill sets helps shed light on overall wage determination dynamics. The remainder of the paper is organized as follows. In Section 2, we describe our two data sources and outline the procedure for merging them. In Section 3, we present our main empirical methodology and the results from the analysis of overall returns to skills. In Section 4, we estimate worker and firm effects, examine the results on the returns to skills in terms of worker and firm pay, respectively, and provide a discussion offering potential interpretations for our findings based on recent related empirical evidence. Finally, in Section 5, we provide concluding remarks.

2 Data

The empirical analysis leverages a dataset that combines two data sources. The first consists of population-level administrative records linking Italian firms and their dependent workers, provided by the Italian Social Security Institute (INPS, 2021) as part of the VisitINPS Program. The second contains the near-universe of online job vacancies posted in Italy from 2014 to 2019, obtained from Lightcast (2020), a leading labor market analytics company.[5]

2.1 Linked Employer-Employee Data

We use administrative records on annual employment relationships, compiled by INPS by annualizing monthly reports submitted by employers (known as *Uniemens*). These reports provide detailed information on several aspects of employment relationships for all non-agricultural private-sector dependent workers from 1974 to 2020. For our analysis, we focus on the years 2014-2019.

The unit of observation is a firm-worker annual employment spell with two unique scrambled identifiers for a given employer-employee pair, which allow tracking matches, individual work histories, and firm workforce composition across years.[6] We exploit information on

[5]Lightcast (www.lightcast.io) was formerly known as Emsi/Burning Glass, which incorporated the initial data provider, WollyBi.

[6]When workers have multiple employers within a year, we select the spell with the most (adjusted) days worked, ensuring one annual spell per worker. If spells tie in days worked, we keep the spell with the highest

individual workers' total annual earnings, contract type (permanent vs temporary, full-time vs part-time), and total annual days worked. We compute full-time equivalent (FTE) daily wages as total annual earnings divided by total annual days worked, adjusted for part-time incidence.[7] We further link annual spells to records containing information on workers' gender, date of birth, and nationality, as well as firms' sector of activity (up to 4 digits) and location (up to the municipality level). For our purposes, we use firm information on the 1-digit sector and province of activity. The resulting dataset, which we refer to as the "full sample", contains 84.7 million firm-worker-year spells on 19.9 million individuals working in 2.4 million firms. Summary statistics for individual workers are provided in Column 1 of Table 1.

To retrieve information on worker occupation, we use additional records from *Unilav* reports. Employers are required to submit these reports to INPS to communicate new hires, contract extensions and conversions, transfers, secondments, or terminations. These reports mandate specifying several details, including the worker's occupation using a 5-digit code from ISTAT's CP2011 classification, which can be mapped to the ISCO-08 classification at the 3-digit level. The administrative records cover all *Unilav* compulsory communications submitted between 2010 and 2017. We can trace at least one compulsory communication for approximately 16.5 million workers. We refer to the subset of the data containing workers with communications (82.9% of the "full sample") as the "*Unilav* sample". We assign to each spell the occupational code from the communication closest to 2014, updating the information in later years if any subsequent communications exist for the same worker.[8]

As shown in Column 2 of Table 1, workers in the "*Unilav* sample" tend to be slightly younger and more likely to be female, foreign, and in part-time or temporary/seasonal employment, compared to those in the "full sample", since here we do not capture high-tenure workers who maintain long-term employment relationships with the same firm without experiencing contractual changes. In contrast, workers in this sample have undergone some form of contractual change since 2010. However, it is important to note that these differences should not raise concerns, given that (i) the secondary dataset, from which we extract skill demand information, pertains to labor demand for prospective hires in recent years, and (ii) the AKM model employed to estimate worker and firm wage heterogeneity is based on a subset of the data in which firms are connected through worker mobility flows.

earnings; if still tied, we select randomly.

[7]Details on the definition of annual earnings and FTE days worked and daily wages are provided in Appendix A.1.

[8]Based on 102,407,832 compulsory communications for 16,478,512 workers made in 2010-2017, an average worker has about 6.2 communications, roughly 2 annually over 3 years. When multiple communications are made for a worker in the same year, we use the mode occupational code.

2.2 Online Job Vacancy Data

Our second data source contains the near-universe of online job vacancies (OJVs) posted in Italy from 2014 to 2019. The data provider, WollyBi (now Lightcast), used web crawling to collect information from more than 6.5 OJVs across approximately 250 online job boards and employment agencies. These records went through a deduplication process and were structured into a standardized format, containing roughly 40 fields for each job posting. These fields include information on the context of each posted vacancy—such as province (NUTS-3), industry (NACE Rev.2 1-digit), and occupation (ISCO-08 4-digit)—and on the specified requirements in terms of education, work experience, and specific skills. To assess the representativeness of the data, we estimated sector-level vacancy rates and compared them with those published by the Italian National Statistics Office (ISTAT), finding that they are reasonably well-aligned in both levels and dynamics (see Figures A.2.1 and A.2.2).[9]

The skill requirements were extracted by the data provider through a proprietary algorithm, which parsed the text of the job description of each OJV and encoded the skill requirements mentioned therein into about 750 unique English-language standardized textual skill tags.[10] These tags correspond to the level 3 skills/competences of the ESCO v1 classification, consisting of phrases like "brainstorm ideas", "perform planning", or "make numerical calculations".[11] To reduce the dimensionality of the ESCO skill set, we perform a keyword-based search within the text of ESCO skill tags and categorize each of them into one of the 10 job skill categories defined by Deming and Kahn (2018, DK), i.e., cognitive, social, character, writing, customer service, project management, people management, financial, computer (general), and software (specific) skills.[12] For example, an OJV having ESCO skill tags containing expressions such as "problem solving" or "critical thinking" will be categorized as having *cognitive* skill requirements. In contrast, if the ESCO skill tags contain words such as "communication" or "teamwork", the OJV is categorized as having *social* skill requirements, and so on for the remaining 8 DK job skill categories. In our analysis, we aim to identify OJVs that feature *both* cognitive and social skill requirements for the same job. Therefore, we construct an additional indicator variable marking OJVs that have both ESCO skill tags categorized as cognitive skill requirements and tags classified as social skill requirements.

[9]ISTAT defines the vacancy rate as the ratio of posted vacancies to the sum of posted vacancies and filled job positions. Appendix A.2.1 provides a detailed account of the methodology used to compute vacancy rates from the WollyBi data and presents the benchmarking exercise carried out to verify its representativeness.

[10]Each OJV can contain multiple (if any) skill requirement tags.

[11]See https://esco.ec.europa.eu/en/classification/skill_main.

[12]The keywords and phrases used to categorize ESCO skill tags into DK skill categories are reported in Table A.2.1 in Appendix A.2.2.

Importantly, the Lightcast data for Italy do not contain information on the firms posting the job vacancies, thus preventing us from linking them with the INPS data at the firm level. Given this limitation, we combine the Lightcast and INPS data at a broader level by creating labor market cells defined by geographical location, industry, and occupation. For this purpose, we use the finest level of detail available in the vacancy data, consisting of NUTS-3 provinces for location and 1-digit NACE sector for industry. As to occupation, in order to maximize the cell-level match rate between the two datasets, we use ISCO-08 codes at the 1-digit level, resulting in an 81% match rate and the creation of approximately 15,000 cells.[13] Subsequently, we select OJVs with complete information regarding province, sector, and occupation, corresponding to around 4.6 million OJVs, or 70% of the dataset. Lastly, within each labor market cell, we calculate the share of OJVs that demand a particular skill. Close to 80% of vacancies state specific skill requirements. Among these, 43% specify cognitive skills, 47% demand social skills, while 27% require both cognitive and social skills for the same job position. Detailed summary statistics are reported in Table A.2.2 in Appendix A.2.3.

3 Overall wage returns to skills

The aim of the first part of our analysis is to investigate the relationship between the variation in overall wages across labor markets and the corresponding differences in skill demand, which proxy heterogeneity in skill utilization and production technology. We follow the approach of Deming and Kahn (2018) and focus on the study of the returns to cognitive and social skills (and to their complementarity), which have been shown to be crucial to appraise the impact of technological change on wage inequality. To this purpose, we analyze the correlation between wage and skill demand differentials across labor markets—defined as province(p)-by-sector(s)-by-occupation(o) cells (NUTS-3 province by 1-digit NACE sector by 1-digit ISCO occupation)—through the following regression model:[14]

$$\log(\bar{w}_{pso}) = \lambda_p + \mu_s + v_o + SD'_{pso}\pi + X'_{pso}\zeta + \upsilon_{pso} \tag{1}$$

where $\log(\bar{w}_{pso})$ is the log of the labor market cell average of individual full-time equivalent gross daily wages; SD_{pso} is a vector of market cell skill requirement shares; λ_p, μ_s, and v_o are province, sector, and occupation fixed effects; and X_{pso} is a rich set of controls measured at

[13] Cell-level match rates are much lower when using 2-digit and 3-digit occupation, amounting to 67% and 50%, respectively.

[14] We cluster standard errors at the province-by-sector level. Furthermore, each observation corresponding to a given labor market cell is weighted by the number of full-time-equivalent days worked in the cell.

the cell level. The inclusion of fixed effects and controls helps account for alternative potential drivers of the correlation between skill demand and wages. In particular, fixed effects capture systematic differences that may arise due to unobserved characteristics related to certain provinces, industries, and occupations. For example, as noted by Deming and Kahn (2018), there could be variation across each of these dimensions in the propensity to advertise vacancies through online job postings or in the propensity to post skill requirements (e.g., if certain requirements are assumed as obvious in the given context). Furthermore, skill requirement levels may be higher in those provinces, industries, and occupations employing more skilled workers, which may also pay higher wages. This would likely be the case in provinces with higher costs of living.

To better account for the variation in skill composition across labor markets, we further include a wide array of controls measured at the finer level of *pso* cells. Specifically, we control for (i) other specific skill requirements, i.e., the share of character, writing, customer service, project management, people management, financial, computer (general), and software (specific) skills (computed from Lightcast data); and for (ii) labor market and socio-demographic characteristics, i.e., the share of jobs requiring college education, or two or more years of experience (computed from Lightcast data), and the share of workers who are either female, foreign, part-time, or under a temporary or seasonal contract (computed from INPS data).

Table 2 reports the estimated coefficients and standard errors for different specifications of Equation (1). All specifications control for province, sector, and occupation fixed effects. The specifications shown in Columns (1)-(4) include different combinations of cognitive and social skill requirements and those in Columns (5)-(6) additionally control for other specific skill requirements, and for labor market and socio-demographic characteristics. The model shown in Column (1) of Table 2 explores the relationship between average wages at the market level and cognitive skill requirements. The estimated coefficient indicates a positive and strongly significant correlation. In particular, it implies that a 10 percentage point (p.p.) increase in the share of vacancies requiring cognitive skills is associated with about 0.9% higher wages, conditional on province, sector, and occupation fixed effects. A similar association is found with respect to social skills, as shown in Column (2), but the magnitude of the wage gain is higher, with a 10 p.p. increase in the share of job postings requiring social skills associated with 1.4% higher wages.

When we include, in Column (3), the share of advertised job postings requiring cognitive skills and the share requiring social skills, both coefficients remain statistically significant at the 1% level but become slightly smaller, which intuitively implies a positive correlation between cognitive and social skill requirements. The specification shown in Column (4) additionally includes the share of vacancies requiring *both* cognitive and social skills for the same job, that is, the intersection between the previous two shares. The coefficient estimate reveals that the wage gains are particularly pronounced when both skills are required together, pointing to a positive and highly significant premium to the complementarity between cognitive and social skills in the same job. Specifically, a 10 p.p. increase in the share of vacancies requiring both cognitive and social skills is associated with 1.6% higher wages. Moreover, requiring only social skills is still associated with some positive and significant wage gains—about two thirds of the returns reported in Column (3)—while requiring only cognitive skills does not exhibit any significant association with wages.

The last two columns of Table 2 add further controls for observable characteristics that vary across cells. Column (5) includes cell-level shares for the full set of skill requirements to test whether the returns to cognitive and social skills are driven by their concentration in particular types of jobs that require certain specific skills. The coefficient on the joint requirement term is slightly smaller but still significant at the 5% level, while the other two coefficients of interest remain rather stable, suggesting that this hypothesis can be safely ruled out. Lastly, Column (6) additionally controls for cell-level labor market and socio-demographic characteristics. The results are largely unaffected by the inclusion of these additional controls, indicating that our estimates do not reflect systematic variation in labor market and socio-demographic attributes. To further assess the robustness of our results, in Columns (3)-(6) we test whether the coefficients on cognitive and social skills (and on their joint requirement when part of the specification) are jointly equal to 0. Similarly, we conduct the same joint significance test also for all 10 specific skill requirements in Columns (5)-(6). The associated F-statistics, reported at the bottom of the table, show that such null hypotheses can always be strongly rejected.

Taken together, these results are consistent with the recent empirical evidence on the US highlighting the growing importance of social skills in the labor market and of the complementarity between cognitive and social skills (Borghans et al., 2014; Deming, 2017; Deming and Kahn, 2018; Weinberger, 2014). Moreover, this simple aggregate analysis shows that information on skill requirements from online job vacancies carries explanatory power in understanding wages. To our knowledge, this is the first work on Italy that exploits this less conventional data source for this purpose.

4 Worker- and firm-pay returns to skills

In the first part of the analysis, we have studied the relationship between overall wages and the demand for skills. The purpose of this second part is to investigate how this relationship is driven by the wage component related to worker heterogeneity—reflecting the labor market level returns to individual skills—as opposed to that related to firm heterogeneity—which captures differences in employer pay premiums.

To this aim, we first derive estimates for both the worker and firm components of the wage process by fitting an AKM model to the matched employer-employee dataset (*Uniemens*).[15] Following the standard practice in the literature, we construct the largest connected set and estimate the model using the firm-worker-year spells that fall within it, leveraging inter-firm worker mobility.[16] Next, we examine the relationship between the cell-level averages of each estimated effect and the corresponding skill requirements.

4.1 Cell-level averages of AKM worker and firm effects

Once we have estimated the two unobserved heterogeneity components $\left(\widehat{\theta}_i, \widehat{\psi}_{J(i,t)}\right)$, we compute their respective averages within province-sector-occupation (*pso*) cells using spells from the *Unilav* sample.[17] These are computed as follows:

$$
\begin{aligned}
\overline{\widehat{\theta}}_{pso} &= \frac{1}{n_{pso}} \sum_i d_{pso} \widehat{\theta}_i \\
\overline{\widehat{\psi}}_{pso} &= \frac{1}{n_{pso}} \sum_i d_{pso} \widehat{\psi}_{J(i,t)}
\end{aligned}
\tag{2}
$$

where i indexes the annual employment spells associated with a given worker, $J(i,t)$ is an index function for the firm j where worker i is employed in year t, d_{pso} is a dummy equal to 1 if a worker's spell falls within a given province-sector-occupation cell, and n_{pso} is the number of spells in each cell.[18] We then fit a regression specification analogous to Equation (1) having

[15] We estimate a canonical AKM model by fitting the following specification:

$$y_{it} = \theta_i + \psi_{J(i,t)} + x'_{it}\beta + \varepsilon_{it}$$

where y_{it} are log FTE individual daily wages, θ_i and $\psi_{J(i,t)}$ are worker and firm fixed effects, and x_{it} includes year dummies and quadratic and cubic terms in age recentered around age 40, following Card et al. (2016, 2018). An overview of the model and its identifying conditions is provided in Appendix B.1.

[16] The "connected set" we derive contains about 80 million firm-worker-year spells, covering 18.5 million workers (93% of the "full sample") employed across 1.6 million firms (67%). Column 3 of Table 1 shows that the summary statistics for workers in this set are broadly in line with those for workers in the "full sample". However, the number of firms is around two-thirds of that of the "full sample", due to the exclusion of firms not involved in worker mobility flows.

[17] These averages are based on spells which are contained in both the *Unilav* sample and the connected set. More than 62 million spells on about 15 million *Unilav* workers (about 93%; see Column 2 of Table 1) are also part of the connected set.

[18] These employment-weighted averages of worker and firm effects are analogous to those derived by Card et al. (2023a, 2023b), who compute average firm premiums at the level of US commuting zone (CZ), industry, and CZ-by-industry. We extend the same concept for both wage components to the level of province-sector-occupation cells. The properties of the second-step regressions where they are used as dependent variables are discussed in Appendix B.2.

each component's average as the dependent variable—that is, for $\phi \in \{\theta, \psi\}$, we estimate:

$$\overline{\widehat{\phi}}_{pso} \;=\; \lambda_p^{\phi} \;+\; \mu_s^{\phi} \;+\; \nu_o^{\phi} \;+\; SD'_{pso}\pi^{\phi} \;+\; X'_{pso}\zeta^{\phi} \;+\; \upsilon_{pso}^{\phi} \tag{3}$$

This exercise sheds light on how each of the two components reflects the relationship between wages and skills. The results are reported in Table 3. As in Table 2, the estimated specifications feature different combinations of cognitive and social skill requirements and progressively include additional controls.

4.2 Results on worker-pay returns to skills

Panel A of Table 3 presents the results from the regression of average worker effects on market-level skill requirements. Columns (1) and (2) reveal a positive relationship between individual worker pay and the demand for cognitive and social skills, respectively. However, when both variables are included in the regression, in Column (3), the sign on the coefficient for cognitive skill demand turns negative. In Column (4), we also include the share of job vacancies in the relevant market that require *both* cognitive and social skills. The coefficient of this joint skill demand is large, positive, and highly statistically significant, while the coefficient for cognitive skills alone is also significant and negative and that for only social skills remains positive but not significant.

In Columns (5) and (6), we add further cell-level controls to account for selection in particular job types and for variation across a rich set of labor market and socio-demographic characteristics. The inclusion of these additional controls does not alter the overall pattern of the results. Focusing on the estimates from the most augmented specification in Column (6), we find that an increase in the share of job ads demanding both cognitive and social skills *simultaneously* is associated with a higher average worker pay. This finding reflects a premium attached to the complementary nature of these skills, as evidenced by their valuation in the job market. This suggests that labor markets with a higher demand for both skills are associated with increased market-level returns for individual workers possessing such a hybrid skill set, regardless of the firm in which they work. Furthermore, it is worth noting that, across specifications, the estimated coefficients for the joint skill requirement term are slightly larger in magnitude (by about 3 p.p.) compared to those related to overall wage returns, discussed earlier and shown in Table 2. Regarding the individual pay returns for each skill independently, we find that while a higher market demand for solely cognitive skills is mildly associated with a lower average worker pay, suggesting a marginally lower wage return for these skills in isolation, a higher demand for social skills alone does not show a significant association with individual worker pay.

4.3 Results on firm-pay returns to skills

In Panel B of Table 3, we consider the relationship between average firm effects and market-level skill demand. In Columns (1) through (3), we find a positive and highly significant association between firm-level pay and the demand for cognitive and social skills. This positive relationship is robust and persists even when controlling for the demand of each skill type simultaneously. However, upon including as an additional control the share of job vacancies that require *both* cognitive and social skills for the same job, in Column (4), while the coefficient for each individual skill remains positive and strongly significant, the coefficient for the joint skill requirement term presents a negative sign. This suggests a reduction in the firm pay premiums offered to workers who possess a combined skill set. Including additional controls in Columns (5) and (6) does not change the signs and magnitudes of these three coefficients of interest, which are all statistically significant at the 1 and 5% level.

These estimates suggest that labor markets in which jobs require both cognitive and social skills tend to be associated with firms that offer lower firm-specific compensation to their employees. Such firms usually occupy the lower rungs of the job ladder, often characterized by lower productivity and a tendency to employ a smaller number of more versatile, generalist workers, who receive limited firm pay premiums. Conversely, in labor markets where there is a higher demand for either cognitive or social skills individually, firms generally offer higher average pay. This suggests that high-paying firms tend to pay higher premiums that reward job-level specialization into either cognitive or social skills, rather than their complementarity.

4.4 Discussion

These results can be better understood by drawing on evidence from recent studies offering possible interpretations to rationalize them. While the aggregate nature of our analysis limits our ability to directly test these mechanisms, they appear broadly consistent with our findings. First, our result that market-level returns are higher when there is joint demand for cognitive and social skills aligns with recent research on multidimensional skill sets and skill unbundling. In this context, workers have the flexibility to market each of their skills independently across distinct markets. In particular, our result is consistent with the findings obtained by Choné and Kramarz (2022) and Skans et al. (2023) who show that in environments where skills can be unbundled, generalist workers—who possess a balanced combination of cognitive and non-cognitive skills—benefit from increased market wages compared to their specialist counterparts. Such gains stem from their ability to market their multidimensional skills to a broader range of firms and across various markets, thus reducing the potential for downward wage pressure from competing specialist workers. In contrast, specialist workers tend to secure higher wage returns for their specific skills within markets predominantly populated by firms that heavily rely on those specific skills.

Second, our findings linking higher firm pay with an increased demand for specialized skills can be contextualized in light of recent research on worker-firm and worker-worker complementarities. Regarding worker-firm complementarities, Böhm et al. (2025) provide evidence of differential returns to similar skills across different firms, giving rise to sorting incentives. They find higher skill returns in more innovative firms, highlighting the complementarity between high-skill labor and firm investment in product and process innovation. As to worker-worker complementarities, Freund (2023) shows that, in productive processes requiring specialized skills, there are substantial complementarities between coworkers that increase in the extent of task-specific skill differentiation, generating incentives for positive assortative matching across the task spectrum. He also documents an increase in specialization and complementarities over time and shows that it significantly contributed to the rise in pay disparities between firms. A different perspective on coworker complementarities, involving workers with varying skill levels, is provided by Aghion et al. (2023). They show that in large and highly innovative firms, low-skilled workers receive a premium for their soft skills, as compared to their counterparts in smaller and less innovative firms. This premium is due to the higher complementarity of their soft skills with the high-skilled workers and other resources present in such firms.

Additionally, our finding that differences in firm pay are linked to returns from specialization can be also interpreted within the context of specialized workers retention and of hiring frictions stemming from skill shortages. Bloesch et al. (2022) document that firms share rents with workers having individual hold-up power, which arises when labor is organized in differentiated positions that are critical in the production process and involve specific skills. In this context, firms engage in rent-sharing to prevent output losses from unfilled positions directed at specialized workers, which aligns with our findings. They also show that wages in occupation with high hold-up potential tend to be more resilient to fluctuations in labor market tightness. In a similar context, Le Barbanchon et al. (2023) examine the recruitment difficulties firms face in tight labor markets, particularly due to skill shortages. They show that such difficulties can limit a firm's ability to expand its workforce and profitability, particularly when it involves recruiting workers in high-skill and job-specific occupations for labor-intensive and large firms. They provide evidence suggesting that firms respond by offering higher wages to retain their hard-to-substitute incumbent employees, a pattern that is consistent with our results.

5 Conclusion

In this paper, we study the relationship between skill demand and wage inequality across labor markets defined by province, sector, and occupation. We leverage a unique dataset that combines Italian employer-employee records with aggregate information on skill demand from online job vacancy data. We document a positive relationship between wages and the demand for cognitive and social skills, with a wage premium for jobs that require a combination of these skills, underscoring the value of their complementarity in the labor market.

Our primary contribution to the literature lies in distinguishing between two sources that can explain the positive relationship between wages and the demand for skills: the market prices of skills, which influence individual skill returns, and the compensation policies of firms, which determine pay premiums within firms. We find that workers possessing a combination of cognitive and social skills receive higher returns in the market but they earn lower premiums from firms. Conversely, specialists with a focus on either cognitive or social skills secure higher premiums from their employers but gain lower market returns.

These findings suggest that the overall observed wage premiums associated with jobs demanding both cognitive and social skills are primarily driven by worker-related effects, highlighting a higher market-level valuation for a hybrid skill set, in line with recent evidence on multidimensional skill unbundling. In contrast, firm pay tends to reward job-level specialization in either cognitive or social skills. This is consistent with a setting in which high-paying firms, with complex organizational structures, offer higher premiums to specialized workers due to their complementarity with other productive inputs within the firm and their central role in the production process.

In conclusion, this study advances our understanding of the relationship between skill demand and wage inequality, by showing how differentiating between the rewards that firms offer for certain skill sets and their valuation at the market-wide level provides essential insights into the complex dynamics of wage determination. This calls for further research into how skill markets and firms' strategies for skill utilization and compensation evolve within modern labor markets and jointly affect wages. Moreover, it highlights the importance for policies that foster the development of diverse skill sets and are responsive to the changing dynamics of skill demand and firm practices.

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Tables

Table 1: Summary statistics, linked employer-employee data (2014-2019)

	Full sample	Unilav sample	Connected set
Age	41.082	39.635	40.971
	(11.589)	(11.880)	(11.572)
Female	0.414	0.427	0.406
	(0.492)	(0.495)	(0.491)
Foreign	0.142	0.161	0.145
	(0.349)	(0.367)	(0.352)
Part-time	0.290	0.331	0.274
	(0.454)	(0.470)	(0.446)
Temporary or Seasonal	0.218	0.271	0.228
	(0.413)	(0.444)	(0.420)
Days worked	231.480	214.796	230.600
	(101.436)	(104.816)	(101.775)
Days worked (rescaled FTE)	208.535	189.268	209.752
	(106.841)	(107.650)	(107.054)
Wage (2019 €)	21,222.790	18,064.730	21,644.100
	(23,817.100)	(21,566.520)	(24,222.260)
FTE daily wage (2019 €)	95.976	90.798	97.058
	(146.125)	(152.362)	(140.803)
Log FTE daily Wage (2019 €)	4.429	4.375	4.438
	(0.474)	(0.463)	(0.478)
N of firm-worker-year spells	84,731,481	66,656,717	78,986,355
N of workers	19,880,740	16,478,512	18,515,229
N of firms	2,483,108	2,407,930	1,652,889

Note: The table reports summary statistics on individual workers based on firm-worker annual employment spells contained in the *INPS* linked employer-employee data over the period 2014-2019. The table displays averages and standard deviations (in parentheses) for spells contained in the "full sample" (shown in Column 1) and in two of its subsets. These are the "*Unilav* sample" (shown in Column 2), which encompasses spells referring to individuals for which at least one *Unilav* compulsory communication was made over 2010-2017; and the "connected set" (shown in Column 3), which contains spells referring to individuals working in firms that are connected by worker mobility flows. For each sample, the total number of firm-worker-year spells, and the associated numbers of workers and firms, are indicated at the bottom of the table.

Table 2: Overall wage returns to skills

	Log(Average Daily Wages)					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive	0.0897***		0.0546***	-0.0110	-0.0213	0.0243
	(0.0165)		(0.0180)	(0.0293)	(0.0317)	(0.0296)
Social		0.1407***	0.1226***	0.0755***	0.0824***	0.0702***
		(0.0180)	(0.0201)	(0.0184)	(0.0248)	(0.0234)
Both required				0.1587***	0.1154**	0.0977**
				(0.0558)	(0.0510)	(0.0475)
Observations	15,229	15,229	15,229	15,229	15,229	15,229
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Other specific skill requirements	No	No	No	No	Yes	Yes
Labor market & socio-demographic controls	No	No	No	No	No	Yes
F-statistic (cognitive and social)			41.90	30.04	12.49	16.98
F-statistic (all specific skill requirements)					7.16	5.60

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports estimated coefficients and standard errors for different specifications of Equation (1), which study the relationship between the log of the labor market cell average of individual FTE gross daily wages and given skill requirements, each measured as the market cell share of vacancies that specify such requirement. In Column (1), the regressor of interest is the share of cognitive skills. In Column (2), the share of social skills. Column (3) includes the share of job postings requiring cognitive skills and the share requiring social skills. Columns (4)-(6) additionally include the share of vacancies requiring *both* cognitive and social skills for the same job. All specifications controls for province, sector, and occupation fixed effects. The specifications in Columns (5)-(6) additionally control for other specific skill requirements, i.e., share of character, writing, customer service, project management, people management, financial, computer (general), and software (specific) skills (computed from Lightcast data). The specification in Column (6) further controls for labor market and socio-demographic characteristics, i.e., share of jobs requiring college education, or two or more years of experience (computed from Lightcast data), and share of workers who are either female, foreign, part-time, or under a temporary or seasonal contract (computed from INPS data). Columns (3)-(6) report F-statistics to test whether the coefficients on cognitive and social skills (and on their joint requirement when part of the specification) are jointly equal to 0. Columns (5)-(6) report F-statistics to test whether the coefficients on all 10 specific skill requirements are jointly equal to 0. Standard errors are clustered at the province-by-sector level. Observations are weighted by the number of FTE days worked in the cell.

Table 3: Worker- and firm-pay returns to skills

Panel A	**Average estimated worker effect**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive	0.0130		-0.0049	-0.0807***	-0.0739***	-0.0297*
	(0.0109)		(0.0117)	(0.0187)	(0.0195)	(0.0178)
Social		0.0612***	0.0628***	0.0072	0.0064	0.0111
		(0.0106)	(0.0117)	(0.0105)	(0.0171)	(0.0155)
Both required				0.1863***	0.1585***	0.1350***
				(0.0362)	(0.0345)	(0.0321)
Panel B	**Average estimated firm effect**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive	0.0742***		0.0641***	0.0814***	0.0632***	0.0652***
	(0.0078)		(0.0090)	(0.0120)	(0.0125)	(0.0138)
Social		0.0567***	0.0354***	0.0481***	0.0493***	0.0357**
		(0.0094)	(0.0106)	(0.0141)	(0.0170)	(0.0172)
Both required				-0.0425*	-0.0607***	-0.0622***
				(0.0241)	(0.0225)	(0.0240)
Observations	15,158	15,158	15,158	15,158	15,158	15,158
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Other specific skill requirements	No	No	No	No	Yes	Yes
Labor market & socio-demographic controls	No	No	No	No	No	Yes
F-statistic/Worker (cognitive and social)			16.94	13.39	9.18	13.78
F-statistic/Worker (all specific skill requirements)					7.08	6.82
F-statistic/Firm (cognitive and social)			63.35	43.99	10.03	8.02
F-statistic/Firm (all specific skill requirements)					14.07	13.97

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: The table reports estimated coefficients and standard errors for different specifications of Equation (3), which study the relationship between the average estimated AKM worker effect, shown in Panel A (the average estimated firm effect, shown in Panel B) and given skill requirements, each measured as the market cell share of vacancies that specify such requirement. The six specifications examined, displayed in Columns (1)-(6), are analogous to those used to estimate Equation (1) (refer to Table 2). Analogous F-statistics are also reported separately for each dependent variable, at the bottom of the table. Standard errors are clustered at the province-by-sector level and bootstrapped (500 repetitions). Observations are weighted by the number of FTE days worked in the cell.

Appendix

A Data Appendix

A.1 Linked Employer-Employee Data

A.1.1 Definition of annual earnings

We use as our annual earnings variable the total gross take-home pay received by a worker during a year. Using, alternatively, the total gross statutory pay does not affect our results. Furthermore, we express earnings across all years in 2019 euros, using revaluation coefficients from the Italian National Institute of Statistics (ISTAT).

A.1.2 Definition of full-time equivalent (FTE) days worked and daily wages

Full-time contracts are typically of 40 hours a week (8 hours a day, 5 days per week), unless otherwise stipulated in collective bargaining agreements. In the case of vertical part-time contracts, the weekly hours are less than 40, but the worker is committed to work for 8 hours a day for less than 5 days per week. Consequently, the days worked under such contracts already represent FTE days. In contrast, horizontal part-time contracts involve working fewer than 40 hours weekly, spread across 5 days. For instance, a 75% horizontal part-time contract will have 30 hours a week over 5 days, which translates to 6 hours per day. This results in the adjusted FTE days worked amounting to 3.75. It is worth noting that we exclude cases associated with mixed (vertical and horizontal) part-time contracts, accounting for approximately 1.5% of the observations in our dataset.

To obtain full-time equivalent (FTE) daily wages, we adopt a two-step process. First, we adjust the total number of days worked in a year to account for the proportion of part-time employment, assigning a value of 1 for full-time and vertical part-time employment and a value less than 1 for horizontal part-time employment, corresponding to the percentage of part-time. Second, we compute FTE daily wages by dividing total annual earnings by the adjusted total number of days worked in the respective year.

A.2 Online Job Vacancy Data

A.2.1 Sector-level benchmarking of online job vacancy data

Online job vacancy data have been widely employed in recent economic research. A key concern, however, is the extent to which they accurately capture job openings across the full economy, as some sectors and occupations may be less prone to advertise vacancies online. To address this issue, several studies using Burning Glass Technologies (BGT) data (now Lightcast) for the United States (e.g., Carnevale et al., 2014; Hershbein and Kahn, 2018; Deming and Kahn, 2018; Acemoglu et al., 2022; Chetty et al., 2020) have evaluated its representativeness by comparing them with nationally representative sources such as the Job Openings and Labor Turnover Survey (JOLTS) from the Bureau of Labor Statistics (BLS) and the Help Wanted Online (HWOL) index compiled by the Conference Board. These studies consistently show that aggregate vacancy counts (e.g., by sector or occupation) derived from BGT data closely align with those obtained from these alternative sources.

We perform a similar benchmarking exercise to evaluate the representativeness of the WollyBi (now Lightcast) data for Italy by comparing it with official statistics produced by ISTAT, the Italian National Statistics Office. ISTAT gathers information on job vacancies from two sources: VELA, a quarterly survey on job vacancies and hours worked for firms with 1–499 employees (*Rilevazione trimestrale sui posti vacanti e le ore lavorate*), and LES, a monthly census on employment, working hours, wages, and labor costs in large firms (*Rilevazione mensile sull'occupazione, gli orari di lavoro, le retribuzioni e il costo del lavoro nelle Grandi Imprese*). These two sources are integrated to produce official job vacancy statistics, which are publicly available through Eurostat, the statistical office of the European Union.[19]

Differently from JOLTS and HWOL for the United States, ISTAT does not release specific figures on the *number* of job vacancies for Italy. Instead, it publishes quarterly statistics on the job *vacancy rate*, defined as follows:[20]

$$\text{vacancy rate}_t = \frac{\#\text{vacancies}_t}{\#\text{vacancies}_t + \#\text{filled jobs}_t} \tag{A.2.1}$$

where t denotes calendar quarters, and both the number of vacancies and filled positions refer to dependent workers. Unfortunately, vacancy rate data for Italy are available only starting from 2016, thus restricting the scope of our benchmarking exercise to the period

[19]The metadata of the official statistics dataset used for the benchmarking exercise are available at: https://ec.europa.eu/eurostat/cache/metadata/EN/jvs_esqrs_it.htm.

[20]The ISTAT definition of the vacancy rate is provided in the document available at: https://www.istat.it/it/files//2022/06/EN_labour_market_Q1_2022.pdf.

2016-2019. Moreover, they are published only at the 1-digit NACE Rev. 2 sector level and are not disaggregated by occupation.[21]

To construct a comparable measure, we estimate vacancy rates using the WollyBi data. For this purpose, we combine it with information on filled jobs for dependent workers drawn from ISTAT's Statistical Register of Active Enterprises (ASIA), available at the 1-digit sector-by-year level on ISTAT's website.[22] The estimation proceeds in three steps. First, we calculate the average number of vacancies (excluding self-employed positions) for each sector in a given month using the WollyBi data. Second, we compute annual averages of these sectoral monthly averages. Third, we combine the aggregates obtained in the previous steps with ASIA's data on filled jobs to derive sector-by-year vacancy rates following the definition in Equation (A.2.1). To compare these estimates with ISTAT's sector-by-quarter vacancy rates, we compute annual averages of the latter.

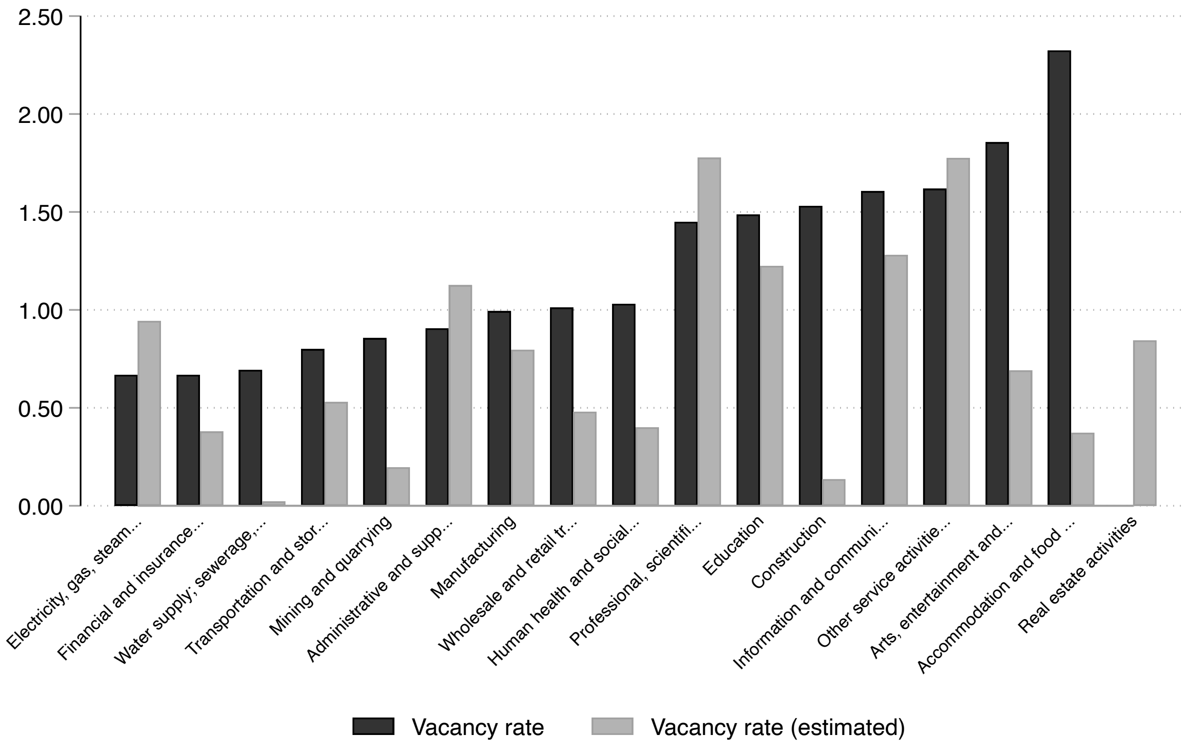
Figure A.2.1 presents average vacancy rates by sector over the 2016–2019 period. The black bars correspond to ISTAT's vacancy rates, while the grey bars represent those estimated from the WollyBi data. Overall, the figure shows a substantial alignment between the two sets of statistics, particularly in sectors such as manufacturing and services related to professional activities, administrative functions, education, and ICT. However, sectors such as water supply and waste management, mining and quarrying, construction, hospitality, and arts and entertainment appear to be considerably underrepresented in the WollyBi data.

Figure A.2.2 compares trends in vacancy rates from the two sources over the period 2016–2019. Overall, the trends appear consistent, with the exception of professional activities, education, and other services, where the estimated vacancy rates exhibit a pronounced increase in 2019, potentially due to noise in the annual estimation.

[21]Specifically, the release covers the non-agricultural private sector (NACE sections B–S). The statistic for section L, "Real estate activities", is confidential.

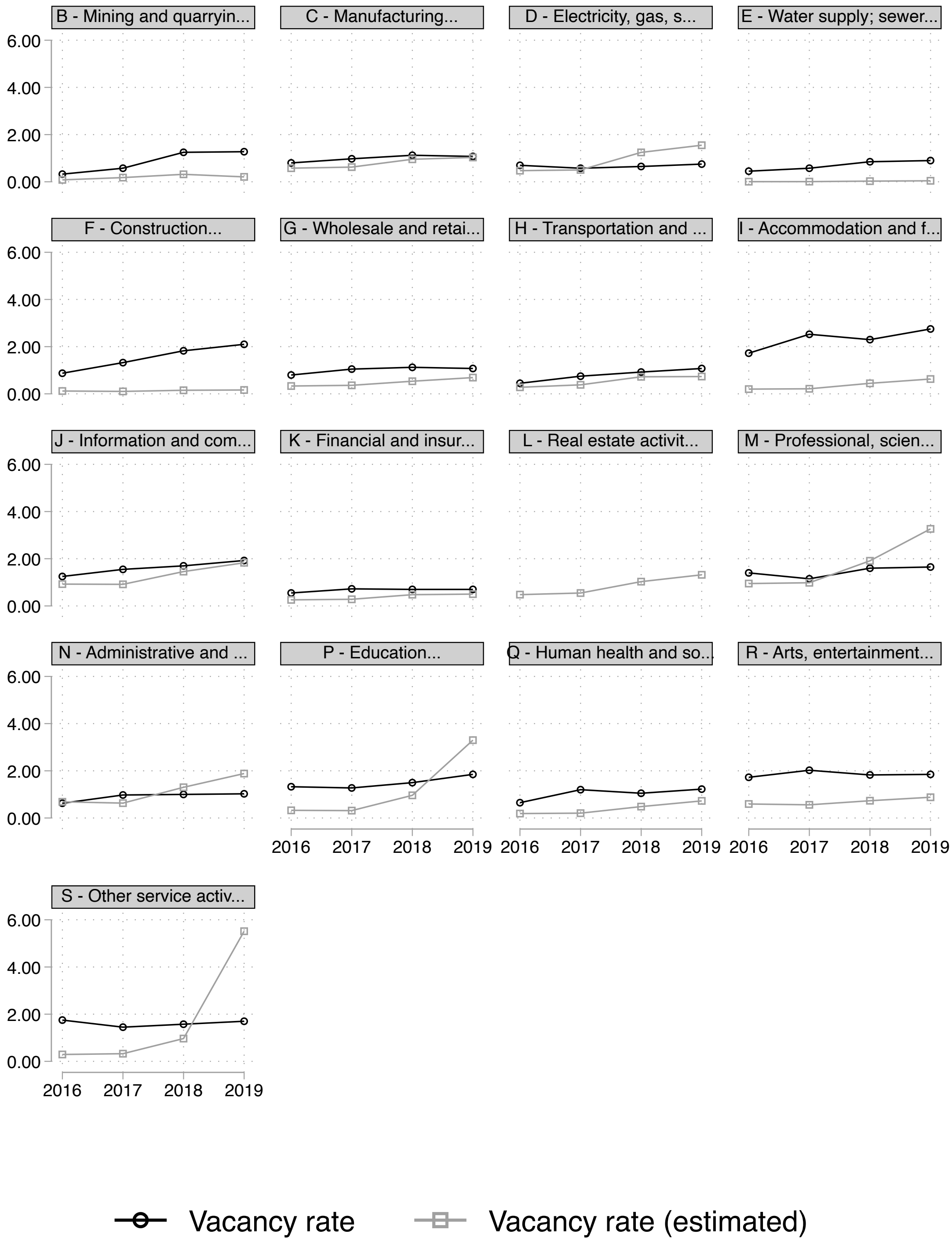
[22]The aggregate data can be accessed at: https://esploradati.istat.it/databrowser/#/en.

Figure A.2.1: Comparison of ISTAT's and estimated vacancy rates, by sector (averages over the 2016-2019)



Note: Black bars represent the vacancy rate published by ISTAT via Eurostat, by 1-digit sector. Grey bars are estimated vacancy rates based on WollyBi data (for vacancies) and ASIA data (for filled positions).

Figure A.2.2: Comparison of ISTAT's and estimated vacancy rates, by sector (trends over the years 2016-2019)



Note: Black lines represent the vacancy rate published by ISTAT via Eurostat, by 1-digit sector and year. Grey lines are estimated vacancy rates based on WollyBi data (for vacancies) and ASIA data (for filled positions).

A.2.2 Skill taxonomy

Table A.2.1: Skill taxonomy from Deming and Kahn (2018)

Skill categories	Keywords and Phrases
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Social	Communication, teamwork, collaboration, negotiation, presentation
Character	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic
Writing	Writing
Customer Service	Customer, sales, client, patient
Project Management	Project management
People Management	Supervisory, leadership, management (not project), mentoring, staff
Financial	Budgeting, accounting, finance, cost
Computer (general)	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)

Note: The table illustrates the 10 job skill categories of the taxonomy derived by Deming and Kahn (2018) (see Table 1 of their paper). The left column shows the skill categories while the right column lists the keywords and phrases they used to identify them.

A.2.3 Summary statistics

Table A.2.2: Summary statistics, Lightcast online job vacancy data (2014-2019)

	Mean	(Std. Dev.)
Education		
Education requirement stated	0.998	(0.042)
High School: Up to Secondary	0.725	(0.447)
College: Post-Secondary	0.273	(0.446)
Experience		
Experience requirement stated	0.620	(0.485)
0-2 years	0.300	(0.458)
2+ years	0.320	(0.467)
Specific skills		
Specific skill requirements stated	0.799	(0.401)
Cognitive	0.432	(0.495)
Social	0.466	(0.499)
Cognitive & Social	0.272	(0.445)
Character	0.421	(0.494)
Writing	0.009	(0.095)
Customer	0.336	(0.472)
Project Management	0.140	(0.347)
People Management	0.176	(0.381)
Financial	0.086	(0.281)
Computer (generic)	0.282	(0.450)
Software (specific)	0.167	(0.373)
N of online job vacancies (OJVs)	4,602,000	

Note: The table reports summary statistics on the job requirements contained in the Lightcast dataset over the period 2014-2019. It displays the share of total vacancies across all labor market cells specifying given education, experience, and specific skill requirements.

B Methodological Appendix

B.1 AKM model specification and identification

We estimate the two-way fixed effects model proposed by Abowd et al. (1999, AKM), which allows to disentangle the wage components associated to worker and firm heterogeneity. It can be written as follows:

$$y_{it} = \theta_i + \psi_{J(i,t)} + x'_{it}\beta + \varepsilon_{it} \tag{B.1.1}$$

where y_{it} is the log daily wage of worker i in year t; θ_i is a worker effect capturing the time-invariant returns to worker i's individual quality, which are portable across employers; ψ_j is a firm effect reflecting the pay premium paid to all workers at firm j (with $J(i,t) = j$ denoting the identity of the firm j where worker i is employed in year t); x_{it} is a vector of time-varying observable characteristics; and ε_{it} is an idiosyncratic error term. Following Card et al. (2016, 2018), our controls x_{it} include a set of year dummies as well as quadratic and cubic terms in age recentered around age 40, yielding interpretable estimates of the year and worker effects under the assumption that the age profile is flat around that age.[23]

Identification of the AKM model parameters hinges on a conditionally *exogenous mobility* assumption, which can be stated as follows:

$$E[\varepsilon_{it} \mid \theta_i, \psi_{J(i,s)}, x_{is}] = 0 \quad \forall\ s, t \tag{B.1.2}$$

This strict exogeneity condition requires that, conditional on fixed effects and observables, worker mobility be exogenous with respect to the idiosyncratic component of wages. In other words, employer transitions must be independent of time-varying unobservables – such as transitory wage shocks, idiosyncratic match effects, and firm-wide shocks – while no restriction is imposed on the correlation between mobility and worker or firm effects (nor on the latter joint distribution), allowing for rich sorting patterns. This assumption is crucial because the model uses within-worker changes in firm affiliation to separate firm effects from worker effects.[24]

The plausibility of the exogenous mobility assumption has been extensively tested across countries using the specification tests originally developed by Card et al. (2013) for Germany, which were later implemented in Portugal (Card et al., 2016), Italy (Macis and Schivardi,

[23]Note that, since we do not observe worker education in the INPS *Uniemens* data, we are unable to additionally interact our time-varying controls with education dummies, as done in Card et al. (2016, 2018).

[24]This entails that worker and firm fixed effects can only be identified within connected sets, i.e., sets of firms that are indirectly connected by the movement of workers between them. Moreover, since firm effects are estimated relative to an excluded firm category, it is not possible to compare them across different connected sets. Hence, the standard practice in the literature is to select the largest connected set.

2016; Devicienti et al., 2019), the United States (Song et al., 2019), Brazil (Gerard et al., 2021), Canada (Dostie et al., 2023), and Israel (Arellano-Bover and San, 2024) – suggesting that the patterns of wage changes experienced by job movers in these countries are broadly consistent with exogenous mobility. Given the existence of evidence in favor of this assumption for Italy, which is based on samples drawn from the same administrative data source used here, we refrain from replicating the above tests and regard the assumption as empirically well supported in our context.

B.2 Linear projections of average estimated AKM effects

Under strict exogeneity, OLS produces unbiased estimates of worker and firm effects. However, it is well-known that plug-in estimates of variance components involving estimated AKM effects are biased due to estimation noise entering quadratic functions. This bias has been dubbed *limited mobility bias* (Abowd et al., 2002; Andrews et al., 2008), since it increases with the noise in firm effect estimates $(\hat{\psi}_j - \psi_j)$, which is particularly pronounced when the number of movers per firm is small. Recent works by Kline et al. (2020) and Bonhomme et al. (2020) have developed flexible bias-correction routines to address limited mobility bias, showing that in the absence of such corrections the variance of firm effects is severely overstated and the covariance between worker and firm effects substantially understated, with analogous implications for their relative contributions in wage variance decompositions.

It is important to note, however, that the main results of this paper, presented in Section 4 – where we regress averages of estimated AKM effects on labor market–level skill demand – are not affected by this issue. In particular, as shown in Kline (2024), the second-step coefficients obtained by projecting an estimated AKM effect on a set of covariates inherit the unbiasedness of the regressand, as they are a linear combination of the effect estimated in the first-step AKM regression. Nevertheless, although point estimates will be unbiased, first-step estimation noise will still affect second-step inference. This is particularly relevant for the case of worker- or firm-level second-step regressions. In our case, however, the dependent variables in the second-step regressions are the weighted averages of each estimated AKM effect – obtained using the person-year observations within each province-sector-occupation cell in the population-level data (see Equation (2)) – which, in large samples, should lead to a substantial averaging out of first-step estimation noise (Kline et al., 2020; Kline, 2024). Hence, severe understatement (or overstatement) of second-step standard errors is unlikely to be a major concern in our setting.