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Demand for Skills and Wage Inequality

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Demand for Skills and Wage Inequality

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Demand for Skills and Wage Inequality*

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May 9, 2024

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 association 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 decomposition 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 more rent-sharing with 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: Returns to skills, wage premia, unobserved heterogeneity, rent-sharing, inequality

JEL Codes: J24, J31, J63

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Domanda di Competenze e Disuguaglianza Salariale

Giuseppe Grasso Konstantinos Tatsiramos

May 9, 2024

Abstract

Questo articolo studia la relazione tra la disuguaglianza salariale e la domanda di competenze, ed il suo legame con l'eterogeneità di lavoratori e aziende. Lo studio combina dati abbinati datore di lavoro-dipendente di fonte INPS con informazioni a livello aggregato su una serie di dettagliati requisiti di competenze, estratti da offerte di lavoro pubblicate online. Studiamo innanzitutto la relazione tra i salari e la domanda di competenze cognitive e sociali in mercati del lavoro definiti come incroci di province, settori e occupazioni. Troviamo un'associazione forte e positiva tra i salari e la domanda di competenze cognitive e sociali, che si accentua quando le due competenze sono richieste congiuntamente per la stessa posizione lavorativa, evidenziando la loro complementarietà. Successivamente stimiamo le componenti del processo salariale specifiche di lavoratori (effetto lavoratore) e aziende (effetto azienda) attraverso un modello AKM. Quindi indaghiamo la loro relazione con la domanda di competenze a livello di mercato del lavoro. La nostra scomposizione suggerisce che nei mercati in cui le aziende richiedono più frequentemente sia le competenze cognitive che quelle sociali, l'emergere di salari più alti è trainato dall'effetto lavoratore, il che riflette un maggior valore di mercato di un insieme di competenze variegato, piuttosto che dalle politiche retributive delle aziende. Al contrario, nei mercati in cui le aziende richiedono prevalentemente competenze cognitive o sociali, salari più alti sono associati a effetti azienda più elevati, a indicare una maggiore condivisione dei rendimenti aziendali con i lavoratori specializzati, nonostante si riscontri un valore di mercato inferiore delle competenze specializzate. Questi risultati evidenziano il ruolo delle eterogeneità di lavoratori e aziende quali meccanismi attraverso cui le variazioni nella domanda di competenze influenzano la disuguaglianza salariale complessiva.

Parole chiave: rendimenti delle competenze, premi salariali, eterogeneità non osservata, condivisione dei rendimenti aziendali, disuguaglianza

Codici JEL: J24, J31, J63

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 (see Acemoglu and Autor, 2011, for a detailed overview). This research 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, Kramarz and Margolis (1999, AKM hereafter), has examined how worker and firm heterogeneity contribute to wage dispersion (see Card et al., 2018, for a comprehensive review). 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 the extent to which 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 market-determined skill prices (reflective of workers' qualities) and firm-specific rent-sharing practices (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 extract 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, we employ a methodology similar to that used by Deming and Kahn (2018), where we regress the logarithm of average wages on average skill requirements, both measured at the level of province-sector-occupation cells. Similar to their focus, our analysis emphasizes the role of cognitive and social skills, as well as their complementarity, which is captured by their joint demand within the same job. This focus is motivated by the importance of these skills in the discussion linking technological change to wage inequality. Our model specification includes fixed effects at the province, sector, and occupation levels, which account for wage variations associated with these dimensions. Additionally, we include various cell-level controls related to other skill requirements reported in job postings, as well as a range of socio-demographic and labor market characteristics.

We find a significant and positive relationship between wages and the demand for cognitive as well as social skills, suggesting that variation in the demand for these particular skills is a strong predictor of wage dispersion, even after controlling for several other factors. Furthermore, we show that these positive returns are particularly pronounced when jobs simultaneously require 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 are closely aligned with the results presented by Deming and Kahn (2018) for the US and are consistent with recent empirical studies that underscore the growing importance of social skills in the labor market and their complementarity with cognitive skills (Borghans, Weel and Weinberg, 2014; Deming, 2017; Weinberger, 2014).

The first part of our study contributes by providing insights for Italy, addressing the gap in research on the economic returns of cognitive and social skills, their complementarity, and their influence on wage inequality beyond the US context. Furthermore, our findings align with and contribute 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, Sotelo and Tannenbaum, 2023; Deming and Kahn, 2018; Deming and Noray, 2020) as well as to personality traits (Brenčič and McGee, 2023).

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 premia accruing to individuals due to market-level skill valuations with those stemming from excess wages shared by firms in the form of rents. 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 rent-sharing, which may differ based on their skill set. 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 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 variations in rent-sharing practices.

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.[1,2]

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 social skills alone are associated with lower worker pay, suggesting that these skills, when required alone, attract lower market returns. However, our analysis does not reveal a significant relationship between markets with a higher demand for solely cognitive 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 premia, 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

[1] Similar approaches conducting AKM wage decompositions to disentangle worker and firm pay, 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, Moser and Sauermann (2023, firm productivity).

[2] 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 worker unobserved heterogeneity.

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 workers are likely to engage in rent-sharing, 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 with whom little rents are shared.

These results relate to several recent strands of literature. 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, this result is consistent with the findings obtained by Choné and Kramarz (2022) and Skans, Choné and Kramarz (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 that associate higher firm pay with an increased demand for specialized skills relate to recent research on pay disparities among firms. Differences in how firms utilize skills offer a plausible explanation for the observed pay differentials.[3] These discrepancies in skill utilization may stem from differences among firms in their ability to adopt new technologies that complement with specific skills during the production process (Deming and Kahn, 2018; Song et al., 2019). Böhm, Esmkhani and Gallipoli (2022) provide evidence of differential returns to similar skills across different firms (worker-firm complementarities), which create strong incentives for worker sorting. They also uncover higher skill returns in more innovative firms, highlighting the complementarity between high-skill labor and firm investment in product and process innovation. 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. This study also documents an increase in specialization and complementarities over time, contributing sig-

[3] Other explanations for firm pay differentials explored in the literature include differences in productivity, compensating wage differentials, and the value of job amenities (Dunne et al., 2004; Faggio, Salvanes and Van Reenen, 2010; Sorkin, 2018; Dupuy and Galichon, 2022).

nificantly to the increase in pay disparities among 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.

Lastly, our finding that differences in firm pay are linked to returns from specialization can be seen within the context of retaining specialized workers and of hiring frictions in the presence of skill shortages. Bloesch, Larsen and Taska (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, Ronchi and Sauvagnat (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.

The remainder of the paper is organized as follows. In Section 2 we provide a description of our two data sources and outline the procedure for merging them. Section 3 presents the results from the analysis of overall returns to skills. In Section 4, we conduct the estimation of worker and firm effects, followed by an examination of the returns to skills in terms of worker and firm pay, respectively. Finally, in Section 5 we offer some 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.[4]

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

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.[5] We exploit information on 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.[6] 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.[7]

[5] 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 earnings; if still tied, we select randomly.

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

[7] 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.

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.

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.

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.[8] 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".[9] 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.[10] 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 con-

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

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

[10] 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.

tain 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.

In order to link Lightcast and INPS data, we create labor market cells defined by province, industry, and occupation. To maximize the cell-level match rate between the two datasets, we use ISCO-08 occupation at the 1-digit level, resulting in an 81% match rate and the creation of approximately 15,000 cells.[11] Subsequently, we select OJVs with complete information regarding province, industry, 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 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. In the spirit of Deming and Kahn (2018), we 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 link between wage and skill demand differentials across labor markets—defined as province(p)-by-sector(s)-by-occupation(o) cells (NUTS-3 location by 1-digit NACE sector by 1-digit ISCO occupation)—through the following regression model:[12]

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

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

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

[12] 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.

province, sector, and occupation fixed effects to account for wage differentials arising due to unobserved characteristics related to different areas, industries, and occupations; and X_{pso} are cell-level controls.[13] Thus, the coefficient vector π measures how the change in demand for specific skills is associated with changes in wages, after accounting for province, sector, and occupation differences, and cell-level covariates.

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, thus leveraging variation in skill demand within each of these dimensions. 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 association. 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

[13] Cell-level controls consist of (i) 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); (ii) and 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).

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 a host of cell-level labor market and socio-demographic characteristics. These include the share of vacancies requiring college education, the share of vacancies demanding 2 or more years of experience, and the respective proportions of workers who are female, foreign, working part-time, and under a temporary or seasonal contract. The results are largely unaffected by the inclusion of these additional controls, indicating that our estimates do not reflect overall 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, Weel and Weinberg, 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 the extent to which 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 rent sharing.

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.[14] 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.[15] We next 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.[16] These are computed as follows:

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

where n_{pso} is the number of workers employed in a given cell. We then fit a regression specification analogous to Equation (1) having each of them as dependent variable, i.e., $\phi \in \{\theta, \psi\}$:

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

This exercise sheds light on how each of the two components reflects the relationship between skill utilization and wages. 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.

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[14]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 daily wages, θ_i and $\psi_{j(i,t)}$ are worker and firm fixed effects, and x_{it} contains year dummies, age and age^2. An overview of the model and its identifying conditions is provided in Appendix B.1.

[15]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.

[16]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%) are also part of the connected set.

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 the demands for cognitive and social skills, respectively, and individual worker pay. However, the premium for cognitive skills in Column (3) is no longer significant once we include the demand for social skills as an additional control in the regression. 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 coefficients on the demand for each skill in isolation turn negative.

In Columns (5) and (6), we add further covariates to control for selection in particular job types and for confounders related to cell-level labor market and socio-demographic factors. Focusing on the results from the most augmented specification of 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 similar in magnitude to those related to overall wage returns, as outlined in Table 2, though they are slightly lower. Regarding the individual pay returns for each skill independently, we find that while a higher market demand for solely social skills is associated with a lower average worker pay, suggesting a lower wage return for these skills in isolation, a higher demand for cognitive skills alone does not show a significant association with individual worker pay.

The findings from this analysis align with recent evidence on the phenomenon of labor market unbundling (Choné and Kramarz, 2022; Skans, Choné and Kramarz, 2023). These studies highlight that generalist workers, who possess a diverse set of skills including both cognitive and non-cognitive skills, earn higher market wages. This premium is attributed to their versatility and the broad applicability of their skills across various firms and markets. Furthermore, this versatility translates to lower downward competitive pressure from specialist workers, who, while facing lower demand in general markets, can gain higher returns only in markets that depend on their specific skills. This dynamic underscores the increasing value of multidimensional skill sets in a labor market that rewards adaptability and a broad skill base.

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 association between the demand for cognitive and social skills and firm-level pay. 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 demand for each individual skill remains strongly significant, the coefficient for the joint skill requirement term has a negative sign. This suggests a reduction in the rents shared with 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 wages and share fewer economic rents with 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, with whom they share limited rents. 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 share rents that rewards job-level specialization into either cognitive or social skills, rather than their complementarity.

These findings collectively imply that while versatility in skill sets is increasingly demanded and rewarded at the worker level, high-paying firms value and compensate expertise in distinct skill types over the complementarity of cognitive and social skills. These results can be contextualized by drawing on recent research that provides evidence on worker-firm and worker-worker complementarities. This body of evidence highlights that: (i) skill returns vary across firms and tend to be higher when specialized skills complement advancements in process and product innovation (Böhm, Esmkhani and Gallipoli, 2022); (ii) in firms where productive processes require specialized skills, there are substantial complementarities between workers that work in teams with heterogeneous talent and task specialization (Freund, 2023); (iii) in large innovative firms (relative to smaller less innovative ones) low skilled workers possessing soft skills receive a wage premium due to their higher complementarity with high-skill workers and firm capital (Aghion et al., 2023); (iv) firms share higher rents with workers having critical roles in the production process to prevent output losses from unfilled positions, which intensifies amid skill shortages and labor market tightness (Bloesch, Larsen and Taska, 2022); and that (v) in tight labor markets, firms offer higher wages to boost the retention of incumbent employees in high-skill and job-specific occupations that are hard to substitute, particularly in labor-intensive sectors (Le Barbanchon, Ronchi and Sauvagnat, 2023).

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 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 wage and the demand for skills: the market prices of skills, which influence individual skill returns, and the compensation policies of firms, which determine rent-sharing within firms. We find that workers possessing a combination of cognitive and social skills receive higher returns in the market but they earn lower rents from firms. Conversely, specialists with a focus on either cognitive or social skills secure higher rents from their employers but face lower market returns.

These findings are in line with recent research on the unbundling of skills, suggesting that generalist workers – due to their ability to flexibly market their diverse skill set across different markets – have an advantage over specialists. Furthermore, they highlight the important role of firms in shaping the wage structure, especially how firms that offer high wages prioritize specialization, reflecting a strategic focus on specific skills within their organizational frameworks. This suggests that the strategies firms use to utilize skills, influenced by their adoption of new technologies and the synergy between high-skill labor and innovation, are crucial in shaping wage differences. Additionally, our study underscores the importance of skill complementarities, both between firms and workers and among coworkers, and the value of retaining specialized workers amid skill shortages and tight labor markets. Collectively, these factors contribute to a deeper understanding of the role of firms in determining wage disparities.

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	0.0164*		0.0106	-0.0380**	-0.0364**	-0.0142
	(0.0098)		(0.0106)	(0.0159)	(0.0170)	(0.0158)
Social		0.0241**	0.0206*	-0.0151	-0.0369**	-0.0474***
		(0.0106)	(0.0115)	(0.0118)	(0.0160)	(0.0160)
Both required				0.1195***	0.0884***	0.0814***
				(0.0326)	(0.0287)	(0.0277)
Panel B	**Average estimated firm effect**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive	0.0698***		0.0592***	0.0693***	0.0529***	0.0564***
	(0.0076)		(0.0088)	(0.0114)	(0.0120)	(0.0134)
Social		0.0569***	0.0372***	0.0446***	0.0461***	0.0343**
		(0.0089)	(0.0101)	(0.0136)	(0.0164)	(0.0168)
Both required				-0.0248	-0.0454**	-0.0495**
				(0.0235)	(0.0216)	(0.0233)
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)			3.16	4.91	3.46	4.45
F-statistic/Worker (all specific skill requirements)					8.15	4.08
F-statistic/Firm (cognitive and social)			62.77	44.96	8.85	7.64
F-statistic/Firm (all specific skill requirements)					11.69	12.01

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

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 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.2.2 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 Estimation Appendix

B.1 Estimation of AKM worker and firm effects

We estimate the log-linear two-way fixed effects model proposed by Abowd, Kramarz and Margolis (1999, AKM), which allows to disentangle the worker and firm heterogeneity effects on wages. The model 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} measures the log of FTE daily wages of worker i in year t. The term θ_i represents the unobserved worker heterogeneity, which reflects the rewards attributable to individual worker qualities across employers. The term $\psi_{j(i,t)}$ denotes the unobserved heterogeneity of the firm j where worker i is employed in year t, reflecting the pay premium paid to all workers employed at firm j. The term x_{it} captures time-varying covariates (i.e., year dummies, age and age^2). Finally, ε_{it} is an idiosyncratic error term. Writing Equation (B.1.1) in matrix notation gives:

$$y = X\beta + D\theta + F\psi + \varepsilon \tag{B.1.2}$$

where X is a matrix containing time-varying observables, and D and F are matrices respectively collecting dummy variables for workers and firms—with d_i $(i = 1, \ldots, N)$ being the i-th row of matrix D and f_j $(j = 1, \ldots, J)$ the j-th row of matrix F. The identification of the parameters of interest requires the following set of assumptions:

$$\mathbb{E}[d'_i\varepsilon] = 0, \forall i \tag{B.1.3}$$

$$\mathbb{E}[f'_j\varepsilon] = 0, \forall j \tag{B.1.4}$$

Such identifying conditions require that mobility must be exogenous. In other words, mobility can be explained by time-varying observables (x_{it}) and by worker and firm types (θ_i and ψ_j), which allows for rich sorting patterns, but it is not allowed to depend on time-varying unobservables (ε_{it}).

In order to separately identify parameter vectors θ and ψ, the model exploits worker mobility across firms. 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.