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Firm human resource practices and educational mismatch

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Abstract

This paper investigates the relationship between human resource practices and educational mismatch. It introduces a novel firm-level measure of educational mismatch, constructed by merging firm- and individual-level data at the sector-firm size-year level. The measure captures both the incidence and the type of mismatch – distinguishing between overeducation, undereducation, and mixed cases – and enables a detailed analysis of how human resource practices relate to skill utilization within firms. Using a rich dataset on Italian firms, we estimate how this measure correlates with different human resource practices, controlling for an extensive set of firm characteristics, as well as year and industry-region fixed effects. The results indicate that on-the-job training is consistently associated with lower levels of educational mismatch. Narrower spans of control and the use of private recruitment agencies are also linked to reduced mismatch, although their effects vary across sectors and types of mismatch. In contrast, public employment services show no systematic association with educational mismatch, while second-level wage bargaining is negatively related to mismatch in firms characterized by overeducation, but positively related in those facing undereducation.

Keywords Educational mismatch · Human resource practices · Managerial practices · Firm-level analysis · Overeducation · Undereducation

JEL Classification D22 · D23 · J24 · O15

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1 Introduction

A persistent mismatch between the skills and qualifications required for a job and those possessed by employees can negatively affect individuals, firms, and economies (McGuinness et al., 2018a, b; Brunello & Wruuck, 2021; Cedefop, 2022). For individuals, this misalignment may lead to wage penalties, job dissatisfaction, and long-term career scarring. It may reduce firms' productivity, and at the macro level, it may hinder economic growth and competitiveness (Coraggio et al., 2024). In recent years, matching skills to jobs has become increasingly challenging due to mega-trends such as technological change (Caselli et al., 2024), digital and green transitions, job automation, artificial intelligence, and demographic shifts (Brunello & Wruuck, 2021). Ongoing shocks and disruptions, such as the 2008–2009 economic crisis and the COVID-19 pandemic, have exacerbated the process (Şahin et al., 2014; Cedefop, 2022; Coraggio et al., 2024).

Recent data confirm that educational mismatch is widespread in Europe, affecting around 40% of the workforce, with most being overqualified (28%) (Cedefop, 2022). This phenomenon is particularly pronounced in Italy, where 30% of workers are overeducated and 15% undereducated, and it is worsening among younger cohorts (Vera-Toscano & Meroni, 2021).

Existing research mainly focused on individual determinants and consequences, especially for overeducation (Leuven & Oosterbeek, 2011; McGuinness et al., 2018a, b). However, understanding the role of firms is essential, as they can complement public policies in reducing mismatch. Moreover, if mismatch hinders productivity, profit-maximizing firms should identify practices to mitigate it, and human resource practices (HRPs) are crucial to this end (Bloom & Van Reenen, 2007; Belfield, 2010; Bloom et al., 2019; Minni, 2023; Coraggio et al., 2025).

This paper explores the factors influencing educational mismatch within firms, focusing on the role of HRPs. Specifically, it investigates the role of recruitment practices (use of public and private employment services) and retaining practices (second-level wage bargaining, on-the-job training, and supervisor monitoring effort).

The contribution of our paper is twofold. First, we develop a new measure of educational mismatch at the firm level, which can be constructed even in the absence of matched employer-employee data, by merging information from individual and firm data. This approach offers two key benefits: (i) it allows us to assess both the incidence of this phenomenon within firms, and its type, and (ii) it allows us to exploit the comprehensive information available in firm survey data, exploring aspects not covered by administrative sources. Second, we analyze the role of HRPs in determining the type and incidence of educational mismatch at the firm level, an area largely neglected in the current literature.

Our analysis relies on two different data sources for the years 2009, 2014, and 2017: the Italian Labor Force Survey (ITLFS) and Italian firm-level data from the Survey for Firms and Labor (*Rilevazione Imprese e Lavoro*, RIL). We follow a realized matches approach for mismatch measurement and construct a measure of educational mismatch in each firm by comparing the expected and the observed distribution of educational levels within firms. We assess the role of HRPs in reducing the incidence of educational mismatch in firms characterized by different types of

mismatch by estimating econometric models that control for firm characteristics, as well as years and industry-region fixed effects. We complement the analysis with a firm-fixed effects model to address endogeneity issues.

The results indicate that on-the-job training is the HRP most consistently associated with lower educational mismatch. More effective monitoring (narrower span of control) is also significantly correlated with lower mismatch. The use of private recruitment agencies is significantly associated with lower mismatch mainly in high- and medium-high-tech manufacturing and in firms where either undereducation or overeducation is the dominant mismatch type. Public employment services show no statistically significant associations, except for a small group of firms with a hybrid type of mismatch involving 'Too little secondary' educated workers relative to sector-firm size-year averages. Second-level wage bargaining shows a significant negative correlation with mismatch only in the construction sector and in firms where overeducation is prevalent, but a positive correlation in firms where undereducation is the dominant mismatch type.

The rest of the paper proceeds as follows. Section 2 reviews existing literature. Section 3 develops a conceptual framework that explicitly sets out our hypotheses on the relationship between specific HRPs and educational mismatch. Section 4 introduces the novel mismatch measure that we propose and employ in the empirical analysis. Section 5 describes the data and illustrates some descriptive evidence and the empirical strategy. Section 6 discusses the econometric results and Sect. 7 concludes.

2 Background literature

2.1 The effects of educational mismatch

Educational mismatch occurs when workers' education levels do not align with job requirements (Brunello & Wruuck, 2021; McGuinness et al., 2018a, b).[1] It negatively affects wages, well-being, and productivity: overeducated workers face wage penalties compared to well-matched workers with the same education level, although they earn more than well-matched colleagues in the same occupation (Caroleo & Pastore, 2018; Cutillo & Di Pietro, 2006; Gaeta et al., 2023; McGuinness et al., 2018a, b); undereducated workers experience the opposite (Cedefop, 2012). Overeducation also has lasting wage penalties, tends to lower job satisfaction, and increases shirking, absenteeism, turnover, and gender inequalities (Büchel, 2002; Castagnetti et al., 2018; Cedefop, 2022; Guvenen et al., 2020; McGuinness et al., 2018a, b). In the long run, it may lead to a scarring effect (Guvenen et al., 2020).

The effects of educational mismatch on firm productivity are ambiguous, but crucial for contextualizing the role of personnel policies in attracting and retaining the best fits. Undereducation generally reduces firm productivity, while overeducation can either benefit firms through lower wages or reduce productivity due to poor alignment between job tasks and workers' qualifications, as well as increased turnover

[1] Instead, skill mismatch refers to the degree to which workers are endowed with skills required for their current job.

(Brunello & Wruuck, 2021; Coraggio et al., 2024). Empirical evidence suggests that undereducation hampers productivity, while overeducation can have a positive effect (Kampelmann & Rycx, 2012; Grunau, 2016; Bisio & Lucchese, 2023). Meeting skill needs through hiring also boosts productivity (Fanti et al., 2021). Finally, skill mismatch, especially overskilling, imposes significant costs in terms of aggregate productivity, due to inefficient resource allocation (Adalet McGowan & Andrews, 2017).

2.2 Firm-level determinants of educational mismatch

While considerable attention has been paid to the role of individual determinants and institutional factors,[2] comparatively, less focus has been placed on firm characteristics and personnel policies as determinants of mismatches. Regarding firm characteristics, overeducation is more common among employees working in small firms, in low- and medium-skilled jobs within sectors such as accommodation and food services, administrative services, transportation, and trade, as well as in firms with a higher share of part-time and shift workers (Belfield, 2010; Cedefop, 2022).

A recent body of literature investigates the role of managerial practices and manager quality. From a theoretical perspective, mismatch is expected to be negatively associated with both factors (Coraggio et al., 2024). Findings indicate that high-quality managerial practices (i.e., structured practices in terms of monitoring, target-setting, and incentives) enhance productivity and foster employees' human capital development (Bloom & Van Reenen, 2007; Bloom et al., 2019). However, these studies do not explicitly examine the effect of managerial practices on mismatch. Coraggio et al. (2025) find that managerial quality, measured with a synthetic index, improves the alignment between workers and their jobs. This finding is consistent with Minni (2023), who shows that top-quality managers enhance worker-job match through both lateral transfers and vertical promotions. Similarly, Cedefop (2012) underlines the importance of HRPs, which include recruitment and selection strategies (e.g., formal vs. informal channels; internal vs. external candidates; temporary agencies), training, performance evaluation, and performance-related pay.

Our paper contributes to this limited literature by assessing the role of the various HRPs in reducing mismatch at the firm level. More specifically, we consider recruitment procedures (proxied by the use of private agencies and public employment services); on-the-job training; monitoring (proxied by supervisors' span of control), and performance-related pay (proxied by second-level wage bargaining linked to productivity). Additionally, we examine how their association with mismatch varies depending on the type of mismatch. In general, mismatch can reflect either overeducation or undereducation. However, at the firm level, the two phenomena can occur simultaneously, i.e. within-firm mismatch can reflect solely overeducation, solely undereduca-

[2] Young workers, women, migrants, previously inactive individuals, and graduates in social sciences and humanities are more likely to be overeducated (Leuven & Oosterbeek, 2011; Adalet McGowan & Andrews, 2015; McGuinness et al., 2018a, b; Caroleo & Pastore, 2018; Coraggio et al., 2024). The presence of unions increases mismatch in the public sector (Belfield, 2010), whereas the relationship between temporary contracts and mismatch is mixed: some authors find that the use of temporary contracts increases overeducation (Belfield, 2010; Croce & Ghignoni, 2012), whereas others find the opposite (Maida & Tealdi, 2021).

tion, or a combination of both. Hence, we discuss the association of various HRPs with overeducation and undereducation, but we also derive implications for those firms characterized by a mix of the two.

2.3 Theoretical lenses to explain educational mismatch

Among the theoretical explanations of educational mismatch, search theory, career mobility theory, and the human capital model, which are not mutually exclusive, are the most relevant to formulate testable hypotheses on the role of HRPs (Hartog, 2000; Belfield, 2010; Leuven & Oosterbeek, 2011). According to search theory, mismatch arises temporarily because of search costs and imperfect information (Coraggio et al., 2024). Career mobility theory builds on a human capital perspective and posits that overeducation may be part of a deliberate career advancement strategy, whereby overeducated workers accept jobs below their qualification level and forgo wage premiums in the short term to acquire specific skills and experience that facilitate their progression to higher-level positions (Rosen, 1972; Sicherman & Galor, 1990; Belfield, 2010). Within the human capital framework, additional explanations focus on a compensation mechanism between education and other components of human capital, such as experience, training, or innate ability (Leuven & Oosterbeek, 2011; Caroleo & Pastore, 2018). Examining these theories through the firm's viewpoint, together with the related empirical evidence, provides a stronger basis for our predictions.

3 Human resource practices and educational mismatch

Effective recruitment strategies can reduce mismatch by better aligning candidate qualifications with job requirements. Theoretically, more rigorous and structured recruitment practices should reduce mismatch because they collect more information on candidates (through tests, interviews, etc.), reducing information asymmetries, and enabling firms to better assess workers' formal qualifications and skills (Belfield, 2010). Empirical evidence indicates that firms, particularly when educational requirements are higher, invest more time in the recruitment process, thus reducing the risk of undereducation (Oyer & Schaefer, 2011), and that formal hiring tests and strong hiring systems reduce overeducation (Belfield, 2010).[3] Pellizzari (2011) also finds that mismatch is more likely to occur where screening is less intensive.

Recruitment practices are certainly structured when they rely on public employment services (PES) or private agencies. Hence, we expect the incidence of mismatch to be lower in firms using these services. However, Italian public employment services have historically been inefficient, facing problems such as a limited number of offices, chronic understaffing, structural undercapacity relative to service demand, and a workforce that is insufficient, at least until the recent reforms under the Next Generation EU program. Moreover, many users of the PES are individuals with lim-

[3] Instead, informal practices could increase educational mismatch because workers may be inclined to accept a job with lower educational requirements while reducing search costs (Bentolila et al., 2010).

ited employability and who require complex interventions, making them unattractive for private agencies (ANPAL 2021; Pastore, 2019; Cicciomessere, 2014). Therefore, we expect public employment services to be less effective than private ones in reducing mismatch.

Since the use of PES and private recruitment agencies is likely to reduce both overeducation and undereducation, we can specify the following hypothesis:

HP1. The use of private agencies and PES for recruitment reduces the incidence of mismatch, with larger effects (in absolute terms) for private agencies.

On-the-job training may affect the incidence of mismatch through multiple channels. On the one hand, firms that do not invest in employee training are less interested in their workers' human capital development. This can result in a heightened propensity to hire underqualified workers as a cost-saving measure, or, conversely, in a higher likelihood to hire overqualified workers to compensate for the lack of such an investment (Verdugo & Verdugo, 1989). However, these firms may have a reduced capacity to retain skilled employees, who may seek opportunities at firms offering superior learning and career development programs. Thus, these firms could have a higher share of undereducated workers, generating a negative correlation between the presence of training and undereducation, whereas the final effect on the share of overeducated workers depends on whether these firms are able to retain these workers.

On the other hand, in line with the human capital theory, firms may view formal education as a solid foundation that makes employees more 'trainable' and thus a more secure investment. This would create an incentive for firms to prioritize candidates with higher educational qualifications (reinforcing the negative correlation between on-the-job training and undereducation implied by the previous channel). Moreover, workers with higher levels of education may seek employers who offer training and career advancement opportunities (Autor, 2001). This could generate an initial positive correlation between on-the-job training and overeducation, but this correlation may become negative over time if on-the-job training provides overeducated workers with skills that help them progress up the occupational ladder, as suggested by career mobility theory, or if overeducated workers who are not interested in higher-responsibility roles move to less-demanding firms, which are usually those that do not invest in training.

While there is solid evidence that workers with higher education are more likely to receive training (Brunello, 2003; Korpi & Tåhlin, 2021), it is more difficult to find studies that disentangle the reasons behind this 'training gap'. According to Korpi and Tåhlin (2021), employer decisions regarding how to structure jobs and whom to hire are the primary factors behind the training gap. This would support the hypothesis of a negative correlation between on-the-job training and undereducation. At the same time, Büchel and Mertens (2004) find that overeducated workers have far less access to on-the-job training measures than adequately educated workers, suggesting that on-the-job training could be negatively correlated with overeducation. Indeed, Belfield (2010), considering the firm's perspective and using a subjective measure, indicates that training is associated with lower overeducation. Wen et al. (2023) find that overeducated, overskilled, and undereducated workers who receive training are less likely to quit, but the implications of these findings for the correlation between

on-the-job training and over- or undereducation are unclear because they depend on the self-selection of these workers into firms that offer training or not. Based on the discussion of the various theoretical channels and of the empirical evidence, we formulate the following hypothesis:

HP2. The availability of on-the-job training is associated with a lower incidence of both undereducation and overeducation.

Supervision and monitoring practices may also affect mismatch by allowing firms to identify mismatched workers and decide whether to invest in their development or to dismiss them (Belfield, 2010; Cedefop, 2012). Indeed, these practices may help reduce information asymmetries, reallocate mismatched workers, and improve job design. Because supervisors have a limited amount of time for monitoring, we anticipate that an increase in their span of control will reduce monitoring effectiveness and increase the likelihood of mismatch within the firm's workforce:

HP3. A wider span of control for supervisors (i.e., lower monitoring effectiveness) is associated with a higher incidence of mismatch.

Performance evaluation and pay-for-performance may increase educational mismatch by providing a monetary compensation for overeducated workers. Indeed, overeducated workers are often found to be more productive than their adequately educated colleagues in the same role. A pay-for-performance system allows firms to recognize and compensate for this surplus productivity directly. Moreover, this system may also help firms attracting and retaining undereducated workers with good skills. Alternatively, it may also reduce educational mismatch by attracting and retaining well-matched workers. If overeducated workers are less skilled than their well-matched counterparts, they may be more penalized in firms with pay-for-performance schemes, and therefore more likely not to join the company or to leave it. Empirical evidence on these effects is scarce and ambiguous. For example, according to Belfield (2010), evaluation programs seem to reduce overeducation, but the estimates are imprecise. In the absence of more information, the overall effect remains an empirical question. Hence, we can formulate the following hypothesis:

HP4. Second-level wage bargaining linked to productivity increases the incidence of mismatch, especially of undereducation.

Table 1 summarizes our hypotheses and the expected effects.

Table 1 Human resource practices and the incidence of mismatch; hypotheses

Hypothesis	Human resource practice	Effect on mismatch incidence
HP1	Use of PES and private agencies for recruitment	Negative, with larger absolute size for private agencies
HP2	On-the-job training	Negative
HP3	Wider supervisors' span of control (lower monitoring effectiveness)	Positive
HP4	Second-level wage bargaining	Positive, especially for undereducation

4 Measuring educational mismatch at the firm level

4.1 Existing measures of mismatch

Occupational mismatch is a vast and multi-faceted concept. As mentioned earlier, mismatch measures refer to either education (also known as qualification mismatch) or skills. Additionally, mismatch can be classified as either vertical, focusing on the level of education or skills, or horizontal, referring to the content of education or skills, by comparing the field of study with the type of education or skills required for a given job. Finally, it may be appropriate to consider the multidimensional nature of skills. For a recent discussion of skill mismatch, horizontal mismatch, multidimensional skills, see, among others, Coraggio et al. (2024); McGuinness et al. (2018a, b). In what follows, we briefly summarize the current state of the art regarding (firm-level) vertical educational mismatch measures, which are more closely related to our approach.

Measures of mismatch fundamentally differ in how the required education level is defined. Three different ways of characterizing such benchmark measures have been proposed and used: worker self-assessment, job analysis, and realized matches (Kampelmann & Rycx, 2012). The worker *self-assessment* approach implements a subjective measure, in which workers are asked whether their level of education fits with the one needed for the job (e.g., Belfield, 2010, using an employer-employee survey; Caroleo & Pastore, 2018, at the individual level). This approach offers the advantage of providing context-specific and up-to-date information, but it also shares the typical limitations of subjective analyses, including potential biases arising from individual responses or the phrasing of questions (Hartog, 2000). The *job analysis* approach is an objective measure (also known as 'normative'), based on professional evaluations of the level of education needed for a given occupation. While usually very attractive, it is not often updated and can make it difficult to aggregate information from detailed jobs into higher-level occupational categories.

Another objective measure determines the benchmark level of education by using observational data and analyzing the educational qualifications of the current workforce (*realized matches* approach, also known as the 'statistical' or 'empirical' approach). Workers are considered mismatched if their education level differs from the statistical norm for their occupation: the mean or the modal years of education are taken as the reference point, and the individual is considered mismatched when actual schooling is higher or lower than required (e.g., among recent studies at the individual level: Wen et al., 2023). Kiker et al. (1997) and Kampelmann and Rycx (2012) start from workers' level of education, transformed into years of education, and then use the mode of workers' years of education within each occupation as the benchmark; finally, they calculate the years of over- and undereducation (Kiker et al., 1997, at the individual level; Kampelmann & Rycx, 2012, as averages within firms). Alternatively, some studies use the mean years of schooling as a benchmark and flag individuals more than one standard deviation away (e.g., Verdugo & Verdugo, 1989, at the individual level).

While objective and up to date, the realized matches measure has the limitation of being endogenous to labor demand and supply allocation; results also depend on

the chosen statistical measure and threshold, and may fail to account for long-term trends, such as increasing education levels in younger generations. To address this last issue, Maida and Tealdi (2021), using an employer-employee dataset for an Italian region, compare each worker's level of education with the mode of workers of the same age group, occupation, and year of labor market entry; they focus on the flow of mismatched, overeducated, and undereducated workers relative to total employment flow. Fredriksson et al. (2018) develop an interesting measure of mismatch based on realized matches, combining objectivity with the theoretical prediction that good matches are more likely to persist over time, and with a multidimensional concept of skills. The required skill benchmark for a job is defined as the average skill level of tenured workers in the same occupation and firm. The idea of using realized matches from a subsample rather than the full set of workers or firms is also implemented by Coraggio et al. (2025), relying on machine learning techniques. They examine the realized distribution of matches in the most productive firms (top decile) and extrapolate this information to other firms; based on workers' observable characteristics and data from the most productive firms, they predict workers' allocation to jobs in other firms. Job allocation quality is defined either as a dummy variable or as a continuous measure at the individual level, and then averages are calculated at the firm level. Two important features emerge: differently from other papers, mismatch is not defined on education or skills, but on workers' observable characteristics (e.g., including experience, tenure, etc.), although education type and level remain dominant; second, by construction, this approach evaluates the effects of good matches, without distinguishing between over- and undereducation.

4.2 A new firm-level measure of mismatch

In this paper, we adopt a realized-matches approach to measuring mismatch, but we propose a measure that differs from the usual one described in the previous section that compares workers' education level with the mean or mode level of education attained by workers in the same occupation. We do not assume that the education level required by a given occupation is unique. Rather, we recognize that within the same occupation, different tasks may require different education levels.[4] Accordingly, we compare the *entire distribution* of education levels attained by workers in a given occupation (possibly within homogeneous groups of firms defined by characteristics such as sector, firm size, or time period) with the distribution observed within an individual firm belonging to the corresponding group. If the *share* of workers with, for example, low education in a specific occupation is higher in the firm than in the benchmark distribution, this suggests that the firm employs undereducated workers in that occupation. Moreover, the *incidence* of undereducation within the firm will be *at least* as large as the difference between the firm's share and the benchmark share of low-educated workers in that occupation.[5]

[4] For example, Fredriksson et al. (2018) find that a substantial part of the overall job-level sorting on talents is across jobs with the same occupational classifications.

[5] We specify "at least" because the allocation of workers with different education levels to specific tasks within the same occupation remains unknown. Indeed, it is conceivable that, within a firm, some highly

The advantages of using the entire distribution of education levels as a statistical benchmark for each occupation (rather than the mean or mode) increase with the breadth of the occupational groups considered, because the greater this breadth, the greater the diversity of tasks required and, consequently, the greater the diversity of education levels needed to perform those tasks. Moreover, by allowing the benchmark education distribution in each occupation to differ across firm groups, we allow the same occupation to require different skills across firms of different sizes, operating in different sectors, and time periods.

As it relies on realized matches, the proposed measure inherits some of the typical limitations of this approach. In particular, the benchmark distribution of educational attainments reflects the actual education levels of workers within a given occupation, rather than the qualifications required for the job. Consequently, if most firms within a certain group (e.g., small firms in specific sectors) employ systematically undereducated or overeducated workers in certain occupations, the measure may fail to identify the presence of undereducation or overeducation within that group, as such deviations become embedded in the benchmark itself. The other limitation that our measure shares with other measures based on realized matches is related to possible cohort effects. Since education levels progressively increased over time, it may be that firms with an older workforce employ relatively more workers with lower levels of education in various occupations. We try to mitigate the consequences of this potential limitation in the empirical analysis by controlling for the firm's share of workers in different age groups. However, this is an issue that deserves further investigation in future research.

If matched employer-employee data or firm-level data on the education level of workers by occupation were available, one could construct occupation-specific mismatch measures at the firm level. Then, some overall measures of undereducation/overeducation for each firm could be obtained by adding the within-firm proportion of undereducated/overeducated workers in the various occupations. Unfortunately, the RIL dataset used in this paper provides only information on the number of employees by occupation and by education *separately*. Consequently, we can only construct an overall mismatch measure at the firm level by aggregating the benchmark shares of the different education levels over all occupations, weighted by each firm's proportion of workers in the different occupations, and comparing this 'expected' distribution of the firm's employees' education with the observed one.

More precisely, our measure of mismatch in firm *i* in year *t* is the sum, over all educational levels, of the absolute differences between the *expected* and *observed* distribution of employees' education. Let $\widehat{sh}_{it}^{e}$ indicate the *expected* share of employees with education *e* for firm *i* in year *t* (whose construction is explained below), and sh_{it}^{e} the corresponding *observed* share. Our measure of mismatch in firm *i* in year *t* is defined as follows:

educated employees in each occupation may be assigned to tasks requiring lower educational qualifications, while a proportion of less-educated workers exceeding that indicated by the benchmark distribution may be engaged in tasks demanding higher levels of education. In such cases, the actual incidence of undereducation would be greater than the difference between the firm's share and the benchmark share of low-educated workers in that occupation, alongside a concurrent presence of overeducated workers.

$$Mismatch_{it} = \frac{\sum_e \left| \widehat{sh}^e_{it} - sh^e_{it} \right|}{2}$$

We divide this metric by a factor of two to ensure it ranges from 0 (no mismatch) to 100 (complete mismatch).

This measure can be interpreted as a lower bound of the within-firm mismatch rate. Suppose that a firm is expected to have 30% of employees with compulsory education, 50% with upper secondary education, and 20% with tertiary education, and that the observed shares are 20%, 60%, and 20%, respectively. Our measure of mismatch is 10, and it tells us that at least 10% of the firm's employees are mismatched (in this case, at least 10% are overeducated).[6]

By taking absolute differences, we initially abstract from the direction of mismatch (i.e., under- versus overeducation). However, as discussed below, we later reintroduce this information to distinguish among different types of mismatch.

The *expected* shares ($\widehat{sh}^e_{it}$) are obtained in three steps. First, using ITLFS data, we calculate sh^e_{ot}, the shares of employees with education *e* for each occupation (*o*) in year *t* (at the sector-firm size level) in the population.[7] Due to data limitations in RIL, we can consider only three educational levels (*e* = *Compulsory*, *Upper Secondary*, *Tertiary*)[8] and four types of occupation (*o* = *Blue Collars*, *White Collars*, *Middle Managers*, *Managers*). Such broad aggregation may mask within-group heterogeneity and should be kept in mind when interpreting the results; however, this concern is partly mitigated by our definition of mismatch, which uses the full distribution of education, rather than a single benchmark. Second, we multiply sh^e_{ot} by the share of employees that firm *i* (belonging to the corresponding sector and size class) reports in each occupation in year *t* in the RIL dataset. The result is the share of employees with a certain educational level that firm *i* is *expected* to have in each occupation in year *t* ($\widehat{sh}^e_{oit}$):

$$\widehat{sh}^e_{oit} = \frac{\#employees_{oit}}{\#employees_{it}} \cdot sh^e_{ot}$$

Third, we calculate $\widehat{sh}^e_{it}$ by summing $\widehat{sh}^e_{oit}$ over all occupations:

[6] Clearly, when matched employer-employee data are available, one can construct an exact measure of the within-firm mismatch rate, and not only a lower bound.

[7] We consider 17 main sectors of the Italian economy and four firm size classes. The reader is referred to Section A.1.1 in the Online Appendix for further details. Our benchmark distribution is defined at the sector–firm size level, which we consider the most appropriate aggregation. Expected education varies systematically with firms' production technologies and organizational structures, which are strongly sector- and size-specific. Smaller firms typically rely on multi-task roles, whereas medium and large firms use more specialized job structures. These differences justify allowing the benchmark to vary across sector-firm size cells. Alternative benchmark definitions could be considered. For example, we did not use a sector-region aggregation because regional variation in production technologies and institutional constraints is relatively limited within a national labor market. One may also want to consider cohort-specific benchmarks, as in Maida and Tealdi (2021). Exploring these alternative aggregation levels to assess the sensitivity of the results – or to identify systematic differences – represents an interesting avenue for future research.

[8] In Italy, compulsory education includes up to the first 2–3 years of the high school.

$$\widehat{sh}_{it}^{e} = \sum_{o} \widehat{sh}_{oit}^{e}$$

The *observed* share of employees with education *e* in firm *i* in year *t* (sh_{it}^{e}) is taken directly from the RIL dataset. Further details on the data and descriptive evidence on the distribution of education by occupation, firm class size, and sectors are provided in Section A of the Online Appendix.

Our measure of mismatch ($Mismatch_{it}$) is a firm-level indicator that reflects how widespread this phenomenon is within individual firms, capturing the *diffusion* of mismatch among a firm's workforce, rather than its *depth*. Other within-firm measures, which quantify mismatch in terms of the total number of years of education above or below the job requirement, as in Kampelmann and Rycx (2012), do the opposite. Such measures are sensitive to the *magnitude* of the mismatch at the individual level, potentially indicating high levels of mismatch even when it is concentrated in a small number of employees. In contrast, our measure focuses on how many employees are affected, regardless of the size of their individual educational gap. Drawing a parallel from a different context, our measure resembles the poverty rate, while the others are more comparable to the poverty gap.

Our mismatch measure provides information about mismatch incidence at the firm level, but it is not informative on whether it is due to overeducation or undereducation. However, by comparing the expected and observed shares for each educational level separately, we can identify four mutually exclusive types of mismatch:

1) Undereducation: firms whose observed shares of workers with compulsory (C) and upper secondary (US) education are larger than expected: $sh_{it}^{C} \geq \widehat{sh}_{it}^{C}$ and $sh_{it}^{US} \geq \widehat{sh}_{it}^{US}$ (with a strict inequality in at least one of these two conditions) or firms whose observed share of workers with compulsory education is larger than expected and the observed shares of workers with upper secondary and tertiary education are lower than expected: $sh_{it}^{C} \geq \widehat{sh}_{it}^{C}$ and $sh_{it}^{US} \leq \widehat{sh}_{it}^{US}$, $sh_{it}^{T} \leq \widehat{sh}_{it}^{T}$ (with a strict inequality in at least two of these conditions).
2) Overeducation: firms whose observed shares of workers with upper secondary and tertiary (T) education are larger than expected: $sh_{it}^{US} \geq \widehat{sh}_{it}^{US}$ and $sh_{it}^{T} \geq \widehat{sh}_{it}^{T}$ (with a strict inequality in at least one of the two conditions) or firms whose observed share of workers with tertiary education is larger than expected and the observed shares of workers with compulsory education and upper secondary education are lower than expected: $sh_{it}^{T} > \widehat{sh}_{it}^{T}$, $sh_{it}^{US} \leq \widehat{sh}_{it}^{US}$, and $sh_{it}^{C} \leq \widehat{sh}_{it}^{C}$ (with a strict inequality in at least two of these conditions).
3) A mix of over- and undereducation with 'too much secondary': firms that present a lower-than-expected share of both compulsory and tertiary educated: $sh_{it}^{C} < \widehat{sh}_{it}^{C}$ and $sh_{it}^{T} < \widehat{sh}_{it}^{T}$);

in this case, overeducation is more likely to occur in the lower part of the occupational ladder, while undereducation in its upper part.

4) A mix of over- and undereducation with 'too little secondary': firms that present a higher-than-expected share of both compulsory and tertiary educated: $sh_{it}^{C} > \widehat{sh}_{it}^{C}$ and $sh_{it}^{T} > \widehat{sh}_{it}^{T}$; in this case, overeducation is more likely to occur in the upper part of the occupational ladder, while undereducation in its lower part.

Clearly, the complement to these four cases is the situation of 'no mismatch', when the observed shares are equal to the expected ones ($sh_{it}^{C} = \widehat{sh}_{it}^{C}$ and $sh_{it}^{US} = \widehat{sh}_{it}^{US}$ and $sh_{it}^{T} = \widehat{sh}_{it}^{T}$).

5 Data, descriptive analysis, and empirical strategy

To construct our measure of educational mismatch, we merge information from two main sources for the years 2009, 2014, and 2017: the ITLSF and RIL. The ITLFS is a sample household survey conducted by the Italian National Statistics Institute (Istat) which provides information on the employment circumstances of the Italian population. We use this dataset to calculate the distribution of educational levels for each occupation (as explained in Sect. 4).

RIL is a mandatory panel survey conducted by INAPP on a representative sample of Italian partnerships and limited liability companies operating in the private, non-agricultural sectors. RIL provides information on a wide range of firms' observable characteristics, including size, industry, and workforce composition (in particular, the number of employees by occupation and by education, separately). We combine this information with the distribution of educational levels from the ITLFS, to construct our measure of educational mismatch.

5.1 Descriptive analysis

The RIL database, consisting of the 2010, 2015, and 2018 waves,[9] contains 84,571 observations for 59,612 firms. Our data cleaning steps exclude, in the following order, observations (i.e., firm-year pairs) referring to inactive firms (1438 observations), firms that changed regional location (NUTS-2) between 2009 and 2017 (329), firms with no employees (10631), and firms with missing information on employees' educational distribution (1265). We also drop observations with inconsistencies in employment shares, namely when the distribution by education (6 observations) or by age (255) falls outside the 99–101% range. Finally, we exclude potential outliers by dropping observations for which the number of employees (706), sales (613), or the job turnover rate (1370) are above the corresponding 99th percentile of the overall distribution. After these cleaning steps, the sample consists of 67,958 observations. By further excluding observations with missing values for variables required in

[9] The information contained in RIL refers to the year prior to the publication of the wave. For example, the 2015 wave contains information on firms that refer to the end of 2014 and, for some variables, to the period 2012–2014. The same lag applies to the other waves.

the empirical analysis, we obtain a final dataset, ITLFS-RIL, of 62,006 observations covering 43,424 firms.[10]

Figure 1 presents the distribution of our mismatch measure across the full sample. The average incidence of educational mismatch is slightly above 30%, but the distribution is positively skewed and exhibits substantial heterogeneity.

To explore two key dimensions of this variation, namely firm size and time, we plot separate histograms in Fig. 2(a) for micro-small firms (fewer than 50 employees) and medium-large firms (50 or more employees) for the years 2009, 2014, and 2017. The histograms reveal two patterns. First, in every year, micro-small firms exhibit a higher average incidence of educational mismatch: 27.50% in 2009, 29.57% in 2014, and 31.91% in 2017, compared to medium-large firms, whose corresponding rates are 19.27%, 22.49%, and 25.09%, respectively. This evidence aligns with Cedefop (2022), which finds that mismatch, particularly overqualification, is more common among workers in small-sized firms. Second, from 2009 to 2017, the entire distribution shifts to the right for both size classes, indicating that educational mismatch became more diffused even as Italy moved from a period of economic downturn and stagnation (2009–2013) into a moderate economic recovery (2014–2017). Similar evidence of post-crisis increases in mismatch is reported by Brunello and Wruuck (2021), who find that labor shortages tend to rise during economic expansions. They

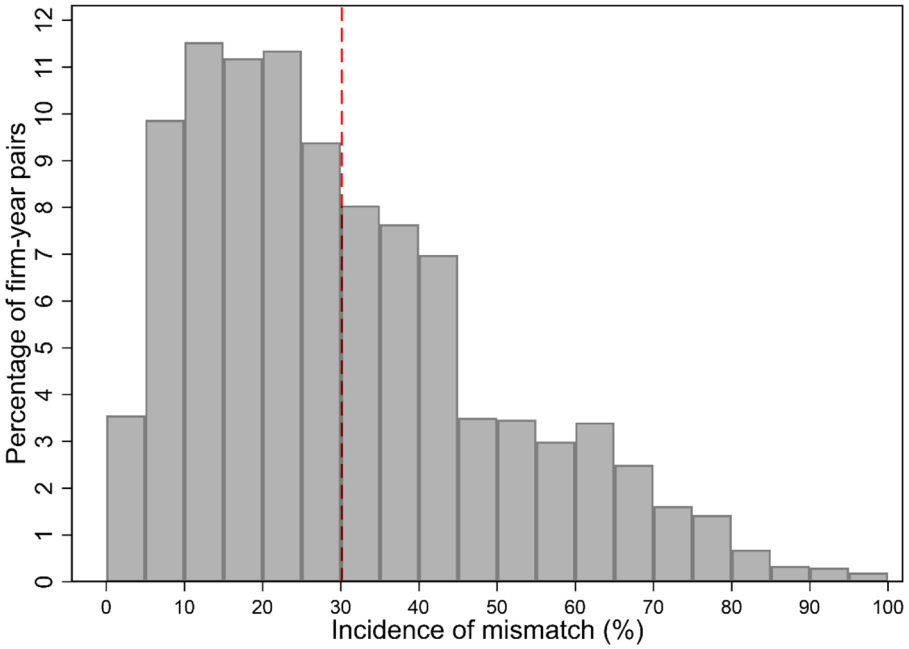
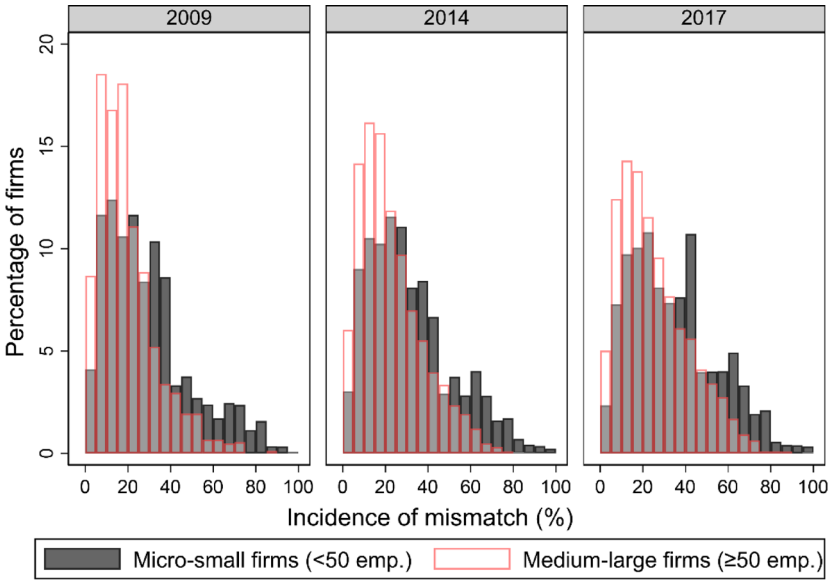
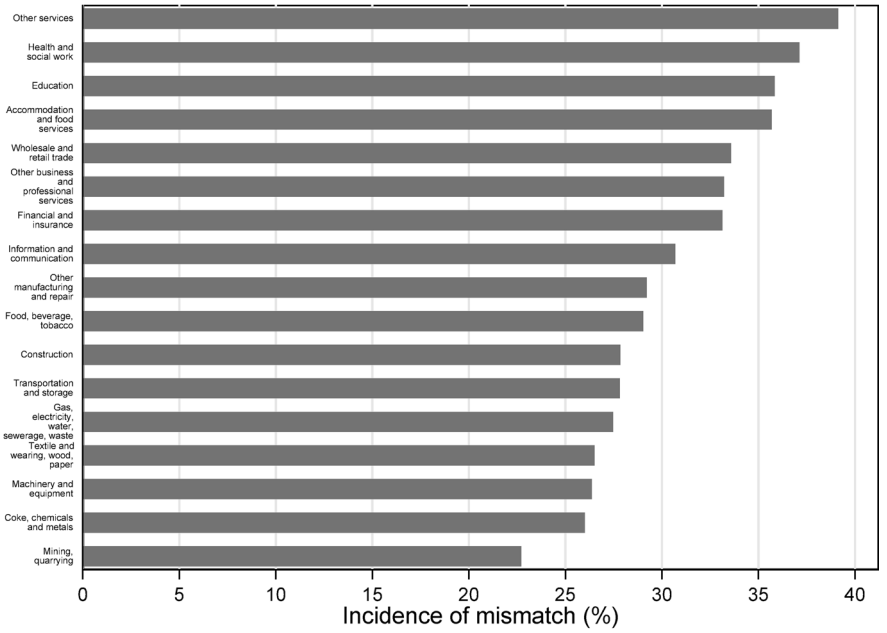


Fig. 1 Distribution of mismatch incidence. ITLFS-RIL database, 2009, 2014, 2017 (N=62,006). The dashed vertical line corresponds to the sample mean (30.12%)

[10] Table A.2 in the Online Appendix compares the original RIL sample with the final ITLFS-RIL sample by industry, firm size, and survey wave, in order to assess the representativeness of the final ITLFS-RIL relative to the original RIL.



(a)



(b)

Fig. 2 (a) Distribution of mismatch incidence by firm size category and year. (b) Average incidence of mismatch by sector. ITLFS-RIL database, 2009, 2014, 2017 ($N = 62{,}006$)

note that two opposing forces influence mismatch over the business cycle. On the one hand, recessions can reduce mismatch by eliminating poor matches through job destruction. On the other hand, they can increase mismatch, as skilled workers may accept jobs below their qualification level due to limited opportunities, and displaced workers may lack the skills required for available vacancies. In such contexts, overall matching efficiency tends to decline. Which effect dominates varies by country and institutional context. Coraggio et al. (2024) confirm this perspective by showing that recessions lead to *persistent* increases in overeducation. Displaced or newly hired workers often remain in positions that require fewer qualifications than they possess. The "sullying" effect, where jobseekers accept jobs below their skill or education level, tends to outweigh the "cleansing" effect that results from the elimination of poor matches. This persistence is consistent with our histograms: the increase started with the Great Recession does not disappear in 2014 and even increases in 2017 suggesting that structural forces kept the average firm-worker matches from realigning even in good times.

Figure 2(b) plots the average incidence of educational mismatch across seventeen sectors for 2009, 2014 and 2017. Accommodation and food services (35.7%), wholesale and retail trade (33.6%), other business services and professional activities (33.2%) are above the sample mean (30.12%), whereas capital-intensive sectors such as manufacturing (from 26% to 29%), construction (27.8%), and utilities (27.5%) record a lower mismatch incidence. This ranking mirrors EU-wide evidence from Cedefop (2022), which shows that over qualification is relatively low in utilities, manufacturing and construction but markedly higher in accommodation and food services, wholesale and retail trade, administrative services, and arts and entertainment related services. This heterogeneity may be partially explained by employer and job characteristics, such as firms' small size and private ownership, routine tasks, and non-standard contracts, which are typical features in hospitality and retail sectors while being less common in utilities or manufacturing.

Regarding the predominant type of mismatch within firms, 'Overeducation' is most common in the health, education, and information sectors, while 'Undereducation' tends to prevail in the mining and quarrying, as well as in industrial sectors (see Figure B.1 in the Online Appendix). The data also reveal substantial regional heterogeneity in both the incidence and type of mismatch, consistent with previous findings (e.g., Cedefop, 2022). Mismatch incidence is generally lower in northern regions, where undereducation is more prevalent (Figure B.2 in the Online Appendix). This pattern likely reflects differences in regional industrial structures, as northern and central Italian regions are more specialized in industrial and manufacturing sectors. Overall, the evidence provided so far suggests that Italy's mismatch problem is not purely macro-cyclical. It is related also to some structural characteristics of specific service sectors, which make it harder for employers and workers to properly match even when the business cycle turns favorable.

Table 2, panel (a), shows the distribution of firms by type of mismatch and the corresponding average incidence of the latter. Firms characterized by either 'Overeducation' or 'Too much secondary' present higher mismatch incidence than those characterized by 'Undereducation' or 'Too little secondary' (34%-37% vs. 22%-20% - column (3)). This is consistent with the evidence from individual data reported in

the Introduction (30% of overeducated workers and 15% of undereducated).[11] Italy's high overeducation rate, despite the low share of tertiary educated individuals, may result from its specialization in low-tech sectors and from the increase of low valued added service sectors (which imply a high share of routine-intensive jobs; Caroleo & Pastore, 2018; Marcolin et al., 2018; Basso, 2020). In terms of firms' distribution, it is worth noting that a firm out of three is characterized by 'Undereducation' and that almost two out of five are characterized by 'Too much secondary'. These two categories account for about 70% of the observations, reflecting widespread inefficiencies in the Italian educational and productive system (Ghignoni & Verashchagina, 2014; Caroleo & Pastore, 2018). In contrast, only 24% of observations have an overqualified workforce.

Since a perfect match is rare (0.06% of firms), to assess the robustness of these statistics, we included in the 'Matched' category those observations for which the mismatch incidence is below 5% (about 4.7% of our sample). Table 2, panel (b), shows that this change does not modify the general pattern described above. The average

Table 2 Descriptive statistics; number of observations, percentage, and incidence of mismatch by category

	(1)	(2)	(3)	(4)	(5)
	Obs.	Obs. (%)	Mismatch (%), average	Mismatch (%), min.	Mismatch (%), max.
	Panel (a)—perfect match				
(1) Undereducation	20,908	33.72	22.14	0.50	100.00
(2) Too little secondary	3,692	5.95	20.34	1.00	83.50
(3) Matched	35	0.06	0.00	0.00	0.00
(4) Too much secondary	22,441	36.19	36.55	1.00	100.00
(5) Overeducation	14,930	24.08	34.10	0.50	100.00
Total	62,006	100.00	30.12	0.00	100.00
	Panel (b)—5 p.p. tolerance for matched firms				
(1) Undereducation	19,294	31.12	23.70	5.50	100.00
(2) Too little secondary	3,498	5.64	21.26	5.50	83.50
(3) Matched	2,914	4.70	3.55	0.00	5.00
(4) Too much secondary	22,011	35.50	37.19	5.50	100.00
(5) Overeducation	14,289	23.04	35.48	5.50	100.00
Total	62,006	100.00	30.12	0.00	100.00

ITLFS-RIL database; 2009, 2014, 2017 (N=62,006). "p.p." stands for percentage points. Categories are defined, based on the statistical approach, as it follows: (1) 'Undereducation': the actual share of employees with compulsory (tertiary) education is greater or equal (lower or equal) to the expected one; (2) 'Too little secondary': the actual share of employees with tertiary (compulsory) education is greater than (greater than) the expected one; (3) 'Matched': the actual shares of employees with compulsory, upper secondary and tertiary education is equal to the expected ones; (4) 'Too much secondary': the actual share of employees with compulsory (tertiary) education is lower than (lower than) the expected one; (5) 'Overeducation': the actual share of employees with tertiary (compulsory) education is greater or equal (lower or equal) to the expected one. In panel (b), category (3) 'Matched' gathers also firm-year pairs for which deviations in absolute values from the expected educational shares are within 5% points

[11] In comparing our measure with individual-data evidence one should keep in mind that our sample of firms includes only limited liability companies and partnerships, and that our measure can be interpreted as a lower bound of mismatch at the firm level.

mismatch incidence increases by about 1pp in all other four categories, with a slightly larger reduction in the share of firms with 'Undereducation' (-2.6pp).

Table A.3 in the Online Appendix provides definitions and detailed descriptive statistics for all regressors, including HRPs and firm-level controls. Readers are referred there for further detail.

For HRPs we consider the following variables, available in the RIL questionnaire: i) a dummy variable for the use of public employment services for recruitment; (ii) a dummy variable for the use of private recruitment agencies; (iii) a dummy variable equal to 1 if the firm offers on-the-job training; (iv) a dummy variable for second-level wage bargaining, indicating whether pay is tied to current production or productivity, which captures the possible presence of pay-for-performance; and (v) the average span of control, namely the mean number of direct subordinates in the immediate lower layer per supervisor in the layer above, averaged across all layers, which (considering the fixed amount of time a supervisor has) proxies monitoring effectiveness.

Table 3, presenting descriptive statistics on HRPs, highlights substantial heterogeneity. On-the-job training is relatively widespread, with about 52% of firms offering it, whereas the use of private recruitment agencies remains limited (12%). The use of public employment services (5%) and second-level wage bargaining linked to productivity (6%) are even more rare. The average span of control is 6.3 subordinates per supervisor, but with considerable dispersion, reflecting heterogeneity in organizational structures. Table B.1 in the Online Appendix further reports differences in HRPs and firm characteristics across mismatch types and multinomial logit estimates relating these variables to mismatch categories.

Table 4 shows the average mismatch incidence by various firm characteristics and the type of mismatch. For firm characteristics that are continuous variables, we calculated and reported the average mismatch incidence below and above the median. The average mismatch incidence is remarkably lower in firms that use private recruitment agencies and second-level wage bargaining (-8pp and −9pp, respectively). It is also lower, but to a lesser extent (-5pp), in firms that use public employment services and offer on-the-job training. A higher number of subordinates per supervisor (span of control) is also associated with lower mismatch incidence (-6pp). Generally, these associations are quite similar across mismatch types, with some exceptions. The lat-

Table 3 Descriptive statistics on human resource practices

Variable	Mean	SD
Human resource practices		
Use of public employment services for recruitment	0.045	0.208
Use of private recruitment agencies	0.124	0.329
The firm offers on-the-job training	0.523	0.499
Average span of control per supervisor	6.304	12.659
Second-level wage barg. (link to prod.)	0.063	0.243
# Observations	62,006	

ITLFS-RIL database, 2009, 2014, 2017 (N=62,006)

Table 4 Incidence of mismatch (%) by firm characteristics and mismatch category

	Whole sample	Categories				
		Undereducation	Too little secondary	Matched	Too much secondary	Overed-ucation
Human resource practices (HRPs)						
Use of public employment services						
No	30.4	22.4	20.7	0.0	36.8	34.6
Yes	25.8	17.6	16.3	0.0	32.1	29.0
Use of private recruitment agencies						
No	31.1	22.9	21.1	0.0	37.3	35.6
Yes	23.5	16.2	16.8	0.0	29.0	27.2
The firm offers on-the-job training						
No	32.6	24.2	22.5	0.0	39.0	37.7
Yes	27.8	20.0	19.0	0.0	33.8	31.9
Average span of control per supervisor						
< Median	33.3	24.4	22.7	0.0	40.1	38.1
>Median	27	19.9	18.5	0.0	32.5	31.2
Second-level wage bargaining						
No	31.1	22.8	21.2	0.0	37.3	35.5
Yes	21.9	16.5	15.8	0.0	27.2	25.4
Selected firm-level characteristics						
No. employees						
< Median	35.2	26.3	27.6	0.0	40.4	41.2
>Median	25.2	17.9	17.4	0.0	31.0	29.9
No. layers						
< Median	32.2	23.6	22.1	0.0	38.2	37.5
>Median	24.0	17.5	17.0	0.0	29.0	27.8
Share employees with fixed-term contracts						
< Median	32.4	23.9	22.5	0.0	38.4	37.5
>Median	26.5	19.3	18.2	0.0	32.8	30.5
Share of female employees						
< Median	28.4	20.7	19.2	0.0	37.1	33.6
>Median	31.9	24.3	22.4	0.0	36.1	34.5
Job turnover rate						
< Median	31.7	23.5	21.4	0.0	37.9	35.9
>Median	28.6	20.7	19.6	0.0	35.0	32.7
Union representation (RSA/RSU)						
No	31.9	23.6	22.0	0.0	37.9	36.3
Yes	23.0	16.6	16.2	0.0	28.6	27.6
CEO education: compulsory	29.2	24.1	21.5	0.0	36.3	35.9
CEO educa-tion: upper secondary	30.8	21.7	20.2	0.0	38.1	34.0
CEO educa-tion: tertiary	29.5	20.0	19.9	0.0	33.1	33.8
CEO age: 15–39 y.o.	33.3	23.9	22.8	0.0	40.2	38.2

Table 4 (continued)

	Whole sample		Categories				
			Undereducation	Too little secondary	Matched	Too much secondary	Overed-ucation
CEO age: 40–49 y.o.		31.0	22.5	20.4	0.0	37.4	35.7
CEO age: 50–59 y.o.		30.4	22.6	20.3	0.0	36.8	33.3
CEO age: 60+y.o.		28.5	21.1	19.9	0.0	34.7	32.9
Female CEO							
	No	29.6	21.7	20.1	0.0	36.1	33.7
	Yes	33.2	25.2	22.2	0.0	39.0	36.8
External (hired) CEO							
	No	30.3	22.3	20.5	0.0	36.8	34.5
	Yes	25.5	18.0	17.2	0.0	29.4	28.5
CEO remuneration: related to performance							
	No	28.3	20.2	19.1	0.0	34.6	32.9
	Yes	32.4	24.5	22.7	0.0	38.6	36.0
# Obs.		62,006	20,908	3,692	35	22,441	14,930
# Firms		43,424					

ITLFS-RIL database; 2009, 2014, 2017 (N=62,006). Categories are defined, based on the statistical approach, as it follows: (1) 'Undereducation': the actual share of employees with compulsory (tertiary) education is greater or equal (lower or equal) to the expected one; (2) 'Too little secondary': the actual share of employees with tertiary (compulsory) education is greater than (greater than) the expected one; (3) 'Matched': the actual shares of employees with compulsory, upper secondary and tertiary education is equal to the expected ones; (4) 'Too much secondary': the actual share of employees with compulsory (tertiary) education is lower than (lower than) the expected one; (5) 'Overeducation': the actual share of employees with tertiary (compulsory) education is greater or equal (lower or equal) to the expected one

ter include larger roles of private recruitment agencies, second-level wage bargaining, and the span of control for firms characterized by 'Overeducation' and 'Too much secondary'.

All of these HRPs are likely to be correlated with firm size, which, as shown in Fig. 2(a), is itself negatively associated with the incidence of mismatch. In particular, firms larger than the median size exhibit a mismatch incidence that is approximately 10pp lower than that of smaller firms. Similar patterns can also be observed for firms with deeper hierarchies and a union representation (-8pp and -9pp). Smaller but notable differences are associated with having higher shares of fixed-term contracts (-6pp) and lower shares of female employees (-4pp). While the relationship with firm size is similar across mismatch types, deeper hierarchies and union representation reduce the mismatch incidence more in firms characterized by 'Overeducation' and 'Too much secondary.' In contrast, lower shares of female employees reduce mismatch incidence more in firms characterized by 'Undereducation' and 'Too little secondary'.

On average, the relationship between CEO education and the incidence of educational mismatch displays an inverted U-shape, with mismatch peaking among firms led by CEOs with upper secondary education (30.8%), even if the difference is small. Notably, when examining firms by their prevalent type of mismatch, we find that this

pattern differs. In firms primarily characterized by 'Undereducation', 'Too little secondary', and 'Overeducation', higher CEO education is associated with lower mismatch incidence. To some extent, this aligns with Coraggio et al. (2025) and Minni (2023), who show that higher managerial quality contributes to better worker-job alignment. In contrast, among firms characterized by 'Too much secondary,' the relationship remains inverted U-shaped, largely driving the average pattern observed in the full sample. Finally, when CEOs are older, males, externally hired and with not-for-performance remunerations, the mismatch incidence is about 4-5pp lower.

As previously observed, these associations may be spurious, due to the potential correlation between various firm characteristics. In the empirical analysis, we examine which correlations remain significant once we control for all other firm characteristics and industry-region fixed effects.

Before examining how HRPs and other firm characteristics affect mismatch incidence, it is useful to assess whether our measure of mismatch is negatively correlated with various dimensions of firm performance, as theory would suggest (Brunello & Wruuck, 2021), to evaluate the effectiveness of the measure. Hence, we estimate a series of OLS regressions in which the dependent variables capture different dimensions of firm performance (labor productivity, several types of investments, and export status), while the key independent variables are the level and type of mismatch. The models also control for firm size class, industry-region fixed effects, and year fixed effects. The level of mismatch is negatively and significantly associated with all dimensions of firm performance considered (Table B.2 in the Online Appendix). However, consistent with previous studies, firms characterized by 'Overeducation' tend to perform better than 'Matched' firms, while those with an undereducated workforce generally show weaker outcomes than firms with a 'Matched' workforce.

5.2 Empirical strategy

To appropriately model the incidence of mismatch, which is a share (as explained in Sect. 4), we employ a fractional logit model. This approach is well suited for dependent variables that fall within the [0,1] interval. Specifically, we estimate (through quasi-maximum likelihood method; Papke & Wooldridge, 1996) a pooled cross-sectional fractional logit model of mismatch incidence as a function of the HRPs adopted by the firm and other relevant firm-level characteristics:

$$\mathrm{E}\left[Mismatch_{it}^{frac} \mid \mathbf{HRP_{it}},\ \mathbf{X_{it}}, catmismatch_{it}\ ,\ \alpha_{jr}, \tau_t\right] = \Lambda(\alpha + \boldsymbol{\beta}'\mathbf{HRP_{it}} + \boldsymbol{\gamma}'\mathbf{X_{it}} + \vartheta' catmismatch_{it} + \alpha_{jr} + \tau_t) \quad (1)$$

where $\Lambda\ (\mathrm{z}) = \frac{\exp(z)}{1+\exp(z)}$ is the logistic link and $Mismatch^{frac}{}_{it} = Mismatch_{it}/100$ is the incidence of mismatch expressed as a fraction between 0 and 1. The vector HRP_{it} includes the use of public and private employment services, on-the-job training, an inverse proxy of monitoring effectiveness (span of control), and the adoption of second-level wage bargaining scheme related to workers' productivity. The vector X_{it} include both workforce and CEO characteristics. $catmismatch_{it}$ is the vector of dummy variables corresponding to the prevalent type of mismatch which characterizes firm *i* in year *t*. To mitigate a possible omitted variable bias, along

with several time-varying firm controls, we account for time-invariant unobserved heterogeneity at the industry-region level by including a vector of industry (NACE 2-digit)-region fixed effects (α_{jr}) and a vector of year fixed effects (τ_t). Standard errors are computed using the robust Huber-White estimator of variance, which provides consistency under general forms of heteroskedasticity and model misspecification. β represents the coefficients of interest and captures the association between the adoption of HRPs and the incidence of mismatch. The sign of each β coefficient indicates the direction of this relationship. This interpretation holds conditional on the prevalent type of mismatch in firm *i* at time *t*, other firm's characteristics, and the included fixed effects. To aid interpretation, we estimate and report the average marginal effects (AMEs) for each practice in $\mathbf{HRP_{it}}$ and for each control variable.

Estimates from this model cannot be interpreted in causal terms because of various potential endogeneity issues, such as unobserved heterogeneity and reverse causality. For this reason, we refrain from interpreting our findings causally and limit our discussion to conditional correlations between HRPs and the incidence of educational mismatch.

Nonetheless, to partially address potential omitted-variable bias, we estimate an alternative specification that replaces industry-region fixed effects with firm fixed effects (α_i). However, incorporating firm fixed effects into the fractional logit model raises the well-known incidental parameters problem (Lancaster, 2000), because the number of parameters to be estimated increases with the number of firms, undermining the consistency of the estimates. In our case, estimating approximately 15,030 firm fixed effects for 33,612 firm-year observations also presents considerable computational challenges. Therefore, we estimate a linear regression model in which firm fixed effects are absorbed prior to estimation:

$$Mismatch_{it} = \alpha + \boldsymbol{\beta'}\mathbf{HRP}_{it} + \boldsymbol{\gamma'}\mathbf{X_{it}} + \boldsymbol{\vartheta'}\, catmismatch_{it} + \alpha_i + \tau_t + \epsilon_{it} \quad (2)$$

While this linear specification allows us to control for time-invariant unobserved heterogeneity at the firm level, we consider it as a robustness check. Our preferred specification remains the fractional logit model with industry-region fixed effects, as it is coherent with the fractional nature of the dependent variable and it exploits the between-firm variation in the data. This choice is reasonable given the low number of observations per firm (1.43), the unbalanced structure of the panel, and the limited within-firm variability in most HRPs over time.

In the last part of the empirical analysis, we explore whether the association between HRPs and mismatch depend on the type of mismatch, as suggested by the descriptive evidence in Table 4, and extend our baseline fractional logit model (Eq. 1) by introducing a vector of interactions between HRP_{it} and $catmismatch_{it}$:

$$\begin{aligned} \mathrm{E}\left[Mismatch_{it}^{frac} \mid \mathbf{HRP_{it}},\ \mathbf{X_{it}}, catmismatch_{it}\ ,\ \alpha_{jr}, \tau_t\right] = &\Lambda(\alpha + \boldsymbol{\beta'}\mathbf{HRP_{it}} \\ &+ \boldsymbol{\pi'}(\mathbf{HRP_{it}} \times catmismatch_{it}) \\ &+ \boldsymbol{\gamma'}\mathbf{X_{it}} + \vartheta' catmismatch_{it} + \alpha_{jr} + \tau_t) \end{aligned} \quad (3)$$

where $\mathbf{HRP_{it}} \times catmismatch_{it}$ denotes all pairwise products of each HRP variable and each dummy variable indicating the firm's prevalent type of mismatch, and all other variables are defined as above.

6 Results

6.1 Main results

Table 5 shows the AMEs of the variables of interest in Eq. (1) from both fractional logit and linear models discussed in Sect. 5.2. In col. (1), we estimate a fractional logit model of mismatch incidence as a function of the vector of HRPs, controlling for industry-region and year fixed effects. Cols. (2) and (3) introduce firm-level controls sequentially: col. (2) adds a set of workforce characteristics, while col. (3) further includes key attributes of the top manager. In col. (4), we account for the prevalent type of mismatch within the firm by including categorical indicators for: (1) 'Undereducation', (2) 'Too little secondary', (4) 'Too much secondary', and (5) 'Overeducation'. This specification also retains the small group of firms with a perfectly matched workforce (35 'Matched' observations). Col. (5) presents results from a linear regression model that includes the same set of regressors as the fully specified fractional logit model in col. (4). Finally, col. (6) replaces industry-region fixed effects with firm fixed effects to better account for unobserved, time-invariant heterogeneity at the firm level. In this specification, there is a significant decrease in the number of observations and firms, because many firms have been surveyed only once across the RIL waves considered.

The estimates highlight the following findings. First, recruitment practices yield mixed results. The use of PES shows no meaningful association with mismatch, while the use of private recruitment agencies is weakly negatively associated with the incidence of mismatch only in the most complete specification (col. 4). These findings provide only partial support for HP1. As expected, private employment agencies appear more effective than PES in reducing mismatch. Based on our estimates, firms that use private agencies for recruitment experience, on average, a 0.57% point reduction in mismatch incidence compared to those that do not, although the statistical significance is limited. The lack of association of PES with mismatch incidence is consistent with prior research highlighting the structural inefficiencies of Italian PES, such as understaffing and inadequate resources (Pastore, 2019; ANPAL 2021). The results suggest that, while structured recruitment has potential, its effectiveness in practice (especially when mediated through public channels) remains questionable.

Second, the availability of on-the-job training is consistently and significantly associated with a lower incidence of mismatch across all specifications, supporting hypothesis HP2. Using the model in col. (4) as the reference, the results indicate that firms offering on-the-job training show, on average, a 0.95percentage point reduction in mismatch incidence compared to those that do not, ceteris paribus.

Third, the average span of control, as an inverse measure of monitoring effectiveness, is positively and significantly associated with the incidence of mismatch. This finding supports HP3 and aligns with previous literature (Belfield, 2010; Cedefop,

Table 5 Incidence of mismatch, HRPs and firm characteristics; fractional logit and linear models

	(1)	(2)	(3)	(4)	(5)	(6)
	Fractional logit (dy/dx)	Fractional logit (dy/dx)	Fractional logit (dy/dx)	Fractional logit (dy/dx)	OLS	OLS, firm FEs
Human resource practices						
Use of public employment services for recruitment	0.6636	0.3017	0.3117	-0.1683	-0.1339	0.3903
	(0.3568)	(0.3507)	(0.3491)	(0.3290)	(0.3098)	(0.4721)
Use of private recruitment agencies	0.2668	0.1582	0.0282	-0.5674*	-0.3748	-0.5993
	(0.2457)	(0.2428)	(0.2420)	(0.2276)	(0.2108)	(0.4126)
The firm offers on-the-job training	-0.4650**	-0.6011***	-0.6788***	-0.9473***	-0.9493***	-0.6241*
	(0.1600)	(0.1592)	(0.1592)	(0.1513)	(0.1551)	(0.2678)
Average span of control per supervisor	0.0780***	0.0569***	0.0569***	0.0605***	0.0568***	0.0565**
	(0.0071)	(0.0068)	(0.0068)	(0.0073)	(0.0076)	(0.0205)
Second-level wage barg. (link to prod.)	-0.5001	-0.1073	-0.4639	-0.3657	0.4529	-0.1572
	(0.3299)	(0.3398)	(0.3391)	(0.3240)	(0.2784)	(0.5330)
Firm-level controls						
Firm size (no. employees, log)	-4.3453***	-4.0262***	-4.0574***	-3.9872***	-4.0430***	-5.7407***
	(0.0671)	(0.0932)	(0.0941)	(0.0907)	(0.0921)	(0.4082)
No. of layers		-0.7193***	-0.8359***	-0.8484***	-0.8148***	-0.4037
		(0.1310)	(0.1315)	(0.1267)	(0.1247)	(0.2941)
Share of employees with fixed-term contracts		0.0126**	0.0127**	0.0211***	0.0216***	0.0097
		(0.0048)	(0.0048)	(0.0046)	(0.0049)	(0.0108)
Share of employees with part-time contracts		0.0032	0.0032	0.0059*	0.0081**	0.0007
		(0.0029)	(0.0029)	(0.0028)	(0.0031)	(0.0070)
Share of female employees		0.0057	0.0047	-0.0134***	-0.0124***	-0.0237*
		(0.0032)	(0.0032)	(0.0031)	(0.0034)	(0.0118)
Share of employees 25–34 y.o.		0.0011	-0.0014	0.0008	0.0016	0.0021
		(0.0062)	(0.0062)	(0.0057)	(0.0066)	(0.0126)
Share of employees 35–49 y.o.		-0.0441***	-0.0462***	-0.0267***	-0.0299***	-0.0079
		(0.0058)	(0.0058)	(0.0053)	(0.0061)	(0.0127)

Table 5 (continued)

	(1) Fractional logit (dy/dx)	(2) Fractional logit (dy/dx)	(3) Fractional logit (dy/dx)	(4) Fractional logit (dy/dx)	(5) OLS	(6) OLS, firm FEs
Share of employees 50+y.o.		-0.0931***	-0.0959***	-0.0547***	-0.0597***	-0.0395**
		(0.0061)	(0.0062)	(0.0057)	(0.0065)	(0.0140)
Job turnover rate		-0.0051**	-0.0053**	-0.0035*	-0.0037	-0.0003
		(0.0019)	(0.0019)	(0.0018)	(0.0019)	(0.0038)
Union representation (RSA/RSU)		0.7040**	0.4998*	0.7566***	1.0651***	-0.6740
		(0.2308)	(0.2313)	(0.2181)	(0.2059)	(0.4731)
CEO education: upper secondary			2.0522***	0.3662	0.5054**	1.1757*
			(0.1941)	(0.1895)	(0.1925)	(0.4594)
CEO education: tertiary			3.4748***	1.0156***	1.2391***	1.1619
			(0.2388)	(0.2331)	(0.2348)	(0.5980)
CEO age:40–49 y.o.			-0.4167	-0.4691	-0.4956	0.6461
			(0.3078)	(0.2930)	(0.3090)	(0.6189)
CEO age:50–59 y.o.			-0.0389	-0.4243	-0.4190	0.7169
			(0.3015)	(0.2872)	(0.3024)	(0.6488)
CEO age:60+y.o.			-0.3139	-0.8007**	-0.7868*	0.4515
			(0.3074)	(0.2929)	(0.3069)	(0.6708)
Female CEO			0.1533	0.2169	0.2669	0.0622
			(0.2039)	(0.1949)	(0.2064)	(0.5525)
External (hired) CEO			0.3319	-0.2139	-0.1679	-0.5615
			(0.3639)	(0.3511)	(0.3301)	(0.5501)
CEO remuneration: related to performance			0.4826**	0.6423***	0.6753***	-0.0753
			(0.1505)	(0.1427)	(0.1454)	(0.2658)
Type of mismatch						
(2) Too little secondary				1.1407***	1.4254***	3.2919***
				(0.2270)	(0.2164)	(0.4801)
(3) Matched				-22.5738***	-22.3988***	-21.3297***

Table 5 (continued)

	(1) Fractional logit (dy/dx)	(2) Fractional logit (dy/dx)	(3) Fractional logit (dy/dx)	(4) Fractional logit (dy/dx)	(5) OLS	(6) OLS, firm FEs
				(0.1094)	(1.6775)	(5.2400)
(4) Too much secondary				11.7789***	11.9033***	10.9890***
				(0.1764)	(0.1836)	(0.3669)
(5) Overeducation				13.0571***	12.7383***	11.7362***
				(0.2198)	(0.2212)	(0.4512)
Industry-region FEs	Yes	Yes	Yes	Yes	Yes	No
Firm FEs	No	No	No	No	No	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2					0.2653	0.4626
Log pseudolikelihood	-26454.242	-26387.421	-26368.857	-25914.385		
#Obs.	62,006	62,006	62,006	62,006	62,006	33,612
#Firms	43,424	43,424	43,424	43,424	43,424	15,030

ITLFS-RIL database; 2009, 2014, 2017 (N=62,006). Coefficients of industry-region FEs, firm FEs and year FEs, are not reported to save space. Full tables are available from authors upon request. Columns (1)-(4) report the marginal effects of the fractional logit model (dy/dx). Categories are defined, based on the realized matches approach, as it follows: (1) 'Undereducation': the actual share of employees with compulsory (tertiary) education is greater or equal (lower or equal) to the expected one; (2) 'Too little secondary': the actual share of employees with tertiary (compulsory) education is greater than (greater than) the expected one; (3) 'Matched': the actual shares of employees with compulsory, upper secondary and tertiary education is equal to the expected ones; (4) 'Too much secondary': the actual share of employees with compulsory (tertiary) education is lower than (lower than) the expected one; (5) 'Overeducation': the actual share of employees with tertiary (compulsory) education is greater or equal (lower or equal) to the expected one. In columns (4), (5), and (6) category (1) 'Undereducation' is the reference (omitted) category. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively

2012), which emphasizes the role of supervision in reducing mismatch. Effective monitoring enables firms to identify mismatched workers, helping to reduce information asymmetries, improve job design, and reallocate workers within the firm more efficiently. Our results confirm that, given the time constrained faced by supervisors, a broader span of control (diluted oversight) is associated with higher mismatch incidence within firms. Specifically, each additional subordinate per supervisor is associated with a 0.06 percentage point increase in mismatch.

Fourth, the role of incentive schemes, proxied by the presence of second-level wage bargaining, yields non-significant and inconclusive results. Thus, results so far do not offer support for HP4; however, to further investigate HP4, one needs to focus on heterogeneous analysis, as the effects may be different for different mismatch types.

Although the economic magnitude of each stand-alone HRP associated with a statistically significant AME may appear modest, it is important to recall that these estimates are conditional on a rich set of covariates. In particular, we control for a broad array of firm-level characteristics as well as industry-region and year fixed effects, all of which capture much of the observed heterogeneity in mismatch incidence (as shown in Tables 2 and 4, and Fig. 2(a) and (b)). Moreover, the combined implementation of multiple HRPs may result in a larger overall change. To illustrate this, we conduct a simple back-of-the-envelope calculation using the AMEs reported in col. (4) of Table 5. Consider two otherwise identical firms: Firm A offers on-the-job training, uses private recruitment agencies, and maintains a span of control that is two subordinates per supervisor narrower than that of Firm B, which does not provide training, does not rely on private recruitment, and has a broader span of control. Based on our estimates, Firm A would experience a mismatch incidence approximately 1.64 percentage points lower than Firm B (-0.95 from training, -0.57 from private recruitment agencies, and -0.12 from a narrower span of control).

Among the firm-level controls, the results broadly align with prior expectations in the literature. Mismatch is consistently lower in larger firms and those with more hierarchical layers, suggesting that greater organizational depth supports more effective worker allocation. In contrast, higher shares of fixed-term and part-time contracts are associated with increased mismatch, consistent with the notion that non-standard employment contracts weaken the quality of job matching (Belfield, 2010; Cedefop, 2022). Workforce composition also plays a role: firms with higher proportions of older and female employees exhibit significantly lower levels of mismatch. Union presence is positively associated with mismatch incidence, while greater external workers' mobility (proxied by the job turnover rate) is linked to lower mismatch. CEO characteristics reveal additional patterns: firms led by more highly educated CEOs and those with performance-based CEO compensation tend to exhibit significantly higher levels of educational mismatch. This result contrasts with the expectation that stronger managerial quality should improve the alignment between workers and jobs (Coraggio et al., 2025; Minni, 2023), if we consider CEO education as a proxy for quality; our result may instead reflect a more strategic use of overqualification. In particular, CEOs with higher education levels and incentive-based remuneration may deliberately accept or promote certain forms of mismatch, particularly 'Overeducation' to improve firm performance. This interpretation is supported by results in Table

B.2 in the Online Appendix, which suggest that some types of educational mismatch may result from managerial decisions aimed at maximizing returns in terms of firm performance rather than inefficiencies in job matching.

In the last three columns of Table 5, we also include four out of five mutually exclusive categories that identify the firm's predominant type of mismatch. Category (1), 'Undereducation', serves as the baseline (omitted) category. Accordingly, the average marginal effects (AMEs) for the remaining four categories reflect the percentage-point difference in mismatch incidence relative to 'Undereducation'. Although these estimates are conditional on HRPs, firm-level controls, and industry-region and year fixed effects, they closely mirror the unconditional differences presented in col. (3) of Table 2.

While the coefficient estimates from the linear model (col. 5) are consistent with the AMEs from the fractional logit (col. 4), the linear model with firm fixed effects (col. 6) preserves the signs of the associations reported in col. 4, though with lower statistical significance. This likely reflects the structure of our data (an unbalanced panel with relatively few observations per firm, as noted in Sect. 5.2) and the limited time variation in both HRPs and mismatch incidence. For these reasons, our preferred specification remains the fractional logit model with industry-region and year fixed effects, while the linear regression with firm fixed effects is presented as a robustness check.

Taken together, these results provide weak support for HP1, broadly confirm HP2 and HP3, and do not support HP4. So far, the results suggest that a well-structured combination of the provision of on-the-job training, maintaining a sufficiently low number of subordinates per supervisor, and the use of private recruitment agencies is associated with a lower incidence of mismatch at the firm level. In contrast, the adoption of second-level wage bargaining and reliance on PES do not appear to be linked to a lower incidence of mismatch. However, before drawing general conclusions, it is necessary to assess how these associations vary across different mismatch types.[12]

6.2 Heterogeneous analysis across mismatch types

As suggested by the descriptive evidence, the relationship between HRPs and the incidence of educational mismatch may vary depending on the prevalent type of mismatch within firms. To examine these heterogeneous relationships, we estimate the fractional logit model in Eq. (3), which includes interaction terms between each HRP and the firm's mismatch type. Figure 3 presents the AMEs of the five HRPs across the four mismatch types: 'Undereducation', 'Too Little Secondary', 'Too Much Sec-

[12] We conducted two robustness checks to assess the stability of our estimates. First, we re-estimated the fractional logit model (col. 4, Table 5) by replacing year fixed effects with industry-year fixed effects, region-year fixed effects, and their combination, while retaining industry-region fixed effects. The estimated marginal effects of the human-resource practices remained highly stable across all specifications, indicating that the results are not driven by time-varying sector-specific or region-specific shocks. Second, we re-estimated the main the fractional logit model (col. 4, Table 5) 17 times, each time excluding one sector ("leave-one-out" robustness check). The marginal effects again showed very limited variation, confirming that no single industry disproportionately influences the estimated associations. Full results are available from the authors upon request.

ondary', and 'Overeducation'. Although Eq. (3) includes the 'Matched' category and its interaction terms with HRPs to avoid omitted variable bias, we do not report the AMEs for these interactions. Since the dependent variable is always equal to zero for the 35 matched observations, there is no within-group variation, and the marginal effects are effectively zero. The full table of coefficient estimates is provided in Table B.3 in the Online Appendix.

PES do not exhibit statistically significant associations for most mismatch types, with the exception of a significant negative association found for firms characterized by 'Too little secondary' mismatch (Fig. 3a). However, this mismatch category accounts for only a small fraction of the sample (5.95% of observations, as shown in Table 2), and thus the estimated AMEs should be interpreted with caution. The results provide partial support for HP1 and align with existing concerns about the relatively low effectiveness of Italian PES in reducing mismatch. PES have long suffered from chronic inefficiencies such as understaffing, and inadequate resources to meet demand (ANPAL 2021; Pastore, 2019; Cicciomessere, 2014). As a result, PES appear less capable than private recruitment agencies of effectively reducing mismatch.

Private recruitment agencies are significantly associated with lower mismatch in firms characterized by either undereducation or overeducation, while their impact is not statistically significant for firms whose prevalent mismatch type is either 'Too Little Secondary' or 'Too Much Secondary' (Fig. 3b). This partially supports HP1, which anticipates that structured recruitment practices, such as those employed by private agencies, reduce mismatch by reducing information asymmetries and improving the alignment between candidates' qualifications and job requirements (Belfield, 2010; Oyer and Schaefer 2011). The absence of significant associations for the 'Too

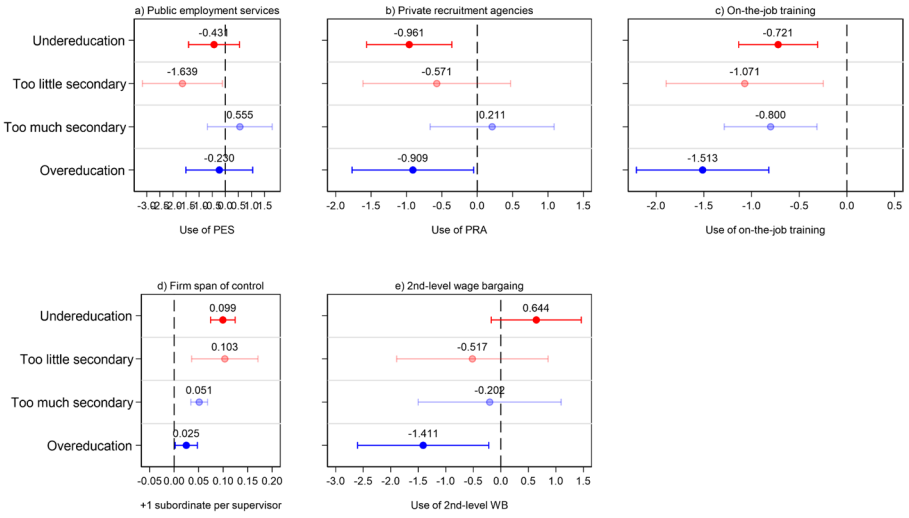


Fig. 3 The association of various HRPs with mismatch incidence by mismatch types. ITLFS-RIL database, 2009, 2014, 2017 (N=62,006). The bars represent the 95% confidence intervals. Results based on col. (7) of Table B.3 in the Online Appendix

Little Secondary' and 'Too Much Secondary' categories call for a deeper investigation of how recruitment relates to mismatch at the individual level.

On-the-job training is consistently associated with lower mismatch across all types (Fig. 3c), with particularly large marginal effects for firms characterized by 'Overeducation'. This suggests that training may help workers move toward better job matches by equipping them with skills for upward mobility. The results are consistent with Hypothesis HP2.

The span of control shows a positive association with mismatch incidence across all mismatch types (Fig. 3d), although the increase is more pronounced in firms where 'Undereducation' and 'Too little secondary' is prevalent. A broader span of control may reduce monitoring effectiveness, limiting a firm's ability to detect or correct mismatches, particularly in jobs where workers' capabilities are harder to observe. These findings provide support for HP3, which anticipates a positive relationship between span of control and mismatch.

Second-level wage bargaining, used as a proxy for performance-related pay, is associated differently with mismatch depending on the type prevalent in the firm (Fig. 3e). Specifically, it is significantly associated with a reduction in mismatch in firms characterized by 'Overeducation' (-1.41 pp). This result supports the idea that performance-based wage schemes may act as a deterrent for overqualified workers who are less productive, discouraging them from joining or remaining in the firm. By contrast, the link is positive and marginally significant for firms with undereducation, where second-level wage bargaining is associated with an increase in mismatch incidence of approximately 0.64 pp. This result (which is significant only at the 10% level) suggests that performance-based pay may attract or retain undereducated workers who possess strong skills, compensating for their formal educational deficits through monetary incentives. Overall, these findings suggest that second-level wage bargaining reduces mismatch in firms with overeducation and increases it in those with undereducation.

Overall, the results highlight the importance of considering not just the overall level of mismatch, but also the type of mismatch present within firms. These findings reinforce the need for a more tailored approach to human resource management, especially when the goal is to optimize worker-job alignment.

6.3 Heterogeneous relationship between HRPs and mismatch across sectors

The role of HRPs in mitigating educational mismatch is likely to depend on sectoral characteristics, including turnover dynamics, required skill specificity, and technology intensity.[13] To explore this heterogeneity, we re-estimate our preferred specification (col. 4 of Table 5) for three broad sectors (Industry, Construction, and Services) and further disaggregate Manufacturing into high/medium-high-tech and

[13] We thank an anonymous reviewer for raising this point and suggesting the sub-sample analysis by sector.

low/medium-low-tech manufacturing, and Services into knowledge-intensive (KIS) and less knowledge-intensive (LKIS) services, following Eurostat definitions.[14]

The results are reported in Table 6. Several patterns emerge. First, PES are not significantly associated with mismatch in any sector, confirming our baseline findings and aligning with long-standing critiques of their limited effectiveness in Italy (ANPAL 2021; Pastore, 2019).

Second, private recruitment agencies show a statistically significant negative association with mismatch only in high- and medium-high-tech manufacturing (-1.19 pp, significant at the 10% level). In these industries, the complexity of production processes and the higher specificity of educational qualifications make precise screening more valuable. Private agencies, with their structured recruitment procedures, may better assess formal qualifications and ensure they align with job requirements. This finding is in line with Pellizzari (2011), who report that recruitment quality matters most in contexts where the cost of educational mismatch is high. The absence of significant association in low-tech manufacturing and Services may reflect less stringent educational requirements and weaker use of formal screening.

Third, on-the-job training is associated with a lower incidence of mismatch in almost all subsamples, with the strongest results observed in low-tech manufacturing and LKIS. These sectors tend to rely more on practical, firm-specific knowledge and have lower formal educational requirements, which makes workplace training an effective substitute for formal qualifications. This is consistent with Cedefop (2012), which highlights the role of training in compensating for gaps in formal education.

Fourth, more effective monitoring (i.e., narrower span of control) is also associated with a lower incidence of mismatch in most sectors, with the largest coefficients in construction and low-tech manufacturing. In these settings, where tasks are less codified and job roles often require informal adaptation, a broader span of control may reduce supervisors' capacity to monitor educational fit and address misallocations. This suggests that closer managerial oversight is critical for preventing educational mismatch, especially in sectors with less formalized skill requirements.

Finally, second-level wage bargaining (as a proxy for performance-related pay) reduces mismatch significantly only in the Construction sector (-3.14 pp, significant at the 10% level). Construction work is typically project-based, with varying educational requirements across tasks and limited formal monitoring mechanisms. In this context, performance-linked pay may help retain workers whose educational background better matches the tasks at hand while discouraging those with mismatched qualifications. Decentralized wage-setting may also enable firms to fine-tune pay structures to align with local labor market conditions, enhancing this relationship. However, because second-level wage bargaining displays opposite associations across mismatch types, its overall impact may be masked also in this sectorial analysis.

[14] We have divided manufacturing into high- and medium-high-technology industries versus low- and medium-low-technology industries, following the Eurostat classification (https://ec.europa.eu/eurostat/statistics-explained/index.php? title=Glossary: High-tech_classification_of_manufacturing_industries). Services were classified into knowledge-intensive services (KIS) and less knowledge-intensive services (LKIS) (https://ec.europa.eu/eurostat/statistics-explained/index.php? title=Glossary: Knowledge-intensive_services_(KIS)).

Table 6 Incidence of mismatch, and human resource practices; fractional logit; subsample analysis by sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Industry (dy/dx)	Construction (dy/dx)	Services (dy/dx)	Manufacturing (dy/dx)	High-tech man. (dy/dx)	Low-tech man. (dy/dx)	KIS (dy/dx)	LKIS (dy/dx)
Human resource practices								
Use of public employment services for recruitment	-0.6020	0.1075	0.2746	-0.6910	-0.5066	-0.7761	-0.4919	0.6247
	(0.4614)	(1.1373)	(0.5039)	(0.4776)	(0.7893)	(0.5922)	(0.8153)	(0.6353)
Use of private recruitment agencies	-0.4659	-0.5928	-0.5396	-0.4520	-1.1937*	-0.0954	-0.1267	-0.9353
	(0.2875)	(0.8334)	(0.3949)	(0.3008)	(0.5213)	(0.3668)	(0.6555)	(0.4898)
The firm offers on-the-job training	-1.0382***	-1.5978***	-0.8147***	-0.9557***	-0.7610	-1.0148***	-0.6801	-0.9177***
	(0.2317)	(0.4364)	(0.2206)	(0.2469)	(0.5110)	(0.2808)	(0.3511)	(0.2787)
Average span of control per supervisor	0.1825***	0.4703***	0.0453***	0.1735***	0.1292***	0.1978***	0.0347**	0.0504***
	(0.0242)	(0.1312)	(0.0071)	(0.0268)	(0.0322)	(0.0399)	(0.0119)	(0.0092)
Second-level wage barg. (link to prod.)	0.3068	-3.1439*	-0.1315	0.3165	-0.5872	0.6928	-0.2444	-0.0018
	(0.4007)	(1.4374)	(0.5886)	(0.4256)	(0.7197)	(0.5254)	(0.8470)	(0.8127)
Type of mismatch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-region FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log pseudolikelihood	-10,046.518	-3,251.7674	-12,550.953	-8,917.7524	-1,894.2612	-7,018.2616	-4,953.05225	-7,564.9789
#Observations	25,248	7,978	28,780	22,365	4,835	17,530	11,311	17,469
#Firms	17,133	5,670	20,621	15,133	3,272	11,861	7,867	12,754

ITLFS-RIL database; 2009, 2014, 2017 (N = 62,006). Coefficients of industry-region FEs, year FEs, types of mismatch and firm controls are not reported to save space. Full tables are available from authors upon request. All columns report the marginal effects (dy/dx). Categories are defined, based on the statistical approach, as it follows: (1) 'Undereducation': the actual share of employees with compulsory (tertiary) education is greater or equal (lower or equal) to the expected one; (2) 'Too little secondary': the actual share of employees with tertiary (compulsory) education is greater than (greater than) the expected one; (3) 'Matched': the actual shares of employees with compulsory, upper secondary and tertiary education is equal to the expected ones; (4) 'Too much secondary': the actual share of employees with compulsory (tertiary) education is lower than (lower than) the expected one; (5) 'Overeducation': the actual share of employees with tertiary (compulsory) education is greater or equal (lower or equal) to the expected one. In all columns category (1) 'Undereducation' is the reference (omitted) category. Robust standard errors are reported in parentheses. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively

Taken together, these results underline that sectoral context matters for understanding the impact of HRPs on educational mismatch. HRPs such as training, structured recruitment, and managerial oversight appear most effective in sectors where the alignment of formal qualifications with job demands is either critical (as in high-tech manufacturing) or more easily influenced by firm-level practices (as in low-tech manufacturing and LKIS). These findings support the case for sector-sensitive HR strategies and policies that account for differences in production processes, educational requirements, and labor market structures.

7 Concluding remarks

This paper complements the existing literature on educational mismatch by investigating this phenomenon at the firm level and assessing the role of human resource practices in mitigating or exacerbating it.

Building on previous theoretical and empirical contributions, we propose a conceptual framework linking recruitment, training, monitoring, and performance-related pay to different types of mismatch, i.e., overeducation, undereducation, and their combinations, and derive a set of testable hypotheses. We introduce a novel firm-level measure of educational mismatch that uses the full distribution of educational levels as a benchmark and that can be implemented even without matched employer-employee data. By comparing the expected and observed distributions of employees' educational attainment (where expected shares are calculated for comparable firms by sector, size, and year), our measure captures the incidence of mismatch among a firm's workforce. This approach also allows us to identify distinct types of mismatch and to explore heterogeneity in HRP-mismatch associations across these types and across sectors.

The empirical analysis, based on Italian data for 2009, 2014, and 2017, indicates that on-the-job training is the HRP most consistently associated with lower educational mismatch, particularly in firms where overeducation is prevalent and in low-tech manufacturing and less knowledge-intensive services. More effective monitoring, proxied with a narrower span of control, is also significantly correlated with lower mismatch across most mismatch types and sectors, suggesting that more focused supervisory oversight is linked to better educational alignment. Private recruitment agencies are significantly associated with lower mismatch mainly in high- and medium-high-tech manufacturing, and in firms where either undereducation or overeducation predominates, whereas public employment services show no consistent association with mismatch. Finally, second-level wage bargaining linked to productivity (as a proxy for performance payment) displays opposite association depending on the type of mismatch: it is negatively associated with mismatch in firms with prevalent overeducation, but positively associated in firms where undereducation dominates.

Overall, these findings confirm that HRPs are linked to educational mismatch in nuanced ways. The type of mismatch prevalent within the firm and the sector in which it operates both shape these associations, underscoring the need for targeted HR strategies. In policy terms, the results suggest that firm-level practices (partic-

ularly those related to training, recruitment quality, and managerial oversight) can address mismatch, provided they are tailored to sectoral conditions and the nature of the mismatch. Given the persistence of educational mismatch and its exacerbation by structural changes and economic shocks, understanding and leveraging these firm-level levers remains a critical priority for both managers and policymakers.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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