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ABSTRACT

AI occupational exposure and wage distribution: the case of Italy

This paper investigates the effect of artificial intelligence exposure on occupations across the entire wage distribution for a sample of Italian employees. We use an employer-employee dataset for the period 2011-2019 and a survey on the characteristics of occupations to build an indicator for AI exposure that particularly accounts for AI's potential as a complement to labour, and to define highly and lowly exposed occupations. Additionally, we decompose the wage gap between highly and lowly exposed occupations. Our findings highlight a positive association between artificial intelligence exposure and wages, especially for occupations at the top of the distribution. Notably, the positive effect of artificial intelligence diminishes around the median of the distribution, thereby suggesting that artificial intelligence could exacerbate wage inequality between low-wage and high-wage workers, contributing to a more polarised labour market. The decomposition analysis shows a decreasing role of the unexplained component of the gap across the wage distribution. Among the explored factors, gender and education contribute significantly to the change. The characteristics that most contribute to explaining the disadvantage of low-paid positions are the same ones that are more highly rewarded in top-paid positions. To prevent rising inequalities, it is crucial to invest especially in education and in workforce training (reskilling and upskilling).

KEYWORDS: artificial intelligence, sector of economic activity, wage distribution; unconditional quantile regression: O-B decomposition
JEL Classification: C21; E24; O33

Questo articolo esamina la relazione tra l'esposizione all'intelligenza artificiale (IA) delle occupazioni e i salari guardando all'intera distribuzione salariale. A partire da un dataset di tipo employer-employee arricchito dalle informazioni derivanti da una survey contenente informazioni dettagliate sulle caratteristiche di ogni singola occupazione, stimiamo un modello di regressione quantilica non condizionata per un campione di lavoratori dipendenti italiani nel periodo 2011-2019. Al fine di verificare l'esistenza di un differenziale salariale attribuibile esclusivamente al tipo di occupazione, definito sulla base di un indicatore di esposizione potenziale che cattura soprattutto la complementarietà all'IA, stimiamo anche il modello di decomposizione Oaxaca-Blinder (1973). I risultati evidenziano l'esistenza di un premio salariale associato alle occupazioni altamente esposte/complementari all'AI, soprattutto per quei lavoratori che si trovano nella parte alta della distribuzione, mentre si riduce per quei lavoratori che si trovano nella parte centrale suggerendo che l'intelligenza artificiale potrebbe aggravare la disuguaglianza salariale tra lavoratori a bassa e ad alta retribuzione, contribuendo così al perdurare di un mercato del lavoro polarizzato. L'analisi dettagliata delle variabili che contribuiscono a spiegare sia la componente spiegata che quella non spiegata suggerisce come, per evitare il possibile aumento delle disuguaglianze, sia necessario ed urgente investire nell'istruzione e nella formazione della forza lavoro e, in particolare, nel reskilling e upskilling dei lavoratori la cui occupazione risulta essere meno complementare all'IA.

PAROLE CHIAVE: *Intelligenza Artificiale, settori di attività economica, distribuzione salariale, UQR: O-B decomposition*

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1. Introduction

The rise of Artificial Intelligence (AI) is reshaping economies worldwide, revolutionizing industries, and altering the dynamics of the labour market significantly. AI's pervasive application in many areas, ranging from automation and machine learning to robotics and natural language processing, is ushering in a new era of productivity and technological innovation. However, alongside its potential for growth and advancement, AI also presents substantial challenges for labour markets, particularly in terms of employment, wages, job displacement, and skills development.

The economic literature on AI and labour markets spans a range of topics including the displacement of jobs due to automation, the creation of new types of work, and the overall impact on income distribution. Early studies on technological change, such as those by Autor (2015) and Brynjolfsson and McAfee (2014), established the foundational understanding that technological innovation has historically led to both the destruction of certain types of jobs and the creation of new ones. However, the speed and scale at which AI is advancing raise unique concerns that have led to an acceleration of these effects in the present era. According to Frey and Osborne (2017), many jobs, particularly those involving manual or cognitive routine tasks, are at high risk of automation. This observation is compounded by the rapid development of AI technologies, capable of performing tasks traditionally requiring human intervention, such as customer service, data analysis, and even medical diagnoses. The displacement effects of AI, as highlighted by the work of Chui *et al.* (2016), are pertinent especially in sectors such as manufacturing, retail, and transport where automation through robotics and AI-driven systems can lead to substantial job losses. These sectors employ a significant proportion of low-skill workers, who are more likely to be impacted by AI-induced automation. Despite this, while AI is set to replace jobs, it is also expected to generate new employment opportunities. Brynjolfsson and McAfee (2014) argue that AI can be a powerful catalyst for job creation in sectors involving higher cognitive tasks, such as technology, healthcare, and education. As AI enhances productivity, a new demand for specialized skills is anticipated, thereby necessitating an evolving labour force.

On the flip side, the growing disparity between low-skill and high-skill workers is becoming a critical issue. Autor *et al.* (2003) in their seminal work on "the polarization of job opportunities" argue that technological advancements, including automation, contribute to the hollowing out of the labour market, where middle-wage jobs are most vulnerable. This phenomenon is expected to accelerate with AI technologies, increasingly capable of performing tasks traditionally done by low-skill workers, such as data entry, assembly line work, and customer service. Acemoglu and Restrepo (2018) emphasize that while AI may lead to new job creation, it could also exacerbate wage inequality between different groups of workers and lead to a more polarized labour market. The displacement of these jobs may result in wage stagnation or declines in certain sectors, as displaced workers are likely to struggle to transition into higher-paying roles without adequate training opportunities. Finally, the substitutive effect of AI on labour could lead firms to curb their labour investment, resulting in reduced workers' income. Through a two-stage overlapping generation model, Benzell *et al.* (2015) demonstrate that high-productivity AI reduces labour inputs and wages.

The widening income gap is a central concern and a substantial body of economic literature advocates for strategies to mitigate these disparities, such as investment in human capital through education and retraining programs (Goldin and Katz 2009). Therefore, the debate on AI and wage distribution also involves policy considerations. Policymakers are focused increasingly on addressing the challenge of skill mismatches in the labour market and the need to ensure that workers displaced by AI technologies are equipped with the necessary skills needed to adapt to new roles in the evolving economy. Acemoglu and Restrepo (2020) suggest that the outcomes of AI-driven automation will largely depend on labour market policies, educational systems, and the structure of welfare states. In this way, governments could play a crucial role in managing transitions by investing in training and reskilling or up-skilling programs, as well as introducing social safety nets to help those displaced by automation (Bessen 2019). If policy interventions are designed effectively, they could mitigate some of the negative effects of AI, ensuring a more inclusive distribution of its economic benefits.

Starting from these considerations, this paper fits into this literature by exploring the effect of AI occupational exposure on wages, focusing on the entire wage distribution by using an employer-employee dataset for Italian workers. Indeed, Italy is an interesting case study due to the coexistence/combination of population ageing and stagnating real wages and real incomes (see, for instance, Brandolini *et al.* 2018). We offer both descriptive and econometric analyses. For the former, we define an index for potential AI occupational exposure that accounts especially for AI's potential complement for labor, describing occupations in terms of their degree of AI exposure and classifying them as highly or low exposed. For the latter, we estimate an unconditional quantile regression (UQR) proposed by Firpo *et al.* (2009) to investigate the effect of AI occupational exposure across the overall wage distribution, i.e. we consider the bottom (10th percentile), the median (50th), and the top (90th). In a second step, we apply a decomposition technique (Oaxaca-Blinder recentered influence function decomposition) on the wage gap between highly and low AI exposed occupations, to better understand the sources of wage inequality. In fact, this methodology helps to break down the overall wage gap into its components and to identify the specific factors—such as differences in characteristics (e.g. gender, education, experience) and differences in returns to those characteristics—that contribute to the wage disparities among workers employed in occupations with varying exposure to AI technologies.

The novelties of our paper are mainly two. First, we construct an alternative general potential AI occupational exposure index, based on the Indagine Campionaria delle Professioni (ICP) survey provided by Istituto nazionale delle politiche pubbliche (Inapp) and three AI exposure "sub" indices that consider different dimensions of the general one. Second, we use novel administrative data that allow exploring the effect of AI across the overall wage distribution through the UQR technique. The data provide detailed information on the type of occupation and the economic activity sector, both used as determinants of the wage regressions. Our findings suggest a positive association, a wage premium-between AI exposure (overall and its main components) and wage for high-paid occupations, i.e., occupations at the top of the wage distribution. Interestingly, the wage premium associated to highly AI exposed occupation diminishes around the median of the distribution, suggesting that artificial intelligence could exacerbate the wage inequality between low-wage and high-wage workers (i.e., Acemoglu and Restrepo 2018) and contribute to a more polarized labour market. Our decomposition analysis shows a decreasing role of the unexplained component of the gap across the wage distribution. The main factors that significantly contribute to this evidence are gender and educational attainment level, especially. In other words, the characteristics that most significantly contribute to explaining the

disadvantage of low-wage workers are the same that are more highly rewarded in top-paid positions. These findings are robust across the different AI index components investigated.
The paper proceeds as follows: Section 2 reviews the existing literature, Section 3 describes our potential AI occupational exposure index. The empirical model is presented in Section 4, while Section 5 discusses the data used and provides a descriptive analysis. Section 6 shows the main findings and Section 7 concludes.

2. Literature review

The economic literature that empirically investigates the relationship between AI and labour market is developing and growing rapidly. The available evidence regarding the nature of this association is mixed: AI can act either as a complement to or a substitute for labour (Autor and Salomons 2018; Bessen 2017). Research on robots, for instance, provides mixed findings: some studies report no effects of robots on labour (Graetz and Michaels 2015), while others find evidence that robot adoption leads to job losses (Acemoglu and Restrepo 2017). Frey and Osborne (2017) take a different approach by categorizing tasks based on their susceptibility to automation, linking these tasks to occupation, employment, and wage data, finding that almost half of US employment is at high risk of automation. The concern about the possible impact on labour is even more relevant if we consider the effect and the advancements of artificial intelligence, but the extent of the potential substitution effect of these latter on the labour market is still uncertain (i.e. Autor and Salomons 2018). Moreover, the relevance and the duration of such effect should also differ across countries (heterogeneity of such effect across countries). Many empirical studies have focused largely on the US, finding that several tasks performed by a significant portion of the workforce, especially those of high-skilled workers, could be substantially replaced by AI (e.g., Felten *et al.* 2018, 2021; Eloundou *et al.* 2023; Webb 2019). Among the works on the US, Felten *et al.* (2018 and 2021) developed one of the most relevant (and widely used) index to measure the occupations exposure to AI. An occupation is defined as exposed if there is an association between the occupation itself and AI, which should entail a risk of being substituted as well as a risk of complementarity. The Felten, Raj and Seamans index for AI exposure is constructed by analysing the alignment between job-related tasks and AI capabilities. By linking these AI research topics to tasks outlined in the Occupational Information Network (O*NET) database, the index measures how various jobs are exposed to AI-driven change.
Few studies (OECD 2023; Albanesi *et al.* 2023; Gmyrek *et al.* 2023; Pizzinelli *et al.* 2023; Cazzaniga *et al.* 2024) adopted a cross-country approach. The OECD (2023), for instance, suggests that, as found for the US, high-skilled occupations (including business professionals, managers, science and engineering professionals, legal, and social and cultural professionals), have been the most exposed ones to recent advances in AI. Albanesi *et al.* (2023), using also the index provided by Felten *et al.* (2018), provide evidence on employment shares and relative wages by occupations in some European countries during the period 2011-2019. They also explore how this association varies across skills and age groups. Their results suggest a positive association between AI-enabled automation and changes in employment shares especially for younger and high-skilled workers, regardless of the exposure measure used. However, they do not obtain

a clear signal for the impact on wages. The magnitude of the estimates varies importantly across countries. Gmyrek *et al.* (2023), for instance, undertake a comprehensive review of emerging market economies and find a relatively lower exposure to AI with respect to advanced economies. Pizzinelli at al. (2023) explore the effect of AI on labour markets in both advanced economies and emerging markets. They use a standard measure of AI exposure (accounting also for AI potential as either a complement to or a substitute for labour). Their findings suggest that among workers, women and highly educated employees face greater occupational exposure to AI, as well as those workers in the upper tail of the earnings distribution. Those findings are confirmed by the work of Cazzaniga *et al.* (2024) which investigate a very large sample of advanced and emerging market and developing economies.

Specifically on Italy, country of our interest, Ferri *et al.* (2024) and Dalla Zuanna *et al.* (2024) after reviewing different measure of AI exposure, investigate the distribution of occupations across sectors, age and gender in the economy. They use, among others, the index proposed by Felten *et al.* (2018, 2021) and the extension of Pizzinelli *et al.* (2023) on 2023 Italian Labour Force Survey data. They suggest that the most exposed occupations to AI are those in the top two quintiles of the income distribution[1], mostly in the service sector, and which employ a large share of women and highly skilled workers.

The automation of routine jobs and the adoption of AI could lead to an increase in wage inequality, as workers with low-skill or/and low-wage jobs are at risk of being displaced, while demand for high-skill, high-wage positions in AI-related fields (e.g., data science, robotics, and software engineering) is likely to increase. Brynjolfsson and McAfee (2014) argue that such technological advancements contribute to a “race between education and technology,” where the gap between the demand for skilled labour and the supply of adequately trained workers widens. As a result, workers with higher levels of education and specialized skills are expected to benefit from increased wages, while those without these qualifications may face diminished earning potential or even long-term unemployment. At the same time, AI is also seen as an enabler of productivity gains, which could lead to overall economic growth. According to Frey and Osborne (2017), AI’s impact on certain industries, such as healthcare, education, and finance, could lead to new opportunities for innovation and job creation. However, these opportunities may be concentrated in specific sectors or regions, with high-skilled workers benefiting disproportionately. The rapid pace of technological change means that workers in lower-wage industries, especially those without access to up-skilling or re-skilling opportunities, could find themselves increasingly at a disadvantage. Studies by Chui *et al.* (2018) highlight how the benefits of AI may not be evenly distributed across society, with many workers being left behind unless targeted efforts are made to address these disparities.

The literature on AI’s impact on wage distribution reflects a broad consensus that the effects will be shaped by both technological and societal factors. While AI has the potential to increase wages for high-skill workers and to promote economic growth, it could also lead to job displacement, wage polarization, and greater income inequality, particularly for low-skill workers. Understanding these dynamics and crafting policies that promote education, re-skilling, and inclusive growth will be crucial to ensuring that AI contributes to a more equitable distribution of wages in the future.

[1] This finding is in line with previous evidence on advances countries. Goos *et al.* (2009), for instance, found that technologies are becoming more intense in the use of non-routine tasks concentrated in high-paid jobs.

3. The potential AI Occupational Exposure index

The rapid advancement of AI and its growing integration into various sectors has led to the development of several methodologies aimed at measuring occupational exposure to AI itself (see, e.g., Felten *et al.* 2021; Pizzinelli *et al.* 2023). These indices are critical for understanding how AI adoption impacts labour markets, skill requirements, and overall job displacement or transformation. Following Arntz *et al.* (2016), we propose an index that combine both task and skill dimensions, offering a more nuanced analysis.

To classify occupations according to their potential[2] AI exposure, we employ the Indagine Campionaria delle Professioni (ICP) conducted by Inapp in collaboration with the National Institute of Statistics (ISTAT). The ICP survey was last run in 2013, and it involves 16,000 workers; it ensures representation across sectors, occupations, firm sizes, and macro-regions, providing data at the five-digit CP-2011 classification[3] (covering 811 occupations) of the Italian labour market. The questionnaire consists of 255 questions, divided into seven thematic sections: Section B - Knowledge requirements; Section C - Skills requirements; Section D - Abilities requirements; Section E - Values requirements; Section F - Work Styles requirements; Section G - Work Activities; Section H - Working Conditions. Sections B, C, D, and G share a consistent structure and highlight skills or task required for the job[4], Section F addresses soft skills. The ICP-Inapp can be considered as the Italian equivalent of the American O*NET, that is the most comprehensive repertoire reporting qualitative and quantitative information on tasks, work context, and organizational features of workplaces at detailed level. A relevant aspect of ICP-Inapp is that tasks, skills, and other characteristics of occupations are specific to the Italian economy, and they allow for the definition of the labour market structure and the industrial relations characterizing the Italian economy.

Our measure of exposure to AI accounts especially for potential complementarity between AI and labor, reflecting lower risks of job displacement, and it is constructed using five of the seven sections of the ICP questionnaire referring respectively to: knowledge, skills, work styles, work activities, and work condition. Therefore, we restrict the analysis to sections B, C, F, G, and H excluding section D on attitudes, and section E on work values[5]. We focus on 26 ICP questions[6] assessing the relevance of each aspect within an occupation by using a 1–5 scale. Table 1 reports the definition of each set, and the aspects related to AI used for the construction of our Potential AI Occupational Exposure index (PAIOE, hereafter).

[2] We use the term "potential" because we are talking about the potential impact or involvement of AI in someone's occupation. It could be direct (working with AI systems) or indirect (being affected by AI in the workplace), and the term acknowledges that this is a possibility that may vary depending on the industry, job, or time in the future.

[3] The CP2011 classification is the Italian Classification of Occupations (Classificazione delle Professioni 2011), which is a system used in Italy to categorize and classify occupations based on the nature of work, skills, and tasks involved. It is part of the broader framework of labour market statistics, and it is aligned with international standards, particularly the International Standard Classification of Occupations (ISCO).

[4] It could be argued that Section G refers to tasks instead of skills, which may lead to a conflation of distinct concepts. However, as proposed by Yamaguchi's (2012) framework, "observed tasks can be seen as a noisy signal of unobserved skills."

[5] The rationale for excluding Section D from the analysis lies in its focus on individual characteristics that are, by definition, "relatively stable over time and hard to modify."

[6] The questions used for each index are reported in table A1.

Table 1 Occupational characteristics and aspects related to AI

Set of occupational characteristics (ICP section)	Definition	Aspects related to AI
B. Knowledge	The set of facts and principles necessary to address the problems and issues related to the work performed	Mathematics, Computer Science and Programming, image generation, reading comprehension
C. Skills	The set of procedures and cognitive processes that determine the ability to perform the tasks of a profession well	Learning capability, problem solving, logical reasoning, text comprehension, monitoring, efficient communication, analysis of complex systems, programming
F. Work styles	The ways of being and doing of the worker necessary for the proper performance of the occupation	Cooperation; teamwork; innovation, analytical thinking
G. Work activities	The set of actions, practices, or similar processes that form the basis of the specific tasks performed in the occupation	Data analysis; decision making and problem solving; think creatively; it/use of computer; info interpretation (and use); grow and activate work teams; motivation of colleagues.
H. Work condition	Physical conditions and working methods that characterize the occupation	The level of automation

Source: ICP questionnaire

Once the ICP survey questions have been identified, following the methodology proposed by Barbieri *et al.* (2022), we compute our PAIOE index as follows: for each question, we calculate the average of the responses given by each worker and then we aggregate it at 5-digit occupational level. To improve the interpretability of the results, all scores were standardized in their range of variation through the following formula:

$$X = \left(\frac{Y - \min}{\max - \min}\right) * 100 \qquad (1)$$

where Y is the original answer (from 1 to 5), max and min are the maximum and the minimum value reported for the question. The standardized value of the PAIOE index is thus in the range [0 -100]. Unlike Dalla Zuanna *et al.* (2024), our index is built starting from the 5-digit occupational code, allowing for a much more detailed identification of occupations that are exposed to AI. As robustness checks, we disaggregated the PAIOE indicator according to three main dimensions (see table 1) – 'knowledge and skills' (Sections B and C), 'labour activity' (Section G), and 'labour style' (Section F) – obtaining three additional potential AI occupational exposure indices.

Table 2 lists the ten occupations (at 5-digit) with the highest and lowest value of PAIOE index which measures the degree to which, potentially, various occupations could be affected, especially in terms of complementarity, by the development and deployment of AI. As occupation with the highest level of the PAIOE index, we find physicists; they are at the forefront of technological advancements and research, and the AI can assist significantly in data analysis, simulations, and computational tasks, making their work more efficient and expanding their ability to address complex scientific problems. The high value of index reflects the integration of AI into scientific research. Occupations related to science, engineering, and academia, particularly those with prevalent complex data analysis and technological advancements, exhibit the highest AI exposure. AI is seen as an enabler in many roles such as automating tasks, optimizing decision-making processes, and advancing research capabilities (Davenport and Kirby 2016). At the same time, there are notable occupations like police chiefs and avionics technicians, where AI is not necessarily part of the core function, but its integration into these fields is becoming increasingly essential. For instance, AI can play a role in predictive policing or aircraft maintenance optimization, which contributes to their higher exposure to AI.

The bottom panel of table 2 suggests that occupations with the lowest value of PAIOE index are, primarily, those service-oriented or involving manual labour, where human interaction, presence, and physical skills are crucial. For these occupations, the integration of AI and automation remains limited, with most of the technological advancements augmenting other aspects of work (e.g., supply chain optimization, surveillance, or robotic assistance) rather than directly replacing these jobs. In comparison to occupations with highest value of PAIOE index, these occupations are less likely to see direct disruption from AI technologies (Frey and Osborne 2017). However, AI's indirect effects, such as through app-based platforms, automated systems, or data analytics could still affect how these jobs are performed, albeit at a lower exposure rate.

Overall, table 2 shows that the highest potential AI exposure is found for occupations that are directly involved with technological innovation, research, or complex data analysis, especially in science and engineering fields. Traditional and interpersonal occupations (like domestic work, street vending, and manual labour) remain relatively shielded due to their human-centric nature (Brynjolfsson and McAfee 2014; Chui *et al.* 2018), but the broader trend of automation across industries suggests that some of these occupations may experience indirect or incremental changes in the future.

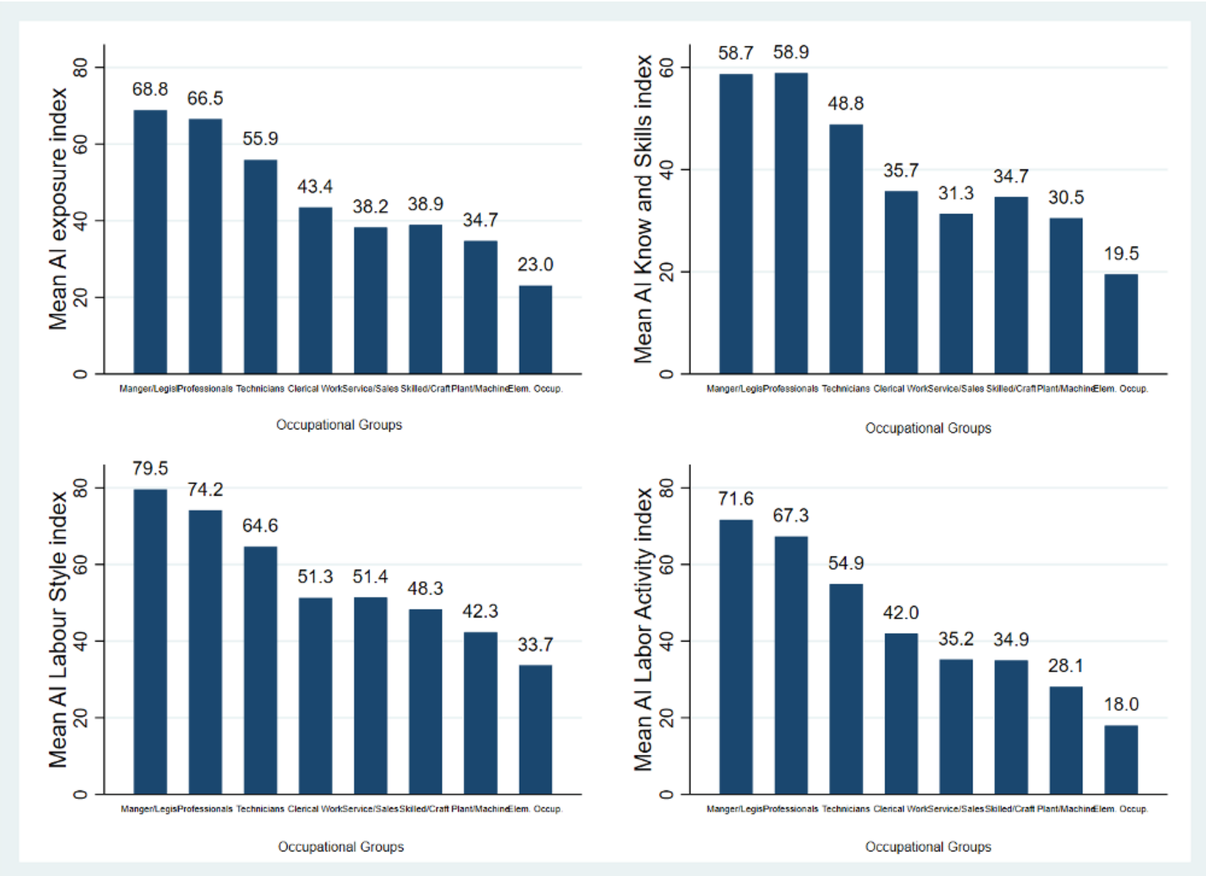
Table 2 Occupations with the highest and lowest value of AIOE index

CP2011 Code	CP2011 Nomenclature	PAIOE index
	Top 10 Occupations	
21111	Physicists	100,00
26132	University professors in industrial and information engineering sciences	98,28
26232	Researchers and technicians with a degree in industrial and information engineering sciences	94,36
11222	Chiefs and deputy chiefs of the State Police, police commissioners, and senior public security officials	93,34
31622	Avionics technicians	89,22
26223	Researchers and technicians with a degree in medical sciences	88,69
26212	Researchers and technicians with a degree in physical sciences	88,30
26113	University professors in chemical and pharmaceutical sciences	88,26
12390	Other directors and department heads	87,43
26114	University professors in earth sciences	87,16
	Bottom 10 Occupations	
74240	Animal-drawn vehicle drivers	10,95
83220	Unqualified personnel responsible for animal care	10,39
84210	Labourers and unqualified personnel in civil construction and related professions	10,18
81110	Street vendors of goods	9,10
54410	Companions and qualified household service personnel	8,57
82210	Domestic workers and related professions	7,41
81613	Unqualified personnel responsible for the safeguarding of equipment and goods	7,31
81420	Unqualified personnel in the catering services	6,87
51220	Retail sales assistants	5,77
81120	Street vendors of services	0

Source: Authors' elaborations on ICP-2013 data

Figure 1 reports the mean value of PAIOE index and of the others three indices for each 1-digit occupation[7]. We notice that high-skilled occupations are those highly exposed to AI, according to all the indices considered (AI overall as average of the other dimensions). Moreover, Figure 1 shows the extent to which different occupational groups are affected by AI, whether in terms of exposure, required skills, or involvement in AI-related tasks. In line with the view that low-skilled occupations are generally little exposed (Dalla Zuanna *et al.* 2024), the four panels of Figure 1 show a decreasing trend in the indices as we move from the left to the right across occupational groups, suggesting that the first group ("Manager/Legislator") has the highest exposure, knowledge, skills, and labour activity related to AI, while the last group has the lowest.

Figure 1. Mean PAIOE indices for each 1-digit occupation



Source: Authors' elaborations on ICP-2013 data.

[7] In the CP2011 occupations are grouped into categories based on a hierarchical structure. The 1-digit occupations represent the broadest level of classification and include the following major groups: Managers/Legislators; Professionals; Technicians and Associate Professional; Clerks; Services and Sales Workers; Skilled Agricultural, Forestry, and Fishery Workers and crafts; Plant and Machine Operators; Elementary Occupations.

4. The empirical methodology

To understand how the AI potential exposure of occupations affects wage distribution, we apply the methodology proposed by Firpo *et al.* (2009), the Unconditional Quantile Regression (UQR), which allows to go beyond the mean in the estimation of explanatory association. Indeed, the UQR is designed to overcome some of the limitations of linear model: it provides a more flexible approach by estimating relationships at various quantiles of the distribution, offering robustness in the presence of outliers and heteroscedasticity. Moreover, unlike the conditional quantile regressions approach, the UQR estimates the effects of covariates on the entire distribution of the outcome variable without relying on specific covariate distributions. This approach is particularly valuable in the context of heterogeneity – where different subgroups or segments of a population may respond differently to covariates, providing a more comprehensive view of treatment effects by capturing heterogeneity across different parts of the distribution (e.g., the effects on low-income vs. high-income individuals, or on the "rich" vs. "poor" segments of the outcome distribution). The UQR method aims to identify how small location shifts in the distribution of explanatory variables affect a statistic of interest (F). To be applied, the method introduced by Firpo *et al.* (2009) involves the calculation of the Recentered Influence Function (RIF) which is defined as:

$$\mathrm{RIF}\left(y; v, F\right) = v\left(F\right) + \mathrm{IF}\left(y; v, F\right) = v\left(F\right) + \lim_{t\to 0} \frac{v((1-t)F + t\Delta y) - v(F)}{t} \quad (2)$$

where the $\mathrm{IF}(y; v, F)$ is the influence function initially introduced by Hampel (1974). According to Firpo *et al.* (2009), once the values of $\mathrm{RIF}(y; v, F)$ are computed for all observations, the effects of a marginal change in the distribution of the variable of interest (i.e. the AI exposure) on the distributional statistic $v\ (F)$ can be correctly calculated through a simple OLS estimation. Following Choe and Van Kerm (2018), we estimate the 'unconditional effect' assuming as marginal change a 10% swapping share of employees from one type of occupation (i.e. high exposed to AI) to another one (i.e. low exposed to AI). The core idea of this methodology is: if the described marginal change engenders significant effects on distributional statistics, then the type of occupation, defined in terms of its AI potential exposure, influences the wage distribution. In other words, the bigger and more distant from zero the estimated coefficients are, the more the AI exposure plays an important role in the wage distribution.

The UQR method also allows for considering relevant characteristics, which may diverge among workers employed in different occupations and therefore potentially lead to incorrect effects on the distributional statistics. We then regressed RIFs on a vector of covariates concerning both workers and firm's characteristics: gender, age (and age square), experience (measured by the number of work arrangements), educational level, citizenship, region of work, sector of activity, firm's size, and type of contract (fixed-term or permanent, and part-time or full-time). In our analysis, we estimate the unconditional effects of the occupational exposure to AI on the wage distribution focusing on the following distributional statistics: the 10th, 50th and 90th quantile. Therefore, we estimate the following model:

$$RIF\,(Y_i;\, Q_\tau) = \alpha_\tau + \beta_{i\tau}\, PAIOE_i + \sum_{k=1}^{n} \gamma_{k\tau} X_{ki} + \varepsilon_i \quad (3)$$

where Y_i is the outcome variable, the (log) of weekly gross wage, i denotes the employee, Q_τ is τth-quantile, PAIOE identifies the dummy for the Potential AI Occupational Exposure index linked to the

occupation performed by employee i. The dummy is equal to 1 if the occupation exhibits an AIOE index above the median and 0 otherwise, X_{ki} is the vector of n control variables, and ε is the error term. The coefficients of interest are $\beta_{i\tau}$.
In a second step, following the methodology of Firpo *et al.* (2018), we identify the effect of unobserved characteristics on the wage gap between high and low AI exposure occupations applying to the RIF-regression the Oaxaca–Blinder (OB) decomposition method. Indeed, the Oaxaca-Blinder (OB) decomposition is a widely used method in economics to decompose differences in mean outcomes between two groups (e.g., male and female workers) into two components: one that reflects differences in characteristics (the "explained" component) and another that reflects differences in returns to those characteristics (the "unexplained" component) (Blinder 1973, Oaxaca 1973). However, while the original methodology was created to analyse differences of outcome means, several articles provided improvements to extend the analysis to other distributional statistics (see Fortin et al. 2011 for a review). Firpo et al. (2018) describe the use of RIF regressions, in combination with a reweighted strategy proposed by DiNardo et al. (1996), as a feasible methodology for decomposing differences in distributional statistics beyond the mean. This methodology has several advantages among which the simplicity of implementation, the possibility of obtaining detailed contributions of individual covariates on the aggregate decomposition, and the possibility of expanding the analysis to any statistic for which a RIF can be defined (Rios-Avila 2020)[8].

5. Data and descriptive evidence

In this study, we use a dataset obtained by linking two administrative datasets on employees to a survey on occupations' characteristics.
The first dataset is the archive of employees collected by the Italian National Social Security Institute (INPS) that records a wide range of individual and work arrangements variables such as annual gross wage, age, gender, annual worked weeks, information on the type of contract (part-time versus full-time, temporary versus permanent), sector of activity, firm size, and geographical localization of the work arrangement.
The detailed information on employees' educational level and occupation, missing in the INPS archive, comes from the archive of Compulsory Communications System (*Sistema delle Comunicazioni Obbligatorie*, COB hereafter) provided by the Ministry of Labour and Social Policies. From year 2009 the COB archive records each job relationship that started, changed (e.g., because of a transformation from a fixed term to an open-ended arrangement), or ended for different reasons, of the contractual arrangement for all individuals working in Italy as employee. For each employee, it gathers information on occupation (5-digit) performed at the time of the communication, and the educational attainment. INPS and COB archives have been merged using the worker's tax code (*codice fiscale*). About this merged INPS-COB dataset, we use a representative sample obtained drawing data from four birth dates for each month and year. Finally, this employer-employee dataset has been merged to the ICP

[8] It is important to note that the decomposition analysis enables us to identify sources that contribute to the wage gap and its components across the wage distribution, but our results cannot be interpreted as causal effects.

containing the PAIOE index, and the other three sub-indices, by using the occupational code at 5-digits. The analysis focuses on the period 2011-2019[9] and, as for sample selection, we consider all employees, except the armed forces, aged between 15 and 64. In the case of multiple contracts associated with the same individual in the same year, we consider the longest contract only. The final sample covers around 13.000.000 individuals, and, as dependent variable, we employ the individual (log) weekly gross wage[10]. The PAIOE index is the main variable of interest that, as introduced in Section 4, takes the value of one if it is higher than the median value of PAIOE index distribution and zero otherwise. The same criterion applies for the AI_knowSkills, AI_LabourActivity, and AI_LabourStyle indices dummies. The explanatory set of variables includes individual level characteristics as well as job and firm characteristics. For the former, we consider gender, age, experience (number of job contracts), citizenship, and three dummy for education (primary, secondary, and tertiary education). For the latter, we include dummies for type of contract (fixed term or permanent, and full-time or part-time), firm size, sector of economic activity[11], and region of work. Table 3 shows the main descriptive statistics for the variables used in the analysis.

Table 3. Descriptive statistics for the whole sample of employees

Variable	Mean	Std. dev.
Weekly wage (FTE)	474.6 €	222.8
PAIOE	36.9	17.9
AI_knowSkills	31.2	16.2
AI_LabourActivity	34.0	19.6
AI_LabourStyle	47.4	18.8
Female	43.2%	0.5
Age	39.5	11.7
Experience	12.1	5.3
Foreign	13.8%	0.3
Primary education	40.0%	0.5
Secondary education	44.8%	0.5
Tertiary education	15.2%	0.4
Fixed term contract	29.6%	0.5
Part time	31.9%	0.5
Firm's size		
0-9 employees	32.4%	0.5
10-49 employees	25.6%	0.4
50-249 employees	16.2%	0.4
>250 employees	25.8%	0.4
Variable	**Mean**	**Std. dev.**

follows

[9] The analysis of the effect of the COVID-19 pandemic on the relationship of interest is out of the scope of the present work.
[10] The weekly gross wage, expressed in euro at current prices (2019), is converted into full time equivalent (FTE) (see Venturini and Villosio 2008). Moreover, we drop the first and the last percentile of the wage distribution.
[11] Starting from the ATECO-2007 classification managed by Istat, we define 12 sectors of economic activity (see table 3).

table 3 *follows*

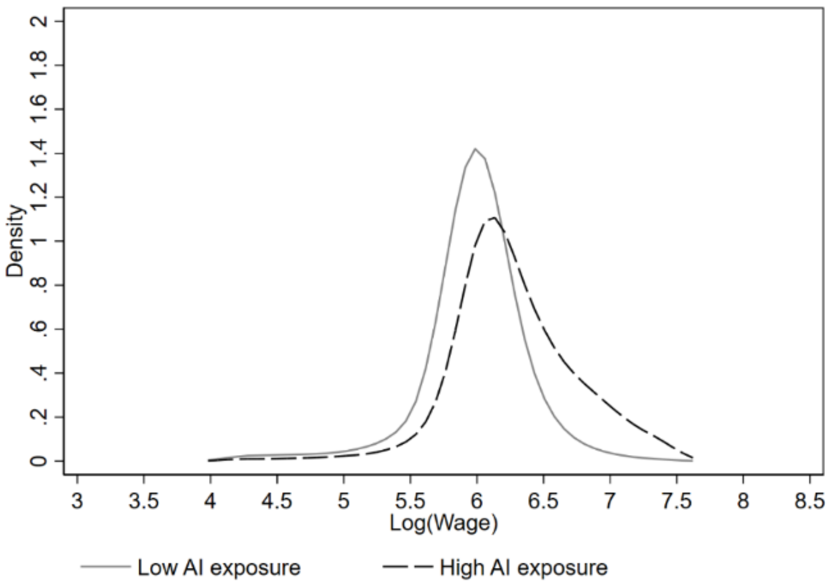
Sector of Economic activity		
Agriculture	0.5%	0.1
Mining and quarrying	0.002	0.0
Manufacturing	22.0%	0.4
Public utilities	1.2%	0.1
Constructions	8.0%	0.3
Wholesale and retail trade	14.8%	0.4
Transportation	6.4%	0.2
Accommodation and food service activities	12.1%	0.3
Information and communication	2.6%	0.2
Financial and insurance activities	1.9%	0.1
Real estate activities and firms' services	15.8%	0.4
Public administration and other services	14.6%	0.4
Regions		
Piemonte	7.2%	0.3
Valle d'Aosta	0.003	0.1
Lombardia	20.5%	0.4
Trentino alto Adige	2.5%	0.2
Veneto	9.6%	0.3
Friuli-Venezia Giulia	2.1%	0.1
Liguria	2.4%	0.2
Emilia-Romagna	8.8%	0.3
Toscana	6.6%	0.2
Umbria	1.3%	0.1
Marche	2.7%	0.2
Lazio	10.0%	0.3
Abruzzo	2.2%	0.1
Molise	0.4%	0.1
Campania	7.4%	0.3
Puglia	5.4%	0.2
Basilicata	0.7%	0.1
Calabria	2.0%	0.1
Sicilia	5.5%	0.2
Sardegna	2.4%	0.2
Observations	12,719,920	

Note: All observations are weighted with individual weights provided by INPS. Values in percent, apart from wage (euros), the indices (overall and its components), age and experience (years). We also control for year dummies.

Source: Authors' elaborations on INPS-COB-ICP data 2011-2019.

Occupations can be classified as low or highly exposed to AI on the base of their value of PAIOE index: an occupation is highly exposed if the related PAIOE index is higher than the median value of index distribution, while it is low exposed if it is lower than that value. Figure 2 shows the Kernel densities for the log wage of workers employed in low and highly AI exposed occupations highlighting that the wage distribution of employees with highly exposed occupations is clearly shifted to the right with respect to the one with low exposed occupations.

Figure 2 Kernel density for the wage distribution of low and high AI occupational exposure's



Source: Authors' elaborations on INPS-COB-ICP data 2011-2019

6. UQR and decomposition analysis

Table 4 reports the estimates of the unconditional quantile regression at the 10th, 50th (median) and 90th percentile of the wage distribution.

The PAIOE index (as well its components, see table 5) is positively associated with wage, suggesting the existence of a wage premium for those workers employed in highly AI exposed occupations, especially at the top of the wage distribution. The relatively high AI exposure of high paid occupations is in line with the available evidence for Italy (see, for instance, Dalla Zuanna *et al.* 2024). In wider terms, this result was also found for advanced economies and emerging markets as well as developing economies (i.e. Pizzinelli at al. 2023, Cazzaniga *et al.* 2024). Table 4 shows a wage premium of +3.4% for employees at the bottom of the wage distribution, which reduces to 1.7% at the median, and increases up to 5.1% at the 90th percentile. The fact that the positive effect of AI reduces at the median might be due to at least two-fold reasons. First, this should be one of the expected effects of AI on the wage distribution. Acemoglu and Restrepo (2018), for instance, suggest that AI might exacerbate wage inequality between different groups of workers and lead to more polarized labour market. Second, and more related to Italy, wages are in general stagnant, and this is especially the case of median/middle-class wages (i.e. Brandolini *et al.* 2018). When we consider the individual characteristics, we see a wage penalty for females especially at the top of the distribution, suggesting that the gender wage gap is more significant at top positions thereby revealing a glass-ceiling effect for females. Indeed, the wage difference between male and female increases from 1.1% to 2.4% from the bottom to the top of the wage distribution (Aina *et al.* 2023). As for age, we note an inverse U-shaped relationship at the 10th and middle of the wage distribution, which reverses to a U-shaped at the 90th percentile. Nonetheless, the mentioned effects are very low in magnitude. Moreover, table 4 highlights a positive association between education and wage, which increases along the wage distribution. The returns to education, in line with previous findings for Italy (i.e. Mussida and Picchio 2014, Aina *et al.* 2023), are especially large for graduates at the top of the wage distribution (+4.4%). Being foreigners and temporary workers are negatively associated with wage, instead. The latter effect confirms the evidence of a wage penalty for fixed-term contract (Brunetti *et al.* 2022) and, more in general, of a wage gap between permanent and temporary workers in Italy (see, for instance, Picchio 2006, Rossetti and Tanda 2007). Notably, there is evidence of a penalization also for part-timers, but from the median of the wage distribution. Whereas at the 10^{th} percentile there is a positive association between being part-timers and wage (+1.7%), the association turns out to be negative at the median and at the 90^{th} percentile of the wage distribution (-0.7% and -0.8%, respectively). Interestingly, the sign of the experience effect, as measured by the number of contracts, changes along the wage distribution, being positive at the bottom (+0.3%) and turning out to be negative at the 90th percentile (-0.1%). The latter effect might be because often employees at the bottom are at the beginning of their career and changing job contract should be both a relatively frequent event (to find the right match requires time/is time consuming) and (hopefully) associated with career improvements. This positive effect turns to be negative at the top of the distribution, i.e. career discontinuity is negatively associated with wages perspectives. Part-time might represent a 'positive' contractual option for those with poorest career developments (+1.7% at 10th percentile), while it affects wages negatively for those at the median and at the top of the wage distribution (-0.7 and -0.8%, respectively). Finally, the higher is the size of the firm, the higher is the positive effect on wages (up to +2.4% at the 90th percentile of the wage distribution for firm's size >250 employees). This is in line with expectations.

Regarding to the sector of economic activity, we do not see a clear pattern with respect to our base category, i.e. agriculture, forestry, and fishing. We note important heterogeneities across sectors. For some sectors, such as mining and quarrying, public utilities, and financial and insurance activities, we note an advantage across the overall wage distribution. Nonetheless, this positive effect on wage reduces as we move from the bottom to the top of wage distribution for mining and quarrying and public utilities, while the reverse is true for financial and insurance activities sector. For mining and quarrying the positive association with wage reduces from 3.1% at the bottom to 1.7% at the 90^{th} percentile; for public utilities we move from 3% at the top to 2.1% at the bottom; for financial and insurance activities the effect more than doubles, i.e. from 3.3 at the top to 7.2 % at the bottom of the distribution. Instead, for the other sectors there is a positive effect on wage, except at the top 90th percentile. For manufacturing, the association is positive at the bottom of the wage distribution (+2.3%), it reduces at the median (+0.2%), and it turns out to be negative at the 90^{th} percentile (-0.6%).

To clearly see whether the role of AI varies with the type of sector, we consider the interactions between these variables. In particular, the sum between the estimate of AI exposure dummy and the one of AI exposure*sector of economic activity dummies shows the effect of AI on each sector along the wage distribution. At the 10th percentile, we note that the effect of AI exposure is positive (and relatively negligible) for all sectors with the partial exception of financial and insurance activity (showing a relatively low wage penalty of -0.1%). At the median of the distribution, we see a wage premium from AI for all sectors, especially for real estate activities and firms' services (0.17 +0.01 = 0.18, that is +18%).

Instead, at the top, we see more heterogeneities across sectors. The wage premium ranges from 0.3% for public administration and other services to 14.9% for mining and quarrying. All in all, these interactions confirm the wage premium associated with AI exposure across the wage distribution, which increases as we move from the bottom to the top of the wage distribution. Nonetheless, as shown for the AI index, the effects are relatively lower for employees at the median of the wage distribution. This might be due, as mentioned above, to an increasing inequality among AI effects on workers (Acemoglu and Restrepo 2018), as well as to relatively stagnant Italian wages, especially at the median of the wage distribution (Brandolini *et al.* 2018).

Table 5 reports the effect of the overall AI exposure index, as showed at the top of table 4, and of its main components (for details on the questions used to build these indicators, see the Appendix table A1). Moreover, we see a positive effect of AI across the overall wage distribution. However, this latter does not increase across the distribution but, for all the indices, it reduces from the bottom to the median and then it increases at the top. Notably, the AI labour activity component follows the general AI exposure index almost perfectly. The AI labour style shows a relatively lower positive effect across the overall wage distribution as compared with the PAIOE (and AI labour activity), i.e. 2.4 % at the 10th percentile, 1.1% at the 50th percentile, and 4.3% at the 90th percentile. Finally, the AI knowledge and skills has the relatively lower effect at the bottom and median of the distribution (1.8 % and 0.9%, respectively), while it increases at 4.8 % at the top of the distribution (see table 5). Overall, our findings are robust to different specifications of the index of AI exposure corresponding to different dimensions of the total PAIOE.

Table 4. Unconditional Quantile Regression of log weekly wage

	10th Percentile	50th Percentile	p0th Percentile
PAIOE index	0.034***	0.017***	0.051***
	(0.001)	(0.000)	(0.001)
Female	-0.010***	-0.007***	-0.023***
	(0.000)	(0.000)	(0.000)
Age	0.005***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)
Age squared	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Education: base Primary education			
Secondary education	0.004***	0.005***	0.020***
	(0.000)	(0.000)	(0.000)
Tertiary education	0.007***	0.012***	0.044***
	(0.000)	(0.000)	(0.000)
Foreign citizenship	-0.004***	-0.006***	-0.002***
	(0.000)	(0.000)	(0.000)
Experience	0.003***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)
Experience squared	-0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)

follows

table 4 *follows*

	10th Percentile	50th Percentile	p0th Percentile
Fixed term contract	-0.015***	-0.008***	-0.021***
	(0.000)	(0.000)	(0.000)
Part-time	0.017***	-0.007***	-0.008***
	(0.000)	(0.000)	(0.000)
Firm's size – base 0-9 employees			
10-49 employees	0.006***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)
50-249 employees	0.009***	0.010***	0.021***
	(0.000)	(0.000)	(0.000)
>250 employees	0.015***	0.015***	0.031***
	(0.000)	(0.000)	(0.000)
Sector of economic activity – base Agriculture, forestry, and fishing			
Mining and quarrying	0.031***	0.012***	0.017***
	(0.001)	(0.000)	(0.001)
Manufacturing	0.023***	0.002***	-0.006***
	(0.000)	(0.000)	(0.001)
Public utilities	0.030***	0.013***	0.023***
	(0.000)	(0.000)	(0.001)
Construction	0.024***	0.005***	-0.018***
	(0.000)	(0.000)	(0.001)
Wholesale and retail trade	0.032***	0.011***	-0.005***
	(0.000)	(0.000)	(0.001)
Transportation	0.020***	0.006***	-0.016***
	(0.000)	(0.000)	(0.001)
Hotel and Restaurant	0.013***	-0.003***	-0.001*
	(0.000)	(0.000)	(0.001)
Information and Communication	0.007***	0.002***	-0.006***
	(0.001)	(0.000)	(0.001)
Financial and insurance activities	0.033***	0.014***	0.072***
	(0.001)	(0.000)	(0.001)
Real estate activities and firms' services	0.005***	-0.009***	-0.020***
	(0.000)	(0.000)	(0.001)
Public administration and other services	0.002***	-0.013***	-0.016***
	(0.000)	(0.000)	(0.001)
Interactions between AI and sector – base AI#agriculture			
AI#Mining and quarrying	-0.031***	-0.011***	0.098***
	(0.001)	(0.000)	(0.002)
AI#Manufacturing	-0.025***	-0.006***	0.023***
	(0.001)	(0.000)	(0.001)
AI#Public utilities	-0.030***	-0.012***	0.033***
	(0.001)	(0.000)	(0.001)

follows

table 4 *follows*

	10th Percentile	50th Percentile	p0th Percentile
AI#Construction	-0.026***	-0.007***	-0.002**
	(0.001)	(0.000)	(0.001)
AI#Wholesale and retail trade	-0.028***	-0.009***	-0.004***
	(0.001)	(0.000)	(0.001)
AI#Transportation	-0.022***	-0.009***	0.013***
	(0.001)	(0.000)	(0.001)
AI#Accommodation	-0.016***	-0.005***	-0.034***
	(0.001)	(0.000)	(0.001)
AI#Information and Communication	-0.007***	-0.005***	-0.004***
	(0.001)	(0.000)	(0.001)
AI#Financial and insurance activities	-0.035***	-0.016***	0.017***
	(0.001)	(0.000)	(0.001)
AI#Real estate activities and firms' services	-0.009***	0.001***	-0.019***
	(0.001)	(0.000)	(0.001)
AI#Public administration and other services	-0.015***	-0.004***	-0.048***
	(0.001)	(0.000)	(0.001)
Observations	12,047,507	12,047,507	12,047,507
Adj. R-Square	0.095	0.272	0.240

Notes: * p<0.10, ** p<0.05, *** p<0.01. We also control for regions and year.
Source: Authors' elaborations from INPS-COB-ICP data, 2011-2019

Table 5. The effect of AI exposure and its components across the wage distribution

	10th Percentile	50th Percentile	90th Percentile
AI know skills	0.018***	0.009***	0.048***
	(0.001)	(0.000)	(0.001)
AI labour activity	0.035***	0.017***	0.051***
	(0.000)	(0.000)	(0.000)
AI labour style	0.024***	0.011***	0.043***
	(0.001)	(0.000)	(0.001)
PAIOE index	0.034***	0.017***	0.051***
	(0.001)	(0.000)	(0.001)

Source: Authors' elaborations from INPS-COB-ICP data, 2011-2019

Tables 6 and 7 report the OB decomposition of the wage gap between low and highly exposed occupations for the benchmark estimates, considering the overall AI exposure index and for those considering its components (knowledge and skills, labour style, and labour activity), respectively. We also report the contribution of the covariates to both the explained and unexplained component of the gap.
Table 6 shows that the total difference increases across the wage distribution, from -18.5% at the 10th up to -50.5% at the 90th percentile. Overall, we see a relatively higher relevance of the unexplained component on the wage gap. However, the latter reduces importantly across the wage distribution from -82.7% (of the total difference) at the bottom down to -56% at the top, while the explained component increases its role, from -17.3% up to around -44% at the 90th percentile.

What are the main characteristics behind such interesting changes across the wage distribution? The OB-RIF analysis shows that the individual characteristic related to gender increases the explained part of the wage premium both for low and high paid workers (by 2.6% and 2.4%, respectively). Conversely, age and education, especially having a university degree pushes downward the wage premium especially for high-paid jobs (-8.5% for tertiary education). The second part of table 6 focuses on the unexplained components of the decomposition, that is, unobserved features that might play a role in explaining the "low-high AI exposed" wage gap. Among low-paid jobs the unexplained part of the wage premium decreases for women, while the advantage related to AI occupational characteristics increases for high-paid employees. Turning to the educational attainment, a higher level of education increases the unexplained part of the wage premium only for high-paid jobs.

Table 6. OB-RIF detailed decomposition with reweighting.

	10th Percentile	50th Percentile	90th Percentile
Total difference	-0.185***	-0.201***	-0.505***
	(0.000)	(0.000)	(0.001)
Explained component	-0.032***	-0.071***	-0.222***
	(0.001)	(0.000)	(0.001)
Unexplained component	-0.153***	-0.130***	-0.283**
	(0.001)	(0.000)	(0.001)
Explained component			
Female	0.026***	0.012***	0.024***
	(0.000)	(0.000)	(0.000)
Age	-0.051***	-0.017***	-0.007***
	(0.001)	(0.000)	(0.000)
Secondary education	-0.003***	-0.003***	-0.008***
	(0.000)	(0.000)	(0.000)
Tertiary education	-0.010***	-0.030***	-0.085***
	(0.001)	(0.000)	(0.001)
Foreign citizenship	-0.004***	-0.007***	-0.010***
	(0.000)	(0.000)	(0.000)
Experience	0.022***	0.004***	-0.003***
	(0.001)	(0.000)	(0.000)
Fixed term contract	-0.014***	-0.006***	-0.013***
	(0.000)	(0.000)	(0.000)
Part-time	0.026***	-0.006***	-0.008***
	(0.000)	(0.000)	(0.000)
10-49 employees	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
50-249 employees	-0.003***	-0.003***	-0.005***
	(0.000)	(0.000)	(0.000)
>250 employees	-0.014***	-0.011***	-0.020***
	(0.000)	(0.000)	(0.000)
Mining and quarrying	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)

follows

table 6 *follows*

	10th Percentile	50th Percentile	90th Percentile
Manufacturing	0.001***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Public utilities	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Construction	0.014***	0.004***	-0.012***
	(0.000)	(0.000)	(0.000)
Wholesale and retail trade	0.020***	0.008***	-0.008***
	(0.000)	(0.000)	(0.000)
Transportation	0.008***	0.002***	-0.005***
	(0.000)	(0.000)	(0.000)
Hotel and Restaurant	0.018***	-0.001**	-0.025***
	(0.001)	(0.000)	(0.001)
Information and Communication	-0.004***	-0.003***	0.007***
	(0.001)	(0.000)	(0.001)
Financial and insurance activities	-0.023***	-0.008***	-0.042***
	(0.001)	(0.000)	(0.001)
Real estate activities and firms' services	-0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Public administration and other services	-0.007***	0.017***	0.044***
	(0.001)	(0.000)	(0.001)
Unexplained component			
Female	-0.034***	0.022***	0.038***
	(0.001)	(0.000)	(0.001)
Age	1.176***	-0.268***	-0.499***
	(0.025)	(0.011)	(0.030)
Secondary education	-0.010***	-0.007***	0.017***
	(0.001)	(0.001)	(0.001)
Tertiary education	-0.014***	-0.020***	0.025***
	(0.001)	(0.001)	(0.001)
Foreign citizenship	0.001***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)
Experience	0.506***	0.111***	0.074***
	(0.011)	(0.004)	(0.006)
Fixed term contract	-0.025***	0.019***	-0.007***
	(0.001)	(0.000)	(0.001)
Part-time	0.047***	0.005***	-0.004***
	(0.001)	(0.000)	(0.000)
10-49 employees	0.009***	-0.006***	-0.003***
	(0.001)	(0.000)	(0.001)
50-249 employees	0.003***	-0.012***	-0.008***
	(0.000)	(0.000)	(0.001)
>250 employees	0.017***	-0.015***	0.032***
	(0.001)	(0.000)	(0.001)
Mining and quarrying	0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)

follows

table 6 *follows*

	10th Percentile	50th Percentile	90th Percentile
Manufacturing	0.019***	-0.001	-0.028***
	(0.002)	(0.001)	(0.003)
Public utilities	0.001***	0.000***	0.006***
	(0.000)	(0.000)	(0.000)
Construction	0.005***	-0.000	-0.012***
	(0.000)	(0.000)	(0.001)
Wholesale and retail trade	0.011***	0.003***	-0.022***
	(0.001)	(0.001)	(0.002)
Transportation	0.005***	0.002***	-0.005***
	(0.000)	(0.000)	(0.001)
Hotel and Restaurant	-0.002***	-0.001***	-0.004***
	(0.000)	(0.000)	(0.000)
Information and Communication	-0.003***	0.001**	-0.008***
	(0.001)	(0.000)	(0.001)
Financial and insurance activities	0.009***	0.002***	-0.005***
	(0.000)	(0.000)	(0.001)
Real estate activities and firms' services	0.001	-0.003***	-0.039***
	(0.001)	(0.001)	(0.002)
Public administration and other services	0.023***	0.009***	-0.065***
	(0.002)	(0.001)	(0.004)
Observations	12,047,507	12,047,507	12,047,507

Note: * p<0.10, ** p<0.05, *** p<0.01
Source: Authors' elaborations from INPS-COB-ICP data, 2011-2019.

Overall, the decomposition analysis shows an increase in the total difference across the wage distribution and, within this latter, a rising relevance of the explained component together with a reduced importance of the unexplained one, as we move from the 10th percentile to the 90th percentile.
A possible explanation for this evidence relies on the idea that increasing prevalence of AI in complementary occupations can lead to greater transparency, standardization, and a focus on observable skills, thereby reducing the influence of unmeasured factors (the "unexplained" component) on wage disparities. As Autor (2014) points out, while some tasks are hard to automate, those that can be automated often become more structured and standardized, which can lead to more transparent evaluation. For example, performance evaluations might become more objective, based on measurable outputs generated through AI-assisted systems, rather than subjective manager assessments. This increased transparency makes it harder for unobserved factors like implicit bias to influence wage outcomes. Moreover, AI may be making certain skills more visible and measurable, thus reducing the "unexplained" portion of the wage gap attributable to unobserved skill differences Goldin e Katz (2009). These patterns are confirmed by the three components of the index, as shown in table 7[12]. Again, labour activity is the component which more strictly follows the general AI exposure index. Notably, for the AI know skill, we see that the explained and unexplained component are equally important at the top of the distribution (both worth 50% of the total difference at the 90th percentile). Finally, the

[12] For the sake of brevity, we do not report the estimates of the effect of the covariates on the explained and unexplained components. Results are available upon request.

AI labour style component shows, on average, the more significant change across the distribution. Indeed, the explained (unexplained) component ranges from 8.8% (91.2%) at the top to 46.2% (53.8%) at the bottom.

Table 7. OB-RIF detailed decomposition with reweighting for the three PAIOE index components

	10th Percentile	50th Percentile	90th Percentile
AI know skills			
Total difference	-0.139***	-0.165***	-0.414***
	(0.001)	(0.000)	(0.001)
Explained component	-0.033***	-0.072***	-0.207***
	(0.000)	(0.000)	(0.001)
Unexplained component	-0.105***	-0.093***	-0.207***
	(0.001)	(0.001)	(0.002)
AI labour activity			
Total difference	-0.193***	-0.207***	-0.512***
	(0.000)	(0.000)	(0.001)
Explained component	-0.038***	-0.071***	-0.209***
	(0.001)	(0.000)	(0.001)
Unexplained component	-0.156***	-0.136***	-0.303***
	(0.001)	(0.001)	(0.002)
AI labour style			
Total difference	-0.147***	-0.152***	-0.396***
	(0.000)	(0.000)	(0.001)
Explained component	-0.013***	-0.036***	-0.183***
	(0.000)	(0.000)	(0.001)
Unexplained component	-0.134***	-0.116***	-0.213***
	(0.001)	(0.000)	(0.001)
PAIOE index			
Total difference	-0.185***	-0.201***	-0.505***
	(0.000)	(0.000)	(0.001)
Explained component	-0.032***	-0.071***	-0.222***
	(0.001)	(0.000)	(0.001)
Unexplained component	-0.153***	-0.130***	-0.283**
	(0.001)	(0.000)	(0.001)

Note: * p<0.10, ** p<0.05, *** p<0.01
Source: Authors' calculations from 2011-2019 INPS-COB-ICP data.

7. Conclusions

In this paper, we investigate the effect of potential AI exposure on the overall wage distribution of a sample of Italian employees by using administrative data covering the period 2011-2019.
We offered both a descriptive and a two steps econometric investigation. For the former, we construct a potential AI occupational exposure index and three other AI exposure indices that consider different dimensions of the general one. We used the index to define and describe highly and low exposed occupations. For the latter, we investigate the effect on wage of our AI occupational exposure index

(also disaggregated in its main components) across the overall wage distribution. As a further step, we offer a decomposition analysis of the wage gap between highly and low AI exposed occupations in its explained and unexplained components.

All in all, our results suggest a potential positive role of AI exposure on wages, particularly for top positions and highly qualified employees. However, the fact that the positive effect of AI diminishes around the median of the wage distribution suggests that AI could exacerbate wage inequality between different groups of workers (low-wage and high-wage workers) and contributes to a more polarized labour market. We also note heterogeneities of the effect of AI both across sectors of economic activity and, within each sector, across the overall wage distribution.

Interestingly, the OB-RIF decomposition analyses show a decreasing role of the unexplained component of the gap across the wage distribution. For low-wage occupations, the unexplained component accounted for more than 82%, whereas for high-wage occupations the relevance of the unexplained and explained components was more balanced (with the unexplained component around 60%). Interestingly, among the explored characteristics, gender and education play a relevant role. These factors contribute to the unexplained component of low-wage positions, possibly suggesting some forms of discrimination for low-paid workers, whereas their role changes for top-level occupations. In other words, the characteristics that most significantly contribute to explaining the disadvantage of low-paid positions are the same that are more highly rewarded in top-paid positions. In particular, skills as measured by tertiary education play a significant role. These findings are robust across the other components of the considered index.

To avoid the exacerbation of the inequalities between low- and high-wage workers observed in our estimates, it is crucial to invest in education and especially in workforce training, i.e. reskilling and/or up-skilling, particularly of the workers at the bottom and the median of the wage distribution. It would also be necessary to reduce the wage disadvantage of women that we have estimated not only at the bottom, but also at the top of the wage distribution, i.e. the glass-ceiling effect. At the bottom, there should be interventions aimed at reducing the risk of career interruptions after childbirth. At the top, instead, to increase the availability of childcare services also into the firms itself. Results, though specific to Italy, should be generalized to other similar European countries.

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Appendix

Table A1. ICP questions used for each index

Index	Question of the ICP questionnaire
PAIOE	1. For each area the question is: How important is this area of knowledge in performing your current job? B9 A. Information Technology B11 A. Technical design B14 A. Mathemathics B24 A. Italian language C1 A. Understanding written texts C4 A. Speaking C7 A. Critical thinking C10 A. Monitoring C15 A. Teaching others C17 A. Solving complex problems C22 A. Programming/coding C29 A. Analysing systems C35 A. Human resources management 2. For each labour style the question is: How important is this labour style in performing your current job? F4 Leadership F5 Cooperation F7 Teamwork F15 Innovation F16 Analytical thinking 3. Automation exposure H49 Automation exposure 4. For each labour activity the question is: How important is this labour activity in performing your current job? G9 A. Analyzing data or information G10 A. Taking decisions and problem solving G11 A. Thinking creatively G19 A. Working with computers G25 A. Interpreting the meaning of information G34 A. Building and activating work teams G36 A. Leading, managing, and motivating subordinates
AI_knowSkills	Questions on the area of knowledge (group 1 above) B9 A.; B9 A.; B11 A; B14 A.; B24 A.; C1 A.; C4 A.; C7 A.; C10 A.; C15 A.; C17 A.; C22 A.; C29 A.; C35 A.
AI_LabourStyle	Questions on labour style (group 2 above): F4; F5; F7; F15; F16
AI_LabourActivity	Questions on labour activity (group 4 above): G9 A.; G10 A.; G11 A.; G19 A.; G25 A.; G34 A.; G36 A.

Source: Questions from the ICP-2013 questionnaire.

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