BANCA D'ITALIA
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**AN ASSESSMENT OF OCCUPATIONAL EXPOSURE TO ARTIFICIAL INTELLIGENCE IN ITALY**

by Antonio Dalla Zuanna*, Davide Dottori**, Elena Gentili*** and Salvatore Lattanzio*

**Abstract**

Artificial intelligence (AI) is a general-purpose technology with broad applicability across domains and economic sectors, which is expected to have a significant impact on the labour market in the coming years. We review some of the most recent measurements of labour market exposure to AI in advanced economies and then assess the implications for the Italian labour market. We find that occupations that are more exposed to AI, i.e. more at risk of being complemented or substituted by it, are in the top two quintiles of the income distribution, mostly in the service sector, and employ a large share of women and of highly-skilled workers. Substitutable workers are more protected from the risk of job displacement as they are less likely to be self-employed or on fixed-term contracts. Current patterns of job-to-job mobility show high degrees of persistence within occupation types. We provide indicative evidence that moving out of the most exposed and substitutable occupations might be difficult and costly in terms of wage, especially when movements are towards less exposed occupations.

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**Keywords**: artificial intelligence, occupational exposure, labour mobility.

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## 1. *Introduction*[1]

The adoption of Artificial Intelligence (AI) technologies by firms in European countries is not yet widespread: according to the Digital Economy and Society Index developed by the European Commission, only about 8 percent of European firms used AI in 2023. In Italy this share was even lower, at 5 percent. However, also due to the rapid development of such technologies which makes them applicable to a wider range of tasks, it is a common opinion among experts in the field that it will become more and more part of the production system in the coming years, with potentially large impacts on the productivity of workers, but also on the actual need for human labor in performing some tasks.[2]

Thus, the expected breakthrough of AI poses a relevant dilemma, since it is believed that it will substantially change several features of the labor markets, but it is not clear when and how this will happen. One approach to trying to predict the impact of AI is to isolate the tasks or occupations that are more similar to what AI is capable of, and build on this to hypothesize which jobs and workers will face competition or will see their productivity increase as the new technology becomes more accessible. In this paper we review the different methodologies that have been developed to achieve this goal, highlighting the critical aspects and limitations of the approach. In particular, we highlight that all these measures are necessarily based on a "static" definition of occupations, ignoring the fact that AI itself may change the type of tasks that a worker in a given occupation can perform. Next, we apply the methodology proposed by Felten, Raj and Seamans (2018, 2021) to the Italian case to identify some characteristics of the workers who are more likely to be exposed. An extension of this methodology, detailed in Pizzinelli et al. (2023), allows us to separate workers at risk of substitution from those who could benefit in terms of productivity gains. We devote the final section of the paper to a detailed analysis of the mobility patterns between job types, to understand whether workers who are more at risk of substitution already have "natural" ways out of their occupations and whether this may entail wage costs for them.

Overall, the different methodologies agree on the fact that occupations requiring cognitive skills are more likely to be exposed to the introduction of AI, a marked difference compared to the introduction of robots, one of the most recent waves of innovation observed. In fact, in our empirical analysis we find that the service sector, which typically employs a large share of high-skilled workers, is likely to be more affected than the industrial and agricultural sectors. This finding is confirmed by most studies, regardless of the method used to identify the most exposed occupations. However, we show that there are differences among exposed service sectors in terms of the substitutability and complementarity between AI and occupations, with the finance and communication sectors having a large share of workers at risk of being replaced by AI.

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[1] The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank. We thank for helpful comments on previous draft Gaetano Basso, Federico Cingano, Roberto Torrini, Eliana Viviano, and other colleagues and seminar participants at the Bank of Italy. We also thank Carlo Pizzinelli for generously sharing the information on occupation classification.

[2] See e.g. John Van Reenen (2023, November, 10): "[…] in practice, it takes a long time between a new general purpose technology and something that can be used not just in one industry, but in many industries and many firms. It usually takes a long time between the invention of that technology and the impact that it eventually has on productivity and therefore people's wages and incomes. Back in history, electricity, if you think that came around the kind of 1880s, it took another 20, 30, 40 years before that really started impacting on productivity. It wasn't until people could figure out ways of using it. For example, building factories, which were lighted and open 24 hours a day, running production lines like Henry Ford did 24/7 with the division of labor, that actually helped really supercharge that technology into really having massive effects on productivity. My best guess, of course I might be wrong and things might be different, and we can talk about that, is that it's going to be similar with AI." (https://cepr.org/multimedia/ais-impact-jobs)

Looking at worker characteristics we show that: (i) a large proportion of workers in occupations potentially exposed to AI, both complement and substitute, are in the top two quintiles of the wage distribution, with potentially ambiguous implications for overall earnings inequality; (ii) women are more likely than men to work in highly exposed occupations; (iii) workers in substitutable occupations in Italy are more concentrated in the North-West of the country, while complement occupations are more present in the South; (iv) the share of self-employed and temporary workers in occupations at high risk of being replaced by AI is lower than the average in the economy, so that displacement effects in the near future may be mitigated by the type of contract of workers in more substitutable occupations.

The analysis of flow data on job-to-job transitions shows no clear patterns out of the occupations which are more at risk of being substituted. In particular we show that (i) mobility between occupations with different exposure has historically been low and remains low; (ii) workers in highly exposed and substitute occupations tend to move into less exposed occupations more than to highly exposed and complementary ones, often experiencing a lower wage premium upon moving; (iii) sectoral changes for these workers are also more common than for others, but do not typically result in higher wages, suggesting challenges in finding new jobs; (iv) women show more persistence in their jobs and are more likely to change sectors when leaving highly substitutable occupations, potentially facing difficulties in reallocating; (v) more educated workers more easily transition from highly exposed and substitute occupations to complementary ones, yet their wage increases if they move towards less exposed occupations are comparable to those of less educated workers. While this analysis does not necessarily represent a response to an increased reliance on AI (due to its still low adoption and the possibility that it involves changes in the task-bundle associated to each occupation), it puts forward some insightful evidence on the current job-mobility patterns according to occupational exposure to AI, thereby providing some hints about their potential attitude to mitigate AI-related effects when they materialize.

The paper is structured as follows: in Section 2 we detail the methodology developed by Felten, Raj and Seamans (2018, 2021) which we use as a benchmark for our discussion. Section 3 highlights the critical aspects of this approach, while Section 4 discusses alternative methods used in the literature to measure task and occupational exposure to AI. Section 5 compares the occupations exposed to AI to the occupations exposed to automation technology. In Section 6 and 7 we report the analysis of the Italian labour market exposure using the method by Felten, Raj and Seamans combined with the extension by Pizzinelli et al. (2023); we first report a snapshot of exposure according to the distribution of workers across occupations in 2023 (Section 6) and then analyse job-to-job transitions across occupations with different exposure to and substitutability with AI (Section 7).

## 2. *The Felten, Raj and Seamans' approach to measure the occupational exposure to AI*

Felten, Raj and Seamans (2018 and 2021; hereafter, FRS) develop one of the first approaches to measure the exposure of occupations to AI.[3] An "exposed" occupation is an occupation "related" to some AI applications , a notion that does not necessarily imply a risk of being "substituted" but could also imply complementarity. Thus, highly exposed occupations need to be understood in an agnostic sense as those that are more likely to change/be affected as a direct consequence of AI diffusion (e.g., due to a reorganization of their tasks), but not necessarily being displaced. The low exposure to FRS measure has

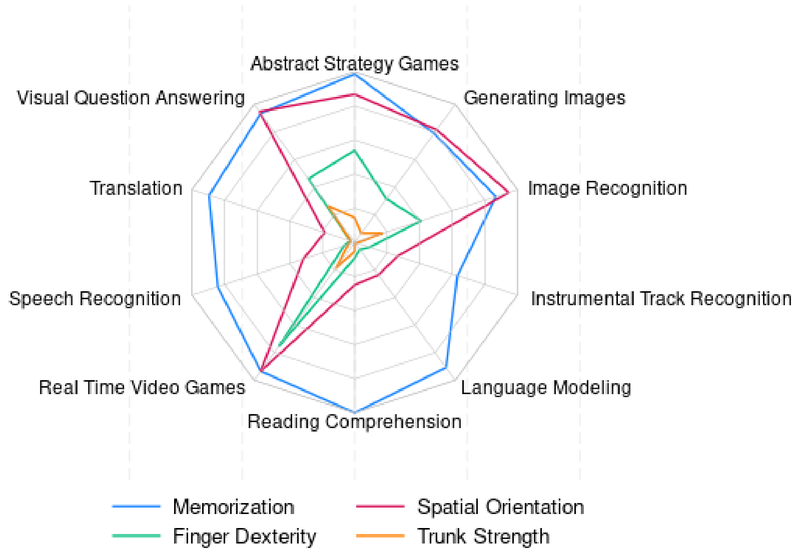
[3] This approach is detailed in Felten et al. (2018) and Felten et al. (2021). The description in the main text is more closely related to the latter work that introduced some methodological refinement.

to be intended as an orthogonality condition, resulting from the fact that the most of the observed skills for a given occupation are poorly related to AI.

FRS focus primarily on human abilities that are surveyed in the Occupational Information Network (O*NET) database, developed by the United States Department of Labour to define and describe professions in the American workplace. Then, they look at ten specific AI applications (AIapps, see Table A1 in the appendix) which the authors consider as those "experiencing the fastest growth and most likely to be used in the medium-term" (Felten et al., 2021; examples of these 10 AIapps are "reading comprehension" or "speech recognition").[4] These AIapps are then mapped into 52 human abilities included in O*NET (as "Memorization", "Finger dexterity", "Trunk strength" and the like). The mapping occurs through a matrix that, for any ability, assigns a measure of relatedness to each of the 10 AIapps. The exposure measure, ranging between 0 and 1, is built exploiting a survey the authors promoted on an online platform.[5] As an example, Figure 1 shows the exposure of four of the abilities surveyed in O*NET (memorization, spatial orientation, finger dexterity and trunk strength) to the 10 AIApps: memorization has a strong connection with almost all AIapps, contrary to more physical abilities such as finger dexterity and trunk strength.

**Figure 1**

**Relatedness of abilities to AI applications**




Source: authors' computations on Felten et al. (2018)'s data.

The ability-specific synthetic measure of AI relatedness is obtained by summing these elementary indicators over the AIapps *i*:

$$A_j = \sum_{i=1}^{10} x_{ij}$$

where j denotes one of the 52 O*NET ability, and $x \in (0,1)$. This method implicitly assigns every AIapp the same weight and assumes that they can be aggregated in a purely additive manner, without any interaction effect. The abilities that feature a higher relatedness are the "cognitive" ones (see Table A2 in

[4] These applications were selected among those monitored by the Electronic Frontier Foundation (EFF), a no-profit organization focusing on issues related to digital rights and privacy. The selection of this set is basically "judgmental", following authors' interactions with experts in the field and considering progresses recorded since 2010.

[5] Their survey was run on MTurk, a crowd-sourcing internet service, and respondents were approximately 2,000 "gig workers", 200 for each AIapp.

Appendix); at the opposite there are the physical abilities, while the "sensorial" abilities are generally in between.

The AI occupational exposure (AIOE) is then obtained as a weighted combination of the relatedness of abilities to AIapps. The weights are based on information from O*NET on the level of prevalence (denoted by $L$) and importance ($I$) of each ability in any given occupation:

$$AIOE_k = \frac{\sum_{j=1}^{52} A_j \times L_{jk} \times I_{jk}}{\sum_{j=1}^{52} L_{jk} \times I_{jk}}$$

where $k$ denotes occupation. The AIOE indicator is defined at the 6-digit level, and standardized so that it has zero mean and unit variance. Table 1 shows the most and least exposed occupations according to the FRS's measurement.

The most exposed occupations are generally white-collar occupations that require cognitive abilities, while the lowest scoring occupations are largely "non-office jobs that require a high degree of physical effort and exertion" (Felten et al. 2021). It is interesting to observe, however, that there is heterogeneity within each group: for example, the most exposed group includes some occupations that involve a specialized knowledge but arguably routine tasks (e.g., judicial law clerks, purchasing agents) together with occupations requiring to operate in a more complex environment or taking rather complex decisions, such as judges and financial managers.

Table 1

| Rank | Highest scoring | Lowest scoring |
|---|---|---|
| 1 | Genetic counsellors | Dancers |
| 2 | Financial examiners | Fitness trainers and aerobics instructors |
| 3 | Actuaries | Helpers—painters, paperhangers, plasterers, and stucco masons |
| 4 | Purchasing agents, except wholesale, retail, and farm products | Reinforcing iron and rebar workers |
| 5 | Budget analysts | Pressers, textile, garment, and related materials |
| 6 | Judges, magistrate judges, and magistrates | Helpers—Brickmasons, Blockmasons, stonemasons, and tile and marble setters |
| 7 | Procurement clerks | Dining room and cafeteria attendants and bartender helpers |
| 8 | Accountants and auditors | Fence erectors |
| 9 | Mathematicians | Helpers—roofers |
| 10 | Judicial law clerks | Slaughterers and meat packers |
| 11 | Education administrators, postsecondary | Landscaping and Groundskeeping workers |
| 12 | Clinical, counselling, and school psychologists | Athletes and sports competitors |
| 13 | Financial managers | Fallers |
| 14 | Compensation, benefits, and job analysis specialists | Structural iron and steel workers |
| 15 | Credit authorizers, checkers, and clerks | Cement masons and concrete finishers |
| 16 | History teachers, postsecondary | Terrazzo workers and finishers |
| 17 | Geographers | Rock splitters, quarry |
| 18 | Epidemiologists | Plasterers and stucco masons |
| 19 | Management analysts | Brickmasons and Blockmasons |
| 20 | Arbitrators, mediators, and conciliators | Roofers |

Source: Felten et al. 2021

### *3. Critical aspects of the Felten, Raj and Seamans' approach*

Some features of the FRS's approach are worth remarking: (i) it focuses on a specific set of AI applications; (ii) it is based on a linear weighting system and additive properties; (iii) its measurement of AI-ability relatedness is based on crowdsourced data, an approach not exempt of limitations and concerns about external validity;[6] (iv) it is based on the current nature of occupations as coded in O*NET, that refers to the US; (v) it is agnostic about complementarity versus substitutability.

For points (i) and (ii) the authors conduct some robustness checks and validations, suggesting that the main results are confirmed; for point (iii) they also put forward that previous studies showed that "surveys and experiments executed through online labour market platforms, such as mTurk, are largely generalizable to in-person or laboratory settings" (Felten et al. 2021).

With respect to point (iv), issues may arise about whether the ranking could be extended to other labour markets, where the level and importance of abilities in occupations is not necessarily the same as in the US. To illustrate, Table 2 reports the most and least exposed occupations as obtained applying the FSR approach to Italian data. The data are sourced from the ICP survey by INAPP, which provides information on the prevalence and importance of the same 52 abilities considered in O*NET in Italian occupations.

Not dissimilarly from FRS, white collars occupations involving cognitive tasks are generally more exposed, while blue-collar occupations involving physical effort or exertion of particular physical tasks are less exposed. Here again, in the most exposed group we find some occupations involving routine tasks (e.g. employee dealing with protocols or secretarial functions) together with more complex occupations, such as judges and government commissioners.[7]

Table 2

| Rank | Highest scoring | Lowest scoring |
|---|---|---|
| 1 | Protocol and document sorting staff | Labourers and unqualified personnel in civil construction and similar professions |
| 2 | Magistrates | Athletes |
| 3 | Payroll clerks | Plasterers |
| 4 | Ushers, doorman and similar professions | Drivers of animal-drawn vehicles |
| 5 | Agents for financial operations on behalf of the company or organization | Unqualified personnel responsible for animal care |
| 6 | Internal cash office employees | Street vendors of services |
| 7 | Control specialists in Public Administration | Dancers |
| 8 | Database management technicians | Road pavers and pavers |
| 9 | General, departmental and equivalent directors of state administrations and public bodies | Acrobats and circus artists |
| 10 | Library technicians | Lifeguards and professions are similar |
| 11 | Treasurers | Cork workers and resin collectors |
| 12 | Directors of the ordinary judiciary | Labourers and unqualified personnel in the construction and maintenance of roads, dams and other works can |
| 13 | Tax and tax experts | Operators of boilers and other naval equipment |
| 14 | Switchboard operators | Deep sea fishermen |
| 15 | Public service technicians for the issuing of certifications and personal documentation | Dance teachers |
| 16 | Secretarial functions | Asphalt workers |
| 17 | Astrologers, fortune tellers, palmists and similar professions | Stone and brick masons |
| 18 | Accountants | Deck sailors |
| 19 | Text editors | Tree fellers and reforesters |
| 20 | Government commissioners, prefects and vice prefects | Porters, people responsible for moving goods and similar |

Source: our computations on Felten and INAPP data.

The fact that FRS measure is based on the *current* nature of occupations can be problematic if new technologies change the type of tasks occupations can perform (Autor, 2024). As an example, it is possible that, thanks to AI, nurses can increase their ability of diagnosing illnesses without the support of medical doctors. Hence, AI can be more important for nurses if it allows them to engage in new

[6] For example, the respondents' perception of relatedness may be influenced by their own experience or by observed progress so far, while they could not fully understand how AI technologies can be used in the workplace or their potential relationship with abilities in an innovative way.

[7] This exercise has been performed on the 2013 wave of ICP survey by INAPP. The same database is used also in Carbonero and Scicchitano (2021); however, this paper, which focus on AI effect on proximity in the workplace, adopts a slightly different methodology, more closed to Felten et al. (2018), so that it is not possible to disentangle in a straightforward way which differences are due to data and which to methodology.

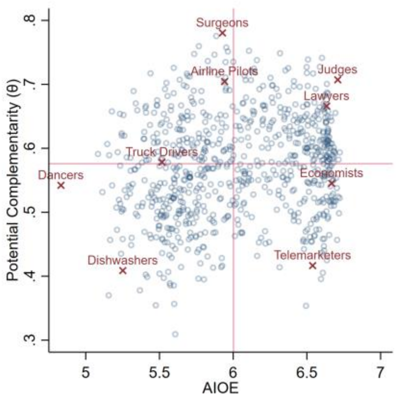
activities, while it may be little relevant to perform most of the tasks it currently involves (in fact, AIOE for nurses is around the middle of the AIOE distribution). However, because predicting the change in the nature of occupations (if it will ever happen) is not obvious, all the existent classifications, including FRS, are based on some descriptions of occupations (and of the tasks preformed) as of today's evidence. This is an important limitation when trying to predict the distributional impacts of the technology.

Point (v) is instead directly addressed by Pizzinelli et al. (2023), who introduce a criterion to distinguish between complementarity and substitution. Their methodology utilizes the FRS framework, where the 52 abilities defined by O*NET for each profession are integrated with two additional sets of characteristics from O*NET: work contexts and "job zones". Work contexts encompass physical and social factors influencing work (e.g., how much time is spent interacting with people or doing some specific physical activity).[8] Job zones group occupations with similar education and experience requirements with the idea that when more training is required, it will be easier to introduce AI knowledge into the training program and thus provide workers with the skills needed to complement AI (a rather strong assumption). The authors assess these characteristics to determine their likelihood of inducing complementarity or substitutability. For example, if an occupation has high levels of the "communication" work context, the authors consider it as being more likely complement to AI, in that this technology can help facilitating collecting information and prepare for interaction, but will likely not substitute the task itself. The final step requires assigning the weight of each work context and job zone to each occupation. This is done exploiting the score provided in the O*NET database, which assigns scores between 0 and 100 for work contexts and job zones to each occupation on the basis of how much the context/zone is relevant into that occupation. The final indicator is then an arithmetic average of these scores across work contexts and job zones. In computing this average the sign of the score is adjusted so that characteristics which are more likely indicating complementarity (e.g. the communication context) receive a positive score, while those which are substitutable receive a negative score. As a consequence, higher values of this index imply higher levels of complementarity.

Clearly, the relevance of the complementarity vs. substitution distinction varies with the degree of AI exposure of each occupation, and is least relevant in the case of those barely exposed. This is the case, for example, of dishwashers (see Figure 2 taken from Pizzinelli et al., 2023).[9]

**Figure 2**

**Relatedness of abilities to AI applications**




Source: Pizzinelli et al. (2023)

[8] The authors collect 11 of these factors in 5 groups which are the "most relevant for the likelihood of AI *replacing* human activities or being adopted in a *supervised* manner". The 5 groups are communication, responsibility, physical conditions, criticality and routine.

[9] Pizzinelli et al. (2023) use the complementarity index to reweight the FRS index, not as a measure that has a meaning per se. The complementarity-adjusted index in Pizzinelli et al. (2023) assigns the highest score to occupations that are highly exposed and substitute, and the lowest score either to occupations that are not exposed, or to those that are exposed but complement.

Table 3 applies Pizzinelli et al. (2023) extension to occupations, defined exploiting the occupation classification as defined in ISTAT data ("Classificazione delle Professioni" - CP). We first divide occupations into three groups based on terciles of the FRS exposure distribution (low-, medium-, and high-exposure). Occupations in the second and third groups are further ranked by the degree of complementarity: those with values of the Pizzinelli et al. measure above the median of the distribution are defined as AI complement. Note that, because the classification of occupations exploited in FRS is a different one ("Standard Occupational Classification" - SOC), Table 3 requires mapping CP into SOC classification. This mapping is not one-to-one, hence the evidence from Table 3 is not directly comparable with the one in Tables 1 and 2, although it is generally consistent.[10] This mapping allows analyses of the Italian labour market exploiting ISTAT data (as done in section 5). Table 3 lists the 10 least exposed occupations according to this definition and, for the middle and highly-exposed occupation, those with the highest FRS index (hence those with higher exposure). Complementary occupations often involve high-level decision-making, while substitute occupations require specialized but standard procedures.

**Table 3**

| Rank | Little Exposure | Middle Exposure & Substitute | Middle Exposure & Complements | High Exposure & Substitutes | High Exposure & Complement |
|---|---|---|---|---|---|
| 1 | Custodians and related professions | IT Services Department Directors and Managers | Entrepreneurs and Managers of Small Enterprises in Transport and Warehousing | Mathematicians | Finance and Administration Department Directors and Managers |
| 2 | Domestic collaborators and related professions | Variety artists | General Directors and Executives of Companies in the Transport and Warehousing Sector | Accounting Specialists | Organization, Human Resources, and Industrial Relations Department Directors and Managers |
| 3 | Unskilled personnel responsible for cleaning in accommodation services and ships | Technicians in the organization of radio, television, film production | Entrepreneurs and Managers of Small Construction Companies | Financial Management Technicians | Notaries |
| 4 | Unskilled personnel responsible for cleaning services in offices and commercial establishments | Composers | Scaffolders | Statistical Technicians | Lawyers |
| 5 | Porters and related professions | Performers of artistic and recreational performances | Stone cutters and polishers, stonemasons | Calligrapher experts | Legal experts in public entities |
| 6 | Unskilled personnel in industrial activities and related professions | Dancers | Entrepreneurs and Managers of Small Businesses in the extraction of minerals, manufacturing, production and distribution of electricity, gas and water, and waste management activities | Economists and Treasurers | Magistrates |
| 7 | Manual and unskilled personnel in the construction and maintenance of roads, dams, and other public works | Restoration technicians | Assemblers of prefabricated and preformed artefacts | Experts, risk assessors, and liquidators | Specialists in economic systems |
| 8 | Manual and unskilled personnel in civil construction and related professions | Network and telematics systems managers | Stone and brick masons | Banking technicians | Clinical psychologists and psychotherapists |
| 9 | Manual and unskilled personnel in mines and quarries | Database managers | Builders and carpenters in construction | Management and control specialists in private enterprises | Archaeologists |
| 10 | Vehicle washing attendants | Application expert technicians | Road pavers and pavement workers | Specialists in control in public administration | Specialists in religious and theological disciplines |

[10] In Table 3, we use the occupation classification as defined in ISTAT data ("Classificazione delle Professioni" - CP), by matching the score assigned to occupations as defined in O*NET to the same occupation in the Italian classification. Note that some carefulness is required in matching the occupation classification used in O*NET (SOC) to the CP classification. The SOC classification can be converted into the 4-digit ISCO-08, as done by Pizzinelli et al. (2023). ISTAT provides a crosswalk between the 3-digit ISCO classification and CP classification. In order to identify the more exposed professions exploiting CP classification and to apply Pizzinelli et al (2023) measure to Italian data, we proceeded as follows: first we match each CP to all the ISCO 3-digit occupations we find in O*NET (where, as mentioned, occupations classifications can be translated into the 4-digit level, hence some CP occupations are merged to more than one O*NET profession – all those which have different ISCO 4-digit, but same ISCO 3-digit). Next, we consider for each CP occupation the highest FRS index and the highest complementarity index. This may overstate the exposure of some professions (note for example that "dancers" are classified as middle exposure here and little exposure in Tables 1 and 2), but guarantees that if any risk of exposure is there we are able to capture it.

## 4. *Alternative measures of the occupational exposure to AI*

The indicator developed by FRS has been extended in several other dimensions and alternative indexes have recently been proposed. AI exposure has been measured relying on experts' judgment (Eloundou et al., 2023; Tolan et al., 2021; Brynjolfsson and Mitchell, 2017; Brynjolfsson et al. 2018; Frey and Osborne, 2017), on authors' judgment according to a review of the literature (Briggs and Kodnani, 2023), or on the similarity between job and patent descriptions (Webb, 2019; Kogan et al., 2021; Meindl et al., 2021). Moreover, the definition of AI has also been questioned.[11] As a consequence, the derived exposure measures do not coincide with that of FRS (as shown in Table A3 in the Appendix, listing the most and the least exposed occupations according to these alternative measures). Even so, most of these studies find that the most exposed occupations are those in the upper part of the income distribution, that mostly require college education and longer training.

Before discussing the single contributions, it is interesting to note that the authors of the cited papers take different stances about the interpretation of their occupational exposure measures. Indeed, the scores of occupational exposure derived in Webb (2019), Kogan et al. (2021), Briggs and Kodnani (2023), Frey and Osborne (2017) and Arntz et al. (2017) can be regarded as measures of the AI technologies' replacing potential for current jobs. Briggs and Kodnani (2023), Frey and Osborne (2017) and Arntz et al. (2017) even provide an estimate of the share of US jobs at risk of displacement according to their scores. On the other hand, Eloundou et al. (2023), Meindl et al. (2021), Tolan et al. (2021) and Brynjolfsson et al. (2018), as FRS, take a more nuanced stance on the extent to which more exposed occupations can be substituted for by AI technologies. Brynjolfsson et al. (2018), for instance, define their measure of occupational exposure as an "indicator for the potential reorganization of a job" rather than considering it a measure of task substitutability.

The methodology most closely related to FRS is devised by Tolan et al. (2021), who incorporate the significance of 14 cognitive abilities in task execution across various occupations and establish correlations with AI applications. Although they embrace a broader conception of AI applications compared to FRS, their metric maintains a high level of correlation with FRS scores. Correspondingly, their findings align closely with those of FRS, indicating that occupations requiring advanced skills are more exposed to AI.

Frey and Osborne (2017) introduce a metric of occupational exposure based on the automation potential of each occupation, where automation is defined as "advances in fields related to machine learning", hence a specific branch of AI. Importantly, they do not investigate the potential for automation of tasks that define an occupation (as done by FRS). Instead, they solicit judgments from a panel of experts directly asking the automation potential of the occupations in which these experts possess confidence (in other words, FRS and similar studies adopt a "task-based" approach, while Frey and Osborne (2017) adopt an "occupation-based" approach).[12] Subsequently, they undertake a probabilistic assignment of automation potential for other O*NET occupations. Their findings suggest that nearly half of all U.S. jobs could face automation within the next two decades. Arntz et al. (2017) build on Frey and Osborne (2017) and show that accounting for the task composition of individual jobs, the share of jobs that could be replaced in the next two decades decreases remarkably (less than 10 percent).

[11] More details on the methodology behind the cited papers is available in Table A4 in the Appendix.

[12] Under the occupation-based approach, it is the occupation that can be either automatized or not, whereas it is the task under the task-based approach. As an occupation can be described as a bundle of tasks, under the latter approach the occupational exposure varies according to a weighted mix of the exposure of its tasks (Arntz et al., 2017). The occupational exposures resulting from the occupation-based approach tend to exhibit a bi-polar distribution, while under the task-based approach most profession have an intermediate exposure. The occupation-based approach has been criticized for its rigidity, as it overlooks that occupations entail different tasks (whose composition and importance can be adjusted in response to automation) and that workers performing the same occupation can have different skills and different ability to adjust to innovations (Bannò et al. 2023).

Brynjolfsson and Mitchell (2017), Brynjolfsson et al. (2018), and Eloundou et al. (2023) derive some rubrics to evaluate whether and to what extent each task can be exposed to AI, exploiting specific task properties they derive. Brynjolfsson and Mitchell (2017) and Brynjolfsson et al. (2018) ask experts' judgments on 23 features that can make each task suitable for machine learning replacement and derive an index of "suitability for machine learning". According to this metric, tasks suitable for machine learning are spread across occupations and the correlation of this measure with wage percentiles is quite low. Thus, machine learning adoption would more likely imply a reallocation of tasks within jobs rather than completely replace some of them. Eloundou et al. (2023) focus on large language models such as generative pre-trained transformers (GPT). They assign a status (directly exposed/indirectly exposed/not exposed) to each task in the O*NET database based on both experts' judgment and GPT-4 judgment.[13] They find occupational exposure at all wage levels, but mostly on higher-income jobs. Particularly, their measure is positively correlated with jobs requiring writing and programming skills, while it is negatively correlated with jobs requiring critical thinking. Interestingly, their measure of occupational exposure shows positive and significant correlation with Brynjolfsson et al. (2018)'s measure of suitability for machine learning but almost no correlation with FRS, suggesting that these measures may offer a different perspective with respect to FRS scores. It is however possible that measures such as those in Brynjolfsson et al. (2017) and Eloundou et al. (2023) more closely capture substitutability than complementarity to AI.

One additional measure based on the task composition of occupations has been introduced in the Goldman Sachs' report by Briggs and Kodnani (2023). They assign binary values (0/1) to a list of tasks contained in the O*NET database and aggregate them at occupational level using O*NET importance and relevance weights. Exploiting this metrics, which indeed is less sophisticated compared to the aforementioned studies, they claim that two-thirds of US jobs are currently exposed to some degree of AI automation and that AI could replace up to one-fourth of jobs.

A different approach compared to the studies mentioned so far, which rely on authors' or experts' judgments in defining AI exposure, consists in exploring the correlation between AI-related patents and task descriptions. The authors adopting this approach interpret the indexes they derive mostly as measures of substitutability. Webb (2019) delineates AI-related patents through the identification of specific keywords and then compares the verb-noun pairs found in the patent descriptions and those present in job task descriptions in O*NET. He finds that occupations necessitating the detection of patterns, judgment-making, and optimization emerge as the most vulnerable. Notably, these tasks are prevalent among highly educated and experienced workers. Conversely, Kogan et al. (2021) opt to identify ground-breaking technologies within patent data, denoted as technologies absent in prior patents but frequently cited thereafter. They construct a distance matrix between the textual descriptions of these patents and occupation descriptions in O*NET. Their findings indicate an impact both at the upper and lower ends of the wage distribution. Occupations held by workers in the lower wage bracket face potential replacement through AI-related automation, whereas for high wage workers the impact is mixed, with some AI-related jobs being in higher demand, but also some skills becoming obsolete. Notably, the overall risk of displacement according to this metric is higher for older workers. Lastly, Meindl et al. (2021) employ a method akin to that of Kogan et al. (2021), with the difference that the comparison is made between patent descriptions and job tasks rather than occupation descriptions. Their findings reveal heightened occupational exposure for high-wage occupations and those requiring medium-to-high levels of education. This measure exhibits a positive correlation with FRS occupational scores.

## 5. *A comparison of occupations exposed to previous automation technologies and to AI*

A natural question following the definition of occupational exposure to AI is whether it is reasonable to expect such a technology to change existing patterns in occupational and sectoral employment. More

[13] GPT-4 is the fourth generation generative pre-trained transformer model developed by OpenAI.

specifically, it is important to understand whether the occupations that were more exposed to the introduction of past automation technologies are similar to those more likely to be exposed to AI.

The difference between occupations exposed to past waves of automation and those exposed to AI follows from the difference between tasks that each technology is capable to perform. Brynjolfsson et al. (2018) describe the application of past automation technology as "limited to areas where knowledge was codified, or at least codifiable". Differently, the AI technologies "infer the mapping function between inputs and outputs (in the case of supervised learning) automatically. While not always interpretable or explainable, these models open up a new set of possibilities for automation and complementarities to labour". In this respect, AI can expand automation to "domains formerly closed to digitization by the high cost or impossibility of writing explicit maps of inputs to outputs and policies".

Similar to exposure to AI, several measures have been developed to establish whether an occupation was exposed to the automation technologies developed in the last 30 years (Acemoglu and Restrepo 2022, 2023; Autor and Salomons 2018; Autor 2015). The conclusions about the level of exposure to past automation can vary according to whether an occupation-based or a task-based approach is adopted, with the latter generally resulting in a milder occupational exposure. However, under both approaches the most exposed occupations are generally those involving repetitive manual tasks, use of machineries in a predictable context, or routine activities; examples are cashiers, clerks, workers on storage and delivery, cleaners, sales personnel, un-skilled workers' occupations (see Caravella & Menghini, 2018; David, 2017; van der Zande et al., 2019). On the contrary, limited possibilities for automation were detected in activities involving perception (identifying objects, orienting), handling of non-standard objects, creativity, or social interaction skills. Examples include cognitive and high skilled occupations requiring decision making and management of human resources (e.g.: academics, managers, technicians and engineers, cultural jobs), but also physical jobs requiring dexterity in providing specialized services to persons (e.g.: barbers) or those involving possibly simpler activities based on social interactions (e.g.: caregivers).[14]

Bannò et al. (2023) investigate the occupational exposure to past automation waves in the Italian context. Considering both the task-based and the occupation-based approaches, their results are consistent with those described above. In particular, among the most exposed occupations they identify: low skilled workers in the primary sector and in manufacturing, workers operating with fixed machineries or in assembly line, assembly workers, drivers of mobile and lifting machinery or vehicles, secretarial clerks, cash handling and customer service clerks, office machine operators. At the other end of the spectrum, among the least exposed occupations there are high-skilled workers in health and social sectors, engineers, architects, teachers, researchers, physicists, mathematicians, chemists, managers, entrepreneurs.

In general, past automation exposure is higher for individuals with low education (less than high school), for those who are low skilled and low wage (Nedelkoska and Quintini, 2018; Minian and Martinez Monroy, 2018). The relationships with age and contract-type are less clear.[15] Men are generally found to be more exposed than females, and blue-collars more exposed than white-collars. This is also related to the sectoral profile of previous automation technologies: in particular, if we consider industrial robots, which have been extensively studied (see Aghion et al. 2022 for a recent survey), there is a concentration in the manufacturing sector, especially in the automotive industry. Also, construction, transport, and commerce are considered as exposed sectors (Frenette and Frank, 2020; Minian and Martinez Monroy, 2018; Piazolo and Dogan, 2021; Bannò et al. 2023), while the education sector and the health sector are

[14] The exposure to automation usually tends to be inversely correlated with workers' human capital endowment, but this correlation is not perfect, as also in occupations usually performed by skilled people there are automatable tasks.

[15] For example, the relationship with age is positive in Zhou et al. (2020), negative in Egana-delSol et al. (2021), U-shaped in Pouliakas (2018) or flat in Yamashita & Cummins (2021); see Bannò et al. (2023) for a survey. As far as contract type is concerned, Frenette and Frank (2020) and Nedelkoska and Quintini (2018) find a higher exposure for workers with fixed-term contracts using OECD countries and Canada data, while McGuinness et al. (2021) and Pouliakas (2018) detect a higher exposure among workers with open ended contracts in European countries and UK.

considered as less exposed (Caravella and Menghini, 2018; Illéssy et al., 2021; Yamashita and Cummins, 2021).[16]

Observably, AI technologies have brought advancements in all those activities (perception, handling with dexterity, content generation, social interactions) that were previously considered inherently human and at low exposure. In fact, some of the occupations with low exposure to earlier automation technologies now appear in the medium or high exposure groups, albeit with different degrees of complementarity (e.g. mathematicians or human resource managers). Other occupations, mainly related to physical strength, were highly exposed to some of the previous technological waves, but appear only mildly exposed to AI.

These conclusions are broadly confirmed by Webb (2019), who exploits his patent-based exposure measures to assess the differences between AI and automation (robotics and computers) in the US. His conclusion is that occupations exposed to AI technology generally employ highly educated individuals, who are in the upper part of the wage distribution, while past waves of automation affect low or middle-skilled individuals. He also concludes that AI-exposed occupations employ a larger number of older individuals, much more than the occupations exposed to past technologies. On the contrary, and similar to past technology, exposed occupations are more likely to be performed by men.

## *6. Potential exposure of the Italian labour market to AI technology*

Applying the methodology proposed by Pizzinelli et al. (2023) to measure occupation exposure and substitutability to AI to the Italian case (see Table 3) allows to investigate the distribution of occupations across sectors in the economy (Figure 3). The analysis is implemented on LFS data from 2023.[17] It is important to recognize that highly exposed occupations are not necessarily facing the introduction of AI technology yet. However, because the adoption rate is growing, AI exposure is also likely to increase in the years to come.[18]

**Overall and sectoral exposure.** In Figure 3, we plot for each sector the proportion in the 5 exposure categories, where the dark bars imply high level of substitutability and light bars high levels of complementarity. Approximately 15 million out of the 22 million of workers are either middle or highly exposed, with slightly below 9 million falling in the highly exposed group alone. Among workers with some type of exposition the complementary workers are more than the substitutable ones (about 9 million compared to 6 million substitutable), but if we focus on those who are highly exposed substitutable workers are the majority (they are about 4.75 million, compared to 4 million substitutable workers – these numbers correspond to the proportions reported in the bar labelled "Overall"). In line with the view that low-skilled occupations are generally little exposed, we find that sectors such as agriculture and manufacturing do not employ many workers in occupations with a strong link to AI. This marks a clear difference compared to robotization which had a strong impact on manufacturing (see Bannò et al., 2023). Also low value added services such as retail and the hospitality sector have low levels of exposure. A much stronger impact in terms of substitutability is instead evident in the transport and

[16] While this note mostly focuses on exposure to technology, several studies analyse the impact of the technology on exposed workers (e.g. in terms of employment levels or wages). The available studies do not agree on the finding of a negative effect in *absolute terms*, while exposed workers seem to consistently lose when compared to less exposed groups (i.e. in *relative terms*). At the firm level, there is evidence of positive or non-negative effect also for the exposed categories in the innovating firm (Aghion et al. 2022; Bessen et al. 2020; Acemoglu et al. 2020; Koch et al. 2021), likely driven by increased productivity and production, while the evidence at the labour market or industry level is mixed (Acemoglu and Restrepo 2020, Dauth et al. 2021; Dottori 2021; Aghion et al. 2022). Graetz and Micheal (2018) find that robots did not significantly reduce total employment, although they did reduce low-skilled workers' employment share. Acemoglu et al. (2020) find that adoption of robots coincides with declines in labour shares and in the share of production workers. Bonfiglioli et al (2022) find that a higher robot exposure is associated with a higher relative demand for high-skill professions.

[17] We use all four 2023 LFS waves, the latest data currently available.

[18] European Investment Bank, *Digitalisation in Europe 2022-2023 – Evidence from the EIB investment survey*, European Investment Bank, 2023.

communication sector and in finance, which includes all the banking system. Major gains in terms of complementarity seem to emerge in professional occupations and in occupations which include several public employees. Health and education sectors, generally not affected by previous innovation waves, are highly exposed to AI, mostly gaining in terms of complementarity.[19]

**Figure 3**

**Distribution of differently exposed occupations across sectors**

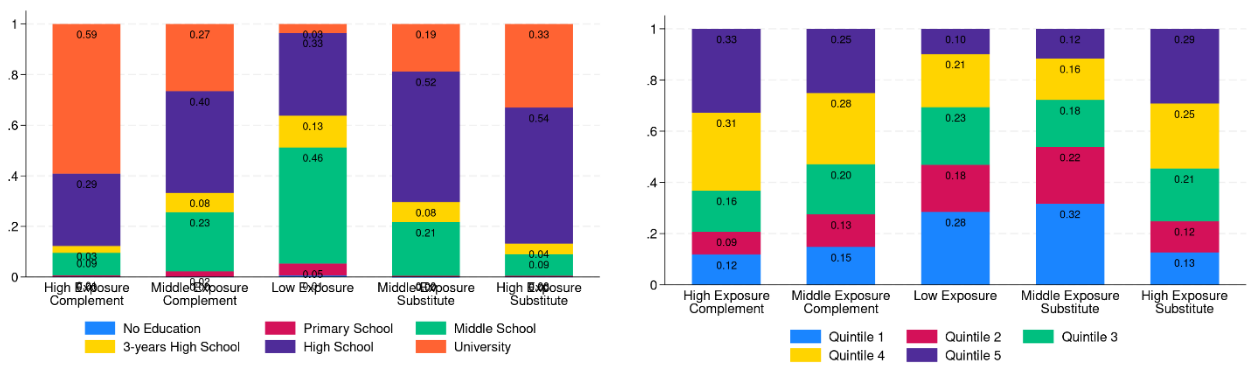

Source: Own elaborations exploiting data of the Labour Force Survey (Q4, 2022) and Pizzinelli et al.'s (2023) measure.

**Exposure by education and monthly salary.** In Figure 4 we characterize the profile of individuals whose job is at risk. Differently from Figure 3, in this figure (and in all subsequent figures) we plot the exposure groups on the x-axis (from the most substitutable to the most complementary) and the proportions of individuals within each group with the characteristics we analyse on the y-axis. In panel (a), it is evident that individuals with higher education levels are most exposed to AI. Notably, university graduates are disproportionately more represented among exposed-complements than among exposed-substitutes, while the opposite is true for high school graduates.

**Figure 4**

**Education and salary of differently exposed occupations**

(a) Education | (b) Salary quintile




Source: Own elaborations exploiting data of the Labour Force Survey (Q4, 2022) and Pizzinelli et al.'s (2023) measure.

[19] We also checked whether the just-described sectoral distribution can be already the result of the breakthrough of the technology, with some sectors moving already out of the substitutable occupations. However, when we compare the distribution within sectors in 2023 (Figure 3) to the same distribution 10 years before (Figure A1), we find very little differences, confirming the hypothesis that the composition by the end of 2023 was not the result of a reaction to the new technological advances.

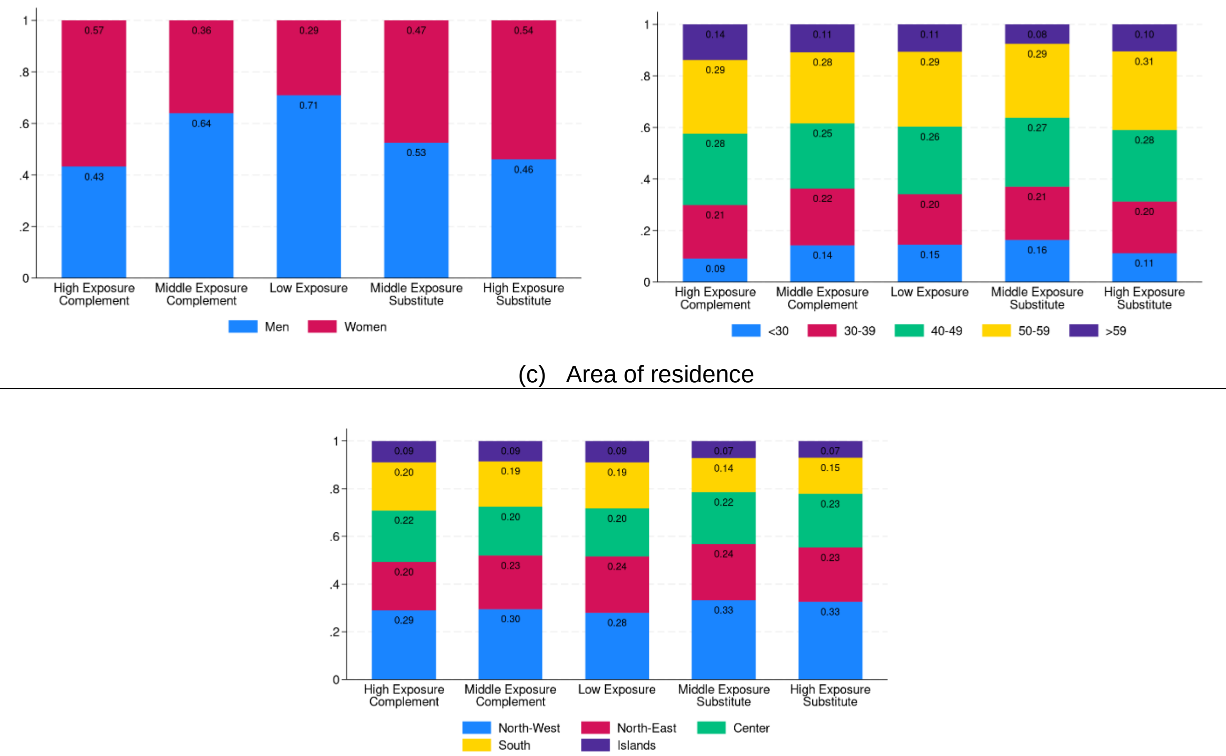
The educational divide is thus only a part of the explanation for the patterns presented in panel (b), looking at monthly salaries, given that the fraction of high salary individuals that is highly exposed and substitutable is relatively similar to those of exposed-complements.[20] Panel (b) shows that a noteworthy portion of individuals in the top quintile of the monthly salary distribution is employed in occupations potentially substitutable by AI technology. This may reflect the fact that several occupations in some high-paying sectors (e.g. the finance sector) are at risk of being substituted.

**Exposure by gender, age and geographical location.** Figure 5 investigates other characteristics of workers by occupational exposure, namely the gender divide and the distribution in terms of age and geographical location. These mostly reflect the occupational distribution across sectors, with a prevalence of the service sector among the most exposed occupations. In addition, we observe some differences compared to the conclusions in Webb (2019). In particular, panel (a) shows that highly exposed occupations (both complement and substitute) are more likely to employ women, while little exposed occupations employ more men and in panel (b) we report no evidence of exposed occupations being those with older workers. The age distribution is in fact quite even across the five groups. Finally, panel (c) highlights some differences between geographical areas, with complement occupations being more prevalent in the south while substitute occupations in the north-west, most likely driven by the concentration of the finance sector in the area.

Figure 5

**Gender, age and location of differently exposed occupations**

(a) Gender (b) Age




Source: Own elaborations exploiting data of the Labour Force Survey (Q4, 2022) and Pizzinelli et al.'s (2023) measure.

**Exposure by job contract.** In terms of type of employment, in Figure 6 we show that there are more self-employed individuals within more complementary occupations, a result which may follow from the

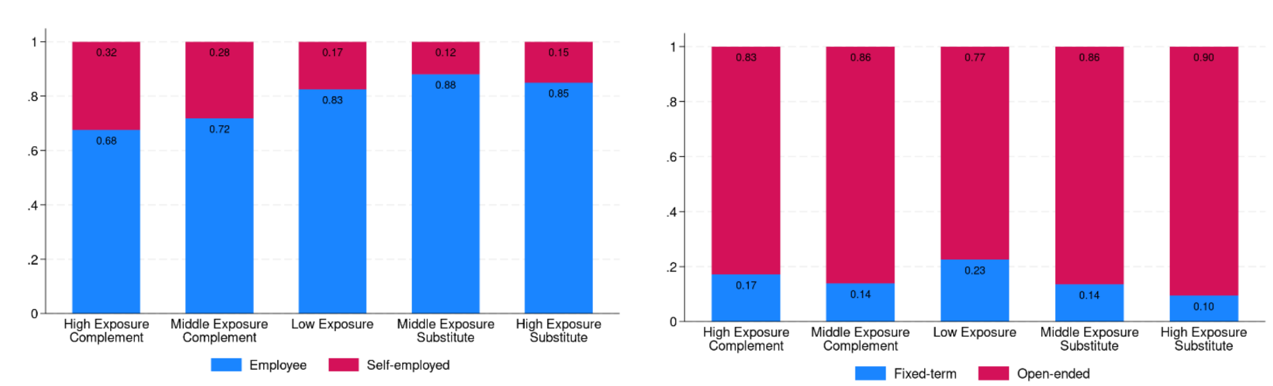
[20] Because monthly salary is available to us only until the survey from the last quartile of 2020, for the figure on monthly salary we exploit the LFS conducted in the last quartile of 2019 (we avoid using 2020 due to the exceptional conditions in that year).

complementarity between professional occupations and AI. Furthermore, occupations characterized by low exposure, as well as those marked by high exposure and complementarity, exhibit higher proportions of individuals with a fixed-term contract. These empirical observations imply that individuals potentially at higher risk of being substituted are not necessarily those subjected to the least robust labour market protections.

Figure 6

**Type of employment and contract of differently exposed occupations**

(a) Type of employment (b) Type of contract




Source: Own elaborations exploiting data of the Labour Force Survey (Q4, 2022) and Pizzinelli et al.'s (2023) measure.

### *7. AI exposure and job-to-job transitions*

This section examines flows in and out of differently exposed occupations, using the same exposure measure as in Section 6. Our goal is to describe job-to-job transitions and the associated wage differentials to understand potential patterns of job mobility if companies start adopting AI more extensively. In fact, given the low adoption of AI by companies, our analyses will not yet represent a "response" of workers to an increased or decreased demand for AI skills by companies (or only represent it to a small extent). In addition, we do not know how tasks themselves will change, so the wage differentials associated to job moves, that are observed today, may not be valid in the future.

With this caveat in mind, we analyse job-to-job transitions using data from CICO (*Campione Integrato delle Comunicazioni Obbligatorie*), a 13 percent sample of workers obtained from the administrative system that collects mandatory notifications that employers submit to the Italian Ministry of Labour when they activate or terminate a contract. For each contract, the data record the start and end dates, the type of contract (full-time or part-time and open-ended, fixed-term or apprenticeship), and, if the contract is terminated, the reason for termination. In addition, we have information on the four-digit occupation assigned to each contract, which we use to classify the exposure and substitutability of workers with AI. The data also report the monthly contractual wage, which is defined as the gross earnings the worker would receive if she had worked the number of monthly hours specified in her contract. Finally, we have information on workers' demographic and personal characteristics, including gender, year of birth, and education level, as well as firm characteristics, such as industry.

The data are transformed into a longitudinal dataset, with the unit of analysis being the worker observed at a quarterly frequency over a period of more than 10 years, from the first quarter of 2013 to the second quarter of 2023. The focus is on workers between the ages of 15 and 64 who do not retire or die during the observation period. In addition, we keep a single observation per worker in each quarter that corresponds to the main employment contract. This is defined as the contract with the longest duration or the one that is still active in 2023Q2.[21] We focus specifically on the subset of workers who change employers between consecutive quarters and, for the event study analysis on contractual wages, who are observed in the same job in the 3 quarters before the move.

**Movements between exposure categories.** We first analyse the patterns of job-to-job transitions over the entire period under study (about 2.5 million job changes), based on the classification of occupations in the origin and destination jobs.

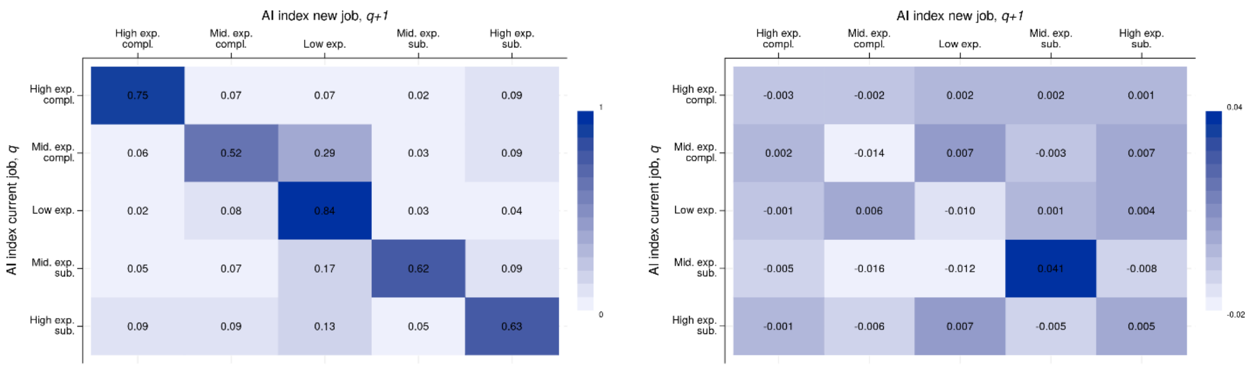
Figure 7, panel (a), reports a transition matrix that shows a high degree of persistence: workers are likely to remain in the same occupation category with their new employer; this persistence is particularly high in low-exposed occupations (85 percent of the moves) and in high exposed complement occupations (75 percent). For high-exposed substitute occupations movements to low-exposed occupations are relatively more common (13 percent) than movements to the high-exposed complement ones (9 percent). Panel (b) shows very little changes in these trends in the last three years by reporting the difference in the frequencies in each origin-destination cell between post- and pre-2020 (the only relevant difference is, if anything, an *increase* in the persistence for middle-exposure and substitute occupations).

Overall, the high degree of persistence which still emerges in the recent years most likely indicates that AI has not yet had a strong impact on the labour market. It also suggests that workers who may face difficulties in their jobs due to the introduction of the new technology do not currently have a clear path out of their type of occupation, but if anything such path leads the majority of workers towards little exposed occupations more than towards the highly complement ones.

**Figure 7**

**Frequency of job-to-job transitions by AI exposure**

(a) Full sample | (b) Post- vs. pre-2020




Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

**Wage changes upon movements, by exposure category.** Figure 8 reports event study estimates where the dependent variable is the log contractual monthly wage of a worker who moves between employers, separately for the occupation type in the destination job, regardless of the job of origin (so most of these movements are within the same occupational category, as shown in Figure 7).[22]

After the move, workers experience a wage gain regardless of their destination occupation. However, the gains are larger if the move is to occupations that are highly exposed to AI, especially if they are also complementary. This evidence corroborates the results of Figure 4, where we showed that highly exposed occupations pay relatively high wages, and this is true for both complementary and substitute jobs. Thus,

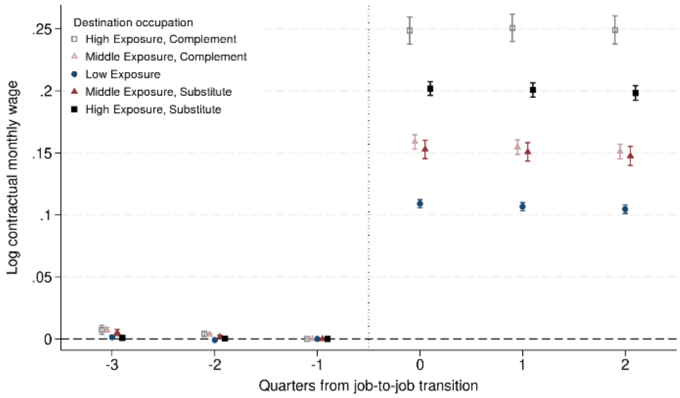
[21] When two contracts have exact same start date and duration, we keep the contract referred to the older employer.

[22] The event study regressions control for education, age, and time dummies. Coefficients are normalized to the quarter preceding the move.

not only is the level of earnings higher in more exposed occupations, but the possibility of wage increases appears to be greater. For the most substitutable workers, if adjustment to AI occurs by seeking shelter in occupations with low exposure to AI it will likely come with a wage cost. Hence, movements out of the more substitutable occupations may increase the wage disparities with highly paid complement workers.

**Figure 8**

**Event study around job moves, log monthly wage**




Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

**Exposure category and sectoral reallocation.** We next examine the relationship between occupational exposure to AI and sectoral reallocation; in the data, about 35 percent of job-to-job transitions are associated with a sector change.[23]

Figure 9 panel (a) reports the average predicted values from a regression of a dummy equal to one for workers who move to another sector after an employer change on dummies for different initial occupations, both unconditional and conditional demographic and job characteristics.[24] The probability of reallocation is highest when workers leave highly exposed and substitutable occupations, while it is lowest for complementary highly exposed occupations. Panel (b) shows how these probabilities changed in the last three years compared to the previous period, also in light of the fact that the pandemic recession boosted the reallocation pattern in the labor market.[25] The probability of sectoral reallocation for highly exposed and substitutable occupations increased (2.5 percentage points - although to a lesser if compared to workers in low-exposure occupations).

**Figure 9**

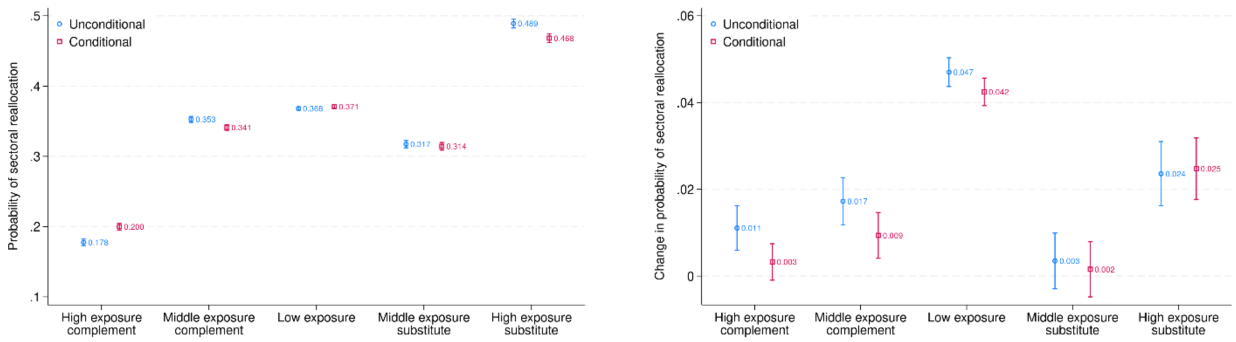
[23] We use 10 sector groups, broadly corresponding to Nace Rev. 2 sections: A (Agriculture); B, D, E (Mining, Utilities); C (Manufacturing); F (Construction); G, I (Trade and hospitality); H, J (Transportation, Information and communication); K (Banks and Insurance); L-N (Professional services); O-Q (Public administration); R-U (Arts and other services).

[24] We control for a quadratic polynomial in age, and dummies for education, gender, immigrants, type of separation (e.g., voluntary quit, layoff, expiration of temporary contract), and type of contract (e.g., permanent, temporary, apprenticeship).

[25] We interact the occupation dummies from the previous regression specification with a binary indicator for the period after the fourth quarter of 2019. The literature has examined whether COVID-19 has triggered a reallocation shock to the economy (Botelho et al., 2020). In general, sectoral labor reallocation tends to increase during recessions (Bluedorn et al., 2021), but policies to mitigate the potential disruptions of the pandemic may have hindered sectoral reallocation (Kudlyak and Wolcott, 2020). Nonetheless, the changes in working arrangements led to a permanent reallocation of the workforce that was higher than in the past (Barrero et al., 2021). For Italy, Basso et al. (2023) show that there was limited reallocation among workers who lost their jobs in the first months of the pandemic, although Gómez and Lattanzio (2024) show higher reallocation rates in the second half of 2020 and in 2021. Finally, Citino et al. (2023) show that the pandemic increased job reallocation only in certain sectors of the economy, such as ICT and construction.

**Sectoral reallocation after job moves by occupation exposure to AI**

(a) Full sample | (b) Post- vs. pre-2020

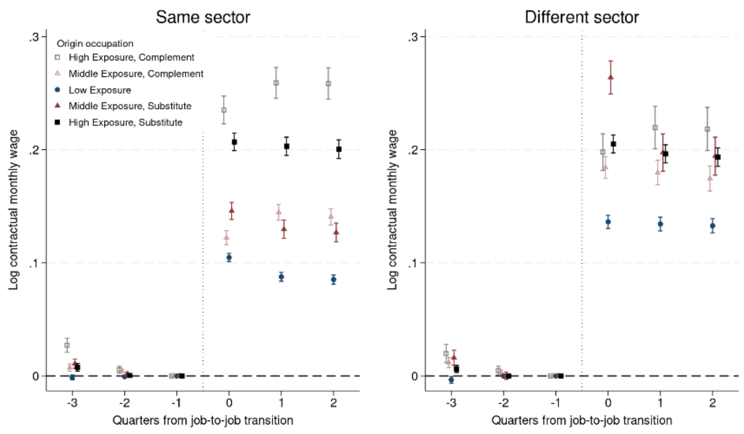



Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

While we cannot attribute the most recent change to AI adoption, the evidence in Figure 9 may suggest that workers who are more at risk of job displacement would also face more difficulties in finding a new job, given the need to move to a different sector. To explore this hypothesis further, we look at the wage gains/losses that follow the move, separately for individuals who stay and those who change sector. Figure 10 shows that changing sector is generally associated with larger gains than staying in the same sector, but only for workers leaving low or medium exposed occupations (these are graphs conditional on the exposure of the occupation at $t-1$ — the "origin" occupation — rather than the destination occupation as in Figure 8). For workers leaving highly exposed substitutable occupations there is no difference between those who stay and those who leave the sector; in other words, on average, movement to another sector is not clearly driven by higher wages. This may signal that highly exposed substitutable workers who change sector may not do it on purpose, or at least these movements are not always motivated by better opportunities in terms of salary.

**Figure 10**

**Event study around job moves, log monthly wage, separately for workers staying and changing sector**



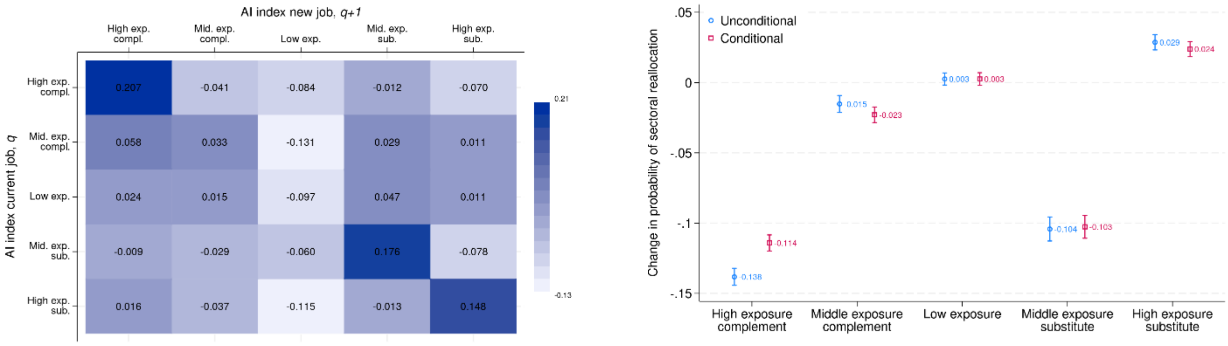

Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

**Heterogeneity in movement patterns: gender.** Finally, we investigate some heterogeneity in the patterns of movement between jobs and between groups of occupations with different levels of exposure to AI. Figure 11 plots the difference between women and men in each cell of job-to-job transition (panel (a)) and for sectoral reallocation after job moves (panel (b)). In Figure 5, we showed a higher prevalence of women in highly exposed occupations and in Figure 11 we also show that women are more likely than men to stay in highly exposed occupations. Women are also generally less likely to change sector, with the exception of women leaving highly exposed and substitute occupations. Combined with the fact that we observe more women in highly exposed and substitutable occupations (54 percent of workers in these occupations are women), this may imply that AI adoption may be particularly disruptive for some groups of women.[26]

**Figure 11**

**Difference between women and men in job moves by occupation exposure to AI**

(a) Frequency of job-to-job transitions | (b) Sectoral reallocation after job moves




Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

**Heterogeneity in movement patterns: education.** We also examine the movements by educational attainment. In Figure 4, we showed that exposure to AI is greater for more educated workers, and Figure 12 panel (a) shows that they are also very likely to stay in highly-exposed occupations. Similarly, low educated workers tend to move within low exposure occupations. In addition, workers in highly exposed and substitute occupations are more likely to transition to highly exposed and complementary occupations if they have a college degree (15 percent) than if they have secondary education (5 percent) or even less (2 percent). Moreover, as shown in panel (b), when low-educated workers end up in a highly exposed complement occupation they generally experience a much lower wage premium than college-educated workers. In turn, for college educated workers, only moving to highly exposed occupations guarantees higher wage premia, when they move to the mildly exposed the returns are similar to those of lower educated workers.

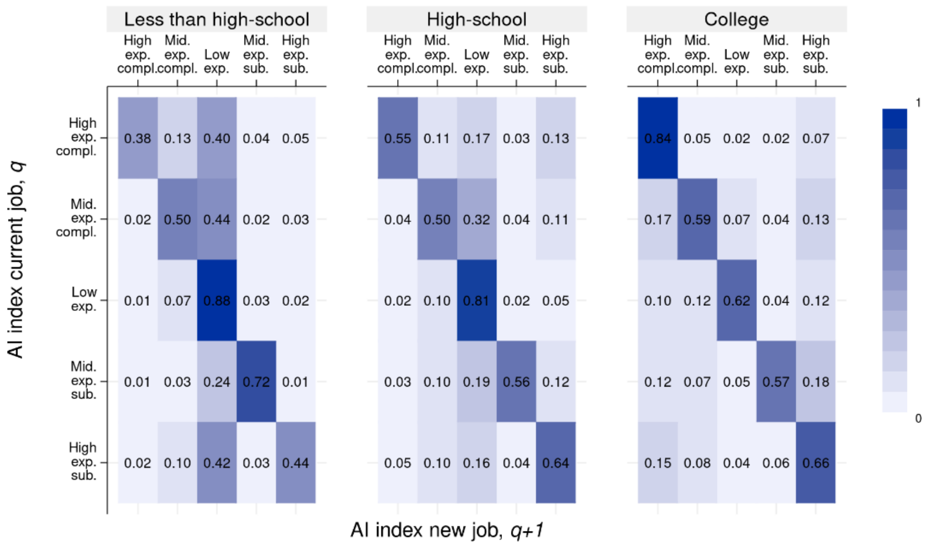
Overall, this evidence supports the hypothesis that AI-exposed occupations require a set of skills that are mostly for highly educated workers; thus, in the absence of changes in the nature of occupations following the introduction of the new technology, low-educated workers rarely move to complement occupations and, when they do it, they face lower expected returns as compared to more educated workers. Similarly, for college-educated workers, any movement to mildly exposed occupations has a return in terms of wage premium which is often comparable to the one of lower-educated workers.

**Figure 12**

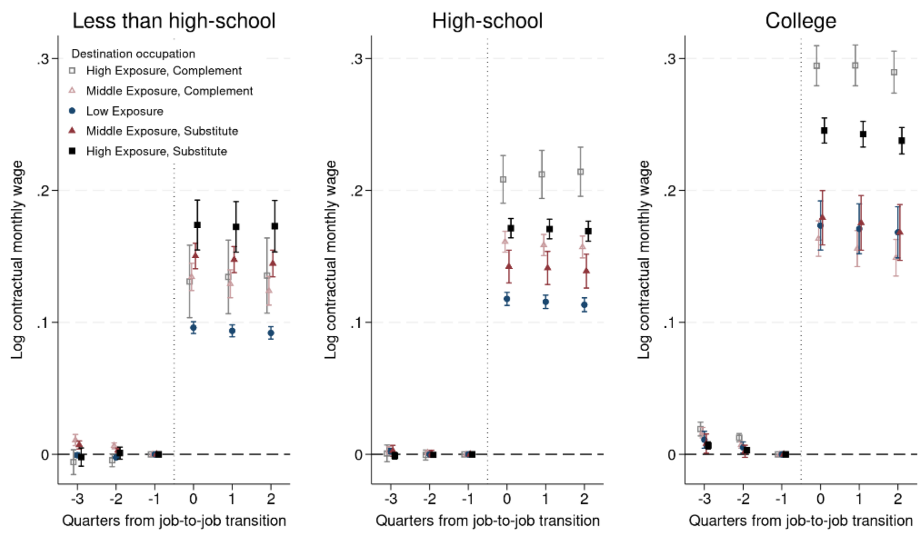
**Difference by education in job moves by occupation exposure to AI**

(a) Frequency of job-to-job transition

[26] When we look at heterogeneity in wage upon job change (not reported), we find that women overall have lower gains than men, but there is no heterogeneity in the gradient by occupational exposure.




(b) Log wage change around movement




Source: Own elaborations exploiting data of CICO (Q1, 2013 – Q2, 2023) and Pizzinelli et al.'s (2023) measure.

**Summary of the evidence from the job-to-job transition analysis.** To summarize, the evidence from this section highlights that (i) mobility between different types of occupations has been historically low and keeps being low in the most recent years; (ii) if anything, workers from highly exposed and substitute occupations are more likely to move into low exposed occupations rather than to the highly exposed and complement ones; (iii) movements towards less exposed occupations are generally associated with a lower wage premium upon moving; (iv) workers who move out of highly exposed and substitute occupations are more likely to change sector, but such sectoral change does not boost the wage premium earned upon moving, potentially implying that these workers may be forced out of their sector and thus signaling more difficulties in finding a new job; (v) women display more persistence in the same occupation category than men in general, but also a larger probability of moving sector if they exit from highly substitutable occupations, with the consequence that reallocating out of these types of occupations may be harder for them; (vi) more educated workers more easily relocate from occupations which are highly exposed and substitute to the complement ones, but in case they move to less exposed occupations the wage return for them is similar to worker who are less educated.

## 8. *Conclusions*

As a general-purpose technology, AI is expected to have a relevant impact on labour markets. This note critically reviews several assessments of occupational exposure to AI. In particular, we focused on the seminal approach of Felten, Raj and Seamans, where the exposure concept used does not necessarily imply a replacement risk, and its subsequent extension by Pizzinelli et al., which aims to disentangle substitution and complementarity. We have also reviewed alternative approaches that have developed their own metrics to measure occupational exposure: some of them (Eloundou et al., 2023; Meindl et al., 2021; Tolan et al., 2021; Brynjolfsson et al., 2018), similar to Felten, Raj and Seamans, provide measures of the AI-relatedness of occupations without taking a position on the AI substitution potential for more exposed occupations; some others (Webb, 2019; Kogan et al., 2021; Briggs and Kodnani, 2023; Frey and Osborne, 2017; Arntz et al., 2017), instead, interpret their scores directly as measures of job substitutability.

Although the evidence resulting from the existing literature does not always provide a comprehensive and consistent picture due to the different methodologies, settings and data used, some peculiarities of AI technologies seem to emerge compared to earlier automation technologies, such as robots. AI technologies are more closely related to occupations where cognitive skills are important and less related to jobs where physical strength is most important. This means that unlike the previous wave of automation, which mainly affected blue-collar workers, AI is more likely to affect white-collar workers. At the sectoral level, while previous technologies were relatively more concentrated in manufacturing and especially in some specific industries (e.g., automotive), the scope for AI applications appears to be broader, extending to many occupations in the service sector. Another peculiarity of AI technologies concerns the enhancement of several activities (related to perception, content generation, handling with dexterity and social interactions) that were previously considered to be inherently human and at low exposure. This tends to increase the educational level of the exposed workers: while the direct impact of previous technologies mainly affected low-skilled workers, the exposure to AI is higher for medium-to-high educated people (thus including also college graduates), although with different degrees of complementarity: in particular, complementarity is generally higher for occupations that often involve high-level and complex decision-making, while the risk of substitution seems to be higher for occupations that require specialized but standard procedures.

We then provide a description of the distribution and characteristics of Italian workers who are potentially exposed to the introduction of AI, exploiting the measure by Felten, Raj and Seamans and the extension by Pizzinelli et al. which allows to separate substitutable and complement occupations. Overall, the results are in line with the evidence provided so far for other labor markets, even though some results for the US described in Webb (2019) do not hold for Italy. In particular, highly exposed occupations (both substitutes and complements) include more women than men, and we also fail in finding an age gradient in exposure. We conclude our empirical analysis by looking at current and past movements between occupations, to get an idea of whether workers who are more at risk of being substituted have a clear pattern out of those occupations. Although this is only indicative, our evidence suggests that this is not the case yet, and in fact changing type of occupation may be difficult and result in lower wages for these workers, in particular for women and for highly educated workers if they have to move to lower exposed occupations. These results for Italy are broadly in line with the international evidence provided in Cazzaniga et al. (2024) who show that also in Brazil and the UK movements from highly exposed to low exposed occupations result in lower (if not negative) wage premia.

Finally, it is worth reiterating that the measure of exposure we use is based on the current nature of the occupations we observe. One of the characteristics of technological progress is that it changes the tasks performed by some occupations and creates new occupations in ways that are difficult to predict (Autor, 2024). This implies that some conclusions may change; for example, if some occupations currently classified as low exposure or substitutes manage to complement their skills with AI to begin performing tasks that are in high demand, this has the potential to raise their wages rather than depress or leave them untouched. Of course, this also depends on the choices that institutions make about what workers in different occupations are allowed to do and how much they encourage innovation in some jobs. Thus, the ultimate impact of AI on inequality will be partly determined by the institutional setting and the ability of workers in occupations that are potentially little or negatively affected to take advantage of it.

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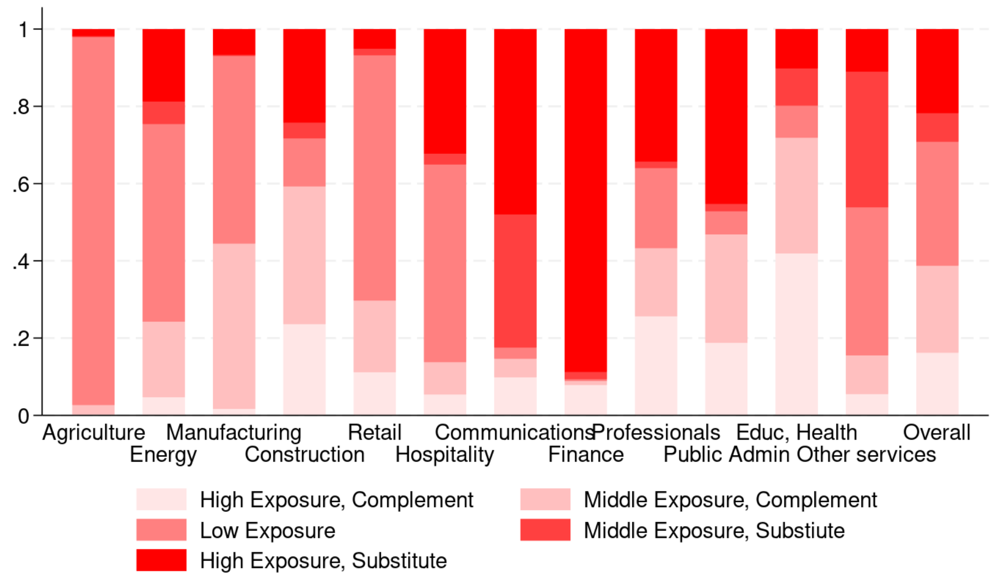
# APPENDIX

## Figures

Figure A1

Distribution of differently exposed occupations across sectors in the last quarter of 2012




Own elaborations exploiting data of the Labour Force Survey (Q4, 2012) and Pizzinelli et al. (2023) measure

## Tables

**Table A1**

| AI application | Description |
|---|---|
| Abstract Strategy Games | The ability to play abstract games involving sometimes complex strategy and reasoning ability, such as chess, go, or checkers, at a complexity at a high level. |
| Generating Images | The creation of complex images |
| Image Recognition | The determination of what objects are present in a still image. |
| Instrumental Track Recognition | The recognition of instrumental musical tracks. |
| Language Modeling | The ability to model, predict, or mimic human language. |
| Reading Comprehension | The ability to answer simple reasoning questions based on an understanding of text |
| Real Time Video Games | The ability to play a variety of real-time video games of increasing complexity at a high level |
| Speech Recognition | The recognition of spoken language into text. |
| Translation | The translation of words or text from one language into another. |
| Visual Question Answering | The recognition of events, relationships, and context from a still image. |

Source: Felten et al. (2021)

**Table A2**

| | Ability | | | | |
|---|---|---|---|---|---|
| 1 | Information Ordering | cognitive | 27 | Sound Localization | sensory |
| 2 | Memorization | cognitive | 28 | Near Vision | sensory |
| 3 | Speed of Closure | cognitive | 29 | Reaction Time | physical |
| 4 | Flexibility of Closure | cognitive | 30 | Depth Perception | sensory |
| 5 | Category Flexibility | cognitive | 31 | Co ntrol Precision | physical |
| 6 | Perceptual Speed | cognitive | 32 | Rate Control | physical |
| 7 | Selective Attention | cognitive | 33 | Originality | cognitiva |
| 8 | Deductive Reasoning | cognitive | 34 | Far Vision | sensory |
| 9 | Speech Recognition | sensory | 35 | Glare Sensitivity | sensory |
| 10 | Inductive Reasoning | cognitive | 36 | Peripheral Vision | sensory |
| 11 | Oral Comprehension | cognitive | 37 | Night Vision | sensory |
| 12 | Time Sharing | cognitive | 38 | Finger Dexterity | physical |
| 13 | Auditory Attention | sensory | 39 | Wrist Finger Speed | physical |
| 14 | Speech Clarity | sensory | 40 | Manual Dexterity | physical |
| 15 | Written Comprehension | cognitive | 41 | Arm Hand Steadiness | physical |
| 16 | Problem Sensitivity | cognitive | 42 | Multilimb Coordination | physical |
| 17 | Oral Expression | cognitive | 43 | Speed of Limb Movement | physical |
| 18 | Mathematical Reasoning | cognitive | 44 | Gross Body Coordination | physical |
| 19 | Number Facility | cognitive | 45 | Gross Body Equilibrium | physical |
| 20 | Written Expression | cognitive | 46 | Dynamic Flexibility | physical |
| 21 | Visualization | cognitive | 47 | Stamina | physical |
| 22 | Response Orientation | physical | 48 | Extent Flexibility | physical |
| 23 | Hearing Sensitivity | sensory | 49 | Static Strength | physical |
| 24 | Visual Color Determinat~n | sensory | 50 | Dynamic Strength | physical |
| 25 | Fluency of Ideas | cognitive | 51 | Explosive Strength | Physical |
| 26 | Spatial Orientation | cognitive | 52 | Trunk Strength | Physical |

Source: Felten et al. (2023) supplementary material and online data

## Table A3: most and least exposed occupations according to different metrics

| Tolan et al. 2021 | Eloundou et al. 2023 human ratings | Eloundou et al. 2023 GPT ratings | Webb 2019 | Kogan et al. 2021 | Mendl et al. 2021 | Frey and Osborne, 2017 |
|---|---|---|---|---|---|---|
| | | | ***Most exposed occupations*** | | | |
| Electrotechnology engineers | Interpreters and Translators | Mathematicians | Clinical labouratory technicians | Production checkers, graders, and sorters in manufacturing | Credit Authorizers | Telemarketers |
| Database and network professionals | Survey Researchers | Correspondence Clerks | Chemical engineers | Miscellaneous precision workers | Statistical Assistants | Title examiners, abstractors, and searchers |
| Software and applications developers and analysts | Poets, Lyricists and Creative Writers | Blockchain Engineers | Optometrists | Punching and stamping press operatives | Computer Network Support Specialists | Sewers, hand |
| Engineering professionals | Animal Scientists | Court Reporters and Simultaneous Captioners | Power Plant operators | Machinery maintenance occupations | Data Entry Keyers | Mathematical technicians |
| Mathematicians, actuaries and statisticians | Public Relations Specialists | Proofreaders and Copy Markers | | Rollers, roll hands, and finishers of metal | Insurance Claims Clerks | Insurance underwriters |
| Information and communications technology operators | | | | Production helpers | Bookkeeping, Accounting, and Auditing Clerks | Watch repairers |
| Physical and engineering science technicians | | | | Lathe and turning machine operatives | File Clerks | Cargo and freight agents |
| Finance professionals | | | | Typesetters and compositors | Bill and Account Collectors | Tax preparers |
| Financial and mathematical associate professionals | | | | Metal platers | Insurance Policy Processing Clerks | Photographic process workers and processing machine operators |
| Life science technicians and related associates | | | | Extruding and forming machine operators | Telemarketers | New accounts clerks |
| | | | ***Least exposed occupations*** | | | |
| Street vendors (excluding food) | | | | Funeral directors | Meat, Poultry, and Fish Cutters and Trimmers | Recreational therapists |
| Vehicle, window, laundry and other hand cleaning | | | | Dancers | Slaughterers and Meat Packers | First-line supervisors of mechanics, installers, and repairers |
| Food preparation assistants | | | | Barbers | Floor Sanders and Finishers | Emergency management directors |
| Domestic, hotel and office cleaners and helpers | | | | Sheriffs, bailiffs, correctional institution officers | Terrazzo Workers and Finishers | Mental health and substance abuse social workers |
| Waiters and bartenders | | | | Pest control occupations | Cement Masons and Concrete Finishers | Audiologists |
| Refuse workers | | | | Optometrists | Hunters and Trappers | Occupational therapists |
| Agricultural, forestry and fishery labourers | | | | Actuaries | Plasterers and Stucco Masons | Orthotists and prosthetists |
| Cashiers and ticket clerks | | | | Podiatrists | Pesticide Handlers, Sprayers, and Applicators | Healthcare social workers |
| Transport and storage labourers | | | | Bartenders | Tapers | Oral and maxillofacial surgeons |
| Hairdressers, beauticians and related workers | | | | Lawyers and judges | Floor Layers, Except Carpet, Wood, and Hard Tiles | First-line supervisors of fire fighting and prevention workers |

**Table A4: methodologies adopted to derive occupational exposure**

| | |
|---|---|
| Arntz et al. (2017) | The authors regress of occupation scores from Frey and Osborne (2017) on individual tasks (as from the PIACC) and socio-economic characteristics. The coefficients of the tasks represent the influence of that task on the occupation-specific automating potential, which are then used to compute the predicted automating potential for each individual job. The predicted individual automating potential is then aggregated for the whole economy. |
| Briggs et al. (2023) | The authors exert occupational exposure to AI assigning 0/1 values to a list of task contained in O*NET and aggregating this values using importance and relevance weights at occupational level. The list of the 13 tasks included is: getting information; monitoring processes, materials, or surroundings; identifying objects, actions, and events; estimating the quantifiable characteristics of products, events, or information; processing information; evaluating information to determine compliance with standards; analysing data or information; updating and using relevant knowledge; scheduling work and activities; organizing, planning, and prioritizing work; documenting/recording information; interpreting the meaning of information for others; performing administrative activities. The baseline assumption is that all these characteristics can be automated up to level 4 of the O*NET level definition. |
| Brynjolfsson and Mitchell (2017); Brynjolfsson et al. (2018) | The authors derive a new metric to evaluate occupational exposure. They regard machine learning algorithms as AI and for each task in O*NET they ask experts' judgments on 23 features that can make the task suitable for machine learning replacement. The expert can rate each of these properties on a scale from 1 (strongly disagree) to 5 (strongly agree). All the features' scores are then aggregated at task and occupation level. In this way, they provide a synthetic measure of occupational exposure to machine learning. |
| Eloundou et al. (2023) | The study focuses on large language models and generative pre-trained transformers and assign a status to each task in the O*NET database based on both experts' judgment and GPT4 judgment (they derive an algorithm to ask directly to GPT4 whether it is able to perform some tasks). The status assigned to each task can be "Not exposed", if GPT cannot reduce the time required by a specific task by at least half maintaining the same quality of the output or if using GPT would reduce the quality of the output; "Directly exposed" if GPT can reduce the time required by a specific task by at least half maintaining the same quality of the output; "Indirectly exposed" if using GPT would not reduce the time required by at least half, but it could with additional software development on top of GPT. Then, the occupational exposure is derived aggregating task scores at occupation level according to three measures of exposures: i) only directly exposed tasks are at risk of replacement, ii) directly exposed task plus a half of indirectly exposed tasks are at risk of replacement, and iii) both directly exposed and indirectly exposed tasks are at risk of replacement. |
| Frey and Osborne (2017) | The authors require expert judgments of automation potential for occupations in which they were confident and probabilistic assignment of automation potential for the other O*NET occupations. Automation potential is defined as "advances in fields related to machine learning, including data mining, machine vision, computational statistics and other sub-fields of artificial intelligence in which efforts are explicitly dedicated to the development of algorithms that allow cognitive tasks to be automated". Scores assigned by the experts range from 0 to 1, where 1 is given to occupations which are fully substitutable by automation in all their tasks. Overall, they rated 70 out of 709 occupations. |
| Kogan et al. (2021) | The authors define the set of patents of interest according to the criterion of "breakthrough technologies", i.e. technologies that are both novel (their descriptions |

| | |
|---|---|
| | are different from the preceding ones) and impactful (they are similar to subsequent patents). Then, they construct a distance matrix between the text of patent description and the description of occupations in O*NET and evaluate occupational exposure to AI according to this matrix. |
| Meindl et al. (2021) | The authors define AI-related patents according to the application domain of the patent and the technology. The technologies considered are: IT hardware, software, connectivity, data management, user interfaces, core AI, geo-positioning, power supply, data security, safety, three-dimensional support systems. The application domains are: consumer goods, home, vehicles, services, industrial, infrastructure, healthcare, and agriculture. Then, they construct a distance matrix similar to the one by Kogan et al. (2021), but they compare O*NET task descriptions to patent descriptions rather than O*NET occupation descriptions. Then, they construct a distance matrix similar to the one by Kogan et al. (2021), but they compare O*NET task descriptions to patent descriptions rather than O*NET occupation descriptions. |
| Tolan et al. (2021) | The authors start from the list of task contained in the European Working Condition Survey, the Survey of Adult Skills and O*NET and the AI benchmarks available in online repositories (such as *Papers with codes*) that list what each technology can do in terms of tasks. Then, they ask to experts to rate the importance of 14 cognitive abilities derived from the psychometric literature (memory processes; sensorimotor interaction; visual processing; auditory processing; attention and search; planning and sequential decision-making and acting; comprehension and compositional expression; communication; emotion and self-control; navigation; conceptualisation, learning and abstraction; quantitative and logical reasoning; mind modelling and social interaction; metacognition and confidence assessment) in performing each task. All this information is eventually combined to obtain a single score of exposure for each occupation. |
| Webb (2019) | The author defines the relevant AI-related patents through text mining of keywords such as "neural networks". Then, he compares the verb-noun pairs in the task descriptions from O*NET with the verb-noun pairs in AI-related patent descriptions and assigns a score to each task according to the relative frequency of the verb-noun pair in patents' data. Finally, he aggregates such scores at occupation level. |