OECD*publishing*

ARTIFICIAL INTELLIGENCE AND WAGE INEQUALITY

OECD ARTIFICIAL INTELLIGENCE PAPERS

April 2024 **No. 13**

OECD
BETTER POLICIES FOR BETTER LIVES

Artificial intelligence and wage inequality

Alexandre Georgieff

This paper looks at the links between AI and wage inequality across 19 OECD countries. It uses a measure of occupational exposure to AI derived from that developed by Felten, Raj and Seamans (2019) – a measure of the degree to which occupations rely on abilities in which AI has made the most progress.

The results provide no indication that AI has affected wage inequality *between* occupations so far (over the period 2014-18). At the same time, there is some evidence that AI may be associated with lower wage inequality *within* occupations – consistent with emerging findings from the literature that AI reduces productivity differentials between workers.

Further research is needed to identify the exact mechanisms driving the negative relationship between AI and wage inequality within occupations. One possible explanation is that low performers have more to gain from using AI because AI systems are trained to embody the more accurate practices of high performers. It is also possible that AI reduces performance differences within an occupation through a selection effect, e.g. if low-performers leave their job because they are unable to adapt to AI tools by shifting their activities to tasks that AI cannot automate.

Keywords: Employment, Skills, Artificial Intelligence.

JEL codes: J21, J23, J24, O33.

Résumé

Cet article examine les liens entre l'IA et les inégalités salariales dans 19 pays de l'OCDE. Il s'appuie sur une mesure de l'impact de l'IA sur les professions dérivée de celle développée par Felten, Raj and Seamans (2019[1]) – une mesure du degré auquel les professions reposent sur des capacités dans lesquelles l'IA a le plus progressé.

Jusqu'à présent (sur la période 2014-18), les résultats n'indiquent pas que l'IA ait affecté les inégalités salariales *entre* les professions. Parallèlement, certains éléments suggèrent que l'IA peut être associée à de plus faibles inégalités salariales *au sein* des professions – conformément aux conclusions récentes de la littérature selon lesquelles l'IA réduit les écarts de productivité entre les travailleurs.

Des recherches supplémentaires sont nécessaires afin d'identifier avec exactitude les mécanismes qui sous-tendent la relation négative entre l'IA et les inégalités salariales au sein des professions. Une explication possible est que les travailleurs peu performants ont plus à gagner de l'utilisation de l'IA car les systèmes d'IA sont entraînés à adopter les pratiques plus précises des travailleurs très performants. Il est également possible que l'IA réduise les écarts de performance au sein d'une profession par un effet de sélection, par exemple si les travailleurs peu performants quittent leur emploi parce qu'ils sont incapables de s'adapter aux dispositifs d'IA en réorientant leurs activités vers des tâches que l'IA ne peut pas automatiser.

Abstract

In dieser Studie werden die Zusammenhänge zwischen KI und Lohnungleichheit in 19 OECD-Ländern untersucht. Dies geschieht anhand eines Maßes des KI-Potenzials verschiedener Berufe, das auf dem von Felten, Raj und Seamans (2019[1]) entwickelten Indikator beruht und misst, inwieweit für bestimmte Berufe Fähigkeiten benötigt werden, bei denen KI besonders große Fortschritte gemacht hat.

Die Ergebnisse liefern keinen Anhaltspunkt dafür, dass KI bereits Auswirkungen auf das Lohngefälle *zwischen* verschiedenen Berufsgruppen hatte (Zeitraum 2014-18). Gleichzeitig gibt es aber Anzeichen dafür, dass KI mit einer geringeren Lohnungleichheit *innerhalb* einzelner Berufsgruppen verbunden sein könnte. Dies deckt sich mit ersten Erkenntnissen aus der Fachliteratur, denen zufolge KI das Produktivitätsgefälle zwischen den Beschäftigten verringert.

Weitere Studien sind nötig, um zu ermitteln, wie der innerhalb einzelner Berufsgruppen festzustellende negative Zusammenhang zwischen KI und Lohnungleichheit genau zum Tragen kommt. Eine mögliche Erklärung ist, dass leistungsschwache Beschäftigte größeren Nutzen aus KI ziehen, weil beim Trainieren der KI-Systeme die erfolgreichen Vorgehensweisen leistungsstarker Beschäftigter berücksichtigt werden. Möglich ist auch, dass KI das Leistungsgefälle innerhalb einzelner Berufsgruppen über einen Selektionseffekt verringert, z. B. wenn wenig leistungsstarke Arbeitskräfte aus dem Beruf ausscheiden, weil es ihnen nicht gelingt, ihre Tätigkeiten in Reaktion auf die KI-Tools auf Aufgaben zu verlagern, die nicht durch KI automatisiert werden können.

Acknowledgements

This publication contributes to the OECD's Artificial Intelligence in Work, Innovation, Productivity and Skills (AI-WIPS) programme, which provides policy makers with new evidence and analysis to keep abreast of the fast-evolving changes in AI capabilities and diffusion and their implications for the world of work. The programme aims to help ensure that adoption of AI in the world of work is effective, beneficial to all, people-centred and accepted by the population at large. AI-WIPS is supported by the German Federal Ministry of Labour and Social Affairs (BMAS) and will complement the work of the German AI Observatory in the Ministry's Policy Lab Digital, Work & Society. For more information, visit https://oecd.ai/work-innovation-productivity-skills and https://denkfabrik-bmas.de/.

Special thanks must go to Stijn Broecke for his supervision of the project and to Mark Keese for his guidance and support throughout the project. The report also benefitted from helpful comments provided by colleagues from the Directorate for Employment, Labour and Social Affairs (Andrew Green, Marguerita Lane, Anna Milanez and Anne Saint-Martin), from the Directorate for Science, Technology and Innovation and from the Directorate for Education and Skills. Thanks to Assa Fofana for providing publication support.

Federal Ministry
of Labour and Social Affairs

Table of contents

FIGURES

TABLES

Executive summary

The last decade has seen impressive advances in Artificial Intelligence (AI). This rapid progress has been accompanied by, amongst others, concerns about the possible effects of AI on the labour market, including on wages and inequality between workers; concerns that have come to a head since the public launch, in late 2022, of generative AI systems.

This paper looks at the links between AI and wage inequality across 19 OECD countries. It uses a measure of occupational exposure to AI derived from that developed by Felten, Raj and Seamans (2019[1]) – a measure of the degree to which occupations rely on abilities in which AI has made the most progress. This measure, which allows for variations in AI exposure across occupations within countries, as well as across countries for a given occupation, is matched to data from the Structure of Earnings Survey (SES) and the US Current Population Survey (CPS) to analyse the relationship with wage inequality.

The results provide no indication that AI has affected wage inequality *between* occupations so far (over the period 2014-18). At the same time, there is some evidence that AI may be associated with lower wage inequality *within* occupations – consistent with emerging findings from the literature that AI reduces productivity differentials between workers. However, this does not appear to affect the gender or age wage gaps within occupations.

The analysis covers a period when AI adoption was still relatively low and also excludes recent advances in AI. GPT-3, an AI model that made headlines at the end of 2022 for its performance in natural language processing, is a striking example of how AI development and adoption are accelerating. Extrapolating the findings of this paper to the current context should therefore be made with caution. This also highlights the need to keep monitoring the impact of AI on wages and inequality, as the full effect may not be observable yet.

Further research is also needed to identify the exact mechanisms driving the negative relationship between AI and wage inequality within occupations. One possible explanation is that low performers (i.e. workers with low productivity) have more to gain from using AI because AI systems are trained to embody the more accurate practices of high performers. It is also possible that AI reduces performance differences within an occupation through a selection effect, e.g. if low-performers leave their job because they are unable to adapt to AI tools by shifting their activities to tasks that AI cannot automate.

Synthèse

La dernière décennie a été marquée par des avancées spectaculaires dans le domaine de l'intelligence artificielle (IA). Ces progrès rapides se sont accompagnés, entre autres, d'un certain nombre de craintes concernant les effets possibles de l'IA sur le marché du travail, notamment sur les salaires et les inégalités entre les salariés ; craintes qui ont atteint leur paroxysme depuis le lancement public, fin 2022, de systèmes d'IA générative.

Ce document examine les liens entre l'IA et les inégalités salariales dans 19 pays de l'OCDE. Il s'appuie sur une mesure de l'impact de l'IA sur les professions dérivée de celle développée par Felten, Raj and Seamans (2019[1]) – une mesure du degré auquel les professions reposent sur des capacités dans lesquelles l'IA a le plus progressé. Cette mesure, qui permet de tenir compte des variations de l'exposition à l'IA entre les professions au sein des pays, ainsi qu'entre les pays pour une profession donnée, est ensuite mise en correspondance avec l'enquête sur la structure des salaires (ESS) et l'enquête sur la population active des États-Unis (CPS) afin d'analyser la relation avec l'inégalité salariale.

Jusqu'à présent (sur la période 2014-18), les résultats n'indiquent pas que l'IA ait affecté les inégalités salariales *entre* les professions. Parallèlement, certains éléments suggèrent que l'IA peut être associée à de plus faibles inégalités salariales *au sein* des professions – conformément aux conclusions récentes de la littérature selon lesquelles l'IA réduit les écarts de productivité entre les travailleurs. Toutefois, cela ne semble pas avoir d'incidence sur les écarts salariaux entre les hommes et les femmes ou entre les groupes d'âge au sein des professions.

L'analyse couvre une période durant laquelle l'adoption de l'IA était encore relativement faible, et exclut les avancées récentes en matière d'IA. GPT-3, un modèle d'IA qui a fait les gros titres fin 2022 pour ses performances en matière de traitement du langage naturel, est un exemple frappant d'accélération du développement et de l'adoption de l'IA. L'extrapolation des résultats de cette étude au contexte actuel doit donc être faite avec prudence. Cela souligne également la nécessité de continuer à surveiller l'impact de l'IA sur les salaires et les inégalités, l'effet complet n'étant sans doute pas encore observable.

Des recherches supplémentaires sont également nécessaires afin d'identifier avec exactitude les mécanismes qui sous-tendent la relation négative entre l'IA et les inégalités salariales au sein des professions. Une explication possible est que les travailleurs peu performants (c'est-à-dire ceux dont la productivité est faible) ont plus à gagner de l'utilisation de l'IA car les systèmes d'IA sont entraînés à adopter les pratiques plus précises des travailleurs très performants. Il est également possible que l'IA réduise les écarts de performance au sein d'une profession par un effet de sélection, par exemple si les travailleurs peu performants quittent leur emploi parce qu'ils sont incapables de s'adapter aux dispositifs d'IA en réorientant leurs activités vers des tâches que l'IA ne peut pas automatiser.

Zusammenfassung

In den letzten zehn Jahren wurden im Bereich der künstlichen Intelligenz (KI) eindrucksvolle Fortschritte erzielt. Parallel dazu wuchs aber u. a. auch die Besorgnis über die möglichen Effekte der KI auf den Arbeitsmarkt, insbesondere auf die Löhne und die Ungleichheit zwischen den Arbeitskräften. Als Ende 2022 dann die generative KI der Öffentlichkeit vorgestellt wurde, erreichte diese Besorgnis einen neuen Höhepunkt.

In dieser Studie werden die Zusammenhänge zwischen KI und Lohnungleichheit in 19 OECD-Ländern untersucht. Dies geschieht anhand eines Maßes des KI-Potenzials verschiedener Berufe, das auf dem von Felten, Raj und Seamans (2019[1]) entwickelten Indikator beruht und misst, inwieweit für bestimmte Berufe Fähigkeiten benötigt werden, bei denen KI besonders große Fortschritte gemacht hat. Unterschiede zwischen dem KI-Potenzial verschiedener Berufsgruppen innerhalb einzelner Länder sowie innerhalb einzelner Berufsgruppen zwischen verschiedenen Ländern können dabei berücksichtigt werden. Die auf diese Weise gewonnenen Werte werden Daten aus der Verdienststrukturerhebung (VSE) und dem US Current Population Survey (CPS) gegenübergestellt, um den Zusammenhang mit der Lohnungleichheit zu untersuchen.

Die Ergebnisse liefern keinen Anhaltspunkt dafür, dass KI bereits Auswirkungen auf das Lohngefälle *zwischen* verschiedenen Berufsgruppen hatte (Zeitraum 2014-18). Gleichzeitig gibt es aber Anzeichen dafür, dass KI mit einer geringeren Lohnungleichheit *innerhalb* einzelner Berufsgruppen verbunden sein könnte. Dies deckt sich mit ersten Erkenntnissen aus der Fachliteratur, denen zufolge KI das Produktivitätsgefälle zwischen den Beschäftigten verringert. Dies scheint allerdings keine Auswirkungen auf das geschlechts- oder altersspezifische Lohngefälle innerhalb einzelner Berufsgruppen zu haben.

Die Studie betrachtet einen Zeitraum, in dem die KI-Durchdringung noch relativ gering war. Zudem sind die jüngsten Fortschritte im Bereich der KI noch nicht berücksichtigt. GPT-3, ein KI-Modell, das Ende 2022 durch seine beeindruckende Leistung im Bereich der maschinellen Sprachverarbeitung Schlagzeilen machte, ist beispielhaft dafür, wie rasch die KI-Entwicklung und -Einführung voranschreitet. Daher ist es nur bedingt möglich, aus den Erkenntnissen dieser Studie auf die aktuelle Situation zu schließen. Dies macht auch deutlich, dass die Auswirkungen von KI auf Löhne und Ungleichheit weiter beobachtet werden müssen, da ihr volles Ausmaß derzeit möglicherweise noch nicht sichtbar ist.

Weitere Studien sind auch nötig, um zu ermitteln, wie der innerhalb einzelner Berufsgruppen festzustellende negative Zusammenhang zwischen KI und Lohnungleichheit genau zum Tragen kommt. Eine mögliche Erklärung ist, dass leistungsschwache (d. h. wenig produktive) Beschäftigte größeren Nutzen aus KI ziehen, weil beim Trainieren der KI-Systeme die erfolgreichen Vorgehensweisen leistungsstarker Beschäftigter berücksichtigt werden. Möglich ist auch, dass KI das Leistungsgefälle innerhalb einzelner Berufsgruppen über einen Selektionseffekt verringert, z. B. wenn wenig leistungsstarke Arbeitskräfte aus dem Beruf ausscheiden, weil es ihnen nicht gelingt, ihre Tätigkeiten in Reaktion auf die KI-Tools auf Aufgaben zu verlagern, die nicht durch KI automatisiert werden können.

1 Introduction

The last decade has seen impressive advances in Artificial Intelligence (AI), particularly in the areas of image and speech recognition, natural language processing, translation, reading comprehension, computer programming and predictive analytics. In late 2022, the public launch of generative AI systems that create new content in response to prompts based on their training data has put AI under the spotlight worldwide. This rapid progress has been accompanied by, amongst others, concern about the possible effects of AI on the labour market, including on wages and inequality between workers.

The effect of AI[1] on wages and wage inequality is theoretically ambiguous. AI could exert downward pressure on the wages of some workers because it is an automating technology and therefore labour demand may fall as tasks are automated (*substitution effect*) (Agrawal, Gans and Goldfarb, 2019[2]). On the other hand, AI may raise wages via the productivity gains induced by automation, both directly as well as indirectly through higher labour demand (*productivity effect*): if automation concerns only some and not all of the tasks performed and if there is sufficient demand for the good/service, the increase in consumer demand resulting from productivity gains can raise labour demand via an increase in the demand for non-automated tasks, which can, ultimately, increase wages (Bessen, 2019[3]; Acemoglu and Restrepo, 2019[4]; Acemoglu and Restrepo, 2019[5]; Lane and Saint-Martin, 2021[6]).[2] For example, although machine translation tools may substitute part of the work of translators, they may increase the overall demand for translators – and therefore their wages – by significantly reducing translation costs.

Some workers may benefit more from AI than others. Previous waves of technological progress were primarily associated with the automation of routine tasks (cognitive & manual). These technologies therefore mainly substituted for workers in low- and middle-skill occupations and contributed to increases in wage inequality between high- and low-skilled workers (Dauth et al., 2017[7]; Acemoglu and Restrepo, 2020[8]; Webb, 2020[9]). However, recent advances in AI mean that non-routine cognitive tasks can also increasingly be automated (Lane and Saint-Martin, 2021[6]; Lorenz, Perset and Berryhill, 2023[10]). In most of its current applications, AI refers to computer software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future. Analysis of patent texts suggests AI is capable of formulating medical prognosis and suggesting treatment, detecting cancer and identifying fraud (Webb, 2020[9]). Thus, in contrast to previous waves of automation, AI might disproportionally affect high-skilled workers. However, as argued above, even if AI primarily automates non-routine, cognitive tasks, this does not necessarily mean that it will reduce the wages of high-skilled workers, since AI-induced automation could increase wages for these workers via a productivity effect.

[1] The OECD AI policy observatory defines AI as a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment.

[2] Depending on the price elasticity of demand for a given product or service, the indirect productivity effect can be strong. For example, during the 19th century, 98% of the tasks required to weave fabric were automated, decreasing the price of fabric. Because of highly price elastic demand for fabric, the demand for fabric increased as did the number of weavers (Bessen, 2016[39]).

To date, most empirical studies on the wage effects of automation technology have focused on industrial robots, and most of these studies suggest that substitution effects prevail. As a result, industrial robots have tended to increase inequality by widening the wage gap between the most exposed occupations (usually routine, manual ones) and the least exposed ones (usually white-collar occupations). Acemoglu and Restrepo (2020[8]) find a negative relationship between the adoption of industrial robots and wages across US commuting zones. Dauth et al. (2017[7]) extend this analysis to the case of Germany and find similar results for medium-skilled workers in machine operating occupations, who are particularly at risk of automation. Webb (2020[9]) finds that US occupations heavily exposed to industrial robots have experienced wage declines. Examining variations between 17 countries (and 14 industries), Graetz and Michaels (2018[11]) stand out by finding a positive relationship between robot adoption and wages. As far as within-occupation inequality is concerned, van der Velde (2020[12]) shows that computerisation has increased differences in performance between workers in a given occupation. According to the theory, this could be due to a combination of two facts: (i) computerisation reduces the prevalence of routine tasks in an occupation; and (ii) differences in skill levels among workers performing more routine tasks have a lower impact on output (Jung and Mercenier, 2014[13]) – notably because routine tasks leave workers with little autonomy (Oldenski, 2012[14]; Marcolin, Miroudot and Squicciarini, 2016[15]) and few opportunities to exploit their creativity (Frey and Osborne, 2017[16]).

Research focusing on AI specifically is less common, and the emerging evidence on the impact of AI on wage inequality is so far mixed. Two studies show that exposure to AI[3] is positively associated with wage growth at the occupation level (Felten, Raj and Seamans, 2019[1]) or the individual level (Fossen and Sorgner, 2019[17]), particularly among those with higher wages and/or higher levels of education. However, Acemoglu et al. (2020[18]) find no relationship between exposure to AI and wage growth at the occupation or industry level. This result is in line with qualitative case-study research which showed that in cases of AI adoption so far, the wages of workers most affected remained unchanged (Milanez, 2023[19]). Nonetheless, in around 15% of the case studies, an increase in wages was reported, most commonly on account of greater complexity of tasks or new skill acquisition following training (e.g. among insurance clerks). Surveys of workers who use AI find that many of them (about 40% in the financial and manufacturing sectors) fear that AI will reduce their wages in the next 10 years (Lane, Williams and Broecke, 2023[20]). Workers with a university degree and managers were the most likely to say they expected their wages to increase, suggesting that AI may indeed increase wage inequality.

By contrast, there is converging evidence that the use of (generative) AI can reduce differences in performance between workers within an occupation (Brynjolfsson, Li and Raymond, 2023[21]; Choi and Schwarcz, 2023[22]; Dell'Acqua et al., 2023[23]; Haslberger, Gingrich and Bhatia, 2023[24]; Noy and Zhang, 2023[25]; Peng et al., 2023[26]), which could have an impact on wage differences within occupations. This could be explained by the fact that AI systems are trained to predict accurate outcomes, i.e. those of high performers, and will therefore embody the practices of high performers (Brynjolfsson, Li and Raymond, 2023[21]). Low performers may therefore have more to gain from using AI. AI can also reduce performance differences within an occupation through a selection effect, if low-performing workers leave their job because they are unable to adapt to AI tools by shifting their activities to tasks that AI cannot automate. For example, some stock analysts who were unable to adapt to AI-based prediction tools by shifting their work to more social activities had to leave the profession (Grennan and Michaely, 2017[27]).

This paper adds to the literature by looking at the links between AI and wage inequality in a cross-country context. It uses a cross-country measure of occupational exposure to AI derived by Georgieff and Hyee (2021[28]) from that developed by Felten, Raj and Seamans (2019[1]) – a measure of the degree to which US occupations rely on abilities in which AI has made the most progress in the early 2010s. This measure, which allows for variations in AI exposure across occupations within countries, as well as across countries

[3] An occupation is "exposed" to AI if it has a high intensity in skills that AI can perform.

for a given occupation, is matched to Structure of Earnings Survey (SES) and US Current Population Survey (CPS) data to analyse the relationship with between- and within-occupation wage inequality.

The paper finds that there is no indication that AI has affected wage inequality *between* occupations so far (over the period 2014-18). At the same time, AI may be associated with lower wage inequality *within* occupations – consistent with the above-mentioned literature. However, this does not appear to affect gender or age wage gaps within occupations.

It should be noted that the analysis was done at a time when AI adoption was still relatively low and also excludes recent advances in AI. The measure of exposure to AI refers to the early 2010s and is linked to changes in wage inequality between 2014 and 2018. Extrapolation to the current context should therefore be made with caution. This also highlights the need to keep monitoring the impact of AI on wages and inequality.

The paper starts out by presenting the data and indicators used in this paper (Section 2). Section 3 then describes the empirical strategy, and Section 4 presents the results.

2 Data and descriptive statistics

This paper looks at the links between AI and wage inequality in 19 OECD countries[4] for 36 occupational categories[5] over the period 2014-18, using a measure of exposure to AI derived from that developed by Felten, Raj and Seamans (2019[1]). The measure of exposure to AI proxies the degree to which tasks can be automated by AI. Thus, the analysis compares occupations with a high degree of automatability by AI to those with a low degree. This section shows some descriptive statistics for AI exposure, wages and inequalities. In the early 2010s, AI exposure was higher in white collar occupations and lower in physical occupations. Trends in inequality over the period 2014-18 are mixed across countries. Still, on average across the countries analysed, real wage growth was lowest in some higher-skilled occupations and strongest in some lower-skilled occupations; and inequality within occupations declined in most occupations.

2.1. AI exposure

The AI exposure measure reflects the potential automation of tasks by AI for 36 occupations in the 19 countries considered. It is a task-based measure of an occupation's reliance on abilities in which AI has made the most progress. This measure was developed for the US by Felten, Raj and Seamans (2019[1]). It was extended to account for variations between countries by Georgieff and Hyee (2021[28]) using data from the Programme for the International Assessment of Adult Competencies (PIAAC). Further details on the measure, including its construction, advantages and limitations, are discussed in Georgieff and Hyee (2021[28]).

It should be noted that the AI exposure measure only captures the potential automation of tasks that is directly related to the capabilities of AI, and not the potential automation of tasks where AI is only an enabler of other technologies (e.g. AI enabling robots to perform tasks associated with cleaners). It is therefore limited to AI algorithms and the associated cognitive abilities, and it is not surprising that it is higher in white collar occupations (e.g. Business professionals, see Figure 2.1) and lower in physical occupations (e.g. Cleaners and helpers). In the early 2010s, based on this measure, AI had made the most progress in applications that affect abilities required to perform non-routine cognitive tasks, in particular:

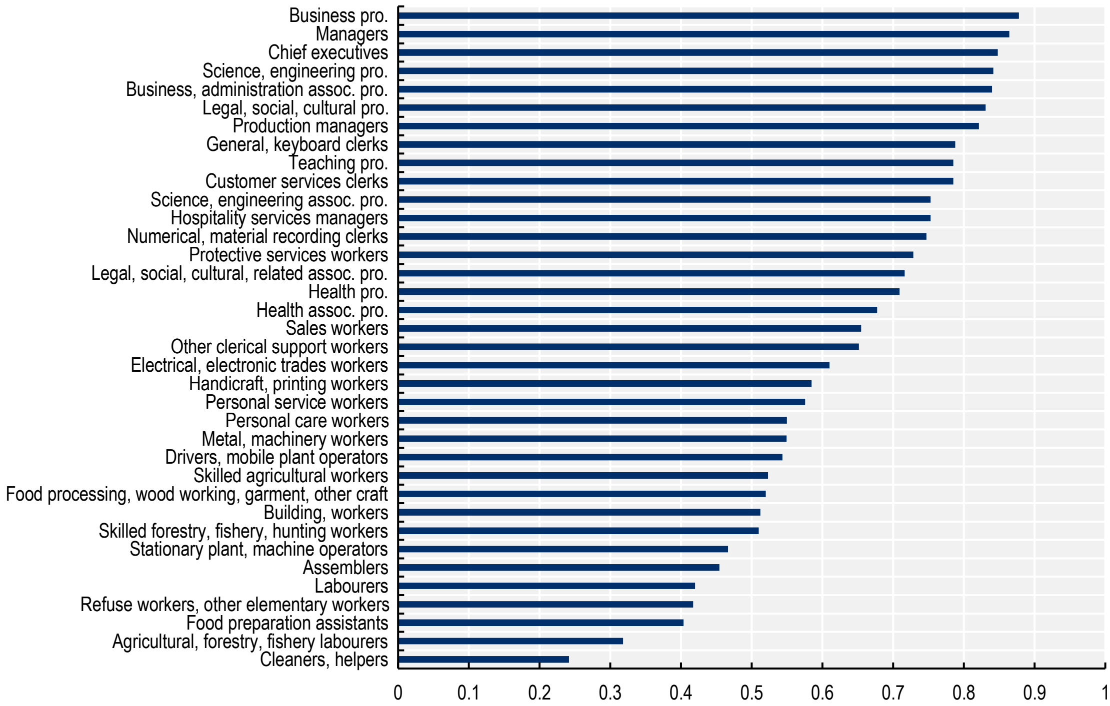
[4] The 19 countries are Belgium, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Lithuania, the Netherlands, Norway, Poland, Slovenia, the Slovak Republic, Spain, Sweden and the United States.

[5] This paper aims to explore the links between employment and AI deployment in the economy, rather than the direct employment increase due to AI development. Two occupations are particularly likely to be involved in AI development: IT technology professionals and IT technicians. These two occupations both have high levels of exposure to AI and some of the highest growth in inequality over this paper's observation period, which may be partly related to increased activity in AI development. These occupations may bias the analysis and they are therefore excluded from the sample. Nevertheless, the results are not sensitive to the inclusion of these occupations in the analysis.

information ordering, memorisation, perceptual speed, speed of closure and flexibility of closure (Felten, Raj and Seamans, 2019[1]; Georgieff and Hyee, 2021[28]).[6]

Figure 2.1. Exposure to AI is higher in white collar occupations and lower in physical occupations

Average exposure to AI across countries, early 2010s



Note: Non-weighted averages over 19 countries for which data are available: Belgium, the Czech Republic (hereafter 'Czechia'), Denmark, Estonia, Finland, Germany, France, Greece, Hungary, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, and the United States.
Source: PIAAC and Felten, Raj and Seamans (2019[1]).

2.2. Wages and inequalities

The analysis links exposure to AI to growth in wages and inequality. Gross hourly wage data are taken from the EU Structure of Earnings Survey (SES) and the US Current Population Survey (US-CPS).[7] Growth rates are measured between 2014 and 2018. The choice of period is determined by the coverage of SES data, which is published every four years, with the last wave in 2018. Self-employed workers are not covered by SES data and are therefore excluded from the analysis.[8]

[6] Perceptual speed is the ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. Speed of closure is the ability to quickly make sense of, combine, and organise information into meaningful patterns. Flexibility of closure is the ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.

[7] Gross hourly wage values are corrected by taking 4/5 of the minimum wage, or ¼ of the median wage if there is no national minimum wage in the country, as the lower bound.

[8] The SES covers all paid employees with an employment contract. Self-employed workers, as well as workers whose only remuneration is fees, commissions or share in profits, are not covered by the SES.

Examining the relationship between exposure to AI and wage inequality should distinguish between inequality *between* occupations and inequality *within* occupations. The impact of AI on each of these two components of inequality may involve different mechanisms (Section 1). A decomposition of Theil's inequality index (Box 2.1) shows that neither of these two components is negligible and that, in most of the countries analysed, inequalities within occupations are greater than inequalities between occupations (Figure 2.2). Wage inequality within occupations may be due to differences in workers' characteristics (e.g. performance and qualifications) (Jung and Mercenier, 2014[13]; van der Velde, 2020[12]; Criscuolo et al., 2022[29]), but it can also result from differences in wage-setting practices between firms with different levels of productivity or wage-setting power (Akerman et al., 2013[30]; Criscuolo et al., 2022[29]).

Box 2.1. Theil's inequality index

The Theil index is a measure of wage inequality that can be easily decomposed into two components: one reflects inequality *within* occupations, the other inequality *between* occupations. The Theil index ranges from zero to infinity, with zero representing an equal distribution and higher values representing a higher level of inequality.

The Theil index is given by the following formula:

$$Theil = \frac{1}{N}\sum_{i}\frac{w_i}{\overline{w}}\ln\left(\frac{w_i}{\overline{w}}\right)$$

Where N is the total number workers, w_i is the wage of worker i and $\overline{w}$ is the average wage of the overall population of workers.

It can be decomposed into:

$$Theil = \sum_{o}\frac{N_o}{N}\frac{\overline{w_o}}{\overline{w}}Theil_o + \sum_{o}\frac{N_o}{N}\frac{\overline{w_o}}{\overline{w}}\ln\left(\frac{\overline{w_o}}{\overline{w}}\right)$$

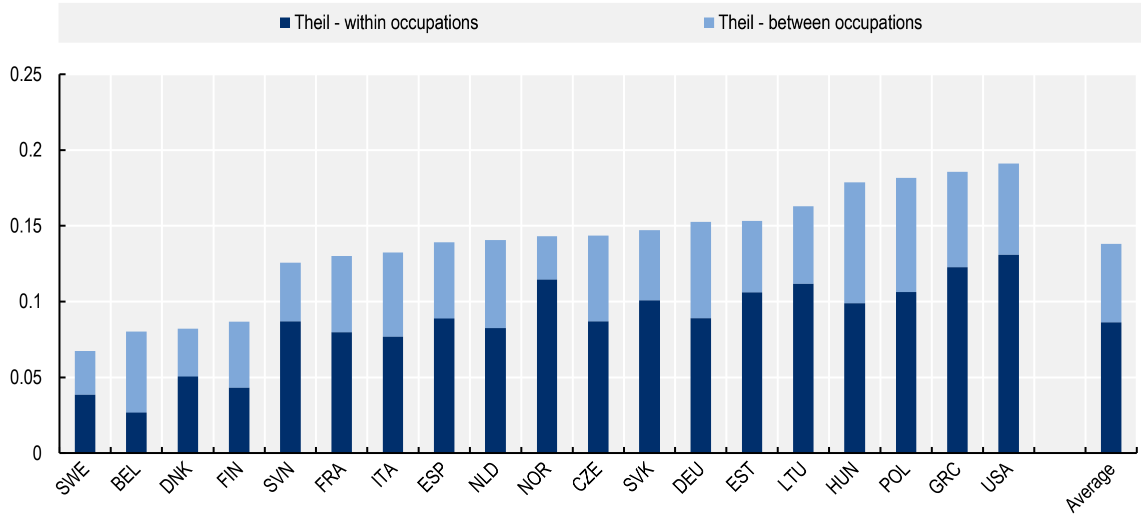
Where N is the total number workers, N_o is the number of workers in occupation o, $Theil_o$ is the Theil index of occupation *o*, $\overline{w_o}$ is the average wage in occupation *o* and $\overline{w}$ is the average wage of the overall population of workers.

The first term in the decomposition is the "within occupation" component. It is equal to a weighted average of the Theil indices for each occupation. The second term is the "between occupation" component. It represents the share of wage inequality that is due to differences between occupations.

Trends in overall wage inequality over the period 2014-18 are mixed across countries (Figure 2.3). Many Central and Eastern European countries experienced large reductions in inequality over the period: Czechia (-17%), Poland (-17%), the Slovak Republic (-15%), Hungary (-15%) and Estonia (-14%). By contrast, inequality increased significantly in Norway (66%) and Greece (34%), mainly due to the increase in inequality within occupations. Nevertheless, in most countries, the three indicators of inequality (overall inequality, inequality between occupations and inequality within occupations) show similar trends.

Figure 2.2. In most countries, inequalities within occupations are greater than inequalities between occupations

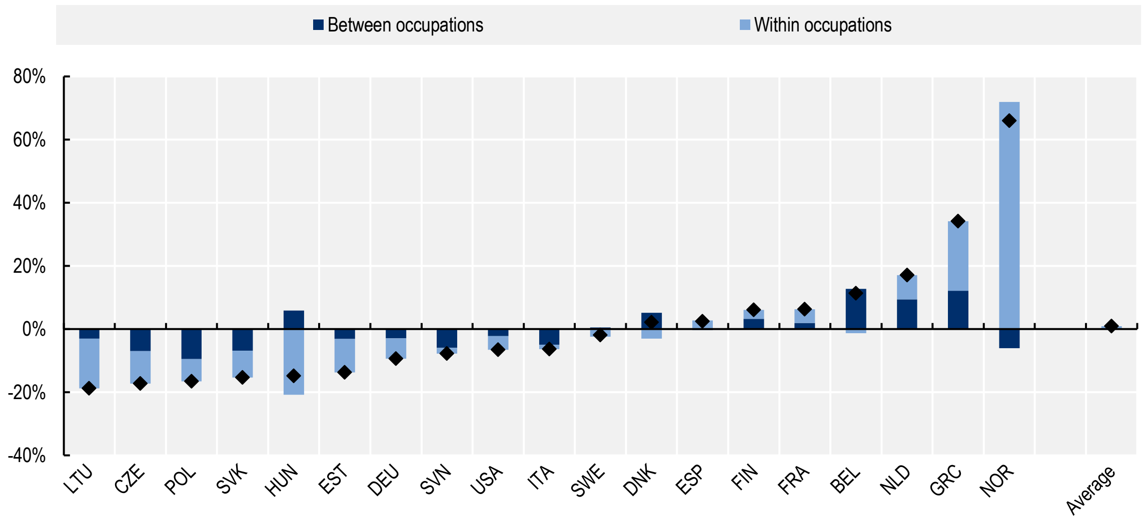
Overall hourly wage inequality (Theil index), 2018



Notes: "Average" is the non-weighted average over the countries analysed. The "within occupation" component of the Theil index shows the part of wage inequality that is due to inequality within occupations. The "between occupations" component shows the part of inequality that is due to wage differences between occupations (see Box 2.1).
Source: SES, US-CPS.

Figure 2.3. Trends in inequality over the period 2014-18 are mixed across countries

2014-18% change in the Theil index



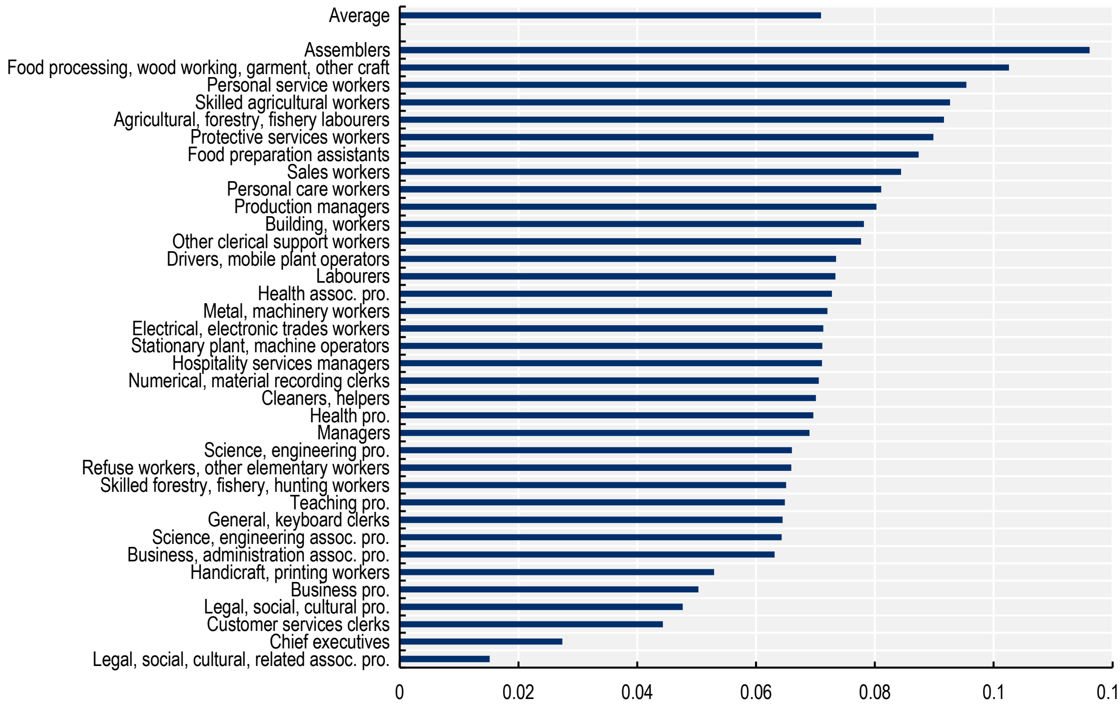
Note: "Average" is the non-weighted average over the countries analysed. The "between occupations" component of the Theil's inequality index shows the part of wage inequality that is due to wage differences between occupations. The "within occupations" component shows the part of wage inequality that is due to inequality within occupations (see Box 2.1).
Source: SES, US-CPS.

On average across the countries analysed, real wages grew in all occupations between 2014 and 2018 (Figure 2.4), a period that coincided with the economic recovery from the global financial crisis. Real wages grew by 7.1% on average across all *occupation x country* cells in the sample.

The gap between high- and low-wage occupations narrowed over the period 2014-18. Real wage growth was lowest in some higher-skilled occupations, including Legal, social, cultural professionals (4.8%) and related associate professional (1.5%), Chief executives (2.7%) and Business professionals (5%) (Figure 2.4). By contrast, it was strongest in some lower-skilled occupations, such as for Assemblers (11.6%), Food processing, wood working, garment and other craft (10.3%) and Personal service workers (9.5%). This may be linked to the regular minimum wage adjustments that have taken place in most countries in recent years to protect the standard of living of low-wage workers against inflation (Araki et al., 2023[31]).

Figure 2.4. Real wages have grown in all occupations between 2014 and 2018

2014-18 log change in real average wage by occupation, simple averages across countries

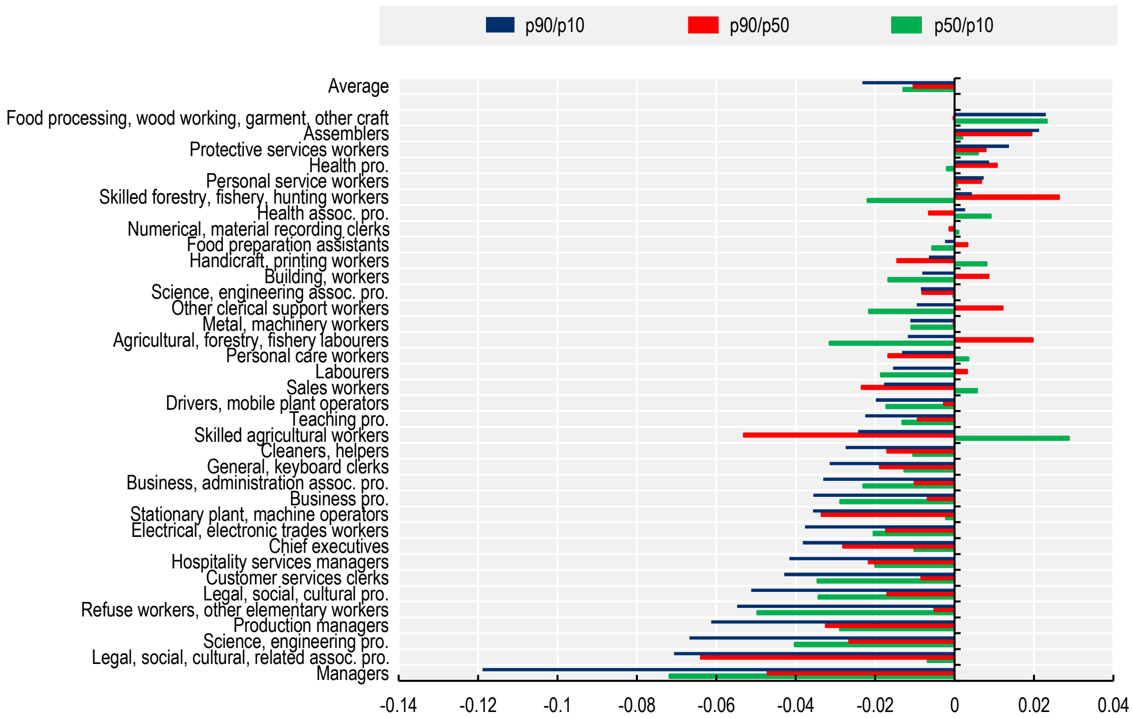


Note: Non-weighted averages over 19 countries for which data are available: Belgium, Czechia, Denmark, Estonia, Finland, Germany, France, Greece, Hungary, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, and the United States. Average is the overall average across all *occupation x country* cells in the sample.
Source: SES, US-CPS.

On average across countries, inequality within occupations declined in most occupations over the period 2014-18 (Figure 2.5). Several decile ratios calculated at occupation level are used for alternative indicators of inequality within occupations – P90/P10 is the main indicator and reflects inequality between the top and the bottom deciles of the distribution, while the P90/P50 focuses on the top of the distribution and the P50/P10 on the bottom of the distribution. Occupations with the largest drops in the P90/P10 ratio include high-skill white collar occupations, such as Managers (-12%), Legal social, cultural and related associate professionals (-7.1%) and Science and engineering professionals (-6.7%). Inequality also declined on average across all *occupation x country* cells in the sample: the P90/P10 ratio fell by 2.3%, around twice as much as the P90/P50 and P50/P10 ratios. Inequalities at the bottom and at the top of the distribution contributed to a similar extent to the reduction in the P90/P10 ratio.

Figure 2.5. In most occupations, wage inequality within occupations has decreased between 2014 and 2018

2014-18 log change in wage inequality within occupation, simple averages across countries



Note: Non-weighted averages over 19 countries for which data are available: Belgium, Czechia, Denmark, Estonia, Finland, Germany, France, Greece, Hungary, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, and the United States. Average is the overall average across all *occupation x country* cells in the sample.
Source: SES, US-CPS.

This study also looks at whether exposure to AI is linked to wage differences between lower-paid socio-demographic groups (e.g. women and youth) and higher-paid ones. In 2018, the hourly wage gap between women and men was mainly due to the wage gap within occupations (Figure 2.6 Panel A),[9] as was the gap between young (14-29) and prime age (30-49) workers (Panel B).[10] On average across the countries analysed, the gender wage gap was 14% in 2018, almost all of which was due to the gender gap within occupations. Similarly, four-fifths of the 27% wage gap between young and prime-age workers was due to inequality within occupations. By contrast, around half of the wage gap between high- and low-educated workers[11] was due to the fact that these two groups work in different occupations (with significant disparities between the countries analysed) (Panel C).

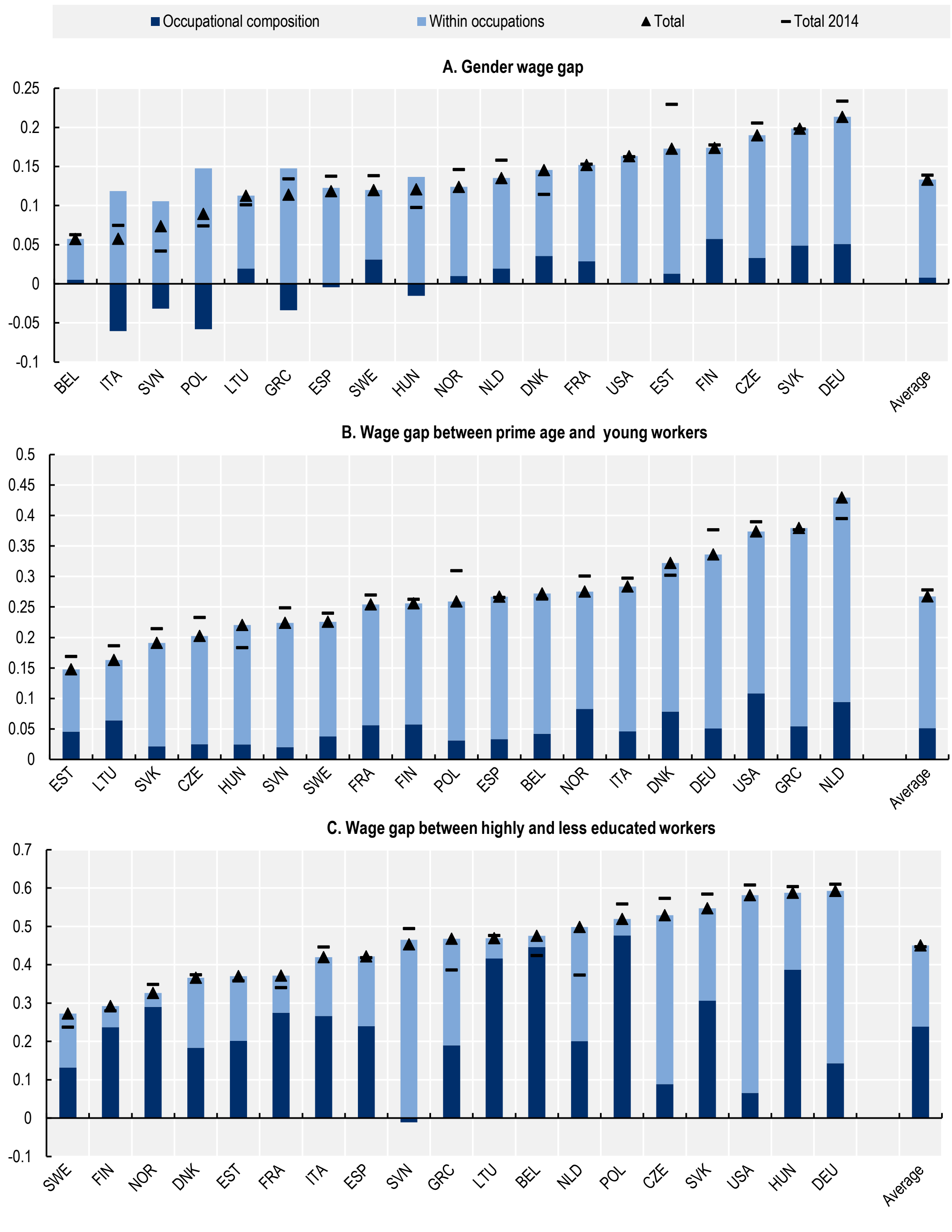
[9] This result is in line with findings in the literature that occupations and sectors explain relatively little of the gender wage gap (OECD, 2017[38]).

[10] These findings result from shift-share decompositions, which consider differences in the occupational composition of employment between demographic groups. It decomposes the gap in average wage between two demographic groups 0 and 1 (e.g. women and men) according to: $\overline{w}_1 - \overline{w}_0 = \sum_o (sh_{o1} - sh_{o0})\, w_{o0} + \sum_o sh_{o1}\,(w_{o1} - w_{o0})$. The term $\overline{w}_g$ is the average wage for demographic group g. The term sh_{og} is the share of workers in occupation o for demographic group g, and w_{og} is the average wage of occupation o for demographic group g. The left-hand side of the equation is the gap in the average wage between the two groups. The first term on the right-hand side of the equation (from left to right) represents the part of the wage gap that is due to the fact that the two groups work in different occupations ("occupational composition" component). The second term represents the part of the wage gap that is due to wage differentials within occupations ("within occupation" component).

[11] High-educated workers are those with tertiary education. Low-educated workers are those with primary or lower secondary education.

Figure 2.6. The gender and age wage gaps are mostly driven by within-occupation differences, whereas the education wage gap is driven by between-occupation differences

Wage gaps, 2018



Note: The wage gap is the difference between the average wage of the higher wage group and that of the lower wage group divided by the average wage of the higher wage group. Higher wage groups include men, prime age workers (i.e. 30-49 year-olds) and highly educated workers (i.e. workers with tertiary education). Lower wage groups include women, young workers (i.e. 14-29 year-olds) and less educated workers (i.e. workers with primary or lower secondary education). The “occupational composition” and the “within occupation” components are obtained via a shift-share decomposition of the wage gap with respect to 2-digit ISCO-08 occupational categories.
Source: SES, US-CPS.

3 Empirical strategy

Examining the relationship between exposure to AI and wage inequality should distinguish between inequality between occupations and inequality within occupations, as the impact of AI on each of these two components of inequality may involve different mechanisms (Section 1).

3.1. AI and wage inequality between occupations

The link between AI exposure and wage inequality between occupations is explored by means of an occupation level[12] regression of average wage growth on exposure to AI and its interactions with two dummies for belonging to the medium and low wage groups of occupation, respectively:[13]

$$\Delta_{2018-2014}\, log\ mean\ wage_{co} = \beta_0 * AI_{co} + \beta_1 * AI_{co} * 1(LW) + \beta_2 * AI_{co} * 1(MW) + 1(LW) + 1(MW) + \gamma * X_{co} + \gamma_c + \epsilon_{co} \quad (1).$$

for country c and occupation o, with all variables defined at the occupation level. In particular, AI_{co} is the measure of exposure to AI for occupation o in country c as measured in the early 2010s; α_c are country fixed effects; and ϵ_{co} is the error term. $1(LW)$ and $1(MW)$ are dummies for belonging to the low and medium wage groups of occupations. The coefficient of interest β_1 captures whether the link between exposure to AI and wage growth varies between high wage occupation – the reference group[14] – and low wage occupations; β_2 does the same for medium wage occupations. The inclusion of country fixed effects means that the analysis only exploits within-country variation in AI exposure to estimate the parameter of interest.

If regression (1) is carried out without the interaction terms, then β_0 provides an indication of whether AI has been associated with the wage gap between the most exposed occupations (generally higher-skilled occupations involving non-routine cognitive tasks) and the least exposed ones.

X_{co} is a vector of controls used in some specifications to account for potential confounding factors which may also have affected wages over the period 2014-18. It includes: exposure to other technological advances (software and industrial robots); offshorability; exposure to international trade; and 1-digit occupational ISCO dummies. Measures of exposure to software and industrial robots were developed by

[12] The analysis is performed at the 2-digit level of the International Standard Classification of Occupations 2008 (ISCO08).

[13] The classification used is the country-invariant classification developed by Goos, Manning and Salomons (2014[35]), which classifies occupations based on their average wage relying on European Community Household Panel (ECHP) data. For example, occupations with an average wage in the middle of the occupation-wage distribution would be classified in the middle with respect to this classification. Low-skill occupations include the ISCO-08 1-digit occupation groups: Services and Sales Workers; and Elementary Occupations. Middle-skill occupations include the groups: Clerical Support Workers; Skilled Agricultural, Forestry and Fishery Workers; Craft and Related Trades Workers; and Plant and Machine Operators and Assemblers. High-skill occupations include: Managers; Professionals, and Technicians; and Associate Professionals.

[14] The group of high wage occupations is taken as the reference group because it is the largest.

Webb (2020[9]).[15] Offshorability is proxied by an index developed by Firpo, Fortin and Lemieux (2011[32]) and made available by Autor and Dorn (2013[33]).[16] These three indices are occupation-level task-based measures derived from the O*NET database for the United States; this analysis uses those measures for all 19 countries, assuming that the cross-occupation distribution of these indicators is similar across countries.[17] Exposure to international trade is proxied by the share of employment within occupations that is in tradable sectors.[18] These shares are derived from the European Union Labour Force Survey (EU-LFS) and the US Current Population Survey (US-CPS). The specifications that include 1-digit occupational dummies only exploit variation within broad occupational groups, thereby controlling for any factors that are constant within these groups.

The main focus of this paper is on whether AI is associated with inequality between occupations based on their initial wage level. However, it may also be of interest to see whether AI is associated with inequality between occupations based on: (i) their reliance on creative intelligence or social intelligence and (ii) their reliance on other digital technologies. Indeed, to harness the productivity effect of AI-induced automation, workers need to both learn to work effectively with the new technology and to adapt to the changing task composition that puts more emphasis on tasks that AI cannot yet perform, such as creative intelligence or social intelligence (Lane and Saint-Martin, 2021[6]; Lassébie and Quintini, 2022[34]).

To test these hypotheses, regression (1) is run by successively replacing the dummies and interaction terms for belonging to medium- and low-wage occupations with dummies for belonging to occupations with a medium or low incidence of: (i) computer use, (ii) social tasks and (iii) creative tasks.

[15] Webb (2020[9]) uses the overlap between the text of job descriptions provided in the O*NET database and the text of patents in the fields of software and industrial robots to construct measures of exposure to each of these technologies. To select software patents, Webb uses an algorithm developed by Bessen and Hunt (Bessen and Hunt, 2007[37]), which requires one of the keywords “software”, “computer”, or “programme” to be present, but none of the keywords “chip”, “semiconductor”, “bus”, “circuity”, or “circuitry”. To select patents in the field of industrial robots, Webb develops an algorithm that results in the following search criteria: the title and abstract should include “robot” or “manipulate”, and the patent should not fall within the categories: “medical or veterinary science; hygiene” or “physical or chemical processes or apparatus in general”.

[16] Autor and Dorn (2013[33]) measure the potential offshoring of job tasks using the average between the two variables “Face-to-Face Contact” and “On-Site Job” that Firpo, Fortin and Lemieux (2011[32]) derive from the O*NET database (they reverse the sign to measure offshorability instead of non-offshorability). This measure captures the extent to which an occupation requires direct interpersonal interaction or proximity to a specific work location. Firpo, Fortin and Lemieux (2011[32]) define “face-to-face contact” as the average value between the O*NET variables “face-to-face discussions”, “establishing and maintaining interpersonal relationships”, “assisting and caring for others”, “performing for or working directly with the public”, and “coaching and developing others”. They define “on-site job” as the average between the O*NET variables “inspecting equipment, structures, or material”, “handling and moving objects”, “operating vehicles, mechanised devices, or equipment”, and the mean of “repairing and maintaining mechanical equipment” and “repairing and maintaining electronic equipment”.

[17] All three indices are available by occupation based on U.S. Census occupation codes. They were first mapped to the SOC 2010 6-digits classification and then to the ISCO08 4-digit classification. They were finally aggregated at the 2-digit level using average scores weighted by the number of full-time equivalent employees in each occupation in the United-States, as provided by Webb (2020[9]) and based on American Community Survey 2010 data.

[18] The tradable sectors considered are agriculture, industry, and financial and insurance activities.

3.2. AI and wage inequality within occupations

To explore the relationship between AI exposure and within-occupation wage inequality, similar occupation-level regressions are run, but using growth in wage *inequality* as the variable of interest (instead of growth in wages):

$\Delta_{2018-2014}\, log\ wage\ inequality_{co} = \beta * AI_{co} + \gamma * X_{co} + \gamma_c + \epsilon_{co}$ (2).

for country *c* and occupation *o.* The coefficient of interest β captures the link between exposure to AI and changes in wage inequality.

Several decile ratios are used for alternative indicators of inequality – P90/P10 reflecting inequality across the whole distribution, P90/P50 focusing on the top of the distribution and P50/P10 on the bottom of the distribution (see Section 2.2 for a more detailed description of these indicators).

4 Results

This section looks at the link between an occupation's exposure to AI in the early 2010s and changes in inequality between 2014 and 2018. There is no indication that AI has affected wage inequality *between* occupations so far. At the same time, higher AI exposure appears to be associated with lower wage inequality *within* occupations – consistent with findings in the literature that AI reduces productivity differentials between workers (Section 1). However, this does not appear to affect gender or age wage gaps within occupations.

4.1. There is no indication that AI has affected wage inequality between occupations (so far)

The analysis suggests that, so far, there is no relationship between exposure to AI and wage inequality between occupations. Occupation-level regressions (see Equation (1) in Section 3.1 without the interaction terms) are run using log change in average occupational wage over the 2014-18 period as the variable of interest (Table 4.1 Columns 1 and 2). Average wage growth in an occupation is not significantly associated with exposure to AI in the occupation, so potential automation by AI does not appear to influence wage disparities between more exposed (generally higher-skilled) occupations and less exposed ones. The same is true when adding interaction terms between exposure to AI and the average wage level (Columns 3 and 4):19 the link between exposure to AI and wage growth does not vary between high wage occupation – the reference group – and low wage / medium wage occupations. This is further evidence that there is no relationship between AI exposure and wage inequality between occupations during the period of observations.

Beyond inequality between high- and low-wage occupations, AI-induced automation may be linked to inequality between occupations based on other characteristics, such as their reliance on high-value added tasks that AI cannot automate or their level of digital skills. However, even when grouping occupations in this way, there is still no relationship, at occupation level, between exposure to AI and wage inequality. Regression (1) is run using interaction terms between exposure to AI and the incidence level of: (i) computer use[20] (Table 4.2 Columns 1 and 2), (ii) social tasks (Columns 3 and 4) and (iii) creative tasks[21]

[19] The wage classification used is the country-invariant wage-based classification developed by Goos, Manning and Salomons (2014[35]) (see footnote 13).

[20] The level of computer use within an occupation is proxied by the share of workers reporting the use of a computer at work in that occupation, calculated for each country in the sample. It is based on individuals' answers to the question "Do you use a computer in your job?", taken from PIAAC. Occupation-country cells are then classified into three categories of computer use (low, medium and high), where the terciles are calculated based on the full sample of occupation-country cells. Data are from 2012, with the exception of Hungary (2017) and Lithuania (2014).

[21] The prevalence of creative and social tasks is derived from PIAAC data. PIAAC data include the frequency with which a number of tasks are performed at the individual level. Respondents' self-assessment are based on a 5-point scale ranging from "Never" to "Every day". This information is used to measure the average frequency with which workers in each occupation perform creative or social tasks, and this is done separately for each country. In line with

(Columns 5 and 6). None of the interaction terms is different from zero at the 5% level, or even at the 10% level when all the controls are included.

Table 4.1. There is no relationship between exposure to AI and wage inequality between occupations

Dependent variable: 2014-18 log change in average wage

	(1)	(2)	(3)	(4)
Exposure to AI	-0.0375*	0.0215	0.0254	0.0805
	(0.0201)	(0.0479)	(0.0758)	(0.0989)
Exposure to AI x Low wage			0.0267	-0.0132
			(0.0849)	(0.119)
Exposure to AI x Medium wage			-0.0892	-0.154
			(0.0821)	(0.120)
Average wage dummies	No	No	Yes	Yes
Controls	No	Yes	No	Yes
Country FEs	Yes	Yes	Yes	Yes
Observations	664	664	664	664
R-squared	0.643	0.650	0.649	0.652

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. The average wage level corresponds to the country-invariant wage-based classification used in Goos, Manning and Salomons (2014[35]). Columns (2) and (4) include controls for exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies. Offshorability is an occupation-level measure from Autor and Dorn (2013[33]) based on data from the United States. Exposure to software and exposure to robots are occupation-level measures developed by Webb (2020[9]) based on data from the United States. Exposure to international trade is proxied by the 2014 share of workers in the country-occupation cell working in: agriculture, industry, and financial and insurance activities.
Source: PIAAC, SES, US-CPS, Felten, Raj and Seamans (2019[1]).

The absence of a relationship between exposure to AI at the occupation level and wages is consistent with findings from the literature and suggests that AI has not (yet) had an effect on wage inequality at the aggregate level (Acemoglu et al., 2020[18]), or at least not a detectable one. Nonetheless, it should be noted that the analysis was done at a time when AI adoption was still relatively low and also excludes recent advances in AI – the measure of exposure to AI refers to the early 2010s and is linked to changes in wage inequality between 2014 and 2018. Extrapolation to the current context should therefore be made with caution.

Nedelkoska and Quintini (2018[40]), creative tasks include: problem solving – simple problems, and problem solving – complex problems; and social tasks include: teaching, advising, planning for others, communicating, negotiating, influencing, and selling. For each measure, occupation-country cells are then classified into three categories depending on the average frequency with which these tasks are performed (low, medium and high). These three categories are calculated by applying terciles across the full sample of occupation-country cells. Data are from 2012, with the exception of Hungary (2017) and Lithuania (2014).

Table 4.2. The relationship between AI exposure and occupational wage growth does not vary by intensity of computer use, social tasks and creative tasks

Dependent variable: 2014-18 log change in average wage

	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to AI	0.0695	0.179*	-0.0446	0.139	0.101	0.232**
	(0.0809)	(0.102)	(0.0648)	(0.0944)	(0.0973)	(0.117)
Exposure to AI x Low computer use	-0.0289	-0.151				
	(0.0970)	(0.129)				
Exposure to AI x Medium computer use	-0.0916	-0.102				
	(0.0993)	(0.126)				
Exposure to AI x Low social tasks			0.0513	-0.0984		
			(0.0780)	(0.103)		
Exposure to AI x Medium social tasks			0.00437	0.0230		
			(0.0712)	(0.0772)		
Exposure to AI x Low creative tasks					-0.0937	-0.213
					(0.104)	(0.136)
Exposure to AI x Medium creative tasks					-0.171*	-0.176
					(0.102)	(0.130)
Computer use dummies	Yes	Yes	No	Yes	No	Yes
Social tasks dummies	No	Yes	Yes	Yes	No	Yes
Creative tasks dummies	No	Yes	No	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	664	664	664	664	664	664
R-squared	0.647	0.651	0.644	0.651	0.645	0.650

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Occupation-country cells are classified into low, medium or high prevalence of computer use/creative tasks/social tasks by tercile of prevalence of computer use/creative tasks/social tasks applied across the full sample of occupation-country cells. Columns 2, 4 and 6 include controls for exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies. Offshorability is an occupation-level measure from Autor and Dorn (2013[33]) based on data from the United States. Exposure to software and exposure to robots are occupation-level measures developed by Webb (2020[9]) based on data from the United States. Exposure to international trade is proxied by the 2014 share of workers in the country-occupation cell working in: agriculture, industry, and financial and insurance activities.
Source: PIAAC, SES, US-CPS, Felten, Raj and Seamans (2019[1]).

4.2. Higher AI exposure is associated with lower wage inequality within occupations

4.2.1. Greater occupational AI exposure is associated with lower growth in wage inequality within occupations

Greater AI exposure at the occupational level is associated with *lower* growth (or higher drop) in wage inequality *within* occupations. Occupation-level regressions (see Equation (2) in Section 3.2) are run using log change in the P90/P10, the P90/P50 or the P50/P10 ratio within an occupation over the 2014-18 period as the variable of interest (Table 4.3). The relationship is statistically significant at the 5% level for inequality between the top and bottom of the distribution (P90/P10), and it only marginally loses significance at the 5% level after inclusion of controls for international trade (i.e. shares of workers in tradable sectors), offshorability, exposure to other technological advances (software and industrial robots) and 1-digit occupational dummies (Table 4.3 Columns 1 and 2). The coefficient of interest is smaller and generally insignificant at the 10% level for the two other indicators of inequality – the P90/P50 (Columns 3 and 4) or the P50/P10 (Columns 5 and 6) ratio. This suggests that the negative relationship between exposure to AI and growth in wage inequality is not concentrated at either the top or the bottom of the wage distribution in an occupation, but concerns the entire distribution.

Table 4.3. Greater AI exposure is associated with lower growth in wage inequality within occupation

Dependent variable: 2014-18 log change in wage inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable is 2014-18 log change in:					
	P90/P10		P90/P50		P50/P10	
Exposure to AI	-0.0850**	-0.164*	-0.0491*	-0.0902	-0.0359	-0.0736
	(0.0350)	(0.0848)	(0.0270)	(0.0664)	(0.0240)	(0.0653)
Controls	No	Yes	No	Yes	No	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	664	664	664	664	664	664
R-squared	0.216	0.231	0.115	0.125	0.144	0.164

Note: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Each observation is a country-occupation cell. Columns 2, 4 and 6 include controls for exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies. Offshorability is an occupation-level measure from Autor and Dorn (2013[33]) based on data from the United States. Exposure to software and exposure to robots are occupation-level measures developed by Webb (2020[9]) based on data from the United States. Exposure to international trade is proxied by the 2014 share of workers in the country-occupation cell working in: agriculture, industry, and financial and insurance activities.
Source: EU-LFS, PIAAC, SES, US-CPS, Autor and Dorn (2013[33]), Felten, Raj and Seamans (2019[1]) and Webb (2020[9]).

As a robustness check, Table A A.1 in the Appendix replicates the P90/P10 regression using the score of exposure to AI obtained when using O*NET scores of "prevalence" and "importance" of abilities within occupations instead of PIAAC-based measures, as in Felten, Raj and Seamans (2019[1]) (Column 1). The results remain unchanged. Columns 2 and 3 replicate the analysis using alternative indicators of exposure to AI constructed by Webb (2020[9]) and Tolan et al. (2021[36])[22] – see Georgieff and Hyee (2021[28]) for a detailed description and comparison of these indicators. While the Tolan et al. (2021[36]) indicator confirms the negative relationship between growth in wage inequality and exposure to AI, the coefficient obtained with the Webb (2020[9]) indicator is negative but not statistically significant. The significantly negative relationship also holds when focusing on wage inequality for full-time workers only (Column 4), when measuring growth in inequality over the period 2010-18 instead of 2014-18 (Column 5), and when each observation (i.e. *occupation x country* cell) is weighted by the occupational employment share in the country (Column 6).

A one standard deviation higher AI exposure score (i.e. the difference between sales workers and stationary plants machine operators, or between managers and sales workers) is associated with

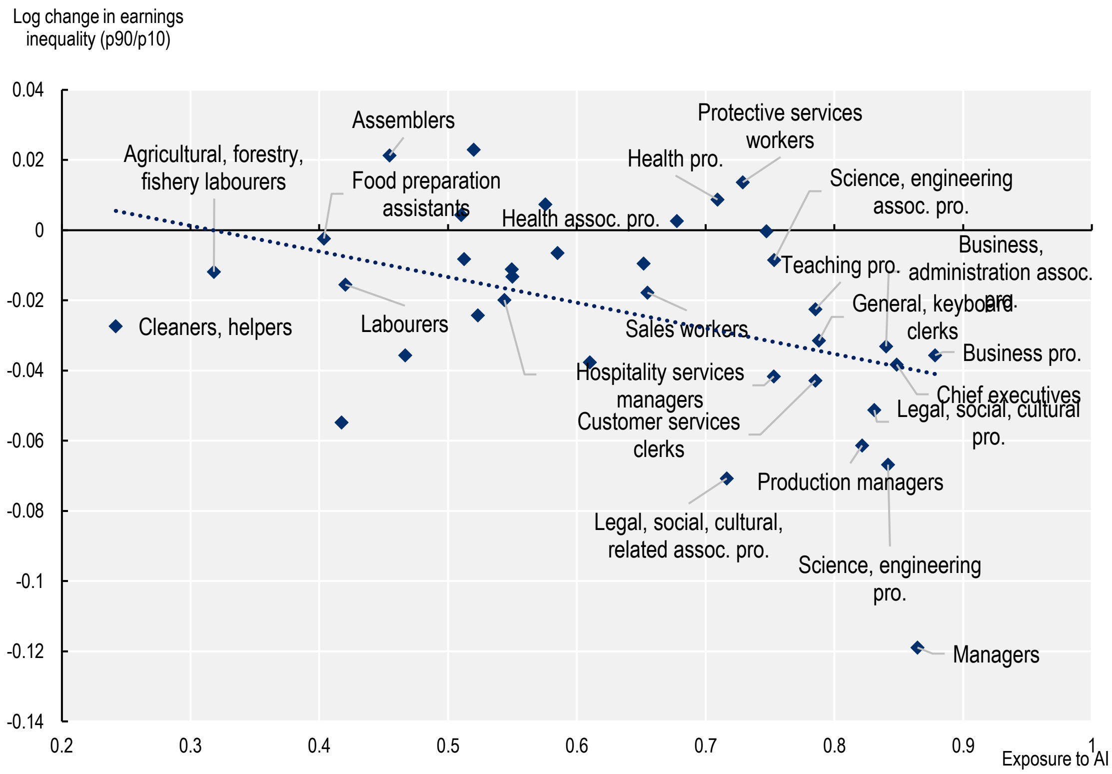
[22] The Webb (2020[9]) indicator is available by occupation based on U.S. Census occupation codes. It was first mapped to the SOC 2010 6-digits classification and then to the ISCO-08 4-digit classification. It was finally aggregated at the 2-digit level by using average scores weighted by the number of full-time equivalent employees in each occupation in the United States, as provided by Webb (2020[9]) and based on American Community Survey 2010 data. The Tolan et al. (2021[36]) indicator is available at the ISCO-08 3-digit level and was aggregated at the 2-digit level by taking average scores.

1.5 percentage points lower growth in the P90/P10 ratio. For reference, the average growth rate for the P90/P10 ratio for the entire sample of 664 *occupation x country* cells was -2.4% over the period 2014-18.

Figure 4.1 illustrates this finding by showing the change in the P90/P10 ratio for each occupation against that occupation's exposure to AI (averaged across all countries analysed). The relationship between exposure to AI and the growth in inequality is negative. The least exposed occupations tend to have experienced higher growth (or a lower drop) in wage inequality between 2014 and 2018. These occupations include: Agricultural, forestry, fishery labourers; Assemblers; Cleaners and helpers; Food preparation assistant; and Labourer. In contrast, the occupations with the highest reduction in inequality were those with relatively high exposure to AI, such as Business Professionals; Legal, Social and Cultural Professionals; Managers; and Science & Engineering Professionals.

Figure 4.1. Greater occupational AI exposure is associated with higher drop in wage inequality within occupation

Log change in wage inequality (2014 to 2018) and exposure to AI (early 2010s), simple averages across countries



Note: Non-weighted averages over 19 countries for which data are available: Belgium, Czechia, Denmark, Estonia, Finland, Germany, France, Greece, Hungary, Italy, Lithuania, The Netherlands, Norway, Poland, the Slovak Republic, Slovenia, Spain, Sweden, and the United States.
Source: SES, US-CPS, PIAAC and Felten, Raj and Seamans (2019[1]).

4.2.2. Within occupations, AI exposure is not associated with changes in wage inequality between demographic groups

Because AI exposure is linked with less growth in wage inequality within occupations, it could also be associated with less growth in wage differentials between lower-paid socio-demographic groups (e.g. women, youth and less educated workers) and higher-paid ones within occupations. To test these possible associations, regressions (see Equation (2) in Section 3.1) are run using as variables of interest occupation-level indicators of inequality between (Table 4.4) and within (Table 4.5) gender and age groups – education is not considered because the level of education in an occupation is very strongly correlated with exposure to AI in that occupation (Georgieff and Hyee, 2021[28]), which reflects significant selection effects that would make the results difficult to interpret.[23] Wage ratios[24] are used as indicators of inequality between demographic groups, and P90/P10 decile ratios are used as indicators of inequality within demographic groups.

Within occupations, AI exposure is not associated with changes in wage inequality *between* demographic groups (Table 4.4). Only the coefficient of inequality *within* prime-age workers is negative and statistically significant at the 5% level (Table 4.5 Column 4), meaning that AI exposure is negatively associated with inequality *within* the group of prime-age workers. However, this result remains suggestive, as it is not robust to the inclusion of the full set of controls.

[23] Georgieff and Hyee (2021[28]) examine which demographic groups (i.e. gender, age and education groups) are more exposed to AI by looking at the link between the share of workers of each group in a particular occupation and the AI exposure score in that occupation. They find that there is no clear relationship between AI exposure and gender and age. However, they find that highly educated workers are the most exposed to AI, while less educated workers are the least exposed.

[24] The wage ratio is the ratio between the average wage of jobs in the occupation belonging to the higher wage demographic group (i.e. male, prime age and highly educated workers) and those belonging to the lower wage group. It is preferred over the wage gap because it remains positive and can therefore be used in log change regressions.

Table 4.4. Within occupations, AI exposure is not associated with the growth in wage inequalities *between* demographic groups

Dependent variable: 2014-18 log change in the wage ratio *between* the indicated groups

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable is the 2014-18 log change in:					
	P90/P10		Male/Female wage ratio		Prime/Young age wage ratio	
Exposure to AI	-0.0716**	-0.145*	-0.0374*	-0.0343	0.0265	0.0507
	(0.0347)	(0.0851)	(0.0210)	(0.0484)	(0.0296)	(0.0712)
Controls	No	Yes	No	Yes	No	Yes
Country FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	660	660	660	660	660	660
R-squared	0.229	0.240	0.038	0.048	0.061	0.078

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Regressions involving education are performed on the limited sample of *occupations x country* cells in which the three levels of education are represented. The wage ratios are the ratio between the average wage of jobs in the occupation belonging to the higher wage demographic group (i.e. men and prime age workers) and those belonging to the lower wage group (i.e. women and young workers). Young age corresponds to 14-29 year-olds and prime age to 30-49 year-olds. Columns 2, 4 and 6 include controls for exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies. Offshorability is an occupation-level measure from Autor and Dorn (2013[33]) based on data from the United States. Exposure to software and exposure to robots are occupation-level measures developed by Webb (2020[9]) based on data from the United States. Exposure to international trade is proxied by the 2014 share of workers in the country-occupation cell working in: agriculture, industry, and financial and insurance activities.
Source: EU-LFS, PIAAC, SES, US-CPS, Autor and Dorn (2013[33]), Felten, Raj and Seamans (2019[1]) and Webb (2020[9]).

Table 4.5. Within occupations, AI exposure might be associated with the growth in wage inequalities *within* demographics groups

Dependent variable: 2014-18 log change in the P90/P10 ratio *within* the indicated group

	(1)	(2)	(3)	(4)	(5)
	Dependent variable is the 2014-18 log change in the in the P90/P10 ratio for:				
	Female	Male	Young	Prime age	Older
Coefficient on exposure to AI in regressions *without controls*	-0.0736*	-0.0344	-0.00867	-0.0857**	0.00955
	(0.0403)	(0.0395)	(0.0420)	(0.0371)	(0.0400)
R-squared	0.175	0.196	0.244	0.186	0.079
Coefficient on exposure to AI in regressions *with controls*	-0.126	-0.0843	-0.00779	-0.0821	0.00614
	(0.108)	(0.0917)	(0.103)	(0.0905)	(0.0997)
R-squared	0.191	0.206	0.252	0.202	0.105
Country FEs	Yes	Yes	Yes	Yes	Yes
Observations	660	660	660	660	660

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Regressions involving education are performed on the limited sample of *occupations x country* cells in which the three levels of education are represented. Young age corresponds to 14-29 year-olds and prime age to 30-49 year-olds. Controls include exposure to other technological advances (software and industrial robots), offshorability, exposure to international trade, and 1-digit occupational ISCO dummies. Offshorability is an occupation-level measure from Autor and Dorn (2013[33]) based on data from the United States. Exposure to software and exposure to robots are occupation-level measures developed by Webb (2020[9]) based on data from the United States. Exposure to international trade is proxied by the 2014 share of workers in the country-occupation cell working in: agriculture, industry, and financial and insurance activities.
Source: EU-LFS, PIAAC, SES, US-CPS, Autor and Dorn (2013[33]), Felten, Raj and Seamans (2019[1]) and Webb (2020[9]).

References

Acemoglu, D. et al. (2020), *AI and Jobs: Evidence from Online Vacancies*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28257. [18]

Acemoglu, D. and P. Restrepo (2020), "Robots and Jobs: Evidence from US Labor Markets", *Journal of Political Economy*, Vol. 128/6, pp. 2188-2244, https://doi.org/10.1086/705716. [8]

Acemoglu, D. and P. Restrepo (2019), "The wrong kind of AI? Artificial intelligence and the future of labour demand", *Cambridge Journal of Regions, Economy and Society*, Vol. 13/1, pp. 25-35, https://doi.org/10.1093/cjres/rsz022. [5]

Agrawal, A., J. Gans and A. Goldfarb (eds.) (2019), *8. Artificial Intelligence, Automation, and Work*, University of Chicago Press. [4]

Agrawal, A., J. Gans and A. Goldfarb (2019), "Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction", *Journal of Economic Perspectives*, Vol. 33/2, pp. 31-50, https://doi.org/10.1257/jep.33.2.31. [2]

Akerman, A. et al. (2013), "Sources of Wage Inequality", *American Economic Review*, Vol. 103/3, pp. 214-219, https://doi.org/10.1257/aer.103.3.214. [30]

Araki, S. et al. (2023), "Under pressure: Labour market and wage developments in OECD countries", in *OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market*, OECD Publishing, Paris, https://doi.org/10.1787/b3013c36-en. [31]

Autor, D. and D. Dorn (2013), "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market", *American Economic Review*, Vol. 103/5, pp. 1553-1597, https://doi.org/10.1257/aer.103.5.1553. [33]

Bessen, J. (2019), "Automation and jobs: when technology boosts employment*", *Economic Policy*, Vol. 34/100, pp. 589-626, https://doi.org/10.1093/epolic/eiaa001. [3]

Bessen, J. (2016), "How Computer Automation Affects Occupations: Technology, Jobs, and Skills", *Boston University School of Law, Law and Economics Research Paper*, Vol. No. 15-49, https://scholarship.law.bu.edu/faculty_scholarship/813. [39]

Bessen, J. and R. Hunt (2007), "An Empirical Look at Software Patents", *Journal of Economics & Management Strategy*, Vol. 16/1, pp. 157-189, https://doi.org/10.1111/j.1530-9134.2007.00136.x. [37]

Brynjolfsson, E., D. Li and L. Raymond (2023), *Generative AI at Work*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w31161. [21]

Choi, J. and D. Schwarcz (2023), “AI Assistance in Legal Analysis: An Empirical Study”, *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4539836. [22]

Criscuolo, C. et al. (2022), “The role of firm performance and wage-setting practices in wage inequality”, in *OECD Employment Outlook 2022: Building Back More Inclusive Labour Markets*, OECD Publishing, Paris, https://doi.org/10.1787/5f622440-en. [29]

Dauth, W. et al. (2017), *German Robots—The Impact of Industrial Robots on Workers*. [7]

Dell’Acqua, F. et al. (2023), “Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality”, *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4573321. [23]

Felten, E., M. Raj and R. Seamans (2019), “The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization”, *NYU Stern School of Business*, https://doi.org/10.2139/ssrn.3368605. [1]

Firpo, S., N. Fortin and T. Lemieux (2011), *Occupational Tasks and Changes in theWage Structure*, IZA Discussion Paper. [32]

Fossen, F. and A. Sorgner (2019), “New Digital Technologies and Heterogeneous Employment and Wage Dynamics in the United States: Evidence from Individual-Level Data”, *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.3390231. [17]

Frey, C. and M. Osborne (2017), “The future of employment: How susceptible are jobs to computerisation?”, *Technological Forecasting and Social Change*, Vol. 114, pp. 254-280, https://doi.org/10.1016/j.techfore.2016.08.019. [16]

Georgieff, A. and R. Hyee (2021), “Artificial intelligence and employment : New cross-country evidence”*, OECD Social, Employment and Migration Working Papers*, No. 265, OECD Publishing, Paris, https://doi.org/10.1787/c2c1d276-en. [28]

Goos, M., A. Manning and A. Salomons (2014), “Explaining Job Polarization: Routine-Biased Technological Change and Offshoring”, *American Economic Review*, Vol. 104/8, pp. 2509-2526, https://doi.org/10.1257/aer.104.8.2509. [35]

Graetz, G. and G. Michaels (2018), “Robots at Work”, *The Review of Economics and Statistics*, Vol. 100/5, pp. 753-768, https://doi.org/10.1162/rest_a_00754. [11]

Grennan, J. and R. Michaely (2017), “Artificial Intelligence and the Future of Work: Evidence from Analysts”, *NBER Economics of Artificial Intelligence Conference Paper*, https://conference.nber.org/conf_papers/f130049.pdf (accessed on 29 May 2020). [27]

Haslberger, M., J. Gingrich and J. Bhatia (2023), “No Great Equalizer: Experimental Evidence on AI in the UK Labor Market”, *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4594466. [24]

Jung, J. and J. Mercenier (2014), “Routinization-biased technical change and globalization: understanding labor market polarization”, *Economic Inquiry*, Vol. 52/4, pp. 1446-1465, https://doi.org/10.1111/ecin.12108. [13]

Lane, M. and A. Saint-Martin (2021), “The impact of Artificial Intelligence on the labour market: What do we know so far?”*, OECD Social, Employment and Migration Working Papers*, No. 256, OECD Publishing, Paris, https://doi.org/10.1787/7c895724-en. [6]

Lane, M., M. Williams and S. Broecke (2023), "The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers", *OECD Social, Employment and Migration Working Papers*, No. 288, OECD Publishing, Paris, https://doi.org/10.1787/ea0a0fe1-en. [20]

Lassébie, J. and G. Quintini (2022), "What skills and abilities can automation technologies replicate and what does it mean for workers?: New evidence", *OECD Social, Employment and Migration Working Papers*, No. 282, OECD Publishing, Paris, https://doi.org/10.1787/646aad77-en. [34]

Lorenz, P., K. Perset and J. Berryhill (2023), "Initial policy considerations for generative artificial intelligence", *OECD Artificial Intelligence Papers*, No. 1, OECD Publishing, Paris, https://doi.org/10.1787/fae2d1e6-en. [10]

Marcolin, L., S. Miroudot and M. Squicciarini (2016), "GVCs, Jobs And Routine Content Of Occupations", *OECD Trade Policy Papers*, No. 187, OECD Publishing, Paris, https://doi.org/10.1787/5jm0mq7kr6s8-en. [15]

Milanez, A. (2023), "The impact of AI on the workplace: Evidence from OECD case studies of AI implementation", *OECD Social, Employment and Migration Working Papers*, No. 289, OECD Publishing, Paris, https://doi.org/10.1787/2247ce58-en. [19]

Nedelkoska, L. and G. Quintini (2018), "Automation, skills use and training", *OECD Social, Employment and Migration Working Papers*, No. 202, OECD Publishing, Paris, https://doi.org/10.1787/2e2f4eea-en. [40]

Noy, S. and W. Zhang (2023), "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.4375283. [25]

OECD (2017), *The Pursuit of Gender Equality: An Uphill Battle*, OECD Publishing, Paris, https://doi.org/10.1787/9789264281318-en. [38]

Oldenski, L. (2012), "The task composition of offshoring by U.S. multinationals", *Économie internationale*, Vol. n° 131/3, pp. 5-21, https://doi.org/10.3917/ecoi.131.0005. [14]

Peng, S. et al. (2023), "The Impact of AI on Developer Productivity: Evidence from GitHub Copilot". [26]

Tolan, S. et al. (2021), "Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks", *Journal of Artificial Intelligence Research*, Vol. 71, pp. 191-236, https://doi.org/10.1613/jair.1.12647. [36]

van der Velde, L. (2020), "Within Occupation Wage Dispersion and the Task Content of Jobs", *Oxford Bulletin of Economics and Statistics*, Vol. 82/5, pp. 1161-1197, https://doi.org/10.1111/obes.12368. [12]

Webb, M. (2020), "The Impact of Artificial Intelligence on the Labor Market", *Working Paper, Standford University*, Vol. January, https://web.stanford.edu/. [9]

Annex A. Additional robustness analysis

Table A A.1. Exposure to AI and growth in inequality – Robustness tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable:					
	2014-18 log change in wage inequality			2014-18 log change in wage inequality for full-time workers	2010-18 log change in wage inequality	2014-18 log change in wage inequality
Exposure to AI (O*NET)	-0.0758**					
	(0.0311)					
Exposure to AI (Webb, 2020[9])		-0.000258				
		(0.000249)				
Exposure to AI (Tolan et al., 2021[36])			-0.0419**			
			(0.0201)			
Exposure to AI (Main measure)				-0.121***	-0.0939**	-0.0697**
				(0.0337)	(0.0445)	(0.0274)
Weights	No	No	No	No	No	Occupational employment share in the country
Observations	664	664	664	664	600	664
R-squared	0.214	0.206	0.211	0.193	0.228	0.251

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Each observation is a country-occupation cell. Alternative measures of exposure to AI are based on those constructed by Webb (2020[9]) and Tolan et al. (2021[36]).
Source: EU-LFS, PIAAC, SES, US-CPS, Felten, Raj and Seamans (2019[1]), Webb (2020[9]) and Tolan et al. (2021[36]).