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Robots & AI Exposure and Wage Inequality: A Within Occupation Approach

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Robots & AI Exposure and Wage Inequality: A Within Occupation Approach*

Florencia Jaccoud†

Abstract

This paper examines the linkages between occupational exposure to recent automation technologies and inequality across 19 European countries. Using data from the European Union Structure of Earnings Survey (EU-SES), a fixed-effects model is employed to assess the association between occupational exposure to artificial intelligence (AI) and to industrial robots—two distinct forms of automation—and within-occupation wage inequality. The analysis reveals that occupations with higher exposure to robots tend to have lower wage inequality, particularly among workers in the lower half of the wage distribution. In contrast, occupations more exposed to AI exhibit greater wage dispersion, especially at the top of the wage distribution. We argue that this disparity arises from differences in how each technology complements individual worker abilities: robot-related tasks often complement routine physical activities, while AI-related tasks tend to amplify the productivity of high-skilled, cognitively intensive work.

Keywords: Inequality; Robots; Artificial Intelligence; Occupations
JEL Codes: J31, O33, J24.

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1 Introduction

Over the past three decades, income inequality within countries has risen by an average of 10% across OECD nations (OECD, 2015). Structural and institutional changes, globalization, and technological advances are among the key factors contributing to this trend. Given the significant job polarization resulting from the widespread adoption of computerization in developed economies, changes in the occupational structure have emerged as a prominent driver of wage inequality (Autor et al., 2003; Goos and Manning, 2007). As a result, highly skilled workers in the United States and several European countries have seen a relative wage increase compared to low-skilled workers, widening the wage gap across different occupations (Acemoglu and Autor, 2011; Goos et al., 2014; Cortes, 2016).

Yet, recent literature emphasizes that within-occupation wage disparities also play a significant role in overall inequality. For instance, Kim and Sakamoto (2008) demonstrate that in the U.S., over half of the rise in total inequality from 1983-1985 to 2000-2002 can be attributed to within-occupation inequality. This trend has persisted over time, as shown by Mishel et al. (2013) for the period from 1979 to 2007. In Europe, Akerman et al. (2013) found that within-occupation inequality explained more than 70% of the rise in wage inequality in Sweden from 2001 to 2007, a pattern echoed across other European nations (Fernández-Macías and Arranz-Muñoz, 2020; van der Velde, 2020). Furthermore, van der Velde (2020) finds that within-occupation wage inequality tends to be higher in jobs with a larger proportion of non-routine tasks.

This paper examines the association between the exposure of occupations to robots and AI and within-occupation wage inequality in 19 European countries. In this context, we define exposure as the relationship between technology and the tasks associated with an occupation. Put simply, when there is a greater overlap between the tasks that a particular technology can perform and those involved within an occupation, the exposure of that occupation will be higher.

While many studies have focused on automation and its relationship with task content, particularly routine tasks, emerging automation technologies target distinct task types. For example, AI has a greater focus on cognitive and complex tasks and is thus more relevant to high-wage occupations (Webb, 2020; Felten et al., 2021; Georgieff and Hyee, 2021; Engberg et al., 2024). Robots, in contrast, typically perform manual tasks such as assembly and welding (Squicciarini and Staccioli, 2022; Montobbio et al., 2022; Prytkova et al., 2024). This distinction in task content is crucial for understanding within-occupation wage disparities (Jung and Mercenier, 2014; van der Velde, 2020). Occupations more exposed to AI involve cognitive tasks, in which there is more heterogeneity in individuals' abilities and performance, resulting in greater wage dispersion. On the other hand, jobs more exposed to robots tend to be more standardized, limiting workers' autonomy and variation in task performance, reducing wage disparity within those occupations.[1] Based on this differentiation in task content, we hypothesize a positive association between AI exposure and within-occupation wage dispersion, and a negative association for occupations more exposed to robots. Thus we argue that these technologies serve as proxies for the underlying task structure of occupations.

[1]It is worth noting that, while robots and AI can be analytically distinguished, the two technologies have become increasingly intertwined–particularly since the 2010s–as AI developments are progressively integrated into robotic systems (Jaccoud et al., 2024).

We use data from the European Union Structure of Earnings Survey (EU-SES) provided by Eurostat for 19 European countries. To capture exposure to these technologies, we use the AI and robot occupational scores developed by Webb (2020). By using patent data, the author links the tasks that these technologies perform with the job task descriptions in the Standard Occupational Classification 2010 (SOC-2010). We then map the SOC-2010 classifications to the International Standard Classification of Occupations 2008 (ISCO-08) in concordance with our database's classification system. Our empirical strategy relies on a fixed-effect model, with the dependent variable being the logarithm of the wage gap at the 2-digit occupational level. The main independent variables are the measures of robot and AI exposure derived from Webb (2020). Additionally, we conduct several robustness checks by incorporating alternative exposure indices to robots and AI, ensuring the robustness of our findings against different specifications.

Our main findings support our hypothesis, indicating that occupations that are more exposed to robots are those in which there is a lower wage disparity, and this is mainly driven by the bottom half of the wage distribution. Conversely, the ones more exposed to AI are associated with larger within-occupation wage inequality, particularly in the upper half of the wage distribution.

This paper contributes to the extensive body of research on automation and inequality. While studies such as Autor et al. (2003); Goos and Manning (2007); Acemoglu and Autor (2011); Goos et al. (2014); Kaltenberg and Foster-McGregor (2020); van der Velde (2020) have primarily examined ICT-related automation, our study broadens the scope by analyzing the roles of both robots and AI in wage inequality. Our results align with van der Velde (2020), which finds a positive link between non-routine task occupations and wage dispersion and similarly suggests a negative relationship between manual tasks and wage variability, mirroring the effects seen with robot exposure. Although there have been several attempts to study the relationship between robots and inequality, they have mainly focused on between-occupation inequality. By focusing on the manufacturing sector and examining the impact of changes in the occupational structure, Brall and Schmid (2023) found that robot adoption primarily increases wage inequality through a compositional effect in Germany. Similarly, Barth et al. (2020) finds that in Norway, while robot penetration generally raises wages, the effect is most pronounced for managers and STEM workers.

Our results should be interpreted with caution for two main reasons. First, the measures of AI and robot exposure used in this study do not reflect actual technology adoption, but rather the degree to which occupations are associated with these technologies based on their task content. As such, we treat exposure to AI and robots as proxies for occupational task structure, not as direct drivers of inequality. This means that the observed associations may be influenced by other mediating factors–such as productivity effects–that can shape wage outcomes. Second, due to the limitations of our data, we cannot make any causal claims regarding the relationship between technology exposure and wage inequality. Despite these limitations, the paper contributes valuable empirical insights by systematically linking occupational task characteristics to patterns of wage dispersion—an angle that remains underexplored in the existing literature.

The rest of the paper is organized as follows. Section 2 reviews relevant literature on AI and industrial robots. Section 3 describes our data sources and key variables. Section 4 provides descriptive evidence of these technologies and their relationship with labor market.

Section 5, presents the empirical strategy and results. Finally, Section 6 concludes.

2 Background literature

Task content of recent automation technologies

The seminal work by Autor et al. (2003) shifted focus to the task content of occupations, highlighting its importance in understanding how technology reshapes employment.[2] From this perspective, occupations involving tasks that follow explicit rules can be easily codified and automated. Consequently, routine tasks are the most susceptible to automation. This insight gained traction in both theoretical and empirical literature, sparking the development of various indicators to measure occupational exposure to automation (Autor et al., 2003; Goos et al., 2009; Acemoglu and Autor, 2011; Autor, 2013; Goos et al., 2014; Nedelkoska and Quintini, 2018; Marcolin et al., 2019; Foster-McGregor et al., 2021; Gregory et al., 2022). Nevertheless, different technologies are designed for distinct activities, leading to varying associations with tasks and occupations. More recent automation technologies, such as industrial robots and AI, perform different activities and, therefore, relate differently to workforce.[3]

In recent years, advancements in AI have been fostered by significant improvements in data mining and computational power, which have directly contributed to the progress of machine learning technologies (Brynjolfsson et al., 2021; Zolas et al., 2021; Bonney et al., 2024). Supervised learning systems form the backbone of AI, where machines are trained to predict outcomes using vast databases. Supervised learning, the core of AI, enables machines to predict outcomes using large datasets. This remarkable progress has led to the development of generative AI based on extensive natural language models. Reflecting this shift, the Organization for Economic Co-operation and Development (OECD) recently updated its definition of AI, describing it as "*a machine-based system that, for explicit or implicit objectives, infers from input 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*" (OECD, 2023).

Due to its transformative potential and cross-industry applications, AI is often seen as a general-purpose technology (GPT) (Brynjolfsson et al., 2017; Trajtenberg, 2018; Filippucci

[2]It is worth noting that the discussion on technology and its implications for employment and workforce composition is longstanding. For a detailed survey of the literature, see Piva and Vivarelli (2018) and Autor (2022).

[3]It is important to note that our distinction between AI and robots focuses on the technological characteristics of these tools and their associated occupational exposure. However, recent research has emphasized that digital transformation at work also includes the increasing use of digital platforms, algorithmic management, and monitoring systems, particularly affecting low-skilled and manual occupations (Fernandez Macias et al., 2023; Filippi et al., 2023; Urzì Brancati et al., 2023). These developments often reshape work organization by influencing task allocation, decision-making, and control mechanisms–without necessarily involving physical robots or advanced AI systems. For example, workers in logistics and delivery may be subject to algorithmic control and performance monitoring via digital platforms, reflecting a different but significant dimension of digital exposure. While not explicitly captured in our current framework, these mechanisms are part of the broader landscape of technological change.

et al., 2024).[4] It combines tangible inputs, such as computing power and IT infrastructure, with intangibles like software, data, and skilled labor (e.g., large datasets are essential for training algorithms, along with expertise from programmers, data scientists, and IT professionals) (Corrado et al., 2021; Filippucci et al., 2024). The combination of all these inputs results in a technology that performs cognitive activities, typically associated with high-skilled workers, which is an aspect that distinguishes this technology from others (Acemoglu et al., 2022; Czarnitzki et al., 2023).

Despite methodological differences, research consistently shows that occupations involving problem-solving, reasoning, and perception–i.e., non-routine cognitive tasks–are more exposed to AI than other types of occupations (Webb, 2020; Felten et al., 2021; Georgieff and Hyee, 2021; Engberg et al., 2024). Empirical evidence indicates that firms highly exposed to AI tend to post more AI-related job openings while reducing non-AI hiring (Acemoglu et al., 2022). Georgieff and Hyee (2021) further emphasize this trend, finding a positive correlation between increases in AI-related job postings and occupational exposure to AI across 36 sectors, underscoring the demand for AI-specific skills (Frank et al., 2019; Webb, 2020). However, it remains challenging to determine ex-ante whether AI exposure leads to the substitution or augmentation of certain occupations, and most indicators of AI exposure do not yet reflect this distinction (Guarascio et al., 2023).

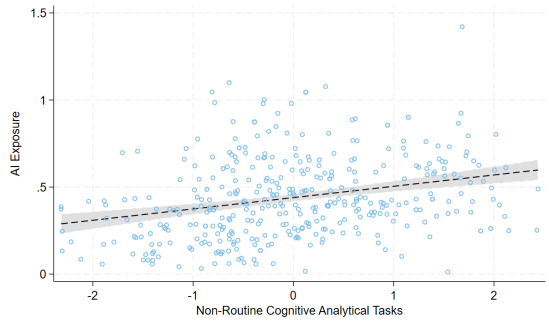
Although AI adoption is still at an early stage, preliminary studies suggest that it has not significantly impacted overall employment in the U.S., though it may positively affect employment at regional or firm levels (Acemoglu et al., 2022; Guarascio et al., 2023; Damioli et al., 2024). Further, it is associated with higher wages for high-skilled workers (Ernst et al., 2019; Felten et al., 2019; Ozgul et al., 2024).

In contrast, industrial robots perform a different set of tasks. More recently, traditional mobile functions have been enhanced through improved sensing capacities and information-sharing with other machines. Industrial robotics can execute various operations, including object manipulation, painting, wire welding, and assembly, among others, implying a strong connection to manual tasks. For example, occupations most exposed to this technology typically involve tasks such as moving objects in factories and welding. This is translated into robots performing more physical and manual activities. For instance, Squicciarini and Staccioli (2022) highlight the high exposure to robots in occupations such as 'Hand and pedal vehicle drivers' (ISCO-08 9331), and 'Vehicle cleaners' (ISCO-08 9122) among others. Empirical studies show that robots have a skilled-biased technological change (SBTC) nature, substituting mostly low-skilled occupations (Graetz and Michaels, 2018; Webb, 2020; Fernández-Macías and Arranz-Muñoz, 2020; Montobbio et al., 2022).

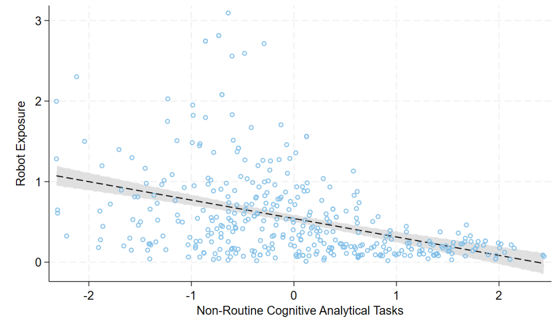
In line with the literature presented above, Figures 2.1a to 2.1d corroborate the different associations of these technologies between different tasks. We observe a positive association between non-routine cognitive intensive occupations and AI exposure, while the opposite is observed for robots. Conversely, Figure 2.1c indicates that there is no correlation between non-routine manual tasks and AI exposure, while a positive association is observed for the case of robot exposure.

[4] Some scholars question the characterization of AI as a GPT, instead arguing that it should be understood more as a system (Vannuccini and Prytkova, 2024).

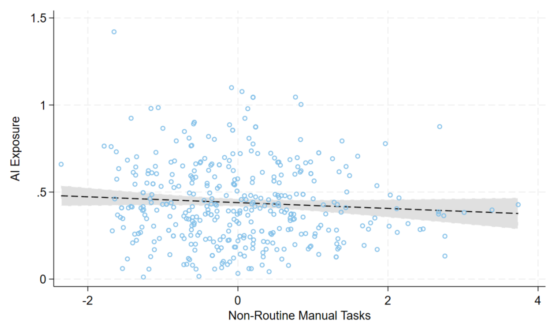
Figure 2.1: Correlation between robot and AI exposure and task content of occupations



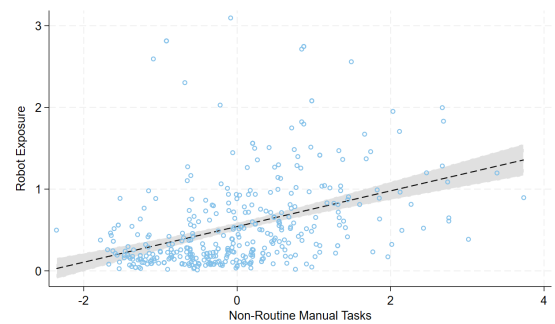
(a) AI Non-routine Cognitive



(b) Robot Non-routine Cognitive



(c) AI Non-routine Manual



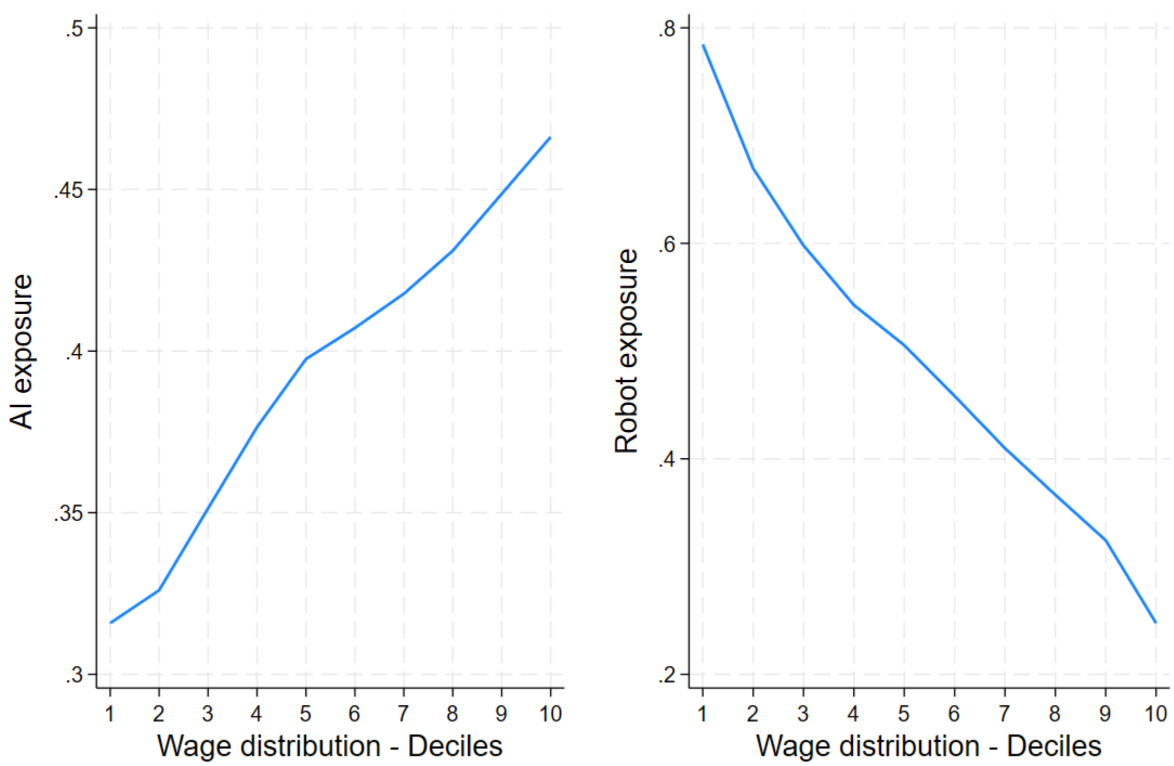
(d) Robot Non-routine Manual

Notes: The AI and robot exposure are built using the indices provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. The task content measures are derived from O*NET database, categorized at the SOC level. Following Hardy et al. (2018), we select task-related items that capture routine and non-routine activities, distinguishing between cognitive and manual dimensions. Task intensity scores for each SOC occupation are then calculated by averaging the importance scores within each category. Finally, occupations are mapped to ISCO-08 classifications.

Figure 2.2 provides further insights into the relationship between technology exposure and wage distribution by depicting the average exposure to robots and AI by wage deciles.[5] The figure reveals an inverse relationship between robot exposure and wage deciles, as illustrated by the downward-sloping curve. Lower-wage deciles show higher exposure to robots, while higher-wage occupations display minimal exposure. This pattern aligns with the nature of industrial robots, which are primarily utilized for manual tasks like welding, assembly, and painting—activities generally associated with lower-skilled roles. Consequently, this observation supports findings in the literature indicating that low-skilled occupations are more susceptible to automation through robotics (Chiacchio et al., 2018; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021). Conversely, the upward-sloping trend for AI exposure suggests that average exposure rises across higher wage deciles. Occupations at the upper end of the wage distribution demonstrate greater average exposure to AI, which is consistent with the discussion above.

[5] Refer to Section 3 for the details on the computation of the indexes.

Figure 2.2: Exposure level by decile of the wage distribution



Notes: Figure 2.2 shows the exposure of robots and AI by deciles of the wage distribution, aggregated for the 19 countries included in the sample. We first compute the deciles for each country by splitting the real hourly wage. We then averaged the AI and robot scores across countries. The robot and AI scores are at ISCO-08 2-digit level. They are built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. Own elaboration based on EU-SES.

Wage disparity and task content of occupations

Several theoretical approaches aim to explain the link between wage dispersion and task content.

The model proposed by Jung and Mercenier (2014) explicitly considers the role of workers' abilities across the different types of tasks. More specifically, it assumes that each worker possesses an innate (unobservable) ability, denoted as z, which can be applied to three types of tasks: manual, routine, and non-routine. A function, $\varphi_t(z)$, summarizes the relationship between the innate ability and a worker's productivity in performing a certain task t. Further, this function is characterized in such a way that:

$$\frac{\partial \varphi_{nr}(z)}{\partial z} > \frac{\partial \varphi_{r}(z)}{\partial z} > \frac{\partial \varphi_{m}(z)}{\partial z} > 0$$

On the one hand, this suggests that workers with greater abilities are more productive. On the other hand, the productivity gap between workers varies depending on the type of tasks they perform. Specifically, productivity differences are more pronounced for workers in non-routine tasks than in routine and manual tasks. This feature arises from the inherent nature of non-routine jobs, which often entail complex problem-solving, design, creativity, and similar aspects. The execution of these activities is closely intertwined with the abilities of workers, leading to greater (unobserved) heterogeneity in performance, which can be translated into different output qualities. For example, in tasks such as creating or designing advertisements, workers with comparable years of experience and education employed in similar-sized firms can produce significantly different outputs based on their creative capacities and abilities. In contrast, tasks associated with more routine and standardized activities, such as moving machine components from one location to another, exhibit greater uniformity and rely less on workers' innate abilities. As a result, this uniformity reflects a lower variability in output per worker. Assuming workers are compensated based on their productivity, the model suggests that the productivity divergence among non-routine workers leads to greater wage disparity.

Various theoretical approaches focus on the differences among workers within specific occupations. For example, Autor et al. (2003) suggests that workers exhibit different productivity levels based on whether they engage in routine or non-routine tasks. Additionally, Bessen (2016) develops a model that examines the relationship between occupations, tasks, and the impact of computer use on employment and wages. As technology adoption becomes more widespread, it can contribute to increased wage inequality within occupations, particularly if some workers receive training to adapt to new technologies while others do not.

Empirical implementations of the model by Jung and Mercenier (2014) provide evidence supporting the hypothesis that wage differentials within occupations are negatively associated with the routine content of those occupations (Cortes, 2016). Additional studies, including those by Autor et al. (2003) and Fortin et al. (2011), have also demonstrated that the task content of occupations accounts for significant variations in wages within specific job categories. Furthermore, van der Velde (2020) examines the relationship between intra-occupational wage dispersion and task content, utilizing a routine index similar to the one developed by Autor et al. (2003). However, it is important to note that this index was created based on a limited set of technologies, primarily focusing on information and communication technologies (ICTs), mainly affecting middle-skill occupations.

In this paper, we aim to extend this analysis by examining two distinct types of technologies–AI and robots–that possess different characteristics, as previously outlined. Similar methodologies to those proposed here can be found in Georgieff (2024), who investigates the relationship between AI and occupational inequality, both between and within occupations. The author reports no significant effect on between-occupation inequality but identifies a negative effect on within-occupation inequality. While his approach is similar to ours, it is limited to analysis at the ISCO-08 2-digit level. In contrast, we will also explore variability at the 3-digit level, due to the significant variation in exposure to these technologies at a more granular level. This topic is discussed further in Section 4 and elaborated upon in the empirical specifications presented in Section 5.

The previous findings indicate that occupations with higher exposure to robots are primarily linked to manual tasks, which typically involve lower complexity. This lower complexity leads to less variation in workers' abilities to perform these tasks, resulting in greater uniformity in both task execution and overall output. As a consequence, this uniformity leads to reduced variability in compensation within these occupations. In contrast, occupations with greater exposure to AI are associated with more complex and non-routine cognitive tasks, where individual differences in abilities have a significant role in performance. The increased variability in workers' abilities for these tasks results in a wider wage range, contributing to greater wage disparity in these occupations.

3 Data

The information for this analysis comes from the European Union Structure of Earnings Survey (EU-SES), which is an enterprise survey carried out by national statistical offices. Each country implements its own questionnaires and fieldwork, and the data collected is harmonized by Eurostat to ensure comparability of results across countries. The survey was initiated in 2002, initially covering 24 European Union member states plus the United Kingdom, and it is conducted every four years. By 2018, the survey's coverage expanded to include 27 countries, though the United Kingdom is no longer part of the sample.

Although it is an enterprise survey, it collects information at the worker-individual level, which makes it suitable for our analysis. It targets enterprises with 10 or more employees in the manufacturing and services sectors (excluding Public administration and defense, and compulsory social security). This is, it excludes self-employment, family workers, and employees of small enterprises (with fewer than 10 employees).[6]

The data includes information on employment, gross earnings, hours worked, types of contracts, union affiliation, education level, and occupations categorized at the 2- or 3-digit ISCO level. It also provides sectoral information at the 2-digit level, with various

[6]However, given that larger companies are the ones that are more technologically advanced, this does not necessarily affect the scope of the analysis. Further, given that the analysis is at the country-occupation level, the absence of the public administration does not represent a major limitation given the level of aggregation. It would have been more important if the analysis had been at the regional level, given that public entities tend to be clustered in capital cities.

aggregations based on the country and year. All of this information is available at the individual worker level.

The SES has a sizable sample, with the number of observations varying across countries. Table 3.1 shows the sample size by country and year. It adopts a two-stage sampling approach: the first stage aims to represent employees at the sectoral level, while the second stage ensures the representation of contract types and occupations. This design enables analyses at a finer level of disaggregation.

Table 3.1: Number of observations in the EU-SES

Year	2002	2006	2010	2014	2018
BE	112,022	165,191	137,254	140,324	185,569
BG	152,977	186,672	204,968	200,680	217,508
CY	13,178	26,476	32,566	31,646	29,367
CZ	1,030,982	1,970,864	1,993,625	2,202,636	2,434,107
EE	78,106	126,515	119,222	122,654	154,944
ES	217,147	235,272	216,769	209,436	218,966
FI	125,169	308,162	315,803	315,187	315,934
FR	121,178	113,641	220,369	267,383	256,600
HU	479,009	781,864	835,207	882,373	875,803
IT	81,975	155,026	264,732	189,221	248,783
LT	145,530	131,201	38,387	44,952	43,164
LU	28,432	31,329	19,439	23,017	57,389
NL	83,107	154,709	173,475	155,625	171,651
NO	598,365	989,569	1,412,590	1,494,178	2,508,093
PL	647,386	652,688	681,761	723,706	861,637
PT	62,587	104,643	120,766	85,201	96,265
RO	230,161	259,140	278,270	286,718	330,622
SE	1,001,456	284,725	285,206	261,559	275,990
SK	419,715	674,408	773,860	887,052	964,342
Total	5,628,482	7,352,095	8,124,269	8,523,548	10,246,734

Notes: This table shows the number of observations across the different waves of the EU-SES for the countries included in the analysis.

From 2010, the SES has been providing information on occupations at the ISCO-08 level, aligning with changes in the International Classification of Occupations. However, data prior to 2010 is based on ISCO-88. To ensure consistency, we converted ISCO-88 occupations to ISCO-08.[7] Although the EU-SES provides information at the 3-digit ISCO level, this is only available for a limited number of countries. Therefore, we opted to conduct our analysis at the 2-digit level.[8]

[7]For further details, please refer to subsection A.1.

[8]Although this sacrifices detail at the occupational level, it was necessary due to limited availability; in 2002, only 12 out of our 19 countries in the sample delivered information at the 3-digit level. Further, this would imply missing information for economically large economies such as France and the Netherlands. The consequences of this decision are further discussed in Section 4 and in Section 5.

Although country coverage improves substantially when working at ISCO-08 2-digit, some of them are not present along all the waves of the SES. Thus, our final dataset results in an unbalanced sample. Table B.2 in Appendix B shows the sample composition by country and year. However, we reproduce our econometric exercise with a balanced sample and observe that the main results still hold.[9]

Variables Our main dependent variable is wage inequality at the occupational level. We use the wage gap because it allows us to analyze inequality across different segments of the wage distribution. Specifically, we construct the wage gap by taking the logarithm of the ratio of real hourly wages between the 90th (p90) and 10th (p10) percentiles for occupation at o in country c at year t.[10] Additionally, to capture inequality at both the upper and lower ends of the wage distribution, we calculate the logarithm of the real hourly wage gap between the 90th and 50th (p50) percentiles, and between the 50th and 10th percentiles (p50/p10). All in all, this results in three outcome variables.

To assess occupational exposure to AI and robots, we employ the exposure scores to these technologies elaborated by (Webb, 2020).[11] The author uses patent data and text analysis to align AI and robot tasks with job task descriptions from O*NET, thus constructing an indicator at the occupational level. The author first defines the technologies and derives a methodology to select patents following these definitions.

Concerning robots, he draws upon the ISO 8373 definition, where robots are described as *"automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment"* (ISO 8373). To extract the text descriptions of tasks performed by technology from patent titles, the author employs a natural language processing algorithm. Subsequently, an intensity score for these tasks is developed by calculating their relative frequency across all patents within a given technology. These tasks are then linked to occupations based on their task content, embedded in the text descriptions of the occupations. Consequently, the index is higher for occupations where there is a greater overlap between the verb-noun pairs of job tasks and technology patents, indicating that the technology targets tasks that are more prevalent within that occupation. The resulting scores cover 772 occupations under the Standard Occupational Classification System of 2010 (SOC-2010).

Since the EU-SES provides data at the ISCO level, SOC-2010 occupations were converted to ISCO-08 using the crosswalk developed by the Institute for Structural Research (IBS).[12] It is important to acknowledge that O*NET captures the task-based nature of the U.S. occupational structure, which is closely tied to its specific productive and institutional context. Therefore, using an indicator based on O*NET tasks assumes a similar structure for European countries, which may not necessarily hold, as noted in Fana et al. (2020). However,

[9]The composition of the balanced can be seen in Table B.3. We conduct the robustness checks on the balanced sample in Section 5.

[10]Given that the distribution of the wage gap is rather right-skewed, as can be inferred from Figure A.7, we use the logarithm to achieve a more symmetric distribution.

[11]This index has also been used in numerous other studies, such as Heß et al. (2023) and Acemoglu et al. (2022).

[12]The crosswalk codes are available for download from the IBS website.

our primary interest lies in ranking occupations according to task content. While it may be unrealistic to assume identical task structures between U.S. and European occupations, it is unlikely that such differences would affect the relative ranking of occupations—-a key focus of our analysis. This is particularly true given the relatively coarse level of aggregation used in the present study.

Furthermore, it is worth noting that using patent data to assess occupational exposure to certain technologies presents, undoubtedly, certain challenges, as patents frame tasks differently than occupational classifications, as they primarily describe technological innovations rather than job tasks or worker activities. In this vein, relying on patent titles to identify the technology's function can be a constrained approach (Guarascio et al., 2023). However, there are significant advantages to using patent data, particularly its ability to reflect changes in technological capabilities over time. While patents do not directly map to occupational classifications, analyzing the co-occurrence of verb-noun pairs between patents and occupations can still yield valuable insights into the linkages between technology and occupational exposure. In particular, because it offers a more objective perspective in comparison to alternative estimations that rely on subjective judgments to identify key abilities that relate to technologies, such as the measure elaborated by Felten et al. (2019). Nevertheless, in light of these divergent approaches, we also use alternative AI and robot indicators in our robustness checks, which are presented in Section 5.

Lastly, we also include additional variables to control for other co-funding factors that affect wage inequality.[13] The complete list of variables used is presented in Table 3.2 and the summary statistics in Table 3.3.

[13] This is further explained in Section 5. For the details on the computation of the control variables, refer to Appendix B.1.

Table 3.2: Description of variables used in the final dataset

Variable name	Variable definition
Log of the wage gap p90/p10	Log real hourly wage gap between the wage of the 90th percentile and 10th percentile at the occupation-country-year cell
Log of the wage gap p90/p50	Log real hourly wage gap between the wage of the 90th percentile and 50th percentile at the occupation-country-year cell
Log of the wage gap p50/p10	Log real hourly wage gap between the wage of the 50th percentile and 10th percentile at the occupation-country-year cell
AI exposure Webb	Exposure to AI for occupation o based on Webb (2020)
Robot exposure Webb	Exposure to robots for occupation o based on Webb (2020)
Robot exposure Montobbio et al	Exposure to robots for occupation o based on Montobbio et al. (2022)
AI exposure Prytkova et al	Exposure to AI for occupation o based on Prytkova et al. (2024)
Robot exposure Prytkova et al	Exposure to AI for occupation o based on Prytkova et al. (2024)
AI exposure Felten et al	Exposure to AI for occupation o based on Felten et al. (2019)
AI exposure OECD	Exposure to AI for occupation o based on Georgieff and Hyee (2021)
AI exposure Engberg et al	Exposure to AI for occupation o based on Engberg et al. (2024)
Nro of 4-digit occupations	Number of 4-digits occupations within major ISCO 2-digit group
Std of routine cognitive intensity	Standard deviation of the intensity of routine cognitive activities at 4-digit level for occupation o
Std of routine manual intensity	Standard deviation of the intensity of routine manual activities at 4-digit level for occupation o
HHI of high-skilled occupations	Herfindahl index of high-skilled employment (tertiary education or more) for occupation-country-year cell
Std of AI exposure	Standard deviation of the AI exposure at ISCO 4-digit level for occupation o
Std of robot exposure	Standard deviation of the robot exposure at ISCO 4-digit level for occupation o

Notes: This Table shows the list of variables used. The data source for constructing the occupation-country-year panel is the EU-SES, while the information on the technology exposure has been elaborated based on the literature cited above.

Table 3.3: Descriptive statistics of dependent and explanatory variables

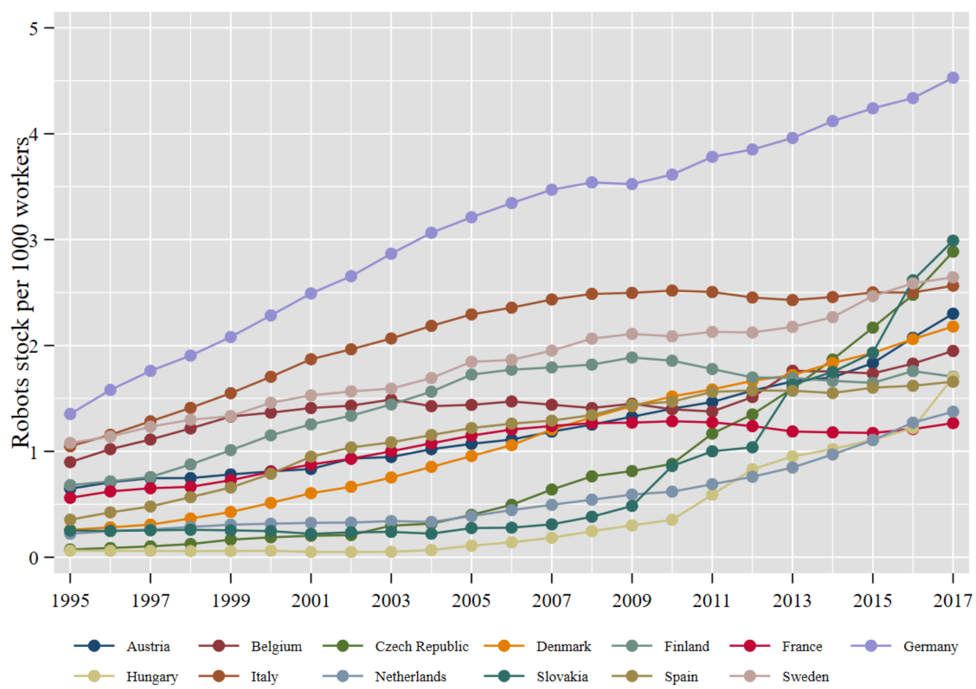
	mean	sd	p50	min	max	obs
Dependent variables						
Log of the wage gap p90/p10	0.98	0.35	0.93	0.26	3.50	2883
Log of the wage gap p90/p50	0.54	0.20	0.51	0.14	2.88	2883
Log of the wage gap p50/p10	0.44	0.20	0.41	0.01	1.31	2883
Independent variables						
AI exposure Webb	0.41	0.15	0.40	0.06	0.91	2883
Robot exposure Webb	0.56	0.45	0.36	0.11	1.61	2883
AI exposure Felten et al	0.67	0.03	0.66	0.61	0.72	2883
AI exposure OECD	0.65	0.19	0.68	0.00	0.96	2067
AI exposure Prytkova et al	0.00	0.02	0.00	0.00	0.12	2883
AI exposure Engberg et al	0.14	0.28	0.00	0.00	1.06	2883
Robot exposure Montobbio et al	0.31	0.10	0.28	0.13	0.56	2883
Robot exposure Prytkova et al	0.24	0.93	0.01	0.00	7.40	2883
Control variables						
HHI index	0.33	0.21	0.24	0.10	1.00	2883
Share of manufacturing	0.23	0.25	0.15	0.00	1.00	2883
Blau index (gender)	0.63	0.13	0.58	0.50	0.99	2883
Share of female	0.45	0.25	0.45	0.00	0.96	2883
Share of unionization	0.70	0.32	0.82	0.00	1.00	2883
Nro of 4-digit occupations	11.53	6.76	11.00	2.00	26.00	2883
HHI of high-skilled occupations	0.59	0.15	0.55	0.33	1.00	2883
Std of AI exposure	0.17	0.07	0.19	0.03	0.36	2883
Std of robot exposure	0.29	0.23	0.22	0.04	0.94	2883
Std of routine cognitive intensity	0.24	0.10	0.22	0.03	0.62	2883
Std of routine manual intensity	0.37	0.14	0.40	0.06	0.73	2883

Notes: This Table shows the descriptive statistics of the dependent and independent variables for the whole sample. Own elaboration based on the five waves of the EU-SES.

4 Descriptive overview

The 2000s saw a significant increase in robot adoption, leading to extensive literature exploring its effects on labor markets at various levels of aggregation (Graetz and Michaels, 2018; Aghion et al., 2019; Acemoglu and Restrepo, 2020).[14] Figure 4.1 illustrates the evolution of robot stock per 1,000 workers-—referred to as robot density—-within the twelve European countries with the highest adoption rates. Germany stands out as a leader in robot penetration over time. However, it is also clear that some Eastern European economies made significant advancements in adoption following the financial crisis. The Czech Republic and Slovakia are particularly noteworthy, with their robot density experiencing average annual growth rates of 18.53% and 13.5%, respectively, from 1995 to 2017.[15] As a result, by 2017, these two countries ranked second and third in robot density, following Germany.[16] Meanwhile, Italy, Sweden, Finland, Denmark, Belgium, Austria, and the Netherlands have also shown a notable increase in robot adoption, albeit at a slower pace.

Figure 4.1: Robot density 1995-2017.



Notes: Figure 4.1 shows the evolution of robots stock per 1000 workers in twelve European countries. *Source:* Own elaboration based on the International Federation of Robotics (IFR) and EU-KLEMS for employment.

In contrast to robots, AI is more recent and not widely diffused yet (Corrado et al., 2021; Vannuccini and Prytkova, 2024). Consequently, systematic databases enabling time series

[14] For a comprehensive review, see (Jurkat et al., 2022).

[15] Refer to Table A.1 for more details on the average growth rate of robot density by country.

[16] This trend may be linked to the rise of Global Value Chains (GVCs), specifically due to Germany shifting production to Eastern European countries.

analysis are currently unavailable. However, there are empirical efforts to assess its pervasiveness. One notable source is the AI Observatory by the OECD, which offers indicators of AI in investment across countries. For instance, Figure A.1 in Appendix B illustrates the increasing development of AI over time, reflecting a sharp rise in venture capital investments in this technology across several European countries. A clear upward trend has been evident since 2016, in line with the findings of Corrado et al. (2021). Additionally, Calvino and Fontanelli (2023) have provided insightful analysis on AI adoption at the firm level in 11 countries, using novel data collected within the framework of the OECD AI Diffusion Project. Noteworthy findings indicate that larger and younger firms have a higher adoption rate of AI, which is strongly correlated with existing complementary capabilities. The authors emphasize that over 20% of large firms in European countries use AI.[17] These findings align with recent Eurostat data on AI usage by enterprises, indicating that 8% of EU enterprises employed at least one AI technology in 2021, with the figure rising to 28% for large enterprises.[18]

In the remainder of this section, we will zoom into the relationship between robots and AI and workforce composition. Although AI is not yet fully widespread, the above-mentioned evidence suggests that its adoption is accelerating quickly. Therefore, the scope of the present analysis is limited to examining the potential channels through which a wider adoption of this technology may affect inequality.

4.1 Inequality and wage variability

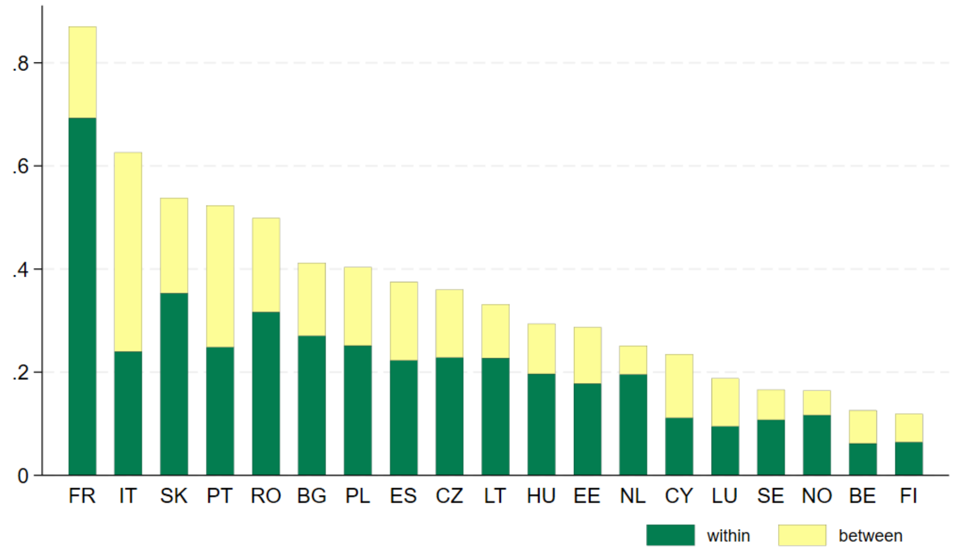
In this section, we will provide empirical evidence of the relevance of within-occupation wage inequality and its relationship with exposure to AI and robots. Figure 4.2 shows the Theil index decomposition into within and between occupation inequality for 19 European countries.[19] This indicates that within-occupation inequality accounts for a significant portion of overall inequality in most of the countries studied. In 15 out of 19 countries, the share of within-occupation inequality exceeds 50%. The figure varies, ranging from 38.35% to 79.60%, with Italy having the lowest proportion and France having the highest.

[17] The surveyed European countries include Belgium, Denmark, France, Germany, Italy, Portugal, and Switzerland, with survey years spanning over 2017–2020.

[18] For further details refer to EUROSTAT - Use of AI in enterprises.

[19] The Theil index serves as a metric to quantify the divergence of a given income distribution from a hypothetical scenario where each individual earns an equal amount. It can be decomposed into inequality within and between groups. Refer to appendix A.3 for details on the computation.

Figure 4.2: Theil index decomposition: between and within occupation inequality.



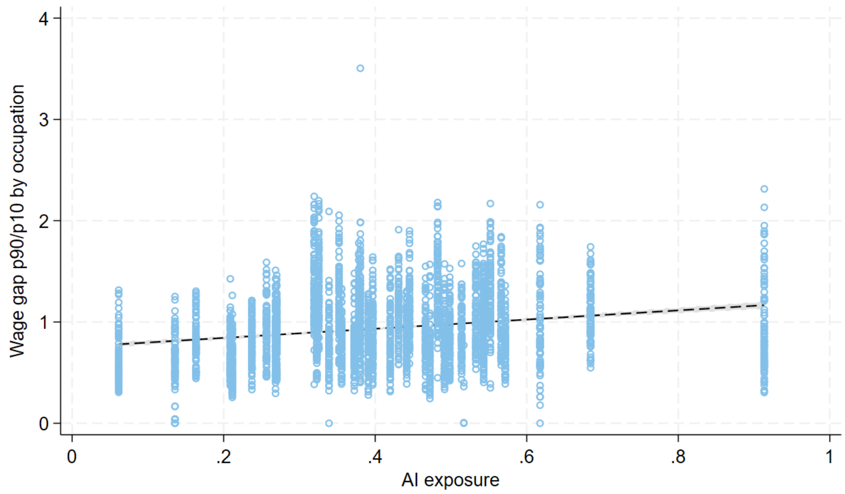
Notes: Figure 4.2 shows the decomposition of the Theil index into within and between occupation inequality at ISCO-08 2-digit level for the real hourly wage. It is the average across the five waves of the EU-SES (2002, 2006, 2010, 2014 and 2018). *Source:* Own elaboration based on EU-SES.

The evidence presented above is based on a relatively broad 2-digit level of occupational classification. To provide a more detailed analysis, Figure A.2 in the appendix illustrates the Theil decomposition for occupations at 3-digit level of the ISCO-08 classification for countries with available data. While the within-occupation component shows a slight reduction, it still accounts for half or more of the overall inequality in most countries. Notable exceptions include Cyprus and Luxembourg, where the within-occupation component explains only 32.6% and 41.2% of the inequality, respectively.

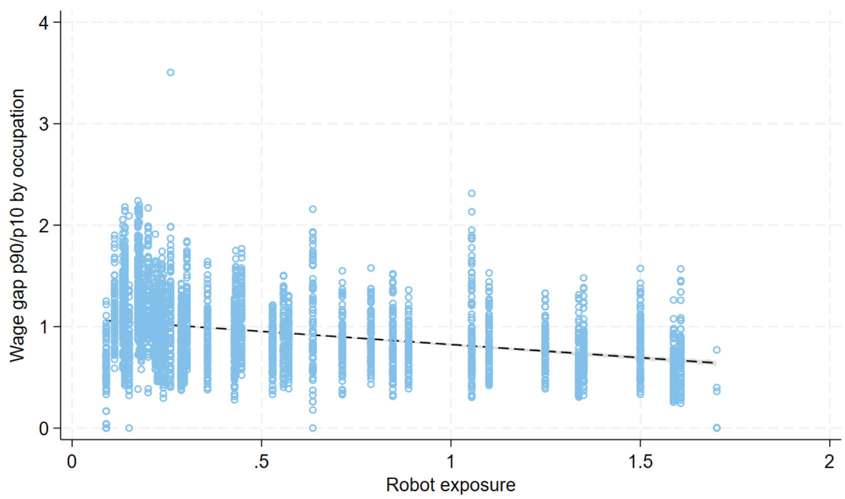
The importance of within-occupation wage disparity is further confirmed in Tables A.2 and A.3, where we conduct an ANOVA analysis to examine the variance of the p90/p10 real hourly wage gap as an indicator of inequality. It suggests that around 67% of the variance of the p90/p10 wage gap is explained by within-occupation variation. It also derives from Table A.2 that inequality is higher in high-paying occupations (i.e., managers, science and engineering professionals) and shows a larger dispersion of the indicator.

Given that occupations involve a combination of tasks, which may relate to specific technologies designed for certain activities, exposure to these technologies may potentially be linked to wage inequality. We aim to explore this further in the remainder of this section. Recalling from Figure 2.2, occupations with higher exposure to robots are predominantly situated at the lower end of the wage distribution, whereas those more exposed to AI are concentrated at the upper end. Consequently, we can expect different patterns in wage variability, as higher-paid occupations exhibit greater dispersion. Hence, Figure 4.3 illustrates the correlation between the logarithm of the p90/p10 wage gap and the occupational exposure scores to robots and AI. It derives from this that greater exposure to AI positively correlates with inequality, while the opposite occurs for robots.[20]

Figure 4.3: Correlation between wage inequality within the occupation and exposure to AI and robots



(a) AI



(b) Robot

Notes: Figure 4.3 shows the correlation between the logarithm of the real hourly wage gap for the p90/p10 and the AI score (panel 4.3a) and the robot score (panel 4.3b). The robot and AI scores are at ISCO-08 2-digit level. They are built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. We mapped ISCO-88 to ISCO-08 to harmonize occupations across the different waves. The details of the harmonization can be consulted in appendix A. For comparability reasons, we restrict the sample to the euro countries. These are Belgium, Cyprus, Estonia, Finland, France, Italy, Lithuania, Luxemburg, Netherlands, Poland, Portugal, Slovakia, and Spain. *Source:* Own elaboration based on EU-SES.

The observed correlations between exposure to AI or robots and wage dispersion can be

[20]This is also observed when analyzing the correlation with the standard deviation of the mean of the real hourly wage in the occupation in Figure A.6 in Appendix A.

better understood by considering the underlying task characteristics that these technologies proxy. Specifically, occupations with higher exposure to robots typically involve manual and standardized tasks. These tasks tend to be less complex and allow for limited variation in how they are performed. As a result, differences in individual performance are relatively minor, leading to more uniform productivity and, consequently, more compressed wage distributions within these roles.

By contrast, occupations with greater exposure to AI are generally characterized by cognitive and complex tasks that are more heterogeneous in nature. These tasks rely more heavily on individual judgment, problem-solving, and other capabilities that vary significantly across workers. This variation contributes to broader differences in performance and output, which in turn results in wider wage dispersion within these occupations.

Thus, in line with recent literature, we treat AI and robot exposure not as direct causes of wage inequality, but as indicators of the underlying task structure within occupations–structures that themselves are closely associated with differences in wage dispersion.[21] In the remainder of the paper, we further examine these associations and how they reflect the differentiated role of technology across occupational task profiles.

5 Empirical strategy and results

In light of the descriptives outlined in 4.1, in this section, we will examine the association between exposure of occupations to robots and AI and within-wage inequality by implementing a fixed-effects model. To do this, we apply the following specification:

$$y_{oct} = \beta K_o^T + \gamma_{ot} + \bar{X} + \epsilon_{oct} \tag{1}$$

Where y_{oct} is the main dependent variable, which is the logarithm of the real hourly wage gap in occupation o in country c at year t. We consider three outcomes for within-occupation inequality y_{oct}: the wage gap between the p90/p10, the p50/p10 and the p90/p50. K_o^T represents the exposure score of each occupation for each technology T (robot and AI). β is the main coefficient and represents the change in wage inequality for a unit change in the robot or AI occupational score. Based on the evidence presented in the previous section, we expect β to have a positive (negative) sign, meaning that increasing exposure to AI (robots) is associated with greater (lower) inequality.

The variable γ_{ot} includes a set of control variables that are occupation-specific.[22] First, we control for the degree of collective bargaining coverage. By regulating the wage relationship, trade unions tend to be associated with a reduction in the dispersion of wages within occupations (Card et al., 2004; Biewen and Seckler, 2019). Additionally, the gender composition of the labor market can influence wage distribution. Nevertheless, empirical evidence has yielded mixed results regarding the direction of this effect (Kollmeyer, 2013). On one hand, there is literature suggesting that an increase in the proportion of women in the labor market can reduce wage inequality. One of the main reasons is the greater propensity

[21] This conceptual distinction is crucial: our empirical strategy does not aim to demonstrate a causal effect of AI or robots on wage inequality, but rather to explore how their exposure is associated with differing patterns of within-occupation inequality, mediated by the nature of task content.

[22] Refer to appendix B.1 for the details on the construction of control variables.

of low-educated women entering the labor force (Esping-Andersen, 2007; Harkness, 2010). Conversely, some scholars argue that higher female participation in the labor market can exacerbate wage inequality, particularly if female employment substitutes for high-skilled male employment (Acemoglu et al., 2004) or due to differing labor characteristics, such as lower trade union affiliation (Card, 2001). Therefore, despite the unclear direction of the effect, we control for the share of female employment in each occupation to net out its impact on wage inequality.[23]

Further, there is evidence that wage dispersion is more pronounced in certain industries. In particular, there is a strand of literature that has pointed to a positive implication of servicification on wage inequality (Blum, 2008; Boddin and Kroeger, 2022), mainly related to their relatively greater share of high-skilled workers. Thus, to account for the industrial composition, we control for the share of manufacturing employment.

The fact that the occupational analysis is conducted at the ISCO-08 2-digit level presents certain challenges. As noted in Section 3, this choice stems from the lack of consistent information on occupations at the 3-digit level for most countries. Two important considerations should be highlighted. First, the number of occupations within each major subgroup at the 2-digit level varies significantly, especially for professional categories. Naturally, this implies that variability in the outcome variable can partly be attributed to greater dispersion within occupational groups. To address this, we control for the number of 4-digit occupations within each major 2-digit category.

A related issue is the substantial variation in technology exposure within each major category (Foster-McGregor et al., 2021).[24] Consequently, we control for the standard deviation in exposure to robots and AI at the 4-digit level for each occupation o. In the same vein, we also include the standard deviation of routine intensity for each occupation o to further control for occupational characteristics.

Finally, $\bar{X}$ represents the set of fixed effects. We control for country and year-fixed effects. The first one accounts for aspects related to institutional dimensions which are time-invariant; while the second captures changes related to business cycles–i.e. the financial crisis. We use five waves of the EU-SES: 2002, 2006, 2010, 2014 and 2018 and 19 countries in our analysis.[25]

Results Table 5.1 shows the association of exposure to robots and AI and inequality within occupations for the logarithm of the p90/10, p90/50 and p50/10 wage gap. When examining AI exposure, the positive coefficient indicates that occupations more exposed to this technology tend to have, on average, higher wage inequality. For the p90/p10 wage gap, a 0.1 increase in the AI exposure score is associated with an increase in inequality of

[23] As an additional measure, we also control for the Blau index to account for labor market diversity instead of the female share. This indicator captures potential non-linearities that may exist in the relationship between inequality and female participation.

[24] As occupations are aggregated, variation in technology exposure is reduced. This trend is evident in Tables C.5 to C.7, where we show correlations between the alternative technology indicators used in this paper. These tables reveal that as occupations are aggregated, the correlation between different measures increases, indicating notable heterogeneity at more granular levels.

[25] The countries included are Belgium, Bulgaria, Cyprus, Czech Republic, Estonia, Finland, France, Hungary, Italy, Lithuania, Luxemburg, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, and Sweden. Table B.2 provides further details on the composition of the sample.

approximately 2.8%. This association is primarily driven by the upper half of the wage distribution. Specifically, a 0.1 increase in exposure corresponds to a rise in wage dispersion of around 1.7% for the p90/p50 gap and 1.1% for the p50/p10 gap.

Unlike AI, occupations that are more exposed to robots have a lower wage inequality. For the p90/p10 wage gap, a 0.1 increase in the robot score is related to a 3.7% decrease in within-occupation inequality. This effect is pervasive across the two portions of the wage distribution as it is highly significant and negative. Nevertheless, it is slightly higher for the lower part of the wage distribution, where a 0.1 change in the robot score exposure is related to a 1.9% decrease in wage inequality, compared to a 1.8% for the upper half.

These findings indicate that occupations most exposed to AI (robots) are those where there is more (less) wage inequality. The contrasting signs observed in the coefficients for robots and AI are likely linked to the different types of tasks characterizing occupations associated with each technology. Specifically, AI exposure tends to be higher in occupations involving non-routine cognitive tasks, while robot exposure is more prevalent in those involving non-routine manual tasks.

Importantly, we interpret exposure to AI and robots not as direct causes of wage inequality, but rather as proxies for the underlying task structure within occupations. That is, these technologies tend to be deployed in occupational settings with distinct task characteristics, which themselves are associated with different degrees of heterogeneity in worker performance and compensation.

Following Jung and Mercenier (2014), this pattern can be explained by differences in the dispersion of (unobserved) worker abilities across occupations. Workers in non-routine cognitive jobs–often those more exposed to AI–typically possess higher skill levels and exhibit a broader distribution of capabilities. Since these tasks rely heavily on individual judgment and problem-solving (e.g., graphical design), performance outcomes are more variable, resulting in greater wage dispersion. In contrast, occupations more exposed to robots involve standardized manual tasks (e.g., moving objects), where worker autonomy and discretion are limited. In these contexts, individual ability has a smaller impact on task execution, leading to more uniform productivity and narrower wage distributions.[26]

[26] It is worth noting that an additional channel that can influence wage inequality is differences within and between firms (Akerman et al., 2013; Card et al., 2018; Card, 2022). For instance, Song et al. (2018) find that for the U.S. two-thirds of wage inequality is explained by wage dispersion between firms, whereas the rest is driven by wage variation within firms. In Europe, it is found that recent increase in inequality at the aggregate level is positively associated with growth in large firms (Mueller et al., 2017). Further, when also incorporating the technical change dimension, there are also large disparities observed between firms that innovate and those that do not innovate (Cirillo et al., 2017). Automation adoption can further spur wage differentials between firms that invest in these technologies and the ones that do not by expanding the demand for workers with specific skills that have higher wages (Bessen et al., 2022).

Table 5.1: Dependent variable: Log of real hourly wage gap.

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
Robot exposure Webb	-0.363***	-0.178***	-0.185***
	(0.023)	(0.012)	(0.015)
AI exposure Webb	0.273***	0.166***	0.107***
	(0.053)	(0.036)	(0.028)
Constant	1.075***	0.635***	0.439***
	(0.069)	(0.042)	(0.038)
Observations	2883	2883	2883
R^2	0.548	0.485	0.453
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.1 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For years before 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

As discussed in Section 2, the literature has largely used indicators that look at the routine content or automation index of occupations. Rooted in the seminal work by Autor et al. (2003), the particularity of these indicators is that they mainly account for the role of computerization–i.e., ICT. The present analysis extends this, going beyond these traditional indicators. Sections 2 and 4 have put forward that when looking at these emerging automation technologies, AI and robots do not perform the same activities and do not target the same types of workers. While AI exposure positively correlates with non-routine cognitive tasks, robot exposure is associated with non-routine manual and routine tasks. This divergence suggests differing relationships with wage inequality within occupations, which have been confirmed in Table 5.1. This relationship is mediated by the tasks performed which involve a different degree of unobserved heterogeneity in workers' productivity. Therefore, Table 5.2 compares the results of our main specification for the overall wage gap (column 1) with the traditional indicators used in the literature (columns 2 and 3).[27] Consequently, the approach followed in this paper allows us to distinguish different patterns between technologies. While the significant and negative coefficient of robots is in line with the automation and routine intensity indexes[28], AI has a different dynamic.

In addition to the correlations between the intensity of non-routine occupations and emerging technologies, Figure 2.2 indicates that, on average, exposure to AI and robotics is greater in high-paying occupations compared to low-paying ones. Given this strong association, we can anticipate a similar relationship with the outcome variables if we use the proportions of high-skilled and low-skilled workers instead of technology indicators. Column 4 of Table 5.2 supports these expectations.

It derives from the analysis that differences in occupational characteristics are crucial, as they mediate the relationship between technology and wage inequality. The key point that is stressed from this approach is that because these technologies are designed to perform certain activities–which are tied to particular tasks and, by extension, occupations–we observe this association with within-occupation wage inequality. It can be argued that this perspective somewhat diminishes the significance of technology itself. Acknowledging that this cannot be fully addressed without counting with information on technology adoption–which is not available for AI at the moment–, we mitigate these factors by controlling for occupational characteristics as described earlier in this Section. Overall, even after accounting for these factors, the smaller yet significant coefficients shown in column 1 of Table 5.2 (when compared to column 4) indicate that the technological component can still play a role.

[27] We use the routine intensity index which is elaborated with the same methodology as in Figures 2.1a to 2.1d in Section 2. The automation index is from Kaltenberg and Foster-McGregor (2020) who map the Frey and Osborne (2017) indicator to ISCO-08.

[28] This is probably explained by the larger correlation between robot exposure and routine tasks as indicated in Figure A.5b.

Table 5.2: Dependent variable: Log of real hourly wage gap. Comparing with other technologies

	(1) Wage gap p90/p10	(2) Wage gap p90/p10	(3) Wage gap p90/p10	(4) Wage gap p90/p10
Robot exposure Webb	-0.178***			
	(0.011)			
AI exposure Webb	0.044***			
	(0.009)			
Routine index		-0.198***		
		(0.007)		
Automation index FO			-0.169***	
			(0.006)	
Share of high-skilled				1.018***
				(0.144)
Share of low-skilled				-1.748***
				(0.110)
Constant	0.973***	0.894***	0.998***	0.977***
	(0.062)	(0.059)	(0.058)	(0.056)
Observations	2883	2883	2883	2883
R^2	0.548	0.523	0.517	0.588
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes	Yes
Sex	Yes	Yes	Yes	Yes
Union	Yes	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes	No

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.2 displays the results of regressing the log of the real hourly wage gap on the AI exposure score at the occupation-country-year level (column 1) and on the routine content of occupations (column 2). The AI and robot scores are at ISCO-08 2-digit level. It is built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For the years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. The task content measures are derived from O*NET database data, categorized at the SOC level. Following Hardy et al. (2018), we select task-related items that capture routine and non-routine activities, distinguishing between cognitive and manual dimensions. Task intensity scores for each SOC occupation are then calculated by averaging the importance scores within each of the four categories. Finally, occupations are mapped to ISCO-08 classifications. The automation risk is the index elaborated by Frey and Osborne (2017) and mapped into ISCO-08 by Kaltenberg and Foster-McGregor (2020). The shares in column 4 represent the proportion of low- and high-educated workers in total employment for each occupation-country-year cell at the ISCO-08 2-digit level. Low-educated workers are defined as those with lower secondary education or below, while high-educated workers are those with tertiary or upper secondary education. All the coefficients are standardized by occupation at ISCO-08 2-digit level. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment (the latter is not included in column 4). All regressions include country and year fixed effects. Column 1 also includes the standard deviation of robot and AI at 4-digit level within ISCO-08 2-digit occupations; the standard deviation of the routine content at 4-digit level within ISCO-08 2-digit occupations. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Robustness checks Our main specification is subject to several challenges that we aim to address further in the robustness checks. First, we reproduce the analysis with a balanced sample. Table C.1 shows that results hold under this sample. The only distinction is that the overall effect of inequality is evenly spread between the different parts of the wage distribution.

Second, as emphasized in Sections 2 and 4, a significant limitation of our study is that we analyze occupations at an aggregate level. This approach leads to considerable heterogeneity, as occupations within major groups at the 2-digit level show varying levels of exposure. This variability is illustrated in Tables C.5 to C.7, which display the Spearman correlation between different indices of AI and robot exposure at the 4-, 3-, and 2-digit levels of the ISCO classification. Notably, the correlation strengthens as we move to higher levels of aggregation.

To address this issue, we replicate the regressions by focusing on countries with consistent information at the ISCO 3-digit level across all SES waves. In this replication, we reproduce Table 5.1, changing only the level of aggregation of occupations while keeping the same control variables. Due to lower data availability in the SES at this more detailed occupational level, the sample of countries is smaller, as discussed in Section 3.[29]

Table 5.3 indicates that results also hold under this specification. This is, we observe a significant and negative coefficient for robot exposure, whereas a positive one is observed for the case of AI. Furthermore, results also reflect that while the coefficient of the p90/p10 wage gap is mostly driven by the bottom half of the wage distribution, the opposite occurs in the case of AI.

Third, we also assess whether our baseline estimation holds after controlling for alternative variables to account for the composition of the labor force, concentration of occupations in certain industries and labor market institutions. The results of these alternative specifications are shown in Appendix C.

Table C.2 presents the regression results with the Blau index as a control variable, replacing the share of female employment in each occupation-country-year cell. While the significance of the variables remains unchanged, Table C.2 reveals that the coefficient for AI nearly doubles. Table C.3 demonstrates that the results remain very close to our main specification when controlling for the HHI-index of the occupation instead of the employment share in manufacturing.

Although our main regression accounts for country-fixed effects to address the diverse institutional regimes across Europe, we have chosen a more conservative approach by including additional variables for control. This decision stems from the significant heterogeneity in labor institutions throughout Europe. The literature on varieties of capitalism highlights that some countries have centrally coordinated labor regimes, where labor relations are facilitated through collective bargaining and joint cooperation in corporate activities. Germany and France serve as prominent examples of this model, which tends to provide greater legal protection for workers. In contrast, more flexible or liberal schemes, like that of the United Kingdom, are characterized by decentralization and a lack of collective coordination, leading to a market-oriented strategy and a generally lower legal framework for employee protection

[29]The included countries are Bulgaria, Cyprus, Czech Republic, Estonia, Lithuania, Luxembourg, Poland, and Slovakia.

Table 5.3: Dependent variable: Log of real hourly wage gap. Occupations at 3-digits.

	(1) p90/p10	(2) p90/p50	(3) p50/p10
Robot exposure Webb	-0.243***	-0.105***	-0.138***
	(0.013)	(0.008)	(0.008)
AI exposure Webb	0.349***	0.200***	0.149***
	(0.040)	(0.029)	(0.022)
Constant	1.069***	0.607***	0.463***
	(0.045)	(0.030)	(0.025)
Observations	2977	2977	2977
R^2	0.450	0.354	0.395
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Union	Yes	Yes	Yes
Sex	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.3 displays the results of regressing the log of the real hourly wage gap on the AI exposure score at the occupation-country-year level. The AI and robot scores are at ISCO-08 3-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For the years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 3-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 3-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 3-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

(Hall and Soskice, 2001).

Accordingly, Table C.4 replicates the main specification shown in Table 5.1, but incorporates the employment protection legislation index from the OECD. Our analysis reveals that the results remain significant and consistent, although the coefficient for AI is slightly smaller in this specification.[30]

Lastly, we also conduct a set of robustness checks with alternative measures of AI and robot exposure. Concerning AI, we explore the measures elaborated by Felten et al. (2019), Georgieff and Hyee (2021), Engberg et al. (2024) and Prytkova et al. (2024), for robots the ones constructed by Montobbio et al. (2024) and Prytkova et al. (2024).[31]

Table C.8 exhibits the results using the AI measure by Felten et al. (2019). Despite the correlation between the Webb AI score and the Felten et al. (2019) measure being so low (see Table C.7), the results still hold, as the AI coefficient is positive and strongly significant. However, the size of the coefficient increases dramatically in comparison to our main specification from Table 5.1.[32] Table C.9 shows the results using the AI exposure measure from Georgieff and Hyee (2021), who introduces country variation into the AI measure elaborated by Felten et al. (2019). We also observe that results hold under this specification. The main difference in these regressions is that the coefficient of AI exposure is larger for the bottom half of the wage distribution, while the opposite is observed in our main results.

Table C.10 presents the results using the AI and robot exposures elaborated by Prytkova et al. (2024).[33] This measure incorporates time variation in the exposure to these technologies.[34] We find that the results do not hold for AI, and even show an opposite coefficient.[35] Regarding robots, Table C.10 indicates a negative coefficient, but it is only significant for the p90/p50 ratio.

In Table C.11, the AI index elaborated by Engberg et al. (2024). The authors elaborate a time-variant measure at the occupational level, distinguishing by different AI applications. We use the exposure to generative AI as this reflects the most recent developments in this technology. It can be inferred from Table C.11 that exposure to generative AI is significant and only driven by the upper half of the wage distribution.[36]

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[30] It is important to note that the sample size is reduced in this case, as there are certain countries—namely Bulgaria, Cyprus, Estonia, Lithuania, Luxembourg, and Romania—for which data on employment protection legislation is unavailable.

[31] Tables C.5 to C.7 shows the Spearman correlation between the different measures at 4-, 3-, and 2- digits of aggregation.

[32] This is probably due to much lower variability in the Felten et al. (2019) measure in comparison to the Webb (2020). Refer to Table 3.3 for the descriptives.

[33] It is worth highlighting that the measure captures neural networks, which is a subset of AI. However, it serves as a good proxy for this technology.

[34] Nevertheless, it is worth noting that the indicators are available for the years between 2012 and 2020. Thus, we applied an imputation for years before 2012. For AI, we used the 2012 values for all preceding years, considering that the progress in AI is more recent, as discussed in Section 4. For robots, we assumed that the compound average annual growth rate for 2002-2010 is the same as the one for the period 2012-2020, and distributed the growth backward accordingly.

[35] A caveat is that exposure to AI is 0 for most occupations, as indicated in the summary statistics presented in Table 3.3.

[36] The generative AI exposure index is available since 2012. Thus, we followed the same approach as the one followed in the measure by Prytkova et al. (2024), imputing the 2012 score for the previous years.

Finally, in Table C.12 the results using the robot exposure developed by Montobbio et al. (2024) are presented. It can be derived from this that the robot coefficient is negative and significant in all cases. However, the coefficients are larger in absolute terms than our specification in Table 5.1. While a 0.1 increase in robot exposure is related to a 12.1% decrease in the log of the p90/p10 wage gap when employing the Montobbio et al. (2024) measure, it is 3.7% for the Webb (2020) robot exposure.[37]

In summary, we can conclude that the results remain consistent across most of the specifications employing alternative measures of AI and robots, all of which have been derived using different methodologies. Our findings indicate that occupations most exposed to AI (robots) are those where there is more (less) wage inequality.

6 Conclusion

In the last few years, there has been a growing interest in understanding the impact of robots and, more recently, AI on the labor market. The increasing adoption of robots in Europe has raised concerns about its potential effects on employment, wage levels, and employment transitions, although fewer studies have focused on its implications for inequality. Similarly, advancements in AI have spurred research into its potential effects on labor markets. However, due to its limited diffusion, there is less empirical evidence available regarding its consequences.

This paper contributes to the literature by examining the association between occupational exposure to robots and AI and wage inequality across 19 European countries. While robots are typically associated with tasks performed by low-skilled workers, AI is more commonly linked to high-skilled occupations. Our analysis reveals that occupations with greater exposure to robots tend to exhibit lower wage inequality, particularly at the bottom of the wage distribution. Conversely, occupations more exposed to AI display higher wage inequality, largely driven by greater dispersion in the upper half of the distribution.

These contrasting patterns are consistent with the differing task characteristics and skill demands associated with each technology. Importantly, we interpret exposure to AI and robots not as direct causal drivers of inequality, but as proxies for the underlying task structure of occupations. Robot-exposed occupations are generally dominated by manual, standardized tasks that allow little autonomy or variation in performance, leading to more homogeneous wages. In contrast, AI-exposed occupations involve complex, cognitive tasks where unobserved individual abilities play a larger role in determining output, resulting in greater heterogeneity in performance and, ultimately, wider wage dispersion.

This study builds on existing literature on technological change and inequality, particularly within the framework of task-based approaches. Most of this research has focused on routine task content linked to ICT, whereas our analysis specifically focuses on robots and AI, two technologies associated with distinct tasks and worker characteristics. Robots represent a more established technology, with relatively few studies addressing its effects on inequality, while AI's rapid development and potential for becoming the next GPT technology underscore the need for timely policy insights.

[37] This is probably due to a more compressed variability in the Montobbio et al. (2024) indicator, as it is depicted in the statistics from Table 3.3.

From our analysis, we can envision two scenarios. First, if AI's development leads to greater standardization of tasks across varying skill levels, it could, in fact, reduce wage inequality—-incipient empirical evidence suggests this as a possible direction (e.g., Engberg et al. (2024) and Georgieff (2024)). However, because AI can both substitute for and complement high-skilled workers, it also has the potential to worsen inequality by increasing the demand for specialized skills. According to the model proposed by Acemoglu and Restrepo (2022), technology not only automates existing tasks but also creates new ones that complement it. Therefore, it is plausible that AI will generate new tasks that are associated with high-skilled workers.

In response to the inequality risks posed by AI, policymakers may consider adaptive and timely measures. Training programs to equip workers with skills that align with AI-driven changes will be crucial for a resilient workforce. Additionally, redistributive policies will play a critical role in narrowing the wage gap between high- and low-paying occupations. These approaches will be key to ensuring that AI's economic benefits are broadly shared and that its adoption fosters inclusive growth across the workforce.

Our paper is subject to certain limitations. Perhaps the most significant limitation is that we cannot establish causality due to the characteristics of our data. Due to limitations in the available data, we primarily focus on occupations at the 2-digit level, even though a more detailed analysis would have been beneficial. While we attempted to provide estimates using the ISCO-08 3-digit level for some countries, this approach was feasible for only a limited number of them. Lastly, technology continually evolves, engaging in new activities over time. Consequently, exposure to technology may not remain constant, as assumed by the index employed in this paper. We partially addressed this issue by exploring a dynamic indicator developed by Prytkova et al. (2024) and Engberg et al. (2024). However, these indicators are only available from 2012 onward, while our dataset begins in 2002. Therefore, it is important to interpret this carefully.

Finally, this paper paves the way for further research. As more data on AI becomes available progressively, it would be relevant to study the implications of AI adoption on inequality. Given that this technology has the potential to both substitute and complement high-skilled workers, it would be interesting to investigate further whether its adoption influences overall employment composition or instead exacerbates wage inequality, particularly among workers more exposed to it.

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Appendices

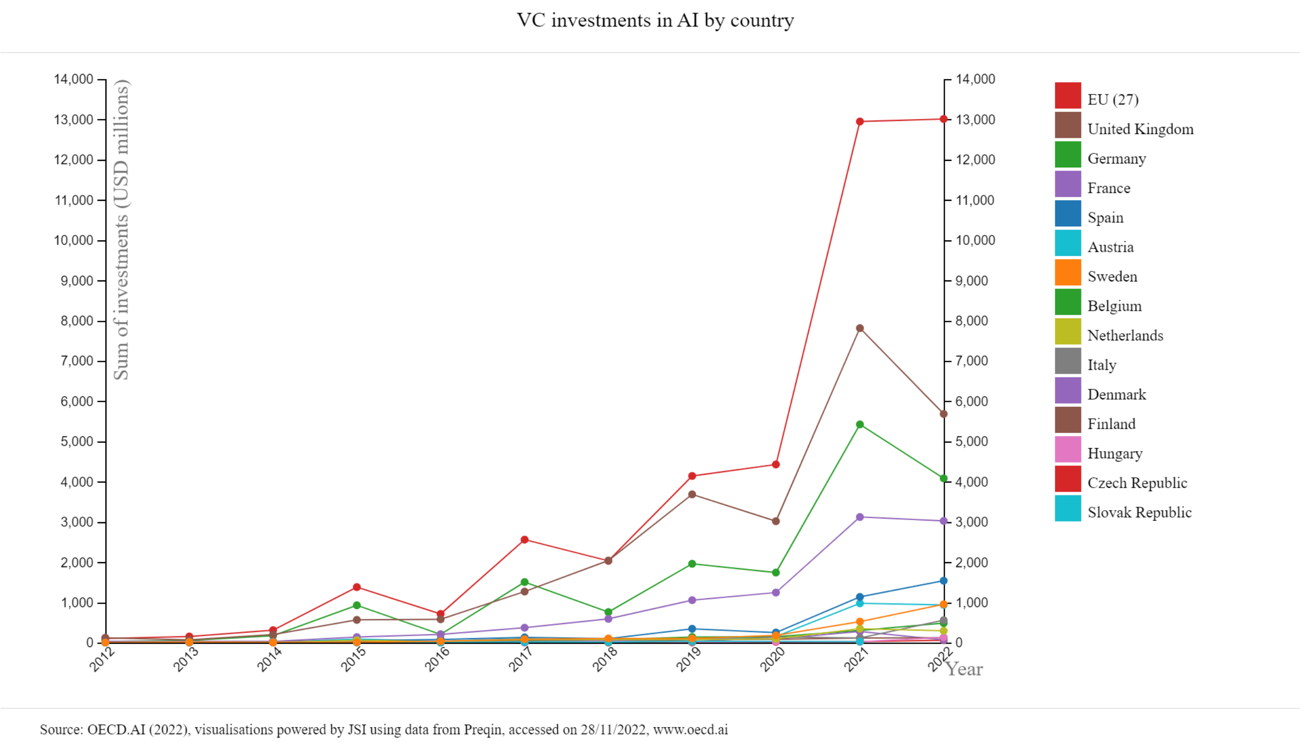
A Appendix A

A.1 Compatibilization between ISCO-08 and ISCO-88

Since there is a break in the ISCO classification from 2010 onwards, we apply a crosswalk between ISCO-88 and ISCO-08. This is done by implementing the function isco88_to_isco08_ndigit in the R package 'occupationcross' (Weksler and Lastra, 2022). Drawing upon the ISCO correspondence tables provided by ILO, this function takes the individual observation at ISCO-88 2-digit (or 3-digit) level and draws an assignment to an ISCO-08 code among all the possible crosses[38]. We have used this function to convert ISCO-88 into ISCO-08 for the 2002 and 2006 waves of the SES.

A.2 Descriptives of AI and robot penetration

Figure A.1: Sum of venture capital investments in AI by country.



Notes: Figure A.1 shows the evolution of the sum of investments in AI in the top fifteen European countries (in U.S. dollars). *Source:* OECD.AI (2022), visualisations powered by JSI using data from Preqin, accessed on 28/11/2022, www.oecd.ai

[38]For more details on the package refer to R package 'occupationcross'.

Table A.1: Annual growth rate of robot density. 1995-2017.

Austria	5.98
	(3.26)
Belgium	3.73
	(5.64)
Czech Republic	18.53
	(9.77)
Denmark	10.27
	(4.92)
Finland	4.43
	(6.13)
France	3.85
	(4.32)
Germany	5.71
	(3.94)
Hungary	18.09
	(21.67)
Italy	4.23
	(4.22)
Netherlands	8.76
	(5.03)
Slovakia	13.50
	(21.10)
Spain	7.48
	(7.07)
Sweden	4.20
	(2.97)
Total	8.37
	(10.86)

Notes: Own elaboration based on International Federation of Robotics (IFR) and EU-KLEMS. Robot density is the ratio between robot stock and employment in thousand.

A.3 Theil decomposition at two and three-digit levels

The Theil index is as follows:

$$T = \frac{1}{N} \sum_{i=1}^{N} \frac{y_i}{\bar{y}} \ln \left(\frac{y_i}{\bar{y}} \right)$$

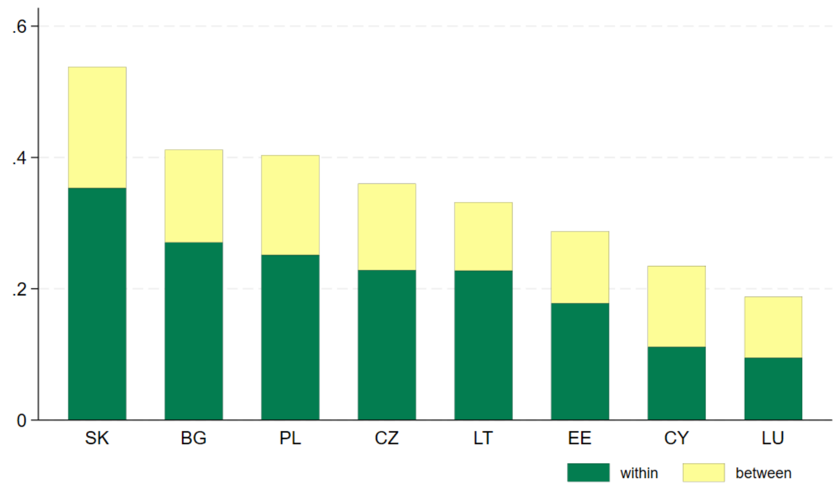
Where y_i is the wage of individual i, N is the total number of employees and $\bar{y}$ is the average wage of the total number of employees N.

It can be further decomposed into between and within-occupation inequality in the following way:

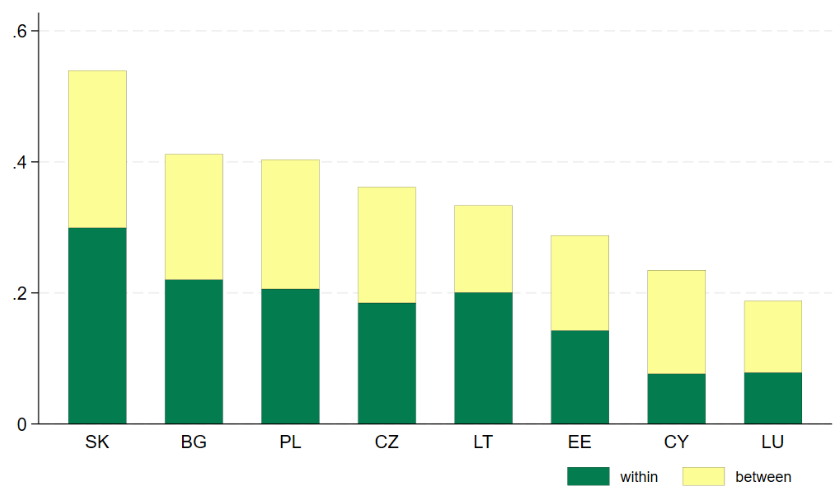
$$T = \underbrace{\sum_{o=1}^{O} \frac{N_o}{N} \frac{\bar{y}_o}{\bar{y}} * T_o}_{\text{Within-Occupation}} + \underbrace{\sum_{o=1}^{O} \frac{N_o}{N} \frac{\bar{y}_o}{\bar{y}} \ln \left(\frac{\bar{y}_o}{\bar{y}} \right)}_{\text{Between-Occupation}}$$

where N_o is the number of employees in occupation o, O is the total number of occupations, $\bar{y}_o$ is the mean wage of occupation o, and T_o is the Theil index for occupation o. In this way, the within-group component is the weighted average of the Theil index across occupations. On the other hand, the between-group component represents the inequality stemming from differences between occupations. This is calculated based on the disparities in average wage over occupations in relation to the average of the entire working population. In the context of this paper, y represents the real hourly wage.

Figure A.2: Theil decomposition: between and within occupation inequality



(a) ISCO08 2-digits



(b) ISCO08 3-digits

Notes: Figure A.2 shows the decomposition of the Theil index into within and between occupation inequality at ISCO-08 2- (panel a) and 3-digit (pabel b) level for the real hourly wage. It is the average across the five waves of the EU-SES (2002, 2006, 2010, 2014 and 2018). We only include the countries that are available at ISCO 3-digit across the five waves. For years prior to 2010, we mapped ISCO-88 to ISCO-08 to harmonize occupations across the different waves. The details of the harmonization can be consulted in appendix A. *Source:* Own elaboration based on EU-SES.

Table A.2: Descriptive of the p90/p10 wage gap by occupation.

ISCO-08 Code	Title	Mean	SD	Frequency
11	Chief Executives, Senior Officials and Legislators	1.42	0.39	83
12	Administrative and Commercial Managers	1.38	0.38	84
13	Production and Specialized Services Managers	1.31	0.37	79
14	Hospitality, Retail and Other Services Managers	1.41	0.36	79
21	Science and Engineering Professionals	1.11	0.27	84
22	Health Professionals	1.12	0.26	79
23	Teaching Professionals	0.79	0.28	66
24	Business and Administration Professionals	1.15	0.28	84
26	Legal, Social and Cultural Professionals	1.25	0.34	84
31	Science and Engineering Associate Professionals	1.09	0.29	84
32	Health Associate Professionals	0.94	0.31	79
33	Business and Administration Associate Professionals	1.09	0.27	84
34	Legal, Social, Cultural and Related Associate Professionals	1.15	0.46	83
35	Information and Communications Technicians	1.09	0.31	78
41	General and Keyboard Clerks	0.88	0.26	79
42	Customer Services Clerks	0.96	0.27	83
43	Numerical and Material Recording Clerks	0.92	0.25	79
44	Other Clerical Support Workers	0.86	0.26	81
51	Personal Service Workers	0.82	0.20	84
52	Sales Workers	0.81	0.22	79
53	Personal Care Workers	0.70	0.22	73
54	Protective Services Workers	0.83	0.24	79
61	Market-oriented Skilled Agricultural Workers	1.04	0.47	68
62	Market-Oriented Skilled Forestry, Fishery and Hunting Workers	1.08	0.45	59
71	Building and Related Trades Workers (excluding Electricians)	0.89	0.28	79
72	Metal, Machinery and Related Trades Workers	0.91	0.26	74
73	Handicraft and Printing Workers	0.91	0.20	79
74	Electrical and Electronics Trades Workers	0.93	0.26	79
75	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	0.88	0.25	84
81	Stationary Plant and Machine Operators	0.95	0.22	79
82	Assemblers	0.81	0.20	69
83	Drivers and Mobile Plant Operators	0.87	0.26	76
91	Cleaners and Helpers	0.61	0.19	79
92	Agricultural, Forestry and Fishery Labourers	0.72	0.26	69
93	Labourers in Mining, Construction, Manufacturing and Transport	0.83	0.20	74
94	Food Preparation Assistants	0.69	0.25	70
96	Refuse Workers and Other Elementary Workers	0.79	0.22	78
Total		0.98	0.35	2,883

Notes: This table shows the descriptive statistics of the p90/p10 real hourly wage gap by occupations at 2-digit level.

Table A.3: Analysis of the variance of the p90/p10 wage gap by occupation.

Source	SS	df	MS	F	Probability
Between groups	117.2643	36	3.2573	38.66	0.0000
Within groups	239.7807	2,846	0.0843		
Total	357.0449	2,882	0.1239		

Bartlett's equal-variances test	
χ^2	327.689
p-value	0.000

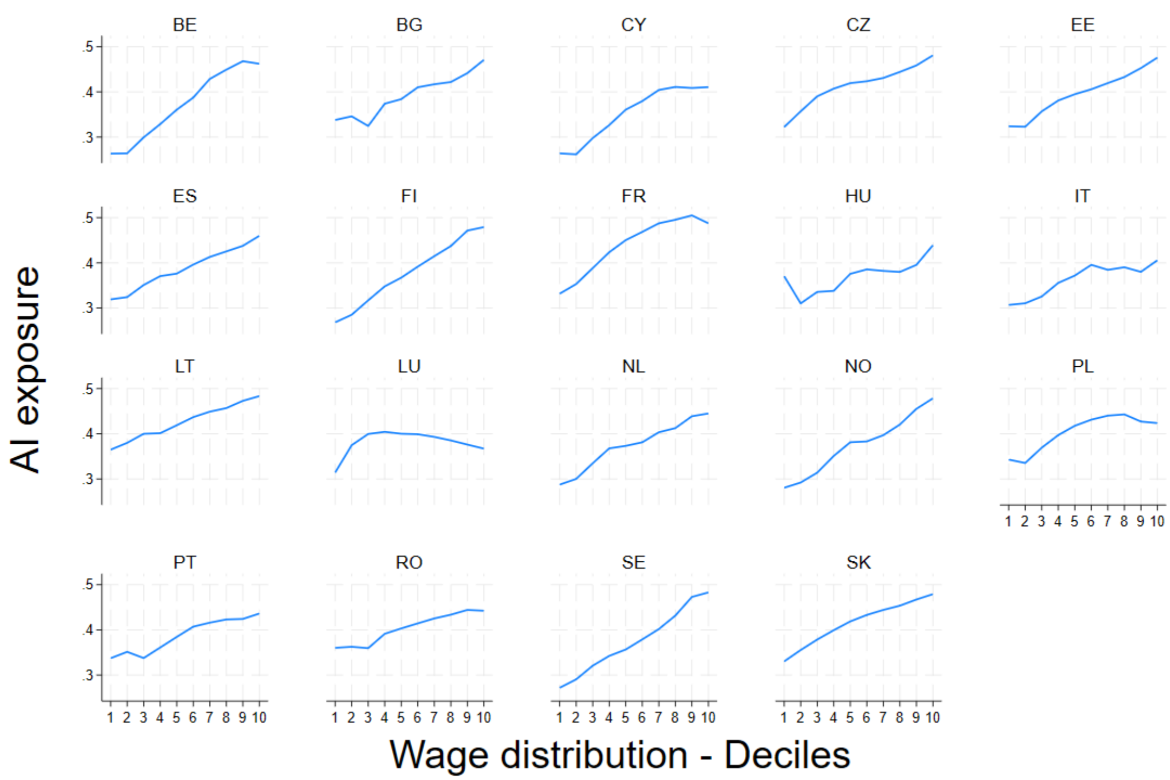
Notes: This table shows the analysis of the variance of the p90/p10 real hourly wage gap by occupations at 2-digit level.

A.4 Exposure level by wage distribution and country

Figure A.3: Robot exposure level by decile of the wage distribution in each country

Notes: Figure A.3 shows the exposure of robots by deciles of the wage distribution by country. To compute them, we split the real hourly wage into deciles. The robot score is at ISCO-08 2-digit level. It is built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For the years prior to 2010, we mapped ISCO-88 into ISCO-08. The details of the harmonization can be consulted in appendix A. Own elaboration based on EU-SES.

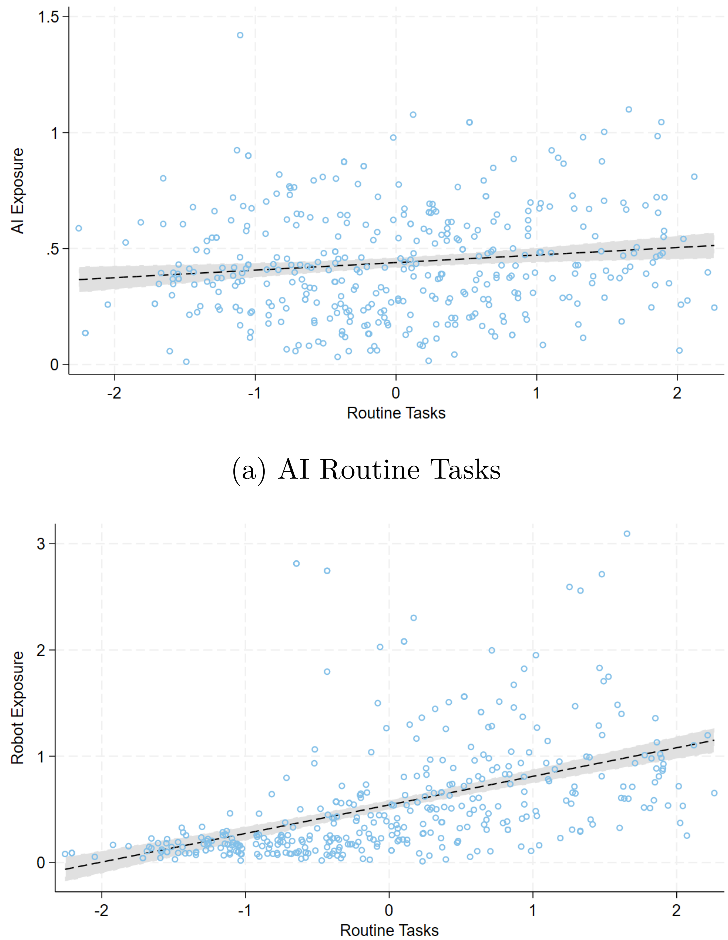
Figure A.4: AI exposure level by decile of the wage distribution in each country



Notes: Figure A.4 shows the exposure of AI by deciles of the wage distribution by country. To compute them, we split the real hourly wage into deciles. The AI score is at ISCO-08 2-digit level. It is built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For the years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Own elaboration based on EU-SES.

A.5 Wage variability by occupation

Figure A.5: Correlation between robot and AI exposure and routine content of occupations

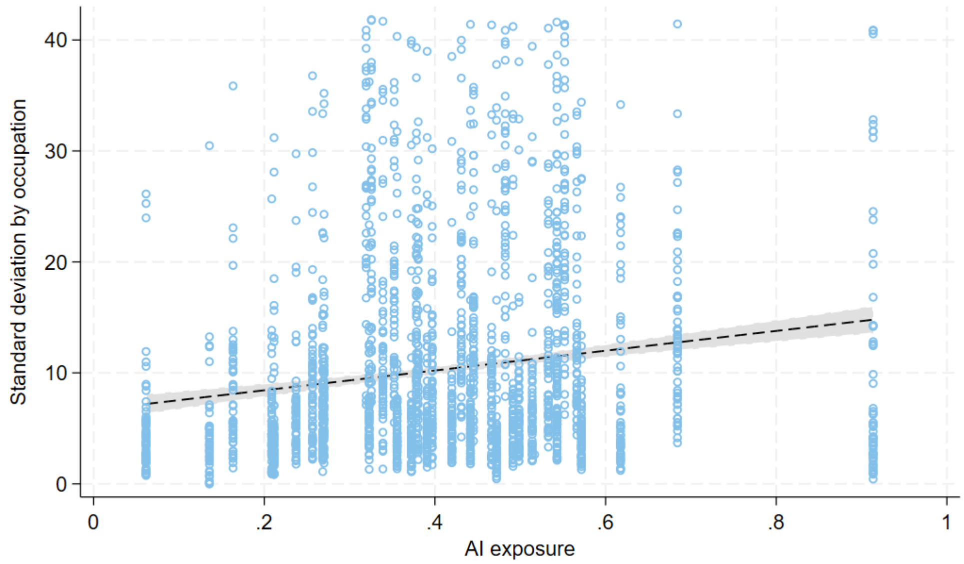


(a) AI Routine Tasks

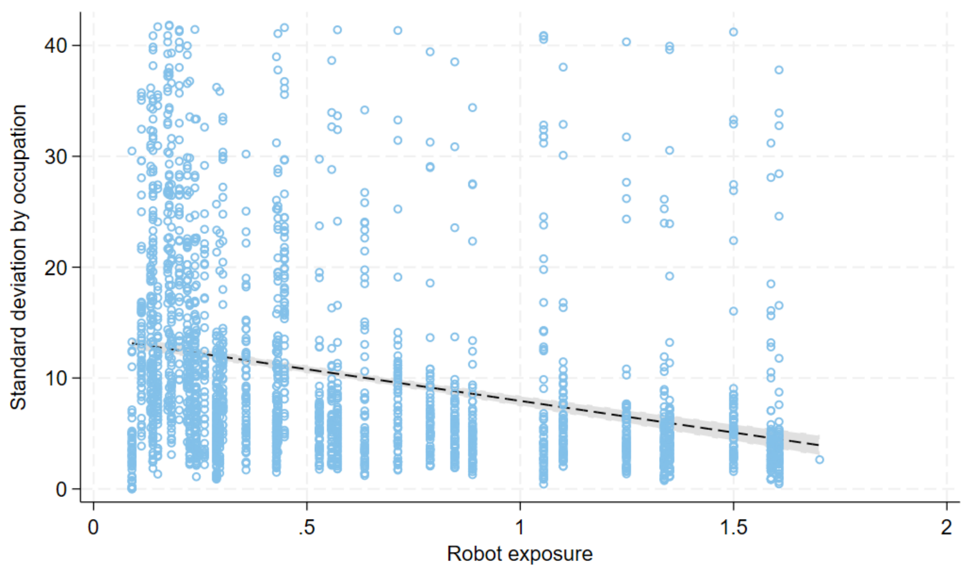
(b) Robot Routine Tasks

Notes: Notes: The AI and robot exposure are built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. The task content measures are derived from O*NET database data, categorized at the SOC level. Following Hardy et al. (2018), we select task-related items that capture routine and non-routine activities, distinguishing between cognitive and manual dimensions. Task intensity scores for each SOC occupation are then calculated by averaging the importance scores within each of the four categories. Finally, occupations are mapped to ISCO-08 classifications.

Figure A.6: Correlation between standard deviation of the real hourly wage by occupation and exposure to AI and robots



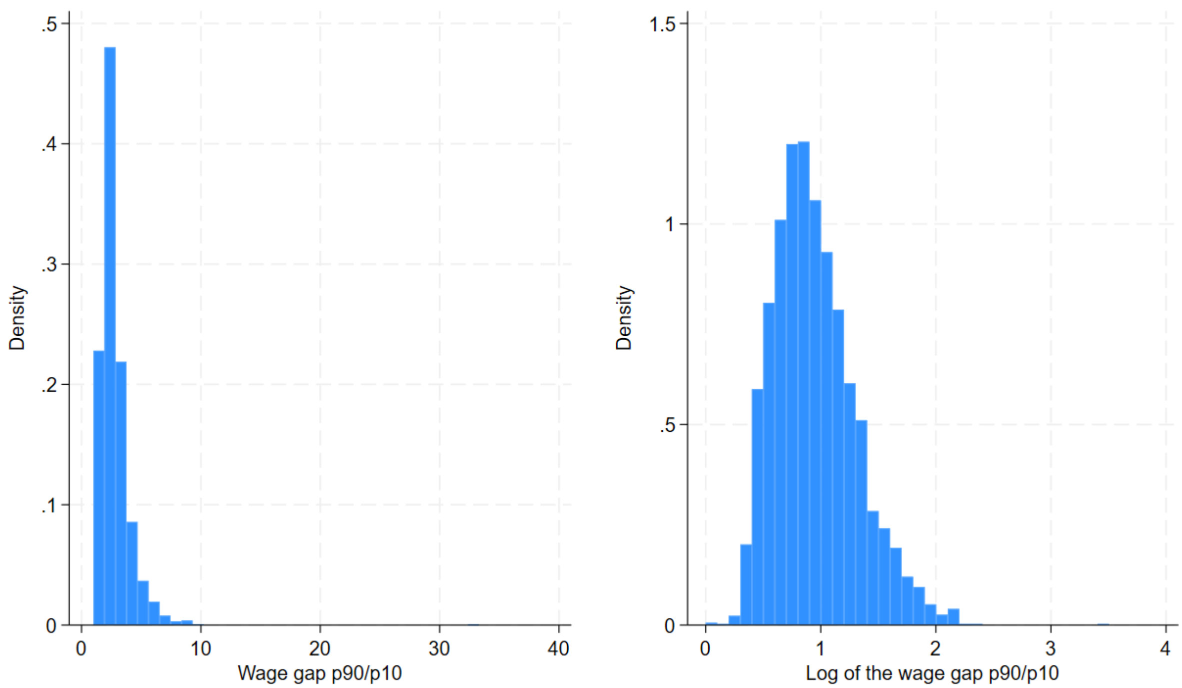
(a) AI



(b) Robot

Notes: Figure A.6 shows the correlation between the standard deviation of the real hourly wage gap and the AI score (panel A.6a) and the robot score (panel A.6b) by occupation. The robot and AI scores are at ISCO-08 2-digit level. They are built using the indexes provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. We mapped ISCO-88 to ISCO-08 to harmonize occupations across the different waves. The details of the harmonization can be consulted in appendix A. For comparability reasons, we restrict the sample to euro countries. These are Belgium, Cyprus, Estonia, Finland, France, Italy, Lithuania, Luxemburg, Netherlands, Poland, Portugal, Slovakia, and Spain. *Source:* Own elaboration based on EU-SES.

Figure A.7: Distribution of the p90/p10 wage gap before and after log transformation



Notes: Figure A.7 shows the distribution of the real hourly wage gap between the p90/p10 at the occupation-country-year cell before and after it is log transformed. Own elaboration based on EU-SES.

B Appendix B

B.1 Construction of control variables for within occupation inequality

Share of female by occupation We compute the share of female employment on total employment for each occupation-country-year cell at ISCO-08 2-digits.

Blau index We estimate the Blau index for each occupation-country-year cell by applying the following equation

$$Blau\_index_{oct} = 1 - \sum_{f} \left(\frac{L_{ofct}}{L_{oct}} \right)^2 \tag{2}$$

Where L_{ofct} is the level of employment in occupation o for category f (i.e. male and female) in country c at time t and L_{oct} is the total employment in occupation o, country c at year t. The index varies between 0 and 1, where values close to 0 (1) indicate lower (higher) diversity.

Share of unionization To account for collective agreement coverage, we created a dummy variable taking value equal to 1 if the worker has any sort of agreement and 0 if she has no agreement at all, as Table B.1 depicts. While this classification is somewhat nuanced, given that the type of collective agreement can significantly impact workers' bargaining power, it is important to note that not all countries provide data for every category, posing challenges for comparison. For consistency, we opted for this approach. Subsequently, we calculated the proportion of workers covered by any form of collective agreement within each occupation-country-year cell.

Table B.1: Classification to account for collective agreement

	Dissemination in SES	Union dummy
A	National level or interconfederal agreement	1
B	Industry agreement	1
C	Agreement for individual industries in individual regions	1
D	Enterprise or single employer agreement	1
E	Agreement applying only to workers in the local unit	1
F	Any other type of agreement	1
N	No collective agreement exists	0

Notes: Own elaboration based on EU-SES classification.

Share of employment in manufacturing We calculate the share of persons employed in manufacturing on total employment for each occupation-country-year cell at ISCO-08 2-digits.

Herfindahl-Hirschman Index for Occupations (at industry level) is calculated by aggregating the square root of the share of employment in the different industries in each occupation. The indicator is as follows:

$$HHI_{oct} = \sum_{i=1}^{I} \left(\frac{L_{oict}}{L_{oct}} \right)^2 \tag{3}$$

Where L_{oict} is the level of employment in occupation o in industry i in country c at time t and L_{oct} is the overall employment in occupation o, country c at year t. In this sense, a higher value of the index indicates that employment is concentrated in fewer industries and lower levels imply that employment in that occupation is more evenly spread across industries.

Herfindahl-Hirschman Index for Occupations (for high-skill employment) is calculated by aggregating the squares of the shares of high-skilled workers—defined as those with tertiary or higher education—in each occupation. The indicator is expressed as follows:

$$HHI_{oct} = \sum \left(\frac{L_{ohct}}{L_{oct}} \right)^2 \tag{4}$$

Where L_{ohct} is the level of high-skilled employment in occupation o in in country c at time t and L_{oct} is the overall employment in occupation o, country c at year t. A higher value of the index for a specific occupation indicates a greater concentration of high-skilled employees within that occupation.

Number of occupations within major subgroups We aggregate the number of 4-digits occupations within each ISCO08 2-digit occupations.

Standard deviation of technology exposure We calculate the standard deviation by major 2-digit ISCO08 groups of the AI and robot exposure scores, along with the routine intensity indexes—both manual and cognitive—defined for each occupation at the 4-digit level.

Task intensity measures We retrieved task data from the O*NET database, which is at the SOC level. In particular, we resort to the Abilities, Skills, Work Activities, and Work Context data files from O*NET. Following Hardy et al. (2018), we select task-related items that capture routine and non-routine activities, distinguishing between cognitive and manual dimensions. Task intensity scores for each SOC occupation is then calculated by averaging the importance scores within each of the four categories. Finally, occupations are mapped to ISCO-08 classifications.

B.2 Descriptive statistics

C Appendix C. Robustness checks

C.1 Regressions with alternative control variables

Table B.2: Composition of the sample (unbalanced)

Country	2002	2006	2010	2014	2018	Total
BE	24	24	20	21	17	106
BG	37	37	37	37	37	185
CY	31	33	30	33	33	160
CZ	37	37	37	37	37	185
EE	37	37	34	35	34	177
ES	37	37	37	35	37	183
FI	37	37	35	35	34	178
FR	37	37	36	36	36	182
HU	25	25	24	25	23	122
IT	36	0	0	36	36	108
LT	36	36	33	34	32	171
LU	34	34	0	32	0	100
NL	37	37	37	37	37	185
NO	0	37	37	37	0	111
PL	0	37	37	37	36	147
PT	36	37	37	37	37	184
RO	37	37	36	35	37	182
SE	0	0	0	0	37	37
SK	36	36	36	36	36	180
Total	554	595	543	615	576	2,883

Notes: This Table shows the composition of the sample used in the analysis. Our unit of analysis are country-occupation-year, therefore each cell of the table refers to the number of occupations included.

Table B.3: Composition of the sample (balanced)

Country	2002	2006	2010	2014	2018	Total
BG	37	37	37	37	37	185
CY	29	29	29	29	29	145
EE	33	33	33	33	33	165
ES	35	35	35	35	35	175
FI	32	32	32	32	32	160
FR	36	36	36	36	36	180
HU	22	22	22	22	22	110
NL	37	37	37	37	37	185
PT	36	36	36	36	36	180
RO	35	35	35	35	35	175
SK	36	36	36	36	36	180
Total	368	368	368	368	368	1,840

Notes: This Table shows the composition of the sample used in the analysis. Our unit of analysis are country-occupation-year, therefore each cell of the table refers to the number of occupations included.

Table C.1: Dependent variable: Log of real hourly wage gap. Balanced panel.

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
Robot exposure Webb	-0.341***	-0.170***	-0.171***
	(0.031)	(0.016)	(0.020)
AI exposure Webb	0.305***	0.178***	0.128***
	(0.076)	(0.053)	(0.037)
Constant	1.018***	0.590***	0.428***
	(0.082)	(0.050)	(0.047)
Observations	1840	1840	1840
R^2	0.516	0.500	0.410
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.1 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.2: Dependent variable: Log of real hourly wage gap. Alternative control for gender

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
Robot exposure Webb	-0.293***	-0.137***	-0.155***
	(0.024)	(0.013)	(0.016)
AI exposure Webb	0.563***	0.284***	0.279***
	(0.045)	(0.030)	(0.025)
Constant	0.907***	0.612***	0.295***
	(0.063)	(0.038)	(0.035)
Observations	2883	2883	2883
R^2	0.533	0.490	0.424
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Blau Index (gender)	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.1 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the Blau index, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.3: Dependent variable: Log of real hourly wage gap.

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
Robot exposure Webb	-0.332***	-0.163***	-0.168***
	(0.023)	(0.013)	(0.015)
AI exposure Webb	0.273***	0.166***	0.108***
	(0.053)	(0.037)	(0.028)
Constant	1.013***	0.606***	0.407***
	(0.066)	(0.042)	(0.037)
Observations	2883	2883	2883
R^2	0.569	0.500	0.472
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
HHI index	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.1 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the HHI index of industry concentration, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.4: Dependent variable: Log of real hourly wage gap. Controlling for labor institutions

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
Robot exposure Webb	-0.343***	-0.179***	-0.164***
	(0.025)	(0.014)	(0.016)
AI exposure Webb	0.190***	0.129***	0.061**
	(0.057)	(0.036)	(0.031)
Constant	0.956***	0.595***	0.361***
	(0.114)	(0.069)	(0.068)
Observations	2109	2109	2109
R^2	0.494	0.431	0.410
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table 5.1 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. They are built using the index provided by Webb (2020) at the SOC-2010 and converted into ISCO-08. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. It also includes the log of employment protection legislation index from the OECD (individual and collective dismissals). For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

C.2 Robustness checks with alternative AI and robot exposure measures

Table C.5: Spearman correlations between AI and robot measures at ISCO-08 4-digit level

	AI Webb	Rob Webb	AI Felten et al	AI Prytkova et al	Engberg et al	Rob Prytkova et al	Rob Montobbio et al
AI Webb	1.00						
Rob Webb	0.27***	1.00					
AI Felten et al	0.09	-0.68***	1.00				
AI Prytkova et al	0.11*	0.07	0.10	1.00			
Engberg et al	0.02	-0.72***	0.93***	0.10*	1.00		
Rob Prytkova et al	0.28***	0.34***	-0.08	0.41***	-0.18***	1.00	
Rob Montobbio et al	0.30***	0.51***	-0.35***	0.19***	-0.34***	0.48***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the Spearman correlation between the different alternatives of the AI and robot scores at ISCO-08 4-digit level.

Correlations

Table C.6: Spearman correlations between AI and robot measures at ISCO-08 3-digit level

	AI Webb	Rob Webb	AI Felten et al	AI Prytkova et al	Engberg et al	Rob Prytkova et al	Rob Montobbio et al
AI Webb	1.00						
Rob Webb	0.29**	1.00					
AI Felten et al	-0.04	-0.80***	1.00				
AI Prytkova et al	0.21*	0.06	0.11	1.00			
Engberg et al	-0.12	-0.84***	0.94***	0.14	1.00		
Rob Prytkova et al	0.43***	0.40***	-0.17	0.49***	-0.26**	1.00	
Rob Montobbio et al	0.40***	0.56***	-0.39***	0.33***	-0.41***	0.65***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the Spearman correlation between the different alternatives of the AI and robot scores at ISCO-08 3-digit level.

Table C.7: Spearman correlations between AI and robot measures at ISCO-08 2-digit level

	AI Webb	Rob Webb	AI Felten et al	AI OECD	AI Prytkova et al	Engberg et al	Rob Prytkova et al	Rob Montobbio et al
AI Webb	1.00							
Rob Webb	0.28	1.00						
AI Felten et al	-0.00	-0.85***	1.00					
AI OECD	0.07	-0.87***	0.94***	1.00				
AI Prytkova et al	0.22	-0.14	0.27	0.31	1.00			
Engberg et al	-0.08	-0.87***	0.96***	0.93***	0.35*	1.00		
Rob Prytkova et al	0.60***	0.37*	-0.11	-0.11	0.35*	-0.17	1.00	
Rob Montobbio et al	0.53***	0.62***	-0.46**	-0.50**	0.19	-0.44**	0.68***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the Spearman correlation between the different alternatives of the AI and robot scores at the ISCO-08 2-digit level.

Table C.8: Dependent variable: Log of real hourly wage gap. AI from Felten et al. (2019)

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
AI exposure Felten et al	3.486***	1.363***	2.123***
	(0.316)	(0.203)	(0.187)
Robot exposure Webb	-0.175***	-0.103***	-0.072***
	(0.028)	(0.016)	(0.018)
Constant	-1.254***	-0.244	-1.010***
	(0.237)	(0.154)	(0.138)
Observations	2883	2883	2883
R^2	0.562	0.487	0.475
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table C.8 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. The AI score is taken from Felten et al. (2019), who produced it at SOC-2009. We map SOC-2009 into SOC-2010, and then converted SOC-2010 into ISCO-08. The robot exposure is from Webb (2020) at the occupational level at SOC-2010 and converted into ISCO-08. We used the crosswalks provided by IBS. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.9: Dependent variable: Log of real hourly wage gap. AI from Georgieff and Hyee (2021)

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
AI exposure OECD	0.463***	0.172***	0.291***
	(0.057)	(0.036)	(0.035)
Robot exposure Webb	-0.161***	-0.109***	-0.053***
	(0.030)	(0.018)	(0.020)
Constant	1.054***	0.723***	0.331***
	(0.071)	(0.047)	(0.042)
Observations	2067	2067	2067
R^2	0.550	0.462	0.481
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table C.9 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. The AI score is taken from Georgieff and Hyee (2021), who modify the AI index from Felten et al. (2019) to account for country variation using the PIAAC. The robot exposure is from Webb (2020) at the occupational level at SOC-2010 and converted into ISCO-08. We used the crosswalks provided by IBS. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.10: Dependent variable: Log of real hourly wage gap. Robot score from Prytkova et al. (2024)

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
AI exposure Prytkova et al	-1.082***	-0.870***	-0.212
	(0.262)	(0.153)	(0.163)
Robot exposure Prytkova et al	-0.006	-0.002	-0.004
	(0.004)	(0.002)	(0.003)
Constant	1.195***	0.712***	0.483***
	(0.064)	(0.041)	(0.035)
Observations	2883	2883	2883
R^2	0.502	0.451	0.415
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table C.10 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. The AI and robot exposure are from Prytkova et al. (2024), who compute the index at the occupational level using patent data at ISCO-08 at 4-digits levels. We aggregated them into 2-digits by taking the mean within occupations by the 2-digits groups. The index has been available since 2012; for details on imputation for previous years, refer to the robustness checks in section 5. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.11: Dependent variable: Log of real hourly wage gap. Robot score from Engberg et al. (2024)

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
AI exposure Engberg et al	0.182***	0.119***	0.062
	(0.059)	(0.031)	(0.038)
Robot exposure Webb	-0.346***	-0.167***	-0.179***
	(0.023)	(0.012)	(0.015)
Constant	1.216***	0.721***	0.495***
	(0.063)	(0.040)	(0.034)
Observations	2883	2883	2883
R^2	0.542	0.479	0.450
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table C.10 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. The AI exposure is from Engberg et al. (2024), who compute a time-variant index based on Felten et al. (2019) and Felten et al. (2021) at ISCO-08 4 digit level. We aggregated them into 2-digits by taking the mean within occupations by the 2-digits groups. The index has been available since 2010; therefore the sample is restricted from those years onwards. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

Table C.12: Dependent variable: Log of real hourly wage gap. Robot score from Montobbio et al. (2024)

	(1) Wage gap p90/p10	(2) Wage gap p90/p50	(3) Wage gap p50/p10
AI exposure Webb	0.487***	0.283***	0.204***
	(0.054)	(0.037)	(0.030)
Robot exposure Montobbio et al	-1.214***	-0.658***	-0.556***
	(0.075)	(0.042)	(0.046)
Constant	1.063***	0.637***	0.426***
	(0.068)	(0.041)	(0.038)
Observations	2883	2883	2883
R^2	0.558	0.502	0.453
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Manufacturing share	Yes	Yes	Yes
Sex	Yes	Yes	Yes
Union	Yes	Yes	Yes
Nro Ocupp	Yes	Yes	Yes
HHI High skill	Yes	Yes	Yes

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Robust standard errors between parentheses. Table C.9 displays the results of regressing the log of the real hourly wage gap on the AI and robot exposure score at the occupation-country-year level. The AI and robot occupational scores are at ISCO-08 2-digit level. The AI exposure is from Webb (2020) at the occupational level at SOC-2010 and converted into ISCO-08. The robot score is based on Montobbio et al. (2024), who compute the index at the occupational level using patent data at SOC-2019. We mapped SOC-2019 into SOC-2010, and then converted it into ISCO-08 using the crosswalks provided by IBS. For years prior to 2010, we mapped ISCO-88 to ISCO-08. The details of the harmonization can be consulted in appendix A. Control variables for each occupation-country-year cell include: the share of employment in manufacturing, the share of female employment, the share of unionized workers, and the HHI index of high-skill employment. Additional control variables at the occupational level include: the number of 4-digit occupations within each ISCO-08 2-digit occupation, the standard deviation of robot and AI exposure at the 4-digit level within ISCO-08 2-digit occupations, the standard deviation of routine task content at the 4-digit level within ISCO-08 2-digit occupations. Country and year fixed effects are also included. For further details on the construction of the control variables refer to appendix B.1. Own elaboration based on the five waves of the EU-SES.

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