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IZA DP No. 17607

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Konstantinos Pouliakas
Cedefop, University of Aberdeen and IZA

Giulia Santangelo
Cedefop

Paul Dupire
Cedefop and ENSAE Paris

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Are Artificial Intelligence (AI) Skills a Reward or a Gamble? Deconstructing the AI Wage Premium in Europe

Understanding the labour market impact of new, autonomous digital technologies, particularly generative or other forms of artificial intelligence (AI), is currently at the top of the research and policy agenda. Many initial studies, though not all, have shown that there is a wage premium to AI skills in labour markets. Such evidence tends to draw on data from web-based sources and typically deploys a keyword approach for identifying AI skills. This paper utilises representative adult workforce data from 29 European countries, the second European skills and jobs survey, to examine wage differentials of the AI developer workforce. The latter is uniquely identified as part of the workforce that writes programs using AI algorithms. The analysis shows that, on average, AI developers enjoy a significant wage premium relative to a comparably educated or skilled workforce, such as programmers who do not yet write code using AI at work. Wage decomposition analysis further illustrates that there is a large unexplained component of such wage differential. Part of AI programmers' larger wage variability can be attributed to a greater performance-based component in their wage schedules and higher job-skill requirements.

JEL Classification: J24, J31, J71, M52

Keywords: artificial intelligence, skills, wage differentials, performance-based pay

Corresponding author:
Konstantinos Pouliakas
European Centre for the Development of Vocational Training (Cedefop)
Europe 123
570 01 Thermi
Thessaloniki
Greece

E-mail: Konstantinos.pouliakas@cedefop.europa.eu

1. Introduction

Understanding the potential labour market impact of new, autonomous digital technologies, particularly generative or other forms of artificial intelligence (AI), is currently at the top of the research and policy debate. With extensive development and diffusion of AI technologies across many aspects of economy and society (Acemoglu et al., 2022a), some have emphasised the possible productivity dividends of AI investments. Others have been mostly concerned about the actual and potential job and income losses for workers. Recent literature has highlighted that a displacement effect, which arises when tasks previously performed by workers are replaced through automation, can possibly be counterbalanced by a reinstatement effect, whereby new tasks are created (Acemoglu and Restrepo, 2018). In addition, a remainder effect can occur (Bessen et al, 2022), when automation raises demand for complementary, non-automated tasks, hence creating jobs and further raising skill demands.

A related strand of the literature has also shown that the earlier wave of machine learning technologies could potentially render a significant part of mostly routine jobs and tasks obsolete (Frey and Osborne, 2017; Arntz et al., 2016; Nedelkoska and Quintini, 2018; Pouliakas, 2018). New generative AI technology, such as generative pre-trained transformer algorithms and large language models (LLMs), can also carry out cognitively complex tasks, such as language, audio or image creation. This widens the scope of jobs that may be potential susceptible to job-task displacement or outright automation (Felten et al., 2021).

While most such studies have focused on the impact of AI on employment, the evidence regarding the wage effects of AI is mixed. With AI having the potential to elevate labour productivity, it has been argued that there is a positive relationship between AI use and wages (Engberg et al., 2024). Several studies that have typically extracted information from online sources have also shown that so-called 'AI skills' are associated with a significant wage premium, both across occupations and within firms or jobs (Alekseeva et al., 2021; Manca, 2023). While such wage dividends tend to reflect the rising demand for people with technical knowledge of AI methods, they are also said to arise due to strong complementarities with other cognitive and non-cognitive skills (Stephany and Teutloff, 2024).

Recent evidence has highlighted though that the use of AI in workplaces mostly reduces any productivity differentials between workers, most notably by positively affecting the performance of least-educated individuals within a given job (Brynjolffson et al., 2023; Peng et al., 2023; Noy and Zhang, 2023; Dell'Acqua et al., 2023; Georgieff, 2024). In this case, AI may be associated with lower wage inequality within occupations and the higher wage premium enjoyed by early AI developers may be dampened over time.

Ultimately a sustained demand by employers for workers in command of AI technologies, let alone those who can develop or manipulate them, depends on the extent of AI adoption within organisations and its impact on business outcomes. With evidence of, at best, modest and heterogeneous productivity gains of AI across organisations (Acemoglu et al., 2022), which could be reflective of a typical J-curve effect associated with new technologies (Brynjolffson et al., 2021), the impact of AI on wages remains to be seen in practice.

The supply side of the equation cannot be neglected. The extent to which the demand for AI skills can be met by an available workforce, either through initial or continuing education and training, will also ultimately determine the outcome of the AI talent race. Some early survey evidence shows that the education and training pathways of AI developers tend to be broader than the typical ICT workforce. They involve a greater diversity of fields of study but also a non-college educational route (Gehlhaus and Mutis, 2021). So, it is likely that the supply of people with knowledge of AI methods may be sufficient to meet any rising demand. Nonetheless, the typical composition of the AI workforce tends to be segregated in terms of age and gender (Green and Lamby, 2023), posing a risk of potential talent bottlenecks constraining growth of this newly emerging workforce segment. And even though those who train in AI techniques have high expectations of future wage increases (Lane et al., 2023), it appears that the AI workforce is no more likely to participate in adult learning than other tertiary-educated workers (op cit., 2023).

Our paper contributes to this strand of the literature by examining wage differentials of the AI developer workforce. The latter is the specific category of workers directly involved with the development of AI technologies. We focus on this group, despite its relatively small employment size, because it may determine whether the EU or other competing regions will largely spearhead AI innovation. Using novel data from the second wave of the Cedefop European skills and jobs survey (ESJS2), we identify the sample of the European workforce that writes programs or code using AI methods (e.g., machine or deep learning). After profiling the sociodemographic and job characteristics of this European AI programmer workforce, the study assesses whether they experience any wage differentials relative to a similarly educated or another comparable programming workforce that does not (yet) employ any AI methods at work. We also exploit relevant decomposition approaches to examine if any wage gap can be attributed to differences in the characteristics of the two groups.

We find that, on average, AI programmers tend to benefit from a significant wage premium relative to the comparison groups. But the wage distribution of AI programmers also presents higher skewness. It is argued that such greater wage variability is likely to arise because of the higher dispersion of AI programmers in diverse economic activities and jobs demanding a wider skill set. We provide first tentative evidence that the wage schedules of AI programmers are comprised of a greater performance-based component, which may also underlie their more uncertain wage prospects.

The paper is structured as follows: section 2 considers the most relevant literature focused on the AI impact on wages. Section 3 describes the data used in the empirical analysis and provides some descriptive statistics related to the European AI programmer workforce. Section 4 outlines the empirical modelling approach and section 5 describes the empirical results. Section 6 offers some concluding remarks.

2. Literature review

Studies of AI and its effect on labour markets have been recently on the rise. An earlier strand of the literature focused on the automation risk of occupations because of their prospective exposure to AI technology (Arntz et al., 2017; Nedelkoska and Quinitni, 2018; Pouliakas, 2018). This exercise aimed to assess the likely employment consequences of occupational AI exposure in the medium-term (Frey and Osborne, 2017; Guarascio et al., 2023) and to underpin potentially vulnerable sectors or occupations (Felten et al., 2021). Even though this approach has been expanded to account for new developments in generative AI (Felten et al., 2023), it fails to account for AI progression curves within jobs. It also narrowly focuses on AI's technical feasibility to carry out job tasks, without accounting for the multitude of economic and social determinants underlying its actual adoption and diffusion in jobs (Guarascio et al., 2023; Svanberg et al., 2024).

Aleskeeva et al. (2022) and Acemoglu et al. (2022a) both find a relatively large increase in AI-related vacancies in the past decade, although with limited aggregate employment and wage effects, potentially because of reduced hiring in non-AI posts. Part of the reason why net AI job market effects tend to be muted can also be attributed to the disproportionate use of AI in larger, wealthier, and innovative firms (Alekseeva et al., 2022; Acemoglu et al., 2022b). Nevertheless, most studies show that there is a wage premium attached to the possession of AI skills. Job postings that require AI skills tend to be associated with higher wage offers (of about 5-10%, on average) when compared to others that concern similar job titles or even within the same firm.

Similarly, workers employed in online freelancing platforms receive significantly higher wages when in possession of AI-related skills (particularly machine or deep learning, Tensor Flow and natural language processing), compared to similarly educated workers (Stephany and Teutloff, 2024; Duch-Brown et al., 2022). Such wage increases can be partially explained by the strong correlation of AI skills with high-level cognitive skills, such as creative problem-solving (Manca, 2022). In general, the surge in AI demand within establishments tends to be associated with greater skills churning (Acemoglu et al., 2022a). This implies potentially higher pay for those workers who manage to continuously upgrade their skillsets in both AI and complementary skills.

More recent studies have sought to better understand the characteristics of the AI workforce and the actual labour market impact of AI systems. Green and Lamby (2023) focus on the AI workforce, defined as the subset of workers with skills in statistics, computer science and machine learning who could actively develop and maintain AI systems. They calculate that this workforce accounts for a very small share of employment (0.34%) in OECD countries but has grown by almost a factor of three compared to a decade before.

Much of the aforementioned research has tried to identify 'AI skills' and the relevant workforce in command of AI methods by extracting relevant web-based information (Alekseeva et al., 2021; Duch-Brown et al., 2022; Green, 2024; Green and Lamby, 2023; Manca, 2023; Stephany and Teutloff, 2024). Online job postings or data from professional social networks are prominent sources from which researchers have sought to underpin the type of AI knowledge, skills and techniques required in job markets. Apart from selection biases associated with the use of online data (e.g. exclusion of part of AI workers or firms that are less inclined to use such online portals), such an approach is structurally constrained to using an imperfect or, at best, partial keyword system for pinpointing relevant AI terms (e.g. machine learning, speech recognition, natural language processing). It is hence devoid of the ability to engage in in-depth understanding of the context and socioeconomic structure in which AI skills are deployed.

Few studies on AI skills demand and the related AI workforce exist to date based on representative workforce survey data.[1] Gehlhaus and Mutis (2021) constitutes a first attempt to identify AI programmers, identified by those occupations in which workers are or can immediately work on the development of AI products. The authors use data from the U.S. Census Bureau and show that such a technical AI workforce accounts for 3% of the total US

[1] Acemoglu et al. (2023) and Calvino and Fontanelli (2023) rely on data from representative firm-level surveys to better understand the adoption of AI and other automation technologies in firms and their associated characteristics. Humlum and Vestergaard (2024) is a notable study of the use of generative AI, drawing on data from a large-scale survey of workers identified through a comprehensive register dataset in Denmark.

labour force. Despite strong demand for AI workers, their supply may be keeping up with demand in some countries. Such supply is however disproportionately comprised of males and tertiary-educated workers and is concentrated in mostly high-skill, technical occupations. Despite such segregation, the educational background, career paths and economic activities of AI developers tend to exhibit greater diversity compared to those of non-AI programmers, possibly expanding the available recruitment pool (Gehlhaus and Mutis, 2021; Green and Lamby, 2023). Importantly, there is evidence of a positive, yet relatively small, wage gain of AI programmers compared to a comparable group of workers who have the knowledge and skills to potentially perform technical AI roles, as is or with some minimal training. There is also a sizeable range in the average earnings of AI technical workers.

Several representative adult worker surveys have recently highlighted that the use of AI tools or applications is expanding fast in advanced economies, over and beyond the share of workers in charge of developing AI algorithmic systems. In a first nationally representative U.S. survey of generative AI adoption at work and at home, Bick et al. (2024) find that 39 percent of the U.S. adult population use such tools. Lane et al. (2023) survey employers and workers in the manufacturing and finance sectors of seven OECD countries. They find that a little above 5 percent of workers develop or maintain AI in companies that use it, although over a third of adult workers use such AI tools for their work. The increasing spread of AI technologies in workplaces tends to be associated with high levels of employee contentment and expectations of future wage increases, particularly among those who develop or maintain AI.

A random probabilistic survey of adult workers in eleven EU Member States was also carried out in Spring 2024 by the European Centre for the Development of Vocational Training (Cedefop, 2024b). The survey reveals that 28 percent of European adult workers either use an AI tool or system at work or are aware of their colleagues doing so. Such interaction with AI technology is mainly done for the purposes of carrying out one's job tasks, while only a minority (about 4-5%) are AI developers.

While positive AI wage gains are still apparent in such survey-based studies, the magnitude of the premium tends to be relatively smaller than for those engaged in AI development tasks.

3. Data and descriptive evidence

3.1. Data: The Cedefop second European skills and jobs survey

To reliably map the size and characteristics of the newly emerging AI developer workforce in EU labour markets, Cedefop integrated questions relating to AI technology in its second wave of the European skills and jobs survey (ESJS). The ESJS is a Cedefop periodic representative European adult worker survey that collects information about the skill needs of their jobs, the use of digital activities at work, skill mismatches, training and related labour market outcomes.

A first ESJS wave, focused on the drivers of European skill mismatches, was carried out in 2014 (Cedefop, 2015b, 2018). A second wave (ESJS2), fielded in Q2 2021, collected information from 46 213 adult workers in the EU27 Member States plus Norway and Iceland (hereafter EU+).[2]

The survey focuses on identifying the skill needs of EU+ workers and the extent to which their jobs are affected by digitalisation (Cedefop, 2022a, 2022b) using a robust, comparable task-based approach (Handel, 2016)[3]. It identifies extensive socio-demographic and job-related characteristics of adult workers.[4] The extent to which different types of skill mismatches are experienced by workers (vertical / horizontal qualification mismatches, skill gaps, skill utilisation) and the propensity of workers to mitigate them by participating in education and training is further measured.

Specifically for the purposes of this paper, the ESJS2 contains data on EU+ workers' use of digital technologies in their main job and associated level of digital skill required. Questions relevant to AI include those that ask respondents if, in the last month, they used any computer devices to write programmes or code using a computer language (e.g. C++, Python, Java); and whether the programmes they write use AI methods, such as machine- or deep-learning algorithms[5]. The information provided in the ESJS2 hence allows us to identify the part of the workforce who write programs or code using AI algorithms.

The AI workforce under analysis is a subset of the overall EU+ programming workforce, although one that can be considered a backbone of the future development of AI technologies in European economies, as it builds and implements AI systems. It is apparent from the definition above that the AI developer workforce identified in this paper should preclude the wider set of workers who may use AI tools or applications (e.g. ChatGPT) at their job. This holds because writing programmes using a relevant computer language is a prerequisite for being counted as an AI developer. To mitigate any miscomprehension regarding what constitutes an AI programmer by the survey respondents, we restrict the sample in the empirical analysis to include only workers with at least an upper secondary education level[6].

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[2] In 2022-23, the ESJS2 was also fielded in five Western Balkan countries and Israel by the European Training Foundation (ETF) in cooperation with Cedefop.

[3] It specifically measures the intensity of foundation skills (literacy, numeracy), digital skills, interpersonal skills, problem-solving skills, and physical skills required in the jobs of adult workers (Cedefop, 2022b). It maps in detail the type of digital activities carried out at work (e.g. online browsing, emailing, word processing, programming), the incidence of technological change and its impact on job tasks. Moreover, it collects information about the nature of work and its organisation (e.g., routine, autonomy).

[4] The survey methodology comprises both Computer Assisted Telephone Interviewing (CATI) and Computer Assisted Web Interviewing (CAWI). The total sample (CATI&CAWI) includes 46213 adult employees and the CAWI sample only includes 30701 adult employees. Some variables are observed only in the CAWI sample.

[5] At the time the survey was developed, machine- or deep-learning constituted key umbrella terms of AI development. They should encapsulate different applications of such methods that have recently received greater attention, including natural language processing or large language modelling, which are forms of generative AI.

[6] We identify n=401 lower educated employees in the ESJS2 sample who claim to use AI methods as part of their computer programming tasks. Scrutinising this part of the workforce further raises some concern about whether it confounded the use of a digital application with actual AI programming. Most are employed in the wholesale and retail trade sector, undertaking service and sales occupations, crafts or related trades or are engaged in elementary work. By contrast, tertiary educated AI programmers are typically employed in the ICT sector, professional and scientific services and manufacturing.

3.2. Descriptive statistics: profiling the European AI developer workforce

Table 1 below profiles the AI developer workforce as identified by the ESJS2[7]. It portrays the individual and job characteristics of AI programmers, including their occupational and industrial distribution. As the focus of the analysis is on investigating if AI development is associated with a wage premium, the table also displays the respective descriptive statistics for two key comparator groups (i) the rest of the workforce with an upper secondary or tertiary level education (Green and Lamby, 2023) and (ii) the residual computer programming workforce. In a similar spirit to Gehlhaus and Mutis (2021), the latter constitutes a main control group as it concerns a cluster of workers with similar knowledge, skills and abilities to the AI subsample, albeit one that does not regularly deploy AI methods as part of their job tasks. We nevertheless also examine wage differences between those developing AI and the rest of the workforce with a comparable education level, as this has been a comparator typically used in the literature.

[INSERT TABLE 1 ABOUT HERE]

The full sample data indicates that the AI developer workforce accounts for 7.9% of the total European adult workforce with upper secondary or higher education.[8] The countries with the highest proportion of AI developers are Spain, Ireland, Romania, and France (around 10% of the sample). Approximately one in two computer programmers used an AI method as part of their main job in the previous month, although the shares are unevenly distributed across EU+ countries. Programmers who use AI techniques at work tend to be mostly concentrated in Spain, Romania, Ireland, France, Italy and Germany, while there is relatively less specialisation in Croatia, Cyprus, Estonia, Iceland or Latvia. More than 70% of the AI programming workforce across the sample comes from five countries (Germany, France, Spain, Italy, and Poland).

The AI workforce tends to be younger. The population of the AI workforce is on average 38 years of age (std. dev.=9.0) with 50% of its population being under 36 and 6% over 55. Overall, the AI workforce appears to be younger by 5 years on average than the workforce with an upper secondary or higher degree and 2 years than the rest of the programming workforce. There is also a greater concentration of males in it, as compared to the rest of the medium- or higher-educated workforce. However, traditional programming occupations tend to be even more male-dominated than newly emerging AI jobs.

The AI developer workforce has a lower mean education level than the rest of the computer programming workforce. It has more graduates from medium-level education, compared to the rest of the ICT programmer workforce (43% vs 40%, respectively). It also has a higher share of workers with Doctoral degrees than the latter (4% vs. 3.5%), but fewer employees with a bachelor's (20% vs. 22%) or master's (23.7% vs. 25.3%) degree. The lower educational

[7] Table A1 in the Annex also shows the results of a probit regression, where the dependent variable takes the value one for adult employees who are identified as AI programmers in the sample and zero otherwise.

[8] It is important to acknowledge that this share is likely to constitute an upper bound of the AI developer workforce in the EU+ sample, as it is mostly driven by the higher frequency of positive values in the CAWI subsample. Only 1.5% of the CATI subsample identified itself as AI programmers. As there is limited evidence of any systematic biases in the characteristics of the ESJS2 internet and telephone subsamples, it is likely that the higher prevalence of AI development in the CAWI component reflects programmers' greater willingness to participate in online surveys, as opposed to completing a telephone interview.

background of AI developers is consistent with previous literature highlighting that the use of AI is transcending traditional educational barriers to labour market success (Stephany and Teutloff, 2024).

AI programmers also tend to have completed more diverse educational studies than non-AI programmers. The most common fields of study of the latter are Information and Communication Technologies (20.2%) and Engineering, manufacturing, and construction (18.9%), accounting for nearly 40% of the total. These fields are also the most common for AI developers, although accounting for a third of the sample (about 16%, respectively). The latter are also more likely to have graduated from Natural sciences, mathematics and statistics programmes (14.5% vs 13.12%), Health and Welfare (6.7% vs 5.5%) as well as Generic programmes (11.6% vs 7.3%).

AI programmers are more evenly spread across different economic activities and occupations, including in those that are 'non-identifiable' by the NACE nomenclature, compared to traditional ICT programmers. The latter are concentrated in the ICT and manufacturing sectors[9]. While nearly one in five ICT programmers are employed in the ICT sector (19%), the same holds for about one in ten AI programmers (12.8%). The AI developer workforce is mostly distributed across the sectors of manufacturing (17%), professional, scientific, and technical activities (10%), wholesale and retail trade (9%), administrative and support activities (8%) and human health and social work (8%).

Of particular interest is the fact that even though AI programmers' jobs tend to more frequently involve the execution of short, repetitive movements or tasks, they require an overall higher skill level, relative to those of comparable non-AI programmers.

Focusing on the wage structure of the AI developer workforce, Figure 1 and Table A2 in the Annex reveal that the hourly net pay of AI programmers tends to have a greater spread than non-AI programmers, although both coding groups earn significantly higher wages than the rest of the sample. For non-AI programmers, hourly wages tend to be more centred around the mean. In general, AI programmers tend to be concentrated in jobs where they receive either very high or very low wages.

[INSERT FIGURE 1 ABOUT HERE]

4. Empirical methodology

To assess whether the AI developer workforce experiences any wage differentials relative to a similarly educated group, or more specifically a comparable programming workforce that does not (yet) employ any AI methods at work, we aim to estimate the following earnings equation:

$$w_i = \alpha_i + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_i \qquad \text{(eq. 1)},$$

where:

[9] A non-trivial part of the AI workforce (6%) could not identify itself with existing sectors as defined by the standard international nomenclature of economic activities (NACE), or with the standard occupational classification (ISCO). This may be indicative of the emergence of new AI-related jobs in the labour market that are yet to be matched to existing taxonomies.

w is the main dependent variable, denoting the logarithm of hourly net pay of each employee i[10];

x_{1i} is the main independent variable, which distinguishes between the following three population groups:

- non-programmers with at least upper secondary education;
- non-AI programmers;
- AI programmers.

x_{2i} is a set of control variables, capturing a rich set of individual (e.g., age, gender, education) and job characteristics (e.g., employer tenure, public-private sector, workplace size, type of contract, remote work, training, occupation and economic activity), including specific indices of job-skill requirements uniquely measured as part of the ESJS2.

ε_i is the error term.

We estimate equation 1 using OLS regression and following a step-wise approach, where five different specifications are considered, in which x_{2i} sequentially includes the following variables:

1. Age, quadratic age, gender, and level of education;
2. Specification (1) and years of employer tenure;
3. Specification (2) and industry (NACE) and occupation (ISCO) dummies[11];
4. Specification (3) and job complexity and job-skill requirement scales, the latter acting as proxies of the within-occupation level of skills complexity implied by the job tasks[12];
5. Specification (4) and a variable capturing if an employee receives any performance-related pay[13].

The preferred specifications to capture the wage returns to AI programming skills are the Mincer-type wage equations (1) or (2). Such estimates are not confounded by individuals' ex post placement into high- or low-skilled jobs, which dilutes the true effect of skill on earnings (Psacharopoulos, 2024). Estimations (3)-(4) control for the sectoral/occupational distribution, but also for within-occupation skill demands. This allows us to understand the extent to which

[10] To avoid extreme outlier values from distorting the analysis, we have truncated the lowest and highest 1% of the hourly wage distribution at its respective values.

[11] Specification (2) mainly considers 1-digit NACE and ISCO categories, considering the limited sample sizes of some detailed sectoral and occupational dummies. We have nevertheless ensured that the main empirical findings are not compromised when 2-digit NACE and ISCO groups are included in the specification. Table 1 further highlights that potential multicollinearity problems due to the high concentration of AI and non-AI programmers in the same broad NACE/ISCO/ISCED groups are likely to be limited. This holds because the former have a greater dispersion across industries, occupations and educational levels relative to the latter.

[12] The job-skill requirements and job complexity indices used in the paper are explained in detail at Cedefop (2022). They are derived by using information on the need for literacy, numeracy, manual and interpersonal skills in one's job, as inferred by the relative complexity of the respective tasks regularly carried out at work. The job complexity index is derived by combining information on the nature of work and how it is organised (e.g. routine, autonomous, planning, unanticipated problems, variety of tasks, need for learning new things, developing new products or work methods). Several studies in the literature have highlighted the importance of skills, tasks and job autonomy for occupational and wage dynamics (e.g. Cetrulo et al., 2020; A. Cetrulo et al., 2024; Fana and Giangregorio, 2024).

[13] As the variable for the performance-based wage component is observed in the CAWI sample only, model (5) is run only on this sample. Estimated results for models (1)-(4), run on the CAWI sample only, are highly comparable to those shown in Table 2 (available upon request).

higher wages may arise because employees with AI knowledge are further compensated since they enter jobs of greater skills complexity. All specifications include country fixed effects and robust standard errors are estimated by clustering at country level. We use suitable weighting schemes at all stages of the descriptive and empirical analysis[14].

As additional analysis, we exploit wage decomposition approaches to examine if and to what extent the AI wage gap can be attributed to differences in the characteristics of AI programmers relative to other similarly educated or skilled workers. Specifically, we adopt the Oaxaca-Blinder (OB) decomposition method developed in 1973 to decompose differences in mean wages across two groups (Oaxaca, 1973; Blinder, 1973).

According to this method, the wage setting model is assumed to be linear and separable in observable and unobservable characteristics. Hence, the overall mean wage gap between group A and group B, $\Delta_O^\mu = \overline{W}_B - \overline{W}_A$, can be decomposed into two terms:

$$\Delta_O^\mu = \Delta_X^\mu + \Delta_S^\mu,$$

where:

Δ_X^μ is the composition effect, "explained" by group differences in observable characteristics such as education or work experience;

Δ_S^μ is the wage structure effect, due to differences in how worker characteristics are rewarded in the labor market for the two groups. This effect is also generally defined as the residual, "unexplained" part of the wage differential that cannot be accounted for by observable differences in wage determinants, and in the context of the gender wage gap it is often interpreted as "discrimination".

Therefore, the OB decomposition allows to distinguish between the two types of effect, while also providing insights into the contribution of each characteristic.

Finally, as a supplement, we also apply the decomposition method proposed by Ñopo (2008), which uses matching comparisons to explain wage differences. The Ñopo approach provides a nonparametric alternative to the OB decomposition, as it does not require the linear regression estimation of earnings equations for the two groups under analysis. Although the Ñopo approach does not allow to measure the contribution of single characteristics, it provides a relevant complement to the OB analysis. It allows to tackle the potential issue of mis-specification due to differences in the supports of the empirical distributions of individual characteristics for the two groups under analysis. This is the case because the Ñopo approach accounts for differences in the distribution of individual characteristics. It does so by paying special attention to group 'differences in the supports' and restricting the comparison only to those individuals with comparable characteristics. This way, it is possible to reduce the risk of biased estimates for the component of the gap attributable to differences in the rewards for individuals' characteristics.

[14] In the ESJS2, weights are calculated independently for each survey mode (telephone and online) before being combined for the final responding sample. The benchmark population data used to calibrate the final net samples are taken from the most recent European labour force survey data. The sample is weighted to match population data on gender by age, gender by educational attainment, gender by industry, gender by occupation and region. Targeted adjustments are applied to account for differences between the telephone and online samples mainly attributed to selection effects. The final weights are adjusted so that countries with larger eligible populations have more influence (weight) on the pan European survey estimates than those with small eligible populations, reflecting differences in population size. Further details about the weighting schemes available in the ESJS2 microdata are available in the survey technical report (available upon request).

In brief, the Ñopo decomposition breaks down overall mean wage gap between group A and group B, $\Delta_O^{\mu} = \overline{W}_B - \overline{W}_A$, into the following four additive elements:

$$\Delta_O^{\mu} = \Delta_X + \Delta_S + \Delta_1 + \Delta_2,$$

where Δ_X and Δ_S are analogous to the elements of the OB decomposition but are computed only over the common support of the distributions of characteristics, while Δ_1 and Δ_2 account for differences in the supports.

In detail,

- Δ_X corresponds to the classic "explained" component; it is the part of the gap attributable to compositional differences between groups A and B for observations that are matched;
- Δ_S corresponds to the classic "unexplained" component; it captures how much of the raw gap remains unexplained by compositional differences in the considered characteristics of matched observations;
- Δ_1 and Δ_2 are the part of the gap attributable to unmatched units in each of the two groups; they denote compositional differences in predictors that led to lacking common support, for units within group 1 and 2 respectively (Sprengholz & Hamjediers, 2024).

5. Empirical findings

5.1. Premium to AI programming skills

Table 2 displays the results of OLS regressions where wage equation (1) is estimated over the selected ESJS2 sample using the different specifications described above.[15] The AI workforce is better compensated, on average, than the rest of the population with an upper secondary or higher education. It is evident that those who code at work, but do not deploy AI methods, earn a positive wage premium that ranges somewhere between an additional 1.5-2.4 EUR per hour (approximately 6-14%), when compared to a general group of medium- or higher-educated workers. This premium is even higher for AI programmers, ranging between 2.3-4.2 EUR or about 11-21% of extra hourly pay relative to all non-programmers.

When comparing the AI programmer workforce to comparable non-AI programmers, we also systematically find a positive wage premium ranging from a high of extra 7-8% for the least comprehensive specification (1) to a low of extra 4-6% for the most comprehensive ones (4)-(5). These findings highlight that an employee's ability to command AI technologies is compensated by European employers over and above the ability to code at work. Given that the coefficient of the AI programming variable is reduced by about one third when controlling for the skills complexity of one's job, this also shows that part of the extra wages of AI programmers, relative to that of non-programmers, is an outcome of the greater skills demand they face.

Our estimates are conservatively higher than the AI wage premium identified in the literature for EU as well as non-EU OECD countries (USA, Canada, Australia, New Zealand), where the observed wage returns range between 6% to 11% (Alekseeva et al., 2021; Manca, 2023).

[15] For robustness purposes we have replicated the analysis using the net monthly or hourly pay variables as right-hand side regressands. The main empirical findings remain statistically significant (available upon request).

However, the higher AI wage premium identified in our study possibly arises because most previous investigations have relied on data from online job advertisements (OJAs) (Green and Lamby, 2023). Although previous research has shown a broad degree of consistency between the wage information provided by official statistics and OJA data (Adrjan and Lydon, 2019; Manca, 2023), the latter tend to under-represent low-paid or lower-skilled jobs, while there is marked variation in the ability to identify AI-related keywords across different linguistic/cultural settings and occupations. Conversely, OJAs tends to over-represent jobs requiring advanced digital skills, especially in the field of AI (Fernandez Macias and Sostero, 2024). As calculations of the AI skills premium using OJAs takes place at a more aggregate job title or firm level and uses a selected part of the higher-skilled workforce, they are likely to under-estimate AI wage differences. Our analysis benefits instead from exploiting in-depth intra-occupational information, collected at the individual worker level.

[INSERT TABLE 2 ABOUT HERE]

5.2. Variation in AI programming wage returns

Underlying the positive mean effects described in the previous section is significant cross-country variation in the wage returns to AI development skills (Figure 2). While those who can code using AI methods receive a marked wage supplement in Germany, Greece, and Spain, relative to comparable programmers who do not regularly employ AI, there is a smaller benefit for AI developers in France.

[INSERT FIGURE 2 ABOUT HERE]

Running separate wage regressions for the male and female subsamples also reveals that regularly using AI methods at work implies a higher compensation in the order of 11% for female employees, relative to non-AI programmers (Table 3). This exceeds the 4% wage premium gained by males. The higher AI wage premium for females is likely to arise because of the scarcer supply of women with knowledge of AI techniques in the workforce, relative to men.

The balance of demand and supply of AI programmers with medium- and tertiary-level education is also reflected in the differential wage returns received at different education levels. Workers who have completed an upper secondary or post-secondary qualification and utilise AI algorithms at work receive, on average, a wage benefit of approximately 4.5%, relative to similarly educated non-AI coders. The wage gain is larger (about 8%) for AI programmers who have completed tertiary education, potentially reflecting their greater scarcity relative to other higher educated programmers.

[INSERT TABLE 3 ABOUT HERE]

5.3. Performance-based AI pay

While part of the greater variation in AI programmers' pay can be attributed to their dispersion across jobs demanding different skillsets, ESJS2 data also reveal that their wages are more dependent on performance-related pay, more than the rest of the workforce (Table 1). About 72% of AI developers receive pay in their main job that varies according to their job performance, such as commissions, bonuses, profit-sharing or stock options. This practice is used much more than the rest of the non-AI programmer workforce (46.1%) or other upper secondary and higher educated non-programmers (26.3%).

When comparing the difference in coefficients between specifications (4) and (5) applied on the same ESJS2 sample, it is found that approximately 15% of the higher wages of AI programmers can be attributed to the fact that they are more dependent on performance-based components.

While performance-based pay generally tends to be more prevalent for workers whose pay is above the highest earnings quartile, this trend does not apply to the AI developer workforce since it consistently applies to each quartile. Performance-based components in remuneration are particularly prevalent for the AI workforce in 'non-identifiable' sectors and professions. 86.5% of the AI workforce in such newly emerging jobs have some form of performance-related remuneration.

5.4. Decomposition analysis

To explore what factors underlie the wage differential between AI programmers and comparably educated workers, we engage in decomposition analysis as described in section 4.[16]

Table 4 below displays the results of the OB decomposition based on wage equation (1) and estimated over the selected ESJS2 sample using the five different specifications. The decomposition is computed using a linear pooled model, where the reference coefficients are the coefficients from a pooled model over both groups.

To compute the individual contributions of the predictors, we apply a detailed decomposition.[17][18] We also allow for the "unexplained" component Δ_S^{μ} to be split into a part related to Group 1 and a part related to Group 2.

Consistently with the regression analysis, the OB decomposition points to a positive and statistically significant wage premium for AI programmers as compared to the rest of the sample. The difference Δ_O^{μ} is indeed positive and statistically significant in all five specifications considered and equals 0.23.

The "explained" part Δ_X^{μ}, that is the composition effect attributable to group differences in observable characteristics, gradually increases over the specifications as additional variables are sequentially included in the list of controls, which further contribute to explaining the wage gap. By further decomposing the composition effect into contributions of single covariates, we

[16] Given the relatively small sizes of the AI and non-AI programmer subsamples in the ESJS2 microdata, and also to retain consistency with previous literature, we use as comparison group the residual sample of workers with at least upper secondary education. The Ñopo decomposition allows us to carry out the comparison on 'matched' units in terms of observable characteristics, hence limiting any lack of common support influence between the two groups.

[17] Given that the choice of base level of a categorical covariate has consequences for the decomposition components Δ_X^{μ} and Δ_S^{μ}, we implement a normalization of the coefficients associated with categorical variables. Namely, we use "deviation contrasts", where the coefficients of the indicators reflect deviations from the unweighted average across categories. This way, the decomposition results based on normalised coefficients are independent of the choice of base level (Jann, 2008).

[18] For all characteristics measured by categorical variables (Level of education, Gender, Country, ISCO-1d, NACE-1d, Job complexity, Skill requirements, Performance-related pay) the detailed decomposition is subsumed by sets of relevant covariates, to account for the contribution of all categories together. For example, the displayed coefficient for "Job complexity" refers to the subsumed contribution of all the following categories: very low, low, medium, and high. We also subsume the covariates of age and quadratic age under one "Age" category.

note that, except for age, the contribution is statistically different from zero for all covariates across all specifications. While the contribution is positive for most of the variables, age and employment duration show negative contributions. This means that the overall difference would be larger if average age and employment duration would be the same in the two groups. As employment duration has a positive effect on wages and AI programmers have, on average, slightly lower tenure than the rest of the sample, eliminating this disadvantage would make the former even better off as their wage premium would increase. The higher skill requirements of their jobs and the receipt of performance-based pay, by contrast, positively contributes to the wage gap. Figure A1 in the Annex shows the contributions of predictors to the explained component Δ_X^μ as a percentage of the total wage gap Δ_O^μ, based on specification (4). Skill requirements results as the predictor with the highest positive percentage contribution to the total wage premia of AI programmers.

The "unexplained" part of the wage differential Δ_S^μ, which corresponds to the wage structure effect, also positively contributes to the wage gap (as the algebraic sum of the coefficients related to Group 1 to Group 2 is positive). By detailing the decomposition and splitting the component into two parts related to groups 1 and 2, we can also observe that while the rewards to employment duration are significant for both groups, the country differences are not significant for the group of AI programmers.

[INSERT TABLE 4 ABOUT HERE]

Table 5 below displays the results of the Ñopo decomposition. As with the OB decomposition, this is based on the wage equation (1) and estimated over the selected ESJS2 sample using the five different specifications.

In the first step of this approach, units from groups 1 and 2 are matched to restrict the comparison only to those individuals with comparable characteristics. Different types of matching approaches can be considered for this purpose. In the table we report the results obtained through propensity score matching. The proportion of matched units from each group are also shown for each specification.[19] For the AI programmers' group, this proportion is always higher than 92%, hence showing a good match. For the comparison group, however, it is lower than 90% for two specifications, the second and the third, where it equals 51.9 and 76.4%, respectively.

The estimated results are in line with those obtained with the OB decomposition. Now considering only matched observations, the decomposition points to a positive difference Δ_O^μ, which is statistically significant in all five specifications considered, and equals 0.23.

In this case as well, the unexplained component for Δ_S^μ, accounts for the highest contribution to the premium and is always statistically significantly different from 0, ranging from 0.20 to 0.10. The explained component for matched observations for Δ_X^μ, shows that the part of the gap attributable to compositional differences between groups positively contributes to the premium only for specifications (4) and (5). However, for specifications (2) and (3), the lack of significant contribution can be attributed to the low performance of the matching approach, which results in a lower proportion of matched units in the group of AI programmers.

[19] The number of observations and the proportions are unweighted.

[INSERT TABLE 5 ABOUT HERE]

6. Conclusion

This paper contributes to the debate on the potential labour market impact of autonomous digital technologies, particularly generative or other forms of AI, by examining if the skills of the AI programming workforce are in high demand in European economies. Using unique representative adult workforce data, collected as part of the second European skills and jobs survey (ESJS2), we identify a specific category of workers who are directly engaged with the development of AI technologies at work, such as machine- or deep-learning. This segment of the workforce is expected to be a key source of competitive advantage for countries in the future world of work since it commands knowledge and skills necessary for writing computer programmes that deploy AI methods.

We exploit rich ESJS2 information on demographic and job characteristics, as well as novel proxies of job-skill requirements, to, first, paint a detailed profile of the European AI programmer workforce. We subsequently examine whether the AI developer workforce experiences any wage differentials relative to a similarly educated workforce or a comparable programming workforce that does not (yet) employ AI methods at work. Our findings confirm that the possession of AI development skills is rewarded in the European job market, as such workers enjoy a non-trivial wage premium in the order of 4-8%, depending on specification, relative to comparable non-AI programmers and 12-24% relative to similarly educated employees. AI wage returns are in general higher among females and tertiary-educated employees, which is indicative of a relative scarcity of such workers with knowledge of AI methods in European economies.

The data further reveals higher dispersion of AI programmers into diverse economic sectors, occupations, and fields of study, relative to other programmers who do not regularly use AI at work. We provide first tentative evidence that the wage schedules of AI programmers are comprised of a greater performance-based component, which may also underlie the higher variability in the pay distribution of AI developers towards very high or very low pay levels. Utilising wage decomposition approaches, we further confirm that the jobs of AI programmers require a higher skill level, which positively contributes to their pay differential, overcoming their lower age and tenure disadvantage.

The analysis reveals that there is a large unexplained component underlying the AI programmer wage gap. AI is still a relatively premature digital technology, at its early phases of deployment in European labour markets. With new jobs and tasks emerging as a result of the further integration of AI in economies, and new learners constantly equipping themselves with AI knowledge and skills, further research needs to keep track of the development of AI skill shortages in the future.

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Tables and Figures

Table 1 **Descriptive statistics**

	Non-AI programmers	*AI programmers*	*t-test*	*Non-programmers*
Gender				
Men	1902.47	1679.91	*	14716.40
	67.55%	60.56%		47.77%
Women	914.00	1094.21	*	16092.47
	32.45%	39.44%		52.23%
Total	2816.47	2774.12		30808.86
	100.00%	100.00%		100.00%
Age				
25-34	961.10	1142.27	*	6740.91
	34.12%	41.18%		21.88%
35-44	844.07	950.26	*	8806.96
	29.97%	34.25%		28.59%
45-64	1011.30	681.59	*	15260.99
	35.91%	24.57%		49.53%
Total	2816.47	2774.12		30808.86
	100.00%	100.00%		100.00%
Education				
Upper secondary	759.33	831.21		11800.06
	27.01%	29.98%		38.36%
Post secondary, non-tertiary	376.62	379.37		5042.41
	13.40%	13.68%		16.39%
Short cycle tertiary	233.77	239.31		2269.06
	8.31%	8.63%		7.38%
Bachelor's or equivalent level	635.65	556.51		5405.53
	22.61%	20.07%		17.57%
Master's or equivalent level	709.32	664.81		5795.18
	25.23%	23.98%		18.84%
Doctoral or equivalent level	96.84	101.56		452.97
	3.44%	3.66%		1.47%
Total	2811.53	2772.76		30765.20
	100.00%	100.00%		100.00%
Field of study				
Generic programmes and qualifications	139.11	260.89	*	2029.06
	7.01%	11.49%		9.98%
Education	71.75	99.84		1329.35
	3.61%	4.40%		6.54%
Arts, humanities and foreign languages	116.52	121.06		1692.40
	5.87%	5.33%		8.32%
Social sciences, journalism, and information	54.66	62.81		763.42
	2.75%	2.77%		3.75%
Business, administration, and law	296.11	299.67		4348.56
	14.91%	13.20%		21.39%
Natural sciences, mathematics, and statistics	244.70	328.13		1569.04
	12.33%	14.45%		7.72%
Information and Communication Technologies (ICTs)	410.81	373.97	*	1174.80
	20.69%	16.47%		5.78%
Engineering, manufacturing, and construction	379.39	397.71		3438.85
	19.11%	17.51%		16.91%

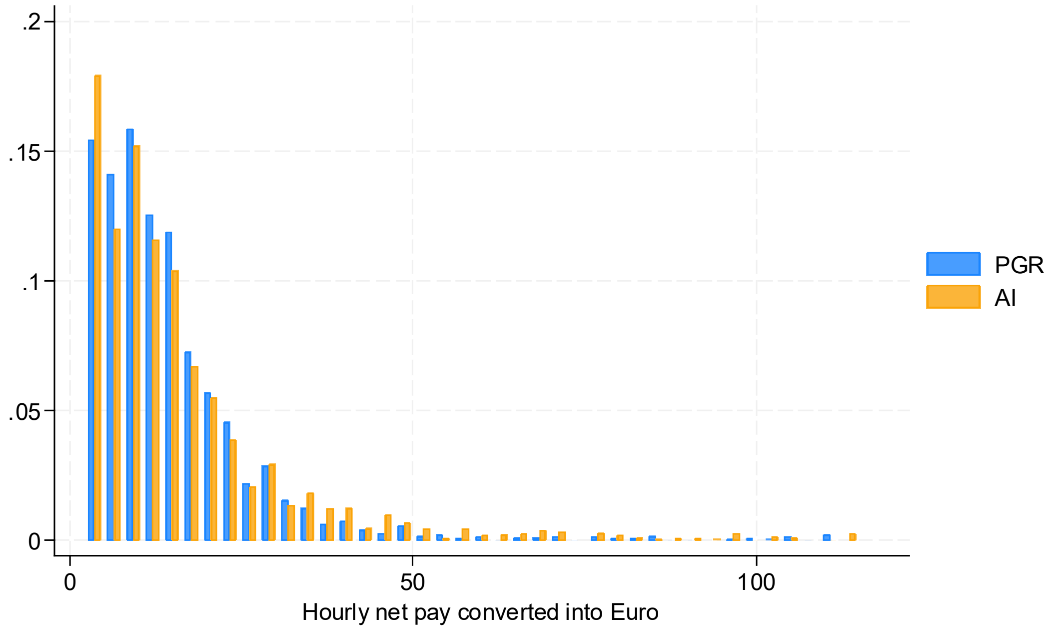
Agriculture, forestry, fisheries and veterinary	34.96 1.76%	45.20 1.99%		470.96 2.32%
Health and welfare (including care and social work)	110.46 5.56%	144.53 6.36%		1927.75 9.48%
Services (Personal, security, transport, hygiene, occupational health services)	126.86 6.39%	137.14 6.04%		1588.98 7.81%
Total	1985.34 100.00%	2270.95 100.00%		20333.17 100.00%
Tenure				
Less than a month	32.85 1.18%	52.72 1.94%		552.17 1.81%
Between 1 month and 5 months	76.30 2.75%	57.35 2.11%		1207.42 3.96%
Between 6 months and 11 months	80.35 2.89%	53.34 1.96%		1058.04 3.47%
Between a year and 5 years	888.22 31.99%	966.66 35.56%	*	9619.13 31.56%
Between 6 years and 40 years	1698.53 61.18%	1588.34 58.43%		18046.04 59.20%
Total	2776.25 100.00%	2718.41 100.00%		30482.80 100.00%
Economic sector				
Agriculture, forestry and fishing	31.04 1.10%	70.09 2.54%	*	451.54 1.47%
Mining and quarrying	10.58 0.38%	13.71 0.50%		109.11 0.36%
Manufacturing	514.47 18.28%	438.01 15.85%		5279.42 17.19%
Electricity, gas, steam and air conditioning supply	34.71 1.23%	20.15 0.73%		436.54 1.42%
Water supply; sewerage, waste management and remediation activities	14.58 0.52%	7.01 0.25%		228.25 0.74%
Construction	113.05 4.02%	130.37 4.72%		1573.68 5.13%
Wholesale and retail trade; repair of motor vehicles and motorcycles	186.55 6.63%	239.26 8.66%	*	2683.84 8.74%
Transportation and storage	154.47 5.49%	161.13 5.83%		1898.16 6.18%
Accommodation and food service activities	70.96 2.52%	105.95 3.83%	*	1122.23 3.65%
Information and communication	541.13 19.23%	333.45 12.07%	*	1313.53 4.28%
Financial and insurance activities	129.05 4.59%	100.19 3.63%		996.01 3.24%
Real estate activities	18.90 0.67%	13.08 0.47%		265.81 0.87%
Professional, scientific and technical activities	235.56 8.37%	277.30 10.04%		1953.23 6.36%
Administrative and support service activities	151.46 5.38%	196.14 7.10%	*	2019.63 6.58%

Public administration and defence; compulsory social security	135.73	87.81	*	1993.54
	4.82%	3.18%		6.49%
Education	193.48	154.57		3144.68
	6.88%	5.59%		10.24%
Human health and social work activities	177.07	205.58	*	4016.78
	6.29%	7.44%		13.08%
Arts, entertainment and recreation	15.42	18.53		458.31
	0.55%	0.67%		1.49%
Other service activities	19.37	37.30		458.79
	0.69%	1.35%		1.49%
NA/Unidentifiable	66.41	153.33	*	301.53
	2.36%	5.55%		0.98%
Total	2814.00	2762.96		30704.60
	100.00%	100.00%		100.00%
Occupation				
Managers	357.06	392.74		2551.83
	12.71%	14.20%		8.31%
Professionals	975.05	682.04	*	6733.80
	34.70%	24.66%		21.92%
Technicians and associate professionals	547.95	396.52	*	5637.86
	19.50%	14.34%		18.35%
Clerical support workers	299.16	305.87		4234.12
	10.65%	11.06%		13.78%
Service and sales workers	139.82	249.22	*	3824.76
	4.98%	9.01%		12.45%
Skilled agricultural, forestry and fishery workers	22.43	42.20		263.50
	0.80%	1.53%		0.86%
Craft and related trades workers	239.98	245.13		3147.01
	8.54%	8.86%		10.24%
Plant and machine operators, and assemblers	73.77	141.79	*	2000.60
	2.63%	5.13%		6.51%
Elementary occupations	88.37	156.49	*	2031.83
	3.15%	5.66%		6.61%
NA/Unidentifiable	66.33	153.24	*	298.30
	2.36%	5.54%		0.97%
Total	2809.92	2765.24		30723.60
	100.00%	100.00%		100.00%
Job-skill requirements				
very low	80.75	23.60	*	5020.71
	2.87%	0.85%		16.30%
low	688.32	251.41	*	11499.85
	24.44%	9.06%		37.33%
medium	1242.10	875.38	*	9443.41
	44.10%	31.56%		30.65%
high	805.30	1623.73	*	4844.89
	28.59%	58.53%		15.73%
Total	2816.47	2774.12		30808.86
	100.00%	100.00%		100.00%
Job complexity				
very low	141.80	86.96	*	5724.78
	5.03%	3.13%		18.58%
low	728.95	478.07	*	10071.31
	25.88%	17.23%		32.69%
medium	1168.55	1126.10		9784.59
	41.49%	40.59%		31.76%
high	777.18	1082.99	*	5228.17
	27.59%	39.04%		16.97%

Total	2816.47 100.00%	2774.12 100.00%		30808.86 100.00%
Performance-related pay				
PRP	899.62 45.09%	1625.93 71.52%	*	5345.97 26.13%
No PRP	1095.35 54.91%	647.40 28.48%	*	15110.05 73.87%
Total	1994.97 100.00%	2273.33 100.00%		20456.02 100.00%

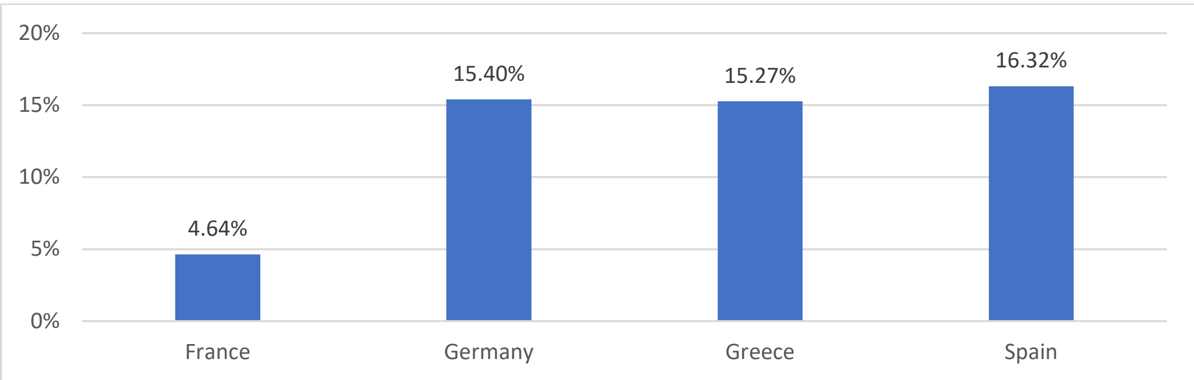
NB: In the third column, the star indicates a statistically significant difference between the main AI programmers group and the non-AI programmers (t tests on the equality of means with $p<.05$).
Source: Cedefop second European skills and jobs survey (ESJS2)

Figure 1 **Hourly net pay of AI and non-AI programmers**



NB: Hourly pay is derived by dividing the usual monthly net pay of workers with (4.33*hours of work). Sample of adult workers with at least upper secondary education. "PGR" are those who used any computer devices to write programs or code using a computer language in the last month but not using AI methods. "AI" includes workers writing programs using AI methods.
Source: Cedefop second European skills and jobs survey (ESJS2)

Figure 2 **AI hourly wage premiums in selected EU countries**



NB: Estimated wage returns following an OLS regression of equation (1), with the log hourly wage as dependent variable and specification (4). Only countries with adequate sample sizes of AI programmers (number of obs. >100) and statistically significant wage premia of AI programmers are displayed.
Source: Cedefop second European skills and jobs survey (ESJS2)

Table 2 **AI programming wage returns**

	(1)	(2)	(3)	(4)	(5)
Non-AI programmers	0.139 ***	0.132 ***	0.099 ***	0.078 ***	0.067 ***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.015)
AI programmers	0.216 ***	0.210 ***	0.186 ***	0.139 ***	0.110 ***
(ref: non-programmers)	(0.026)	(0.026)	(0.026)	(0.023)	(0.022)
Female	-0.130 ***	-0.125 ***	-0.119 ***	-0.114 ***	-0.107 ***
	(0.014)	(0.014)	(0.012)	(0.011)	(0.013)
Age	0.019 ***	0.013 **	0.012 **	0.013 **	0.009
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Age (quadratic)	0.000 **	0.000 *	0.000 *	0.000 *	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Level of education					
Post-secondary non tertiary education (ISCED 4)	0.033	0.036	0.023	0.018	0.007
	(0.021)	(0.021)	(0.020)	(0.019)	(0.018)
Short-cycle tertiary education (ISCED 5)	0.146 ***	0.143 **	0.098 *	0.091 *	0.077 *
	(0.040)	(0.040)	(0.038)	(0.036)	(0.033)
Bachelor’s or equivalent level (ISCED 6)	0.211 ***	0.210 ***	0.150 ***	0.139 ***	0.135 ***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.027)
Master’s or equivalent level (ISCED 7)	0.322 ***	0.323 ***	0.243 ***	0.224 ***	0.207 ***
	(0.020)	(0.021)	(0.021)	(0.021)	(0.027)
Doctoral or equivalent level (ISCED 8)	0.456 ***	0.460 ***	0.369 ***	0.343 ***	0.345 ***
(ref: Upper secondary education - ISCED 3)	(0.043)	(0.045)	(0.038)	(0.036)	(0.043)
Tenure					
Between 1 month and 5 months		-0.067	-0.061	-0.062	-0.036
		(0.041)	(0.036)	(0.038)	(0.038)
Between 6 months and 11 months		-0.026	-0.028	-0.032	-0.020
		(0.045)	(0.039)	(0.041)	(0.046)
Between a year and 5 years		0.002	-0.002	-0.010	0.000
		(0.043)	(0.037)	(0.040)	(0.036)

	(1)	(2)	(3)	(4)	(5)
Between 6 years and 40 years		0.092	0.074	0.061	0.066
(ref: Less than a month)		(0.045)	(0.039)	(0.041)	(0.037)
Job complexity (index)					
low				0.012	0.018 *
				(0.007)	(0.008)
medium				0.038 **	0.041 **
				(0.012)	(0.012)
high				0.036	0.029
(ref: very low)				(0.019)	(0.018)
Job-skill requirements (index)					
low				0.039 ***	0.016
				(0.007)	(0.010)
medium				0.079 ***	0.054 **
				(0.012)	(0.015)
high				0.129 ***	0.101 ***
(ref: very low)				(0.018)	(0.023)
Performance-related pay					0.075 ***
					(0.015)
Occupation dummies (ISCO)			x	x	x
Sector dummies (NACE)			x	x	x
Country dummies	x	x	x	x	x
Number of observations	37321	36947	36753	36753	25103
Adjusted R-squared	0.45	0.46	0.48	0.48	0.47

NB: OLS regressions of equation (1) using the log hourly wage as dependent variable. Specifications (1)-(5) gradually include control variables as described in the main text. The construction of the job complexity and job-skill requirements indices is described in Cedefop (2024a). *** p<.001, ** p<.01, * p<.05; Robust standard errors in parenthesis, clustered at country level.

Source: Cedefop second European skills and jobs survey (ESJS2)

Table 3 **AI programming wage returns by gender and education level**

	Non-AI programmers	*AI programmers*	*Difference in wage returns*
Gender			
Males	0.084*** (0.013)	0.119*** (0.023)	3.5%
Females	0.058*** (0.020)	0.174*** (0.032)	11.6%
Education level			
Upper secondary or post-secondary (ISCED 3-4)	0.085*** (0.032)	0.133*** (0.023)	4.8%
Tertiary (ISCED 5-8)	0.070*** (0.012)	0.150*** (0.024)	8.0%

NB: Based on separate estimations of equation (1) with specification (4) on subsamples of workers by gender and highest level of educational attainment. Robust standard errors in parenthesis, clustered at country level.
Source: Cedefop second European skills and jobs survey (ESJS2)

Table 4 **Oaxaca-Blinder decomposition**

Group 1: "AI programmers"
Group 2: "Workers with at least upper secondary education"

	1		2		3		4		5	
group_1	2.5359	***	2.5386	***	2.5368	***	2.5368	***	2.5347	***
	(0.0191)		(0.0191)		(0.0189)		(0.0188)		(0.0197)	
group_2	2.3057	***	2.3042	***	2.3049	***	2.3049	***	2.3008	***
	(0.0047)		(0.0047)		(0.0047)		(0.0047)		(0.0053)	
Δ difference	0.2302	***	0.2344	***	0.2320	***	0.2320	***	0.2339	***
	(0.0197)		(0.0197)		(0.0194)		(0.0194)		(0.0204)	
Δ_X explained	0.0291	**	0.0324	***	0.0534	***	0.1007	***	0.1335	***
	(0.0093)		(0.0095)		(0.0101)		(0.0110)		(0.0131)	
Δ_S unexplained1	-0.2010	***	-0.2020	***	-0.1786	***	-0.1313	***	-0.1004	***
	(0.0188)		(0.0191)		(0.0193)		(0.0200)		(0.0212)	
Δ_S unexplained2	0.4021	***	0.4039	***	0.3571	***	0.2625	***	0.2008	***
	(0.0362)		(0.0363)		(0.0355)		(0.0366)		(0.0388)	
EXPLAINED										
Age	-0.0241	***	-0.0024		-0.0042		-0.0071	**	-0.0039	
	(0.0024)		(0.0025)		(0.0024)		(0.0024)		(0.0027)	
Level of education	0.0301	***	0.0298	***	0.0229	***	0.0212	***	0.0197	***
	(0.0030)		(0.0030)		(0.0024)		(0.0023)		(0.0025)	
Gender	0.0154	***	0.0148	***	0.0136	***	0.0129	***	0.0125	***
	(0.0016)		(0.0016)		(0.0015)		(0.0015)		(0.0016)	
Country	0.0077		0.0060		0.0076		0.0068		0.0114	
	(0.0081)		(0.0082)		(0.0082)		(0.0082)		(0.0094)	
Employment duration			-0.0159	***	-0.0138	***	-0.0131	***	-0.0135	***
			(0.0015)		(0.0014)		(0.0014)		(0.0015)	
ISCO-1d					0.0208	***	0.0176	***	0.0177	***
					(0.0039)		(0.0034)		(0.0040)	
NACE-1d					0.0065	*	0.0084	***	0.0067	*
					(0.0029)		(0.0023)		(0.0030)	
Job complexity							0.0088	**	0.0066	
							(0.0033)		(0.0039)	
Skill requirements							0.0452	***	0.0417	***
							(0.0058)		(0.0071)	
Performance-related pay									0.0344	***
									(0.0047)	
UNEXPLAINED1										
Age	0.1479		0.1800		0.1368		0.1143		0.1025	
	(0.2681)		(0.2745)		(0.2739)		(0.2747)		(0.2727)	
Level of education	0.0180		0.0166		0.0135		0.0097		0.0048	
	(0.0106)		(0.0106)		(0.0107)		(0.0107)		(0.0114)	

Gender	-0.0021		-0.0018		-0.0009		-0.0002		0.0005
	(0.0035)		(0.0035)		(0.0035)		(0.0035)		(0.0035)
Country	0.0200		0.0307		0.0274		0.0252		0.0081
	(0.0214)		(0.0217)		(0.0213)		(0.0212)		(0.0208)
Employment duration			-0.0473	*	-0.0493	*	-0.0470	*	-0.0379
			(0.0218)		(0.0215)		(0.0214)		(0.0218)
ISCO-1d					-0.0096		-0.0047		-0.0085
					(0.0231)		(0.0238)		(0.0234)
NACE-1d					0.0370		0.0357		0.0341
					(0.0227)		(0.0228)		(0.0231)
Job complexity							-0.0351		-0.0308
							(0.0198)		(0.0199)
Skill requirements							-0.0216		-0.0218
							(0.0368)		(0.0369)
Performance-related pay									-0.0316
									(0.0262)
Intercept	-0.3849		-0.3802		-0.3335		-0.2075		-0.1199
	(0.2702)		(0.2746)		(0.2757)		(0.2776)		(0.2780)
UNEXPLAINED2									
Age	-0.0209		-0.0213		-0.0232		-0.0261		-0.0347
	(0.0245)		(0.0240)		(0.0239)		(0.0239)		(0.0303)
Level of education	0.0030		0.0026		0.0021		0.0015		0.0002
	(0.0018)		(0.0017)		(0.0017)		(0.0017)		(0.0023)
Gender	0.0000		0.0000		0.0000		0.0000		0.0000
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
Country	0.0019	*	0.0022	*	0.0022	*	0.0020	*	0.0021
	(0.0009)		(0.0009)		(0.0009)		(0.0009)		(0.0013)
Employment duration			-0.0027	*	-0.0021		-0.0020		-0.0020
			(0.0011)		(0.0012)		(0.0012)		(0.0015)
ISCO-1d					-0.0074		-0.0068		-0.0066
					(0.0042)		(0.0043)		(0.0049)
NACE-1d					0.0016		0.0017		0.0019
					(0.0018)		(0.0019)		(0.0027)
Job complexity							0.0001		0.0001
							(0.0004)		(0.0006)
Skill requirements							0.0008		0.0013
							(0.0005)		(0.0007)
Performance-related pay									-0.0021
									(0.0011)
Intercept	0.4181	***	0.4232	***	0.3839	***	0.2916	***	0.2405
	(0.0442)		(0.0434)		(0.0434)		(0.0439)		(0.0493)
N	37321		36947		36753		36753		25103

NB: OB decomposition of equation (1) using the log hourly wage as dependent variable. Specifications (1)-(5) gradually include control variables as described in the main text. The construction of the job complexity and job-

skill requirements indices is described in Cedefop (2024a). The detailed decomposition is subsumed by sets of covariates. *** p<.001, ** p<.01, * p<.05; Robust standard errors in parenthesis.
Source: Cedefop second European skills and jobs survey (ESJS2)

Table 5 **Ñopo decomposition**

	1	2	3	4	5
Δ	0.230***	0.234***	0.232***	0.232***	0.234***
	(0.0231)	(0.0200)	(0.0205)	(0.0198)	(0.0209)
Δ_X	0.0270	-0.0140	0.0105	0.0949***	0.111***
	(0.0141)	(0.0223)	(0.0217)	(0.0201)	(0.0247)
Δ_S	0.201***	0.219***	0.193***	0.123***	0.102***
	(0.0205)	(0.0261)	(0.0267)	(0.0254)	(0.0289)
Δ_1	-0.0000817	0.00901	-0.00192	-0.000419	0.00522**
	(0.000507)	(0.00726)	(0.00446)	(0.00142)	(0.00174)
Δ_2	0.00236*	0.0204**	0.0309***	0.0143	0.0141
	(0.000983)	(0.00623)	(0.00733)	(0.00887)	(0.00721)
Group "Workers with at least upper secondary education"					
N	34837	34504	34325	34325	22896
% matched	99.9	51.9	76.4	96.4	94.6
Group "AI programmers"					
N	2484	2443	2428	2428	2207
% matched	99.6	93.3	92.0	93.5	93.4
Bandwidth	0.00211	0.0000328	0.0000780	0.000275	0.000497

NB: Decomposition of equation (1) using the log hourly wage as dependent variable. Specifications (1)-(5) gradually include control variables as described in the main text. The construction of the job complexity and job-skill requirements indices is described in Cedefop (2024a). *** p<.001, ** p<.01, * p<.05; Robust standard errors in parenthesis.

Source: Cedefop second European skills and jobs survey (ESJS2)

Annex

Table A1 **Probit, AI programming**

	(1)		(2)		(3)		(4)		(5)	
Female	-0.246	***	-0.233	***	-0.178	***	-0.134	**	-0.124	*
	(0.041)		(0.041)		(0.037)		(0.047)		(0.052)	
Age	-0.002		-0.015		-0.014		-0.008		-0.000	
	(0.012)		(0.012)		(0.012)		(0.011)		(0.012)	
Age (quadratic)	-0.000	*	-0.000		-0.000		-0.000		-0.000	*
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Level of education										
Post-secondary non tertiary education (ISCED 4)	0.006		-0.002		-0.007		-0.052		-0.090	
	(0.087)		(0.094)		(0.095)		(0.087)		(0.070)	
Short-cycle tertiary education (ISCED 5)	0.098		0.109		0.086		0.005		0.010	
	(0.079)		(0.080)		(0.071)		(0.061)		(0.065)	
Bachelor’s or equivalent level (ISCED 6)	0.089		0.092		0.073		-0.027		-0.010	
	(0.064)		(0.069)		(0.078)		(0.070)		(0.063)	
Master’s or equivalent level (ISCED 7)	0.175	**	0.176	**	0.132	*	-0.051		-0.045	
	(0.058)		(0.062)		(0.067)		(0.056)		(0.050)	
Doctoral or equivalent level (ISCED 8)	0.540	***	0.543	***	0.513	***	0.243	*	0.199	
(ref: Upper secondary education - ISCED 3)	(0.084)		(0.082)		(0.076)		(0.112)		(0.105)	
Tenure										
Between 1 month and 5 months			-0.384	***	-0.368	***	-0.448	***	-0.381	***
			(0.073)		(0.076)		(0.095)		(0.096)	
Between 6 months and 11 months			-0.371	***	-0.298	***	-0.428	***	-0.338	**
			(0.090)		(0.089)		(0.091)		(0.122)	
Between a year and 5 years			-0.030		-0.002		-0.149	*	-0.085	
			(0.064)		(0.061)		(0.069)		(0.089)	
Between 6 years and 40 years			0.122	*	0.165	**	-0.032		-0.003	
(ref: Less than a month)			(0.062)		(0.059)		(0.056)		(0.079)	
Job complexity (index)										
low							0.138		0.106	
							(0.070)		(0.077)	
medium							0.193	*	0.117	
							(0.076)		(0.093)	
high							0.202	*	0.132	
(ref: very low)							(0.082)		(0.091)	
Job-skill requirements (index)										

low							0.556	***	0.502	***
							(0.072)		(0.100)	
medium							1.136	***	1.023	***
							(0.073)		(0.110)	
high							1.802	***	1.707	***
(ref: very low)							(0.108)		(0.141)	
Performance-related pay									0.664	***
									(0.053)	
Occupation dummies (ISCO)					x		x		x	
Sector dummies (NACE)					x		x		x	
Country dummies	x		x		x		x		x	
Number of observations	37321		36947		36753		36753		25103	
Pseudo R-squared	0.07		0.07		0.10		0.22		0.28	

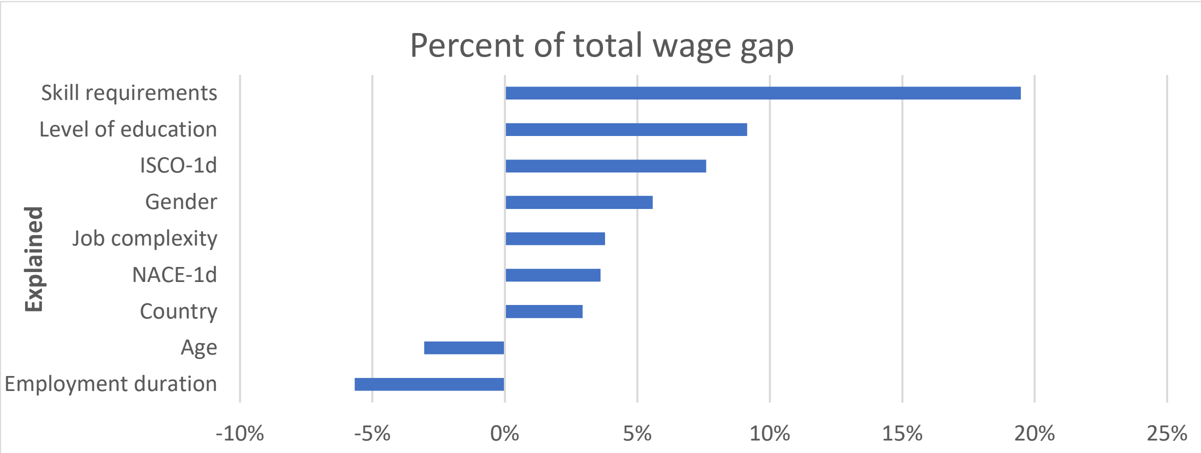
NB: Probit regressions with dependent variable equal to one if an adult worker is an AI programmer and zero otherwise. Specifications (1)-(5) gradually include control variables as described in the main text. The construction of the job complexity and job-skill requirements indices is described in Cedefop (2024a). *** p<.001, ** p<.01, * p<.05; Robust standard errors in parenthesis, clustered at country level.
Source: Cedefop second European skills and jobs survey (ESJS2)

Table A2 **Wage distributions, AI and non-AI programmers**

	Hourly wage						
	mean	sd	skewness	kurtosis	p25	p75	iqr
Non-programmers	12.368	10.066	3.758	26.657	6.383	14.936	8.553
Non-AI programmers	15.605	14.035	3.649	21.090	8.114	18.476	10.361
AI programmers	17.062	15.491	2.644	12.146	8.083	20.329	12.246
Total	12.976	11.019	3.713	24.657	6.672	15.396	8.725
Observations	37393						

Source: Cedefop second European skills and jobs survey (ESJS2)

Figure A1 **Percentage contributions of predictors to the explained component**



NB: OB decomposition of equation (1) using the log hourly wage as dependent variable and specification (4). The construction of the job complexity and job-skill requirements indices is described in Cedefop (2024a). The detailed decomposition is subsumed by sets of covariates. *** p<.001, ** p<.01, * p<.05; Robust standard errors in parenthesis.
Source: Cedefop second European skills and jobs survey (ESJS2)