Workplace Coordinated Income Settings Moderate the Effect of Computers on Earnings – But Less so for Highly Paid Employees

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Abstract

Linking institutional theories of income setting with computer usage, we examine whether income coordination in large firms or through collective agreements moderates the impact of computers on individual earnings. We analyze linked employer–employee data from the European Structure of Earnings Survey (ESES) for the year 2014 matched to data on occupational computer usage from the Programme for the International Assessment of Adult Competencies (PIAAC). The results show that, as expected, the average computer premium is lower in large firms and in firms covered by a collective agreement, while highly paid workers enjoy higher returns for using computers at work in large and, surprisingly, covered firms. We conclude by suggesting that higher rewards for computer usage in large and covered firms for those at the high end of the earnings scale may be the result of sorting into highly paid workplaces or flexible pay practices that have also become more prevalent in unionized workplaces.

Keywords: labor unions, firm size, computerization, linked employer–employee data, workplace inequality

Introduction

The diffusion of computer-based technologies is one of the main explanations for rising earnings inequality in many industrialized countries, and this has been supported by abundant evidence of the positive relations between computerization and earnings inequality. This relationship has been found at the country (Machin/Van Reenen 1998), industrial (Autor/Katz/Krueger 1998; Michaels/Natraj/Van Reenen 2014), occupational (Autor/Levy/Murnane 2003), workplace (Bresnahan/Brynjolfsson/Hitt 2002), and individual

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(Dolton/Pelkonen 2008; Krueger 1993; Spitz-Oener 2008) levels. The canonical thesis regarding why computerization is positively related to rising inequality argues that technological changes increase productivity differences among workers (Acemoglu/Autor 2011). Employees in occupations adopting new technologies can increase their productivity and earn higher wage premiums than others (Acemoglu 1998; Goldin/Katz 2018; Juhn/Murphy/Pierce 1993; Krueger 1993). This is known as skill-biased technological change (SBTC), as gains primarily benefit high-skilled workers, contributing toan increase in earnings inequality. An alternative explanation is routine-biased technological change (RBTC) (Autor et al. 2003), which emphasizes the substitution of routine tasks in middle-skilled jobs leading to wage polarization: high-skilled workers gain, while middle-skilled positions shrink, further amplifying earnings inequality. Both perspectives highlight the central role of skills and tasks, as well as shifts in their demand, suggesting a universal pattern across workplaces and countries. However, the increasing inequality has not been uniform across countries. Recent studies show that the impact of computerization on earnings is lower in countries with coordinated industrial relations systems, while Anglo-Saxon countries experience particularly high income inequality (Hope/Martelli 2019; Kristal/Edler 2021). Here we take the question of whether institutions can moderate the effect of computers on earnings a step further by theorizing about the role of workplace coordinated settings in moderating inequality and by empirically examining the relations between computers and earnings distribution within firms. Research on the central role of workplaces in creating and moderating inequality has flourished over the last two decades. With the use of data linking employers to their employees, one of the significant and recurrent findings is that firms pay dissimilar wages to similar workers (Card/Heining/Kline 2013). Studies on the institutional features of workplaces show that those with strong coordinated wage settings advance workers' well-being (Bryson/Barth/Dale-Olsen 2013; Fitzenberger/ Kohn/Lembcke 2013) and moderate the level of income inequality (Hirsch/Mueller 2020; Kristal/Cohen/Navot 2020; Melzer et al. 2018; Ochsenfeld 2018; Schweiker/Groß 2017). Although workplace wage-setting has not been specifically examined, findings for a particular workplace or workplaces within a specific country suggest that organizations may also play an important role in mitigating the relations between computer use and earnings. The adoption of a high-performance human resources strategy for implementing new technologies (Fernandez 2001) and helping workers adapt to software systems (Shestakofsky 2017) has been found to moderate these relations.

In this paper, we investigate the varying impact of firm characteristics on the distribution of the computer earnings premium, which indicates how much those who use a computer at work earn in comparison to similar workers who do not use a computer. Our research question is: "Does the computer earnings premium throughout the earnings distribution differ between firms depending on (a) whether the firm is covered by a collective agreement and (b) the size of the firm?" Our general argument is that the effect of computers on the earnings structure is governed by the institutional context, which shapes the income-determination norms and practices of firms. Specifically, we contend that the way collective agreements and large workplaces standardize earnings can moderate the computer earnings premium, in particular at the lower tail end and middle of the income distribution. The premium from computer use tends to increase along the wage distribution, while collective agreements reduce inequality by raising wages more at the lower and middle levels, potentially partially offsetting the unequal impact of computer use. Firm size can also moderate this effect. On the one hand, the structure of large firms with greater horizontal and vertical differentiation and internal job hierarchies (Davis/Cobb 2010; Kalleberg/Van Buren 1996) can increase within firm wage inequality, including variation in the computer earnings premium. On the other hand, the greater formalization of pay structures in larger firms (Cobb/Lin 2017) may limit wage claims associated with computer use by standardized wages.

We empirically test our argument by analyzing the individual's computer earnings premium in a representative sample of 114,759 firms and their 2,039,045 employees across 9 European countries, which enables us to examine to what extent earning inequalities related to computer use reflect a common global trend and how they are shaped by the institutional context. In particular, we compare the relationship between computer use and earnings in firms that differ in their number of employees. Additionally, for Germany and the UK, we analyze how computer use relates to earnings inequality in firms covered by collective agreements versus those that are not. The analyses are based on two sources: the employer–employee survey from the European Structure of Earnings Survey (ESES) for the year 2014 and data from the Survey of Adult Skills (PIAAC[3]). By matching these datasets and applying firm fixed-effects unconditional quantile regression, we assess whether employees in different parts of the earnings distribution benefit unequally from the computer earnings premium, and how wage coordination and firm size shape this relationship.

Workplace Coordinated Income-Setting and Earnings Inequality

Collective Agreements

One important institutional factor that contributes to shaping the compensation practices and standardizing earnings of workplaces and thereby also affecting the computer earnings premium is whether or not a workplace is covered by a collective agreement. Historically, collective agreements driven by unions and the threat of labor withdrawal, usually lead to wages that are, on average, above the market equilibrium, as unions can act as monopolistic providers of labor and serve as a collective voice for their members (Freeman/Medoff 1984). In addition to increasing wages for individual members relative to similar nonunion workers (Farber et al. 2021) and for unionized establishments in the U.S. (Frandsen 2021; Lee/Mas 2012) and Germany (Fitzenberger et al. 2013; Hirsch/Mueller 2020), unions are known to increase wages for low- and middle-wage workers more than for higher-wage workers, yielding a more equal income distribution. Firpo, Fortin and Lemieux (2009) demonstrate that union wage premium decreases as one moves from the left to the right tail of the wage distribution. Estimates based on unconditional quantile regression further show that unionization progressively increases wages in the three lower quintiles of the distribution and actually reduces wages in the top quintile.

[3] Programme for the International Assessment of Adult Competencies.

The well-known explanation for the equalizing effect of unions is that they standardize wages by reducing managerial discretion over pay and by regulating wages within collective bargaining contracts based on position and seniority (Freeman 1980), so that lower-skilled workers receive a larger premium relative to their alternative nonunion wage. A more recent explanation for why wage differences between broad skill groups tend to be compressed in the unionized sector points to selection into unionism that varies across the wage distribution (Card 1996; Hirsch/Schumacher 1998). A positive selection into unions (i.e., positive unmeasured attributes such as motivation and reliability) occurs toward the bottom of the distribution. This happens because workers in this segment are more likely to seek employment in unionized firms, while employers can avoid hiring workers from the union job queue in the lower tail of the ability distribution. By contrast, there is negative selection to union status by workers in the right-hand tail of the skill distribution, since these workers can obtain higher rewards in nonunionized workplaces. Since among low-wage workers, unmeasured skills correlate positively with union status (i.e., union members are positively selected), a positive bias arises in the union wage premium in OLS estimates for these workers. By contrast, among high-wage workers, unmeasured skills are correlated negatively with union status (i.e., union members are negatively selected), which leads to a negative bias in the union wage premium in OLS estimates for these workers.

Since collective agreements are more related to increasing earnings for low- and middle-paid workers than for their higher-paid counterparts, we expect that the average computer earnings premium (similar to other premiums on skill, high status, or powerful position) should be lower in firms covered by a collective agreement:

> *H1a: The computer earnings premium will be lower in firms covered by a collective agreement than in establishments that are not covered by a collective agreement.*

As the practices and norms of equity fostered by unionization mute the upward pressure of high-skilled workers (Freeman 1980), and since among high-wage workers unmeasured skills are correlated negatively with union status (Hirsch/Schumacher 1998) and unobserved heterogeneity is higher in unionized workplaces (Card 1996; Lemieux 1998), we further expect:

> *H1b: The computer earnings premium will be more equally distributed in firms covered by a collective agreement than in firms that are not covered by a collective agreement.*

Studies in countries characterized by pluralist industrial relations, such as the U.S. or UK, show that unionization by means of firm-level wage agreements leads to rising wages primarily for workers at the lower tail of the wage distribution (Blau/Kahn 1996) and therefore to a reduction of wage inequality within establishments (Blanchflower/Bryson 2009; Kristal 2020). Most countries in Europe have a stronger corporatist tradition than the U.S. or UK and are characterized not only by higher union density but also by strongly regulated labor markets and centralized wage-setting that lead to an overall equalized wage distribution (Visser/Checchi 2009). This is because multi-employer or sector-level bargaining and mandatory extension of collective agreements relate to lower levels of wage dispersion in corporatist countries (Addison et al. 2014; Canal Domínguez/ Gutiérrez 2004; Hirsch/Mueller 2020; King/Reichelt/Huffman 2017). In light of this, Zwysen (2023) finds that central agreements contribute to lower wage inequality within and between firms, in comparison to firms without agreements or those who have firm-level agreements. We therefore expect:

> *H2a: The computer earnings premium will be lower in firms covered by a sectorial collective agreement than in firms that are covered by a firm-level collective agreement.*
>
> *H2b: The distribution of the computer earnings premium will be more equal in firms covered by a sectorial collective agreement than in firms covered by a firm-level collective agreement.*

Workplace Size

Workplace size is another institutional factor affecting compensation practices as it impacts certain internal human resource strategies and the firm's ability to pay employees.. Empirical studies report a generally positive relation between organizational size and the average wages paid by organizations to their workers across countries even when controlling for differences in workers' productivity and consequently the potential selection effects of large establishments (Bayard/Troske 1999; Janietz/Bol 2010; Kalleberg/Van Buren 1996; Ohlert 2016). A study by Cobb and Lin (2017) demonstrates that large firms not only raise average wages but also contribute to a reduction in overall wage inequality by compensating low- and middle-wage employees with a higher wage premium than smaller firms.

Larger firms pay higher average wages for various reasons, including their different resources, structure, and needs. First, their greater capital intensity and market power enable them to pay higher wages (Albæk et al. 1998; DiPrete 1990). Second, they often adopt a distinct human resource strategy, such as establishing internal labor markets that encourage employee loyalty and productivity by offering opportunities for promotion, enhanced job security, and wages that exceed market averages (Kalleberg/Van Buren 1996; Lazear/Rosen 1981; Shapiro/Stiglitz 1984). By providing these incentives, internal labor markets both motivate employees and help maintain a stable workforce, reduce turnover-related transaction costs, and enhance overall organizational stability.

But how do these differences in human resource strategies between large and small workplaces affect the firm's wage-setting and, consequently, the expected computer earning premium? In large firms, higher wages and internal labor markets reduce the need for individual wage negotiation (Sørensen/Kalleberg 1981). Workers in such "closed positions" (Sørensen 1983, 2000) are shielded from competition, which means that wage settings and career advancement are primarily governed by internal rules and hierarchies, rather than being shaped by market forces or competition, which in turn significantly reduces the role of individual negotiations. In contrast, in small firms the market mechanism leads to greater remuneration based on workers' relative performance, skills, and credentials, as well as on the broader market forces of supply and demand. With a limited pool of workers possessing computer skills,[4] those proficient in

[4] Goldin and Katz (2018) demonstrate that technological progress exceeded educational investments, resulting in a mismatch between the demand for and supply of skills, which has contributed to rising wages for skilled workers (Goldin/Katz 2018).

using computers can negotiate higher wages. We therefore expect that for workers in large firms, which are less exposed to the market mechanism, the use of a computer is rewarded less than in small firms where workers using a computer enjoy a higher competitive advantage:

H3a: The computer earning premium will be lower in large firms than in small firms.

But do all workers in large workplaces profit from higher wages? Davis and Cobb (2010) demonstrate in their study that firm size matters for the dispersion of wages within firms but also for earning inequalities on the macro level of economies. In this context the authors speak of a "paradox of hierarchy": "unequal organizations aggregate into collectively more equal societies" (p. 37). This means that, at the macroeconomic level, countries with strong employment concentration—where a large proportion of the labor force is employed by a few large firms rather than distributed across many smaller ones—tend to exhibit lower overall income inequality.[5] This results from the more formalized bureaucratic procedures and the standardized wage policies of large firms. However, this relation reverses at the workplace level. Within larger firms, there are greater differences between the top and bottom wages in the firm's internal job hierarchy leading to higher within-firm wage inequality (Davis/Cobb 2010; Kalleberg/Van Buren 1994; Van der Meer/Wielers 1998). In this context, we also expect greater within-firm inequalities in the computer earnings premium in large firms compared to smaller ones. In large firms, which typically have a more heterogeneous workforce than their smaller counterparts, human resource practices differ systematically across the wage distribution, resulting in distinct compensation mechanisms, depending on the position of employees in the hierarchy. The computer earnings premium is expected to be smaller for workers in the middle and at the bottom of the wage distribution. This is because formalized bureaucratic wage-setting in large firms can mitigate earnings inequality, particularly at the lower end of the earnings distribution. Research has shown, for instance, that policies that formalize personnel systems are associated with reduced wage inequality (Huffman/King/Reichelt 2017). Conversely, employees at the higher end of the earning structure often benefit more from performance-based pay systems (Lemieux/MacLeod/ Parent 2009) or profit-sharing schemes (Schweiker/Groß 2017). In the case of the latter, higher rents from profit-sharing schemes may not necessarily reflect increased productivity, but rather the stronger bargaining power of high-ranking employees who can secure higher earnings (Schweiker/Groß 2017).

Against this background, we expect that individuals at the upper end of the wage structure can leverage their computer skills to make higher wage claims, whereas at the lower end, more standardized, coordinated wage settings lead to lower computer earning premiums:

H3b: The computer earning premium is expected to be more unequally distributed in large than in small firms, with individuals at the upper end of the wage structure earning the highest computer earning premium.

[5] Conversely, in countries with lower employment concentration, earning inequality is higher. Further research indicates that the rise in earnings inequality at the macroeconomic level is more significantly driven by inequalities between firms rather than within them (Tomaskovic-Devey et al. 2020; Zwysen 2023; Song et al. 2019; Barth et al. 2016). Research on financialization identifies factors such as downsizing, outsourcing, offshoring, and subcontracting as critical drivers of increasing earnings inequality (Beyer 2018; Köhler et al. 2018). These changes result in greater internal homogeneity within firms while increasing differentiation between them, leading to a division of high and low earners across workplaces (Godechot et al. 2024).

Data and Variables

We empirically test our argument that collective agreements and large workplaces moderate the computer earnings premium by analyzing an individual's computer earnings premium for firms covered and not covered by collective agreements in the UK and Germany, and for firms that differ in size in these and seven additional European countries. Our main data source is the large, matched employer–employee dataset from the European Structure of Earnings Survey (ESES) for the year 2014. The ESES is a large enterprise[6] survey, conducted in the Member States of the European Union (EU), in EU candidate countries, and in European Free Trade Association (EFTA) countries. Of the 24 countries whose data is available in the ESES, we exclude post-socialist economies and countries that are not covered by the PIAAC. The remaining nine countries in our analyses are Belgium, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, and the UK.

The sampling procedure of the ESES data was carried out in two stages. In the first stage, firms with more than ten employees in the private nonagricultural sector were selected in each country according to region, group size, and economic sector.[7] In the second, these firms reported data on a random sample of their workers. Therefore, our sample includes only firms with more than 10 employees in the private nonagricultural sector. The sample is furthermore restricted to workers aged 20 or older. As we estimate firm fixed-effect models, we additionally restricted our sample to firms for which employers reported information on at least 5 employees. On average, this leads to around 7 observations per firm (see the marked row in Appendix A).[8]

The matched employer–employee ESES data allows us to study how firm features affect the earning returns of their employees. Another advantage of the ESES data is that the survey provides comparable and harmonized data on hourly gross earnings before any tax and social security contributions are deducted. Hourly gross earnings refer to wages and salaries and are defined as gross earnings in the reference month divided by the number of hours paid during the same period. The number of hours paid includes all normal and overtime hours worked and remunerated by the employer during the reference month. The ESES records the earnings actually received by an employee of a business in the reference month and year. Employees are all persons who have a direct employment contract with the enterprise or local unit and receive remuneration, irrespective of the type of work performed, the number of hours worked (full- or part-time) or the duration of their contract (fixed or indefinite). The survey also collects information on individual characteristics of employees (sex, age, educational level, occupation, tenure, part-time employment, type of employment contract) and their employer (size of the firm, collective pay agreement, economic activity, and form of economic and financial control).

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[6] An enterprise is a firm or a combination of firms that engages in economic activities which are classified into multiple industries.

[7] The most commonly used source as the sampling frame is the business register. In the UK no sampling is done; the data on ESES 2014 are based on administrative data.

[8] For robustness, we also estimated models for firms for which employers reported information on at least 10 employees. The findings are similar to those reported in Tables 2and 3.

In all the analyses we use the grossing-up factor for employees included in the database.[9] Table 1 presents descriptive statistics for all variables used in the analyses.

Because the ESES data does not include information on employees' computer use, we matched the probability of computer use from PIAAC to the ESES data at the occupational level and used it as a measure for employees' computer use in the workplace. The PIAAC data is a cross-sectional sample on adult competencies and skills used at home and in the workplace of an assortment of developed countries (2011–2019). The nine countries included in our analyses participated in the first-round data collection, conducted in 2011–2012 by the OECD. Using a computer at work is a dummy variable in PIAAC based on the survey question "Do you use a computer in your job?" "Computer" is broadly defined, covering a mainframe, desktop, or laptop computer or any other device that can be used to do such things as send or receive email messages, process data or text, or find things on the Internet.

[9] The grossing-up factor for employees in the ESES data is calculated by the number of employees in the population divided by the number of employees in the sample. By weighting the analyses with this grossing-up factor for employees, we obtain population estimates of the total number of employees and their aggregate earnings.

Table 1. Descriptive statistics of mean values relevant variables by country, 2014

	Italy	Spain	UK	Netherlands	Belgium	France	Germany	Norway	Sweden
Individual-level									
Hourly wages (Euro)	15.69	11.36	23.26	19.04	18.66	18.23	17.54	31.26	21.59
Probability of computer use in occupation[a]	0.79	0.78	.80	0.82	0.81	0.81	0.80	0.84	0.85
Male	0.58	0.54	0.61	0.61	0.57	0.59	0.53	0.62	0.61
Age: 20 - 29	0.10	0.13	0.22	0.25	0.19	0.15	0.16	0.24	0.22
Age: 30 - 39	0.28	0.34	0.27	0.22	0.26	0.27	0.21	0.24	0.24
Age: 40 - 49	0.35	0.30	0.26	0.26	0.29	0.29	0.27	0.25	0.26
Age: 50 - 59	0.24	0.19	0.20	0.21	0.23	0.24	0.26	0.19	0.20
Age: 60 and older	0.03	0.05	0.06	0.07	0.03	0.05	0.10	0.08	0.07
Basic education	0.29	0.43	0.16	0.16	0.30	0.19	0.11	0.27	0.11
Secondary education	0.47	0.23	0.38	0.41	0.39	0.40	0.71	0.42	0.62
Tertiary education	0.24	0.34	0.47	0.43	0.32	0.40	0.18	0.31	0.28
Tenure(in decades)	9.01	9.09	7.64	10.41	9.27	10.77	9.21	9.60	7.00
Permanent contract	0.88	0.82	0.90	0.71	0.89	0.95	0.88	0.97	-
Full-time job	0.78	0.77	0.83	0.53	0.74	0.84	0.62	0.78	0.82
Firm-level									
Collective agreement	-	-	0.43	-	-	-	0.42	-	-
Coll. agreement: Industry level	-	-	0.12	-	-	-	0.26	-	-
Coll. agreement: Company level	-	-	0.28	-	-	-	0.07	-	-
Firm size: > 250 people	0.65	0.42	0.97	0.83	0.65	0.53	0.37	0.44	0.44
N (without grossing-up factor)	67,718	150,817	23,755	41,550	96,059	167,996	607,961	757,067	126,122
N of firms (without grossing-up factor)	5,639	13,157	2,371	2,483	5,155	15,172	39,141	27,749	3,892
N (calculated with grossing-up factor)	2,553,518	6,331,320	3,437,516	2,187,362	1,726,792	8,274,446	24,779,008	1,794,588	1,997,650
N of firms (calculated with grossing-up factor)	279,112	640,044	342,968	128,846	72,732	1,051,528	1,760,978	79,740	93,420

Sample restrictions: Workers (1) aged 20 - 65, (2) in the private sector, (3) in firms with >= 5 employees in the sample.

[a] *occupational classification ISCO02 (2-digit) are used*

On the basis of the PIAAC data, we calculated the probability of computer use at work in the different occupations and countries by using logistic regression. To achieve better compatibility between the two data sources, we restricted our data in the same way to only workers aged between 20 and 65 years who are employed in the private nonagricultural sector. We used the 2-digit International Standard Classification of Occupations (ISCO) occupational class, as this is the finest-grained occupational classification available, allowing us to estimate robust probabilities per occupation within country using the PIAAC data. Appendix B presents the PIAAC sample sizes by occupation and country and Appendix C shows the probabilities of computer use by occupation and country. Since the sampling of the PIAAC data collection is complex and varies by country, we use the sampling designs' replication weights[10] for the estimation of the probabilities of computer use at work by occupation and country to secure representability.[11] The range is between 0.69 (low probability of using a computer at work) and 0.98 (high probability of using a computer at work). As a robustness check, we compared the mean probability of computer use after matching the ESES data with the mean probability of the PIAAC data and found similar probability levels across the datasets. Furthermore, we replaced the probability by using the odds ratio as well as the percentage of computer use and found very similar results when we reran all the analyses (data not shown).[12]

Workplace Covariates

Most importantly, for the current research, the ESES includes information on whether the workplace is covered by a collective pay agreement, and if so, which kind (national, industrial, local), as well as information on the size of the firm (up to 250 employees, larger than 250 employees). Besides the UK and Germany, all countries in the ESES data feature almost full coverage of collective agreements of firms in the private sector, which makes it impossible to study the differences in the effect of computer use on wages between firms covered and not covered by a collective agreement for these countries. We therefore test the effect of computer use on earnings in firms covered and not covered by a collective agreement in Germany and the UK only.

Germany and the UK differ considerably in the prevailing type of collective agreement: In Germany, the most common form of collective agreement is at the sectorial level ("*Fleachentarifvertrag*"), whereas in the UK a firm-level collective agreement is the most common form (Schnabel/Zagelmeyer/Kohaut 2006).[13] In Germany, unions are seen as a social

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[10] This is done by using the PIAAC "repest" macro tool developed by the OECD.

[11] Following the estimation of the odds ratio we transformed the odds ratio to probability between 0 and 1. To convert odds to probability, we divide the odds by one plus the odds. For example, to convert odds of 1/9 to probability, 1/9 has to be divided by 10/9, yielding a probability of 0.10.

[12] To make sure that the findings for computer use measured at the occupation level are not severely biased by capturing additional other features of occupations, we additionally estimate the interaction between firm size and computer use employing the PIAAC data in which computer use is measured at the individual level. The results (not shown) are similar to those presented in Table 3.

[13] Large firms are strongly oversampled in the ESES data for the UK, which might explain the relatively high share of workers covered by collective agreements in the ESES data (42%) as compared to other sources (28% in Visser 2016).

partner within a consensus-based industrial relations framework in industry-wide bargaining. Bargaining, therefore, is traditionally conducted between sectoral unions and employers' organizations, and collective agreements almost always apply to all of the covered firms' workers irrespective of the union status of the latter. Even though the share of firms covered by a sectoral agreement has declined, especially due to newly founded firms that are uncovered or covered by a firm-level agreement (Addison et al. 2014; Addison et al. 2017; Kohaut/Ellguth 2008), sectoral agreements ("*Fleachentarifvertrag*") still serve as a reference point for wage-setting in noncovered firms and in firms covered at the firm level, showing positive spillover effects (Fitzenberger et al. 2013). Since the 2000s, by invoking "opening clauses," German establishments have had the opportunity to use supplementary company agreements that allow performance-oriented remuneration (Addison et al. 2017).

In contrast to Germany, in the UK unions are free to act in relatively adversarial fashion, and collective bargaining coverage at the firm level depends on trade union density. In other words, in the UK the decision to engage in bargaining is voluntary and in firms that lack workers' representation there is usually no collective agreement in force. Despite the dramatic decline in union membership during the 1980s and 1990s, unions continue to play an important role at the workplace: lowering quit rates; achieving wage and fringe benefit premiums for their members; and continuing to compress wage differentials (Bryson/Forth 2011). Lower wage dispersion in unionized workplaces arises both because unions raise the wages of the lowest-paid and also because they encourage the use of more objective criteria in pay-setting. Nonetheless, performance-related pay jobs are more likely to be unionized and in larger organizations, contributing substantially to higher wage dispersion, especially at the upper tail of the distribution (Bryan/Bryson 2016).

Method

To analyze how and to what extent collective agreements and firm size interact with the computer earnings premium along the earnings distribution, fixed-effects unconditional quantile regressions at the individual level are estimated by utilizing the recentered influence function (RIF). In comparison to conventional hierarchical models that use random effect estimators, this model has the advantage of controlling for (observed and unobserved) firm-fixed effects by removing all firm-level heterogeneity. We therefore do not have to concern ourselves with relevant missing firm factors that might lead to biased estimates (Allison 2009). In our case, this also means that firm factors such as the size of the firm along with the (type of) collective agreement cannot be directly included as independent variables in the models. To still be able to test our hypotheses, we estimate models in which we add the interaction effects of the probability of using a computer in an occupation and (a) (type of) collective agreement as well as (b) firm size, respectively, to measure the impact of firm-level characteristics on within-firm earning inequalities.

The unconditional quantile regressions enable us to study whether the interaction effects of the probability of computer use in an occupation and the firm variables change at different levels of earnings distribution. Unlike conditional quantile regression, which is the traditional method used in earlier research and only focuses on within-group variation, unconditional quantile regression allows us to compare workers with different values on the control variables. More specifically, we use this method to examine whether the probability of computer use in an occupation and its interaction with the firm variables have a different impact on earnings depending on where workers are located along the earnings distribution. To calculate the fixed-effects (FE) unconditional quantile regressions, we follow Borgen (2016) and use the FE estimator on the recentered influence function (RIF) transformed dependent variable, introduced into the econometric literature by Firpo et al. (2009).[14] We calculate these models separately by country to identify whether there is an all-embracing tendency in the impact of the organizational features of firms on the computer earnings premium in the selected European countries, or if noticeable differences can be discovered.

Results

The aim of our analyses is to examine whether workers' earnings premium in occupations with a higher probability of computer use at work is smaller in firms with coordinated wage-setting, particularly in those covered by a collective agreement or that are large. To this end, we estimate an unconditional quantile regression with firm fixed effects. Using this method, we investigate whether the computer earnings premium in firms with and without a collective agreement and in both large and small firms behaves similarly at the 10th, 25th, 50th, 75th and 90th percentiles of the workers' logged earnings distribution. Our dependent variable is log hourly earnings, and as control variables at the individual level we use gender, age, education (three categories: basic, secondary, and tertiary), tenure (in decades), permanent contract, and full-time job.
Table 2 presents the results for collective agreements in Germany and the UK. It shows the results of the interaction between "probability of computer use" and "collective agreement" as well as "probability of computer use" and "type of collective agreement" along the unconditional distribution of earnings. We also report the coefficients for gender (male) and tertiary education. Evidently, the earnings premium associated with working in occupations that have a higher likelihood of computer use, as well as with tertiary education and being male, increases along the income distribution, which explains part of the inequality of earnings within firms.

A first look at the data shows that, similarly to tertiary education, using a computer at work has the largest effects at the upper end of the wage distribution. At the lower end, the effect is smaller.[15]

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[14] As stata command -xtrifreg- (Borgen 2016) is used. It is implemented as a wrapper around the rifreg command developed by Firpo, Fortin, and Lemieux (2009) and the xtreg command.

[15] This pattern is consistent with the skill-biased technological change (SBTC) hypothesis discussed in the introduction, because the computer wage premium is higher at the top end of the wage distribution, where high-skill tasks are more common. At the middle of the wage distribution, where routine tasks are more prevalent, the computer wage premium is lower. However, there is no clear evidence of wage polarization, as the computer wage premium does not increase at the lower end of the wage distribution, which would have been expected according to the predictions of the routine-biased technological change (RBTC) hypothesis.

Table 2. Unconditional FE quantile regression of collective agreement on computer earning premium using the recentered influence function, dependent variable: log hourly wages

	Percentiles	***10***	***25***	***50***	***75***	***90***
UK	Computer use	0.601*** (0.003)	1.249*** (0.004)	1.729*** (0.005)	1.722*** (0.006)	1.454*** (0.010)
	Computer use * collective agreement	-0.369*** (0.004)	-0.274*** (0.006)	0.241*** (0.008)	-0.102*** (0.010)	-0.136*** (0.014)
	Male	0.017*** (0.001)	0.055*** (0.001)	0.101*** (0.001)	0.153*** (0.001)	0.220*** (0.001)
	Tertiary education	0.027*** (0.001)	0.097*** (0.001)	0.146*** (0.001)	0.147*** (0.001)	0.054*** (0.002)
UK	Computer use	0.582*** (0.002)	1.250*** (0.004)	1.765*** (0.005)	1.707*** (0.006)	1.437*** (0.010)
	Computer use * company agreement	-0.333*** (0.004)	-0.467*** (0.007)	-0.007 (0.009)	0.265*** (0.011)	0.344*** (0.016)
	Computer use * industry agreement	-0.363*** (0.006)	0.151*** (0.011)	0.586*** (0.014)	-0.911*** (0.016)	-1.220*** (0.016)
	Male	0.027*** (0.001)	0.097*** (0.001)	0.147*** (0.001)	0.147*** (0.001)	0.054*** (0.002)
	Tertiary education	0.017*** (0.001)	0.054*** (0.001)	0.101*** (0.001)	0.153*** (0.001)	0.221*** (0.001)
Germany	Computer use	0.564*** (0.002)	0.862*** (0.002)	0.922*** (0.002)	1.215*** (0.003)	1.530*** (0.006)
	Computer use * collective agreement	-0.485*** (0.002)	-0.615*** (0.003)	-0.525*** (0.003)	0.009* (0.005)	2.178*** (0.010)
	Male	0.009*** (0.000)	0.030*** (0.000)	0.064*** (0.000)	0.146*** (0.000)	0.260*** (0.000)
	Tertiary education	0.093*** (0.000)	0.182*** (0.000)	0.308*** (0.000)	0.484*** (0.000)	0.652*** (0.001)
Germany	Computer use	0.469*** (0.002)	0.712*** (0.002)	0.764*** (0.002)	1.191*** (0.003)	2.021*** (0.006)
	Computer use * company agreement	-0.449*** (0.004)	-0.447*** (0.005)	0.303*** (0.006)	0.321*** (0.010)	0.397*** (0.020)
	Computer use * industry agreement	-0.345*** (0.003)	-0.350*** (0.003)	-0.356*** (0.003)	0.030*** (0.006)	1.714*** (0.012)
	Male	0.092*** (0.000)	0.180*** (0.000)	0.307*** (0.000)	0.484*** (0.000)	0.657*** (0.001)
	Tertiary education	0.009*** (0.000)	0.030*** (0.000)	0.063*** (0.000)	0.146*** (0.000)	0.262*** (0.000)

Sample weights are applied. The coefficients are followed by robust standard errors in parentheses.
** $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$*
Source: Authors' calculations of the PIAAC and ESES data.
Notes: The analysis covers wage and salary workers (1) aged 20–65 years (2) in the private sector, (3) in firms with 5 or more employees in the sample. Controls include: age: 30 – 39, age: 40 – 49, age: 50 – 59, age: >=60, secondary education, tenure (in decades), permanent contract, fulltime job

Can a collective agreement moderate the unequal effect of computers on earnings?

In line with hypothesis 1a, for both the UK and Germany, the computer earnings premium tends to be lower in firms covered by a collective agreement than in those not covered by one. At most of the percentiles of the workers' logged earnings distribution, collective agreement weakens the relations between computer usage and earnings. As regards our hypothesis 1b that the computer earnings premium is more equally distributed in firms covered by collective agreements, the results are mixed. The computer earnings premium is indeed more equally distributed at the lower tail of the distribution in covered firms in Germany (10th–50th quantile) and in covered firms in the UK (10th–25th quantile). For top earners, however, at the upper tail of the distribution (50th–90th quantile), the computer earnings premium is higher in covered firms in Germany, but not in the UK. Upon consideration of the different types of collective agreement, the picture becomes clearer. Regarding H2a and H2b, the results mostly show a different pattern than hypothesized. While in Germany both sectoral and local agreements increase equality of the computer premium at the lower tail of the earnings distribution, but not at the upper tail, the pattern in the UK depends on the type of agreement. For firms covered by local agreements, which represent the common level of collective bargaining in the UK, the pattern is similar: Local agreements relate to a more equal distribution of the computer premium at the lower tail of the earnings distribution, but not at the upper tail. An explanation for these findings could be that workers in positions at the high end of the earnings distribution are more often in jobs where they benefit less from the union earnings premium and more from performance-based pay (Bryan/Bryson 2016; Fitzenberger et al. 2013). As highly paid workers are mainly in positions with more information exchanges, better access to knowledge and job control, they can use this positional power coupled with the use of a computer at work to make them indispensable and raise their relative earnings by claiming higher pay for performance.

To examine the returns for using a computer at work in large firms throughout the earnings structure, we run the same firm fixed-effects unconditional quantile regression models, including the interaction between "probability of computer use" and "firm size." The results are shown in Table 3. In line with hypothesis 3a, for most percentiles in all countries we find that the computer earnings premium is lower in large firms (Table 3 shows this by the negative coefficients of the interaction term between "probability of computer use" and "large firm").

Table 3. Unconditional FE quantile regression of firm size on computer earning premium using the recentered influence function, dependent variable: log hourly wages

	Percentiles	***10***	***25***	***50***	***75***	***90***
Italy	Computer use	0.084*** (0.004)	0.321*** (0.005)	0.615*** (0.007)	1.352*** (0.013)	1.998*** (0.020)
	Computer use * large firm	0.124*** (0.005)	-0.088*** (0.006)	0.089*** (0.009)	-0.055*** (0.017)	-0.333*** (0.026)
	Male	0.019*** (0.000)	0.043*** (0.001)	0.081*** (0.000)	0.206*** (0.001)	0.318*** (0.001)
	Tertiary education	0.088*** (0.001)	0.011*** (0.001)	0.210*** (0.001)	0.422*** (0.001)	0.513*** (0.002)
Spain	Computer use	0.115*** (0.003)	0.251*** (0.003)	0.736*** (0.004)	1.784*** (0.007)	2.259*** (0.010)
	Computer use * large firm	-0.030*** (0.004)	-0.094*** (0.004)	-0.194*** (0.006)	0.037*** (0.011)	0.524*** (0.016)
	Male	0.050*** (0.000)	0.073*** (0.000)	0.124*** (0.000)	0.182*** (0.001)	0.203*** (0.001)
	Tertiary education	0.095*** (0.001)	0.143*** (0.000)	0.258*** (0.001)	0.324*** (0.001)	0.288*** (0.001)
UK	Computer use	0.645*** (0.019)	1.504*** (0.028)	1.977*** (0.028)	0.862*** (0.025)	0.981*** (0.032)
	Computer use * large firm	-0.198*** (0.019)	-0.373*** (0.028)	-0.153*** (0.028)	0.836*** (0.026)	0.426*** (0.032)
	Male	0.018*** (0.001)	0.055*** (0.001)	0.101*** (0.001)	0.152*** (0.001)	0.220*** (0.001)
	Tertiary education	0.025*** (0.001)	0.095*** (0.001)	0.148*** (0.001)	0.148*** (0.001)	0.053*** (0.002)
Netherlands	Computer use	0.144*** (0.007)	0.425*** (0.008)	1.108*** (0.012)	1.985*** (0.018)	0.972*** (0.025)
	Computer use * large firm	0.110*** (0.007)	-0.013 (0.008)	-0.103*** (0.013)	-0.102*** (0.019)	0.583*** (0.028)
	Male	-0.026*** (0.001)	0.015*** (0.001)	0.083*** (0.001)	0.174*** (0.001)	0.199*** (0.001)
	Tertiary education	0.005*** (0.001)	0.085*** (0.001)	0.272*** (0.001)	0.438*** (0.001)	0.427*** (0.002)
Belgium	Computer use	0.399*** (0.005)	0.574*** (0.005)	0.832*** (0.006)	0.979*** (0.010)	2.105*** (0.021)
	Computer use * large firm	-0.117*** (0.006)	-0.091*** (0.006)	-0.082*** (0.006)	0.234*** (0.012)	0.663*** (0.026)
	Male	0.006*** (0.001)	0.023*** (0.000)	0.034*** (0.000)	0.076*** (0.001)	0.163*** (0.001)
	Tertiary education	0.063*** (0.001)	0.166*** (0.001)	0.258*** (0.001)	0.704*** (0.001)	0.636*** (0.002)
France	Computer use	0.314*** (0.003)	0.749*** (0.003)	1.637*** (0.004)	2.918*** (0.006)	3.421*** (0.012)
	Computer use * large firm	-0.204*** (0.003)	-0.437*** (0.004)	-0.594*** (0.004)	-0.386*** (0.008)	0.368*** (0.016)
	Male	0.035*** (0.000)	0.061*** (0.000)	0.094*** (0.000)	0.163*** (0.000)	0.266*** (0.001)
	Tertiary education	0.127*** (0.000)	0.200*** (0.000)	0.271*** (0.000)	0.278*** (0.001)	0.312*** (0.001)
Germany	Computer use	0.573*** (0.002)	0.918*** (0.002)	1.003*** (0.002)	1.307*** (0.003)	1.544*** (0.005)
	Computer use * large firm	-0.501*** (0.003)	-0.739*** (0.003)	-0.709*** (0.003)	-0.206*** (0.005)	2.121*** (0.010)
	Male	0.010*** (0.000)	0.032*** (0.000)	0.065*** (0.000)	0.147*** (0.000)	0.256*** (0.000)
	Tertiary education	0.093*** (0.000)	0.181*** (0.000)	0.308*** (0.000)	0.485*** (0.000)	0.654*** (0.001)

Norway	Computer use	0.329*** (0.006)	0.663*** (0.005)	1.353*** (0.008)	2.590*** (0.016)	2.401*** (0.024)
	Computer use * large firm	-0.218*** (0.008)	-0.380*** (0.007)	-0.472*** (0.011)	0.065*** (0.023)	1.210*** (0.038)
	Male	0.011*** (0.001)	0.029*** (0.000)	0.086*** (0.001)	0.203*** (0.001)	0.245*** (0.001)
	Tertiary education	0.059*** (0.001)	0.090*** (0.001)	0.159*** (0.001)	0.236*** (0.001)	0.242*** (0.002)
Sweden	Computer use	0.454*** (0.006)	0.610*** (0.005)	1.176*** (0.007)	2.488*** (0.013)	3.069*** (0.025)
	Computer use * large firm	-0.361*** (0.007)	-0.322*** (0.006)	-0.207*** (0.009)	0.439*** (0.018)	1.686*** (0.036)
	Male	0.016*** (0.001)	0.037*** (0.000)	0.060*** (0.000)	0.115*** (0.001)	0.184*** (0.001)
	Tertiary education	0.081*** (0.001)	0.090*** (0.001)	0.112*** (0.001)	0.180*** (0.001)	0.238*** (0.002)

Sample weights are applied. The coefficients are followed by robust standard errors in parentheses.
** p < 0.1; ** p < 0.05; *** p < 0.01*
Source: Authors' calculations of the PIAAC and ESES data.
Notes: The analysis covers wage and salary workers (1) aged 20–65 years (2) in the private sector, (3) in firms with 5 or more employees in the sample. Controls include: age: 30 – 39, age: 40 – 49, age: 50 – 59, age: >=60, secondary education, tenure (in decades), permanent contract, fulltime job
Sample weights are applied. The coefficients are followed by robust standard errors in parentheses.

In line with hypothesis 3a, we find that large firms, similarly to those covered by collective agreements, relate to a more equal distribution of the computer premium at the lower tail of the earnings distribution (10th–50th quantile) but contrary to H3a, this does not hold at the upper tail (75th–90th quantile) with the Netherlands as an outlier at the lower tail and Italy following a distinct pattern. Hence, we find that the computer earnings premium for the upper part of the earnings distribution is higher in large firms than in small firms. This pattern supports hypothesis 3b. In large firms the greater differentiation of managerial and professional occupations (Kalleberg/Van Buren 1994), as well as the introduction of profit-sharing schemes (Schweiker/Groß 2017; Hanley 2011), may explain the stronger rise in the computer earnings premium for workers at the top of the earnings structure. Contrarily, the higher bureaucratic control linked to greater earnings standardization for jobs in the internal labor market may explain why the computer premium at the lower tail of the earnings distribution is more equally distributed in large firms.

Conclusion

This paper speaks to an important question in an age of rapid proliferation of new computer technologies and rising income inequality: Can institutions moderate the computer earnings premium? In order to address this question, we investigate the impact of firm coordinated wage-setting on the distribution of the computer earnings premium. Our results indicate that coordinated wage-setting, as measured by collective agreements and large-sized firms, moderates the returns to computer use for workers at the lower end and in the middle of the earnings distribution. For workers at the very top of the wage scale, we find that large firms, local agreements – and in Germany also sectoral agreements – increase the computer earnings premium. The stronger rise in the upper end of the earnings distribution in Germany can likely be attributed to "opening clauses" or rather supplementary agreements for expert workers and workers in managerial occupations. Using "opening clauses," German firms apply supplementary agreements that allow performance-oriented remuneration, which makes it possible for highly paid workers also to negotiate higher computer earning premiums. In the UK as well, more flexible working practices and compensation were recorded in many agreements in the 1990s (Dunn/Wright 1994) and possibly have come to include performance-oriented remuneration.

More generally, our findings strongly support the idea that workplaces are the location where sorting and rewarding mechanisms reside. That coordinated wage-setting moderates the impact of computer use on earnings may be a result of internal labor markets and stronger bureaucratic control, leading to higher wage standardization that restricts higher wage claims by those who use a computer at work. More flexible wage-setting at the very high end of the wage scale, such as performance-based pay, profit-sharing schemes, or opening clauses in collective wage agreements, may facilitate higher wage claims by those who work in occupations which are characterized by a higher probability of using a computer at work. Highly paid workers are not only more likely to be exempt from coordinated wage-setting, but due to their use of computers in positions with more information exchanges, better access to knowledge, and job control, they may gain more power and status, which allows them to claim higher wages. Another possible explanation for the higher rewards to computer use in large firms is sorting between firms, where high-skilled workers are increasingly employed in larger and better-paying firms, with a resulting increase in the dispersion of earnings across establishments and firms (Barth et al. 2016; Song et al. 2019; Tomaskovic-Devey et al. 2020).

Despite these insights, several limitations should be noted. Since the ESES data is not panel data, we cannot empirically distinguish whether earning differences across firms stem from coordinated pay-setting institutions or from workers with distinct unobserved abilities sorting into firms that differ in their pay-setting institutions. Another limitation concerns the measurement of computer use. Due to the lack of linked employer–employee data with information on computer use in the workplace, we rely in our analyses on a measure for employees' computer use derived from a separate dataset on adult competencies, which we matched to our employer–employee data based on the two-digit ISCO occupational classification. However, this variable[16] may capture not only computer use but also unobserved occupation-specific skills that are themselves associated with a wage premium. Future research should therefore use linked employer–employee data that provides direct measures of computer use in the workplace, allowing for a clearer disentanglement of skill heterogeneity from the effect of computer use itself.

To conclude, in this paper we make use of insights from the employment relations literature to clarify the role of computerization in the evolution of income inequality. By taking an alleged universal technological trend and showing there are institutional contingencies that matter, we

[16] Probability of computer use in occupation.

seek to contribute to the growing literature that emphasizes social and economic relations in the study of the adoption, implementation, and impact of new technologies at work (see among others Cameron/Rahman 2021; Kristal 2019, 2020; Litwin 2011). These and other studies provide an important lens through which to examine the relationship between new technologies, employment relations, employment practices, and income generation.

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Appendix A. Number of workers sampled in a firm, ESES 2014

	Sample restrictions: Observed employees per firm	Number of firms	Mean number of employees per firm	Median number of employees per firm
Italy	N>= 1	1,534,868	3.732	3
	N>= 5	279,112	9.126	6
	N>= 10	64,314	19.243	14
Spain	N>= 1	1,821,684	4.943	4
	N>= 5	640,044	9.834	7
	N>= 10	229,436	16.726	16
UK	N>= 1	12,437,472	1.468	1
	N>= 5	342,968	9.986	7
	N>= 10	92,182	20.459	14
Netherlands	N>= 1	2,083,908	2.304	1
	N>= 5	128,846	16.907	8
	N>= 10	48,746	33.922	17
Belgium	N>= 1	73,966	23.386	20
	N>= 5	72,732	23.742	20
	N>= 10	70,960	24.146	20
France	N>= 1	2,379,468	5.056	4
	N>= 5	1,051,528	7.964	6
	N>= 10	149,610	18.858	16
Germany	N>= 1	3,290,814	9.212	5
	N>= 5	1,760,978	15.402	9
	N>= 10	842,414	25.143	20
Norway	N>= 1	125,296	15.103	6
	N>= 5	79,740	22.491	10
	N>= 10	42,888	36.109	18
Sweden	N>= 1	104,536	19.342	11
	N>= 5	93,292	21.398	12
	N>= 10	59,406	29.611	17
Total	N>= 1	23,852,012	3.596	1
	N>= 5	4,449,240	12.459	7
	N>= 10	1,599,956	23.524	20

Appendix B. Sample sizes in PIAAC across occupations and countries

		Countries								
ISCO 1-digit	ISCO 2-digit	Belgium	France	Germany	Italy	Netherlands	Norway	Spain	Sweden	UK
Legislators, senior officials, and managers	Chief executives, senior officials and legislators	14	15	11	2	25	41	6	14	19
	Administrative and commercial managers	103	78	17	5	89	126	14	73	220
	Production and specialized services managers	73	193	87	13	179	57	39	66	187
	Hospitality, retail and other services managers	8	41	9	5	46	23	16	20	112
	Missing values	-	-	1	-	-	-	-	-	-
	Sum	*198*	*327*	*125*	*25*	*339*	*247*	*75*	*173*	*538*
Professionals	Science and engineering professionals	56	75	105	30	69	154	45	100	135
	Health professionals	122	64	48	30	102	111	82	133	67
	Teaching professionals	241	188	145	139	196	319	188	252	317
	Business and administration professionals	78	132	121	44	146	87	46	135	87
	Information and communications technology professionals	49	42	53	16	84	5	38	96	68
	Legal, social and cultural professionals	53	41	91	19	91	93	56	89	132
	Missing values	-	-	12	-	-	-	-	-	-
	Sum	*599*	*542*	*575*	*278*	*688*	*769*	*455*	*805*	*806*
Technicians and associate professionals	Science and engineering associate professionals	126	304	69	73	104	199	84	151	55
	Health associate professionals	43	71	212	52	87	114	75	39	180
	Business and administration associate professionals	212	291	247	188	236	176	63	253	221
	Legal, social, cultural and related associate professionals	47	119	45	21	112	96	30	43	92
	Information and communications technicians	21	30	24	22	13	2	6	38	51
	Missing values	-	-	-	1	-	-	-	-	-
	Sum	*449*	*815*	*597*	*357*	*552*	*587*	*258*	*524*	*599*
Clerical support workers	General and keyboard clerks	128	163	165	55	105	65	162	36	91
	Customer services clerks	59	37	51	72	85	34	74	42	172
	Numerical and material recording clerks	128	117	183	76	162	83	106	58	155
	Other clerical support workers	45	26	32	22	40	10	41	19	348
	Missing values	-	-	4	6	-	-	-	-	-
	Sum	*360*	*343*	*435*	*231*	*392*	*192*	*383*	*155*	*766*

Service and sales workers	Personal service workers	50	102	142	75	84	105	144	93	163
	Sales workers	115	167	245	121	166	204	155	112	261
	Personal care workers	133	172	113	78	157	305	75	324	433
	Protective services workers	23	62	42	23	59	25	71	32	77
	Missing values	-	-	1	-	-	-	-	-	-
	Sum	*321*	*503*	*543*	*297*	*466*	*639*	*445*	*561*	*934*
Skilled agricultural, forestry and fishery workers	Market-oriented skilled agricultural workers	8	47	24	11	17	2	20	21	18
	Market-oriented skilled forestry, fishery and hunting workers	0	4	0	3	1	5	9	7	1
	Subsistence farmers, fishers, hunters and gatherers	0	0	0	0	0	0	2	0	0
	Missing values	-	-	3	-	-	-	-	-	-
	Sum	*8*	*51*	*27*	*14*	*18*	*7*	*31*	*28*	*19*
Craft and related trades workers	Building and related trades workers, excluding electricians	104	86	118	60	61	108	83	83	53
	Metal, machinery and related trades workers	96	81	128	60	51	69	80	79	96
	Handicraft and printing workers	16	24	23	14	8	4	12	18	14
	Electrical and electronic trades workers	49	31	44	20	36	71	25	29	57
	Food processing, wood working, garment and other craft and related trades	31	49	54	44	35	5	45	14	17
	Missing values	-	-	1	4	-	-	-	-	-
	Sum	296	271	368	202	191	257	245	223	237
Plant and machine operators, and assemblers	Stationary plant and machine operators	45	115	127	72	23	50	42	63	106
	Assemblers	27	35	35	38	6	4	3	34	13
	Drivers and mobile plant operators	104	147	102	69	78	75	114	120	145
	Missing values	-	-	2	4	-	-	-	-	-
	Sum	*176*	*297*	*266*	*183*	*107*	*129*	*159*	*217*	*264*
Elementary occupations	Cleaners and helpers	121	190	72	78	72	60	142	32	185
	Agricultural, forestry and fishery laborers	4	0	4	38	11	3	42	4	5
	Laborers in mining, construction manufacturing and transport	51	89	64	58	54	8	76	20	136
	Food preparation assistants	19	22	29	11	15	19	23	17	0
	Street and related sales and service workers	4	2	0	0	0	0	1	0	0
	Refuse workers and other elementary workers	29	34	43	11	26	6	59	9	58
	Missing values	-	-	-	1	-	-	-	-	-
	Sum	*228*	*337*	*212*	*197*	*178*	*96*	*343*	*82*	*384*

In cases in which the cell size is smaller than 7, the estimation of computer use in occupations by country is based on the ISCO 1-digit.

Appendix C. Probabilities of computer use for the ISCO-2-digit occupations by country

ISCO 1-digit	ISCO 2-digit	Belgium	France	Germany	Italy	Netherlands	Norway	Spain	Sweden	UK
Legislators, senior officials, and managers	Chief executives, senior officials and legislators	0.81	0.81	0.81	*0.80*	0.81	0.85	*0.80*	0.85	0.78
	Administrative and commercial managers	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
	Production and specialized services managers	0.90	0.9	0.90	*0.90*	0.90	0.91	0.90	0.91	0.89
	Hospitality, retail and other services managers	0.81	0.81	0.81	*0.80*	0.81	0.85	0.80	0.85	0.78
Professionals	Science and engineering professionals	0.92	0.92	0.92	0.92	0.92	0.93	0.92	0.93	0.92
	Health professionals	0.85	0.85	0.85	0.84	0.85	0.87	0.84	0.87	0.83
	Teaching professionals	0.84	0.84	0.84	0.82	0.84	0.86	0.82	0.86	0.81
	Business and administration professionals	0.97	0.97	0.97	0.97	0.97	0.98	0.97	0.98	0.97
	Information and communications technology professionals	0.92	0.92	0.92	0.92	0.92	*0.93*	0.92	0.93	0.92
	Legal, social and cultural professionals	0.83	0.83	0.83	0.82	0.83	0.86	0.82	0.86	0.81
Technicians and associate professionals	Science and engineering associate professionals	0.78	0.78	0.78	0.76	0.78	0.82	0.76	0.82	0.74
	Health associate professionals	0.79	0.79	0.79	0.78	0.79	0.83	0.78	0.83	0.75
	Business and administration associate professionals	0.75	0.75	0.75	0.72	0.75	0.80	0.72	0.80	0.69
	Legal, social, cultural and related associate professionals	0.78	0.78	0.78	0.76	0.78	0.82	0.76	0.82	0.74
	Information and communications technicians	0.96	0.96	0.96	0.96	0.96	*0.96*	*0.96*	0.96	0.96
Clerical support workers	General and keyboard clerks	0.90	0.90	0.90	0.90	0.90	0.91	0.90	0.91	0.89
	Customer services clerks	0.84	0.84	0.84	0.83	0.84	0.86	0.83	0.86	0.82
	Numerical and material recording clerks	0.83	0.83	0.83	0.82	0.83	0.86	0.82	0.86	0.81
	Other clerical support workers	0.79	0.79	0.79	0.77	0.79	0.83	0.77	0.83	0.74
Service and sales workers	Personal service workers	0.76	0.76	0.76	0.73	0.76	0.81	0.73	0.81	0.70
	Sales workers	0.77	0.77	0.77	0.75	0.77	0.82	0.75	0.82	0.72
	Personal care workers	*0.76*	*0.76*	*0.76*	*0.73*	*0.76*	*0.81*	*0.73*	0.81	*0.70*
	Protective services workers	*0.78*	*0.78*	*0.76*	*0.75*	*0.78*	*0.82*	*0.75*	*0.82*	*0.73*
Skilled agricultural, forestry and fishery workers	Market-oriented skilled agricultural workers	*0.75*	0.75	0.75	0.73	0.75	*0.81*	0.73	0.81	0.70
	Market-oriented skilled forestry, fishery and hunting workers	*0.75*	*0.76*	*0.75*	*0.73*	*0.76*	*0.81*	0.73	0.81	*0.70*
	Subsistence farmers, fishers, hunters and gatherers	*0.75*	*0.76*	*0.75*	*0.73*	*0.76*	*0.81*	*0.73*	*0.81*	*0.70*

Craft and related trades workers	Building and related trades workers, excluding electricians	0.75	0.75	0.75	0.73	0.75	0.81	0.73	0.81	0.69
	Metal, machinery and related trades workers	0.76	0.76	0.76	0.74	0.76	0.81	0.74	0.81	0.71
	Handicraft and printing workers	0.77	0.77	0.77	0.75	0.77	*0.82*	0.75	0.82	0.72
	Electrical and electronic trades workers	0.77	0.77	0.77	0.75	0.77	0.82	0.75	0.82	0.72
	Food processing, wood working, garment and other craft and related trades	0.76	0.76	0.76	0.73	0.76	*0.81*	0.73	0.81	0.70
Plant and machine operators, and assemblers	Stationary plant and machine operators	0.76	0.76	0.76	0.73	0.76	0.81	0.73	0.81	0.70
	Assemblers	0.76	0.76	0.76	0.73	*0.76*	*0.81*	*0.73*	0.81	0.70
	Drivers and mobile plant operators	0.76	0.76	0.76	0.73	0.76	0.81	0.73	0.81	0.70
Elementary occupations	Cleaners and helpers	0.75	0.75	0.75	0.72	0.75	0.81	0.72	0.81	0.69
	Agricultural, forestry and fishery laborers	*0.76*	*0.75*	0.75	0.72	0.75	*0.81*	0.72	*0.81*	*0.69*
	Laborers in mining, construction manufacturing and transport	0.76	0.76	0.76	0.73	0.76	0.81	0.73	0.81	0.70
	Food preparation assistants	0.75	0.75	0.75	0.73	0.75	0.81	0.73	0.81	*0.69*
	Street and related sales and service workers	*0.76*	*0.75*	*0.75*	*0.73*	*0.75*	*0.81*	*0.73*	*0.81*	*0.69*
	Refuse workers and other elementary workers	0.76	0.76	0.76	0.73	0.76	0.81	0.73	0.81	0.70

For cells with fewer than 7 observations, the estimation of computer use in occupations by country is based on the ISCO 1-digit category, shown in italics.
Source: Authors' calculations of the PIAAC data.