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Is the wage premium on using computers at work gender-specific?

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ABSTRACT

Past research on the relationship between computers and wages has revealed two stylized facts. First, workers who use a computer at work earn higher wages than similar workers who do not (termed as 'the computer wage premium'). Second, women are more likely to use a computer at work than are men. Given the recognized computer wage premium and women's advantage in computer use at work, we ask: Is the wage premium on using computers at work gender- or non-gender-specific? Given gendered processes operating at both the occupational and within-occupation levels, we expect that returns to computer usage are gender-bias. This contrasts the skill-biased technological change (SBTC) theory assumption that the theorized pathways through which computers boost earnings are non-gender-specific productivity-enhancing mechanisms. Analyzing occupational data on computer use at work from O*NET attached to the 1979–2016 Current Population Surveys (CPS) and individual-level data from the 2012 Survey of Adult Skills (PIAAC), we find that the computer wage premium is biased in favor of men at the occupation level. We conclude by suggesting that computer-based technologies relate to reproducing old forms of gender pay inequality due to gendered processes that operate mainly at the structural level (i.e., occupations) rather than at the individual level.

1. Introduction

Information technologies (IT) play a growing role in advanced labor market economies. Half a century ago, Blau and Duncan predicted, "[I]n the long run, technological progress has undoubtedly improved chances of upward mobility and will do so in the future" (1967:428). Feminist writing in the late 1990 s has also been generally positive about the possibilities of IT empowering women and reducing gender inequality, pointing to a future where the male/female dichotomy may be blurred within the zeros and ones of cyberspace (Plant, 1998; Haraway, 1997). Economists too offer an optimistic view of the relationship between technology, wages, and gender inequality, focusing on wage returns to using computers at work. According to skill-biased technological change (SBTC) theory, the more technologically skilled workers are, the more attractive they will become to employers, thus increasing their pay. Indeed, many studies have established a computer wage premium, indicating that workers who use a computer at work earn higher wages than similar workers who do not (see Kristal and Edler, 2021 for a literature review). In the US, the computer wage premium spans between 14 to 19% points (Fig. 1). The theorized pathways through which computers boost earnings, according to the SBTC thesis, are non-gender-specific productivity-enhancing mechanisms (Autor et al., 2003; Krueger, 1993). Hence, similarly to education and abstract skills, computer use should increase both men's and women's wages.[1]

We know from Krueger's (1993) pioneering study that women are more likely to use a computer at work than are men, a finding that recurs in all studies, including recent ones (see Fig. 1). Given women's advantage in computer use and the optimistic prediction suggested by Blau and Duncan (1967), Plant (1998), Haraway (1997), and the SBTC theory, we ask: Is the wage premium on using computers at work gender- or non-gender-specific? This question lies at the heart of this paper. Our overall argument is that the computer wage premium is, in part, gender-specific because gender as a status distinction can be an important mechanism whereby workers may (or may not) gain earnings advantages from using computers at work. That is to say that since gendered evaluations of competence play a critical role in employment relations (Ridgeway, 2011) and since gendered work was found to be devaluated (England, 1992; Kilbourne et al., 1994), the way new

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[1] According to the same logic, computer use should similarly affect men's and women's occupational skill requirements (but not necessarily their employment shares), see Black and Spitz-Oener (2010).

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technologies are diffused across jobs and rewarded in the labor market may be biased not only by skill (Autor et al., 2003) and class (Kristal, 2013, 2019, 2020) but also by gendered evaluations of new technologies. We, therefore, expect that using a computer at work will be more poorly rewarded in what became perceived as female-typed computer-use tasks compared to gender-neutral or male-typed computer-use tasks.

Previous literature presents mixed findings on the relationship between using computers at work, gender and wages. On one side, studies on the earlier diffusion of computers over the 1980 s show that computerization relates to an increase in the demand for women's employment (Weinberg 2000) and their relative productivity (Ding et al., 2010), and that computer wage premiums are, on average, higher for women (Brynin, 2006a; b). But a zoom-in on computer programming in recent decades suggests conflicting findings. Cheng et al. (2019) find a strong relationship between the rise of programming-intensive occupations from 1994–2015 and the endurance of the gender wage gap among college graduates. The authors explain this finding by two mechanisms: (1) men have experienced greater employment growth in programming-intensive occupations relative to women; and (2) wage returns have increased more for men than women in occupations with higher programming intensity.

Two main lacunas arise from past research. First, when workers use computers at work, they usually do it for tasks not limited to programming. For example, most workers use computers for simpler tasks such as word processing, calendar, email, spreadsheets, graphics, or similar tasks. As shown in Fig. 2, measuring computer usage at the individual (2a and 2b) or occupational (2c and 2d) level reveals that in 2015, about 73% of women and 53–63% of men used a computer at work for simple tasks. Yet, we still don't know if the wage premium from using a computer at work in such everyday simple tasks is gender-specific.

Second, we still don't know whether findings on gender bias in discrimination (see Penner et al., 2023 for a literature review). According to our argument, the computer wage premium is gender-specific due to what became perceived as female-typed and consequently lower-status computer-use tasks. Therefore, because we assume that computer use status identifies the job more than the worker, gender-specific wage premiums for using computers are probably more significant at the occupation than at the individual level.[2]

To examine our argument on gender-biased technological change and to fill these two lacunas, we follow the research agenda of DiMaggio et al. (2004) by moving beyond the binary classification of computer users versus nonusers by adding a distinction between simple and complex levels of computer usage at work. Unlike previous studies, we study the common uses of computers at work in simple tasks and the less common uses in complex tasks such as programming. Taking the research on the relationship between technology, wages and gender inequality a step further, we study relations between computerization and gender wage gaps through the lens of gendered processes operating at both the occupational and within-occupation levels. Hence, our research offers the most comprehensive analysis of the timely question of whether the wage premium on using computers at work is gender-specific. We do so across different computer usages, between and within-occupations, and over a long period, covering early and more recent diffusion of computers at work.

Informed by our argument and research suggesting that inequality is due mainly to gendered processes operating at the structural level rather than at the individual level (England, 1992; Mandel, 2018; Tomaskovic-Devey, 1993), we first conceptualize relations between IT and gender inequality around occupations. Our research strategy is based on analyzing occupational-level job measures for computer use at work from O*NET, attached to the 1979–2016 Current Population Surveys (CPS). Previous studies on computerization and gender inequality have also utilized occupational data on computers, although

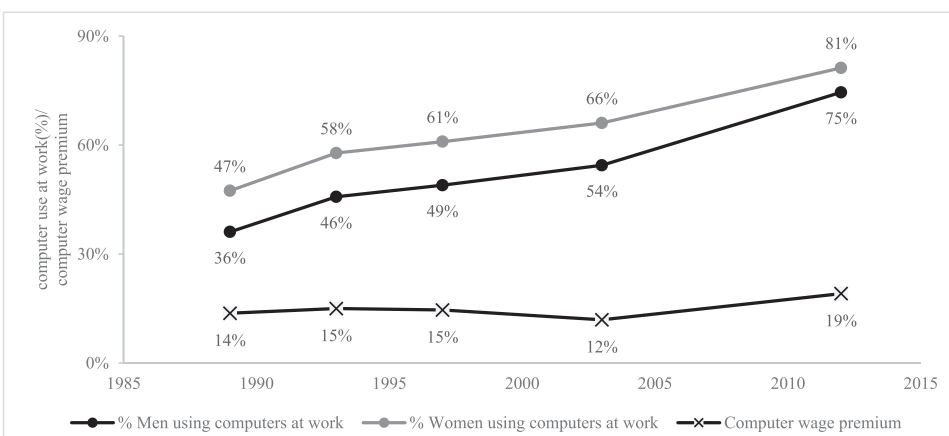

Fig. 1. Computer use at work by gender (%) and findings from OLS regression estimates of the effect of computer use on wages, 1989–2012.
Source: Authors' calculations of individual-level data on computer use at work from the October CPS and PIAAC. Notes: Samples include workers aged 25–64 who were working in the week prior to the survey (or: had job but were not at work). Computer use at work is a dummy variable based on the survey question "Do you use a computer in your job?" A 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. OLS models include in addition to a measure of computer use also an intercept, a dummy for large city, three regions, race and ethnicity, education level (less than secondary, secondary and postsecondary nonacademic and academic education), part-time employment, experience, and experience^2, and public sector. Dependent variable: Ln Hourly Wage. Estimates are weighted by CPS earnings weights or by PIAAC weights.

employment and wage returns on computerization are a between- or within-occupations phenomena. Extant research on the gender pay gap suggests that gendered processes operating at the occupation level primarily include occupation segregation and devaluation – the tendency to devalue and poorly reward activities and jobs traditionally done by women. Distinct gendered processes occur within the occupation, including but not limited to workplace segregation and within-job wage

[2] Our analytical strategy does not enable us to precisely compare the size of gender-specific wage premiums for using computers between the occupation and individual levels. However, it is possible to explore differences in the direction of the wage premium, namely, if the coefficient of the computer wage premium for women is negative, zero, or positive.

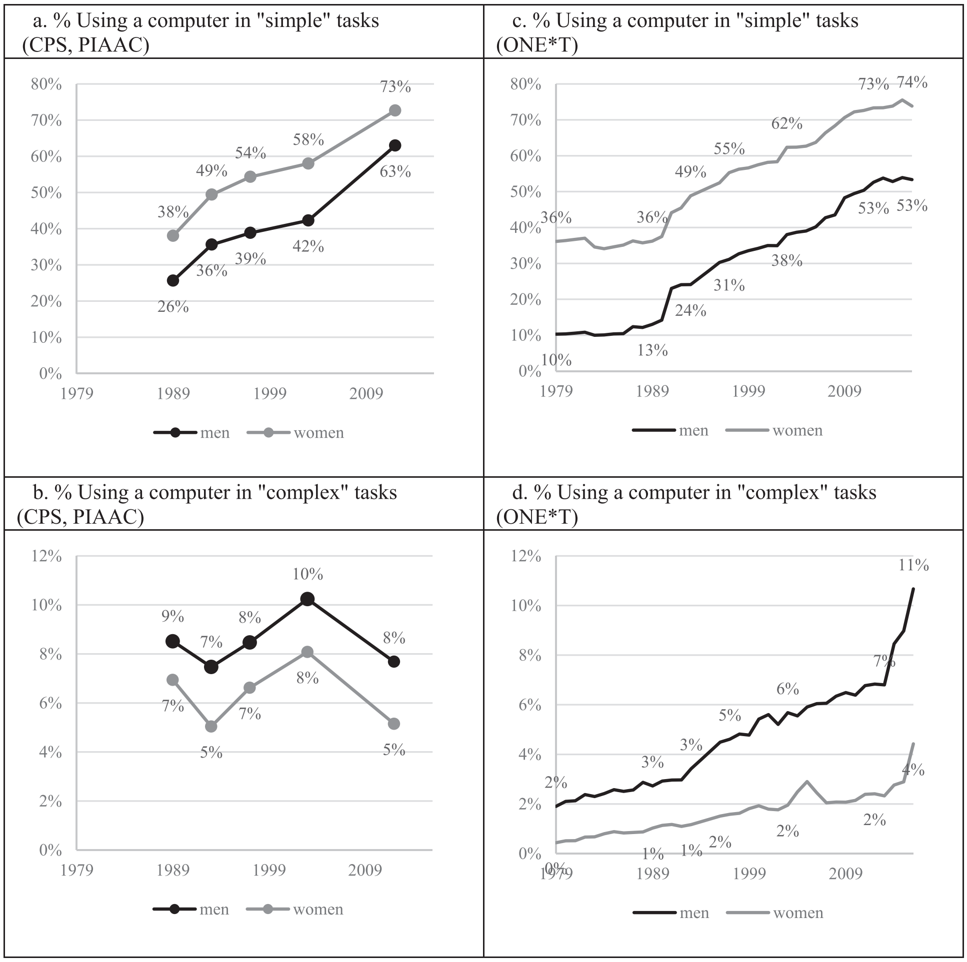

Fig. 2. Computer use at work by gender and task, 1979–2015.
Source: Authors' calculations of the October CPS, PIAAC, and the 1979–2016 Current Population Surveys outgoing rotation group, with appended data on occupations from O*NET. Notes: Samples include workers aged 25–64 who were working in the week prior to the survey (or, with job but not at work). In the CPS data (see endnote #8) computer use at work is a dummy variable based on the survey question "Do you use a computer in your job?" A 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. Complex tasks are defined as those who use computers in programming. Simple tasks in CPS are word processing, bookkeeping, computer assisted design, calendar, email, inventory control, desktop publishing, analysis, spreadsheets, sales, invoicing, graphics, databases and instructions.

for shorter periods and with narrower measurements of computer usage. We further consider the likelihood that wage premiums for computer usage are gender biased through the lens of gendered processes operating within occupations. To explore this question, we utilize the most recent information on computer usage by individuals from the Survey of Adult Skills, developed by the OECD Programme for the International Assessment of Adult Competencies (PIAAC) and conducted in 2012 in the US. The findings suggest that the computer wage premium is biased in favor of men at the occupation level, but not at the individual level. Based on these findings, we suggest in the conclusions that computer-based technologies relate to reproducing old forms of gender pay inequality due to gendered processes that operate mainly at the structural level (i.e., occupations) rather than at the individual level.

2. How does gender affect the computer-earnings relationship between and within-occupations?

As access to computers at work has spread swiftly, and as computers are used for a wide variety of work-related tasks and activities, people are likely to use a computer for different objectives. Different usages of computers by individual workers can be influenced by their skills and their allocation to jobs. For example, Handel (2016) showed that in the 2000 s, a large proportion of clerical and sales workers spent most of their time entering data or filling out forms (31%). A much smaller group served more complex functions such as programming in a computer language such as C+ +, Java, Perl and Visual Basic (2%). Dolton and Pelkonen (2008) found that 99% of engineers and 98% of secretaries in the UK used a computer at work in 2004. Most employees in these two occupational groups used computers for tasks such as emailing or word processing; 22% of engineers used a computer for programming, but no secretaries did so.

These differences in computer usage between occupations and occupational tasks may yield different returns. Plausibly, returns to computer usage may be due to computer-specific skills or general cognitive skills, which are assumed to enhance workers' productivity hence their earnings (Autor et al., 2003). However, they may also be due to an important status distinction unrelated to productivity: the categorical distinction between men and women. DiMaggio and Bonikowski (2008) were the first to suggest status distinction as a mechanism whereby workers may gain earnings advantages by using new technology, arguing that new technology at home contributes to earnings by signaling status or competence. Hence, workers who know how to use a new technology (i.e., the internet) may be seen by employers as more competent and intelligent, without necessarily being so.

Given the importance of status distinction beyond skills as a mechanism whereby workers may gain earnings advantages from using computers at work, we expect that returns to computer usage are also an outcome of gender-bias. In particular, a result of the gendering of occupational activities, namely the tendency to classify an activity as suitable for men or women. Scholars have shown that labeling a job as male- or female-typed shapes pay rates (Cohen & Huffman, 2003; Levanon et al., 2009; Mandel, 2013, 2018), revealing a negative association between women's percentage in occupations and their rewards. These findings are consistent with the devaluation processes and evidence that the gender composition of a job and its association with stereotypically feminine tasks have independently negative effects on wages (England, 1992; Tomaskovic-Devey, 1993). In other words, occupations are central to mitigating the effect of computers on wages, certainly due to the technological skills they require, as predicted by the SBTC thesis, but possibly also due to the tendency to devalue and poorly reward activities traditionally performed by women (England, 2010).[3] Accordingly, we expect the following:

H1. : Given the levels of complexity of computer use, the wage returns to using computers at work within that occupation will be higher in male-typed than in female-typed occupations.

Gendered processes operating within occupations may also generate gender inequality in the earnings outcomes of computerization, although less significance than at the occupation level. Given the differential sorting of men and women across workplaces and the within-job wage discrimination in favor of men (Penner et al., 2023; Petersen and Morgan, 1995), we may expect a gender bias in returns for computer usage, with women's computer premiums lower than men's.

Our expectation seems contrary to evidence that computer premium are, on average, higher for women (Brynin, 2006a; b). Yet, the latter findings may be a result of downplaying the higher gender disparities at the top of the occupational and organizational hierarchies, where all forms of the glass ceiling – in access, work conditions, and rewards –intensify, resulting in greater gender discrimination (Arulampalam, Booth and Bryan, 2007; Blau and Kahn, 2017). Indeed, a recent study by Mandel and Rotman (2021) has shown that downplaying the effect of wages at the top results in underestimation, or even reversal, of the gender gaps in education premiums (i.e., wage returns to a college degree). In the context of computer wage premium, Brynin (2006a, 2006b) utilizes a binary classification of computer users versus nonusers, masking differences between simple and complex computer usages, which probably conceals a gender bias, particularly in the high returns to computer-programming.

Given the within-occupation gendered processes outlined above, we expect a gender bias in returns for simple and complex computer usage. In both cases, women's computer premiums should be lower than men's due to workplace segregation and within-job wage discrimination. Women's lower returns in complex tasks should also be due to a glass ceiling effect. Accordingly, although we cannot directly observe the different mechanisms (i.e., workplace segregation, within-job wage discrimination, glass ceiling), we expect the following outcomes:

H2. : Within occupations, the wage premiums on simple and complex computer usage would be higher for men than women.

[3] An occupation's gender composition is also likely related to its lower status in terms of computer usage. As gendered evaluations of competence play a critical role in everyday social relations (Ridgeway 2011), employers' underestimation of traits and skills identified with femininity can also shape the status ranking of what are considered simple or complex usages of computers at work, and subsequently their wage premiums. Sadly, based on O*NET data we cannot fully distinguish between the actual and perceived levels of computer usage; hence we cannot empirically disentangle the two obstacles.

3. Research Strategy 1: occupations

3.1. Data

We first employ longitudinal occupational-level data to study the relations between computer usages, occupational gender composition, and earnings. Available data on occupational-level job measures from the Department of Labor's Dictionary of Occupational Titles (DOT) and its recent successor, the Occupation Information Network (O*NET), is frequently used to measure occupational skills in specific years (Autor, Levy and Murnane, 2003; Levanon and Grusky, 2016) and longitudinal changes within occupations (Liu and Grusky, 2013). These measures are utilized here primarily to measure the use of a computer at work. Their repeated occupational activities measurements allow the study of longitudinal changes in computer usages at work and wage returns to computer usages.

The DOT was last updated for most occupations in 1977 (based on data collected from 1966 to 1974) and for a small subset of occupations in 1991 (based on data collected from 1981 to 1990); the O*NET has been continually updated since 2003. To maximize the longitudinal quality of occupational data, three versions were used: (1) O*NET 4.0 (consisting of the DOT "analyst database," revised into the O*NET data structure and recoded into the 2000 Standard Occupational Classification system); (2) O*NET 9.0 (released December 2005); and (3) O*NET 20.0 (released August 2015). Without a sounder assumption, we followed Liu and Grusky (2013) in assuming that occupational change is linear over time and interpolated to secure purged occupational measures for all years from 1979–2016.

To analyze the effect of computer usages on occupational wages over time, we merged the rich occupational information from O*NET with a sizeable representative household data source: the monthly outgoing rotation group supplements to the 1979–2016 Current Population Surveys (CPS-ORG). We followed established conventions by restricting the CPS samples to civilian wage and salary workers who were currently working, aged 18–65 years, with a valid occupation, who reported hourly wages of more than $2 (in 2015 dollars). Following conventional practice, we measured earnings as hourly wages; top-coded wages were replaced by 1.5 times the top-coded value. Wages were converted into constant 2016 dollars (to account for inflation) using the Consumer Price Index for All Urban Consumers Research Series (CPI-U-RS). Because wage allocations in the CPS-ORG data suppressed the extent of between-occupation inequality (Mouw and Kalleberg 2010), we excluded all allocated earners (i.e., survey respondents whose wages were imputed because they did not provide wage data). We also left out the years 1994 and 1995 because of lack of documentation on whether wages were imputed.

We merged the occupational information with the CPS-ORG data using a crosswalk between the federal government's more detailed Standard Occupational Classification (SOC) used in O*NET and the less detailed Census Occupational Codes (COC) used in CPS. We started by using a Bureau of Labor Statistics (BLS) crosswalk between O*NET-SOC 2010 codes and O*NET-SOC 2000 codes. We then used a BLS crosswalk to assign a three-digit Census 2000 occupation code to each of the O*NET-SOC 2000 codes. Next we used a further crosswalk created by Autor and Dorn (2013) that matched three-digit Census 2000 occupation codes to earlier Census codes, and an additional BLS crosswalk that matched 2010 occupation codes to Census 2000 codes. Using these four crosswalks, we created a consistent set of 330 occupations matching the 1980, 1990, 2000 and 2010 census codes and O*NET-SOC 2000 and O*NET-SOC 2010 codes. The number of cases in an occupation in our O*NET-CPS dataset ranges from 10–8460, with a mean of about 320.[4]

[4] In additional analyses we dropped occupations with fewer than 50 cases. The results (not shown) were similar to those reported.

3.2. Occupational variables

To identify occupations that require a use a computer at work, we relied on the O*NET variable "Interacting with Computers," which identifies occupations in which workers use computers and computer systems (including hardware and software) to program, write software, set up functions, enter data or process information. Occupations where workers reported that in their current job, working with computers was "important", "very important", or "extremely important" were defined as using a computer at work (*computer use* = 1); those who reported that it was "not important" or "somewhat important" were defined as not using a computer at work (*computer use* = 0).

We further differentiated between two levels of computer use according to the same O*NET variable. Simple tasks included processing digital or online data and operating computer systems or computerized equipment. Complex tasks were defined as resolving computer problems, setting up computer systems, networks, or other information systems, implementing security measures for computer or information systems, and programming computer systems or production equipment. Our method for measuring simple and complex computer tasks is highly correlated with Cheng et al.'s (2019) approach that utilized individual-level data from the October CPS, with one important advantage: our method made it possible to track computer usage from the late 1970 s, while the individual-level approach was limited to data since 1997. We also analyzed individual-level data for a robustness check of the occupational-level computer measures. Comparing the percentage of workers who directly used a computer at work – overall and by the two levels – based on the O*NET data (matched to CPS-ORG) to the individual-level data from the October CPS yielded similar results (see Fig. 2).[5]

For the gendering of occupational activities, we used the common measure of the percentage of women in an occupation. For simplicity of interpretation, in the main analyses we examined the gender of occupation by three categories: (1) Male-typed occupations (with more than 60% men, similarly to Levanon et al., 2009 and Mandel, 2013); (2) Female-typed occupations (likewise defined); and (3) Mixed-typed occupations (all other).

In estimating the relations between computer usage and wages, we controlled for indicators for computer-skills by utilizing measures for general cognitive and computer-specific skills at the occupation level. Cognitive skill was assessed according to the most influential paper that used this perspective and data source to test the SBTC thesis (Autor et al., 2003; see Appendix A for details on the construction of this variable). Computer-specific skill was measured by the O*NET data on work-related areas of knowledge using the following question: "What level of knowledge of computers and electronics is needed to perform your current job?" The correlations between occupational cognitive skill and computer-specific skill, presented in Table 1, were only moderately strong in 2015 (upper part of the correlation matrix), and even weaker in 1979 (lower part of the correlation matrix).

Table 1
Descriptive statistics of occupational-level variables in 1979 (lower part of the correlation matrix, N = 260) and in 2015 (upper part of the correlation matrix, N = 316).

	1.	2.	3.	4.	5.	6.
1. Computer use in simple activities	**1.000**	-0.304	0.385	0.515	0.359	0.380
2. Computer use in complex activities	-0.057	**1.000**	0.237	0.425	-0.100	0.325
3. Cognitive skill	0.264	0.173	**1.000**	0.485	0.157	0.652
4. Computer-specific skill	0.488	0.337	0.387	**1.000**	0.132	0.557
5. Percentage female	0.282	-0.064	0.166	0.140	**1.000**	0.344
6. Percentage of college graduates	0.170	0.177	0.710	0.334	-0.012	**1.000**
Mean 1979	0.14	0.02	32.20	26.78	0.33	0.23
SD 1979	—	—	22.22	22.82	0.32	0.28
Mean 2015	0.53	0.08	51.96	43.65	0.39	0.35
SD 2015	—	—	20.81	17.99	0.30	0.33

Source: Data are from the 1979-2016 Current Population Surveys outgoing rotation group, with appended data on occupations from O*NET.

3.3. Method of analysis

To examine our first hypothesis, we estimate the wage payoff over time for occupation-based differential computer usages. We use annually repeated cross-sectional data to estimate, for each year from 1979–2016, a random-intercept hierarchical model (in multilevel modeling also termed intercept-only modeling) to predict logged hourly wages.[6] The two-level model can be represented as follows:

$$(wages)_{ij} = \beta_{0j} + \beta X + \varepsilon_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + \gamma_0 (occupation - level \quad characteristics)_j + \mu_{0j} \tag{2}$$

On the individual level, the dependent variable is the (logged) hourly wages of individual i in occupation j, and β_{oj} is the intercept denoting mean wages. The vector X denotes individual-level explanatory variables, including gender, race/ethnicity, marital status, region, metropolitan area, education level, potential years of work experience, employment status, industry (1-digit), and sector operationalized in standard ways.[7] β denotes their coefficients, and ε_{ij} is the error term. This equation allows the intercept to vary across occupations (i.e., to be random), while the effects of all other variables (including gender) are constrained to be identical across occupations (i.e., fixed).

On the second level, occupational-level characteristics – differential computer usages – explain this random effect as presented in Eq. 2. Hence Eq. 2, which estimates the between-occupation variance in the level-1 intercept (β_{0j}), is aimed at revealing the wage payoff for occupation-based differential computer usages. The occupational level includes measures for computer use, percentage of women in an occupation, occupational ethnic composition (i.e., percentage of non-Hispanic White workers), and measures for general cognitive and computer-specific skill. These models aim to capture the level of the occupational wage premium for simple and complex computer usages

[5] Like other O*NET variables, "Interacting with Computers," was constructed by both analyst and incumbent ratings of occupational skills and activities, aimed at providing a rich description of the use of computers at work. However, the O*NET raters (both analyst and incumbent) may have perceived the degree of importance and difficulty level of computer-related tasks in a gendered way, to begin with.

[6] We also consider using the longitudinal structure of the occupational data to estimate OLS model with occupations fixed-effect on an unbalanced panel of 327 occupations from 1979–2016. But since the number of occupations that switched from female- to male-typed occupations (or vice versa) is too small, this analytical strategy does not fit well to study our first hypothesis.

[7] Union status is not included in the vector of individual-level explanatory variables since such data are available only from 1983. When union status is included (in the years for which the variable is available), the key results of interest are similar to those presented in Fig. 3. Although we have experimented with a host of different specifications at the individual level (e.g., hours worked instead of part-time status), none of them has affected the results in any appreciable way.

over time, controlling for measured productivity-enhancing mechanisms and the occupation's gender. At the second stage of analysis we replace the continuous variable of the percentage of women in an occupation with the categorical variable and add an interaction between the occupation's gender and computer usages.

4. Research Strategy 2: individuals

To examine our second hypothesis, we utilized individual-level data on the use of computers at work to estimate whether men and women differed in their wage returns to computer usages. This empirical examination enabled to further clarify whether computerization-related gendered processes operating at the occupational or within occupation level primarily accounted for gender (in)equality.

The most recent information on individual computer use by individuals comes from the Survey of Adult Skills, developed by the OECD Programme for the International Assessment of Adult Competencies (PIAAC) and conducted in 2012 in the U.S.[8] For a representative sample of adults, PIAAC measures key cognitive and workplace skills needed for individuals to advance in their jobs and participate in society, providing data on workers' cognitive skills, demographic characteristics, education, employment, hourly wages,[9] and most importantly for the current study, use of computers (at both work and home).[10]

The PIAAC data make it possible to classify workers as using a computer at work and to distinguish workers who use computers in programming vs. other tasks such as spreadsheets, word processing, emails, and chats. To be included in the former category, workers need to use a computer in their current job as well as use programming language to program or write computer code frequently (less than once a week but at least once a month, at least once a week but not every day, or every day). Workers who use a computer in their current job but not for programming are defined as using computers for other tasks.

To examine whether men and women obtain different returns to computer usages, we estimate wage returns to individual computer usages by gender using OLS regressions and controlling for female (=1); region (Midwest, South, West, Northeast [the omitted category]); large city (=1); race and ethnicity (Black, White, Hispanic [the omitted category] and Other); education level (three ordinal categories: less than secondary [the omitted category], secondary and postsecondary nonacademic, academic education); potential years of work experience and its squared term, part-time employment; and public sector (= 1).[11] Uniquely to PIAAC, we have data on respondents' scores on the numeracy tasks as a measure of general cognitive skill.[12] Numeracy is measured on 500-point scales that describe gradations in task complexity. All analyses are applied to a restricted sample that includes employed wage and salary workers aged 25–64.

5. Results

As discussed earlier in the paper, one of the main motivations for analyzing if the wage premium on using computers at work is gender-specific is that women are more likely to use a computer at work than men (Fig. 1). In Table 2, we show that also workers employed in female-typed occupations have consistently been more likely than those employed in male-typed occupations to use a computer at work (Table 2). For example, the percentage of female-typed occupations in which workers use a computer at work in the 1980 s was 31%, compared to 10% among male-typed occupations; in the 2010 s, the numbers rose to 71% and 49%, respectively.

As access to computers at work has spread swiftly, and as computers are used for a wide variety of work-related tasks and activities, people are likely to use a computer for different objectives that yield different returns. Indeed, the results presented in Table 2 reveal that women's entire advantage in using computers lies in simple tasks. Workers employed in male-typed occupations had an advantage in using a computer at work for complex tasks, and the gaps widened over time. Of male-typed occupations, 3% were characterized by using a computer for complex tasks in the 1980 s, rising to 9% by the 2010 s. The number of female-typed occupations was zero in the 1980 s and 1990 s – meaning that there was not even one female-typed occupation characterized by complex use of computers. In the 2000 s and 2010 s, the number remained close to zero: only statistical clerks, HR and labor relations managers, and technical writers were defined as both female-typed and as using computers for complex tasks. This may be partly a result of the underrepresentation of women among STEM degree holders (DiPrete & Buchmann, 2013; Xie and Shauman, 2003) and STEM occupations (Landivar, 2013). Table 2 also shows that occupations requiring a STEM degree are more likely to be male-typed within both simple and complex usages of computers at work. These descriptive differences between occupations in their gender-type and the common computer usage provoke to study if the wage return to computer usage relates to the occupation gender type.

5.1. Is the wage return to computer use at work related to the occupation's gender type?

Our first hypothesis is that the wage returns to using computers at work will be higher in male-typed than female-typed occupations. To examine this hypothesis, we utilize data from O*NET for about 320 occupations attached to the 1979–2016 CPS-ORG data to first describe the wage payoffs for simple and complex usages. Fig. 3a presents findings on the wage payoff for differential occupation-based computer usages in each year between 1979 and 2016. In the model estimated for each year, between-occupation wage variance is explained by measures for simple and complex computer usages as well as ethnic composition (i.e., percentage of non-Hispanic White workers) and general cognitive and computer-specific skills.

As expected, Fig. 3a shows that the occupational wage premium for

[8] Individual-level data on computer use at work are available also from the October supplements to the CPS. The CPS began including questions about what workers do with a computer at work in 1989, and continued in intermittent years (1993, 1997) up to the most recent survey to include this supplement in 2003. Since the information on different usages of computers at work is limited and inconsistent over time, we do not utilize the October CPS data in this paper.

[9] In the public use files, earnings data for the US are reported only in deciles. We therefore run analyses on the actual restricted-use file by submitting our Stata code to the National Center for Education Statistics (NCES).

[10] Because PIAAC collects data using complex sample and psychometric designs, all our analyses of PIAAC data use a PIAAC-based tool that allows analyses and estimations using replicate weights and plausible values. We use the 'repest' macro for Stata, which is based on the Jackknife method to estimate the variance and bias of populations. For more information on this OECD-designed macro, see https://econpapers.repec.org/software/bocbocode/S457918.htm

[11] There is no information on marital status in PIAAC, and too many values are missing from the closest variable of living together, which precludes using it in the models.

[12] Because the PIAAC was designed to provide accurate estimates of proficiency in this domain across the adult population and its major subgroups, rather than on the level of individuals, each respondent was given a subset of the test items used in the numeric assessment. The OECD imputed proficiency scores for each respondent on the basis of performance on test items and background characteristics. The uncertainty of imputation was reflected in ten plausible values for each respondent on the scales for cognitive proficiency.

Table 2
Percentage of male- and female-typed occupations in which workers use a computer at work in simple and complex tasks by decade.

	Female-typed occupations (N = 892)	Male-typed occupations (N = 1794)	Mixed-typed occupations (N = 626)
Workers not using computers at work	1980 s – 69% 1990 s – 52% 2000 s – 38% 2010 s – 29% Examples: Occupational therapists, kindergarten and earlier school teachers, social workers, door-to-door sales, cleaners, waiters and waitresses	1980 s – 90% 1990 s – 82% 2000 s – 70% 2010 s – 51% Examples: Clergy and religious workers, athletes, salespersons, mail carriers, fire fighters, janitors, machinery maintenance occupations, butchers and meat cutters, sawyers	1980 s – 83% 1990 s – 61% 2000 s – 46% 2010 s – 29%
Workers using computers in “simple” occupational tasks, no requirement for STEM degree	1980 s – 31% 1990 s – 47% 2000 s – 59% 2010 s – 68% Examples: Secretaries and stenographers, typists, receptionists and other information clerks, registered nurses, bank tellers	1980 s – 2% 1990 s – 6% 2000 s – 16% 2010 s – 32% Examples: Chief executives, construction inspectors, financial service sales occupations, shipping and receiving clerks	1980 s – 11% 1990 s – 30% 2000 s – 41% 2010 s – 58%
Workers using computers in “simple” occupational tasks, requirement for STEM degree	1980 s – 0% 1990 s – 1% 2000 s – 1% 2010 s – 1% Examples: Psychologists	1980 s – 5% 1990 s – 8% 2000 s – 9% 2010 s – 6% Examples: Chemical engineers, actuaries, chemists, drafters, chemical technicians, sales engineers	1980 s – 4% 1990 s – 7% 2000 s – 8% 2010 s – 6%
Workers using computers in “complex” occupational tasks, no requirement for STEM degree	1980 s – 0% 1990 s – 0% 2000 s – 2% 2010 s – 2% Examples: Human resources and labor relations managers, technical writers, statistical clerks	1980 s – 0% 1990 s – 0% 2000 s – 0% 2010 s – 1% Examples: Broadcast equipment operators	1980 s – 0% 1990 s – 0% 2000 s – 2% 2010 s – 2%
Workers using computers in “complex” occupational tasks, requirement for STEM degree	1980 s – 0% 1990 s – 0% 2000 s – 0% 2010 s – 0%	1980 s – 3% 1990 s – 4% 2000 s – 5% 2010 s – 9% Examples: Aerospace engineers, electrical engineers, computer systems analysts and computer scientists, mathematicians and statisticians, computer software developers	1980 s – 2% 1990 s – 2% 2000 s – 3% 2010 s – 5%
	100%	100%	100%

Source: Data are from the 1979-2016 Current Population Surveys outgoing rotation group, with appended data on occupations from O*NET.
Notes: Level of computer use was defined according to the O*NET variable “Interacting with Computers.” Male-typed occupations defined as occupations with more than 60% men. Female-typed occupations defined as occupations with more than 60% women.

simple usages is lower than for complex usages. When the demographic, geographic, sectoral and educational composition of occupations, as well as productivity-enhancing measures (i.e., cognitive and computer-specific skill) are controlled for, the premium for simple usages is 2.9 log points (on average over the years) compared to 26.7 for complex usages. Another difference relates to changes over time. Returns to simple usages increased somewhat in the 1980 s, decreased in the 1990 s, only to increase again from the early 2000 s; conversely, returns to complex usages increased continually until 2011.

To examine whether the wage payoff for simple and complex activities relates to the occupation gender-type, we next look at how the between-occupation variance in wages, presented in Fig. 3a, relates to the percentage of women in an occupation. The results are presented in Fig. 3b: an occupation’s gender typing tends to be a central intervening mechanism by which occupational computer usages affect earnings. This was true particularly in the early 1980 s, when computers entered occupations, and the wage payoff for simple and complex usages was similar in occupations with a similar representation of women and men.

There appear to be two main inferences when comparing the findings in Fig. 3b to a, together with the patterns between gender-typed occupations and computer usage (Table 2). The first inference relates to cross-section differences in computer wage returns by the gender of occupation and the second to longitudinal changes. Both inferences support our first hypothesis that computer wage returns are higher in male-typed than female-typed occupations.

First, there seems to be a wage penalty in simple usages for female-typed occupations that conceals their wage premium on using a computer at work. At the same time, the findings for complex usages imply a wage gain for using a computer at work in male-type occupations, particularly over the 1980 s. To directly examine the interactions between computer usages and occupations’ gender-type, we next re-estimate the model in Fig. 3a with interactions between computer usages and three categories of gender-typed occupations. Fig. 4 plots the mean marginal effects of computer usages across different levels of gender-typed occupations compared to mixed occupations (right column) and occupations not using computers at work (left) in four years – 1980, 1990, 2000, and 2010.

Demonstrating the important role of gender in the relations between computer usage and wages, we find that when computers appeared in the labor market in the 1980 s, the wage returns to simple use of computers were very similar to returns to complex use among different gender-type occupations. In contrast, thirty years after, by 2010, we find a wage penalty for female-typed occupations (compared to mixed ones) in simple as well as complex computer usages (there were no female-typed occupations with complex computer usages in previous years). Also, in line with our first hypothesis, we find a wage payoff for male-typed compared to mixed occupations among occupations that do not use computers at work, those that use computers for simple tasks (only in 2010), and those that use computers for complex tasks (in 2000 and 2010, but not in the 1990).

The second inference from Fig. 3 is that since the 1990 s, the wage premium from using a computer at work has increased only for occupations classified as non-female-typed complex computer usage. At the same time, the returns have vanished for all simple-usage occupations. The widening wage gaps between complex and simple computer usages may be related to differences in supply and demand for workers with different unmeasured technological skills. It also can be a result of changing tasks within an occupation, although the models partly discard these two options by controlling for cognitive and computer specific skills. We contend that the widening wage gaps between complex and simple computer usage may also result from status devaluation. Once an occupation is labeled as using computers for simple tasks, or as a female-typed occupation, the computer wage premium does not increase over time. Indeed, in more recent years the wage returns to simple use of computers are lower than returns to complex also among mixed occupations, possibly due to the gendering of simple computer usages (Fig. 4).

Taken together, our findings shed new light on whether the wage return to computer use at work relates to the occupation’s gender type. This timely question arises from previous studies showing, on one side, a

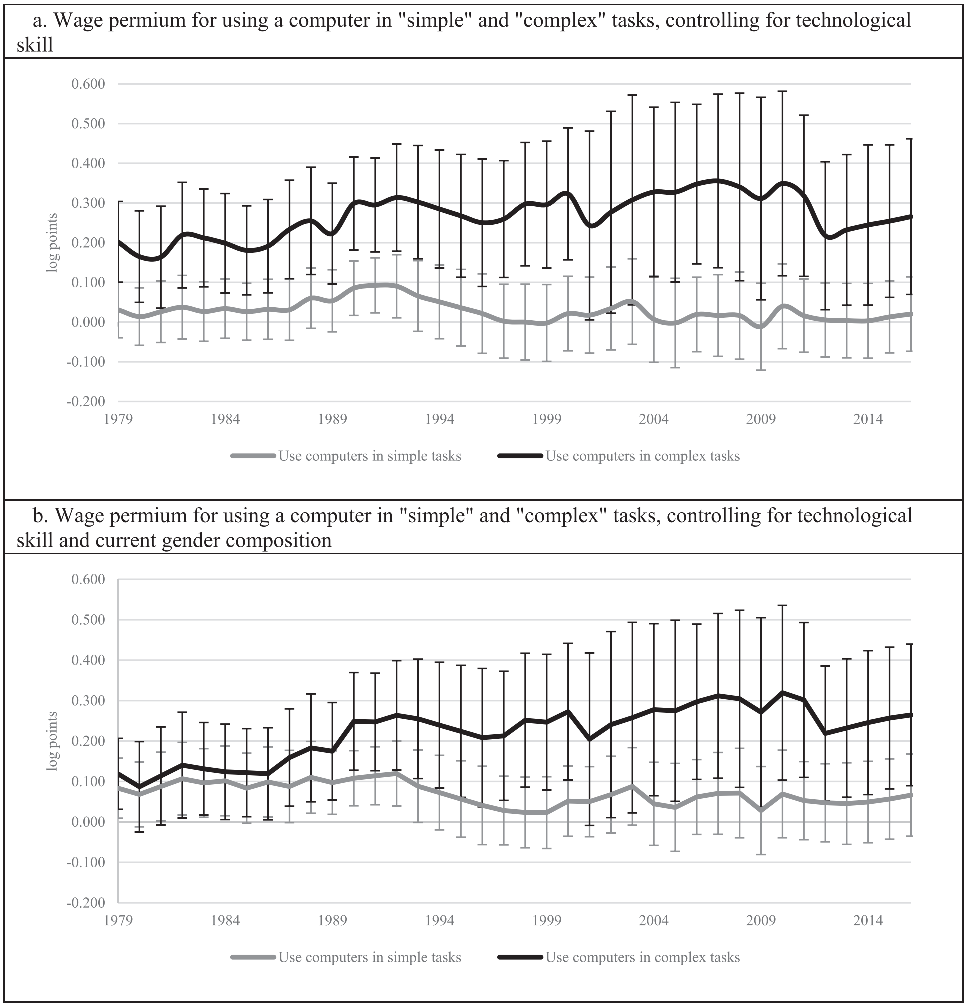

Fig. 3. Occupational wage payoff for "simple" and "complex" computer usages, 1979–2016.
Source: Data are from the 1979–2016 Current Population Surveys outgoing rotation group, with appended data on occupations from O*NET. Notes: Results from Hierarchical Linear Model in each year for the effects of occupational-level variables on the "average" natural log of wages. The plot lines are flanked by 95% confidence intervals to illustrate their statistical significance. The vector of individual-level explanatory variables includes race, gender, marital status, region, metropolitan residence, education, work experience, employment status, sector, and industry (1-digit). Occupational-level variables include measures for computer use, occupational ethnic composition, general cognitive skill and computer-specific skill, and the percentage of women in an occupation. All results at the occupational level are weighted by the occupation's contribution to the total work hours.

wage premium from using a computer at work and women's advantage in computer use. But on the other side, the rise of occupations with higher programming intensity partly explains the slow convergence of the gender wage gap. Our study provides new insights into this puzzle by conducting a comprehensive investigation of the wage return to computer use at work in both simple and complex usages and over the long period between 1979 and 2015. First, we find that computer's wage premium is gender-biased in complex but also in simpler computer usages, the more common use of computers at work. Second, we see a wage penalty for workers employed in female-typed occupations typified by simple and complex usages and a wage payoff for male-typed occupations. Notably, these relationships emerged about a decade after computers entered the labor market, suggesting that simple and complex computer usages have developed into a gender status marker unrelated to productivity. Our findings imply that the status devaluation of simple computer usage partly explains the widening gaps between wage returns to simple computer use in female-typed occupations and complex use in male-typed occupations. We next examine within occupations if the wage premium on using computers at work is gender- or non-gender-specific.

5.2. Does the wage return to computer use at work vary by gender within occupation?

Our last analysis examines whether men and women obtain different returns to computer usage within occupations based on individual-level PIAAC data. The findings on the average computer wage premium presented in Table 3 align with previous studies and our findings based on occupational data. Utilizing individual data, we find a wage premium for computer usage in simple and complex tasks; the latter reveals higher returns. Controlling for individuals' demographic, education, employment and cognitive skill characteristics, the results of model 5 indicate that workers who use a computer at work in complex tasks earn 33% (based on the exponents of the beta coefficients, e^{β}) more than similar workers who do not use a computer at work. In comparison, workers who use a computer at work in simple tasks earn 21% more than similar workers who do not use a computer at work.

As discussed above, we expect women's wage returns from other computer use should be lower than men's (within-occupation) due to workplace segregation and wage discrimination. Women's wage returns from computer programming should also be lower than men's due to a glass ceiling effect. Despite that, findings on the wage returns to

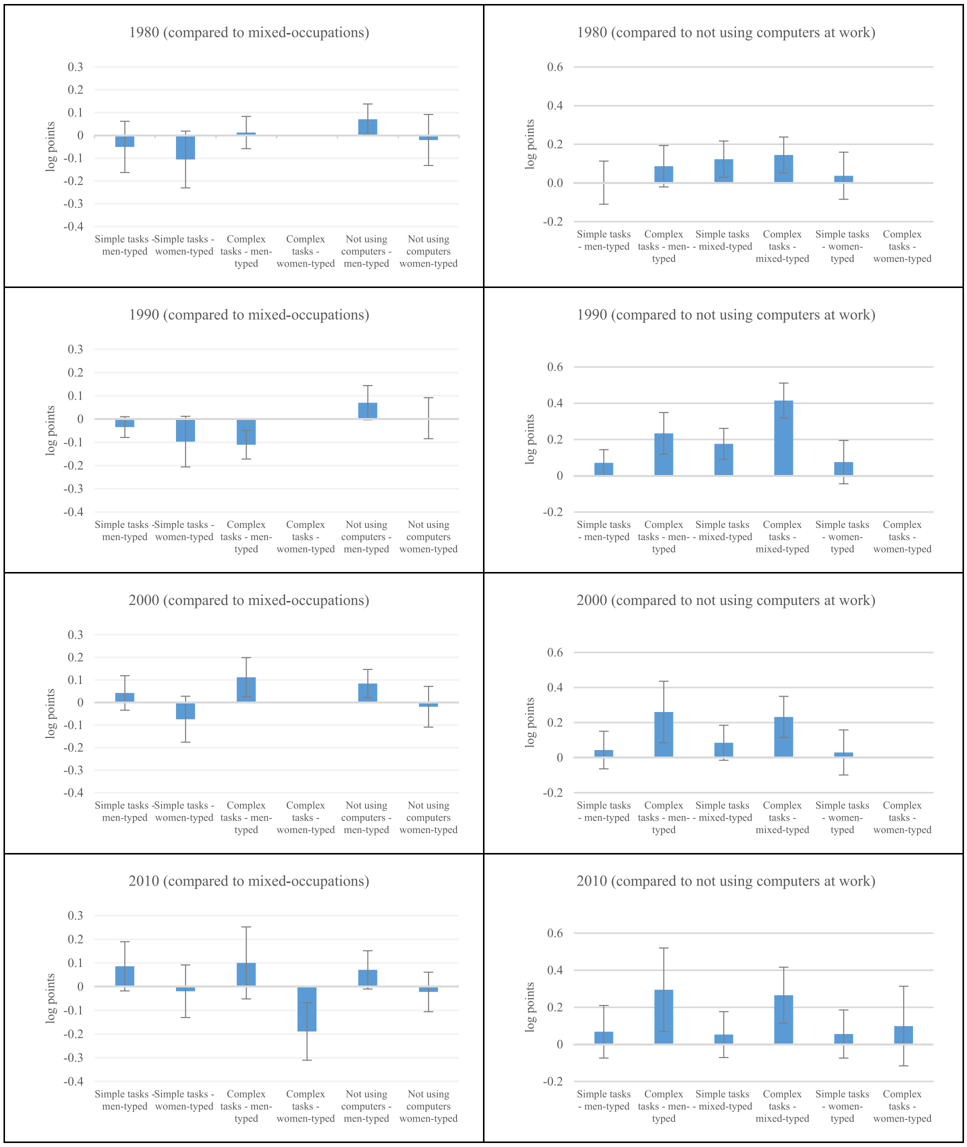

Fig. 4. Average marginal effects of computer usages on wages by the gender-type of occupations in four years: 1980, 1990, 2000, and 2010.
Source: Data are from the 1979–2016 Current Population Surveys outgoing rotation group, with appended data on occupations from O*NET. Notes: Results from Hierarchical Linear Model in each year for the effects of occupational-level variables on the "average" natural log of wages. The plot bars are flanked by 95% confidence intervals to illustrate their statistical significance. For the vector of individual-level explanatory variables see Fig. 3. Occupational-level variables include measures for occupational ethnic composition, general cognitive skill and computer-specific skill, and interactions between computer usages and gender-type of occupations (three categories). All results at the occupational level are weighted by the occupation's contribution to the total work hours.

computer usage by gender provide only weak support to our second hypothesis. Although we have expected to find a negative coefficient for the interaction between females and other computer use and between females and computer programming, the coefficients in model 5 are negative but not statistically significant in all specifications; possibly due to relatively high standard errors. In additional analyses (not shown), we included two-digit occupation dummies instead of one-digit in the model. The results are similar to those presented in Table 3, yielding a higher computer wage premium in complex than simple tasks, with a negative yet insignificant coefficient for the interaction between gender and computer usage.

6. Conclusions and discussion

This paper asks whether the wage premium on using computers at work is gender- or non-gender-specific. Our findings indicate that the computer wage premium is gender-biased due to gendered processes that operate mostly at the structural level. In particular, we find a wage penalty for female-typed occupations and a wage payoff for male-typed occupations (compared to mixed occupations) in both simple and complex computer usages. Notably, these relationships emerged about a decade after computers entered the labor market. We also consider the relations between computerization, gender, and wages within occupations. Utilizing the most recent individual-level data on computers use at work we find only suggestive evidence that the wage premiums on simple and complex computer usage are higher for men.

Our findings on a gender bias in the computer wage premium may have implications for the promise of computer technologies at work for reducing gender pay inequality. As women flooded into the labor market in the second half of the 20th century, the gender wage gap steadily narrowed as the result of a decrease – even a reversal – of gender differentials in educational attainment, as well as an increase in female participation in formerly male-typed jobs (Blau and Kahn, 2017; England Levine, and Mishel, 2020). This conjured up a vision of a time

Table 3
OLS regression estimates of the effect of computer use (programming, other use, do not use) on individual pay, 2012.

Dependent variable:	Ln Hourly Wage	Ln Hourly Wage	Ln Hourly Wage	Ln Hourly Wage	Ln Hourly Wage
Models	Model 1	Model 2	Model 3	Model 4	Model 5
Programming	.503 * *	.415 * *	.474 * *	.423 * *	.287 * *
	(.038)	(.037)	(.043)	(.042)	(.047)
Other use	.255 * *	.188 * *	.280 * *	.192 * *	.192 * *
	(.027)	(.030)	(.031)	(.032)	(.032)
Female	-.213 * *	-.180 * *	-0.040	-.015	-.102
	(.056)	(.055)	(.138)	(.125)	(.056)
Programming	-.107	-.074	—	-.084	-.087
* Female	(.075)	(.078)		(.086)	(.072)
Other use	.053	.054	—	.050	-.012
* Female	(.055)	(.055)		(.061)	(.050)
Secondary and postsecondary nonacademic	.236 *	.172	.299 *	.244	.206 *
	(.102)	(.100)	(.134)	(.125)	(.098)
Academic education	.681 * *	.544 * *	.718 * *	.585 * *	.508 * *
	(.112)	(.115)	(.144)	(.139)	(.103)
Secondary	—	—	-.164	-.187	—
* Female			(.148)	(.148)	
Academic	—	—	-.113	-.128	—
* Female			(.143)	(.149)	
Numeric skills	—	.002 * *	—	.002 * *	—
		(.000)		(.000)	
Constant	2.13 * *	1.706 * *	2.064 * *	1.639 * *	2.53 * *
	(.112)	(.127)	(.146)	(.145)	(.649)
9 one-digit occupation dummies	No	No	No	No	Yes
20 one-digit industry dummies	No	No	No	No	Yes
Observations	2980	2980	2980	2980	2980
R-squared	0.325	0.347	0.324	0.348	0.439

Source: Authors' calculations of PIAAC data.
Notes: Samples include workers aged 25-64 who were working in the week prior to the survey (or had a job but were not at work). All models also include an intercept, a dummy for large city, three regions, race and ethnicity, education level (less than secondary, secondary and postsecondary nonacademic and academic education), part-time employment, experience, and experience^2, and public sector. Sample weights are applied. * * $p < 0.01$, * $p < 0.05$.

when women and men would earn identical wages. However, in the 1990s the narrowing of the gender wage gap slowed significantly, mainly because of structural forms of gender inequality. At the structural level, little has changed in the tendency to devalue and poorly reward activities and jobs traditionally done by women (England, 2010), a tendency that has perhaps even intensified (Mandel, 2018).

This paper contributes to our understanding of the persistence of gender inequality by rejecting the idea that IT will lead to pay equality, providing evidence that in fact, it benefits men more than women, mainly due to structural forms of gender inequality. By demonstrating that wage returns to using computers at work favor men, this study adds new evidence on how new ways of organizing work reproduce old forms of inequality. This is presumably because workplace relations that are implicitly biased by the gender frame infuse gendered meanings into new workplace procedures and structures that actors create (Ridgeway, 2011). For example, Cha and Weeden (2014) demonstrate how rising payoffs for long work hours favor men (who typically do not bear the burden of child and homecare). Fixed-term contract employment also disfavors women (Gash and McGinnity, 2007). Even in gig work, workers embrace the traditional gendered division of labor (Milkman et al., 2021).

In line with this literature, the current paper highlights how new computer-based technologies must be understood in the particular social context of gendered processes. While this paper focuses on the implications of IT for gender pay inequality, further research should consider the consequences of new technologies beyond using computers at work, such as AI and online labor platforms, for men's and women's employment and labor market outcomes. Moreover, this paper also highlights the increasing importance of structural forms. Computer uses were found to contribute to our understanding of the gender wage gaps at the occupational level but less in the within-occupational level. More investigation is needed in examining the role of structural forms of persistence gender inequality in the labor market and its increasing contribution in comparison to the within-occupation level that was found to be with less significance not only in this paper (Mandel and Semyonov, 2014).

This paper also contributes to our understating of IT wage premiums, suggesting that while SBTC certainly plays a role in explaining rising inequality, it is rather restrictive to assume that computers have impacted the labor market and wage inequality solely via skills, productivity, and market forces. Computer usages have in fact developed into a gender status marker unrelated to productivity. Here too this study adds new evidence to those already accumulated (see Braverman, 1974; Noble, 1984; and Kristal, 2013, 2019, 2020 for a more recent formulation) on how computerization is a process that reflects preexisting social realities and is biased in favor of already privileged social groups.

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Declaration of Competing Interest

None.

Appendix A. Cognitive skill computed based on O*NET data

Data source		**O*NET 4.0**	**O*NET 9.0**	**O*NET 20.0**
Data released		**2002**	**2005**	**2015**
Years covered		**1970s-1980s**	**Early 2000s**	**Early 2010s**
Variables:	**Description**	**Correlation**		
Non-Routine Cognitive Skill				
Analyzing data or information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.	0.8701	0.7214	0.7364
Thinking creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.	0.7847	0.7774	0.6573
Interpreting information for others	Translating or explaining what information means and how it can be used.	0.8945	0.8979	0.8478

(continued on next page)

(*continued*)

Data source		O*NET 4.0	O*NET 9.0	O*NET 20.0
Establishing and maintaining personal relationships	Developing constructive and cooperative working relationships with others, and maintaining them over time.	0.8007	0.9049	0.6818
Guiding, directing and motivating subordinates	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.	0.8262	0.8590	0.7707
Coaching/developing others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.	0.8604	0.9066	0.7784
Number of occupations (3-digit COC occupations)		325	327	326

Source: O*NET.

Appendix B. Descriptive statistics of individual-level variables

Data source:	PIAAC	CPS-ORG
Year:	2012	1979-2016
Hourly wage (logged)	3.00	2.97
Computer use	0.79	—
Computer use in simple activities	0.71	—
Computer use in complex activities	0.08	—
Female	0.49	0.49
Black	0.12	0.08
Hispanic	0.13	0.09
Other	0.07	0.05
White	0.78	0.78
Midwest	0.22	0.25
South	0.36	0.30
West	0.23	0.24
Northeast	0.19	0.21
Metropolitan area	0.19	0.73
Less than high school	0.02	0.09
High school graduate or some college	0.62	0.62
College graduate	0.36	0.29
Potential years of work experience	23.7	21.5
Part-time employment	0.15	0.13
Public sector	0.23	0.20
Numeric skill	265	—
College degree in STEM	0.25	—
N	2980	3600,507

Source: Authors' calculations of the PIAAC, and the 1979-2016 Current Population Surveys outgoing rotation group.
Notes: Samples include workers aged 25-64 who were working in the week prior to the survey (or had a job but were not at work).

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