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Technological Progress, Occupational Structure and Gender Gaps in the German Labour Market

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Abstract

We analyze if technological progress and the change in the occupational structure have improved women's position in the labour market. We show that women increasingly work in non-routine manual and in interactive occupations. However, the observed narrowing of the gender wage gap is entirely driven by declining gender wag gaps within, rather than between, occupations. A decomposition exercise reveals that while explained factors have become more important contributors to the gender wage gap, the importance of unexplained factors factors has strongly declined. Therefore, unequal treatment based on unobservables, i.e. discrimination, is likely to have declined over time. Finally, technological change as measured by job tasks plays an ambiguous role. Institutional factors, and in particular part-time employment, are still a major driver of the gender wage gap.

Keywords: Technological progress, job tasks, occupational structure, gender gaps, gender wage gap

JEL Codes: J24, J31, O33

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1 Introduction

Despite a significant reduction in the gender wage gap over the last decades in many industrialised countries, there remains a substantial gap, particularly at the top of the wage distribution (Blau and Kahn, 2017). At the same time, technological progress has changed the structure of occupations toward non-routine jobs that are less easily automated. It has also affected the task content within occupations, in particular increasing the value of social tasks (Black and Spitz-Oener, 2010; Cortes et al., 2023).

There is some evidence to suggest that technological progress has had a positive impact on women, and there are two main reasons for this: First, a smaller share of women were employed in routine occupations in the 1980s, making them less exposed to the substitution effects of technology.[1] Second, according to the neuroscience literature, women have a comparative advantage in social skills (Greenberg et al., 2018; Chapman et al., 2006; Baron-Cohen et al., 2005); they also have a comparative advantage in occupations that require these skills. Therefore, women sort into occupations with a higher level of social skills, assuming sorting based on comparative advantage (Cortes et al., 2023). However, women may not be able to benefit due to lower returns to tasks within occupations, as shown for Germany (Storm, 2023), and due to selection into occupations with lower wage growth, as shown for the US and Portugal (Cortes et al., 2020).

In this paper, we analyze how technological change has affected the occupational structure and thus the relative position of women in the German labour market over the period 1984-2017. We address three questions. First, how has the change in occupational structure affected women differently than men? Second, has the change in occupational structure led to a reduction in the gender wage gap? Third, which factors explain the narrowing gender gap within occupations?

Our analysis is based on data from the Socio-Economic Panel (SOEP) for West Germany

[1]This is shown for Germany by Black and Spitz-Oener (2010), for Portugal Cortes et al. (2020) and for the US by Cortes and Pan (2019).

over the time period 1984-2017. We focus on West Germany due to missing pre-1990 data for East Germany and persistent labor market differences between East and West Germany. We complement the SOEP with data from the BIBB Employment survey that provides individual-level data on tasks performed on the job. This allows us to categorize occupations into task groups, but also to create gender-specific and time-varying task intensities. First, we provide descriptive evidence on the evolution of female employment across task groups over time. Second, we examine how the change in the occupational structure has affected the gender wage gap. Third, we conduct a Blinder-Oaxaca decomposition to determine factors that are related to the change in the gender wage gap over time, explicitly taking into account the role of composition effects. We include part-time workers as they make up a large share of the female work force in Germany. Moreover, our data allow us to also include workers in the upper part of the income distribution. To examine differences across occupations and study the importance of social skills[2], we distinguish between four categories (Koomen and Backes-Gellner, 2022): routine, non-routine manual (NRM), non-routine interactive (NRI), and non-routine cognitive (NRC).

Germany provides an interesting setting for the analysis, as it is a technological frontier country in Europe, e.g. in terms of robot adoption (Dauth et al., 2021), and features strong employment polarization, i.e. a strong decline of employment in routine occupations and a corresponding increase of employment in non-routine manual and cognitive occupations (Bachmann et al., 2019). Furthermore, the unconditional gender gap has declined from 30% to 24%, but a significant gap remains. While the share of women in academic occupations has increased significantly, women are still underrepresented in managerial positions. Furthermore, between 1985 and 2017, the share of non-working women decreased strongly from from 52% to 30%, while the corresponding share of non-employed men remained virtually

[2]Although there is no single definition, social skills, as commonly measured in the literature, typically include dimensions such as communication, teamwork and coordination, social perception, negotiation, and presentation (Deming, 2017; Borghans et al., 2014; Deming and Kahn, 2018; Atalay et al., 2020; Cortes et al., 2023). In addition, the concept of social skills can be extended to include customer service and service orientation (Langer and Wiederhold, 2023).

unchanged.

Our results are as follows. First, we find that while the female share in non-routine manual and in interactive occupations increased strongly over time, the female share in non-routine cognitive and in routine occupations remained relatively constant. Second, we confirm the decline of the gender wage gap in Germany over the last decades previously found in the literature and show that this decline is entirely driven by a reduction of the gender wage gap within occupations, not between occupations. Third, our decomposition exercise reveals a strong increase of the explained part (composition effects) and a corresponding strong decrease of the unexplained part (payoffs to characteristics). Overall, these results are in line with a reduction in wage discrimination in the labour market.

Our results suggest that technological change, which leads to changes in the employment weights of occupational groups, has not been an important driver of the gender wage gap. Rather, the narrowing of the gender wage gap is due to changes within task groups. Furthermore, while task intensities play a role in the gender wage gap within task groups, institutional aspects, especially part-time employment, are more important determinants.

The study contributes to the literature that studies the impact of technology on labour-market outcomes. To date, there is only a relatively limited number of studies that focuses on the impact on women. For Germany, Black and Spitz-Oener (2010) show that exposure to technology contributed to a narrowing of the gender wage gap in the time period 1979–1999. However, more recent evidence shows that while women sort into interactive occupations, they receive lower returns to interactive tasks within these occupations (Storm, 2023). Moreover, Genz and Schnabel (2023) show that digital investments lead to greater job losses for women. For the US, Cortes et al. (2023) show that the increasing importance of social skills within occupations is associated with women sorting into higher paying occupations. Comparing developments in the US and Portugal, Cortes et al. (2020) point out that women have indeed benefited from changes in occupational structures, but they have moved into occupations with lower wage growth. In particular, women are underrepresented in high-paying STEM occupations.

Our contributions are as follows. First, we provide evidence for Germany which complements the analysis of Cortes et al. (2023, 2020). Second, we take into account a large part of the labour market as our analysis also includes part-time and high-skilled workers, often not included in other studies due to data limitations. Third, the use of individual-level data allows us to study the importance of developments other than technological change not just between task groups, such as the overall increase in educational attainment, and increased availability of flexible work arrangements and childcare, taking into account both composition effects and changes in the pay-offs to such characteristics. Fourth, using individual-level data on tasks performed at the job, we can analyse the role of task changes within occupations over time.

2 Previous Literature

We relate to three strands of the literature that evaluate the impact of technological change on (i) occupational structures and skill requirements, (ii) gender gaps and female labour market participation, and (iii) the impact of technology on gender gaps.

There is a large body of evidence documenting the polarization of labour markets (Bachmann et al., 2019; Goos et al., 2009; Autor et al., 2003). Labour-market polarization can be explained by a model of work tasks (Autor et al., 2003) according to which technology acts as a substitute for routine work and as a complement to non-routine (cognitive) work. Task-biased technological change also affects skill requirements. Evidence from the early 2000s already showed that jobs had become more complex, and that analytical and interactive tasks had gained importance since the early 1980s (Spitz-Oener, 2006). More recently, the combination of cognitive and social skills has been found to be particularly important for labour-market success in terms of employment (Deming and Kahn, 2018; Weinberger, 2014) and wages (Deming, 2017; Böhm et al., 2024).

The literature on the gender wage gap shows that while this gap has declined in recent decades in many industrialised countries, there was less convergence in the upper part of the wage distribution (Blau and Kahn, 2017; Blau et al., 2024; Granados and Wrohlich, 2018). In Germany, the gender wage gap for full-time workers has fallen from 30% to 19% over the last decade (Granados and Wrohlich, 2018), but further narrows when gender differences in education, work experience and sector choice are taken into account (Anger and Schmidt, 2010; Bredtmann and Otten, 2014). Over the last decades, other factors have played an important role for the labour-market situation of women besides technological progress. First, increased female educational attainment coincides with changing social norms regarding working women. This has allowed women to enter higher-paying occupations (Fortin et al., 2015; Goldin, 2006). Second, changes in parental leave policies (Kluve and Schmitz, 2018; Schönberg and Ludsteck, 2014; Kluve and Tamm, 2013) and in labour market institutions, such as part-time work and alternative work arrangements (Bachmann et al., 2020; Fitzenberger et al., 2004), helped to reconcile family and career and therefore contributed to the strong increase in female labour-force participation.

The impact of technological progress on women has so far only been investigated by a relatively small, but growing number of papers. For Germany, Black and Spitz-Oener (2010) show that women have experienced a relative increase in the importance of interactive and analytical tasks and a greater decrease in the intensity of routine task than men. These gender-specific changes in tasks and in task prices explain part of the narrowing of the gender wage gap. Other studies emphasize the role of declining returns to manual skills (Yamaguchi, 2018) and the impact of computerization for the convergence of the gender wage gap (Beaudry and Lewis, 2014) and the decline in the part-time penalty (Elsayed et al., 2017). Cortes et al. (2023) show that the increasing importance of social skills in high-wage occupations since the 1980s has been an important factor in the sorting of women into these occupations.

Comparing developments in the US and Portugal, Cortes et al. (2020) point out that the overall impact of technology on the gender gap is ambiguous. While the change in the occupational structure would have led to a reduction in the gender wage gap, this effect is counteracted by the selection of women into occupations with lower wage growth on average. While women sort into NRC occupations, they select less into STEM NRC occupations that experienced the highest wage growth. Evidence from Germany also shows that women who move into male-dominated occupations experience stronger wage growth (Busch, 2020). However, Storm (2023) points out that women do not fully benefit due to lower returns to interactive tasks.

Furthermore, there is evidence that the rise of the service economy has led to a narrowing of the gender wage gap (Ngai and Petrongolo, 2017) and that the rise of low-skilled services is driven by the entry of high-skilled women into the labour market who outsource home production (Cerina et al., 2021).

3 Data

3.1 German Socio-Economic Panel

We use data from the German Socio-Economic Panel (SOEP) for the years 1984-2017. The SOEP is a representative annual panel survey of private households/persons in Germany.[3] For the analyses, we consider individuals between the ages of 20 and 64. We exclude observations with missing employment status, missing occupation code and missing wage information. We also exclude apprentices, self-employed persons, persons who worked in the armed forces, in sheltered workshops, or in agriculture, forestry, and fishing. To avoid structural breaks, we focus on persons working in West Germany. Moreover, the labor market situation of women differs significantly between East and West Germany (Jochmann-Döll and Scheele, 2020), which justifies a separate analysis. In order to fully capture the development

[3]See Goebel et al. (2019) for a general data description and SOEP (2018) for details on the SOEP version used.

of female employment, we consider all employees who are in full-time, part-time or marginal employment.

We use information on actual hours worked last month and actual monthly earnings to construct a measure of hourly earnings. We adjust wages for inflation using the Consumer Price Index with 2017 reference prices. Observations with zero wages are excluded, and wages below the first percentile of the annual wage distribution are set to the first percentile.[4] To classify occupations, we use the definition of occupational fields by the the German Federal Institute for Vocational Education and Training (BIBB) (Tiemann et al., 2008) which defines 54 different occupational groups based on similar tasks performed within an occupation.

The SOEP provides rich information on educational attainment, work experience, demographics, and job characteristics that we can use to examine the role of compositional changes in the workforce over time. To account for a sufficient number of observations in smaller occupational fields, we pool the years 1985 to 1989 and 2013 to 2017 for the early and late periods. Therefore, data are aggregated by treating each year as a cross-section.

Table 1 shows characteristics for men and women in the periods 1985-89 and 2013-2017. Hourly wages have increased for both men and women over the period, but average wages for women in 2013-2017 are still below the level of men's wages in 1985-89, indicating a significant unconditional gender gap. Overall educational attainment has increased, but with similar trends for both sexes. However, the share of part-time work is significantly higher for women and increased further between 1985 and 2017. While only 5% of men work part-time in the period 2013-17, the share for women is 34%. In addition, men have more full-time work experience and work in companies with more employees than women. Furthermore, men have moved out of manufacturing, while women have mainly moved into public administration. In terms of demographics, men and women in the workforce have become more similar over time, and men are now less likely to be married and have children.

[4]In the SOEP, information on hours worked by employees and their wages is self-reported. Therefore, the calculation of hourly wages may lead to unreasonably low wages. We bottom code wages and exclude observations to reduce the impact of these measurement biases.

Table 1: Summary Statistics SOEP for Working Men and Women

	Men		Women	
	1985-89	2013-17	1985-89	2013-17
Hourly Wage	17.1	19.7	12.9	15.4
Education				
low education	0.12	0.09	0.26	0.09
medium education	0.64	0.54	0.57	0.6
high education	0.24	0.36	0.17	0.3
Part-time share	0.01	0.05	0.27	0.34
Work-experience FT (in years)	19.6	19.4	11.3	11.6
Tenure (in years)	12.8	12.3	9.0	10.3
Sector				
Manufacturing	0.43	0.35	0.26	0.13
Utilities & Construction	0.13	0.1	0.02	0.02
Retail, Transport, Logistics	0.12	0.16	0.17	0.18
Services	0.06	0.13	0.12	0.15
Public administration	0.17	0.19	0.29	0.43
Others	0.09	0.08	0.13	0.09
Firm size				
< 200 empl	0.41	0.42	0.54	0.5
$200 - 2000$ empl	0.25	0.24	0.23	0.22
> 2000 empl	0.34	0.34	0.22	0.28
Demographics				
Married/registered partnership	0.71	0.57	0.55	0.51
No. children household	0.7	0.54	0.43	0.45
Age	40.72	43.76	37.95	43.73
Migration background	0.13	0.26	0.11	0.24
Observations	14,104	24,839	8,334	25,663

Source: authors' calculations based on SOEP v.37.

Finally, the average age of both men and women has increased, but more so for women.

3.2 Data on Task Intensities

For the task categorization, we use four waves of the BiBB Employment Survey: the BiBB/IAB Employment Survey for 1986 and 1992 and the BiBB/BAuA Employment Survey for 2012 and 2018.[5] The Employment Survey data is a cross-sectional, representative employment survey for Germany that provides extensive information on working conditions, job content, and qualifications of the employed. In order to achieve comparability with the

[5]For more information on the datasets see BIBB (1986, 1992, 2012, 2018) and Rohrbach-Schmidt and Hall (2013, 2020).

SOEP sample, the same groups as described above are excluded.

The BiBB Employment Survey is the only data source for Germany that allows for the analysis of changes and variations in task content within occupations and over a long period of time. However, there are data limitations due to some changes in task items and changes in question wording over time. We follow Rohrbach-Schmidt and Tiemann (2013) to mitigate these concerns in order to make task groups more comparable over time. Thus, we restrict the analysis to items available in both periods and aggregate individual items into more aggregated groups to maintain a constant number of task items over time.[6] In addition, we closely follow Koomen and Backes-Gellner (2022) and distinguish between four task groups: routine and non-routine manual (NRM), non-routine interactive (NRI), and non-routine cognitive (NRC).[7] Table A1 shows the assignment of task items to task groups. For the analysis we use the task measure of Antonczyk et al. (2009). Accordingly, each task intensity in period t is defined by

$$TI_{ijt} = \frac{\text{No. of tasks in groups performed by worker } i \text{ in period } t}{\text{Total no. of tasks performed by worker } i \text{ in period } t} \tag{1}$$

where j represents one of the four task groups. By dividing by the total number of tasks performed by a worker in each period, this also allows us to control for changes in reporting behavior over time. Since each TI_{ijt} is standardized by the total number of tasks, all TI_{ijt} add up to one.[8] To assign task groups, we aggregate the individual-level data to the occupational field level. We pool data from the 1986 and 1992 waves and determine tasks group based on the dominant task intensity within in occupational field. Table A2 shows the assignment of occupational fields to task groups.

[6]In addition, to achieve a harmonized classification while maximizing the number of task items, we exploit the richness of the Employment Survey and substitute skills for specific task items when they are valid proxies. For example, we use the skill advanced knowledge of law as a proxy for applying law.

[7]To precisely identify routine tasks, we follow Koomen and Backes-Gellner (2022) in using two questions from the Employment Survey: 1. "How often does it happen in your work that one and the same work step is repeated down to the last detail?"; 2."How often do you find that your work is prescribed down to the last detail?".

[8]Since information on the importance of a task item is not available in all waves of the Employment Survey, we must make the assumption that all tasks are equally important.

For the decomposition, we also examine the role of gender-specific task intensities. Therefore, we aggregate the data at the occupation-gender-period level. This allows us to examine variation across occupations, across gender, and over time. However, the variation in the data over time is limited. One reason is that the data only indicate whether a task is performed, not at what intensity; we cannot capture whether a task item has become more important over time. Second, we lose variation in task intensity by aggregating individual-level data to the occupational field level. However, the data do not allow us to examine variation at a more disaggregated level.

Table 2: Summary Statistics Task Groups and Task Intensity

	Men		Women	
	1985-89	2013-17	1985-89	2013-17
Task groups				
Routine	0.36	0.29	0.24	0.15
NRM	0.19	0.16	0.15	0.18
NRI	0.14	0.18	0.22	0.33
NRC	0.31	0.37	0.39	0.33
Task intensity				
Routine	0.32	0.29	0.25	0.24
NRM	0.17	0.10	0.09	0.10
NRI	0.25	0.29	0.28	0.33
NRC	0.28	0.32	0.40	0.33

Notes: Task intensity and task groups are determined using BiBB/BAuA Employment Survey data and merged to the SOEP at the occupational field level. The shares are obtained by aggregating SOEP data using SOEP weights. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012 and 2018.

Table 2 shows the employment shares of the different task groups and the average task intensities for men and women and over time after merging the BiBB data with the SOEP data. The development will be discussed in more detail in Section 4.

4 The Evolution of the Employment Structure and of Wage Gaps over Time

4.1 Employment Trends Across Task Groups

According to task-biased technological change, automation will lead to a decline in routine employment and an employment shift towards non-routine occupations. Moreover, women are more likely than men to select into interactive occupations due to their comparative advantage in interactive tasks. To answer our first research question regarding the evolution of the employment structure, we use two approaches: first, we describe the evolution of the distribution of total female employment across task groups. Then, we show the evolution of the share of women's employment relative to men's employment within a task group, i.e., the female share. Finally, we look at the change in the employment share of the different task groups, and the contribution of the evolution of female and male employment to this change.

The theoretical expectations regarding task-biased technological change are borne out by the evidence. Figure 1 shows the evolution of the distribution of female employment across task groups, as well as the evolution of the share of nonworking women in all women of working age. It becomes apparent that the share of routine occupations in total female employment declined over the years 1984 to 2017. Concurrently, the share of non-routine occupations in total female employment increased, and more so for interactive occupations than for manual occupations. By contrast, the share of non-routine cognitive occupations in total female employment declined. This was accompanied by a sharp decline in the share of women not working, from about 55% in 1985 to 30% in 2017. For comparison, the evolution of employment in task group in total male employment is displayed in Figure A1.

A question emerging from the trend in the occupational structure of female employment displayed in Figure 1 is how this trend compares to the evolution of the occupational structure of male employment, and what the trends for women and men imply for gender employment

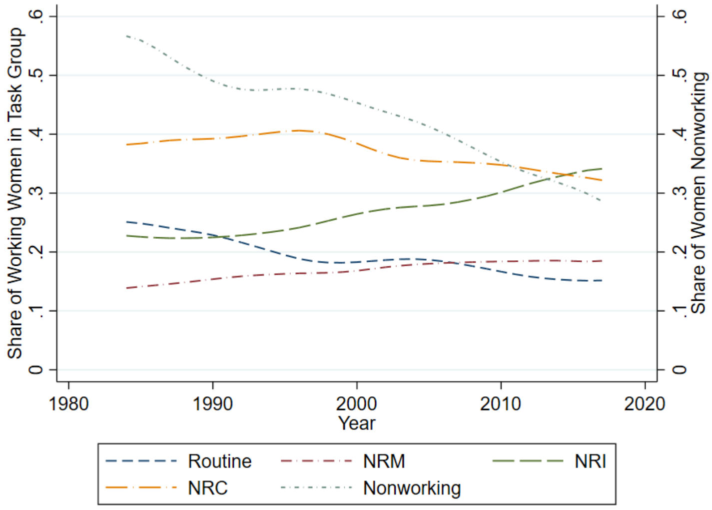

Figure 1: Trend in the Share of Nonworking Women and Task Group Shares in Female Employment

Notes: Share of nonworking women: share of nonworking women in all women of working age; Task group shares: employment share of the respective task group in total female employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

gaps. Therefore, Figure 2 displays the evolution of the employment share of women relative to men, the female share, for the different task groups, over the time period 1984 to 2017. It becomes apparent that the female share in routine occupations was only 30% in 1985, suggesting that women were exposed less strongly than men to automation in the early period. This is in line with the results in Black and Spitz-Oener (2010) and Cortes et al. (2020) that women were differently exposed to automation due to their lower employment share in routine occupations. As a consequence of the relatively low initial level, the female share in routine occupations remained almost constant over time.

Figure 2 also shows that women increased their share in interactive occupations from 50% in 1985 to more than 60% in 2017. This speaks to the comparative advantage of women in interactive tasks. In comparison, the female share in cognitive occupations remained almost constant over time, at about 45%. By contrast, the female share in non-routine manual occupations increased sharply from 30% in 1985 to 50% in 2017. This increase is much stronger in Figure 2 than in Figure 1.

To make the evolution of employment shares by task group and gender more transparent,

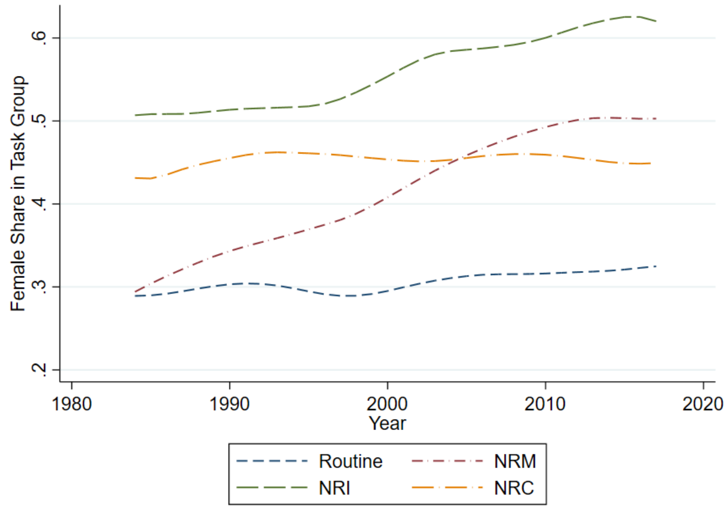

Figure 2: Trend in the Female Share across Task Groups
Notes: Female share: employment share of women in total employment of respective task group. The female and male employment share within a task group add up to 1. The evolution of the male share is displayed in Figure A2. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

Table 3 shows the change in the employment share of task group j in total employment, as well as the contributions of women and men to the change in employment shares. Therefore we define the change in the (gender-specific) employment share of task group j as follows:

$$\Delta e_j = \frac{E_{jt2}}{E_{t2}} - \frac{E_{jt1}}{E_{t1}} \tag{2}$$

$$\Delta e_{gj} = \frac{E_{gjt2}}{E_{t2}} - \frac{E_{gjt1}}{E_{t1}} \tag{3}$$

where E_t is total employment in period t, E_{jt} is employment in task group j in period t and E_{gjt} is gender-specific (i.e. female or male) employment in task group j in time period t.

The results show that the routine employment share in total employment declined by 9 pp. This was driven to some extent by a reduction of the share of women working in routine occupations (-2 pp), but more strongly by a reduction of the share of men working in routine occupations (-7 pp). Furthermore, while the share of men working in manual occupations also declined (-3 pp), the share of women in manual occupations increased (+3 pp). This resulted in an overall stable manual employment share in total employment.

In comparison, the employment share of interactive occupations in total employment experienced strong employment growth (+8.4 pp), mostly due to an increase in the share of women employed in interactive occupations in total employment (+7.3 pp), but to a smaller part also due to an increase in the share of men working in interactive occupations (+1.1 pp). Finally, the employment share of cognitive occupations in total employment remained relatively stable, as did the employment shares of women and men employed in routine occupations in total employment.

Table 3: Change in Employment Shares in Total Employment by Task Group between 1985 and 2017

Task Group	Change Total	Change Women	Change Men
Routine	-9.11	-2.06	-7.06
NRM	-0.03	3.12	-3.15
NRI	8.41	7.31	1.1
NRC	0.74	0.64	0.1

Notes: Change Total: change in employment share of each task group in total employment. The employment shares of all task groups in each period add up to one. The sum of total employment changes is zero. Change Women (Men): change in fe(male) employment in each task group in total employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

4.2 Trends in Gender Wage Gaps Across Task Groups

The second question we want to answer in this paper is whether the change in the occupational structure and especially the selection of women into interactive occupations contributed to an improvement of the labour market condition of women in terms of wages. To answer this question, we first provide descriptive evidence on the gender wage gap by task group. Second, we perform a shift-share decomposition following Cortes et al. (2020) which allows us to decompose the reduction of the gender wage gap over time into a between-component, i.e. task groups with a low gender wage gap growing more strongly, and a within-component, i.e. a reduction of the gender wage gap within task groups.

Figure 3 shows average hourly wages for women and men in the period 1985-89. On average, workers earn relatively high wages in interactive and cognitive occupations, and relatively low wages in routine and manual occupations. Accordingly, the selection of women into interactive occupations would imply a higher share of women working in higher-paying occupations, all else equal. Since the average wage in period t is the weighted sum of the average wage of women in task group j, it can be expressed as

$$w_{ft} = \sum_j w_{fjt} \frac{E_{fjt}}{E_{ft}} \tag{4}$$

where j indicates the task group and E_{ft} denotes total female employment in period t and E_{fjt} denotes female employment in task group j. Therefore, an increase in the share of women working in interactive occupations should also lead to an increase in average female wages. However, Figure 3 shows that there are significant unconditional gender wage gaps within task groups and that this gap is particularly large in interactive occupations. A persistence of these gender gaps within task groups limits the potential of the convergence in wages that could be achieved by occupational sorting across task groups. Therefore, wages of women need to catch up to those of men to fully benefit from the reallocation across task groups.

To explore this issue in more detail, we perform the shift-share analysis outlined in more detail in the Appendix B.1. We can thus decompose the change in the unconditional gender wage gap between 1985 and 2017 into between- and within-effects.[9] Cortes et al. (2020) argue that the between-effect captures the impact of task-biased shocks on gender-specific reallocation between task groups. The within-effect can be further decomposed into a common and gender-specific wage trends within task groups. While the common wage trends can be linked to technological change, gender-specific wage trends may capture other

[9]The between-effect is the product of the change in employment shares weighted with mean wages across both periods, while the within-effect is the product of the change in average wages within task groups weighted using mean employment shares in the task group across both periods.

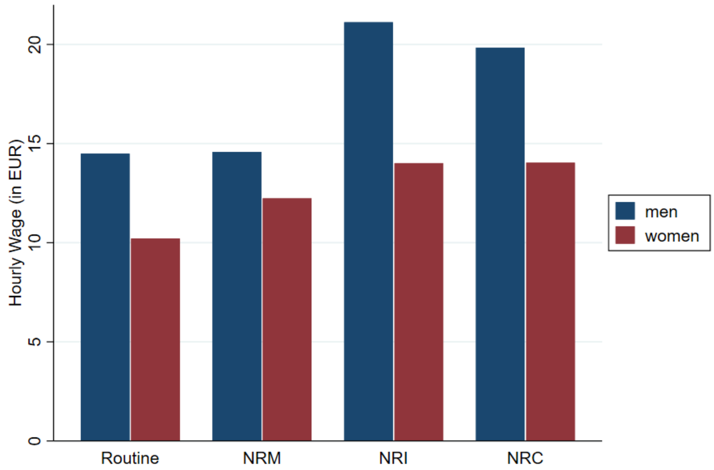

Figure 3: Mean Wages for Men and Women in the Early Period (1985-89)
Notes: Mean hourly wages for each task group by gender. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992.

developments within task groups, including changes in workforce composition, changes in task content within occupations, or a reduction in discrimination.

Table 4 displays the results of this decomposition, i.e. the contribution of the between- and the within-effect to wage changes by gender and task groups, and the implications for the change of the gender wage gap. Overall, it becomes apparent that the narrowing of the gender wage gap by 5.7% was mainly driven by the within-effect which contributed 7.5% to the narrowing of the gender wage gap. By contrast, the between-effect hampered the narrowing of the gender wage gap, i.e. the gender wage gap would have been 1.6% smaller without the between-effect.

The positive contribution of the within-effect to women's wages is mainly due to the high within-effect of cognitive (+7.5%) and interactive occupations (+4.4%). While average wages for men in cognitive occupations also increased strongly (+4.9%), average wages for men in interactive occupations remained fairly constant, resulting in a strong positive contribution of the within-effect to women's wages in these two task groups. In contrast, there was little change in wages in routine and manual occupations, neither for women nor for men.[10]

The decomposition can be further refined by separating the within-effect into an effect

[10]The change in average wages for women and men is illustrated in Figure A3.

which is common to both women and men, and a gender-specific wage effect. The results of this more detailed decomposition in Table A3 show that the gender-specific wage trend can explain the full within-effect (-7.5%), while the contribution of the general wage trend to the gender wage gap is virtually zero. This stands in contrast to Cortes et al. (2020) who find for the US and Portugal that the general wage trend, which can be related to technological change, contributes negatively to the gender wage gap. The authors argue that this occurs because women on average sort into lower-paid occupations. Our results show that this is not the case in Germany.

Turning to the between-effect, its positive contribution to the gender wage gap can be analysed in more detailed using the results in Table 4. It becomes apparent that the reallocation of women, especially their selection into interactive occupations, contributed to an increase in average female wages (+1.6%). However, the reallocation of men out of routine and manual and into interactive and cognitive occupations contributed to a much stronger increase of male wages (+3.5%). While women were more successful than men in entering interactive occupations, they sorted into lower-paying manual occupations and sorted out of cognitive occupations.

The overall result regarding the between-effect is opposite to the evidence presented in Cortes et al. (2020) who find that the between-effect, which they describe as employment channel, contributed to a closing of the gender wage gap. There are a number of potential explanations for this result, including changing worker composition due to the strong increase of female labour force participation in Germany, and the prevalence of part-time employment for women on the German labour market. In the following section, we therefore analyse these factors in more detail.

Table 4: Decomposition of the Change in the Gender Wage Gap

	Between-effect		Within-effect	
	men	women	men	women
Routine	-19.	-20.2	0.8	0.7
NRM	-7.2	9.3	-0.4	0.8
NRI	13.1	29.	0.6	4.4
NRC	16.5	-16.4	4.9	7.5
Sum	3.5	1.6	5.8	13.3
Contribution (in%)	1.8		-7.5	
GWG Change (in%)	-5.7			

Notes: Decomposition of the change gender wage gap (GWG) into a between- and within-effect over the period 1985-89 to 2013-17 (for details see Section B.1). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 198,1992, 2012 and 2018.

5 Decomposing the Gender Wage Gap

Given the differences between our results for Germany and the existing evidence for Portugal and the US (Cortes et al., 2020), we now explore in more detail the determinants of the gender wage gap and of its change over time. We therefore conduct a Blinder-Oaxaca (BO) decomposition separately for two time periods (see Appendix B.2 for more details). In our analysis, we construct the counterfactual wage distribution by using the male wage distribution. This approach assumes that there is no wage discrimination against men.

The decomposition allows us to quantify the importance of composition effects. This decomposition also allows us to explore the "payoffs" to specific characteristics, which could have changed over time given the changing position of women in the labour market. In doing so, we account for factors that are related to the strong increase in female labour force participation over the time period analysed. We pay particular attention to educational attainment, which strongly grew over time for women, and work experience, i.e. tenure, and part-time employment, which have played an important role for female employment in Germany over the last decades (Bachmann et al., 2020). To explore the potential role of technology, we use indicators for task intensities as explanatory variables. In addition, we also conduct separate analyses by task groups.

Table 5: Overall BO Decomposition Gender Wage Gap by Period

	1985-89	(in%)	2013-17	(in%)
Overall		100		100
Difference	0.296***		0.240***	
	(0.039)		(0.049)	
Explained	0.037	12.6	0.189***	78.8
	(0.038)		(0.056)	
Unexplained	0.259***	87.4	0.051**	21.2
	(0.030)		(0.024)	
Explained				
Education	0.023*	7.7	0.016	6.7
	(0.012)		(0.017)	
Experience	-0.009	-3.1	0.126***	25.6
	(0.023)		(0.019)	
Job characteristics	0.036***	12.0	0.058***	24.3
	(0.011)		(0.016)	
Demographics	0.021***	7.1	0.007***	3.0
	(0.005)		(0.003)	
Task intensities	-0.033	-11.1	-0.019	-7.83
	(0.023)		(0.030)	
Unexplained				
Education	0.002	0.5	-0.004	-1.5
	(0.011)		(0.011)	
Experience	-0.010	-3.5	-0.083***	-34.7
	(0.021)		(0.023)	
Job characteristics	-0.064 **	-21.51	-0.040	-16.7
	(0.026)		(0.034)	
Demographics	0.040***	13.4	0.065***	26.9
	(0.010)		(0.013)	
Task intensities	0.023	7.8	-0.046	-19.0
	(0.055)		(0.090)	
Constant	0.268***		0.159*	
	(0.057)	90.62	(0.091)	66.15
Observations Men	14004		24367	
Observations Women	8240		25327	

Notes: BO decomposition of the GWG at the mean. The counterfactual is calculated putting a weight of 1 on group 1 (men). Percentages are relative to the unconditional gender wage gap in each period and are based on the mean estimate. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Education: primary, secondary, and tertiary education. Experience: full-time work experience, tenure, and part-time dummy. Job characteristics: 6 industry groups and firm size. Demographics: married, no. children in HH, dummy migration background, age groups. Task intensities: gender-specific task intensities for routine, NRM, NRI and NRC tasks. Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

The results of the Blinder-Oaxaca decomposition in Table 5 show that the raw gender wage gap declined from 30% to 24% over the period 1985 to 2017. This was accompanied by a decline of the unexplained part of the decomposition (from 87.3% to 21.2%) and a corresponding increase of the explained part (from 12.7% to 78.8%). This is in line with evidence from Austria (Böheim et al., 2021) and indicates that the payoff to characteristics became more similar between men and women over time which may be due to a decline in wage discrimination towards women.

Looking at variable groups of explained factors,[11] the variable groups contributing to the gender wage gap in the early period are education (7.7%, significant at the 10% level only), job characteristics (12%) and demographics (7%). In the later period, labour market experience (25.6%) and job characteristics (24%) are the dominant factors for the observed part of the decomposition, while demographics play a less important role (3%). By contrast, we do not find that task intensities play a significant role for the explanation of the overall gender gap.

A detailed decomposition reveals that more women working part-time (captured by a part-time dummy) is the driving factor (-14.7% in 1985-89 compared to 30% in 2013-17) behind the increasing importance of explained factors between the two periods (see Table A4). At the same time, the part-time wage penalty for women falls between the two periods as shown by the coefficient on part-time employment for the unobserved part of the decomposition (positive in the early period, negative and much larger in the later period). This could indicate that part-time work is becoming more of a norm in the labour market. Finally, unobserved factors captured by the constant also play a less important role for the gender wage gap. This result can be interpreted as further evidence for declining wage discrimination towards women.

Returning to composition effects, work experience in full-time employment also contributes to the gender wage gap (5.4% in 1985-89 and 17.0% in 2013-17). This can be explained by women having lower full-time work experience, probably because of more frequent career interruptions for child rearing reasons. Sorting into different sectors also plays

[11]The variable groups are education (primary, secondary or tertiary education), experience (full-time work status, full-time work experience, job tenure), job characteristics (1-digit industries, firm size), demographics (age groups, marital status, number of children in household, migration background)

an important role (Table 1): while both men and women sorted out of the manufacturing sector, men sorted into the high-paying service sector and women sorted into the public sector. More women working in the public sector is a particularly important contributor to the gender wage gap (5.5% in 1985-89 and 16.7% in 2013-17).

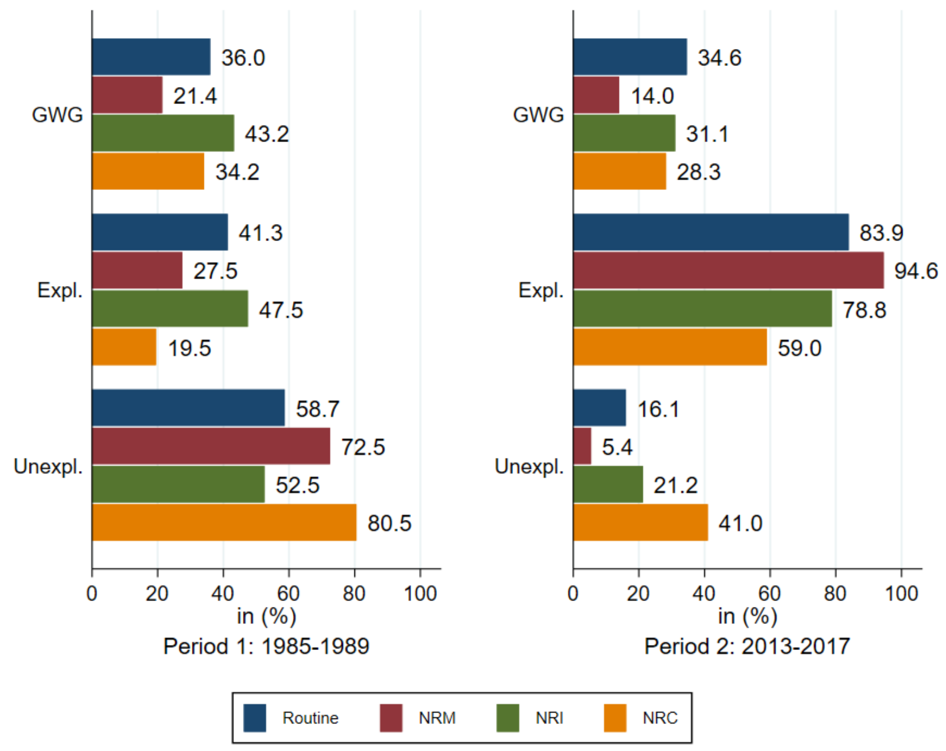

Figure 4: BO Decomposition by Task Group: Gender Wage Gap and Explained and Unexplained Share

Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution shares of the explained and unexplained part are calculated based on the coefficients of the decomposition (see Table A7). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Performing the same Blinder-Oaxaca decomposition separately by task group reveals two additional results. First, the gender wage gap declines particularly strongly in non-routine manual (from 21.4% to 14%) and non-routine interactive occupations (from 34.2% to 28.3%) (Figure 4). In the non-routine manual occupations, this decline is mainly driven by personal care occupations; in the non-routine interactive occupations, this decline is mainly driven by social and sales professions (Table A2). Second, the increased contribution of the explained part, and the corresponding decreased contribution of the unexplained part, to the gender wage gap occurs in all task groups. This trend is particularly pronounced in non-routine manual occupations and (to a smaller extent) in routine occupations (Figure 4).

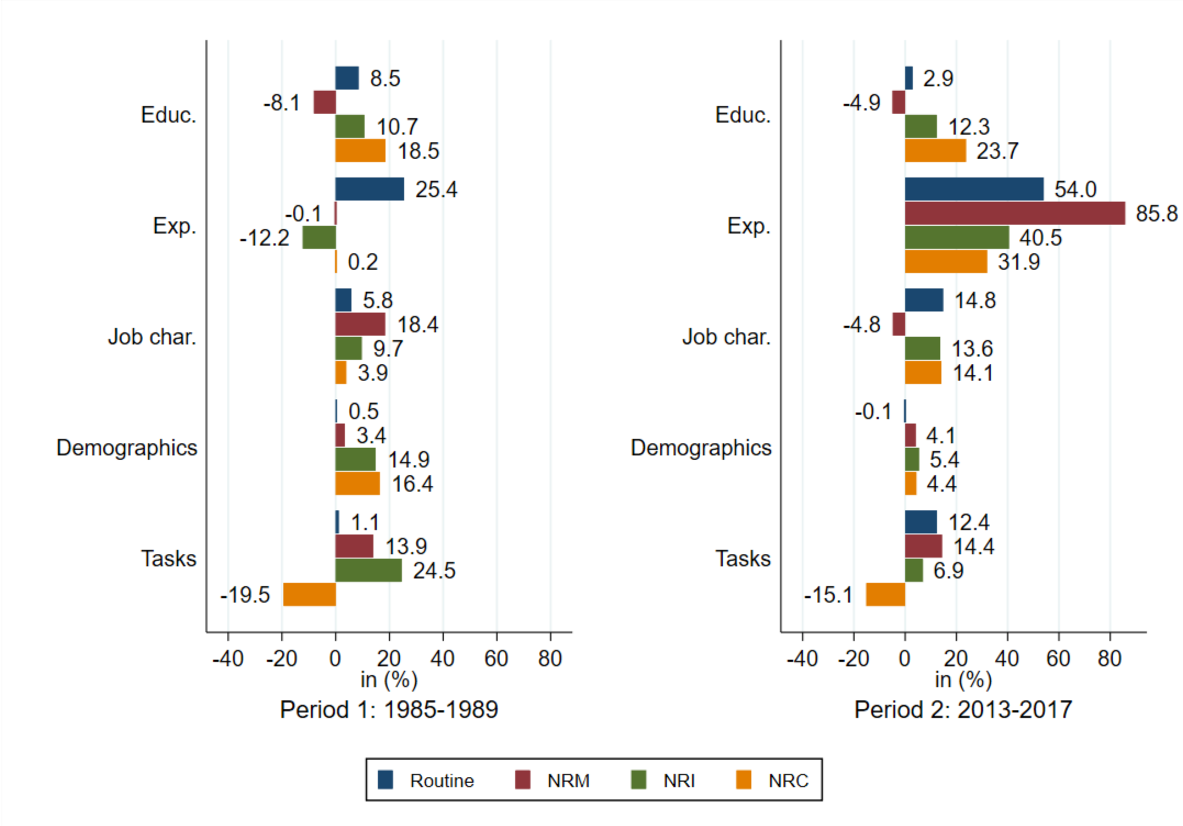

Figure 5: Detailed BO Decomposition by Task Group: Explained Part by Variable Group
Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution of the variable groups are calculated based on the coefficients of the decomposition (see Table A7) and relative to the gender wage gap. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

A detailed decomposition of the explained part by task groups yields further insights (see Figure 5 where each color represents a different decomposition by task group).[12] Compared to the overall decomposition, task intensities plays a role for the evolution of the gender wage gap within task groups, and their importance for the gender wage gap changes over time. Differences in interactive task intensity contributed positively to (i.e. increased) the GWG in non-routine manual and cognitive occupations (Table A7), but for different reasons:

[12]The decomposition of the unexplained part does not show important differences between task groups, see Figure A4.

While women have a higher non-routine interactive task intensity in manual occupations, they have a lower non-routine interactive task-intensity in cognitive occupations (see Tables A5 and A6). Accordingly, a higher interactive task intensity is associated with higher wages (relative to men) in non-routine manual occupations and with lower wages relative to men in cognitive occupations.

In addition, non-routine cognitive tasks contributed negatively to the gender wage gap in non-routine cognitive occupations (strongly in the first period, less strongly in the second period), whereas they contributed positively to the gender wage gap in non-routine interactive occupations in the first period and in the second period. However, the non-routine cognitive task intensities is lower for women than for men in interactive occupations and higher for women than men in cognitive occupations (see Tables A5 and A6). This implies that a higher share of cognitive tasks within task groups, has positive wage impacts and reduced the GWG.

Overall, the detailed decomposition yields two main conclusions. First, the contribution of the different task intensities varies by task group. This implies that the gender-specific payoffs to same tasks differ by task groups. This is probably due to jobs consisting of task bundles which implies that the composition of tasks, in addition to the intensity of individual tasks, matters for their payoff (Autor and Handel, 2013) – and that this seems to matter for gender differences as well. Second, the importance of task intensities is falling relatively strongly over time in two out of the four task groups. This indicates that women are becoming more similar to men with respect to the tasks they perform and the corresponding payoffs they receive.

Apart from task intensities, there are also insights for other factors. First, labour-market experience is the only component that became more important across all groups. Therefore, women with strong labour-market attachment are a major driver of the decrease of the gender wage gap. Second, job characteristics became more important for three of the four task groups, with non-routine manual occupations being the exception. This indicates that sorting into different industries is an important determinant of the gender pay gap. Third, demographic factors played a significant role for the gender wage gap in the early observation period, but are negligible in the second observation period. Therefore, differences in demographic characteristics, such as household context, have become less important for the gender pay gap over time.

6 Conclusion

In this paper, we analyse how the structural change of the labour market has affected employment and wage gaps between women and men in Germany in the period 1984 to 2017. Our analysis is based on panel data from the German Socio-Economic Panel and proceeds in three steps. First, we provide evidence on the evolution of the occupational employment structure of women and men. Second, we analyse how the gender wage gap has evolved over time and whether this was due to changes between or within occupations. Third, we perform a decomposition analysis to examine which factors explain the evolution of the gender wage gap. An important focus of our analysis is the role of technological progress which we capture by including the intensity of specific job tasks and by performing some of the analyses separately by task groups.

Our results are as follows. First, with respect to the occupational structure, we find that while the female share in non-routine manual and in interactive occupations increased strongly over time, the female share in non-routine cognitive and in routine occupations remained relatively constant. Second, we confirm the decline of the gender wage gap in Germany over the last decades previously found in the literature. A shift-share analysis shows that this decline is entirely driven by a reduction of the gender wage gap within occupations, not between occupations. This means that the overall change in the occupational structure of the labour market did not contribute to the narrowing of the gender wage gap. The dominating within-effect is caused by narrowing gender wage gaps in cognitive and interactive occupations. Our results stand in contrast to evidence in Cortes et al. (2020) which shows an important role of the between-effect for the evolution of the gender wage gap in the US and Portugal.

In the final step of the analysis, we therefore conduct a Blinder-Oaxaca decomposition to take into account composition effects with respect to various factors such as part-time employment (particularly relevant for German women), education and job tasks. The decomposition of the overall gender wage gap reveals a strong increase of the explained part (composition effects) and a corresponding strong decrease of the unexplained part (payoffs to characteristics). The increase in the explained part is driven by variables related to experience and job characteristics. The decline in the unexplained part is driven by a decline of the contribution of the constant. Overall, these results are in line with a reduction in wage discrimination in the labour market.

To account for the role of technology, we control for gender-specific task intensities in the decomposition. While we find no effect of task intensities on the overall gender wage gap, we show that task intensities play a multifaceted role in the evolution of the gender wage gap within task groups. However, their contribution differs by task groups, i.e. by occupations, and declines over time. This is in line with the general picture that women become more similar to men during our observation period, reducing gender gaps in the labour market. Other factors, however, play a more important role. In particular, part-time employment contributes to a larger gender wage gap, but this contribution is double-edged: on the one hand, more women working part-time contributes to the gender wage gap; on the other hand, the wage penalty to working part-time has gone down over time.

Overall, our results show that structural change in the labour market affects women and men very differently as both initial levels and changes over time of occupational sorting differ strongly between women and men. However, the changing occupational structure, i.e. shifting employment weights between occupations, is not a major driver of the evolution of the gender wage gap in Germany. The same conclusion emerges from a decomposition analysis including task intensities. Therefore, technological change has apparently not been an important driver of the gender wage gap. Rather, changes of the gender wage gap within occupations play a role in this context. Furthermore, institutional aspects, and especially part-time employment, are important determinants of the gender wage gap. It is therefore likely that the differences between our results for Germany and those from Cortes et al. (2020) for Portugal and the US are largely caused by institutional factors.

Technological change therefore does not seem like neither boon nor bane for the position of women in the German labour market. This is likely the result of two competing forces. On the one hand, women have been argued to be better able to benefit from the increased demand for social skills than men (Cortes et al., 2023). On the other hand, there is evidence for a gender gap in digital skills (Bachmann and Hertweck, 2023) which means that women may benefit less from technological change than men. Therefore, appropriate measures to improve the digital literacy of women is crucial for further advancing women's position in the labour market.

Given the continued importance of institutional factors for gender disparities on the labour market, these factors should remain high on the policy agenda. Part-time employment, in particular, is still a major contributor to the gender wage gap, it seems important to enable women to increase their working time if they wish to do so. Measures dedicated to this objective, e.g. increased provision of flexible working time provisions (Maraziotis, 2024), should be considered in this context.

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A Appendix A – Additional Figures and Tables

A.1 Figures

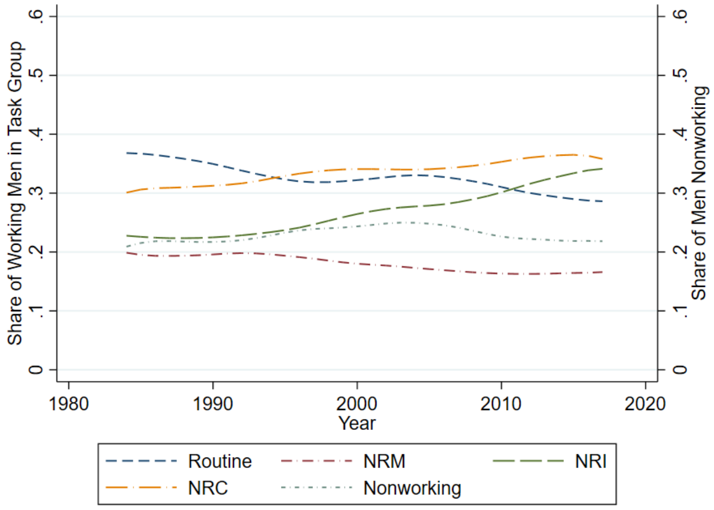

Figure A1: Trend in the Share of Nonworking Men and Working Men across Task Groups
Notes: Share of nonworking men: share of nonworking men in all men of working age; Task group shares: employment share of the respective task group in total male employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

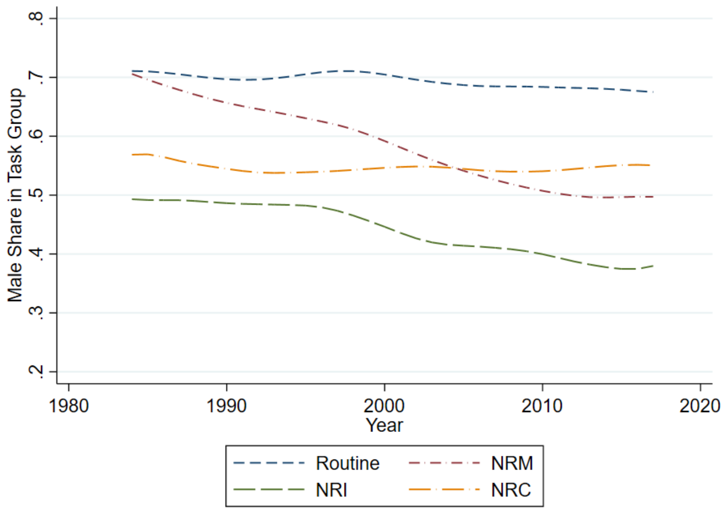

Figure A2: Trend in the Male Share across Task Groups
Notes: Male share: employment share of men in total employment of respective task group. The female and male employment share within a task group add up to 1. The evolution of the male share is displayed in Figure A2. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

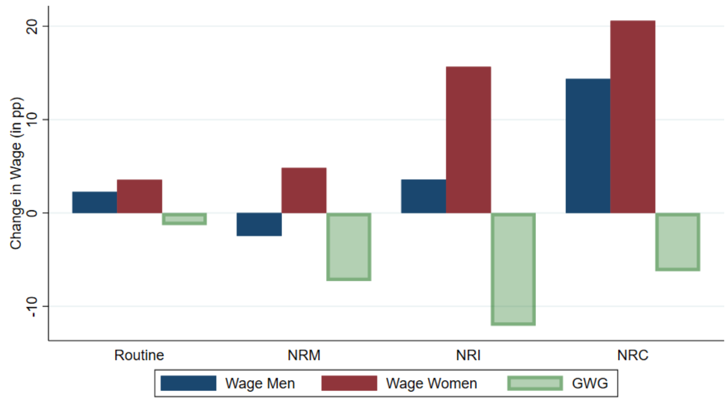

Figure A3: Change in Wages and Unconditional Gender Wage Gap 1985-2017
Notes: Change in log wages and the gender wage gap between the period 1985-89 to 2013-2017. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

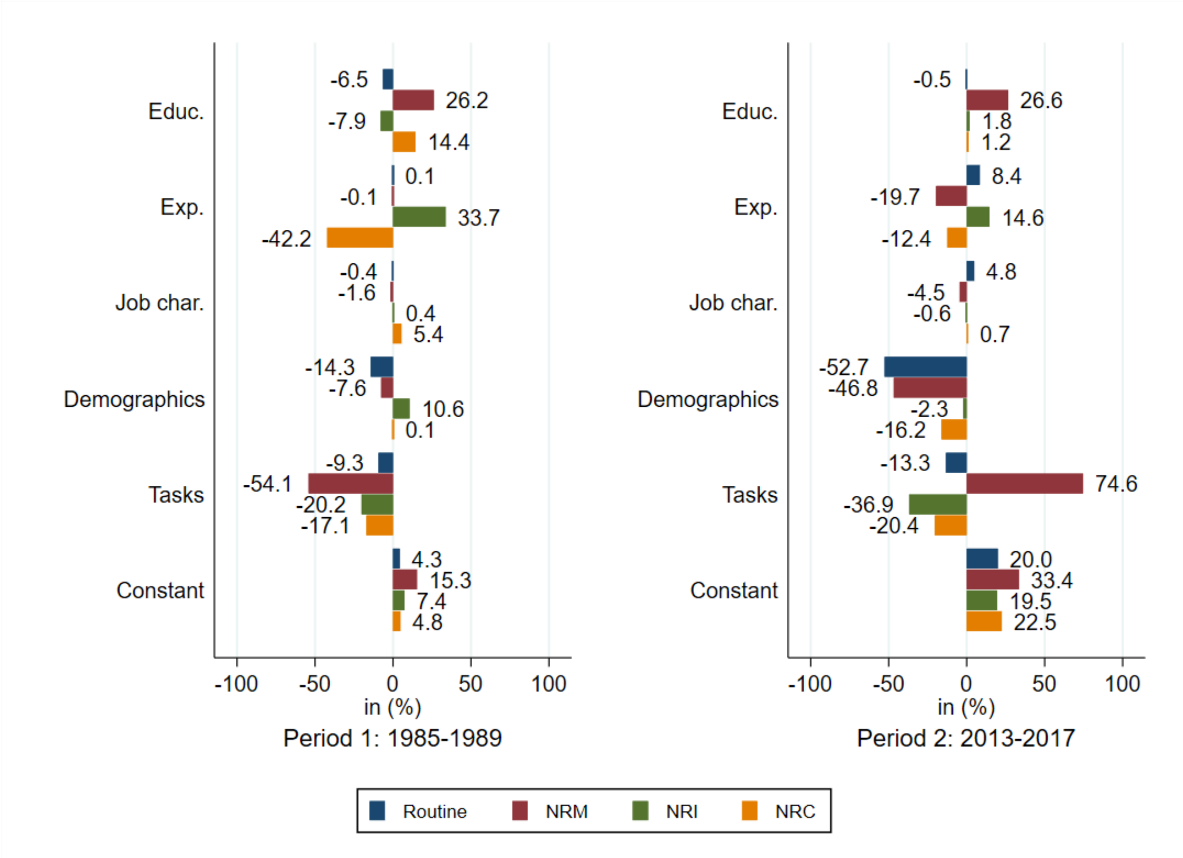

Figure A4: Detailed BO Decomposition by Task Group: Unexplained Part by Variable Group

Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution of the variable groups are calculated based on the coefficients of the decomposition (see Table A7) and relative to the gender wage gap. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

A.2 Tables

Table A1: Assignment of Task Items

Task Groups	Task Items
Routine	operating, manufacturing, storing, cleaning, measuring
NRM	repairing, accommodating, caring, protecting
NRI	teaching, consulting, buying and promoting, managing personnel, organizing for others
NRC	investigating, researching and constructing, programming, applying law, writing and calculations

Source: Employment Survey waves 1986,1992, 2012 and 2018 following Koomen and Backes-Gellner (2022).

Table A2: Assignment of task groups and gender wage gaps by occupational field

TG	Occupational Field	1985-89	2013-17	Δ
Routine				
1	Metal, plant construction, sheet metal construction, installation, assemblers	0.35	0.01	-0.33
1	Goods inspectors, dispatch finishers	0.36	0.19	-0.17
1	Butchers	0.32	0.17	-0.16
1	Metal production, processing	0.38	0.25	-0.13
1	Unskilled workers n.e.c.	0.26	0.14	-0.12
1	Agriculture, animal husbandry, forestry, horticulture	0.28	0.18	-0.10
1	Cleaning, waste disposal	0.27	0.19	-0.09
1	Precision engineering, related occupations	0.33	0.26	-0.07
1	Baking and confectionery	0.29	0.24	-0.05
1	Transport occupations	0.30	0.28	-0.02

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Table A2 – continued from previous page

Task Group	**Occupational Field**	**1985-89**	**2013-17**	**Δ**
1	Beverages, luxury food production, other food professions	0.44	0.46	0.01
1	Packers, warehouse, transportation workers	0.13	0.15	0.02
1	Chemical and plastic professions	0.37	0.38	0.02
1	Spinning professions and textile production	0.27	0.37	0.09
1	Paper production, processing, printing	0.27	0.38	0.11
1	Industrial and tool mechanics	0.12	0.30	0.19
1	Miners, mineral extractors and stone processing, building material production, ceramic, glass professions	0.49	0.68	0.19
1	Chefs	0.11	0.34	0.23
NRM				
2	Driving, aircraft construction, maintenance occupations	0.14	-0.21	-0.35
2	Personal care professions	0.36	0.07	-0.29
2	Personal protection and security occupations	0.28	0.08	-0.20
2	Electrical professions	0.28	0.20	-0.07
2	Hotel, restaurant and catering occupations, housekeeping	0.11	0.05	-0.07
2	Building trades, woodworking and plastic processing	0.24	0.23	0.00
2	Healthcare professions without a license to practice	0.08	0.17	0.09
2	Janitors	0.19	0.31	0.12
NRI				
3	Social professions	0.34	0.12	-0.22
3	Sales professions (retail trade)	0.39	0.22	-0.17
3	Wholesale and retail traders	0.34	0.20	-0.14
3	Health professions with license to practice medicine	0.23	0.18	-0.06
3	Teachers	0.09	0.11	0.03

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Table A2 – continued from previous page

Task Group	Occupational Field	1985-89	2013-17	Δ
3	Other commercial professions (excluding wholesale, retail, banking)	0.11	0.17	0.06
3	Management, auditing, management consulting	0.16	0.24	0.09
NRC				
4	Technicians	0.30	0.06	-0.24
4	Office support occupations, telephone operator(s)	0.19	-0.02	-0.21
4	Specialist technical staff	0.15	-0.05	-0.20
4	Engineer(s)	0.20	0.03	-0.16
4	Advertising specialists	0.35	0.19	-0.16
4	IT core professions	0.28	0.13	-0.16
4	Legal professions	0.37	0.25	-0.13
4	Commercial office occupations	0.28	0.16	-0.13
4	Security professions	0.23	0.11	-0.12
4	Administrative professions in the public service	0.26	0.15	-0.11
4	Technical draughtsperson, related professions	0.23	0.18	-0.05
4	Designers, photographers, advertising producers	0.28	0.24	-0.04
4	Finance, accounting, bookkeeping	0.34	0.31	-0.03
4	Banking and insurance specialists	0.26	0.29	0.02
4	Chemists, physicists, natural scientists	0.24	0.28	0.04
4	Publishing, library, translation and related scientific professions	0.12	0.19	0.07
4	Surveying	0.15	0.28	0.13

Notes: This table shows the assignment of occupational fields to task groups and the gender wage gaps by occupational field over the period 1985-2017. The Δ column represents the difference in gender wage gaps between the two periods. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

Table A3: Detailed Decomposition of the Gender Wage Gap

	Between-effect		Within-effect			
			Overall		Gender-specific	
	men	women	men	women	men	women
Routine	-19.	-20.2	0.6	0.3	0.2	0.4
NRM	-7.2	9.3	-0.5	-0.4	0.1	1.2
NRI	13.1	29.	1.0	1.6	-0.4	2.8
NRC	16.5	-16.4	6.0	5.7	-1.1	1.7
Sum	3.5	1.6	7.1	7.2	-1.4	6.1
Overall	1.8		-0.1		-7.5	
GWG Change			-5.7			

Notes: Decomposition of the change gender wage gap (GWG) into a between- and within-effect over the period 1985-89 to 2013-17 (for details see Section B.1). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table A4: BO Decomposition Gender Wage Gap by Period: Full Model

	1985-89	2013-17
Difference	0.296***	0.240***
	(0.039)	(0.049)
Explained	0.037	0.189***
	(0.038)	(0.056)
Unexplained	0.259***	0.051**
	(0.030)	(0.024)
Explained		
Education (Reference Group: Medium education)		
Low education	0.010***	0.000
	(0.004)	(0.003)
Higher education	0.013	0.016
	(0.010)	(0.015)
No educational info	0.000	0.000
	(0.000)	(0.000)
Tenure	0.018***	0.014***
	(0.004)	(0.004)
Part-time	-0.044*	0.071***
	(0.024)	(0.016)
Work experience full-time	0.016**	0.041***
	(0.008)	(0.010)
Industry sector (Reference Group: Manufacturing)		
Utilities + construction	-0.004	-0.002
	(0.002)	(0.003)
Retail, transport, logistics	0.008	0.003
	(0.009)	(0.011)
Services	-0.003	0.001
	(0.002)	(0.002)
Public administration + health	0.016	0.039**
	(0.011)	(0.017)
Others	0.003**	0.002
	(0.002)	(0.004)
Firm size (Reference Group: < 200 employees)		
No info	0.000	0.000
	(0.000)	(0.000)
200-2000 employees	0.001	0.002
	(0.001)	(0.002)
>2000 employees	0.013***	0.012*
	(0.004)	(0.006)
Married and registered partnership	0.010***	0.004**
	(0.002)	(0.002)
No. of children in household	0.003*	0.002**
	(0.002)	(0.001)
Migration background	-0.000	-0.000
	(0.000)	(0.000)
Age group (Reference Group: age 30-54)		
Age 20-29	0.010***	0.001
	(0.003)	(0.002)
Age 55-64	-0.002***	0.000

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Table A4 – continued from previous page

	1985-89	2013-17
	(0.001)	(0.001)
Task intensities (Reference Group: Routine)		
NRM	0.009	-0.000
	(0.008)	(0.002)
NRI	-0.007	-0.008
	(0.016)	(0.012)
NRC	-0.035	-0.010
	(0.023)	(0.027)
Unexplained		
Education (Reference Group: Medium education)		
Low education	0.006	-0.002
	(0.005)	(0.004)
Higher education	-0.004	-0.001
	(0.008)	(0.009)
No educational info	-0.001	-0.001
	(0.000)	(0.001)
Tenure	0.006	-0.014
	(0.015)	(0.011)
Part-time	0.037*	-0.067***
	(0.022)	(0.017)
Work experience full-time	-0.053***	-0.002
	(0.019)	(0.016)
Industry sector (Reference Group: Manufacturing)		
Utilities + construction	-0.001	0.002
	(0.001)	(0.001)
Retail, transport, logistics	0.000	-0.010
	(0.006)	(0.007)
Services	0.004	-0.000
	(0.005)	(0.006)
Public administration + health	-0.047***	-0.035*
	(0.018)	(0.020)
Others	-0.005	0.000
	(0.005)	(0.004)
Firm size (Reference Group: < 200 employees)		
No info	-0.000	-0.001
	(0.001)	(0.001)
200-2000 employees	-0.007*	0.001
	(0.004)	(0.006)
>2000 employees	-0.009**	0.003
	(0.004)	(0.007)
Married and registered partnership	0.040***	0.052***
	(0.008)	(0.010)
No. of children in household	0.007	0.002
	(0.007)	(0.004)
Migration background	-0.003	0.007
	(0.003)	(0.005)
Age group (Reference Group: Age 30-54)		
Age 20-29	-0.007	0.004
	(0.006)	(0.006)

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Table A4 – continued from previous page

	1985-89	2013-17
Age 55-64	0.003	-0.000
	(0.003)	(0.004)
Task intensities (Reference Group: Routine)		
NRM	0.019	-0.028
	(0.015)	(0.031)
NRI	0.026	-0.019
	(0.032)	(0.087)
NRC	-0.022	0.001
	(0.030)	(0.057)
Constant	0.268***	0.159*
	(0.057)	(0.091)

Notes: BO decomposition of the GWG at the mean. The counterfactual is calculated putting a weight of 1 on group 1 (men). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table A5: Summary Statistic Women by Task Group

	Routine		NRM		NRI		NRC	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Education								
Low education	0.58	0.27	0.21	0.10	0.15	0.05	0.13	0.04
Medium education	0.39	0.62	0.47	0.73	0.52	0.50	0.75	0.62
High education	0.02	0.09	0.31	0.15	0.34	0.43	0.12	0.33
No information	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.01
Work experience (full-time)	0.32	0.48	0.25	0.37	0.32	0.34	0.21	0.27
Share part-time	11.89	12.04	10.35	11.45	10.44	10.00	11.89	13.08
Tenure	9.16	8.73	7.44	9.33	8.96	9.12	9.50	12.61
Sector								
Manufacturing	0.49	0.28	0.09	0.03	0.15	0.09	0.24	0.18
Utilities + construction	0.01	0.01	0.01	0.00	0.00	0.00	0.05	0.05
Retail, transport, logistics	0.12	0.19	0.02	0.04	0.41	0.33	0.12	0.09
Services	0.05	0.18	0.08	0.04	0.02	0.06	0.24	0.30
Public administration	0.16	0.2	0.67	0.74	0.31	0.48	0.22	0.31
Others	0.17	0.14	0.13	0.14	0.1	0.05	0.13	0.08
Firm size								
No info	0.01	0.02	0.01	0.01	0.02	0.01	0.00	0.00
<200 employees	0.53	0.56	0.58	0.63	0.61	0.5	0.48	0.38
$200-2000$ employees	0.25	0.21	0.26	0.2	0.13	0.18	0.26	0.27
>2000 employees	0.20	0.20	0.15	0.16	0.24	0.31	0.26	0.34
Demographics								
Married/registered partnership	0.63	0.60	0.50	0.49	0.56	0.5	0.51	0.5
No. children in HH	0.54	0.42	0.57	0.51	0.44	0.45	0.3	0.44
Age	40.74	46.95	36.35	43.43	37.92	42.57	36.75	43.5
Migration background	0.24	0.42	0.14	0.28	0.06	0.22	0.05	0.15
Task intensity								
Routine	0.75	0.63	0.18	0.26	0.10	0.17	0.06	0.11
NRM	0.09	0.10	0.39	0.23	0.04	0.10	0.01	0.03
NRI	0.06	0.17	0.22	0.29	0.63	0.42	0.23	0.33
NRC	0.11	0.09	0.24	0.22	0.25	0.31	0.72	0.52
Wage	10.24	10.91	12.25	12.83	14.06	16.52	14.1	17.83
Observations	2770	3882	1207	4965	1630	8439	2633	8041

Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table A6: Summary Statistic Men by Task Group

	Routine		NRM		NRI		NRC	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Education								
Low education	0.23	0.17	0.15	0.13	0.03	0.03	0.03	0.03
Medium education	0.71	0.71	0.74	0.74	0.45	0.40	0.57	0.39
High education	0.06	0.11	0.11	0.11	0.51	0.56	0.40	0.57
No information	0.00	0.02	0.01	0.01	0.00	0.01	0.00	0.01
Work experience (full-time)	0.01	0.05	0.01	0.06	0.03	0.07	0.00	0.03
Share part-time	11.89	12.04	10.35	11.45	10.44	10.00	11.89	13.08
Tenure	11.65	11.99	11.58	10.28	12.59	11.26	15.14	13.95
Sector								
Manufacturing	0.63	0.54	0.32	0.26	0.31	0.19	0.32	0.32
Utilities + construction	0.08	0.07	0.42	0.32	0.02	0.02	0.07	0.06
Retail, transport, logistics	0.14	0.24	0.08	0.07	0.21	0.27	0.09	0.08
Services	0.01	0.03	0.02	0.07	0.04	0.09	0.15	0.26
Public administration	0.04	0.03	0.09	0.18	0.34	0.37	0.3	0.23
Others	0.11	0.09	0.08	0.10	0.09	0.06	0.07	0.06
Firm size								
No info	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00
<200 employees	0.43	0.47	0.58	0.64	0.46	0.41	0.25	0.28
$200-2000$ employees	0.28	0.26	0.18	0.16	0.2	0.22	0.29	0.27
>2000 employees	0.29	0.27	0.23	0.19	0.34	0.37	0.46	0.45
Demographics								
Married/registered partnership	0.68	0.6	0.66	0.53	0.75	0.58	0.75	0.56
No. children in household	0.73	0.54	0.62	0.55	0.77	0.55	0.66	0.53
Age	39.56	44.12	39.35	42.53	42.32	43.8	42.22	43.98
Migration background	0.21	0.39	0.17	0.30	0.04	0.18	0.05	0.16
Task intensity								
Routine	0.6	0.54	0.35	0.37	0.07	0.12	0.09	0.15
NRM	0.19	0.12	0.42	0.21	0.04	0.06	0.06	0.05
NRI	0.11	0.19	0.14	0.24	0.58	0.43	0.35	0.33
NRC	0.11	0.15	0.11	0.18	0.36	0.39	0.55	0.47
Wage	14.51	15.64	14.6	14.75	21.16	22.74	19.89	23.61
Observations	6067	7481	2930	4046	1575	4303	3432	8537

Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table A7: BO Decomposition Gender Wage Gap by Task Group and Period

	Routine		Manual		Interactive		Cognitive	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Difference	0.360***	0.346***	0.214***	0.140**	0.432***	0.311***	0.342***	0.283***
	(0.030)	(0.061)	(0.078)	(0.071)	(0.129)	(0.078)	(0.037)	(0.045)
Explained	0.149***	0.291***	0.059	0.133**	0.205**	0.245**	0.067	0.167***
	(0.055)	(0.098)	(0.084)	(0.063)	(0.090)	(0.120)	(0.043)	(0.044)
Unexplained	0.211***	0.056	0.155	0.008	0.227***	0.066	0.275***	0.116***
	(0.052)	(0.084)	(0.106)	(0.038)	(0.065)	(0.114)	(0.046)	(0.025)
Explained								
Education	0.03***	0.0*	-0.017	-0.0***	0.046	0.038*	0.063***	0.067***
	(0.008)	(0.009)	(0.014)	(0.006)	(0.029)	(0.023)	(0.022)	(0.022)
Experience	0.091**	0.187***	-0.000	0.120***	-0.053	0.126***	0.001	0.090***
	(0.040)	(0.049)	(0.067)	(0.032)	(0.035)	(0.040)	(0.021)	(0.019)
Job characteristics	0.021*	0.051*	0.039*	-0.007	0.042**	0.042*	0.013	0.040***
	(0.013)	(0.028)	(0.022)	(0.038)	(0.018)	(0.022)	(0.015)	(0.011)
Demographics	0.002	-0.001	0.007	0.006	0.064***	0.017	0.056***	0.012***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.013)	(0.011)	(0.008)	(0.004)
NRM TI	0.027*	0.016	-0.026	0.010	-0.006	-0.029	0.028	-0.011
	(0.014)	(0.018)	(0.017)	(0.018)	(0.019)	(0.082)	(0.022)	(0.012)
NRI TI	-0.023	-0.002	0.056**	0.037*	-0.034	0.006	0.049*	0.003
	(0.017)	(0.008)	(0.022)	(0.020)	(0.033)	(0.014)	(0.026)	(0.010)
NRC TI	0.000	0.029	-0.000	-0.028	0.146**	0.045	-0.144***	-0.035*
	(0.004)	(0.053)	(0.031)	(0.027)	(0.069)	(0.058)	(0.051)	(0.020)
Unexplained								
Education	-0.001	0.017	-0.003	-0.006	0.002	-0.002	0.019*	0.002
	(0.014)	(0.019)	(0.013)	(0.008)	(0.030)	(0.027)	(0.011)	(0.012)
Experience	-0.051	-0.182***	-0.016	-0.066***	0.046	-0.007	0.000	-0.046
	(0.045)	(0.042)	(0.072)	(0.021)	(0.041)	(0.055)	(0.034)	(0.043)
Job characteristics	-0.034**	-0.046	-0.116*	0.105*	-0.087	-0.115	-0.058**	-0.058**
	(0.016)	(0.047)	(0.060)	(0.056)	(0.094)	(0.116)	(0.028)	(0.027)
Demographics	0.016	0.069**	0.033	0.047*	0.032	0.060*	0.016	0.064***
	(0.017)	(0.031)	(0.027)	(0.026)	(0.030)	(0.032)	(0.015)	(0.018)
NRM TI	0.007	0.096*	-0.277**	-0.250	0.036	0.129	-0.015	0.012
	(0.013)	(0.056)	(0.112)	(0.189)	(0.035)	(0.218)	(0.015)	(0.044)
NRI TI	-0.027	-0.042	0.029	-0.074	0.044	0.650	-0.034	0.073
	(0.019)	(0.107)	(0.132)	(0.146)	(0.822)	(0.715)	(0.096)	(0.137)
NRC TI	-0.020	0.004	-0.252***	-0.047	-0.063	-0.169	0.441	0.123
	(0.025)	(0.081)	(0.090)	(0.096)	(0.199)	(0.115)	(0.317)	(0.191)
Constant	0.322***	0.141	0.758***	0.299	0.218	-0.480	-0.094	-0.054
	(0.079)	(0.233)	(0.105)	(0.195)	(0.999)	(0.720)	(0.402)	(0.307)
Observations Men	6067	7481	2930	4046	1575	4303	3432	8537
Observations Women	2770	3882	1207	4965	1630	8439	2633	8041

Notes: BO decomposition of the gender wage gap at the mean by task group. The counterfactual is calculated putting a weight of 1 on group 1 (men). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Education: primary, secondary, and tertiary education. Experience: full-time work experience, tenure, and part-time dummy. Job characteristics: 6 industry groups and firm size. Demographics: married, no. children in HH, dummy migration background, age groups. Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

B Appendix B: Decomposition of the gender wage gap – technical details

B.1 Shift-Share Decomposition

Female wages in period t are a weighted average over female wages within task groups and can be described as follows:

$$w_{ft} = \sum_j w_{fjt} \frac{E_{fjt}}{E_{ft}} \tag{5}$$

where j indicates the task group and $E_f t$ denotes total female employment in period t and $E_f jt$ denotes female employment in task group j.

Thus, the change in female log wages over time can be decomposed into two parts:

$$\Delta w_{ft} = \underbrace{\sum_j \overline{w}_{fjt} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right)}_{BetweenTaskGroups} + \underbrace{\sum_j \Delta w_{fjt} \left(\frac{\overline{E}_{fjt}}{E_{ft}} \right)}_{WithinTaskGroups} \tag{6}$$

The first part of the right-hand side describes the change in female wages due to the change in employment shares in task group j. If wages were the same across all task groups, the between effect would not matter. However, if there different wages are paid across task groups, female wages will increase if they shift employment towards higher paying occupations. The second part of equation 6 describes the change in wages due to changes in wages within task group j. The upper bar indicates the mean in wages and employment share within task group j over the two time periods. The decomposition of male wages work accordingly.

This decomposition can be applied to changes in the gender wage gap (GWG). Therefore, changes in the gender wage gap are the difference between changes in male and female wages. The gender wage gap will be reduced if female wages grow more than male wages.

$$\Delta GWG = \Delta w_{mt} - \Delta w_{ft} \tag{7}$$

By plugging in equation 6 for female and male wages into 7, the change in the GWG can be decomposed into a within and between effect.

$$\Delta GWG_{between} = \sum_j \overline{w}_{mjt} \Delta \left(\frac{E_{mjt}}{E_{mt}} \right) - \sum_j \overline{w}_{fjt} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right) \tag{8}$$

$$\Delta GWG_{within} = \sum_j \Delta w_{mjt} \left(\frac{\overline{E}_{mjt}}{E_{mt}} \right) - \sum_j \Delta w_{fjt} \left(\frac{\overline{E}_{fjt}}{E_{ft}} \right) \tag{9}$$

B.2 Blinder-Oaxaca Decomposition

To explore the reduction of the gender wage gap in more detail, and thus to answer our third research question, we perform an Oaxaca-Blinder (OB) decomposition. This allows us to decompose the difference in mean wages between the two groups into an explained and an unexplained part. The explained part captures the contribution of differences in the characteristics of the two groups, such as differences in full-time work experience. The unexplained part captures how differences in returns to characteristics, such as different returns to experience, can explain differences in wages between the groups (Fortin et al., 2011). Therefore, we assume a linear model:

$$W_g = X_g \beta_g + v_g, \quad E(v_g) = 0, \quad g \in \{m, f\} \tag{10}$$

where X_g are gender-specific characteristics and β_g presents gender-specific coefficients. Since error v_g is assumed to be zero in expectation, the difference in gender-specific mean wages can be expressed as follows:

$$
\begin{aligned}
\Delta W &= \mathbb{E}[W_m] - \mathbb{E}[W_f] \\
&= \mathbb{E}[X_m]\beta_m - \mathbb{E}[X_f]\beta_f \\
&= \underbrace{(\mathbb{E}[X_m] - \mathbb{E}[X_f])\beta_m}_{\text{explained}} - \underbrace{\mathbb{E}[X_f](\beta_m - \beta_f)}_{\text{unexplained}}
\end{aligned}
\tag{11}
$$

The decomposition is weighted using a discriminatory coefficients. For this application, we assume that wage discrimination only affects women and that there is no discrimination against men. Accordingly, the male coefficient represents the non-discriminatory coefficient.

Furthermore, the OB decomposition allows to further decompose the explained and unexplained part into contributions by groups of predictors. Therefore, we group our control variables into several categories: education, experience, demographics, job characteristics, and task intensities. For education, we differentiate between workers with primary, secondary and tertiary education. For experience, we account for full-time work experience, tenure and an indicator for part-time employment. We consider the latter to be important as a high share of women in the German labour force work part-time. We also control for age, migrant background, being married or in a registered partnership, and the number of children in the household, which is captured by demographics. In addition, job characteristics include broad industry dummies and controls for firm size. Finally, we also include controls for gender task intensities within occupations. Since the AFL task intensities add up to one, we exclude routine task intensities, so that the task intensities have to be interpreted with respect to this category. We estimate the decomposition for the whole sample and separately for each task group.