

Bachmann, Ronald; Stepanyan, Gayane

Conference Paper

It's a Woman's World? Occupational Structure and the Rise of Female Employment in Germany

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Bachmann, Ronald; Stepanyan, Gayane (2020) : It's a Woman's World? Occupational Structure and the Rise of Female Employment in Germany, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/224626>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

It's a Woman's World? Occupational Structure and the Rise of Female Employment in Germany

Ronald Bachmann (RWI, DICE/Heinrich-Heine-Universität Düsseldorf, IZA)

Gayane Stepanyan (Heinrich-Heine-Universität Düsseldorf)

PRELIMINARY AND INCOMPLETE

PLEASE DO NOT CITE

Abstract

We analyse whether the rise in female labour force participation in Germany over the last decades can be explained by technological progress increasing the demand for non-routine social and cognitive skills, traditionally attributed to women. We do so by examining which task groups and occupations drive the increase in the female share and how this is related to wages at the individual level. Our findings show that the share of women indeed rises most strongly in non-routine occupations requiring strong social and cognitive skills. While the female share in high-paid occupations increases over time, the share of women in the upper parts of the overall wage distribution rises significantly less.

JEL Codes: J21, J31, O33

Keywords: female labour market participation; occupations; tasks; technological progress

All correspondence to: Ronald Bachmann, RWI – Leibniz Institute for Economic Research, Hohenzollernstraße 1-3, 45128 Essen, Germany. E-mail: bachmann@rwi-essen.de. DICE: Düsseldorf Institute for Competition Economics / Heinrich-Heine-Universität Düsseldorf, Universitätsstraße 1, 40225 Düsseldorf, IZA: Forschungsinstitut zur Zukunft der Arbeit GmbH (IZA), Schaumburg-Lippe-Str. 5-9, 53113 Bonn, Germany.

1. Introduction

The position of women in the labour market has been the subject of intense debate and scrutiny for a number of decades, especially in the context of the gender wage gap, but also with respect to a relatively low female labour market participation. While the gender wage gap has substantially fallen over time in many industrialised countries, it is still sizeable (Blau and Kahn, 2008); and although the labour market participation of women has increased strongly in many industrialised countries during the last decades, there is evidence that women tend to mainly find jobs with bad working conditions and in atypical employment (Bachmann et al., 2020). Therefore, gender equality in the labour market is still far from being realized.

Technological progress, however, could change this picture. For example, there is evidence for the labour market for highly skilled workers in the US that the probability for a man to work in non-routine cognitive and highly paid job has decreased in recent decades. On the other hand, the probability for a woman to work in such occupations has increased more than the supply of women per se on the labour market (Cortes et al., 2018). This development can be explained by a greater demand for social skills, where women have a comparative advantage. The greater demand for social skills can in turn be explained by a team model where social skills reduce the coordination costs when workers trade tasks to work more efficiently together. (Deming, 2017). Against the background of technological change, social skills are therefore a prerequisite for sustainable employment, with women benefiting relative to men.

In this paper, we therefore analyse which type of occupations have been the main drivers of the increase in the labour market participation of women in Germany since the mid-1980s. We do so by examining which task groups and occupations drive the increase in the female share and how this is related to wages at the individual level. Furthermore, using a shift-share analysis, we investigate whether the increase in the female share is due to the growth of occupations which had a high female employment share in the mid-1980s, or whether it is due to a similar growth in the female share across all occupations.

The German case is particularly interesting because the increase in female labour market participation is among the highest amongst industrialised countries. For example, from 2007 to 2017, the employment rate of women rose by about eight percentage points, while that of men rose by only four percentage points. Furthermore, the German economy features fast technological progress, e.g. in terms of robot

adoption (Suedekum et al., 2017) and a strong polarization of employment, at least for men (Bachmann et al., 2019).

In order to answer the question of which occupations explain the increase in female employment, we use data from the Socio-Economic Panel (SOEP) for the time period 1984-2017. For most of our analyses, we categorize jobs in two ways: on the one hand, we use the percentiles of wage distribution to divide into high-wage and low-wage occupations; on the other hand, we use a task-based categorization into unemployment, non-routine-cognitive, non-routine manual and routine jobs.

In order to understand whether and in which occupations there has been an increase or decrease in female employment, it is helpful to look at the level of the individual occupations (hereafter: job level), especially the percentile of the occupation in the wage distribution and the changes over time in the proportion of women. This also provides an opportunity to find out whether the increase in female employment is due to variation within (an increase within occupations) or between (a shift from one occupation to another). Furthermore, it can be qualitatively examined whether the occupations that are decisive for the increase of women in high-wage/cognitive occupations match the argumentation of Cortes et al. (2014) of increased demands on social skills or whether other factors explain the change in the German labour market.

The paper is structured as follows. First the existing literature is briefly summarized in Section 2. Section 3 contains the methodology and results for the task-based and the wage-based approach. Section 4 contains the shift-share analysis on the occupational drivers of the female employment share, as well as a more detailed analysis of the link between task groups and wages in this context. Section 5 features evidence on which specific occupation groups feature the highest growth rate in the female employment share. Section 6 summarizes the main results and the Section 7 concludes.

2. Literature

There is a large literature on the gender gap. As for the gender wage gap, it has been found that it has substantially fallen over time in many industrialised countries, but it is still sizeable (Blau and Kahn, 2008). For the German labour market in particular, clear differences for the entire life cycle between men and women in labour market participation and employment can be observed up to the year 2000 (Fitzenberger et al.

2004). In addition, even if one checks for educational level, work experience and choice of sector, there is a difference in hourly wages of 13 per cent between all employed women and men aged 15 to 65 (Anger and Schmidt 2010).

There is also a large gap in participation rates between women and men, which is increasing over the life cycle. This gap, and its increase over the life cycle, can be explained by various factors. One important factor is the presence of children, as having children is related to mothers' return to the labour market after they gave birth (Schönberg and Ludsteck, 2014), differences in the childcare system (i.e. Baker and Milligan, 2008, for pre-school and Felfe et al., 2016, for after-school care) and the reconciliation of work and family life in general (i.e. Gregory and Connolly, 2008).
[To be completed]

With respect to the polarisation between low- and high-wage/skill jobs, there is now ample evidence that the share of medium-wage and medium-skill jobs has significantly declined in most industrial countries (e.g. Goos et al., 2009 for Europe; Autor et al., 2003 for the US). This development can be explained by a model of job tasks – as in e.g. Autor et al. (2003) – that defines jobs as routine work if the tasks in the job are a clearly definable and limited set of cognitive and manual activities that can be performed by following explicit rules. These can be more easily replaced by computing technology. Therefore, computer capital acts as a substitute for routine jobs and as a complement for non-routine (cognitive) jobs. This can explain a large part of the decreased demand for routine work and the increased demand for well-trained professionals with university degrees. The subdivision by Autor et al. (2003) is not unproblematic, however, since, for example, activities that authors consider non-programmable are partly dependent on the state of technology. For example, the authors consider the activities of truck drivers to be non-programmable, i.e. they describe them as an example of non-routine.

Looking at worker flows, it has been shown that the decline in routine jobs is mainly related to the decrease in the transition of unemployed and non-participants in the labour market into routine jobs (Cortes et al. 2018). Furthermore, routine workers have been found to display higher churning flows through unemployment, i.e. a higher transition rate from employment to unemployment, but also a higher transition rate in the reverse direction (Bachmann et al., 2019).

However, more recent literature also discusses a reversal of the trend of job polarization. Beaudry et al. (2016) argue that since 2000 there has been a decrease in

the demand for highly skilled workers. The authors expect that the effect of this development will primarily affect the low-skilled, as their occupations are increasingly being performed by the highly skilled, which are displacing the low-skilled from these occupational segments (Beaudry et al. 2016). Caines et al. (2017) propose a different task categorisation that orders occupations according to the complexity of the requirements and tasks. The paper notes a trend towards more complex occupations and a positive relationship between complexity and wage increases. It also questions the job polarization literature and the categorization into routine and non-routine occupations, since in the authors' findings only task complexity and in some model specifications also social skills have a significant (and positive) relationship with wages. In addition, their model predicts that even less complex non-routine occupations are exposed to automation (Caines et al. 2017).

The automation literature is in some ways a continuation of the job polarisation literature, but it is more concerned with the possible effects of technological change on the labour market. Frey and Osborne (2017) argue that the traditional definition of routine jobs as being the only jobs that can be automated is no longer valid with regard to recent technological innovations. Big data makes it possible to program even very complex tasks. In addition, an improvement in the robots' ability to perform manual tasks can be seen, so that according to the authors not only the traditional routine jobs are highly likely to be automated, but about 47 percent of all jobs (Frey and Osborne 2017). The authors also expect that workers will need to invest more in creative and social skills to remain employed.

Acemoglu and Restrepo (2017) also expect that robots and computer-based technologies will lead to automation of workplaces. They study the effect of industrial robots on local labor markets in the US between 1990 and 2007 and estimate that one robot more per thousand workers reduces the ratio of employment to population by about 0.18 to 0.34 percentage points and that of wages by 0.25 to 0.5 percent (Acemoglu and Restrepo 2017). However, they also explain that due to the low number of robots used in the industries to date, the effect has remained relatively small and could only have a greater impact in the future. In addition, some model specifications of the authors suggest that robots, unlike other computer capital, have a generally negative effect on labour demand and that this effect is not heterogeneous for different skill levels of workers. In addition, the authors estimate that the effects of robots have a stronger impact on men than on women. However, at least for Germany,

job creation in other sectors has been shown to even lead to positive net effects from robot technology (Südekum et al., 2017).

Given the speed of technological innovation, one may wonder why not even more jobs have been automated in the last decades. Taking this question as a starting point, Autor (2015) argues that the literature often overestimates the substitutability of machines for workers and underestimates the complementarity between human work and machines, so that automation scenarios are generally overestimated. Although mainly routine jobs of medium qualification are automated, this does not apply to all medium qualification jobs. Accordingly, some medium-skilled occupations are characterised by a bundle of automatable and non-automatable tasks and tasks that cannot be unbundled easily. Examples are occupations in the health sector, some craft and repair occupations but also typical white-collar occupations in which coordination and decision-making tasks are involved. Human labour is therefore likely to have a comparative advantage in carrying out these bundles, with relatively high levels of worker competence being a prerequisite (Autor 2015).

This view of automation is also held by other authors. For example, Arntz et al. (2017) replicate the automation scenarios of Frey and Osborne (2017) with German data and then reassess taking into account the whole spectrum of tasks in the professions. As a result, the risk of occupations being automated is re-estimated and revised from 39% to 9% (Arntz et al. 2017). Furthermore, they note that workers specialize in non-automatable niches of their occupations. The fact that the requirements and tasks in occupations change due to technological change is implicit in the literature described so far.

However, there is also measurable evidence for the job polarization thesis and task changes in occupations. Black and Spitz-Oener (2010) show that the requirements for skills and competences within occupations have changed, so that interactive and analytical skills have become more important and routine tasks have decreased. The authors also note that the requirements for women have changed more than for men. The decrease in routine and increase in non-routine interactive and analytical tasks may also explain part of the decrease in the gender pay gap (Black and Spitz-Oener 2010).

[Deming, 2017; Cortes et al., 2018 – see introduction]

3. The evolution of female employment according to task categories

To answer the research question, we use data from the Socio-Economic Panel (SOEP) for the years 1984 to 2017 (Bohmann and Giesselmann, 2018). The SOEP is a representative annual repeat survey (panel) of private households/persons in Germany. In order to avoid structural breaks, we focus on persons working in West Germany using the weights provided. In order to identify occupations, we use the internationally comparable ISCO88 classification (International Standard Classification of Occupations) of the ILO (International Labor Organization).

In order to categorize jobs, we use two procedures: first, a task categorization, and second, a categorization according to the hourly wage. In the task categorization, we use the one from Cortes (2016), applied to Germany in Bachmann et al. (2019). The occupations are divided into the categories “Routine”, “Non-routine Cognitive” (NRC), and “Non-Routine Manual” (NRM). Cognitive occupations are those that are intellectually demanding, i.e. that require creativity and problem-solving skills. This includes both analytical and interactive professions. Routine occupations are cognitive and manual occupations as defined by Autor et al. (2003), i.e. occupations that are easily programmable and follow a specific and limited set of rules. The non-routine manual occupations are all occupations in the service sector that are not primarily characterized by cognitively demanding tasks and manual occupations that are not very well programmable. Table A.1 in the appendix shows how the occupations are assigned to each task category.

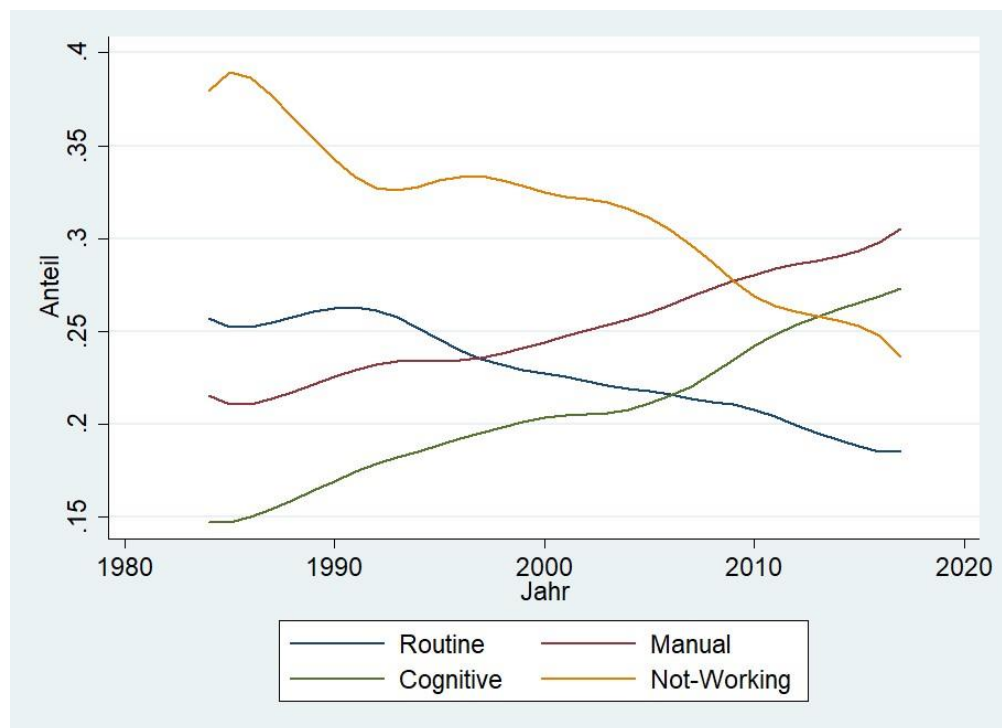
Looking at task groups and non-employment for Germany during the time period 1984-2017 (Figure 1), the developments on the labour market correspond to those described in the job polarisation literature: There is a decline in routine occupations and an increase in manual and cognitive occupations. Furthermore, there is a strong decline in the share of non-employed persons over this time period.

In addition to the task-oriented categorisation of occupations, we differentiate occupations according to the level of the average wage in the occupation, because occupations with good pay can generally be seen as desirable and scarce positions that individuals strive for. This categorisation is useful for identifying whether female employment has increased mainly in low-wage occupations or more in the high-wage sector.

While it is true that cognitive occupations and occupations with high hourly wages correlate positively, it is useful to look at both categorizations because they define in

a different way which occupations are considered good or desirable. For the wage-oriented categorization, the jobs at each job level are defined either as low and medium wages or as a high-wage sector or as Bottom80 for the lower 80% and Top20 for the upper 20% of the wage distribution. In calculating the wage distribution, all workers are included in full-time, part-time or marginal employment and, in order to ensure comparability between the different job types, hourly wages are used.

Figure 1: Share of task groups and non-employment in working-age population, 1984-2017, all workers



To create the categorisation, the hourly wage was calculated according to the following formula: $\text{Hourly wage} = \text{Gross monthly wage} / (\text{Weekly working time} \times 4.33)$, with 4.33 being the average number of weeks per month. In addition to a variable for the weekly, contractual working time, SOEP also contains a variable for the actual working time, i.e., the actual working time exceeding or falling short of the contractual working time. Since there are relatively many missings, the hourly wage is calculated using the maximum of the two variables in order to include as many observations as possible. Although this has the effect that the hourly wage of a person may be slightly underestimated, as the actual working time is probably rather overestimated, it should not have a strong effect on the results.

In order to now compile the wage distribution of the individual jobs, the individual data are collapsed separately for each year and for each job level of the ISCO88 classification. This means that each job is assigned the arithmetic mean of all hourly wages of the individuals who perform this job per year. Then the wage distribution is created and each job is assigned its percentile. For parts of the analysis, it is useful to take the percentiles of one year and use them to look at the changes, since it is difficult to follow the development of changing jobs in the top 20. In this case, we follow Cortes et al. (2018) and for such cases use the wage distribution of the year 1985 at the beginning of the observation period.

In addition, the individual salary distribution is also used to define which persons are in the top 20 percentage percentiles. This is interesting in order to see later whether the development is comparable, i.e. whether if the share of women in the top 20 occupations increases, the share of women in the top 20 individual hourly wages increases proportionally. It is conceivable that the share of women in well-paid jobs increases, but that women are paid less than men in these jobs and therefore do not move up into the top 20 individual hourly wages.

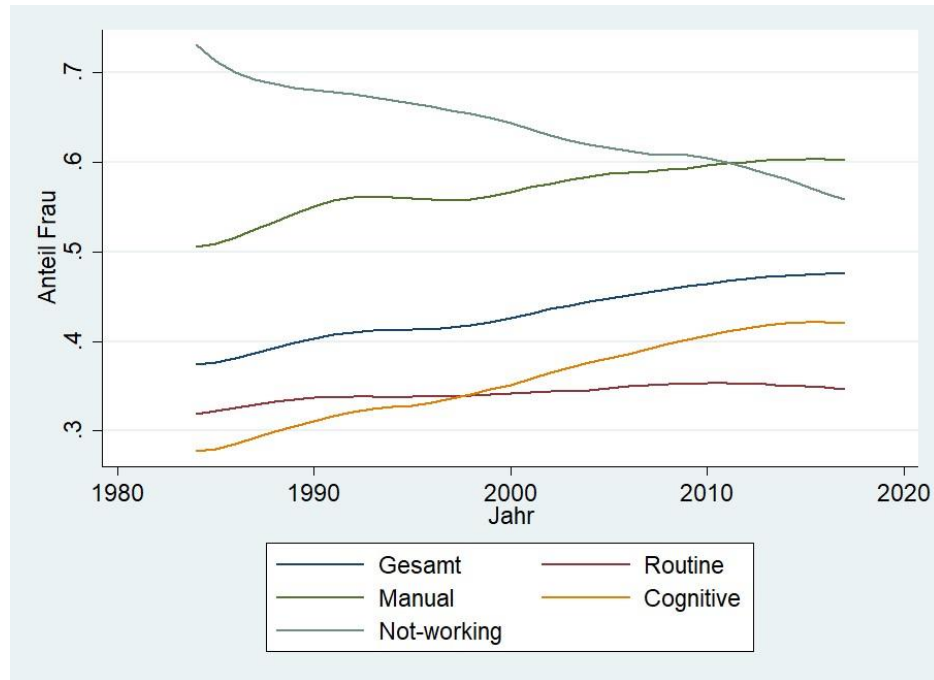
Figure 2 shows the development over time of the proportion of women in the various categories of the labour market. On the X-axis are the years for the observation period 1984-2017 and the Y-axis is the proportion of women from 0 to 1 and from 0 to 100%, respectively.

Two things are directly visible in the graph, namely that the proportion of women in non-working and cognitive occupations has changed most. While women accounted for more than 70% of the non-working population in 1984, this proportion tends to become more balanced over time, reaching nearly 50% in 2017. This development reflects the longstanding increase in female employment in most industrialised countries.

However, the relatively strong increase of women in cognitive occupations in Germany from 27% to over 42% has not yet been discussed in detail in the literature. The increase in the proportion of women in cognitive occupations is stronger than the increase in female employment for the labour market as a whole and, accordingly, also stronger than the increase for routine and manual jobs. The share of women in routine jobs increases only by about 3 percentage points for routine jobs and by 10 percentage points for non-routine manual jobs. In any case, the development for cognitive jobs corresponds in content to the results of Cortes et. al., who found a disproportionate

increase in women in cognitive jobs. However, Cortes et al. (2018) restrict their analysis to women with a university degree only, whereas here all women are considered, so that the results are not entirely comparable.

Figure 2: Share of women in non-employment and employment according to task categories, 1984-2017



Note: "Gesamt" (total) shows the overall employment rate of women.

In order to understand and classify these developments on the labour market, however, it is necessary to take a closer look at developments separately for women and men. Since the proportion of women may be related to both the fact that the proportion of working women is increasing generally or only in certain sectors, it could also be a development determined by a decline in the proportion of men in certain sectors, while the proportion of women in the individual sectors is proportional and has not changed.

Figures 3 and 4 show the development of the shares of the different categories for men and women separately over time. The shares add up to 1 for each year and reflect the development of the categories within the sexes. This means that the graph shows the respective share of the category in all persons of working age between 20 and 64 years of the respective sex. While the cognitive occupations are increasing for both women and men, the developments in the other categories are different. In general, the changes are greater for women, but this can be explained mainly by the general

increase in female employment or the decline in the proportion of those not in work. The proportion of men not in work has declined slightly but is characterised by minor fluctuations (presumably unemployment), which are not fully apparent in this chart as the lines are slightly smoothed. The share of routine jobs has fallen slightly for women from 15.9 to 13.6%, while it has fallen more sharply for men. The share of women in manual jobs has increased at a similar rate as in cognitive occupations, while the share of men has remained relatively constant.

Figure 3: Distribution of women across employment according to task categories and non-employment, 1984-2017

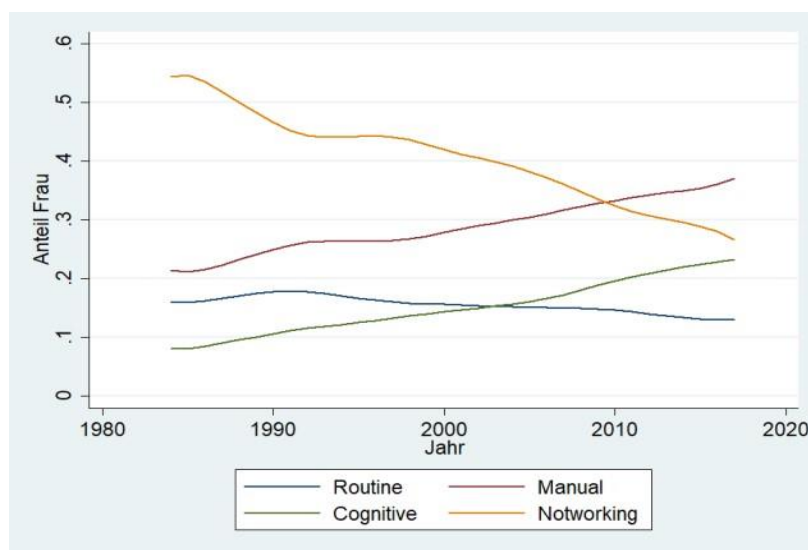


Figure 4: Distribution of men across employment according to task categories and non-employment, 1984-2017

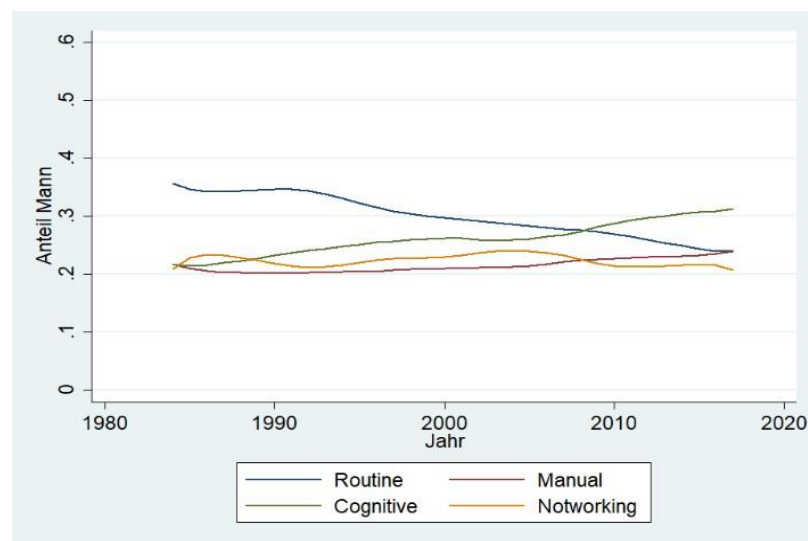


Table 1 summarizes the changes in a table. The five-year averages from 1985 to 1990 and 2010 to 2015 have been calculated so that individual outlier years or slight fluctuations do not distort the results. In the third column, Difference shows the share at the two different points in time. It can be seen that the share of women in cognitive jobs has increased more than that of men (12 vs. 8 percentage points). In general, it is clear what the job polarisation literature describes, namely that routine jobs decrease while at the upper end cognitive and at the lower end non-routine manual jobs increase. The decrease in routine jobs could therefore be related to automation and increased use of computer technology.

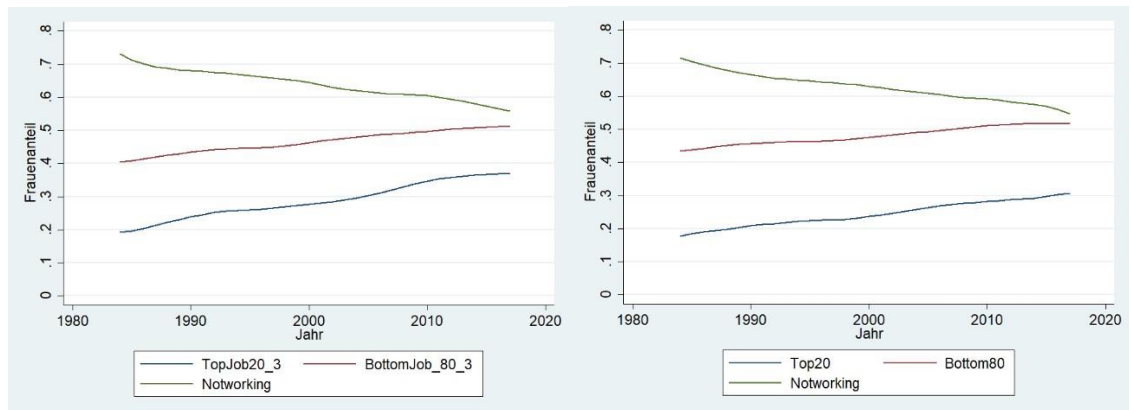
Table 1: Distribution of women and men across employment according to task categories and non-employment, selected time periods

Women	1985-1990	2010-2015	Difference
Routine	0.168	0.138	-0.030
Manual	0.225	0.344	0.120
Cognitive	0.092	0.214	0.122
Not-Working	0.516	0.304	-0.212
Men			
Routine	0.340	0.256	-0.084
Manual	0.201	0.229	0.028
Cognitive	0.220	0.301	0.080
Not-Working	0.238	0.214	-0.024

3. The evolution of female employment by tasks and wage categories

In the following, the development of women's employment is now described using the wage categorisation. Again, both the changes in the labour market between and within the genders are described, only that here they are divided into Top20, Bottom80 and non-working. The Top20 and Bottom80 are, as already discussed, considered once at job level and once at individual level. Figure 5 shows the development between the genders. The proportion of women earning in the Top20 percentile has increased from 18% to 30% between 1984 and 2017. In contrast, the share of women in jobs at the 3-digit ISCO88 level that are part of the top20 percentile of the wage distribution of 1985 has increased by 16 percentage points from 20 to 36% in the same period. The shares in the bottom80 have increased by 9 and 11 percentage points respectively, i.e. each less than the increase in the high wage sector.

Figure 5: Share of women in top and bottom of wage distribution and non-employment at the individual level (left panel) and the occupational level (right panel)



In order to see whether there has been a disproportionate increase in the proportion of women in the top 20 percentile of the wage distribution, it is necessary to look at developments within the sexes. Table 2 shows the change for men and women at the individual level. It is clearly evident that there has been little change for men. For women, on the other hand, the share of women in the top20 share has increased by 3.5 percentage points and for the bottom80 by 14. On closer examination, this increase is disproportionately high because 20% of the increased employment of women is in the high-wage sector.

Table 2: Distribution of men and women across the top 20 and bottom 80 percent of the individual wage distribution and non-employment

Men	1985-1990	2010-2015	Difference
Top20	0.205	0.207	0.002
Bottom80	0.562	0.565	0.003
Non-employment	0.233	0.228	- 0.005
Women			
Top20	0.049	0.083	0.034
Bottom80	0.458	0.600	0.142
Non-employment	0.493	0.317	-0.176

In comparison, the development at the three-digit occupational level is different. Table 3 shows that the development of women and men at the job level differs

markedly from the development at the individual level. On the one hand, the shares within men change significantly. The share of all men in the top 20 occupations increases by 7 per cent, while it decreases for the other categories. For women, on the other hand, it increases by 8 percentage points for Top20 occupations and by 13 for Bottom80 occupations. This implies a disproportionate increase of women in top20 occupations, as 38% of the increase in female employment has taken place in top20 occupations.

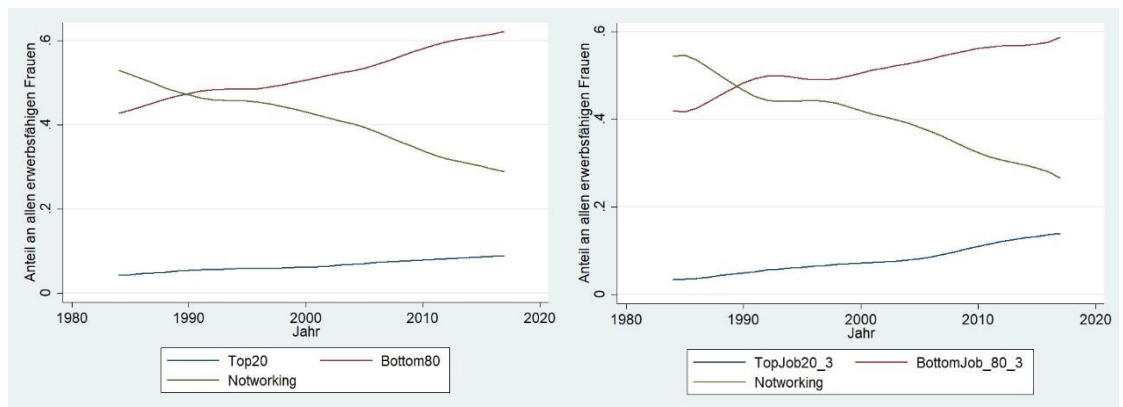
Table 3: Distribution of men and women across the top 20 and bottom 80 percent of the occupational wage distribution and non-employment

Men	1985-1990	2010-2015	Difference
Top20_Job	0.15	0.22	0.07
Bottom80_Job	0.61	0.56	-0.05
Non-employment	0.24	0.21	-0.02
Women			
Top20_Job	0.04	0.12	0.08
Bottom80_Job	0.44	0.57	0.13
Non-employment	0.52	0.30	-0.21

These different developments may be due to the fact that the definition of the individual Top 20 is more technical than that of the job level, as it always assigns 20 percent of all workers to the Top 20 each year. At the job level, on the other hand, more than 20% of all workers may be in top 20 occupations, for example if the occupations that were in the top 20 in 1985 show a strong increase. Another possible explanation is that although women are more likely to be in the top 20 occupations, they are not in the top 20 due to receive individually lower wages due to discrimination or other reasons. Figure 6 shows these results for women graphically and in addition that the development at the job level is more volatile than the individual level.

The reason why the percentages of non-working persons for the job and individual level differ slightly is due to a different amount of missing data resulting from using two different definitions of non-working persons. Both definitions consider 20 to 64-year-olds as working people, using the fact that no wage was generated and whether the individuals have a job or not.

Figure 6: Share of women in top and bottom of wage distribution and non-employment at the individual level (left panel) and the occupational level (right panel)



4. Dissecting the growth of women’s employment in “good” jobs

It has already been noted that the proportion of women has increased in good, i.e. cognitive or top 20 professions. However, it is not yet clear whether this development is due to an increase in the proportion of women within occupations (within-Variation) or whether jobs in which women are increasingly to be found account for a larger proportion of cognitive occupations (between-Variation). To answer this question, the share of women in cognitive jobs is compared with two counterfactual shares. These were calculated according to the formula of Cortes et. al. This formula decomposes the share of women in cognitive jobs at time t , noted here with φ , as the sum of all multiplication of the share of women per cognitive job with the share of the job in the total number of jobs.

$$\varphi_t = \frac{Woman_t^{cog}}{Job_t^{cog}} = \sum_{j \in cog} \left(\frac{Woman_t^j}{Job_t^j} \right) \times \left(\frac{Job_t^j}{Job_t^{cog}} \right)$$

If you now compare two points in time and keep one of these two multiplicands constant at the value of the first point in time, you get a counterfactual result that can be compared with the real proportion of women in cognitive jobs. If you keep the proportion of women per job constant, i.e. $\left(\frac{Woman_t^j}{Job_t^j} \right)$, constant, you calculate the between-variation and if you keep the proportion of women per job i.e. $\left(\frac{Job_t^j}{Job_t^{cog}} \right)$, constant, the within-variation. Table 4 shows the results of the within and between variation for the 3-digit ISCO88 occupational level.

Table 4: Decomposition of increase in female share in cognitive jobs and jobs in the top 20 of the occupational wage distribution, in %

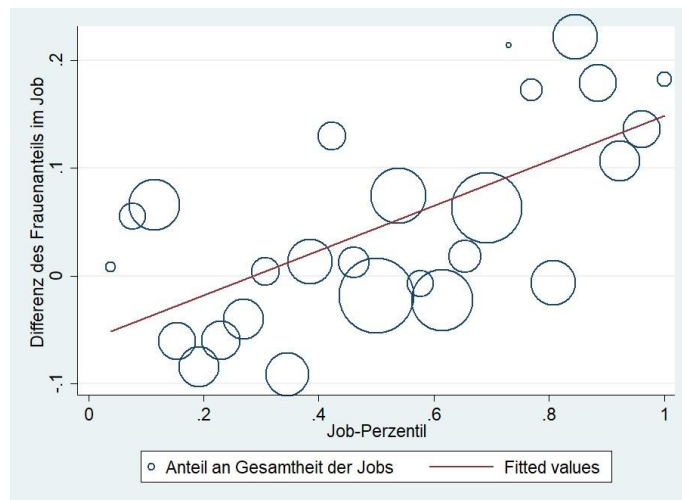
	1985	2015	Within	Between
Cognitive_Job	28.3	41.8	41.0	28.2
TOP20_Job	19.6	36.5	37.8	18.9

The results clearly show that the increase in women is almost entirely due to within-variation. If the proportion of women per occupation had remained constant in all occupations (between), the proportion of women for task-oriented categorisation would not have increased at all instead of 41% and for wage categorisation it would even have fallen slightly.

We now examine the changes in the proportion of women in the professions, as well as the link between occupations and wages in more detail. First, the change in the proportion of women in occupations is graphically linked to the percentile of the wage distribution. This change is then quantified in some regressions and tested for significance. Second, the occupations in which the proportion of women has increased are identified in order to find out whether they display the characteristics predicted by the recent literature on the importance of social, interactive and cognitive skills (Deming, 2017; Cortes et la., 2018).

For Figures 7 and 8, the 5-year average from 1985 to 1990 and 2010 to 2015 of the proportion of women in employment was calculated. The difference between these two averages was then calculated, indicating by how much the proportion of women has increased or decreased. This variable was then related to the percentile ranking of the corresponding occupation to see if there is a positive relationship between a well-paid occupation and the increase in the proportion of women in the job. The size of the circles in the graph reflects the proportion of the respective job in the total number of jobs. At the two-digit level in Figure 7, this positive relationship is clearly visible.

Figure 7: Correlation between the growth in the female share in an occupation and the wage ranking of the respective occupation, ISCO 2-digit occupations



Particularly in the uppermost areas of the percentile rankings, the share of the majority of occupations seems to have risen by between 10 and 20 percentage points. At the three- and four-digit ISCO88 level the development is similar. Especially the strong increases of more than 50 percentage points can, however, be caused by small numbers of cases within the profession and must therefore be interpreted with caution in the qualitative analysis. The charts also quickly show that it is precisely occupations with small case numbers (correspondingly small circles) that record these sharp increases.

Figure 8: Correlation between the growth in the female share in an occupation and the wage ranking of the respective occupation, ISCO 3-digit and 4-digit occupations (left and right panel, respectively)

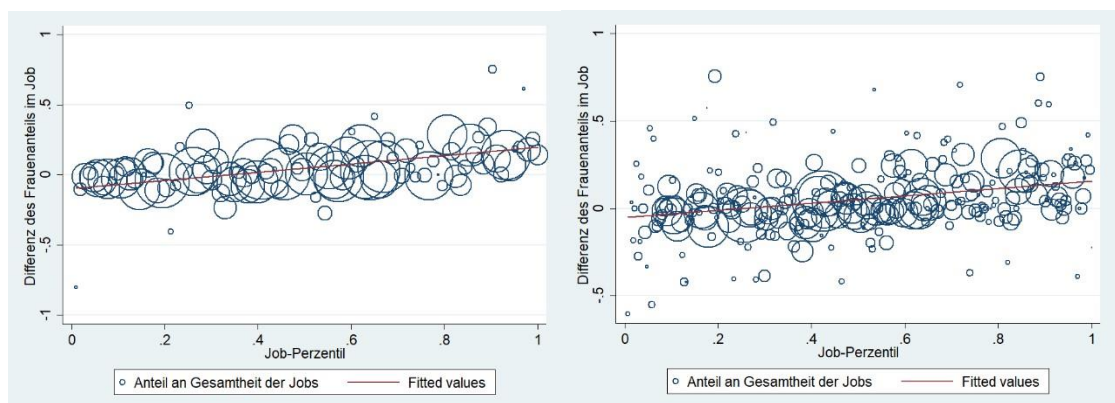


Table 5 shows the regression output that estimates these changes. The dependent variable is the difference in the proportion of women between 2015 and 1985 and the

explanatory variables are either the percentile of the wage distribution of the respective occupation or two dummies for manual and cognitive occupations. The percentile of the job and the cognitive dummy is significant at the 1% level. The coefficients of the cognitive dummies are largest at the three-digit ISCO level 0.177 and weakest at the four-digit level level with 0.101. The results can be interpreted as meaning that a cognitive occupation is associated with an increase of the difference in the proportion of women by about 0.177, i.e. 17.7 percentage points.

The routine dummy is negative for the two- and three-digit ISCO level but never significant. The manual dummy is positive for all ISCO levels, but is only slightly significant at the three-digit ISCO level. Since the proportions at the four-digit ISCO level deviate from the true proportions in the population due to small case numbers and can be erroneous, the lack of significance at this level could be due to measurement-error bias.

Table 5: Regression of the change of the share of women on (i) task groups and (ii) percentile of occupation in wage distribution separately

VARIABLES	(1)		(2)		(3)		(4)		(5)		(6)	
	ISCO_2	ISCO_2	ISCO_3	ISCO_3	ISCO_3	ISCO_3	ISCO_4	ISCO_4	ISCO_4	ISCO_4	ISCO_4	ISCO_4
Difference in share of women (2010/15-1985/90)												
Manual			0.0265				0.0772*					0.0389
			(0.0392)				(0.0409)					(0.0318)
Cognitive			0.120***				0.177***					0.101***
			(0.0392)				(0.0402)					(0.0288)
Percentile	0.209***			0.294***				0.210***				
	(0.0491)			(0.0556)				(0.0426)				
Constant	-0.0600*	-0.00245	-	-	-	-	-0.0311	-	-	-	-	0.00975
	(0.0291)	(0.0285)	0.0971***	(0.0323)			(0.0278)	0.0530**	(0.0248)			(0.0193)
Observations	26	26		103			103		267			267
R-squared	0.430	0.317		0.217			0.163		0.084			0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

However, the job percentiles are highly significant at all levels. Since the percentiles from 0 to 1 and the difference in the proportion of women can have values between -1 and 1, the interpretation using the example of the two-digit job level is as

follows: An increase in the job percentile by 1 is associated with an increase of the proportion of women by 0.2 percentage points. In other words, a jump from 0 to 100 percentage percentile correlates with an increase of the proportion of women by c.p. 20.9 percentage points.

Table 6 shows the regression output when both categorizations are combined. Although the cognitive dummy and percentiles both represent good jobs and probably explain in part the same part of the variation in the difference in the proportion of women, they are different. Therefore, they may partly explain different parts of the variation in the difference in female percentages. For example, the cognitive dummy might reflect women's preference for prestigious and demanding jobs, and the job percentile might reflect the incentive to pursue a high-income job. However, the cognitive dummy loses its significance at all levels if the job percentile is included in the model, which suggests that both variables explain the same part of the variation in the dependent variable.

Table 6: Regression of growth rate of share of women on task groups and percentile of occupation in wage distribution jointly

	(1)	(2)	(3)
VARIABLES	ISCO_2	ISCO_3	ISCO_4
Difference in share of women (2010/15-1985/90)			
Percentile	0.202** (0.0733)	0.286*** (0.0784)	0.194*** (0.0523)
Manual	0.0536 (0.0359)	0.0930** (0.0388)	0.0437 (0.0311)
Cognitive	0.0454 (0.0439)	0.0592 (0.0499)	0.0347 (0.0333)
Constant	-0.0909** (0.0407)	-0.141*** (0.0401)	- 0.0674** (0.0281)
Observations	26	103	267
R-squared	0.492	0.262	0.092

Standard errors in parentheses
 *** p<0.01, ** p<0.05, * p<0.1

Interestingly, the coefficients of the job percentile are hardly changed, suggesting that the difference or increase in the number of women in a job is better explained by the location in the wage distribution of the job than by the task categorization. On the other

hand, dummy variables can only represent mean value comparisons and the results could change significantly if, for example, the intensity of individual tasks were used as an explanatory variable. However, what is interesting about the model with both categorizations is that the constant (i.e. the routine dummy) is still negative, but is larger and significant at all levels.

5. Which specific occupations drive the growth in female employment?

In order to better understand the changes in female employment described above, we will now look at the specific occupations in which a particularly strong increase in the proportion of women has been recorded. We report the occupational groups at the 2-digit level (Table 7) and recur to the 3- and 4-digit ISCO level for further interpretation (results available from the authors upon request).

Table 7 lists the ten occupational groups at the 2-digit level in which the increase in the proportion of women has been particularly strong. Overall, five of the occupational groups in the top ten are cognitive occupational groups. The strongest increase is in the group of other scientists and related professions. This increase reflects a quite diverse group of occupations (3- and 4-digit level, not reported), where the proportion of women for legal professions, psychologists, archives and museum scientists, as well as personnel specialists and tax consultants, in particular, has increased by many percentage points.

The sharp increase in the professional category of members of legislative bodies and senior administrative staff is mainly due to sub-group 114, senior officials of interest groups. These include political parties, workers' and trade associations. It is not very surprising that there is an increase here, as women in the public perception are increasingly striving for the upper echelons of the public sector, and it is precisely here that institutional change has been called for and pushed forward. However, the sharp increase should be viewed with caution. Firstly, because the number of cases for occupational group 11 is relatively small and, secondly, because the increase of 20 percentage points is relatively strong, but women were not represented in this group at all in 1985 and thus still only represent one fifth of all employed persons in this group.

Table 7: Top 10 occupations with strongest increase of share of women from 1985 to 2015

Increase of share of women, 1985/2015 in percentage points	Occupation ISCO code	
22	24	Other researchers and related professions
21	11	Members of legislative bodies Administrative staff and senior officials
18	22	Bioscientists and physicians
18	23	Teaching professionals
17	33	Teaching associate professionals
14	12	Managing directors and divisional managers in large companies
13	42	Customer service clerks
11	21	Physicists, mathematicians and engineers
7	71	Mineral extraction and construction professions
7	51	Personal and protective service workers

The increase of 18 percentage points in the group of life scientists and medical doctors is relatively evenly spread amongst the professions in this 2-digit group, with the exception of female veterinary surgeons, who increased more strongly by 41 percentage points. While the increase in the number of female teachers (groups 23 and 33) and office workers in contact with clients (group 42) as typical female occupations is not surprising, the increase in the groups of managers and business unit managers in large enterprises, physicists, mathematicians and engineers, extractive and construction occupations and personal service and security workers is less typical. In the case of female managers, the main occupations are personnel managers and advertising and public relations managers.

In the group of physicists, mathematicians and engineering scientists, on the other hand, it is primarily women (interior) architects among whom the proportion of women has risen sharply. In the building professions, it is mainly female building cleaners and who have become more numerous. The increase in the group of personal service occupations and security staff is interesting, as it can partly be explained by

traditional women's occupations, hairdressers, beauticians and related occupations, but also by an increase in policewomen and, to a lesser extent, prison guards. This development can be viewed from two sides, on the one hand women seem to be choosing more traditionally male professions. On the other hand, it can be interpreted to mean that public efforts to recruit more women can be successful.

In the changes outlined here, two general interrelated developments can be identified. On the one hand, these are largely areas and occupations that require cognitive and social skills and, on the other hand, they are occupations that are less easily automated as a result. The first argument can be shown by the fact that the professions are characterised by a high degree of interactivity (especially teachers, psychologists, personnel or advertising and public relations managers, doctors and policewomen) or require creative, cognitive and management skills (especially legal professions, archives and museum scientists, heads of interest groups, architects and bioscientists). In terms of interactivity, it is also significant that only those office workers who have contact with clients have seen an increase in the proportion of women. Assuming that these professions tend to be less automated, it can be concluded that women are more likely to work in professions where less disruptive technological shocks occur, i.e. where they are further away from the productivity front. Another important finding is that more than half of the 10 occupational groups typically require a university degree.

6. Summary of the results

When looking at the evolution of the female share, the task and the two wage categorisations yield similar results in the sense that during the period under consideration, there has been an increase in female employment in the 'good' professions and that this increase is stronger than for men. This fact and the general increase in female employment also leads to a larger proportion of women in these jobs, so that the proportion of women has increased from 18% to 30% in the top 20% of the overall wage distribution, from 20% to 36% for the top 20% occupations with the highest hourly wage and from 27% to 42% for the cognitive occupations.

What is particularly interesting about this development is that the proportion of women in the top 20% of occupations with the highest hourly wage has risen more strongly than the proportion of women in the top 20% of the overall wage distribution. Women therefore are more often found in high-paying occupations, but are still paid

less than, so that not all women who are in a top 20% of occupations also move up into the top 20% of the overall wage distribution. This result could be explained, among other things, by the "child penalty" discussed in the literature or the more frequent part-time work of women (Kleven et al. 2018).

In addition to these common features, the quantitative analysis showed that both task and wage categorisation can explain significant changes in the proportion of women in occupations. When including both in the same regression, the routine dummy is negative and significant. This means that even within a given part of the wage distribution, routine work displays a lower increase in the female employment share.

Both the developments of the task categories in the labour market in Figure 1 and the change for men and women separately seem to follow the logic of the job polarisation literature. The decline in the demand for highly qualified workers after the year 2000 (Beaudry et al. 2016) discussed in the literature cannot be identified from the task categorisation used in the data. Rather, manual and cognitive jobs continue to increase, while routine jobs decrease, as described in the job polarization literature. In addition, evidence was also found in other papers that job polarization in Germany took place a decade after the US (Dustmann et al. 2009).

It is not possible to say clearly whether the lack of a decline in demand for highly qualified labour is a delay in the German labour market or whether it is a divergent development. The results of the qualitative description of the occupational groups in which a particularly strong increase in female employment has taken place and the job polarisation and automation literature make the following development of female employment appear plausible: Women increasingly practice cognitively demanding and interactive occupations or non-routine manual jobs in the service sector. These sectors are relatively unlikely to become automated, mainly due to the requirements for interactivity, cognitive or social skills. This development is accompanied by a slight decline in routine work, which is also in line with the sharp drop in routine tasks observed especially among women (Black and Spitz-Oener, 2010).

There are three plausible explanations for the stronger decline of men in routine occupations. Firstly, their share in this occupational category is larger than that of women, so that automation and job polarisation affect men more. Second, a stronger negative effect on men has been described in the literature, e.g. of robots (Acemoglu and Restrepo 2017). Third, it could be that women also perform more interactive

activities within routine jobs, so that, according to the author's argument regarding the bundling of tasks, women are also less exposed to automation within routine jobs (Author 2015).

Looking more closely at the 'good' occupations, and linking this to the low proportion of women on the productivity front and the individual top 20 hourly wages, it can be concluded that while women are generally more strongly represented in the well-paid and cognitive occupations, they are not in the highest-paid occupations, as these are typically found on the productivity front, where highly-skilled workers benefit from strong wage increases complementary to the new technological capital employed, as predicted by economic models of job polarisation and automation (Author and Dorn, 2013).

It is also interesting whether women are increasingly in the cognitive, non-routine manual professions because the requirements and tasks in these professions have changed due to technological change in a way that gives them a competitive advantage over men or because women prefer professions in which cognitive, social or interactive skills are required. Cortes et al (2018) and Deming (2017) find evidence for the first explanation that women benefit from the changes in tasks and requirements caused by technological change. However, the experimental literature also shows that women have stronger preferences for occupations with such requirements (Azmat and Petrongolo 2014). The results are not contradictory, however, but rather complementary, so that both probably explain part of the increase in these occupations. The automation literature, which considers a large proportion of occupations to be at risk of becoming automated, also stresses the importance of creative and social skills for remaining employed (Frey and Osborne, 2017).

7. Conclusion

This study has looked at the increase in female employment in Germany and has examined in which professions or occupational groups the increase has mainly taken place. Overall, the number of women working in 'good' jobs has risen disproportionately. This is especially true for cognitive occupations according to a categorization according to tasks, but also for occupations in the upper areas of the wage distribution according to a categorization according to wages.

This increase in female employment in the 'good' professions can be fully explained by within-variation, i.e. a growing proportion of women in all types of

‘good’ occupations, not a disproportionate growth of occupations with a high share of women at the beginning of the observation period. In addition to the increase in cognitive occupations, non-routine manual occupations have also seen a strong increase, which among women mainly include simple occupations in the service sector. Routine occupations have not led to an increase in female employment and have declined slightly over the observation period.

This trend for women in the labor market is in line with the job polarization literature, which generally finds a decline in medium-skilled, routine occupations and increases at the lower end in non-routine manual occupations and at the upper end in cognitive occupations. The disproportionate increase in female employment in cognitive and well-paid occupations is also partly the result of changing demands of technological change, with social skills playing an important role. At the same time, while women are more strongly represented in well-paid occupations at the end of the observation period, their individual wages have not increased to the extent that one may have expected, i.e. even when in high-paying occupations, they are often paid less than men.

At the detailed occupational and professional level, it is noteworthy that in the 10 occupational groups with the highest increase in the proportion of women, more than half of them generally require a university degree. In addition, the increased proportion of women among the leaders of interest groups and the police can be seen as an indication that political will can influence the labour market participation of certain groups. The findings that women generally work more in areas that are less exposed to automation provide a good starting point for further research into the consequences of automation.

Our results are thus in line with the results described by Cortes et al. (2018) as the “end of men”, and the increased demand for social skills as described by many authors should be investigated in more detail, in particular whether men are increasingly adapting to the changed requirements or are actually experiencing a decline in the labour market. Furthermore, for the years after 2000, the divergent development of the demand for highly qualified work in the USA and Germany is a puzzle which is however beyond the scope of our study.

References

- Acemoglu, Daron; Restrepo, Pascual (2017): Robots and Jobs. Evidence from US Labor Markets. Cambridge, MA: National Bureau of Economic Research.
- Anger, Christina; Schmidt, Jörg (2010): Gender Pay Gap. Gesamtwirtschaftliche Evidenz und regionale Unterschiede. *IW-Trends-Vierteljahresschrift zur empirischen Wirtschaftsforschung* 37 (4): 3–16.
- Arntz, Melanie; Gregory, Terry; Zierahn, Ulrich (2017): Revisiting the risk of automation. *Economics Letters* 159: 157–160. DOI: 10.1016/j.econlet.2017.07.001.
- Autor, D. H.; Levy, F.; Murnane, R. J. (2003): The Skill Content of Recent Technological Change. An Empirical Exploration. *The Quarterly Journal of Economics* 118 (4): 1279–1333. DOI: 10.1162/003355303322552801.
- Autor, David H. (2015): Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives* 29 (3): 3–30. DOI: 10.1257/jep.29.3.3.
- Autor, David H.; Dorn, David (2013): The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review* 103 (5): 1553–1597. DOI: 10.1257/aer.103.5.1553.
- Azmat, Ghazala; Petrongolo, Barbara (2014): Gender and the labor market. What have we learned from field and lab experiments? *Labour Economics* 30: 32–40.
- Bachmann, R., M. Cim, C. Green (2019), Long-run patterns of labour market polarisation: Evidence from German micro data. *British Journal of Industrial Relations* 57(2): 350-376.
- Bachmann, R., R. Felder, M. Tamm (2020), Labour market participation and atypical employment over the life cycle – A cohort analysis for Germany. Evidence-based HRM, forthcoming.
- Beaudry, Paul; Green, David A.; Sand, Benjamin M. (2016): The great reversal in the demand for skill and cognitive tasks. *Journal of Labor Economics* 34: 199-247.
- Black, Sandra E.; Spitz-Oener, Alexandra (2010): Explaining Women’s Success.

Technological Change and the Skill Content of Women's Work. *Review of Economics and Statistics* 92 (1): 187–194. DOI: 10.1162/rest.2009.11761.

Bohmann, Sandra; Giesselmann, Marco (2018): Eine kurze Einführung in das Sozioökonomische Panel (SOEP) - Teil 1. Was sind Paneldaten? Berlin: Deutsches Institut für Wirtschaftsforschung (DIW) (SOEP Survey Papers, 489).

Brenke, Karl (2015): Wachsende Bedeutung der Frauen auf dem Arbeitsmarkt. *DIW-Wochenbericht* 82 (5): 75–86. Online verfügbar unter <https://www.econstor.eu/bitstream/10419/106812/1/816662703.pdf>.

Caines, Colin; Hoffmann, Florian; Kambourov, Gueorgui (2017): Complex-task biased technological change and the labor market. *Review of Economic Dynamics* 25: 298–319. DOI: 10.1016/j.red.2017.01.008.

Cortes, G.M. (2016), Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. *Journal of Labor Economics* 34 (1): 63-105.

Cortes, Guido Matias; Jaimovich, Nir; Siu, Henry E. (2018): The “end of men” and rise of women in the high-skilled labor market. Cambridge, MA: National Bureau of Economic Research (Working paper series / National Bureau of Economic Research, 24274).

Deming, David J. (2017): The Growing Importance of Social Skills in the Labor Market*. *The Quarterly Journal of Economics* 132 (4): 1593–1640. DOI: 10.1093/qje/qjx022.

Dustmann, Christian; Ludsteck, Johannes; Schönberg, Uta (2009): Revisiting the German Wage Structure. *The Quarterly Journal of Economics* 124 (2): 843– 881. DOI: 10.1162/qjec.2009.124.2.843.

Felfe, C., R. Iten and S. Stern (2016), Child Care Institutions - A Relevant Tool to Enhance Gender Equality? In: Liebig, B., L. Criblez, K. Gotschall and B. Sauer (Eds.), *Gender Equality: Theories, Practices and Perspectives*. Germany, Verlag Barbara Budrich: 199-215.

Fitzenberger, Bernd; Schnabel, Reinhold; Wunderlich, Gaby (2004): The gender gap in labor market participation and employment. A cohort analysis for West Germany. *Journal of Population Economics* 17 (1): 83–116. DOI: 10.1007/s00148-003-0141-6.

- Frey, Carl Benedikt; Osborne, Michael A. (2017): The future of employment. How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114: 254–280.
- Goos, Maarten; Manning, Alan; Salomons, Anna (2009): Job Polarization in Europe. *American Economic Review* 99 (2): 58–63. DOI: 10.1257/aer.99.2.58.
- Gregory, M. and S. Connolly (2008), Feature: The Price of Reconciliation: Part-Time Work, Families and Women's Satisfaction. *The Economic Journal* 118 (526): F1-F7.
- Hernandez-Arenaz, Inigo; Iriberry, Nagore (2016): Women ask for less (only from men). Evidence from alternating-offer bargaining in the field.
- Kleven, Henrik; Landais, Camille; Søgaaard, Jakob Egholt (2018): Children and Gender Inequality. Evidence from Denmark. Cambridge, MA: National Bureau of Economic Research.
- Schönberg, U. and J. Ludsteck (2014), Expansions in maternity leave coverage and mothers' labor market outcomes after childbirth. *Journal of Labor Economics* 32 (3): 469-505.
- Spitz-Oener, Alexandra (2006): Technical Change, Job Tasks, and Rising Educational Demands. Looking outside the Wage Structure. *Journal of Labor Economics* 24 (2): 235–270. DOI: 10.1086/499972.
- Suedekum, J., W. Dauth, S. Findeisen, and N. Woessner (2017), German Robots–The Impact of Industrial Robots on Workers. CEPR Discussion Paper DP12306.

Appendix

Table A.1: Mapping of ISCO groups to task categories

ISCO	Description	Task category
11	Members of legislative bodies and senior officials	NRC
12	Managing directors and divisional managers in large companies	NRC
13	Small business managers	NRC
21	Physicist, mathematician and engineers	NRC
22	Teaching professionals	NRC
23	University teachers	NRC
24	Other researchers and related professions	NRC
31	Technical experts	Cognitive
32	Life science and health professionals	Cognitive
33	Teaching associate professionals	NRM
34	Other skilled workers (medium qualification level)	NRM
41	Office clerks	Routine
42	Customer service clerks	Routine
51	Personal and protective service workers	NRM
52	Models, sales persons and demonstrators	NRM
61	Skilled agricultural and fishery workers	Routine
71	Extraction and building trades workers	Routine
72	Metal, machinery, and related trades workers	Routine
73	Precision, handicraft, craft printing and related trades workers	Routine
74	Other craft and related trades workers	Routine
81	Stationary plant and related operators	Routine
82	Machine operators and assemblers	Routine
83	Drivers and mobile plant operators	NRM
91	Sales and services elementary occupations	NRM
92	Agricultural, fishery and related labourers	NRM
93	Labourers in mining, construction manufacturing and transport	NRM