

# Gender-specific employment polarization – the role of tasks from 1980 to 2010

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## Abstract

The empirical literature suggests that labor markets of most industrialized countries are polarized. This means that employment in occupations at the bottom and the top of the skill distribution increases more strongly than in medium ranked occupations. This pattern has also been detected for Germany in the last decades. We study gender-specific changes in occupations using German register data and find - in contrast to common perception- only weak evidence for employment polarization over a thirty years period. We show that employment increases along the analytical tasks distribution. This increase is higher for women indicating that female employment disproportionately shifted towards high analytical tasks occupations.

**Keywords:** Polarization, tasks, gender-specific occupational changes.

**JEL classification:** J24, J31.

## 1. Introduction

Many recent studies (Goos et al. 2014, 2009, Autor et al. 2006) point out that labor markets of most industrialized countries are polarized. This means that employment in occupations at the bottom and the top of the skill distribution<sup>1</sup> increases more strongly than in medium ranked occupations. This U-shaped pattern of employment growth along the skill distribution is known as “job polarization” following the terminology of Goos and Manning (2007). It has been rationalized by the tasks based approach (TBA) introduced by Autor et al. (2003)<sup>2</sup>, which gives a nuanced view of skill biased technological change (SBTC) by showing how the computerization substituted for routine tasks (predominantly used in occupations in the middle of the skill distribution) and complemented non-routine cognitive tasks (predominantly used in occupations at the upper tail of the skill distribution). Non-routine manual tasks (predominantly used in occupations at the lower tail) should be less affected by computerization.

The polarization pattern has been detected also for male workers in Germany (Dustmann et al. 2009). However, the gender-specificity has been widely ignored up to now. It is an open question whether male and female workers are equally affected by task biased technological change. We close this gap and show that employment growth in jobs with high analytical and interactive tasks is higher for female workers than for male workers. Hence, female employment disproportionately shifted towards high analytical tasks occupations and benefit stronger from technological changes in the last decades than male employment.

## 2. Data

Our empirical work (which considers the period 1980-2010) is based on two data sets: The employment register data (BeH) 1975-2010 of the German Federal Employment Services and several waves of the BIBB/IAB- and BIBB/BAuA-Employment survey cross-sections (“Qualification and Career Survey”). The BeH covers nearly 80 percent of the German workforce and is therefore highly representative for dependent workers, excluding only the self-employed, civil servants, individuals in (compulsory) military service, and - before the year 1999 - individuals in so-called ‘marginal part-time jobs’ (jobs with no more than 15 hours per week or temporary jobs that last no longer than 6 weeks).<sup>3</sup> Furthermore it contains important personal characteristics (sex, age, education, job status) as well as information on region, industry, establishment identifiers and wages. Of particular interest for our analysis is the information on occupations. The classification scheme (KldB88) distinguishes between more than 330 occupational groups (3-digit level). It is clear that results based on such a detailed categorization fail when a large part of the 3-digit-occupations in the survey is small or not observable in certain cross-sections. Therefore and because of fundamental systematical problems of this classification, we use a higher aggregation level of occupations: Occupational Fields. These are defined by determining similarities between the activities carried out in the (3-digit) occupational orders they contained and then bundled accordingly. Moreover the aggregation takes into account educational and professional circles as well as industry information. Thus, in contrast to the 3-digit occupational classification scheme, they show greater intra-homogeneity and, at the same time, greater inter-heterogeneity.<sup>4</sup> An additional advantage is that the occupational field classification is much more robust with regard to outliers. At the 3-digit level, the (not gender-specific) employment growth rates from 1980 to 2010 range between -100 and +46,000 percent. At the occupational field

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<sup>1</sup> The skill distribution is approximated by occupation’s average years of schooling (Autor et al. 2008) or occupational mean wage (Autor and Dorn 2013).

<sup>2</sup> For a systematic discussion see Acemoglu and Autor (2011) or Autor (2013).

<sup>3</sup> A more commonly used data set in Germany is the SIAB, which is a 2 percent random sample of the data set we use.

<sup>4</sup> See Tiemann et al. (2008) for further information.

level the corresponding rates are between -86 and +300 percent. In contrast to other studies we are not obliged to exclude occupations with small observation numbers or very high employment growth rates.

For the tasks measures we use the BIBB/IAB- and BIBB/BAuA-Employment Surveys. These are representative cross-sections of working population in Germany conducted at 6-7-year intervals. In every cross-section between 20.000 and 35.000 employed respondents were asked about their qualification, job characteristics of the current job and further personal information (for more details see Hall 2009, Rohrbach 2009, Zopf/Tiemann 2010, p. 410). It should be noted, that the comparability of the waves is restricted because of changing study population (for example: the first two waves included German respondents from West Germany, while the last and current waves also include East Germans and Non-Germans), and changing questions, response categories and inconsistent item batteries. In order to harmonize the datasets we restrict our analyses to employed, 18- to 65 year old respondents in West Germany excluding foreigners and apprentices. Moreover, we include only those variables recurring all-along the five cross-sections with an (almost) identical wording and pertaining to workplace, working appliances and working conditions sections of the questionnaire. Then we differentiate the five task categories into (nonroutine) analytical, (nonroutine) interactive, routine cognitive, routine manual and nonroutine manual tasks, as suggested by TBA. Following Antonczyk et al. (2009) our tasks variables measure the number of individual tasks belonging to one category over the total number of individual tasks at time  $t$ . By adding up to one, the index yields an approximation of how individuals' jobs are structured in terms of the five TBA tasks. In both data sets we use the same occupational classification. Hence, information about requirements, tasks and other characteristics which employees perform in their current job can be aggregated to the occupational level for every cross-section.

### 3. Gender-specific employment polarization

Figure 1 displays the actual data points for gender-specific employment changes of all 54 occupational fields from 1980-2010. The size of the red bubbles represents full-time equivalents of female employment within each occupational field, the blue bubbles depicts male employment, accordingly. The occupational fields are ranked according to the median log wage of full-time working men. This restriction makes sure that the ranking is not influenced by the selection of women into occupations and working-time differences between occupations. It is obvious that gender-specific employment growth rates are by far highest for occupational fields with a very small number of female workers at the top right of the ranking. These are Engineers (+800 percent), Chemists, Physicists and natural scientists (+720 percent), Occupations in advertising (+700 percent) and Occupations in law (530 percent). The relative increase of male employment is strongest in Occupations in computer science, information and communication technology (+280 percent) and Occupations in social work (+200 percent). But also within these fields, female employment increases in relative terms even more than male employment. Altogether, female employment increases within 34 occupational fields and decreases within 20 fields, the corresponding numbers for male employment are 20 and 34.<sup>5</sup>

Identifying these differences in occupational employment growth between men and women we are interested whether male and female employment growth exhibits different polarization patterns. Polarization means that employment in occupations at the bottom and the top of the skill distribution increases more strongly than in medium ranked occupations. To investigate this

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<sup>5</sup> This picture of increasing employment for women and decreasing employment for men is corroborated by the numbers for total employment: male employment decreases by 6 percent, female employment increases by 13 percent in this 30 years period.

question, we propose a very straightforward polarization measure. We simply split the ranking which is a commonly used as proxy for the skill distribution) into two halves and run the linear regression

$$\Delta Emp_{occ,1980-2010} = \alpha + \beta rank_{occ,1980} + \varepsilon_{occ}$$

for both halves of the ranking and for male and female employment separately. Thereby, each observation is weighted by gender-specific employment numbers. If the polarization hypothesis holds, the estimated coefficient  $\beta$  should be statistically significant and negative at the lower part of the distribution and positive at the upper part of the distribution. The statistical significance can be seen at a glance at the t-ratio of  $\beta$ .<sup>6</sup> Therefore we take the latter as our polarization measure. The measures as well as the fitted values of the regressions are displayed in Figure 1. For male workers, the t-ratio is -0.4 at the lower part of the distribution and +2.68 at the upper part of the distribution. The negative sign at the lower part and the positive sign at the upper part indicate employment polarization for male workers for the time period 1980 to 2010. But having in mind that the critical value of a t-distribution with 25 degrees of freedom is about 1.8 for the ten percent level of significance (one sided test), this evidence is rather weak. For female employment, the polarization measure is statistically different from zero at the ten percent level at the upper part of the distribution (1.82) but it is also positive at the lower part. Hence, female employment in medium ranked occupations increases more strongly than in low ranked occupations. This is contradicting the polarization hypothesis.

To sum up, this descriptive evidence suggests that occupational employment growth differs between men and women. In contrast to common perception we find only weak evidence for polarization among male workers and no evidence among female workers in these 30 years-period.<sup>7</sup> Given these results, TBA should have more explanation content for male employment changes than for female ones. Therefore, the next section examines the determinants of gender-specific employment growth as proposed by TBA.

### 3. The role of tasks

Figure 2 shows gender-specific employment growth rates depending on the analytical tasks content in 1980. The occupational fields are ranked according their analytical tasks content in 1980. The fields with highest analytical tasks in 1980 are engineers, chemists, physicists, natural scientists and occupations in law displayed on the far right. On the far left, we observe occupations in warehousing, office hands, telephone operators and unskilled laborers with very low analytical tasks. For both gender, it is obvious that the higher the analytical tasks content of an occupational field in 1980, the higher is its employment growth rate in subsequent years. This relationship is statistically different from zero for both gender, and much more pronounced for female employment. The t-ratio of the estimated coefficient of the analytical tasks rank is 6.45 for female employment and 3.72 for male employment. Hence, female employment disproportionately shifted towards high analytical tasks occupations.

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<sup>6</sup> The idea to use the t-ratio instead of the estimated coefficient is borrowed from Dauth (2015). Building upon the approach of Goos/Manning (2007) he estimated a quadratic function and took the t-ratio of the squared term as polarization measure. However, a significant t-ratio does not necessarily indicate a polarization pattern since it might be due to high employment growth at one end of the distribution, only. Our approach, however, looks at both ends of the distribution, separately and is therefore more reliable.

<sup>7</sup> Splitting the 30-years period into three decades, the results (not presented in the paper for sake of brevity) show significant polarization in the decade 2000 to 2010, only. The polarization is more pronounced for male employment.

Turning to interactive tasks, Figure 3 suggests that the effects of interactive tasks on growth rates of occupational fields are statistically significant and comparably the same for male and female employment. This is not true for the routine-cognitive dimension. It can be seen from Figure 4, that the increase of the pink line is rather flat and statistically not significant, whereas it is significant for the more ascending blue line. This result is contrary to the predictions of TBA that computerization substituted for routine-cognitive jobs. According to the theory, employment also should have substantially decreased with increasing routine-manual tasks. Figure 5 shows that this is actually true for female employment but not for male employment.

The relevance of analytical tasks for employment growth is corroborated by a multivariate analysis which takes the occupational gender-, age- and qualification-structure into account. Moreover, it controls for share of manufacturing workers, the region type and the spread across (aggregated) federal states. Table 1 shows in the first column for total employment that the coefficient for the analytical tasks measure is positive and statistically significantly different from zero (at the 95% confidence level) while the impact of the remaining tasks measures as well as qualification effects are rather weak. This is worth mentioning since it suggests that technological change in Germany is rather analytical tasks-biased than skill-biased or routine-biased. Moreover, Table 1 indicates that employment increases in occupations which are prevailed in dense metropolitan areas and their surroundings. By contrast, occupation with a high share of manufacturing workers exhibit distinctly lower employment growth rates. The gender-specific analyses presented in the middle and the right panel of Table 1 point out that the latter factors are less important for female workers: female employment growth is mostly driven by an occupation's high share of analytical tasks.

## **5. Conclusion and Discussion**

The empirical literature suggests that labor markets of most industrialized countries are polarized. This means that employment in occupations at the bottom and the top of the skill distribution increases more strongly than in medium ranked occupations. This pattern has also been detected for Germany in the last decades. We study gender-specific changes in occupations over a thirty years period using German register data and find - in contrast to common perception- only weak evidence for employment polarization among male workers and no evidence among female workers. We show that employment primarily increases along the analytical tasks. This increase is more distinct for women indicating that female employment disproportionately shifted towards high analytical tasks occupations. The results suggest that technological change in Germany is rather analytical tasks-biased than skill-biased or routine-biased.

## References

- Antonczyk, D., Fitzenberger, B., Leuschner, U. (2009): Can a task-based approach explain the recent changes in the German wage structure? ZEW Discussion Papers, No. 08-132, Centre for European Economic Research.
- Acemoglu, D., Autor, D.H.: Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings. In: C. David, A. Orley (eds.) Handbook of Labor Economics, vol. Volume 4, Part B. pp. 1043-1171. Elsevier, (2011).
- Autor, D.H. (2013): The "task approach" to labor markets: an overview. Journal for Labour Market Research 46(3), 185-199.
- Autor, D.H., Dorn, D. (2013): The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, American Economic Review, 103(5), 1553-1597.
- Autor, D.H., Levy, F., Murnane, R.J. (2003): The Skill Content of Recent Technological Change: An Empirical Exploration, Quarterly Journal of Economics 118(4), 1279-1333.
- Autor, D. H., Katz, L.F., Kearney, M. S. (2006): The Polarization of the U.S. Labor Market, American Economic Review Papers and Proceedings 96, 189-194.
- Autor, D. H., Katz, L.F., Kearney, M. S., (2008): Trend in U.S. Wage Inequality\_ Re-assessing the Revisionists, Review of Economics and Statistics 90, 300-323.
- Dauth, W. (2014) Job polarization on local labor markets, IAB Discussion Paper 18/2014, Nuremberg.
- Dustmann, C., Ludsteck, H., Schönberg, U. (2009): Revisiting the German Wage Structure, Quarterly Journal of Economics 124(2), 843-881.
- Goos, M., Manning, A., (2007): Lousy and lovely jobs: The rising polarization of work in Britain“, The Review of Economics and Statistics 89(1), 118-33.
- Goos, M., Manning, A., Salomons, A. (2009): Job polarization in Europe. In: The American Economic Review Papers and Proceedings, Vol. 99, No. 2, p. 58–63.
- Goos, M., Manning, A., Salomons, A. (2014): Explaining Job Polarization: Routine-Biased Technological Change and Offshoring, American Economic Review, 104(8): 2509–2526.
- Hall, A. (2009): Die BIBB/BAuA-Erwerbstätigenbefragung 2006: Methodik und Frageprogramm im Vergleich zur BIBB/IAB-Erhebung 1998 (Diskussionspapiere des Bundesinstituts für Berufsbildung 107). Bundesinstitut für Berufsbildung, Bonn (2009)
- Rohrbach-Schmidt, D. (2009): The BIBB/IAB- and BIBB/BAuA-Surveys of the Working Population on Qualification and Working Conditions in Germany. Data and methods manual (BIBB-FDZ Daten- und Methodenberichte Nr. 1/ 2009). BIBB, Bonn.

Tiemann, M, Schade, H.-J., Helmrich, R., Hall, A., Braun, U., Bott, P. (2008): Berufsfeld-Definitionen des BIBB auf Basis der KldB 1992 (Zweite Fassung, Wissenschaftliche Diskussionspapiere des Bundesinstitutes für Berufsbildung, Heft 105). BIBB, Bonn.

Zopf, S., Tiemann, M. (2010): BIBB/BAuA-Employment Survey 2005/06 Schmollers Jahrbuch 130, S. 409 – 420.

Tables

**Table 1: Regression results for the time period 1980-2010**

	All				Male				Female			
	Dep. Var.: employment growth (in %)		S. coeff.	Coefficients	Dep. Var.: male employment growth (in %)		S. coeff.	Coefficients	Dep. Var.: female employment growth (in %)		S. coeff.	Coefficients
	t-values				t-values				t-values			
% Analytical tasks	3.609	2.22	0.611	3.250	2.49	0.681	5.154	2.33	0.482			
% Interactive tasks	0.201	0.31	0.040	-0.117	-0.17	-0.022	-0.190	-0.25	-0.031			
% Routine cognitive tasks	0.327	0.55	0.129	-0.123	-0.20	-0.046	-0.024	-0.03	-0.007			
% Routine manual tasks	1.414	1.37	0.302	1.583	1.34	0.397	0.632	0.56	0.081			
% Female	-0.075	-0.18	-0.042	0.415	0.99	0.204	-0.225	-0.46	-0.070			
% Skilled	-0.952	-1.40	-0.378	-1.188	-1.83	-0.497	0.028	0.03	0.009			
% High-skilled	-0.445	-0.44	-0.110	-1.125	-1.23	-0.351	1.849	1.02	0.228			
% Manufacturing	-1.139	-2.43	-0.623	-1.244	-2.21	-0.748	-0.573	-1.08	-0.217			
% Age category 30-50	-1.954	-1.30	-0.284	-1.301	-1.05	-0.193	-1.459	-0.62	-0.135			
% Age category >50	-1.647	-0.86	-0.152	-1.406	-0.82	-0.146	0.790	0.28	0.052			
% Dense metropolitan areas	4.131	3.41	0.717	4.678	3.20	0.942	1.972	0.98	0.222			
% Metropolitan surroundings	7.188	2.68	0.716	6.518	2.70	0.754	3.448	0.69	0.213			
Constant	-70.076	-0.29	.	-181.225	-0.75	.	117.386	0.30	.			
R squared	0.609			0.581			0.632					

Notes: Each regression is based on 54 observations of occupational fields. All covariates are from the initial year 1980. All regressions include federal state covariates. S. coeff. denotes standardized coefficients.

Figures

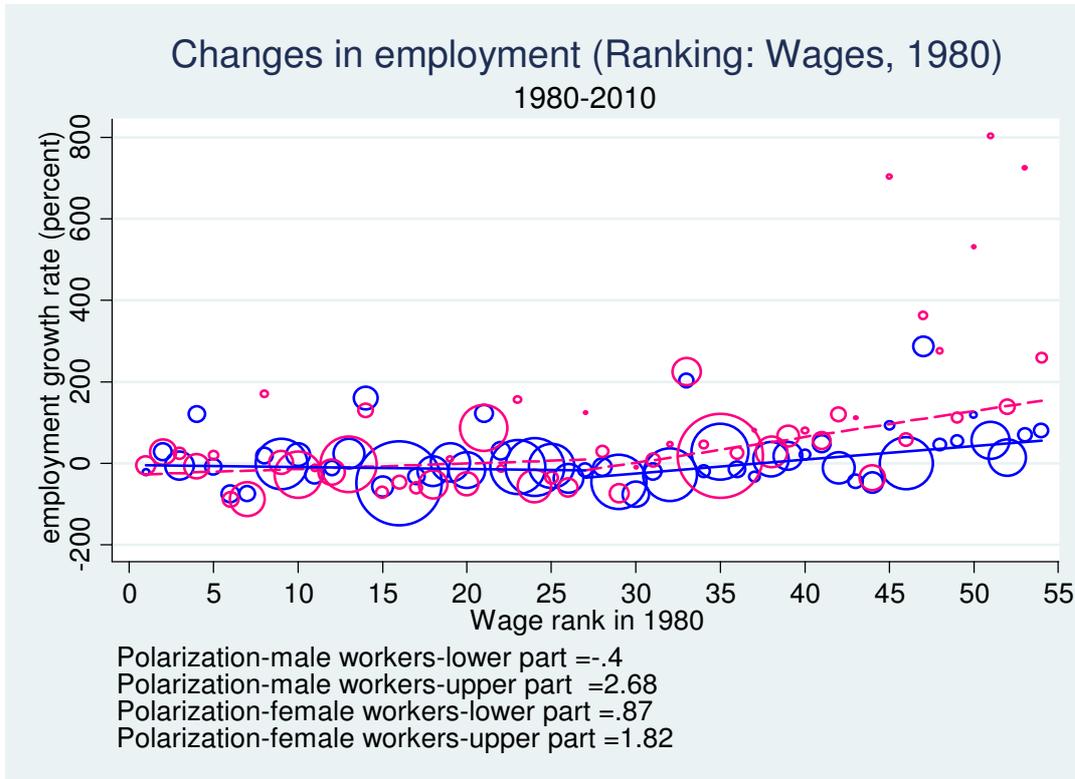


Figure 1: Gender-specific employment growth rates of occupational fields ranked by median log wage

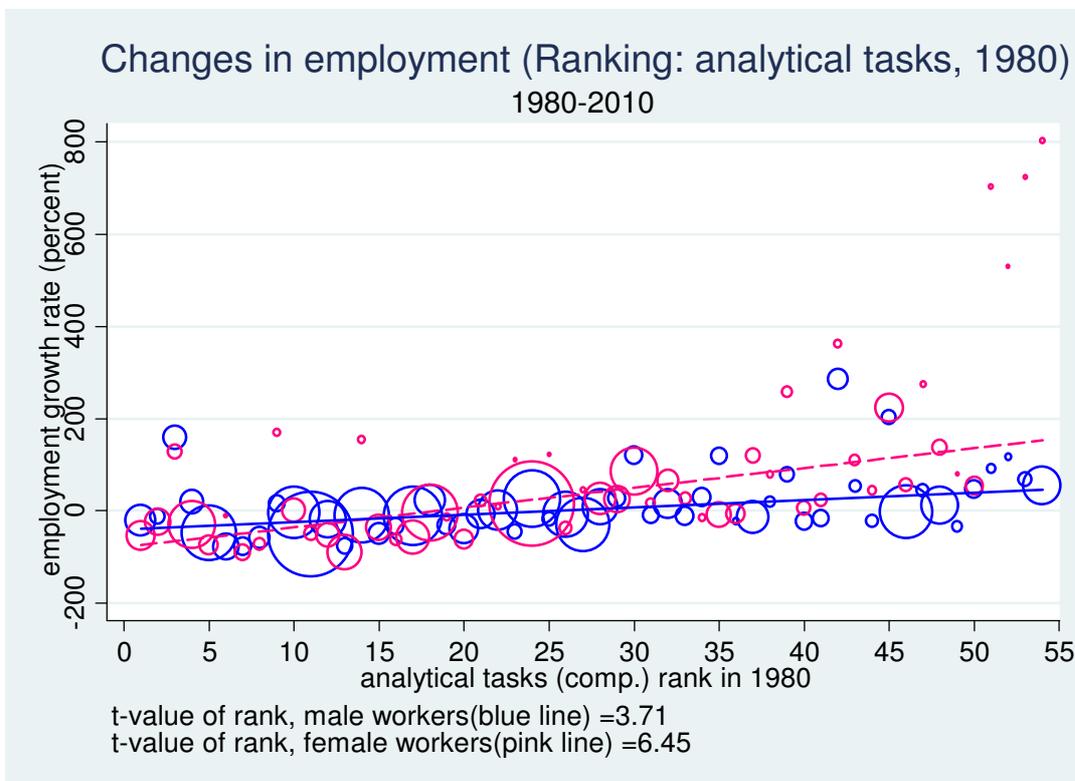


Figure 2: Gender-specific employment growth rates of occupational fields ranked by analytical tasks composition

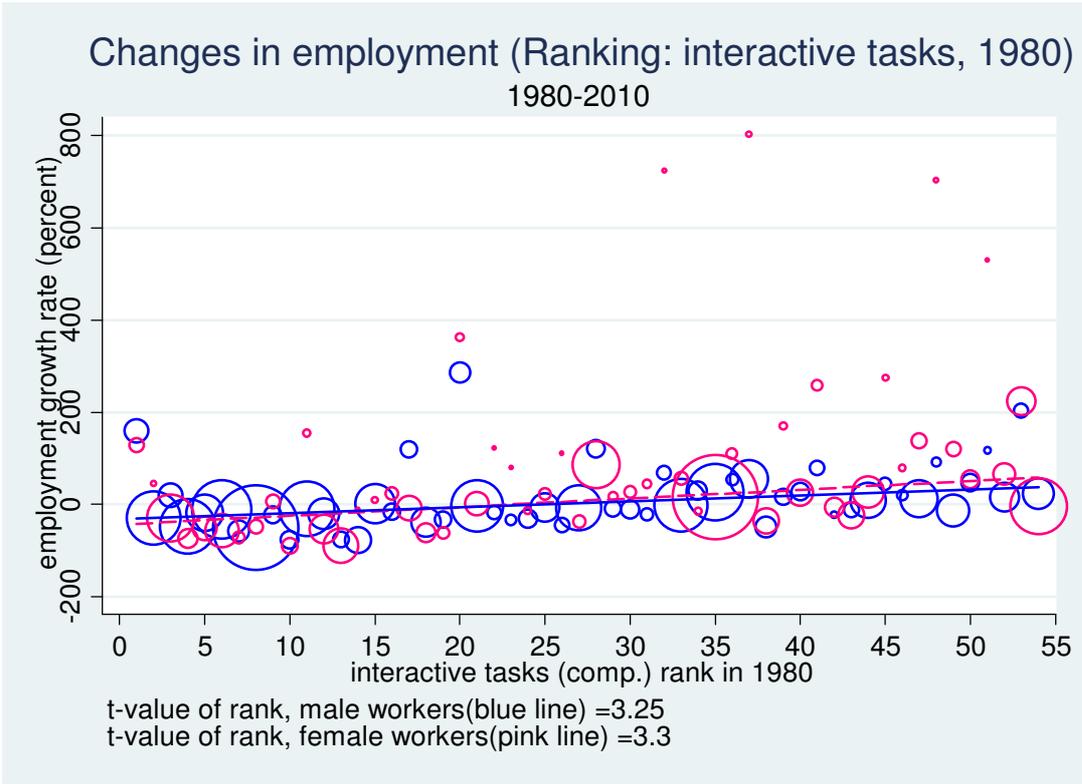


Figure 3: Gender-specific employment growth rates of occupational fields ranked by interactive tasks composition

### Changes in employment (Ranking: routine cognitive tasks, 1980-2010)

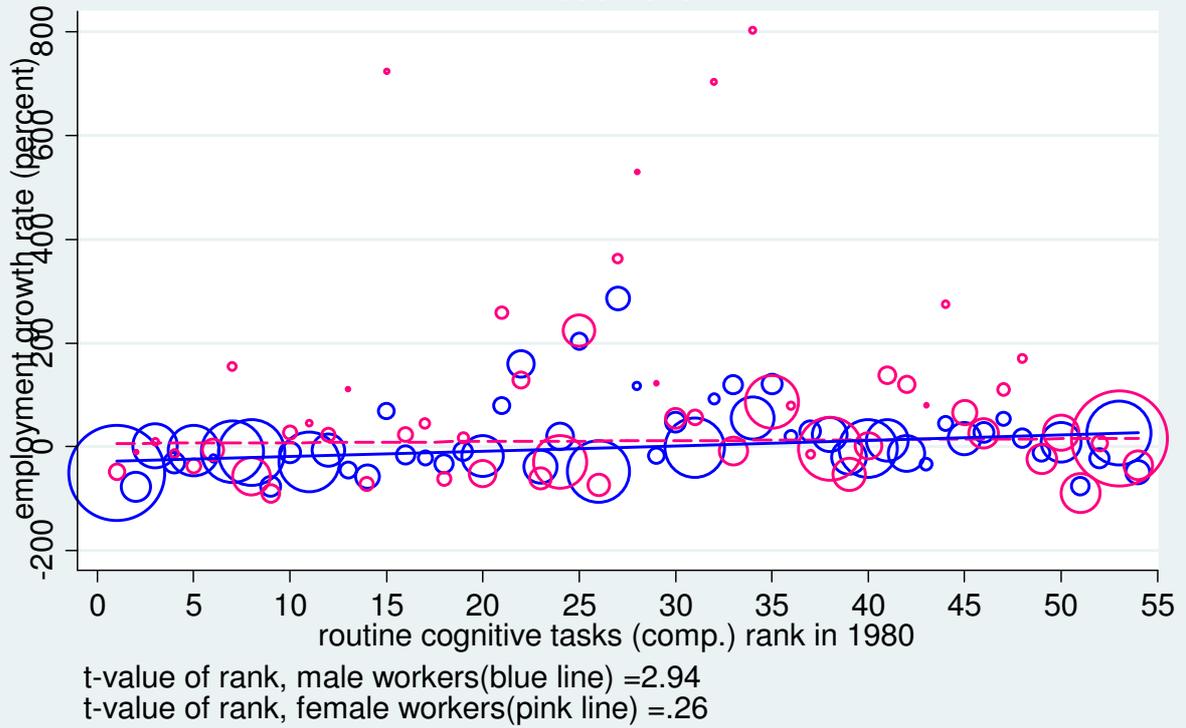


Figure 4: Gender-specific employment growth rates of occupational fields ranked by routine-cognitive tasks composition

### Changes in employment (Ranking: routine manual tasks, 1980-2010)

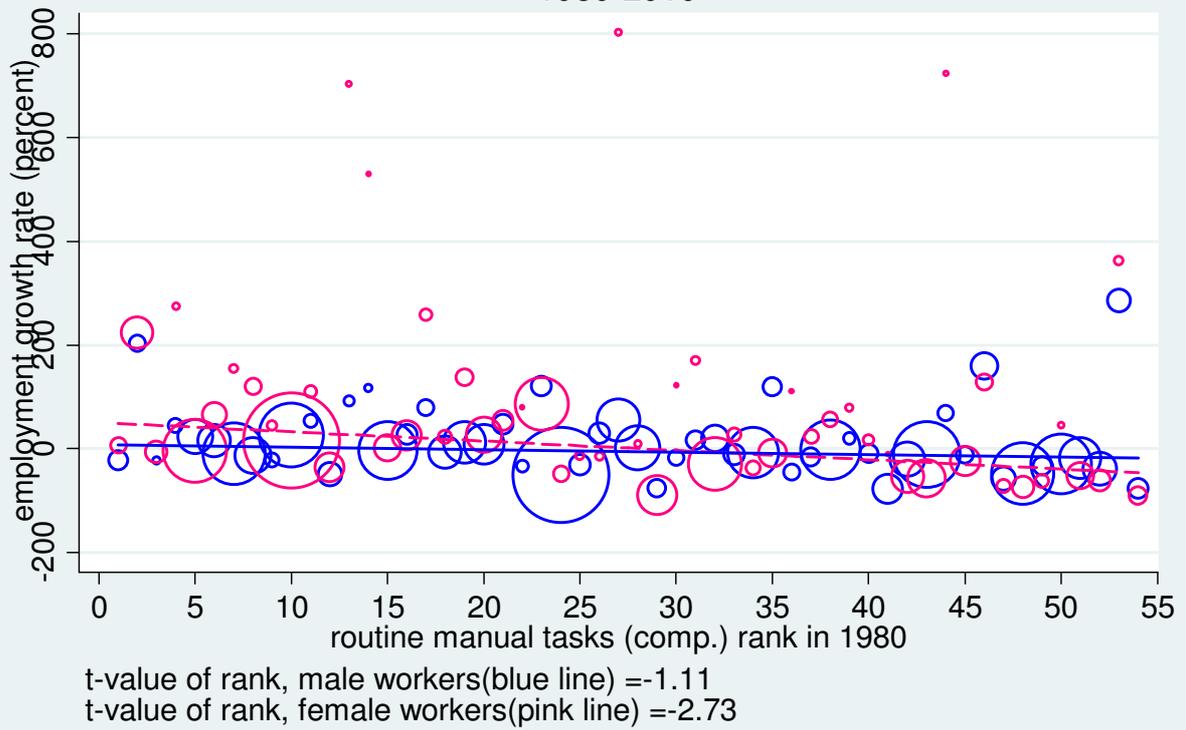


Figure 5: Gender-specific employment growth rates of occupational fields ranked by routine-manual tasks composition