Why has technological change not closed the gender wage gap?

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Introduction | Motivation

- Driven by technological advances, labor markets in high-income countries have experienced relevant structural changes (Autor et al, 2003; Goos et al, 2009)
  - Decline in the demand for labor in routine tasks while increasing in jobs where workers are complemented - Routine Biased Technological Change (Autor et al, 2013)
- Intense debate worldwide on the impacts of technological change on inequality and the extent to which labor markets are increasingly polarized

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- Intense debate worldwide on the impacts of technological change on inequality and the extent to which labor markets are increasingly polarized
- However, evidence linking RBTC to the dynamics of the gender wage gap is scarce
  - Although these structural changes are in principle "gender-neutral", they might have had relevant implications for the evolution of gender wage disparities

$\Rightarrow$ How have changes in wages and employment structure across occupations associated with technological progress affected the gender wage gap?

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- The occupations that lost the most in terms of employment and wage returns are traditionally male industrial-goods-producing occupations
- Recent work suggests that women have relatively benefited from technological change (Ngai and Petrongolo, 2017; Cortes et al., 2018; Black and Spitz-Oener, 2010)
    - Women more likely to be employed at cognitive high-wage occupations
- Despite this, the convergence in the gender wage gap stagnated in the last decades (Blau and Khan, 2017; Olivetti and Petrongolo, 2014)
    - putting in question the extent to which the impact of technological change on occupational wages has been favorable to female workers

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$\Rightarrow$ Puzzle: **Why is it that the large wage gains in the occupations in which women are increasingly employed in detriment of male occupations have not led to a further reduction in the gender gap?**

This paper

- This paper uses administrative panel data for Germany to investigate the effect of technological change on wage trajectories of men and women across occupations differently affected by RBTC
  - One of the highest and most persistent gender gaps among developed countries.
  - Having a large industrial sector the effect of RBTC on the employment structure has been remarkable (Dustman et al, 2009)

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What I do:

1. I estimate changes over time in occupation-specific wage premiums:
   - component of the worker's potential wage that is common to all workers in each occupation in a given year, after accounting for the effect of occupation-specific returns to the individual's skills $\Rightarrow$ Panel data approach (Cortes, 2016)
   - five broad occupation groups distinguishing between tasks that can be automated and those where technology complements work
2. How changes in wage premiums for male and female workers affect the gender wage gap: *composition or sorting* channel and gender differences *within occupations*

Related literature

- **Relevance of occupational structure** to explain the gender wage gap (Goldin, 2014)
    - occupation and industry accounted for 51% of the 2010 US gap (Blau and Khan, 2017), 44% of the 2017 UK gap (Petrongolo and Ronchi, 2020)

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  - Ngai and Petrongolo (2017), Cerina et al (2017): reallocation of labor from goods-producing sectors to service industries
  - Cortes et al (2018); Borghans et al (2014): rise in the use of interpersonal tasks in the US ⇒ women have an (acquire or innate) advantage in those increasingly valued skills
- Black and Spitz-Oener (2010): West Germany - women have witnessed increases in nonroutine analytic and interactive tasks within industry and occupation cells between 1979-1999

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⇒ By looking not only employment but mostly at wage dynamics across occupations:

- **I show that wage premiums for male workers grew more rapidly than those of females *within* analytical and interactive non-routine occupations**

Data and sample

1. **Administrative social security records** for Germany: *Sample of Integrated Labour Market Biographies* (SIAB 7514) of the Institute for Employment Research (IAB)
   - Mandatory notifications made by employers to social security agencies
   - 2% random sample. Represents 80% of all employees in Germany (self-employed, civil servants, and family workers not included).
   - Individuals' full employment histories, detailed data for workers' occupations along with sociodemographics such as age, gender, level of education. Wage: daily gross wage.
   - Sample: male and female workers between 25 and 55 years old in West Germany for the period 1975-2010. I restrict my main analysis to full-time workers so that wages are comparable

2. **Tasks** - Representative labor force cross-sections: *Qualification and Career Surveys* - BIBB/IAB and BIBB/BAuA
   - 1979, 1985/86, 1991/92, 1998/99 and 2012, each covering 20,000 - 35,000 individuals
   - Worker self-reports on the task content of their work. Tasks: activities that individuals have to perform in their jobs

Broad occupation groups

- Five dimension classification based on the task content of occupations - Spitz-Oener (2006) inspired on Autor et al. (2003)
  - Routine/ non-routine: routines are based on well-defined rules and procedures ⇒ they could be carried out by a computer that executes a program (automation)
  - Analytical: necessity to think or analyze / Interactive: need to communicate with others: dealing with clients, counseling or teaching

  1. **Analytical non-routine** (e.g. researching and analyzing)
  2. **Interactive non-routine** (e.g. managing and teaching)
  3. **Cognitive routine** (e.g. calculating and bookkeeping)
  4. **Manual routine** (e.g. operating machines)
  5. **Manual non-routine** (e.g. serving and repairing)

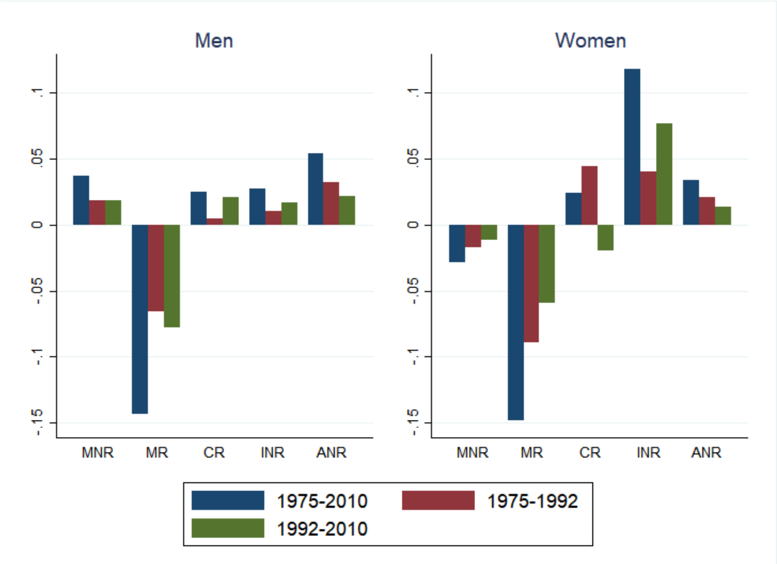
- I use information on tasks from BIBB and aggregate it at 3-digits occupational level to classify occupations in the SIAB data Details

⇒ **Changes along these task groups are interpreted as being related to routine biased technological shocks**

Summary statistics

	Men		Women	
	Mean	Sd	Mean	Sd
A. Worker characteristics				
Age	39.42	8.58	38.26	8.97
Experience	11.64	7.92	11.10	7.94
German nationality	0.89	0.31	0.91	0.28
Real daily wage	109.4	138.7	72.4	88.5
Low Skill	0.10	0.30	0.15	0.36
Medium Skill	0.76	0.43	0.74	0.44
High Skill	0.14	0.35	0.11	0.31
B. Occupation classification				
Analytical NR	0.14	0.34	0.05	0.21
Interactive NR	0.07	0.26	0.11	0.32
Cognitive R	0.13	0.33	0.41	0.49
Manual R	0.53	0.50	0.17	0.37
Manual NR	0.13	0.34	0.26	0.44
N of individuals	565,230		446,611	
Observations	6,924,032		3,199,340	

Changes in employment shares by occupation groups



Empirical approach | Occupational wage premiums

- Follow panel-data approach of Cortes (2016) for the estimation of unbiased and consistent occupation-specific time-varying changes in wage premiums
- Assuming that individual skills are time-invariant and productivity is log-linear in skills, the potential wage in occupation j for individual i of skill level z_i:

$$w_{ijt} = \theta_{jt} + z_i a_j \tag{1}$$

- θ_{jt}: wage premium in occupation j at time t
- z_i: individual's time-invariant skills
- a_j: occupation-specific return to skills

$\gamma_{ij} = z_i a_j$: occupation-spell fixed effect, which varies for an individual across occupation spells, but it stays constant whenever the individual stays in the same occupation

Empirical approach | Occupational wage premiums

- Empirically, the observed wage for individual i of gender g in period t will depend on the occupation chosen by the individual:

$$w_{ijt} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\gamma_{ij} + X_{it}\delta + u_{it} \tag{2}$$

$D_{ijt} = 1$ if individual i selects into occupation $j \in \{ANR, INR, CR, MR, MNR\}$ at time t

- θ_{jt}: occupation-time fixed effects
- γ_{ij}: occupation-spell fixed effects for each i (individual's skills and occupation-returns to skill)
- X_{it}: year fixed effects and controls (place of work at federal state, experience, German nationality)

- Identifying assumption: $E(u_{it}|D_{ijt}, z_i, \theta_{jt}) = 0$
  Selection into occupations only depends on occupation wage premiums and individual's workers ability

Empirical approach | Gender-specific occupational wage premiums

- I allow **occupation wage premia to differ by gender**, the regression being estimated is:

$$w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\beta_{jt}\, fem_i + \sum_j D_{ijt}\gamma_{ij} + X_{it}\delta + u_{it} \quad (3)$$

where θ^M_{jt} and θ^F_{jt} are the occupation-year fixed effects for male and female workers:

$$\theta^M_{jt} = \theta_{jt} \qquad \theta^F_{jt} = \theta_{jt} + \beta_{jt}$$

- Because of the inclusion of the occupation-spell fixed effects, the occupation-time fixed effects are identified only from variation over time within occupation spells

- $\hat{\theta}^g_{ANRt}$, $\hat{\theta}^g_{INRt}$, $\hat{\theta}^g_{CRt}$ and $\hat{\theta}^g_{MRt}$ with $g = \{M, F\}$ should be interpreted as a *double difference*:

  $\Rightarrow$ identify **changes over time in the occupational wage premium relative to the base year and relative to the changes in MNR for men**

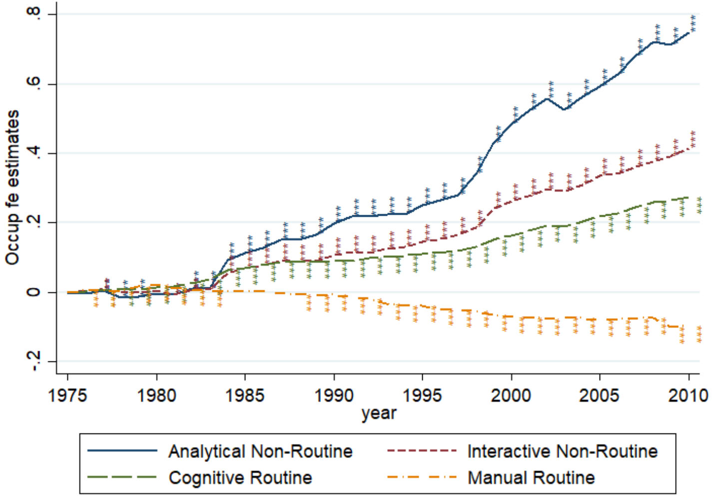
Empirical approach | Decomposition

$$E\left[\hat{\theta}_{jt}^{M}|male\right] - E\left[\hat{\theta}_{jt}^{F}|female\right] = \sum_{j} s_{jt}^{M}\hat{\theta}_{jt}^{M} - \sum_{j} s_{jt}^{F}\hat{\theta}_{jt}^{F} \tag{4}$$

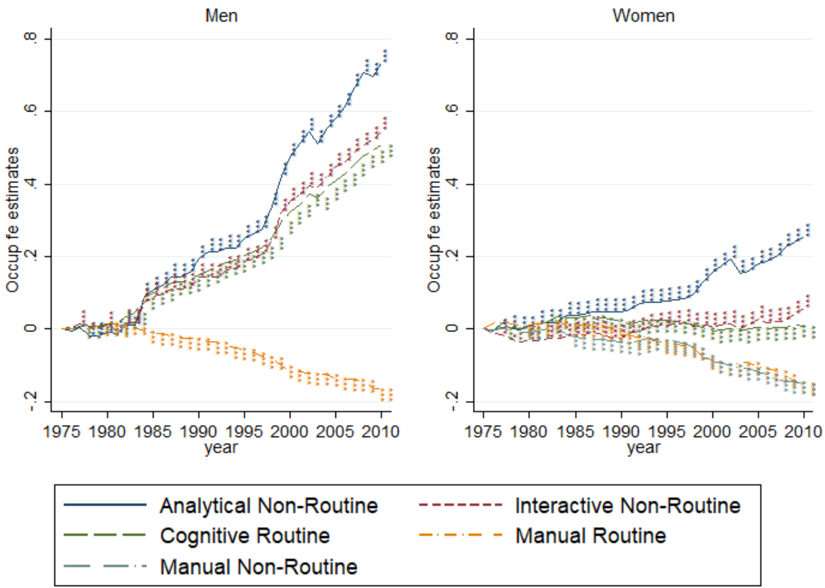
- Two complementary channels explain how changes in occupation-specific wage premiums affect the gender gap:
  1. **composition or sorting across occupations**: women (men) are less (more) likely to be employed at occupations that most increase wage premiums
  2. **within occupations differences**: women (men) obtain a smaller (larger) increase in occupation premium than men for the same occupation group
- Following the approach of Card et al.(2016) perform Oaxaca-Blinder style decomposition:

$$\begin{aligned} E\left[\theta_{jt}^{M}|male\right] - E\left[\theta_{jt}^{F}|female\right] &= E\left[\theta_{jt}^{M} - \theta_{jt}^{F}|male\right] + E\left[\theta_{jt}^{F}|male\right] - E\left[\theta_{jt}^{F}|female\right] \\ &= \underbrace{E\left[\theta_{jt}^{M} - \theta_{jt}^{F}|female\right]}_{\textit{within occupation}} + \underbrace{E\left[\theta_{jt}^{M}|male\right] - E\left[\theta_{jt}^{M}|female\right]}_{\textit{sorting across occupations}} \end{aligned}$$

Change in occupational premiums. Mixed-by-gender fixed effects



Change in gender-specific occupational premiums



Changes in the gender wage premiums gap (1975-2010)

Gender gap in the base year	0.455
Change in gender gap in mean log wages	-0.097
A. Mixed by gender occupation wage premiums	
$E[\theta_{jt}^{ALL} \mid male]$	0.175
$E[\theta_{jt}^{ALL} \mid female]$	0.290
$E[\theta_{jt}^{ALL} \mid male] - E[\theta_{jt}^{ALL} \mid female]$	-0.116
% of the initial wage gap	*-25.39*
B. Gender-specific occupation wage premiums	
$E[\theta_{jt}^{M} \mid male]$	0.161
$E[\theta_{jt}^{F} \mid female]$	-0.022
$E[\theta_{jt}^{M} \mid male] - E[\theta_{jt}^{F} \mid female]$	0.182
% of the initial wage gap	*40.06*
Observations in last year	278,142

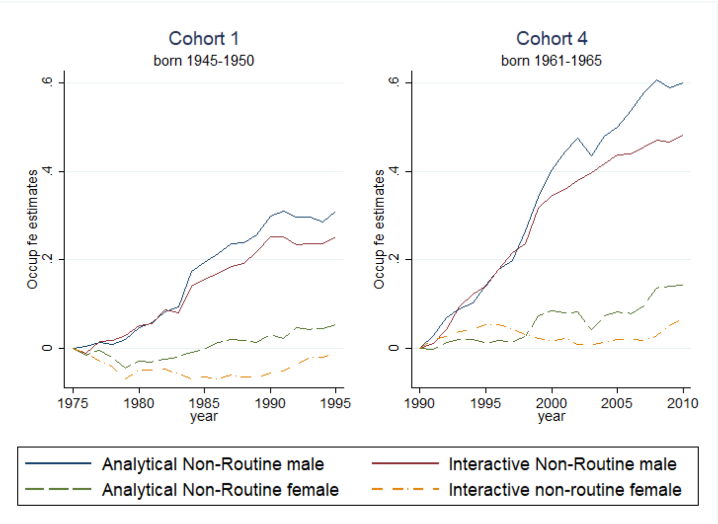
Decomposition of the gender wage premiums gap

Gender-specific occupation wage premiums	
$E[\theta_{jt}^M \mid male] - E[\theta_{jt}^F \mid female]$	0.182
Decomposition	
Sorting across occupations	
$E[\theta_{jt}^F \mid male] - E[\theta_{jt}^F \mid female]$	-0.021
% of the gender difference in occup premiums	*-11.47*
Within occupation differences	
$E[\theta_{jt}^M - \theta_{jt}^F \mid male]$	0.203
% of the gender difference in occup premiums	*111.47*
Observations in last year	278,142

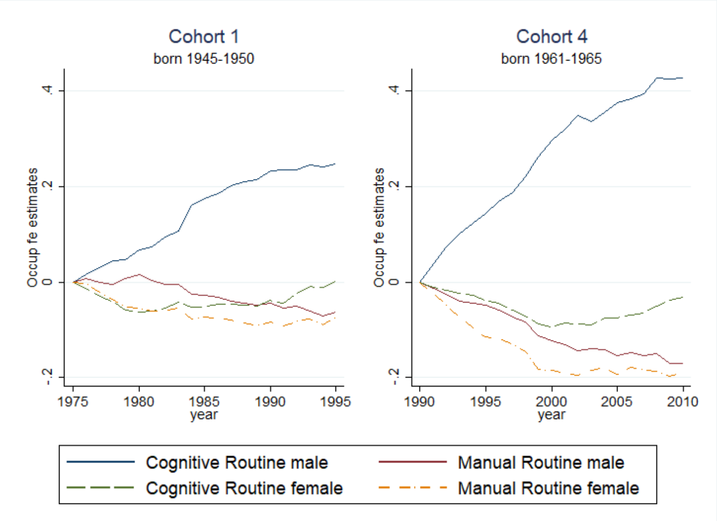
- The fact that occupational wage premiums for men grew more rapidly than female premiums *within* certain occupation groups is the main explanatory factor of the average gender differences over time

- **Did technological change affect differently workers that entered the labor market at different periods?**

Change in gender-specific occupational premiums. Non-routine cognitive



Change in gender-specific occupational premiums. Routine occupations



Decomposition of the changes in the gender wage premiums gap

	Cohort 1 (1)	Cohort 4 (2)
Gender gap in the base year	0.319	0.223
Change in gender gap in mean log wages	0.164	0.248
Gender-specific occupation wage premiums		
$E[\theta_{jt}^M \mid male]$	0.068	0.119
$E[\theta_{jt}^F \mid female]$	-0.028	-0.058
$E[\theta_{jt}^M \mid male] - E[\theta_{jt}^F \mid female]$	0.095	0.177
% of the initial wage gap	*29.96*	*79.38*
Sorting across occupations		
$E[\theta_{jt}^F \mid male] - E[\theta_{jt}^F \mid female]$	-0.010	-0.026
% of the gender difference in occup premiums	*-10.20*	*-14.67*
Within occupation differences		
$E[\theta_{jt}^M - \theta_{jt}^F \mid male]$	0.105	0.203
% of the gender difference in occup premiums	*110.20*	*114.66*
Observations in last year	44,757	53,884

Robustness checks

1. **Changing returns to education**
   - Concern: differences in the changes in wage premiums across occupation groups are driven by increasing returns to education
2. **Occupation specific tenure profiles**
   - Concern: heterogeneous returns to tenure across occupations, tenure profile more steeper in cognitive occupations
3. **Changes in selection into occupations and attrition**
   - Concern: the patterns are driven by changing characteristics of working women and men over time
4. **Extended sample including part-time workers**
   - Concern: excluding part-time workers could be biasing the results given the relevance of part-time jobs for female employment

Details

Conclusion

- This paper uses administrative panel data for West Germany to investigate the effect of technological change on the dynamic of gender wage differentials.
- Main findings:
  - The effect of gender differences in sorting across occupations has mostly benefited women contributing to narrow the gender wage gap
  - However, wage gains for male workers within cognitive occupations grew more rapidly than those of females
    $\Rightarrow$ This effect is stronger for younger cohorts of workers, then we should not assume that it will be reverted in near future

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  - However, wage gains for male workers within cognitive occupations grew more rapidly than those of females
    $\Rightarrow$ This effect is stronger for younger cohorts of workers, then we should not assume that it will be reverted in near future
- It can be misleading looking only at job automation exposure
  - although lower exposition to automation of work and occupational upgrading, women still face certain constrains that did not allow them to benefit from the increased overall wage returns in the upper part of the skill distribution
- Policy implications: policies aimed at reducing gender wage inequalities both between and within occupations continue to be relevant

Further results | Mechanisms

- What explains that wage premiums for males grew more rapidly than those of female workers?
  - I provide evidence that two factors play a role:

1. **Gender differences in wage gains when switching out of routine jobs**
   I find significantly lower wage growth for female switchers than that of males

2. **Gender segregation within broad occupation groups**
   Women moved disproportionately to interactive occupations, and within this group to occupations that were already highly feminized (e.g. social workers, nursery teachers) which experienced lower wage growth compared to male occupations

Thank you for your attention!

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Appendix | Task based approach

1. **Task intensity** (Spitz-Oener, 2006): intensity of this task type for performing the occupational activity

$$SO_{ict} = \frac{N^{o}\ activities\ in\ cat\ c\ performed\ by\ i\ t}{Total\ N^{o}\ of\ activities\ in\ c\ at\ t}$$

2. **Task composition** (Antoczyk et al., 2009): shares of different tasks in an individual occupational activity ($\sum = 1$)

$$AFL_{ict} = \frac{N^{o}\ activities\ in\ cat\ c\ performed\ by\ i\ t}{Total\ N^{o}\ of\ activities\ performed\ by\ i\ at\ t}$$

where c defines the broad occupational categories (c =1 ANR, c =2 INR, c=3 CR, c=4 MR, c=5 MNR), t describes the year of observation (t=1979, 1985/86, 1991/92, 1998/99 and 2012).

- Both indices are sensitive to the number of characteristics included in the survey

Appendix | Task based approach

- Although the surveys include a rich set of workplace activities, the number and the definition of the surveyed activities differs across waves
  - Merge some of the activities into one variable to maintain a total number of activities which is similar in each survey. I constructed a list of 17 tasks.
- I take means of both indices for each category at the occupational level (3 digits of Kldb) to be able to merge it with the SIAB data
  - classification based on the highest value of each index at the occupational level.
- Example (BIBB 1979):

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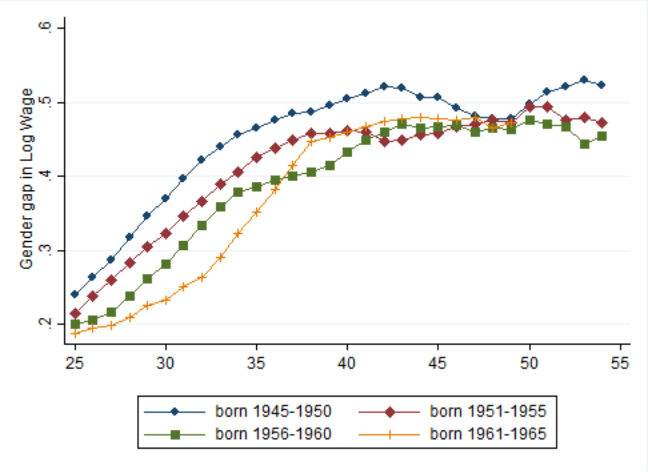
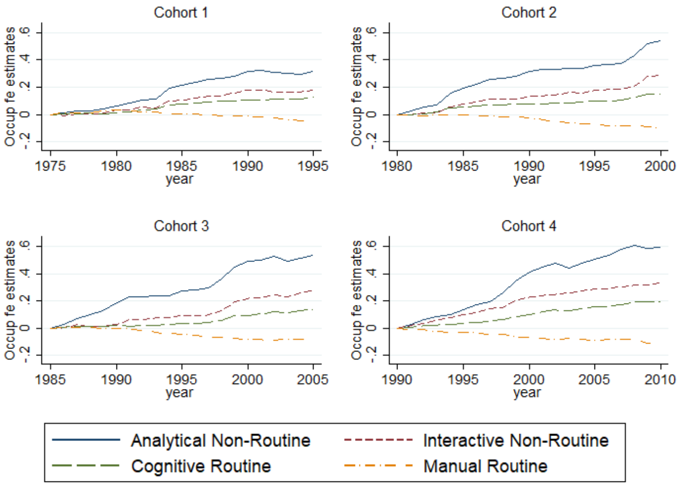
Appendix | Trends in gender wage gap by cohort

Gender gap in mean of Log daily real wage by age for each cohort

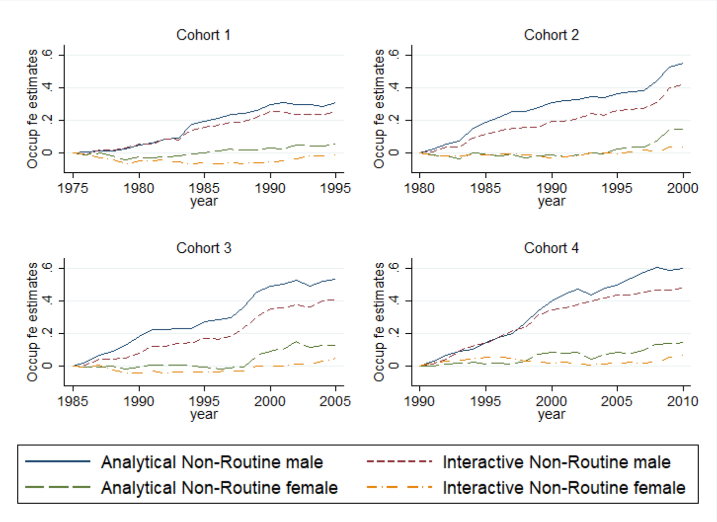


- Did technological change affect differently workers that entered the labor market at different periods?

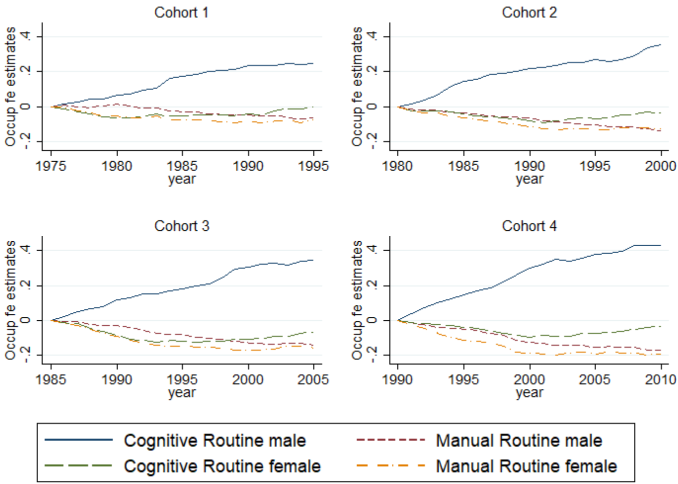
Change in occupational premiums by cohorts. Mixed-by-gender fixed effects



Change in gender-specific occupational premiums. Non-routine cognitive occupations



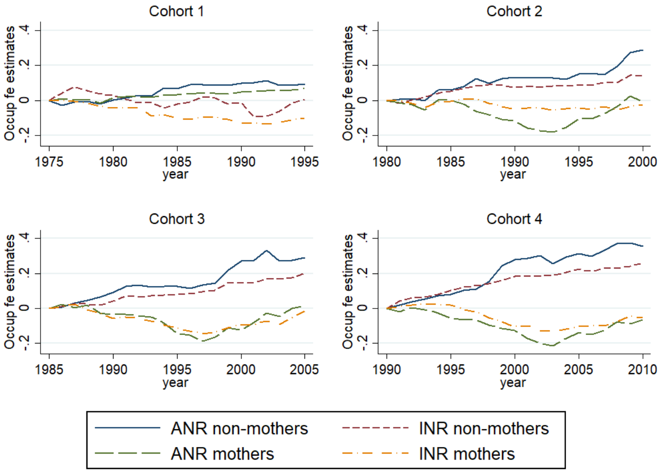
Change in gender-specific occupational premiums. Routine occupations



Causes of gender differences in wage premiums gains

- How childbirth is related with lower gender-specific wage premiums for women: estimate changes in the occupation premium over the work-life for mothers and non-mothers

Change in occupational premia for mothers and non-mothers. Non-routine cognitive



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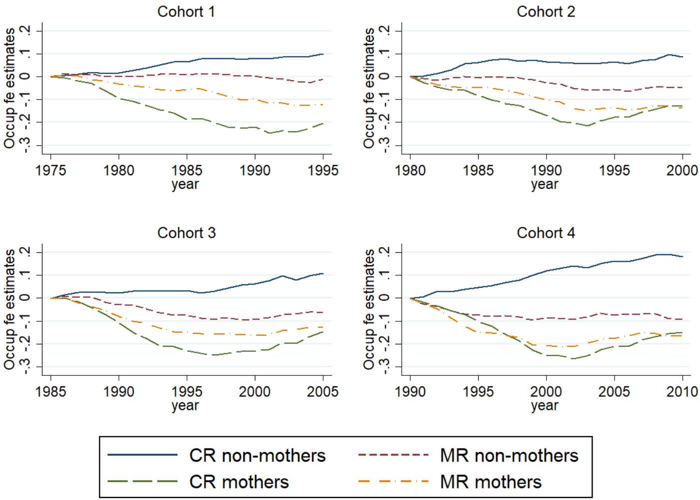
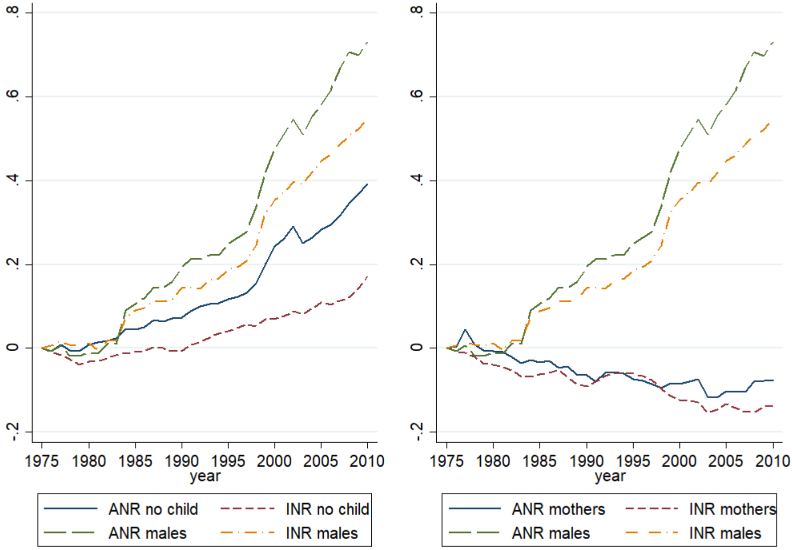


Causes of gender differences in wage premiums gains

Change in occupational premiums mothers and non-mothers compared to men. Cognitive non-routine



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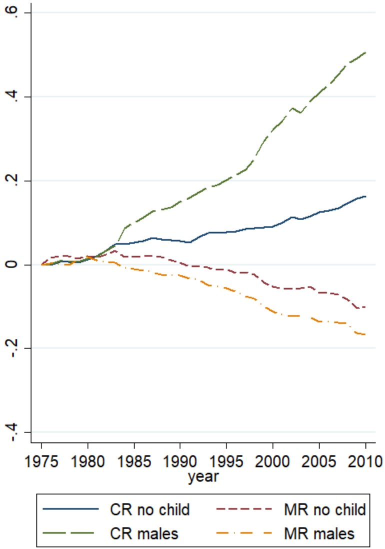
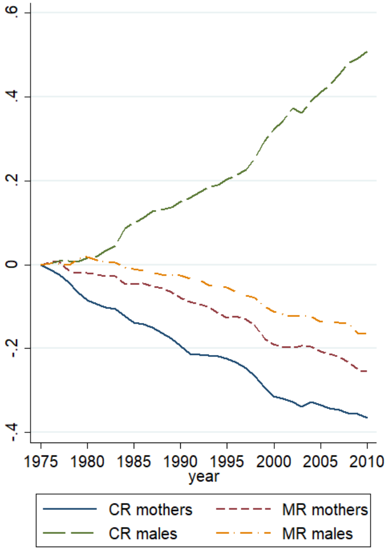




Robustness | Changing returns to education

- Concern: differences in the changes in the wage premium across occupation groups are driven by changes over time in the return to education
  - individual skills (z_i) are fixed, but the return to education is allowed to vary over time: $\varphi_{jt}(z_i) = E_i \alpha_{jt} + \eta_i b_j$, where E_i captures the education and η_i all other individual abilities or skills.
- The regression to be estimated for the potential wage of individual i of gender g at year t is:

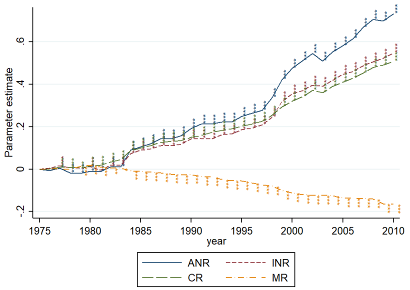
$$w_{it}^g = \sum_j D_{ijt} \theta_{jt}^g + E_i \alpha_t^g + \sum_j D_{ijt} v_{ij}^g + X_{it} \delta^g + u_{it} \tag{5}$$

  where $g = \{M, F\}$ and $v_{ij}^g = E_i \alpha_j^g + \eta_i b_j^g$.
- The occupation spell estimated through this regression will now contain the return to education in the base year and the return to unobserved ability, but not the changes in the returns to education over time

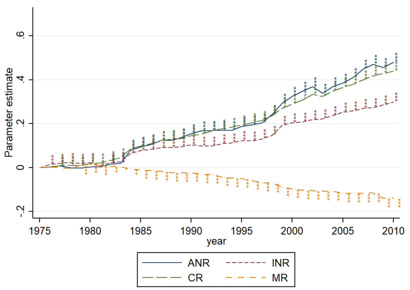
Robustness | Changing returns to education

Change in occupation premiums controlling for time-varying returns to education. Men

a) Baseline changes in occupation premiums



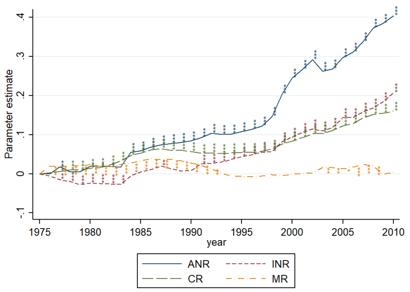
b) Controlling for changing returns to education



Robustness | Changing returns to education

Change in occupation premiums controlling for time-varying returns to education. Women

a) Baseline changes in occupation premiums



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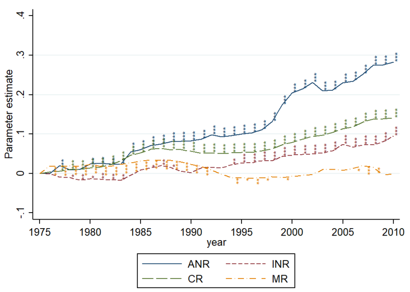

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Robustness | Occupation specific tenure profiles

- Concern: heterogeneous returns to tenure across occupations, tenure profile more steeper in cognitive occupations

- To estimate wage premiums controlling for the effect of occupation-specific tenure profiles, I introduce a return to individual's occupational tenure (Cortes, 2016):

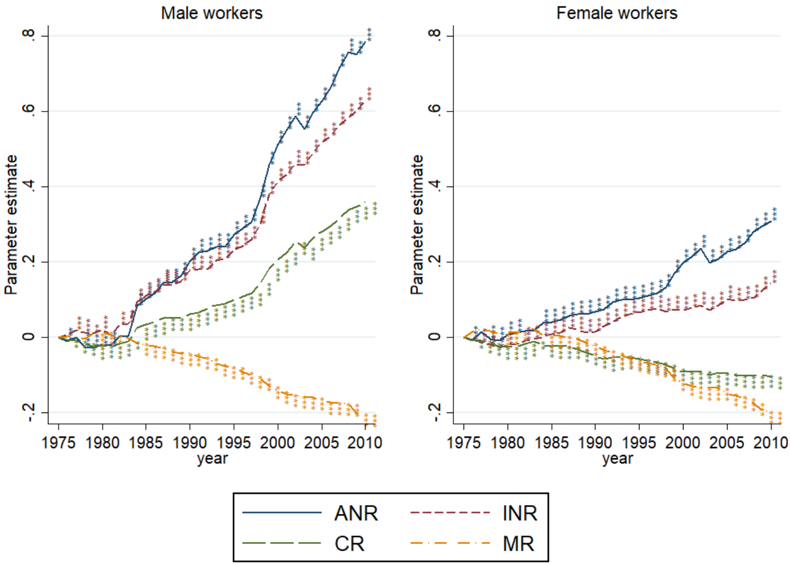
$$w_{it} = \sum_j D_{ijt}\theta_{jt} + \sum_j D_{ijt}\beta_{jt}\, fem_i + \sum_j D_{ijt}\gamma_{ij} + \sum_j D_{ijt}F_j(Ten_{ijt}) + X_{it}\delta + u_{it} \quad (6)$$

where Ten_{ijt} is individual's i's tenure in occupation j at time t and $F_j(Ten_{ijt})$ is a non-linear function that captures the occupation-specific returns to tenure

- An individual's occupational choice will depend, on his/her skill level z_i and the occupation wage premium θ_{jt}, but also on his/her tenure in the current occupation Ten_{ijt}

Robustness | Occupation specific tenure profiles

Change in occupational premiums controlling for heterogeneous occupation tenure profiles

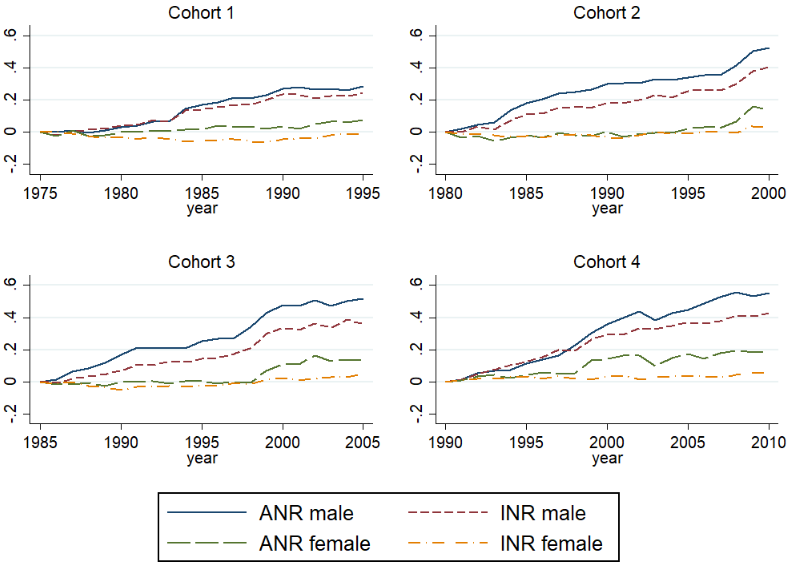


Robustness | Changes in selection into occupations and attrition

- Concern: the patterns are driven by changing characteristics of working women and men over time
- Nonrandom attrition in terms of which individuals are still observed at longer time horizons may be biasing the estimations for the changes in wage premiums.
  - This would be the case for example if many women leave the labor market after 30 or 35 years old due to maternity, and the characteristics of these women are different than those who remain employed within each occupation group
- To address this concern I run the regressions for the estimation of the time-varying occupation premiums imposing the condition that the individuals are observed employed in at least 16 years or 20 years

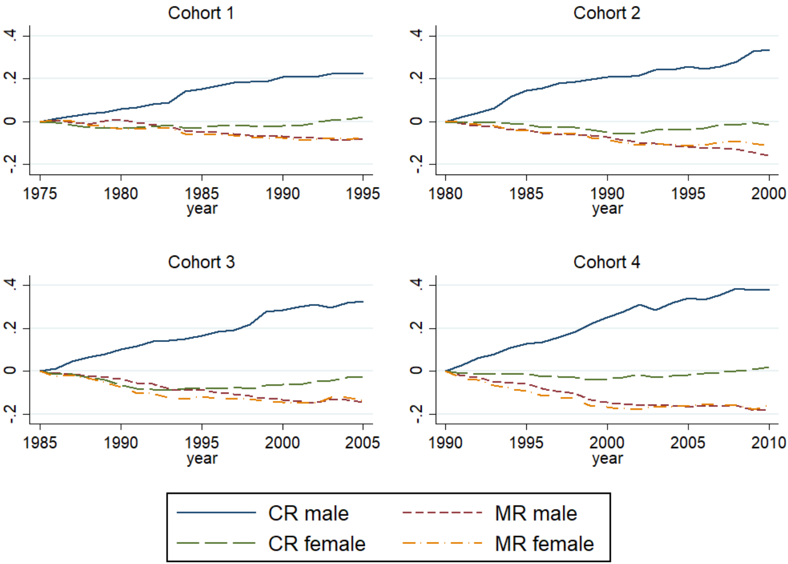
Robustness | Changes in selection into occupations and attrition

Change in occupational premiums controlling for attrition. Non-routine cognitive



Robustness | Changes in selection into occupations and attrition

Change in occupational premiums controlling for attrition. Routine occupations



Robustness | Extended sample including part-time workers

- Concern: excluding part-time workers could be biasing the results given the relevance of part-time jobs for female employment
- I conduct a robustness check using data on hours worked from an alternative dataset: the German Socio-Economic Panel Study (SOEP-Core).
- I impute the average hours worked by gender and year to part-time and full-time workers in the SIAB data, and construct an approximately hourly wage, dividing the administrative information on individual's daily wages by the average hours worked (divided by seven to convert from hours per week to daily hours worked)
- Then I use this measure of hourly wages to estimate wage premiums across occupation groups

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Robustness | Extended sample including part-time workers

Change in gender-specific occupational premiums. Including part-time workers (using hourly wage)