RUHR
ECONOMIC PAPERS

Eduard Storm

Task Returns and the Gender Pay Gap

rwi #1037

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Prof. Dr. Thomas K. Bauer
RUB, Department of Economics, Empirical Economics
Phone: +49 (0) 234/3 22 83 41, e-mail: thomas.bauer@rub.de

Prof. Dr. Ludger Linnemann
Technische Universität Dortmund, Department of Business and Economics
Economics – Applied Economics
Phone: +49 (0) 231/7 55-3102, e-mail: : Ludger.Linnemann@tu-dortmund.de

Prof. Dr. Volker Clausen
University of Duisburg-Essen, Department of Economics
International Economics
Phone: +49 (0) 201/1 83-3655, e-mail: vclausen@vwl.uni-due.de

Prof. Dr. Ronald Bachmann, Prof. Dr. Manuel Frondel, Prof. Dr. Torsten Schmidt, Prof. Dr. Ansgar Wübker
RWI, Phone: +49 (0) 201/81 49-213, e-mail: presse@rwi-essen.de

Editorial Office

Sabine Weiler
RWI, Phone: +49 (0) 201/81 49-213, e-mail: sabine.weiler@rwi-essen.de

Ruhr Economic Papers #1037

Responsible Editor: Ronald Bachmann

ISSN 1864-4872 (online) – ISBN 978-3-96973-206-9

Ruhr Economic Papers #1037

Eduard Storm

Task Returns and the Gender Pay Gap

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973206
ISSN 1864-4872 (online)
ISBN 978-3-96973-206-9

Eduard Storm[1]

Task Returns and the Gender Pay Gap

Abstract

Using worker-level task data, I explore if women's perceived comparative advantages in interactive tasks can contribute to a reduction in the gender pay gap. I find women receive lower returns to interactive tasks, even within occupations, despite increasing female employment shares in interactive-intensive occupations. Perceived comparative advantages in interactive tasks thus do not appear to pay off financially.

JEL-Codes: J16, J21, J24, J31

Keywords: Gender pay gap; task returns; job hierarchies

September 2023

1 Edurad Storm, RWI. - I thank Ronald Bachmann, Scott Drewianka, Myrielle Gonschor, John Heywood, and all participants at the SOLE 2021 and EEA 2021 for valuable comments and insights. All remaining errors are my own. Declarations of interest: none. *- All correspondence to: Eduard Storm, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: eduard.storm@rwi-essen.de*

1 Introduction

Recent research in labor economics highlights an increasing trend of female employment in occupations intensive in interactive tasks, such as managerial jobs, motivated by the hypothesis that women have a comparative advantage in social skills (Cortes et al. 2021). Many of these jobs tend to be high-paying, motivating the research question of this note: *Can task specialization reduce the gender pay gap?*

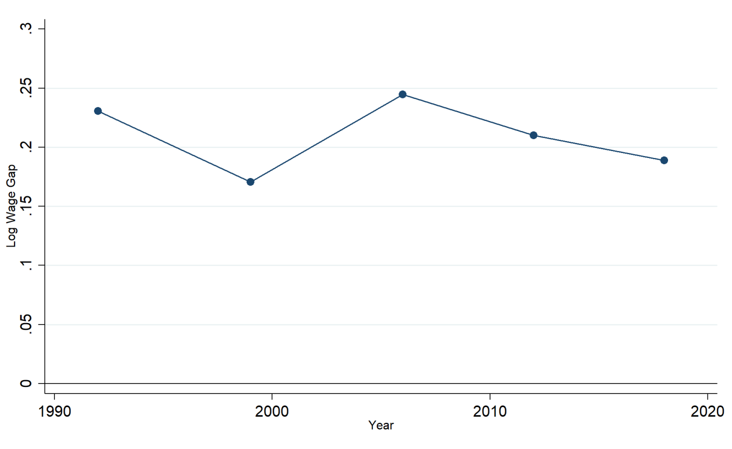


Figure 1: Gender Pay Gap in Germany, 1992-2018

Source: BIBB/IAB/BAuA, own calculations.

The evidence on this topic is sparse and mixed. Black & Spitz-Oener (2010) find a reduction of the gender pay gap in Germany due to beneficial changes in women's task composition between 1979-99 resulting from technological change. A decline in the (unconditional) pay gap from 25% in 2006 to 20% in 2018 suggests this trend continued (Figure 1), though substantial within-occupation gender wage gaps still exist (Bachmann & Gonschor 2022). In contrast, Cortes et al. (2020) find no evidence of a declining pay gap in the US and Portugal due to technological change, despite women being disproportionately employed in occupations less exposed to automation. Overall, these findings suggest changes in employment structure are insufficient to explain still-existing pay gaps.

Using German individual-level data on job tasks, I do not find that task specialization can reduce the gender pay gap —neither between nor within occupations. Running detailled decompositions along the wage distribution, gender-specific differences in task specialization only have modest explanatory power for the pay gap. Instead, I find women receive *lower* returns to interactive tasks. To shed light on this result, I study job hierarchies and find that the same job tasks receive higher returns in higher job hierarchies. Since men are overrepresented in these high-tier job, this channel can explain persistent within-occupation pay gaps.

2 Data

I use German employment surveys, assembled by the Institute for Vocational Education (BIBB), Institute of Employment Research (IAB) and Institute of Occupational Safety and Health (BAuA), respectively. This cross-sectional data typically covers around 20,000 individuals in each of five waves: 1992, 1999, 2006, 2012, 2018. The key information for the purpose of this note are data on wages and tasks performed at the workplace.

Following conventional task definitions and sample restrictions (see Storm (2022) for details), I pool job activities of 46,856 West German worker observations into $J = 5$ task groups: (i) Non-routine Analytic (NRA), (ii) Non-routine Interactive (NRI), (iii) Routine Cognitive (RC), (iv) Routine Manual (RM), and (v) Non-routine Manual (NRM) and define task measures T_{ijt} for worker i performing task j at time t as:

$$T_{ijt} = \frac{\text{No. of activities performed by i in task j at time t}}{\text{Total no. of activitites by i across } \textit{all} \text{ j's at time t}} \tag{1}$$

This definition implies (i) $T_{ijt} \in [0, 1]\ \forall j$ and (ii) $\sum_J T_{ijt} = 1$, thus describing the relative importance of each task j.

3 Methodology & Results

I explore task returns along two dimensions. First, I aggregate eq. (1) at the occupation-level (KLdB92, 3-digit level). To this end, I calculate leave-one-out-means $\boldsymbol{T_o^{i \neq i'}} = \big(T_{1o}, ..., T_{5o}\big)$ for each task j. This way, I exclude workers' own task composition for the calculation of occupational averages. Second, I subtract these occupation-level measures from worker i's individual task content $\boldsymbol{T_{it}} = \big(T_{i1t}, ..., T_{i5t}\big)$ to create within-occupation task specialization measures $\widetilde{\boldsymbol{T}}_{\boldsymbol{iot'}} = \boldsymbol{T_{it}} - \boldsymbol{T}^{\boldsymbol{i \neq i'}}_{\boldsymbol{ot'}} = \left(\widetilde{T}_{i1ot'}, ..., \widetilde{T}_{i5ot'}\right)$, capturing i's degree of task specialization relative to peers i'.

To address time-varying skill requirements, I pool $\boldsymbol{T}^{\boldsymbol{i \neq i'}}_{\boldsymbol{o}}$ for the years 1992-1999 (90s sample) and, respectively, for the years 2006-2018 (00s sample) and denote these subsamples t'. Subsequently, I run wage regressions by gender g:

$$ln\ w^{g}_{iot} = \underbrace{\boldsymbol{\lambda^{g} T^{g}_{ot'}}}_{\text{Occupational returns}} + \underbrace{\boldsymbol{\Omega^{g}} \widetilde{\boldsymbol{T}}^{\boldsymbol{g}}_{\boldsymbol{iot'}} \times \boldsymbol{T^{g}_{ot'}}}_{\text{Individual returns}} + \boldsymbol{\gamma X_{it}} + \delta_r + \eta_s + \theta_t + \epsilon_{iot} \tag{2}$$

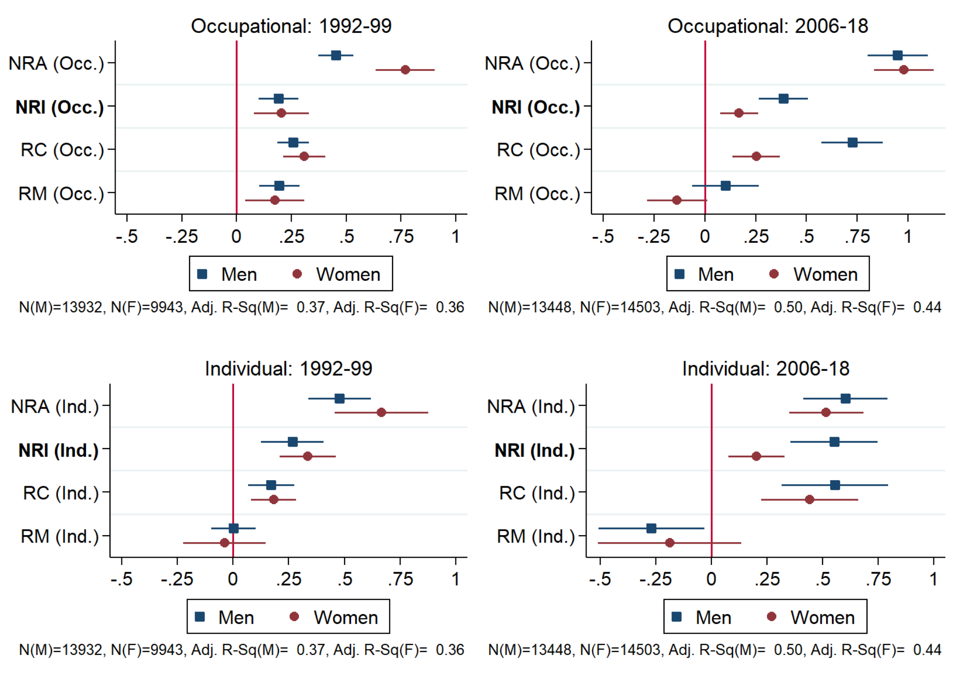
where w_i is the hourly real wage, $\boldsymbol{X_i}$ comprises control variables, δ_r, η_s, and θ, respectively, denote 11 states, 34 sectors, and five year dummies, and ϵ_{iot} is the error.[1] Of key interest are the vectors of coefficients $\boldsymbol{\lambda^{g}} = \left(\lambda_{1o}, ..., \lambda_{5o}\right)$ and $\boldsymbol{\Omega^{g}} = \left(\Omega_{1o}, ..., \Omega_{5o}\right)$. To calculate real hourly wages, I use information on weekly working hours and monthly labor income, assuming hours worked are stable throughout a month. Subsequently, I compute nominal hourly wages and convert them into real terms using CPI = 100 based on the consumer price index from the Federal Statistical Office.[2] I interpret $\boldsymbol{\lambda^{g}}$ as *occupational* wage returns, attributed to occupational sorting, and $\boldsymbol{\Omega^{g}}$ as *individual* wage returns, attributed to task specialization within occupations. Conventional methods define tasks at the occupation-level, thus implicitly assuming $\boldsymbol{\Omega^{g}} = 0$. Instead, eq. (2) generalizes the notion of gender-specific comparative advantages beyond the occupational dimension.

The main finding of this paper is displayed in Figure (2), summarizing gender-specific task returns. The reference group comprises workers without vocational schooling who are performing NRM tasks. For brevity, I focus on returns to interactive tasks. The top two panels in Figure (2) display occupational task returns and show that employment in NRI-intensive occupations is correlated with positive task returns. Relative to NRM, a 1 pp. increase in the occupational NRI-intensity, is associated with a return of 15-25% in the 90s sample. In the 00s sample, however, occupational returns have nearly doubled

[1]Control variables include socio-economic characteristics (age, citizenship, vocational schooling) and job-specific variables (firm tenure, firm size, occupational tenure, employment type, and job hierarchy level).

[2]The data can be downloaded here: `https://www.destatis.de/DE/Themen/Wirtschaft/Preise/Verbraucherpreisindex//_inhalt.html` (Date accessed: 08/21/2023).

for men while remaining flat for women. Similarly, *individual* task returns have been accelerating in the past 20 years —but only for men. What can explain these trends? In the following I explore two mechanisms, namely gender-specific task specialization and differences in job hierarchies.

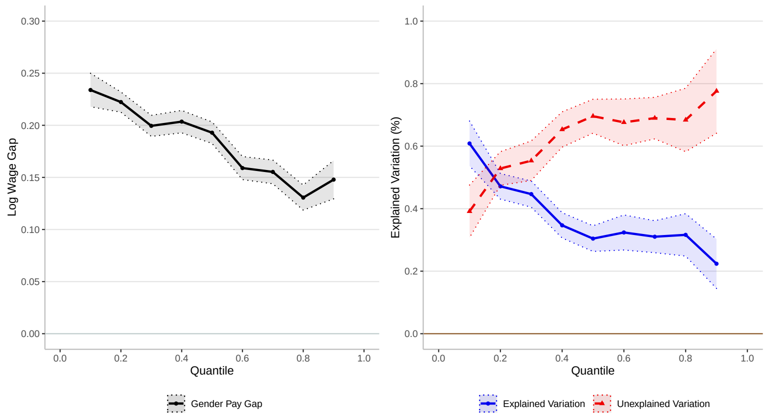


NOTE. —The top panels display occupation-level task returns, while the bottom panels display individual returns. The reference task group is NRM. Horizontal lines represent 95% confidence intervals.

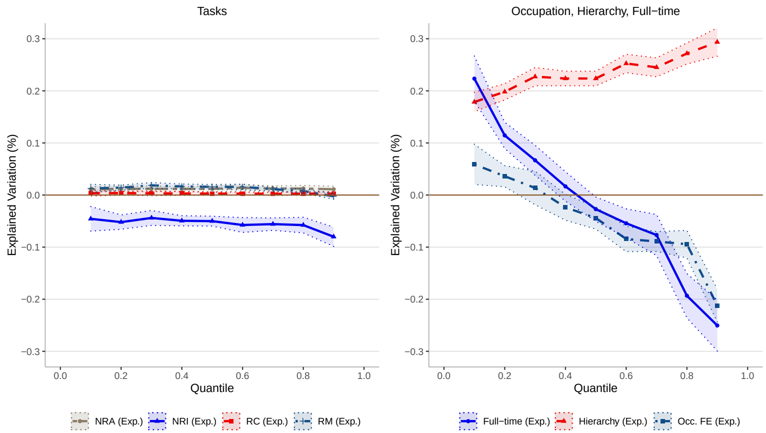
Figure 2: Task Returns at Occupation-level and Individual-level, 1992-2018

Source: BIBB/IAB/BAuA, own calculations.

To begin with, I explore if one-directional task returns are due to compositional effects as men and women may specialize in different tasks. Figure 3 explores this mechanism by decomposing wage differences along the wage distribution via a RIF-decomposition (see Storm (2022) for details). This method allows me to gauge if gender-specific task specialization contributes to the pay gap. However, task specialization only has modest explanatory power, thus cannot explain the pay gap. While the gender pay gap declines across the wage distribution —from 24% for low-wage jobs to 15% for high-wage jobs —up to 80% of the gap among high-wage earners remain unexplained. Instead, employment types (full-time vs part-time) explain 20% of wage variation in low-wage jobs, while job-specific hierarchy levels explain 30% in high-wage jobs.[3] This observation motivates a closer inspection of another mechanism: differences in job hierarchies.



(a) RIF-Decomposition of Gender Pay Gap, 1992-2018



(b) RIF-Decomposition: Key covariates, 1992-2018

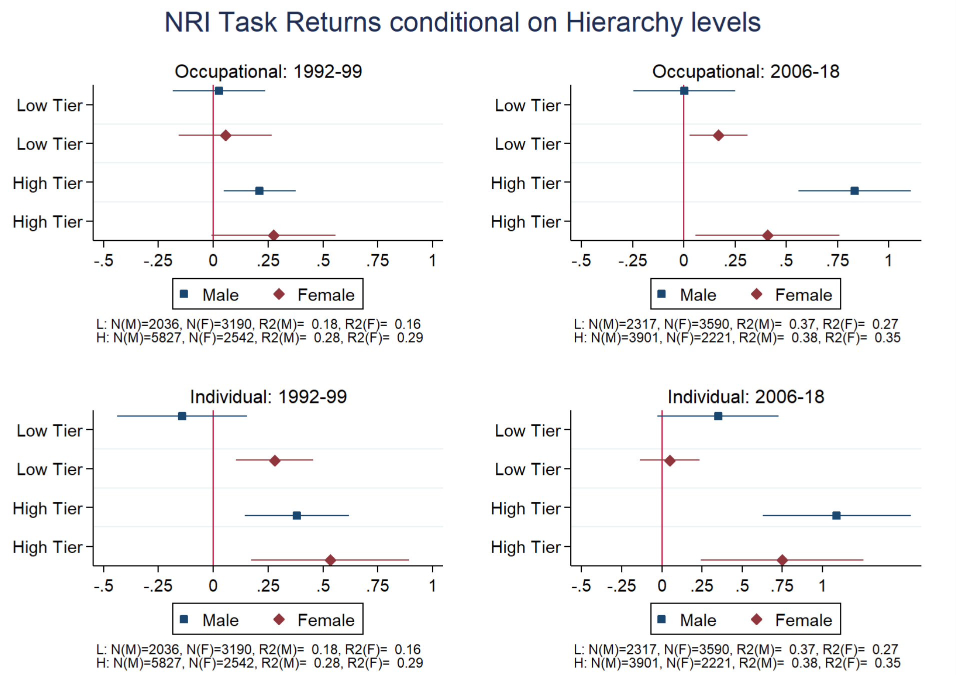
NOTE. —The panels summarize the results of a RIF-Decomposition with log hourly real wage as dependent variable and various controls, summarized on page 3, footnote 1. The top panels display the pay gap along the wage distribution and the variation explained by differences in observables. The bottom panels illustrate how much of the pay gap can be explained by differential task specialization and other key covariates. Coefficients are depicted with 95% confidence intervals.

Figure 3: Gender Pay Gap: RIF-Decomposition, 1992-2018

Source: BIBB/IAB/BAuA, own calculations.

[3]Full-time employment requires at least 35 weekly working hours. Women represent 88% (34%) of all part-time (full-time) employed workers. I separate job hierarchy levels into two tiers, following Cassidy (2017). Low-tier positions comprise employees charged with basic tasks, e.g., messengers. High-tier positions comprise employees with extensive decision-making powers or providers of independent services, e.g., supervisors or researchers.

I underline the importance of job hierarchies by running the baseline model (2) conditional on hierarchy levels (Figure 4). For brevity, I focus on returns to interactive tasks. Occupational task returns were similar for men and women in the 90s sample, yet, women (men) received higher task returns in low-tier (high-tier) hierarchies in the 00s sample. Disparities in task returns have become even more pronounced within occupations. While women had higher task returns in the 90s, men received higher task returns in the 00s sample (albeit not significantly different).



NOTE. —The top panels display occupation-level task returns, while the bottom panels display individual returns. Each panel comprises gender-specific task returns at low-tier and high-tier job hierarchies, as defined on p.4, footnote 2. Horizontal lines represent 95% confidence intervals.

Figure 4: NRI Task Returns by Hierarchy Level: Occupation-level & Individual-level, 1992-2018

Source: BIBB/IAB/BAuA, own calculations.

While female employment in low tier jobs has remained steady at 60%, the female employment share increased from 30% to 36% in high-tier jobs. Favorable task returns for women in interactive jobs may reduce the pay gap —but only in low-wage jobs. In high-wage jobs, men's (i) overrepresentation in high-tier jobs and (ii) greater task returns indicate frictions in job ladders. These findings are robust to alternative (i) sample restrictions, (ii) occupational definitions, (iii) reference groups, and (iv) task definitions. Also, men and women perform similar activities within broad task groups, making more nuanced task specialization unlikely. These tests are reported in the online appendix accompanying this paper.

4 Conclusion

This letter shows perceived comparative advantages of women in interactive tasks are unlikely to eliminate the gender pay gap. Despite rising female employment shares in interactive-intensive occupations, gender-specific task returns tend to favor males. Recent research has challenged other prominent explanations, such as unobserved institutional factors (Oberfichtner et al. 2020) and taste-based discrimination (Lochner & Merkl 2022). Instead, I view my findings as consistent with sorting in internal labor markets (Huitfeldt et al. 2023) or the presence of frictions, such as (i) barriers to high-tier job hierarchy levels (Hirsch 2013), and (ii) non-pecuniary job preferences (Lochner & Merkl 2022). Combining these channels with task specialization is a promising avenue for future research.

References

Bachmann, R. & Gonschor, M. (2022), 'Technological progress, occupational structure and gender gaps in the german labour market', *IZA DP No. 15419* .

Black, S. E. & Spitz-Oener, A. (2010), 'Explaining women's success: Technological change and the skill content of women's work', *Review of Economics and Statistics* **92**(1), 187–194.

Cassidy, H. (2017), 'Task variation within occupations', *Industrial Relations: A Journal of Economy and Society* **56**(3), 393–410.

Cortes, G. M., Jaimovich, N. & Siu, H. (2021), 'The growing importance of social tasks in high-paying occupations: Implications for sorting'.

Cortes, G. M., Oliveira, A. & Salomons, A. (2020), 'Do technological advances reduce the gender wage gap?', *Oxford Review of Economic Policy* **36**(4), 903–924.

Hirsch, B. (2013), 'The impact of female managers on the gender pay gap: Evidence from linked employer-employee data for germany', *Economics Letters* **119**(3), 348–350.

Huitfeldt, I., Kostøl, A. R., Nimczik, J. & Weber, A. (2023), 'Internal labor markets: A worker flow approach', *Journal of Econometrics* **233**(2), 661–688.

Lochner, B. & Merkl, C. (2022), 'Gender-specific application behavior, matching, and the residual gender earnings gap', *LASER Discussion Papers - Paper No. 139* .

Oberfichtner, M., Schnabel, C. & Töpfer, M. (2020), 'Do unions and works councils really dampen the gender pay gap? discordant evidence from germany', *Economics Letters* **196**, 109509.

Storm, E. (2022), 'Task specialization and the native–foreign wage gap', *LABOUR* **36**(2), 167–195.