Gender (In)equality in England: Occupations, Tasks and Wages*

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Abstract

This study examines the relationship between gender, occupational sorting, task allocation, and wage disparities within the UK labour market. Utilising data from the Skills and Employment Survey, which offers repeated cross-sectional information on wages, occupations, and tasks, I investigate whether workers with similar occupations and education perform comparable tasks, explore the presence of wage differences for those undertaking analogous tasks, and assess patterns of occupational and task segregation by gender over time. Findings will enhance understanding of how task allocation contributes to wage gaps and inform policies to reduce gender inequality in the labour market.

Keywords: These, are, not, keywords.
JEL Codes: A, B, C.

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1 Introduction

1. To what extent do workers within the same occupational category and with comparable skill sets engage in similar versus differentiated tasks, and how does this vary by gender?

2. Do wage differentials exist among workers performing the same tasks, and how are these differences moderated by both occupational context and gender?

3. What are the observable patterns of occupational and task segregation along gender lines, and how do these patterns contribute to the overall wage gap?

Goldin (2014) highlights the need to look within occupations to understand how jobs are organized and compensated and how this might diferentially affect men and women.

Within-occupational gender differences might also persist, even after conditioning on differences in human capital and occupational choices. **cortes2018occupation<empty citation>**

A commonly used measure to summarize differences in the distribution of women and men across occupation categories is the index of segregation developed by Duncan (1955).

The index of occupational segregation by sex is computed as

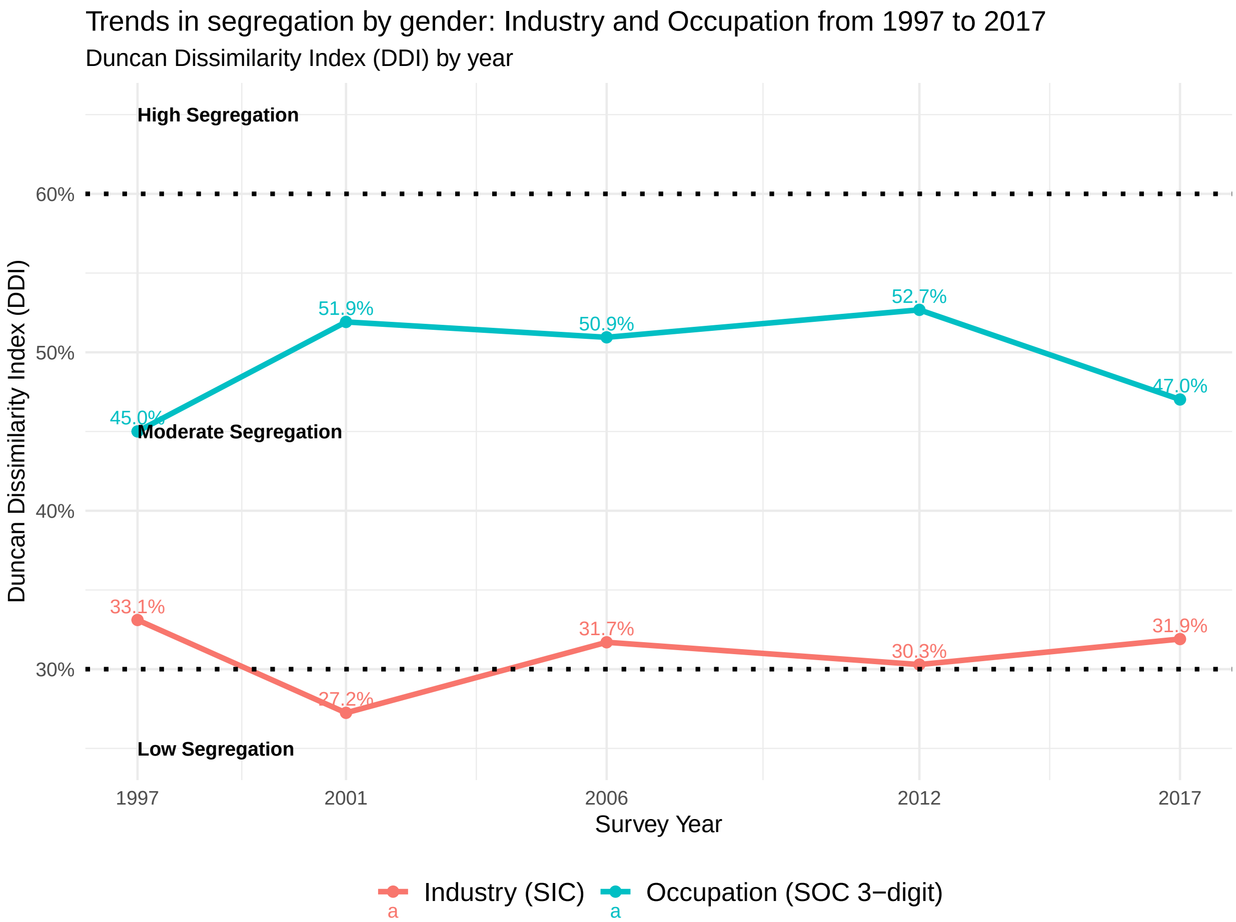
$$D = 0.5 \sum_{j} |M_j - F_j|, \tag{1}$$

where M_j (F_j) is the fraction of all employed males (females) who work in occupation j. The index, which ranges between zero and one, indicates the proportion of women or men that would need to change occupations for the occupational distribution of men and women to be the same. In other words, if the distribution of men and women across occupational categories were identical (complete integration), the segregation index would equal zero. If all the occupations were either completely male or completely female (complete segregation), the segregation index would equal one.

The evolution of gender segregation in the UK labor market from 1997 to 2017 reveals persistent disparities in the distribution of men and women across both occupations and industries. Using the Duncan Dissimilarity Index (D-index), I find that occupational segregation—measured at the 3-digit SOC level—remains consistently moderate to high, with values ranging from 45.0% in 1997 to 52.7% in 2012, before declining slightly to 47.0% in 2017. These figures suggest that nearly half of either male or female workers would need to change occupations to achieve gender parity, highlighting substantial and enduring occupational sorting by gender.

By contrast, industrial segregation—based on 2-digit SIC codes—remains lower and more stable, fluctuating between 27.2% and 33.1% over the same period. While both forms

Figure 1: Title



Notes: Notes here.

of segregation exhibit some variation, there is no strong or consistent trend toward greater integration over the 20-year span.

These results align with recent research documenting the persistence of occupational segregation despite broader gains in gender equality in education and employment. Studies such as England (2010), Blau and Kahn (2017), and Oesch et al. (2020) emphasize that, even as gender gaps in labor force participation and earnings have narrowed, occupational sorting continues to play a central role in maintaining inequality. Similarly, ILO (2021) and Rubery and Tavora (2020) note that gendered occupational patterns remain entrenched, even within high-skilled sectors. UK-specific analyses based on SES data (e.g., Green and Henseke, 2021) reinforce the view that occupational clustering and gendered task content have proven resilient. The higher and more variable levels of segregation observed at the occupational level underscore the value of disaggregated classifications such as 3-digit SOC codes in capturing structural barriers to gender integration.

Table 1: Task measures from the Skills and Employment Survey

Skill	**Task**
Literacy	Reading written information, e.g. forms, notices, or signs Reading short documents, e.g. letters or memos Reading long documents, e.g. long reports, manuals, etc. Writing material such as forms, notices, or signs Writing short documents, e.g. letters or memos Writing long documents with correct spelling/grammar
Numeracy	Adding, subtracting, multiplying, or dividing numbers Calculations using decimals, percentages, or fractions More advanced mathematical or statistical procedures
Numeracy	Adding, subtracting, multiplying, or dividing numbers Calculations using decimals, percentages, or fractions More advanced mathematical or statistical procedures
Physical	Carrying, pushing or pulling heavy objects Working for long periods on physical activities mend, repair, assemble, construct or adjust things knowledge of how to use or operate tools, equipment or machinery
Professional communication	Instructing, training, or teaching people Persuading or influencing others Making speeches or presentations Planning the activities of others Listening carefully to colleagues
Problem solving	Spotting problems or faults Working out the cause of problems or faults Thinking of solutions to problems Analysing complex problems in depth
Computer use complexity	Importance of computer use and complexity of computer use: Not at all = 0 Straightforward use = 1 Moderate use = 2 Complex use = 3 Advanced use = 4

Source: Adapted from Lindley (2015).
Notes:Based on the factor analysis conducted in Green (2012).

2 Section

This is also a short section.

3 Data and Methodology

To capture gender segregation in the nature of work performed, I construct a *task-based Dissimilarity Index*, denoted D_{task}. This measure extends the standard D index (typically applied to occupational or industry categories) to account for gender differences in task use across occupations.

Each respondent in the SES dataset reports the importance of 11 skill types in their job, using a scale from 0 to 4:

- 0 = Does not apply in job
- 1 = Not very important
- 2 = Fairly important
- 3 = Very important
- 4 = Essential

To simplify the construction of a task use indicator, I convert each continuous skill score into a binary indicator, where a skill is considered used if its value exceeds 2.5:

$$\text{TaskUsed}_{i,s} = \begin{cases} 1 & \text{if Skill}_{i,s} > 2.5 \\ 0 & \text{otherwise} \end{cases}$$

for individual i and skill s. I then compute, for each occupation j and skill s, the weighted share of men and women who report using the skill, using grossing weights $w_i = \text{gwtall}$. Let:

- $M_{j,s}$ = weighted number of men in occupation j using skill s
- $F_{j,s}$ = weighted number of women in occupation j using skill s
- T_j^M, T_j^F = total weighted men and women in occupation j

Then the task-level gender difference is:

$$d_{j,s} = \left| \frac{M_{j,s}}{T_j^M} - \frac{F_{j,s}}{T_j^F} \right|$$

If either gender is absent from occupation j, I assign $d_{j,s} = 1$, reflecting complete segregation.

I then compute the mean difference across all skills within occupation j:

$$D_j = \frac{1}{S} \sum_{s=1}^{S} d_{j,s}$$

where $S = 11$ is the number of skills. This yields an occupation-level segregation score $D_j \in [0, 1]$.

Finally, I compute the aggregate index in two forms:

Unweighted average:

$$D_{\text{task}}^{\text{unweighted}} = \frac{1}{J} \sum_{j=1}^{J} D_j$$

Weighted average:

$$D_{\text{task}}^{\text{weighted}} = \sum_{j=1}^{J} \left(\frac{W_j}{\sum_{j=1}^{J} W_j} \right) D_j$$

This index reflects the extent to which men and women perform different tasks across occupations, even when working in similar jobs or industries. It captures a dimension of gender segregation that is not visible through occupation or industry codes alone.

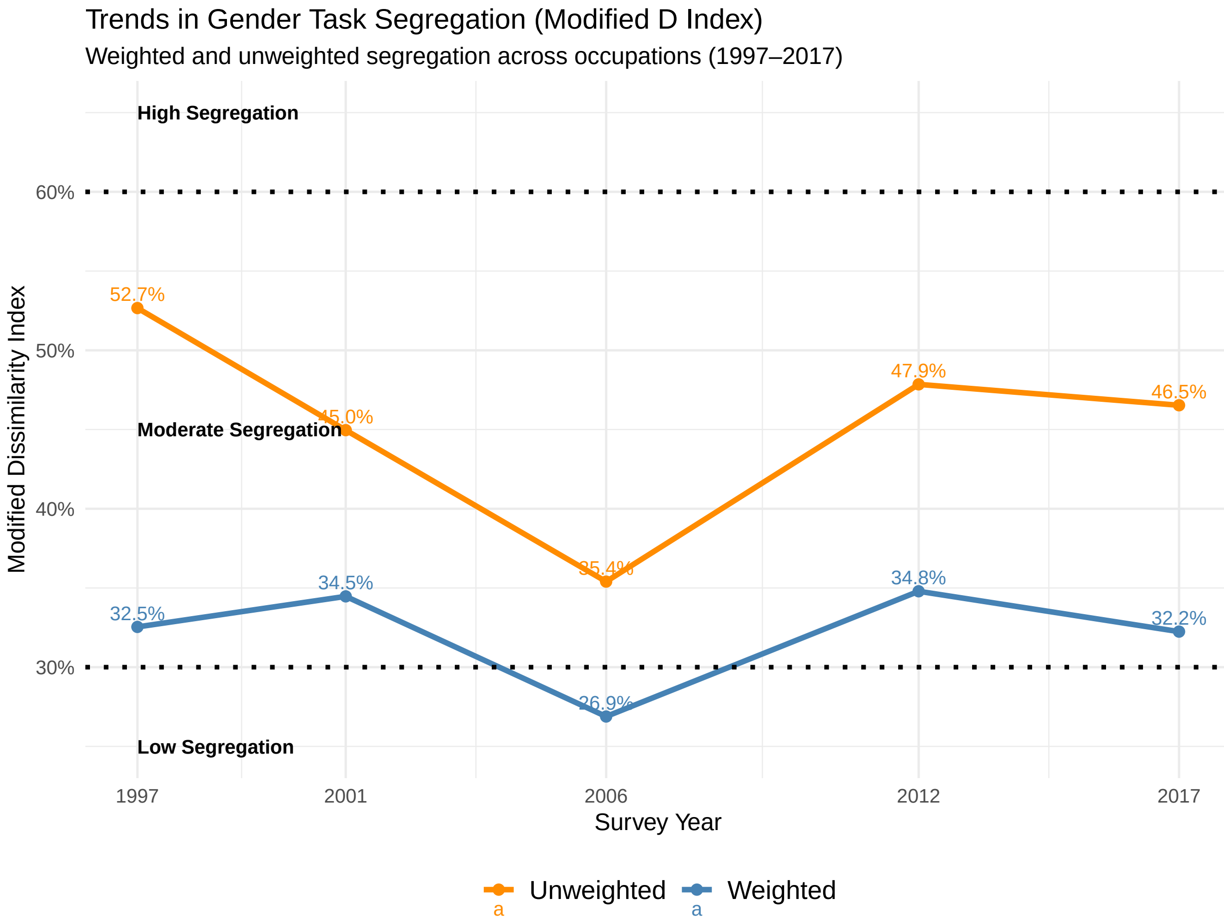
Figure X displays trends in gender task segregation across UK occupations from 1997 to 2017, measured using a modified version of the Duncan Dissimilarity Index. The figure distinguishes between an unweighted version of the index, which gives equal weight to each occupation, and a weighted version that adjusts for the employment size of occupations to reflect aggregate worker experience.

The unweighted index reveals persistently moderate levels of task segregation, with values ranging from 52.7in 1997 to 46.5% in 2017. Although there is an overall decline across the two decades, the pattern is non-linear, with a noticeable dip in 2006 followed by a rebound in 2012. This suggests that the degree of task differentiation between men and women within occupations remains substantial and relatively stable when each occupation is treated equally, regardless of size.

By contrast, the weighted index—which accounts for the number of individuals employed in each occupation—shows a consistently lower level of task segregation, ranging from 36.9% in 2006 to 34.8% in 2012, and ending at 32.22017. This indicates that the average worker in the labour market experiences significantly lower task segregation than the unweighted average suggests, implying that larger occupations tend to exhibit more gender-integrated task profiles.

The divergence between the weighted and unweighted trends underscores the importance of accounting for employment size when assessing the extent of gender segregation. While smaller occupations may exhibit higher levels of gendered task differentiation, they employ fewer individuals and therefore contribute less to aggregate patterns. The weighted index suggests a modest downward trend in task segregation over time, albeit from already

Figure 2: Task Seggregation



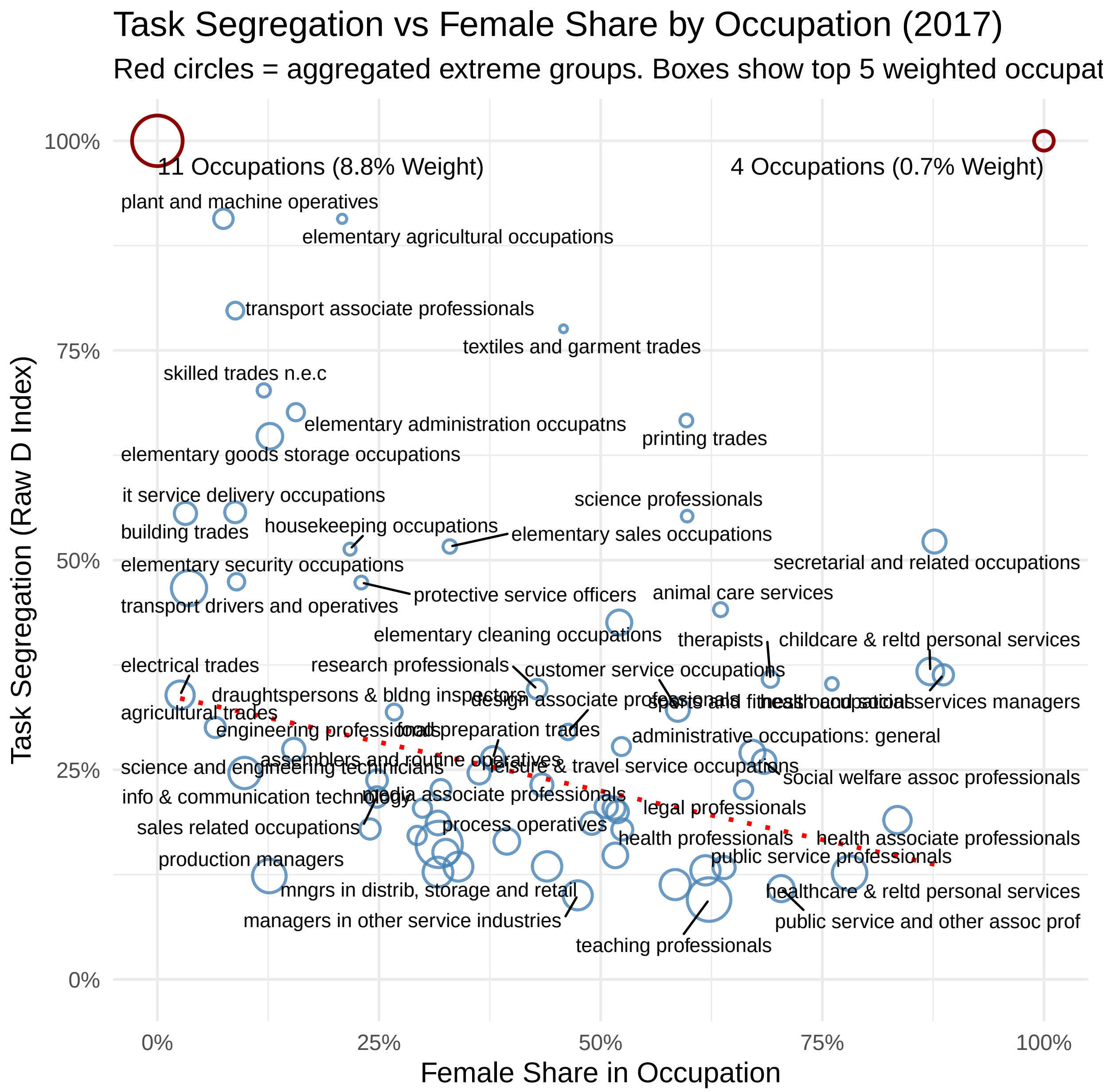
Notes: Notes here.

relatively low levels. Together, these findings point to a persistent but gradually declining pattern of gender-based task differentiation within occupations, with significant variation across the occupational structure.

The scatter plot illustrates the relationship between task segregation and female occupational share in the UK labour market in 2017. Each point represents a 3-digit SOC occupation, with task segregation measured by the modified D on the vertical axis and the proportion of women in each occupation on the horizontal axis. A negative association emerges: occupations with a higher share of women tend to exhibit lower levels of task segregation, suggesting that in more gender-balanced or female-dominated roles, men and women are more likely to perform similar tasks. This pattern is captured by the downward-sloping trend line, indicating that gender-based task differentiation diminishes as female representation increases.

However, beyond this general trend, a number of occupations lie well above the trend line,

Figure 3: Title



Notes: Notes here.

indicating significantly higher levels of task segregation than would be predicted based on their gender composition alone. These outliers are concentrated in both male- and female-dominated fields, revealing that high task segregation is not confined to one side of the gender distribution. On the male-dominated side, occupations such as plant and machine operatives, transport associate professionals, and skilled trades (not elsewhere classified) display relatively high levels of task segregation, even after accounting for their low female share. On the female-dominated side, occupations such as textiles and garment trades, printing trades, and science professionals also show elevated levels of task segregation despite having moderate to high female representation.

These patterns suggest that in some occupations, the division of tasks between men and women is especially pronounced. In these cases, gendered role expectations or organizational structures may contribute to sharp internal task differentiation. Such deviations from the average pattern highlight the importance of examining within-occupation task segregation directly, rather than relying solely on measures of occupational gender composition, in order to uncover the mechanisms through which gendered labour market inequalities are maintained.

4 Gender Wage Gap

The empirical analysis estimates the gender wage gap using the following log-linear regression model:

$$\log(wage_i) = \alpha + \beta \cdot Female_i + \mathbf{X}_i'\gamma + \delta_{j(i)} + \theta_{k(i)} + \varepsilon_i \tag{2}$$

where $\log(wage_i)$ denotes the natural logarithm of hourly wages for individual i, and $Female_i$ is a binary indicator equal to one if the individual is female and zero otherwise. The vector $\mathbf{X}_i$ includes individual-level controls such as age, education, and region. The terms $\delta_{j(i)}$ and $\theta_{k(i)}$ represent fixed effects for occupation (3-digit SOC) and industry (2-digit SIC), respectively, and ε_i is the error term. In extended specifications, the model incorporates additional variables capturing task and skill requirements derived from job-level data. The coefficient β measures the conditional gender wage gap, interpreted as the average percentage difference in hourly wages between women and men, conditional on observed characteristics, occupational sorting, and task content.

Table X reports estimates of the gender wage gap from a series of linear regressions where the dependent variable is the log of hourly wages. Column (1) presents the baseline specification, which includes controls for individual-level characteristics such as age, education, and region. In this model, women earn approximately 14.9% less than men. Column (2) adds controls for occupation and industry, reducing the estimated wage gap to 6.1% and explaining 59.2% of the initial difference. This substantial reduction highlights the central role of occupational and industrial sorting in shaping gender disparities in pay.

Columns (3) through (14) sequentially introduce a wide range of skill and task measures, including indicators of cognitive, manual, interpersonal, and planning-related demands. Across these models, the adjusted gender wage gap remains consistently between

Table 2: Gender Wage Gap

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Female	-0.149***	-0.061*	-0.063*	-0.060*	-0.059*	-0.064*	-0.056*	-0.060*	-0.061*	-0.061*	-0.064*	-0.054+	-0.074**	-0.064*
	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.028)	(0.027)	(0.029)	(0.027)	(0.028)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation and Industry	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
% Gender Gap Explained	0%	59.2%	57.6%	59.5%	60.4%	57.1%	62.4%	59.9%	59.1%	59.2%	57.3%	63.6%	50.6%	56.8%
Observations	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	16,735,292	15,821,040	16,735,292	15,821,040

Source: Adapted from Lindley (2015).
Notes: Stadardt errors are clustered at the occupation level. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

5.4% and 7.4%, with relatively minor variation in the percent of the gap explained. The highest explanatory power is reached in column (12), where 63.6% of the original gap is accounted for, while the lowest occurs in column (13), at 50.6%. These changes, though measurable, are modest compared to the explanatory contribution of occupation and industry introduced in column (2).

Overall, the results suggest that while gender differences in task and skill requirements explain a small additional portion of the wage gap, the vast majority of the explained component derives from gender sorting into different occupations and industries. Even after accounting for detailed task characteristics, a persistent and statistically significant wage penalty of around 6% remains for women, pointing to the enduring role of within-job and potentially discriminatory mechanisms in the gender wage structure.

5 Conclusion

We may have reached the conclusion too quickly.

Table 3: Occupations characteristics from the O*NET database

Construct	**Based on Questions from Job Surveys**
Competition	"How competitive is your current job?"
Social Contribution	• "How important is concern for others to the performance of your current job?" • "How important is assisting and caring for others to the performance of your current job?" • "How important is service orientation to the performance of your current job?" (actively looking for ways to help people)
Inflexibility	• "How often does your current job require you to meet strict deadlines?" (1: never, 2: once a year or more but not every month, 3: once a month or more but not every week, 4: once a week or more but not every day, 5: every day) • "How many hours do you work in a typical week on your current job?" (1: less than forty hours, 2: forty hours, 3: more than forty hours)
Interactional Skills	• "How much contact with others (by telephone, face to face, or otherwise) is required to perform your current job?" • "How important are interactions that require you to work with or contribute to a work group or team to perform your current job?" • "How important is establishing and maintaining interpersonal relationships to the performance of your current job?" • "How important is social perceptiveness to the performance of your current job?"
Cognitive Skills	• Written comprehension • Mathematical reasoning ability • Deductive reasoning • Inductive reasoning
Physical Skills	• General physical activities • Handling and moving objects

Source: Adapted from **cortes2018occupation<empty citation>**

Table 4: *Table A1.* O*NET 13.0 – Work Activities & Work Context.

A. Characteristics Linked to Technological Change/Offshorability	
Information Content	
4.A.1.a.1	Getting Information (JK)
4.A.2.a.2	Processing Information (JK)
4.A.2.a.4	Analyzing Data or Information (JK)
4.A.3.b.1	Interacting with Computers (JK)
4.A.3.b.6	Documenting/Recording Information (JK)
Automation/Routinization	
4.C.3.b.2	Degree of Automation
4.C.3.b.7	Importance of Repeating Same Tasks
4.C.3.b.8	Structured versus Unstructured Work (reverse)
4.C.3.d.3	Pace Determined by Speed of Equipment
4.C.2.d.1.i	Spend Time Making Repetitive Motions
B. Characteristics Linked to Non-Offshorability	
Face-to-Face	
4.C.1.a.2.l	Face-to-Face Discussions
4.A.4.a.4	Establishing and Maintaining Interpersonal Relationships (JK,B)
4.A.4.a.5	Assisting and Caring for Others (JK,B)
4.A.4.a.8	Performing for or Working Directly with the Public (JK,B)
4.A.4.b.5	Coaching and Developing Others (B)
On-Site Job	
4.A.1.b.2	Inspecting Equipment, Structures, or Material (JK)
4.A.3.a.2	Handling and Moving Objects
4.A.3.a.3	Controlling Machines and Processes
4.A.3.a.4	Operating Vehicles, Mechanized Devices, or Equipment
4.A.3.b.4	Repairing and Maintaining Mechanical Equipment (*0.5)
4.A.3.b.5	Repairing and Maintaining Electronic Equipment (*0.5)
Decision Making	
4.A.2.b.1	Making Decisions and Solving Problems (JK)
4.A.2.b.2	Thinking Creatively (JK)
4.A.2.b.4	Developing Objectives and Strategies
4.C.1.c.2	Responsibility for Outcomes and Results
4.C.3.a.2.b	Frequency of Decision Making

Source: Adapted from Fortin and Lemieux (2016)
Notes: (JK) indicates a work activity used in Jensen and Kletzer (2007), (B) a work activity used or suggested in Blinder (2007).

Table 5: Classification of tasks Germany

Category	Tasks
Abstract tasks	calculating and correcting text/data; executing, interpreting, and advising on law/rules; planning, projecting, and designing; programming; researching, analysing, and evaluating
Interactive tasks	advertising, publishing, and public relations; coordinating and organising; negotiating and advising; teaching and training
Manual tasks	repairing, restoring, and renovating; securing; serving and accommodating guests
Routine tasks	cleaning and rubbish removal; equipping and operating machinery; manufacturing or producing; measuring length/weight/temperature

Source: Adapted from Miriam Koomen et al. (2022)
Notes:

Table 6: Major Occupational and Industry Classification Systems (Latest Versions)

Name	**Abbreviation**	**Country / Organization**	**Details**
Standard Occupational Classification	SOC2010	UK (ONS)	Latest UK occupational classification; 4-digit structure; used in SES2017 and LFS.
International Standard Classification of Occupations	ISCO08	International Labour Organization (ILO)	Global occupation classification for international comparison; 4-tier hierarchy.
Standard Industrial Classification	SIC2007	UK (ONS)	Current UK industry coding system based on NACE Rev. 2; used for business and labor statistics.
National Statistics Socio-Economic Classification	NS-SEC2010	UK (ONS)	Socio-economic class measure based on occupation (e.g. managerial, routine); based on SOC2010.
Occupational Information Network	O*NET	U.S. (Department of Labor)	U.S. occupational database linking SOC codes to tasks, skills, work context, etc.; widely used in job-task research.
European Skills, Competences, Qualifications and Occupations	ESCO	EU (European Commission)	European job and skill classification; aligned with ISCO08; used for labor mobility and training.

Source: Author own elaboration.
Notes:

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MAG ID: 4306180917.

Appendices

A Appendix A

Proof of the shortness of the paper.

B Appendix B

This paper is robust to boring bits.

Online Appendix

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Reviewer Appendix

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