

**How Education Affects the Gender Pay Gap, Glass Ceiling & Sticky Floor Effects  
Across Multiple Industry Sectors**

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1. Introduction

Gender inequality, particularly the persistent gender pay gap, remains a critical concern for scholars and policymakers in most industrialized societies (Huffman, et al., 2016) (Christofides, et al., 2013). Work establishments are widely recognized as central sites where group-based inequalities in employment outcomes are created and sustained (Huffman, et al., 2016). While organizational practices, such as those that formalize personnel systems or target gender inequality, are often assumed to have uniform effects across the wage hierarchy, empirical studies reveal a more complex reality (Huffman, et al., 2016).

Traditional analyses of the gender wage gap frequently rely on standard modeling approaches, such as Ordinary Least Squares (OLS) regression, which estimate effects on gender differences in conditional means of the wage distribution (Huffman, et al., 2016). This mean-focused approach, however, neglects considerable heterogeneity in gender inequality across organizational hierarchies and earnings distributions. Research has documented greater inequality at both ends of the wage spectrum, identifying the "glass ceiling" effect at the top of the wage distribution and the "sticky floor" phenomenon at the bottom (Huffman, et al., 2016) (Arulampalam, et al., 2007). The "glass ceiling" describes a situation where the gender pay gap widens towards the top of the wage distribution (Arulampalam, et al., 2007) (Collischon, 2017), with women often underrepresented in higher hierarchical levels (Jochmann-Döll & Scheele, 2020). Conversely, the "sticky floor" phenomenon refers to a widening of the gender pay gap at the lower end of the wage distribution (Arulampalam, et al., 2007) (Christofides, et al., 2013), where women may be promoted as often as men but receive smaller wage increases, remaining stuck at the bottom of the wage scale for their new grade (Booth, et al., 2003).

To address these nuances, this study aims to comprehensively analyze the gender pay gap and the sticky floor and glass ceiling effects across multiple industries using quantile regression, which explicitly considers the heterogeneous effects of independent variables on gender inequality across the earnings distribution (Christofides, et al., 2013) (Arulampalam, et al., 2007). Unlike OLS, quantile regression allows for the examination of policy effects at various points in the wage distribution, such as among high- and low-paying jobs (Huffman, et al., 2016). The magnitude of the gender pay gap varies substantially across countries and between the public and private sectors (Arulampalam, et al., 2007). Furthermore, studies indicate that diverging fields of study choices, which often link directly to industries and occupations, contribute significantly to the gender wage gap among highly educated workers (Hägglund, 2024).

By investigating these effects across multiple industries, this paper seeks to provide a more nuanced understanding of how gender inequality manifests within different economic contexts. The primary object of this paper is to anwer the hypothesis “Does the magnitude of the gender pay gap, including the presence and intensity of sticky floor and glass ceiling effects, vary significantly across different industries” by analysing the SOEP dataset provided by the DIW Berlin. Such detailed analysis is crucial for the thoughtful design and implementation of policies aimed at addressing gender inequality, ensuring they are tailored to effectively benefit specific groups of workers, whether they are employed in low-wage or high-wage positions

1. Literature Review

The issue of gender inequality in the labour market remains a significant focus for scholars and policymakers in industrialised societies (Huffman, et al., 2016). One of the most visible indicators of this inequality is the persistent gender pay gap (GPG), which describes the difference in earnings between men and women (Huffman, et al., 2016) (Arulampalam, et al., 2007) (Jochmann-Döll & Scheele, 2020). While the mean GPG has been extensively studied, more recent attention has shifted to understanding how this gap varies across the wage distribution, leading to the identification of phenomena such as the "glass ceiling" and "sticky floor" effects (Huffman, et al., 2016) (Arulampalam, et al., 2007).

* 1. Understanding the Gender Pay Gap

The gender pay gap is a multifaceted issue, often measured in two primary ways: the "gross" or "raw" gap, which is the unadjusted difference in earnings, and the "net" or "adjusted" gap, which accounts for differences in measurable characteristics such as education, age, and occupation (Lang & Groß, 2020). In Germany, the gross gender pay gap was substantial, with women’s mean hourly gross earnings being 21% lower than men’s in 2016, placing it among the largest in the EU (Lang & Groß, 2020). In the next three years the gross gender pay gap didn’t decrease significantly and was still at a high value of 20 % in 2019 (Jochmann-Döll & Scheele, 2020). Even after adjustments for education, job positions, and labour market experience, the "net" gender pay gap in Germany has hovered around 10% between 1993 and 2010 (Lang & Groß, 2020).

Several theoretical approaches attempt to explain the persistence of the GPG:

**Human Capital Theory:** This approach explains pay differentials based on varying human capital accumulation, such as education and work experience (Busch & Holst, 2009). While qualifications are generally a prerequisite for higher positions, studies in Germany show that even in managerial roles where human capital accumulation is balanced between genders, a significant GPG exists (Busch & Holst, 2009). The theory suggests that women might self-select into lower-hierarchy or less demanding occupations due to family orientation (Busch & Holst, 2009).

**Labour Market Segregation:** The approach involves both horizontal segregation (women concentrated in certain occupations or industries) and vertical segregation (women in lower hierarchical levels) (Busch & Holst, 2009). In Germany, women are found to head smaller firms and are more frequently employed in health care, welfare, and private services (Winters, 2018). Female managers are also more common in the public sector than in the private sector (Busch & Holst, 2009). Occupations disproportionately employing women are often lower paid, and wages in such "women's jobs" are typically lower than in "men's jobs" (Hägglund, 2024) (Busch & Holst, 2009).

**Discrimination:** Beyond legitimate differences explained by human capital, the GPG also includes an "illegitimate" or "unexplained" part attributed to discrimination and prejudice (Busch & Holst, 2009). This can take various forms like employers or male colleagues have a “taste” for discriminating against women or demanding compensation for working with them, particularly in traditionally male-dominated, high-paying jobs (Collischon, 2017). Furthermore, employers rely on gender stereotypes as a proxy for missing information about a worker's productivity or labour market attachment, potentially leading to lower initial pay, especially for low-skilled women (Huffman, et al., 2016) (Lang & Groß, 2020).

**Wage Bargaining and Compensation Structures:** Gender differences in wage negotiations, salary expectations, and entitlement perceptions can contribute to the GPG (Collischon, 2017).

**Social and Cultural Factors:** Societal norms and gender-specific role ascriptions play a significant role. The "male breadwinner model" (MBM), which posits that fathers should be the primary financial providers while mothers attend to family work, significantly influences the "just gender pay gap" (JGPG) (Lang & Groß, 2020).

* 1. The Glass Ceiling and Sticky Floor Effects

The "glass ceiling" refers to the phenomenon where the gender wage gap widens significantly towards the top of the wage distribution (Huffman, et al., 2016) (Arulampalam, et al., 2007) (Collischon, 2017). This phenomenon implies that while women may advance to a certain level, an invisible barrier prevents them from achieving the highest echelons of the wage hierarchy (Busch & Holst, 2009) (Winters, 2018). It has been documented through observations of greater inequality at the top of the wage distribution (Huffman, et al., 2016). The glass ceiling effect is contrasted with the "sticky floor" effect, where the gap is more pronounced at the bottom (Huffman, et al., 2016) (Christofides, et al., 2013). This indicates that women in low-wage jobs find themselves "stuck" at the lower end of the wage scale, struggling to achieve wage increases or promotions that would lift them out of low-paying positions (Huffman, et al., 2016) (Booth, et al., 2003). The concept suggests that while women may be promoted at similar rates to men, their wage increases following promotion are considerably smaller, keeping them at the lower wage points of their new, higher job grade (Booth, et al., 2003). This can arise from women having worse market alternatives or from firms being less willing to match outside offers for female employees (Booth, et al., 2003).

The presence of "glass ceiling" and "sticky floor" effects is not attributable to a single cause but rather a complex interplay of various factors. Work establishments play a critical role in creating and maintaining gender inequality (Huffman, et al., 2016). Policies that formalize personnel systems, such as written job descriptions and personnel reviews, can reduce favoritism and biases, increasing accountability and limiting managerial discretion when setting wages (Huffman, et al., 2016). These policies have been found to reduce gender inequality, particularly benefiting women in low-wage jobs and mitigating the "sticky floor" effect (Huffman, et al., 2016). Generous work-family reconciliation policies (e.g., formal childcare, maternity pay, flexible work arrangements, family leave) are systematically related to features of unexplained gender wage gaps (Christofides, et al., 2013). While these policies generally reduce the mean and median unexplained wage gaps (Christofides, et al., 2013), their effects can vary across the wage distribution. Some findings suggest that while these policies reduce the wage gap at the bottom (sticky floor), they may be positively correlated with a wider gap at the top (glass ceiling) (Arulampalam, et al., 2007). Furthermore, differences in wage negotiations can also contribute to the "glass ceiling" (Collischon, 2017). Since high-paying jobs frequently involve variable pay components and individual negotiations, these differences can be amplified, resulting in a wider gender wage gap at the top (Collischon, 2017).

In conclusion, the evidence from various studies consistently points to the pervasive nature of gender inequality in earnings, manifesting not only as an average pay gap but also through distinct "glass ceiling" and "sticky floor" effects. In Europe, and specifically in Germany, the "glass ceiling" appears to be a particularly robust phenomenon, observed across different sectors (public and private), regions, and when analyzed with various econometric methods (Huffman, et al., 2016) (Collischon, 2017). While "sticky floor" effects are less consistently found, they are present in some contexts, especially for low-wage workers who benefit from certain organizational policies (Huffman, et al., 2016) (Arulampalam, et al., 2007). The underlying causes are complex and multifaceted, including organizational policies, national work-family reconciliation policies, labor market institutions, and various forms of discrimination (taste-based, statistical, status beliefs, and monopsonistic) (Collischon, 2017) (Huffman, et al., 2016).

1. SOEP Dataset

The SOEP dataset provided by the DIW Berlin, which is used for further analysis of the gender pay gap and the “sticky floor” and “glass ceiling” effects respectively, comprises 23,522 observations. It provides a comprehensive overview of individuals with various demographic, socioeconomic, and employment characteristics. Key variables of the dataset, to answer the centralised question regarding the magnitude of the gender pay gap and sticky floor and glass ceiling effects across different industry sectors are:

**age:** The age of the individual, ranging from 17 to 102 years, with a mean of approximately 48.28 years (see Table 1).

**female:** A boolean variable indicating gender. The dataset shows a slight majority of female respondents (54.20%, N=12,760) compared to male respondents (45.80%, N=10,762) (see Table 1).

**pers:** The number of people residing in the individual's household, with a mean of approximately 2.91 (see Table 1).

**children:** The number of children that live in a household. With 39.70% of households having children (see Table 1).

**years\_of\_education:** The total years of education, ranging from 7 to 18 years, with a mean of approximately 12.40 years (see Table 1).

**employment\_status:** Categorical variable detailing the employment situation, including (see Table 1).:

* Employed Full-Time: 37.00% (N=8,700)
* Employed Part-Time: 14.80% (N=3,481)
* Training/Apprenticeship: 3.00% (N=695)
* Irregular/Marginal employment: 6.10% (N=1,446)
* Unemployed: 39.00% (N=9,169)

**industry\_sector:** A categorical variable representing the industry in which an individual is employed. The most common sectors include Public Administration, Education and Health (19.70%), Manufacturing (11.00%), Services (9.20%) and Trade (6.7%) (see Table 1).

**gross\_salary\_year:** The annual gross salary in Euros of the individual, ranging from 0 to 269,425 €. The mean yearly salary is approximately €16,776 (see Table 1).

This comprehensive set of variables allows for a detailed analysis of factors influencing salary and gender-based pay disparities.

Table 1: Summary of SOEP dataset

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Metric** | **N** | **%** | **Mean** | **Min/Max** |
| *Female* | 12760 | 54.20 | 0.542 | - |
| *Male* | 10762 | 45.80 | 0.458 | - |
| *Age* | 23522 | - | 48.282 y | 17 y/102 y |
| *People in Household* | 23445 | - | 2.907 | 1/13 |
| *Household with Children* | 9337 | 39.70 | 0.397 | - |
| *Single Parent Household* | 817 | 3.50 | 0.035 | - |
| *Years of Education* | 21911 | - | 12.401 | 7 y/18 y |
| *Gross Salary Year* | 23522 | - | 16775.77 € | 0 €/269425 € |
| *Gross Salay Month* | 23522 | - | 1771.89 € | 0 €/35261 € |
| *Employed Full-Time* | 8700 | 37.00 | 0.370 | - |
| *Employed Part-Time* | 3481 | 14.80 | 0.148 | - |
| *Training Apprenticeship* | 695 | 3.00 | 0.030 | - |
| *Irregular employment or in marginal* | 1446 | 6.10 | 0.061 | - |
| *Unemployed* | 9169 | 39.00 | 0.390 | - |
| *Working in Agriculture* | 176 | 0.70 | 0.007 | - |
| *Working in Manufacturing* | 2599 | 11.00 | 0.110 | - |
| *Working in Energy* | 214 | 0.90 | 0.009 | - |
| *Working in Constructions* | 674 | 2.90 | 0.029 | - |
| *Working in Trade* | 1584 | 6.70 | 0.067 | - |
| *Working in Traffic* | 578 | 2.50 | 0.025 | - |
| *Working in Gastronomy & Hotel* | 457 | 1.90 | 0.019 | - |
| *Working in Telecommunication* | 493 | 2.10 | 0.021 | - |
| *Working in Services* | 2174 | 9.20 | 0.092 | - |
| *Working in Public Administration, Education and Health* | 4637 | 19.70 | 0.197 | - |

1. Methodoligy

This chapter outlines the methodological approach employed to investigate the gender pay gap across various industry sectors and to analyze the presence of a "glass ceiling" effect within the provided dataset. The analysis leverages a combination of data preprocessing, exploratory data analysis, and advanced econometric modeling, specifically focusing on Quantile Regression.

* 1. The Significance of Skewness in Salary Distribution

The distribution of salary data is almost universally characterized by positive or right-skewness. This means that a large proportion of individuals earn lower to moderate incomes, while a smaller number of individuals earn significantly higher incomes, creating a long tail to the right of the distribution. This pattern is widely observed in economic studies, including those on regional income and wages in Germany (Immel, 2021).Figure 1 shows the distribution of the yearly salary of the working population based on the SOEP dataset. Based on the distribution, it is clear that the yearly salary is positive skewed. Additionally, a calculated skewness factor (Joanes & Gill, 1998) of **1.6** indicates a strong right-skewness and therefore a small number of inidviduals earn siginifcantly higher incomes than a large proportion of the working population.

Figure 1: Histogram of yearly salary in € of the working population (SOEP dataset)

A graph of a salary

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Standard regression methods like Ordinary Least Squares (OLS), which model the conditional mean, can provide misleading insights when applied to highly skewed data like salaries.

To analyse the impact of different factors on the salary, the “gross salary year” variable of the SOEP dataset is chosen. The yearly salary typically represents the complete financial compensation an individual receives over a full year. This includes not just the regular base pay, but also potential bonuses, commissions, profit-sharing, or other forms of variable compensation that might not be evenly distributed or even present in a single monthly paycheck. Furthermore, analyses of the gender pay gap and, especially, the "glass ceiling" and “sticky floor” are concerned with long-term structural inequalities in earnings. A yearly salary provides a more stable and representative measure of an individual's earning capacity and position within the income hierarchy over an extended period. On top of that the “gross monthly salary” variable of the SOEP dataset is even more skewed than the yearly salary (skweness of **3.6**), this implicates an increased number of outliers on the higher end of the income scale.

* 1. Econometric Model: Quantile Regression

Given the inherently skewed nature of salary distributions and the research questions concerning the gender pay gap, particularly the "glass ceiling" effect which by definition occurs in the upper echelons of the income distribution, a modeling approach that can robustly account for these distributional characteristics is essential. This leads directly to the application of Quantile Regression (QR).

As stated in "Quantile regression: A short story on how and why" (Waldmann, 2018), QR "quantifies the association of explanatory variables with a conditional quantile of a dependent variable without assuming any specific conditional distribution. It hence models the quantiles, instead of the mean as done in standard regression.". This underscores that the quantile function QY(τ∣x) = inf y ∈ R∣F(y∣x) ≥ τ (Čížek, 2000) completely describes the conditional distribution of the response variable Y given covariates (potential confounding variables) X. This choice is particularly justified given the characteristics of salary data and the research questions:

**Addressing Skewness and Heterogeneity:** Compared to Ordinary Least Squares (OLS) regression models, QR estimates the effects of predictors at various conditional quantiles (percentiles) of the dependent variable's distribution. This allows for the investigation of heterogeneous effects, meaning that the impact of factors like gender, age, or years of education on salary may differ significantly at the low, middle, and high ends of the pay scale.

**Robustness to Outliers:** QR minimizes the sum of asymmetrically weighted absolute residuals, making it inherently more robust to outliers in the salary data compared to OLS (which minimizes squared residuals). Outliers only have an influence on the quantile curves close to them, threrefore extreme values do not disproportionately pull the more central quantile estimates (Waldmann, 2018). This is a critical advantage given the presence of high earners who can exert undue influence on mean-based models.

The specific characteristics of the SOEP dataset and the research questions align with the strengths of Quantile Regression (Friedrich & Hirtz, 2021).

* 1. Multi-Factorial QR Model

The selection of the econometric model's specification is critical for accurately capturing the complex dynamics of the gender pay gap and its variation across different segments of the labor market. For this analysis, the quantile regression model was specified as follows:

gross\_salary\_year ~ female + age + years\_of\_education + employment\_status + industry\_sector + female:employment\_status + female:industry\_sector + female:years\_of\_education + female:age + industry\_sector:years\_of\_education

This specification was chosen over simpler alternatives due to several distinct advantages directly relevant to the research objectives:

**Comprehensive Control for Key Determinants of Salary:** The model includes age, years\_of\_education, employment\_status, and industry\_sector as main effects. These variables are widely recognized as fundamental determinants of an individual's gross annual salary

**Unpacking Industry-Specific Gender Pay Gaps:** A primary objective of this paper is to analyze the gender pay gap across different industry sectors. The “female:industry\_sector” interaction term is important for this purpose. It allows the gender effect on salary to vary by industry. Additionally, the interaction “industry\_sector:years\_of\_education” allows the return on educational investment to vary by industry. This acknowledges that the value placed on years of education may not be universal across all sectors, and incorporating this interaction enhances the model's ability to explain salary variations.

**Accounting for Varying Returns to Human Capital:** Similarly, the inclusion of female:years\_of\_education and female:age interaction terms enables the model to capture how the returns to education and age might differ between genders.

1. Results and Discussion

To analyse how the gender pay gap is impacted across different industry sectors, relavant data is extracted based on the SOEP dataset. By industry sector grouped data in Table 2 reveals variability in educational profiles across sectors. The median years of education range from 11.5 to 13 years, with Industry “Administration, Education & Health” showing the highest median education at 13 years, followed by “Services” at 12 years. All four sectors include individuals with up to 18 years of education, indicating the presence of highly educated individuals across these fields. The median female education closely mirrors the overall median education within each sector, suggesting similar educational attainment between genders at the median level.

Table 2: Working population across industry sectors

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Metric | Manufacturing | Trade | Services | Administration,  Education &  Health |
| Persons [n] | 2537 | 1505 | 2074 | 4489 |
| Females [%] | 30.23 | 63.19 | 58.05 | 70.28 |
| Median education [years] | 11.5 | 11.5 | 12 | 13 |
| Minimum education [years] | 7 | 7 | 7 | 7 |
| Maximum education [years] | 18 | 18 | 18 | 18 |
| Median male education [years] | 11.5 | 11.5 | 13.5 | 14.5 |
| Median female education [years] | 11.5 | 11.5 | 12 | 12 |
| Males employed full-time [%] | 92.99 | 84.66 | 77.01 | 83.58 |
| Females employed full-time [%] | 58.02 | 33.02 | 38.12 | 42 |
| Males employed part-time [%] | 1.98 | 4.69 | 12.87 | 10.42 |
| Females employed part-time [%] | 31.03 | 43.32 | 39.37 | 46.28 |
| Males employed irregular/marginal [%] | 0.51 | 6.68 | 6.78 | 3.67 |
| Females employed irregular/marginal [%] | 7.3 | 18.4 | 18.44 | 7.92 |

Significant differences are observed in female employment status across these industries. While industry sector “Manufacturing” has the highest percentage of females employed full-time (58.02%), sectors “Trade” and “Services” show a higher proportion of females in part-time or irregular/marginal employment. Notably, sector “Administration, Education & Health” has a substantial portion of females in part-time roles (46.28%), which is the highest among the listed industries, possibly reflecting sector-specific work arrangements or preferences.

The core analysis of the gender pay gap and glass ceiling effects primarily focuses on individuals in "Full-Time" employment. This deliberate choice was made because annual salaries and career progression dynamics are typically more standardized and directly comparable within this employment category. Other employment statuses, such as part-time or irregular/marginal employment, often involve different compensation structures (e.g., hourly wages vs. fixed salaries, varying benefits), work patterns, and career trajectories. As illustrated in the Table 2, the distribution of females across employment types varies significantly by industry (e.g., in Industry 2, 43.32% of females are part-time, compared to 31.03% in Industry 1).

During the data preprocessing phase, several smaller industry sectors were grouped into an "Others" category. This decision was primarily driven by the limited number of observations within these smaller categories. Sectors with a proportion less than 5% were consolidated. This approach was adopted to ensure robustness in the quantile regressions.

The results of the qunatile regression with, the graph in Figure 2 shows the relative gender pay gap across industries, specifically for full-time employment, broken down by salary quantiles. The vertical axis indicates the female-male salary difference in percentages, where negative values reflect lower female salaries compared to males. Across all analysed industries, a consistently large gender pay gap (~30 %) in lower salary quantiles can be observed. The gender pay gap decreases slightly in the industries “Manufacturing” and “Administration, Education” and decreases strongly (down to ~ 10 %) in the industry sector “Trade” in higher quantiles. In these three industry a mild to pronounced sticky floor effect is observable, espescially in the qunatiles 0.1 to 0.3. But no clear glass ceiling effect can be observed. In the “Services” industry sector the gender pay gap worsens significantly toward higher quantiles. Furthermore, the “Services” sector shows signs of both sticky floor and glass ceiling effects, because a large gender gap at the bottom and a widening gender gap at the top is present. According to Figure 2, the “Trade” sector performs the best in relatated to the gender pay gap. The gender pay gap overall is the least pronounced and it decreases significantly through salary quantiles.

Figure 2: Relative gender pay gap across 4 industries

A graph of different colored lines

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This diagram displayed in Figure 3 shows the relative gender pay gap by industry sector, broken down by years of education (10.5, 12, and 15 years) and salary quantiles for full-time employees. The vertical axis indicates female – male salary difference (%), where more negative values indicate a larger gender pay gap against women. For individuals with 10.5 years of education, the gender pay gap is widest at the lower quantiles—especially in Services and Administration—indicating a strong sticky floor effect where women face steep penalties in lower-paying roles. With 12 years of education, the gap narrows modestly, but the sticky floor remains visible, particularly in lower quantiles. There's limited evidence of a glass ceiling, as the gap does not consistently widen at higher wage levels. At 15 years of education, the sticky floor weakens, but a glass ceiling effect emerges. In sectors like Services and Trade, the pay gap grows in higher quantiles, showing that even well-educated women struggle to achieve pay parity in top-earning roles. Figure 3 illustrates both sticky floor and glass ceiling effects in the labor market, influenced by industry sectors and level of education. Lower-educated women face disproportionately large wage penalties at the bottom of the pay scale, while even highly educated women encounter persistent barriers to closing the pay gap at the top, particularly in sectors such as Services and Administration, Edcuation & Health.

Figure 3: Relative gender pay gap across 4 industries and 3 education levels

A graph of different colored lines

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In conclusion, across all industries and quantiles, women consistently earn less than men, even in full-time roles. The gap is most severe in traditionally female-dominated or service-oriented sectors such as “Administration, Education & Health” and “Services”. The “Trade” sector shows the most equitable outcomes, while “Manufacturing” lies in the middle. The sticky floor effect — where gender wage gaps are more pronounced at the bottom of the wage distribution — is clearly evident in “Administration, Education & Health” and “Manufacturing” and “Trade”.

1. Conclusion

The analysis of the SOEP dataset, via the quantile regression model predictions for full-time employees, has yielded crucial insights into the persistent gender pay disparities and the mechanisms behind them across different income levels, industries, and educational backgrounds. Overall, the findings consistently reveal a pervasive gender pay gap: across all examined salary quantiles, industry sectors, and education levels, females are predicted to earn less than their male counterparts. A particularly compelling finding is the strong evidence of a "glass ceiling" effect. As individuals move up the salary distribution, the gender pay gap generally widens or becomes more negative. This suggests that women face growing disadvantages and barriers as they approach higher income echelons, even after accounting for factors like industry and employment status. This pattern indicates that the mechanisms conserving the gender pay gap are more pronounced at the top tiers of the labor market.

* 1. Limitations

While this study provides valuable insights, several limitations warrant consideration. The analysis is constrained by the variables available in the dataset. Important factors that could influence salary and the gender pay gap, such as specific job roles, management responsibilities, actual work experience (distinct from age), career interruptions (e.g., for childcare), negotiation behaviors, firm size, regional economic conditions, or unobservable skills and preferences, are not included. Furthermore, the decision to group smaller industry sectors into an "Others" category, while necessary for model robustness due to limited data points in those specific sectors, results in a loss of granularity for these consolidated industries. This prevents a detailed analysis of pay gaps within those specific, smaller sectors.

The quantile regression models establish conditional associations between variables and salary quantiles. While these relationships are highly informative, the cross-sectional nature of the data does not allow for direct causal inferences regarding the mechanisms driving the gender pay gap or glass ceiling effects. Although Quantile Regression is more robust than OLS, it still relies on certain assumptions, such as the correct specification of the linear functional form within each quantile. While interaction terms were included to capture complexity, potential non-linear relationships not explicitly modeled could still exist.

* 1. Outlook and Future Research

Building upon the findings and addressing the limitations, future research could explore several promising avenues. Incorporating more granular data on job characteristics (e.g., detailed job titles, management levels, full-time equivalent hours, performance metrics) and individual-level factors (e.g., detailed work history, career breaks, negotiation training, family responsibilities) could further refine the estimates of the gender pay gap.

This study provides a solid foundation for understanding the complex nature of the gender pay gap and the presence of glass ceiling effects. Future research, especially with more granular data and longitudinal designs, promises to deepen our understanding of these persistent disparities. Furthermore analyses would greatly benefit from the inclusion of data on hours worked per week for each individual. This would enable the calculation of an hourly salary, which is a more standardized measure of compensation. By converting all salaries to an hourly basis, it would become feasible to directly compare compensation across different employment statuses (full-time, part-time, irregular/marginal). This would allow for a more comprehensive analysis of the gender pay gap that spans all employment types, revealing whether disparities persist or change when accounting for working hours, and providing a more granular understanding of "sticky floor" effects across the entire labor force.

By using alternative model specifications to conduct sensitivity analyses, different definitions of key variables, or other robust regression techniques the consistency of the findings can be confirmed. Also extending the analysis to compare gender pay gaps across different countries or regions could provide valuable insights into the influence of varying legal frameworks, cultural norms, and labor market structures on salary equality. The findings can be translated into actionable policy recommendations aimed at mitigating the gender pay gap. For instance, industry-specific findings could inform targeted interventions, while the evidence of a glass ceiling could highlight the need for policies addressing promotion criteria, leadership opportunities, and equitable compensation at higher organizational levels.

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Appendix

R Script

For a better reading and reviewing experience, the final R script is also available here: <https://github.com/mnpt97/business-research-tools/blob/main/final_code.r>