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Investigating the Gender Wage Gap in Germany from 2011 to 2022. Did COVID-19 Play a Role?

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Xhoiel Rica BSc

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## Zusammenfassung

Die geschlechtsspezifische Lohnlücke bleibt ein ernstes globales Problem, selbst in Ländern mit hochentwickelten Volkswirtschaften wie Deutschland. Diese Arbeit untersucht die Lohnlücke zwischen Männern und Frauen in Deutschland im Zeitraum 2011 bis 2022 anhand von Daten des Sozio-oekonomischen Panels (SOEP). Die unbereinigte Lohnlücke verringerte sich im Laufe des Zeitraums allmählich, wobei die größte Lücke im Jahr 2012 und die geringste im Jahr 2022 zu beobachten war. Jährliche OLS-Regressionen zeigen, dass sich die bereinigte Lohnlücke in den Jahren vor der COVID-19-Pandemie verringerte und 2018 ihren niedrigsten Wert erreichte, sich jedoch in den Jahren 2020 und 2022 wieder vergrößerte. Die Ergebnisse der Oaxaca-Blinder-Dekomposition zeigen, dass zwischen 2011 und 2016 die unerklärte Komponente zurückging, während die erklärte Komponente zunahm. Nach 2016 kehrte sich dieses Muster um: Die erklärte Komponente verringerte sich, während die unerklärte Komponente anstieg.

# ABSTRACT

The gender wage gap remains a serious global issue, even in countries with highly developed economies, such as Germany. This thesis examines the gender wage gap in Germany from 2011 to 2022 using data from the Socio-Economic Panel (SOEP). The raw wage gap gradually decreased over the period, with the widest gap observed in 2012 and the narrowest in 2022. Annual OLS regressions show that the adjusted wage gap decreases through the pre-COVID-19 years, reaching its lowest point in 2018 but widened again in 2020 and 2022. The Oaxaca-Blinder decomposition results show that between 2011 and 2016 the unexplained gap decreased, while the explained gap increased. After 2016, the pattern reversed as the explained gap decreased, while the unexplained gap increased.

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# Acknowledgments

This work is dedicated to my family, whose support throughout these years has made it possible for me to be here. I am deeply grateful.

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Studying at the University of Vienna has been a truly meaningful experience, shaping me both academically and personally. I will remember these years as among the most important and valuable of my life. I look forward to the future with appreciation for the knowledge and support I have received along the way.

# 1. INTRODUCTION

The gender wage gap is a very important and relevant topic that goes beyond individual consequences. It has a significant impact on the economy, as it reduces overall economic growth and development. Talafha (2025) finds that a one-percentage-point increase in the gender wage gap is linked to a 0.013% decline in economic development. The gender wage gap also generates long-term economic costs. Lower earnings can discourage women from remaining fully engaged in paid employment, leading to reduced working hours or increased labor market withdrawal, which in turn weakens labor force participation and overall productivity. Additionally, families may also invest less in girls' education if they expect lower returns compared to boys, which will reduce female labor force participation also in the future. In the long run, this means lower family income and fewer resources for children's health, schooling, and well-being, all of which are essential for a country's development (Morrisson & Jütting, 2005). Therefore, it is very important to understand the causes of this gap in order to be able to design policies that promote fairness and equality in the labor market. This challenge became even more difficult with the spread of COVID-19 in January 2020.

Unfortunately, we have all experienced the consequences of the Coronavirus pandemic, which affected various aspects of our lives, from our physical and mental health to our society and economy. It was very difficult not only on an individual level but also for the governments who had to balance the infection control and economic stability.  At the same time, the pandemic introduced a lot of changes to the labor market globally, including Germany. This shift brought new attention to the gender wage gap topic and highlighted it as a renewed area of concern. These changes in the labor market include job losses, shifts to remote work and changing employment patterns, which had an unequal impact across genders and sectors, with some groups being more affected than others. Women were often disproportionately impacted, particularly in service sectors like hospitality, retail, and tourism, which were hit the hardest by the pandemic (Alon et al. 2020). These developments highlight the need to investigate whether the wage gap widened or narrowed during the pandemic.

Even though Germany is one of the most powerful economies in the region and has implemented various gender equality policies in the workforce, it is still behind many European countries in narrowing the gender wage gap. According to Eurostat[1] (2025), Germany has one of the largest and most persistent gender pay gaps in the European Union. This pattern is clearly illustrated in Figure 1, which shows the unadjusted gender pay gap across selected European countries from 2011 to 2021. This persistent wage gap provides a strong motivation for a detailed empirical analysis of the factors driving the gender wage gap in Germany.

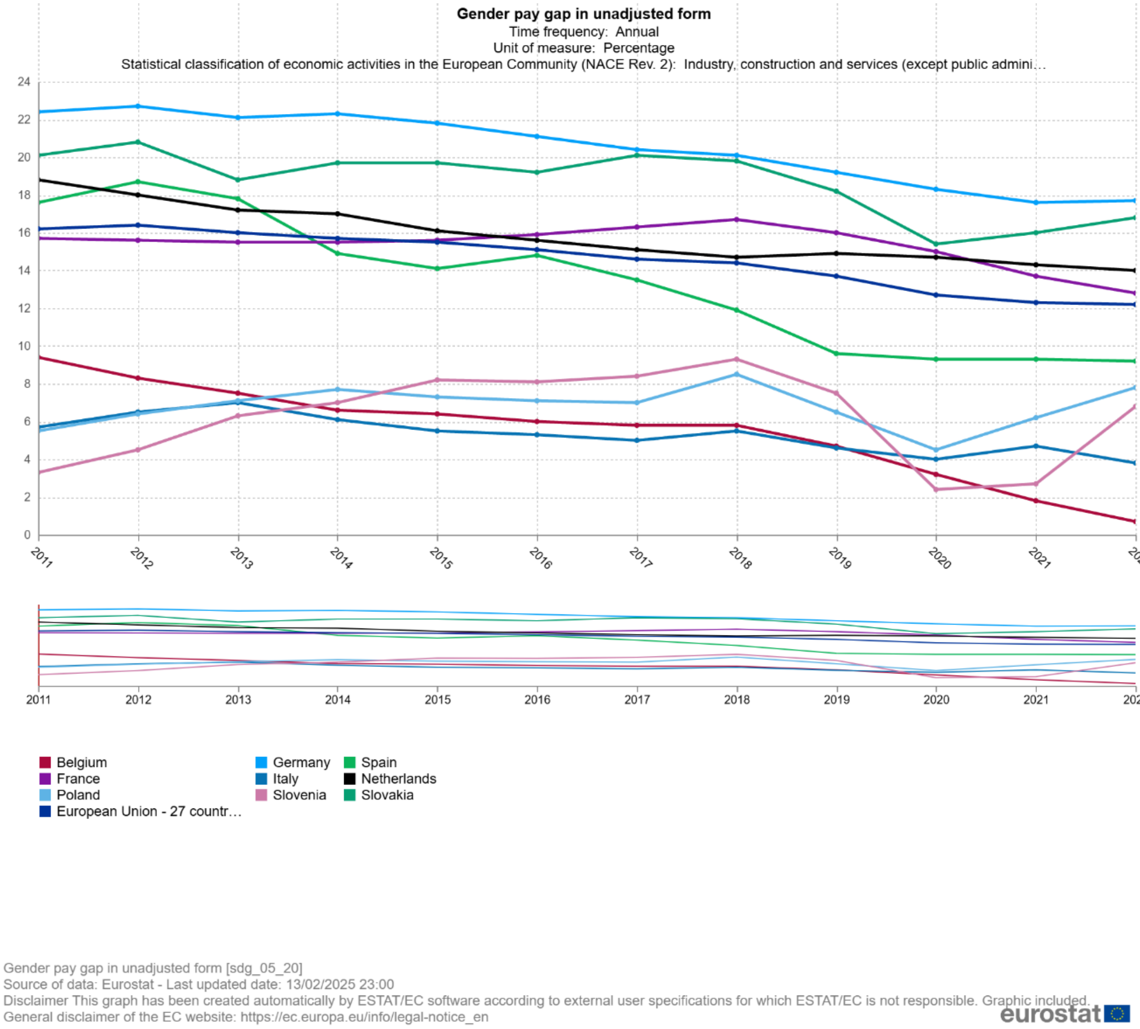


*Figure 1. Unadjusted gender pay gap across selected EU countries, 2011-2022.*

*Source: Eurostat (earn_gr_gpg, earn_gr_gpgr2)*

[1] https://ec.europa.eu/eurostat/databrowser/bookmark/8cc7796f-02de-4b94-8323-a41c8c621446?lang=en&createdAt=2025-09-26T15:13:28Z

As shown in Figure 1, throughout the entire period, Germany ranks among the countries with the widest pay gaps, and remaining well above the EU-27 average, while other countries, such as Italy, Poland, Belgium, Slovenia, France and Netherlands maintain significantly lower gaps. Germany's gap shows only modest reductions over time, highlighting the persistent nature of gender wage gap in this country. Figure 1 shows that Germany continues to underperform in reducing the gender wage gap, even in comparison to countries with less economic power, despite undergoing numerous policy interventions in the past years, most notably the Act on Pay Transparency between Women and Men (Entgelttransparenzgesetz) in 2017. This persistence suggests that formal policy measures alone may be insufficient to address the underlying structural drivers of gender wage inequality.

This study analyzes the evolution of the gender wage gap in Germany for more than a decade (2011-2022) using data from the German Socio-Economic Panel (SOEP), applying OLS regression analysis and Oaxaca-Blinder decomposition method. The impact of COVID -19 on the gender wage gap can be understood through two main arguments. From one perspective, the pandemic may have widened the gap, as women were overrepresented in sectors that were most severely affected by lockdowns such as hospitality, retail, and personal services, leading to higher rates of job loss, reduced working hours and income reduction among female workers (Alon et al. 2020). From another perspective, the crisis may have narrowed the gender wage gap, as the expansion of remote work allowed many women to better balance paid labor with household responsibilities. Additionally, men involved more in household responsibilities during lockdowns which might have contributed to more balanced and more equal household responsibilities (Alon et al. 2020).

Overall, the impact of the pandemic on gender wage inequality reflects a combination of changes in labor market and shifts in household responsibilities. This thesis contributes to this discussion by examining whether the gender wage gap narrowed or widened in Germany during the COVID-19 period, without limiting the analysis only to the pandemic period. The main aim of this thesis is to study the gender wage gap from 2011 to 2022 and to identify the extent of this gap, its evolution over time, and its potential underlying factors.

# 2. LITERATURE REVIEW

This chapter is divided into two sections. The first section reviews the literature on the gender wage gap in general and its main determinants. The second section includes studies on the gender wage gap in the context of the COVID-19 pandemic, discussing how the crisis affected male and female workers differently and whether it changed or re-shaped the existing inequalities.

## 2.1 GENDER WAGE GAP LITERATURE

Kunze (2005) examines gender wage differentials between women and men during the early career stage using West German administrative data from 1975 to 1990. The author shows that differences in occupational qualification play an important role in explaining the pay gap, approximately 50%. Consistent with earlier findings (Brown and Corcoran 1997; Paglin and Rufolo 1990; Neal and Johnson 1996), the author shows that men and women often pursue different occupational qualifications even prior to labor market entry, which explains a considerable share of the observed wage gap. Kunze's findings show that the educational and occupational choices women and men make continue to shape their earnings in the long run, making occupational segregation a key factor in understanding the persistent wage gap in Germany.

On the other hand, Maier (2007) focuses on the structural determinants of wage inequality. The author shows that women's concentration in certain sectors, occupations, and small firms contributes significantly to the gap. The author also points to the absence of gender-neutral job evaluation systems and highlights how collective agreements play only a limited role in reducing inequality. Maier (2007) argues that, without stronger institutional measures, especially stricter enforcement of equal pay policies, the gender wage gap will continue to persist, even in advanced labor markets such as Germany.

More recent work has examined long-term trends and distributional changes. Bonaccolto Töpfer, Castagnetti, and Rosti (2023) analyze the gender pay gap in West Germany between 1984 and 2020 using SOEP data. They find that the gap has narrowed for workers in the lower and middle parts of the wage distribution, but has widened at the top, pointing to the persistence of a glass ceiling. The narrowing of the gap cannot be explained by women's gains in education, since wage differences remain even between men and women with the same qualifications, especially at the top of the wage distribution.

Beyond the German context, several studies provide international evidence. Blau and Kahn (2017), use PSID data to analyze gender wage inequality in the US from 1980 to 2010. They show that even though women made considerable gains in education and work experience during this time, the overall gender wage gap did not disappear. In the 1980s, factors like education, experience, race, and region explained much of the difference in wages, but by 2010 these factors had lost much of their explanatory power. By then, women had surpassed men in terms of education, so these traditional factors no longer explained much of the remaining pay gap. From the 1990s onward, the unexplained part of the wage gap stayed relatively stable, while differences in occupations and industries became the main drivers of persistent wage inequality. Goldin (2014), in her paper "A Grand Gender Convergence: Its Last Chapter", shows that the gender wage gap in the United States has sharply decreased compared to earlier decades. She links this development to women's growing human capital, especially their higher levels of education and work experience compared to men.

## 2.2 THE GENDER WAGE GAP AND COVID-19

The COVID-19 pandemic has introduced new aspects to the gender wage gap discussion. Brodeur, Gray, Islam, and Bhuiyan (2021), show that job losses were uneven across sectors and worker groups. COVID-19 caused a shift toward remote work and away from jobs that involve face-to-face (F2F) interactions with clients or coworkers. However, the ability to work from home is limited to a specific set of occupations, leaving workers in certain industries, often characterized by lower skill or education levels, more exposed to labor market disruptions.

Reichelt, Makovi, and Sargsyan (2021), using data from the United States, Germany, and Singapore, show that women faced a higher risk than men of experiencing job loss, reductions in working hours, and transitions to remote work during COVID-19, although the size of these differences varied across countries. The study finds that among couples who were both employed prior to the pandemic, changes in employment status influenced their gender-role attitudes. Specifically, men who became unemployed while their female partners remained employed adopted more egalitarian views, whereas women in the reverse situation adopted more traditional attitudes. These results indicate that gender-role beliefs are not fixed but may shift in response to changing economic and social circumstances.

Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020) argue that the economic downturn caused by the pandemic differs from previous recessions when it comes to gender effects. In other recessions, men were hit harder because industries like manufacturing and construction which are mainly men dominated suffered most. With COVID-19, it was the opposite. Service sectors which are female dominated, took the biggest hit, and they were especially affected by lockdowns and social distancing. On top of that, when schools and childcare facilities closed, the caregiving load fell mostly on women, especially mothers, which made it even harder for them to stay active in the labor market. The authors point out that these setbacks could negatively affect women's wages in the long run due to lost work experience. However, according to the authors the shift toward flexible work and greater involvement of fathers in childcare could, over time, help reshape gender roles and support more equality in the labor market. In contrast, in some households, the lockdown experience might reinforce or bring back the traditional gender roles, hurting women's long-term careers (Arntz et al. 2020).

In another study, Arntz, Ben Yahmed and Berlingieri (2019) examine how working from home affects both labor market outcomes and life satisfaction. The results indicate that childless employees work approximately one additional hour of unpaid overtime per week and report higher levels of job satisfaction after transitioning to remote work. For parents, working from home helps narrow the gender gap in working hours and monthly earnings, as mothers increase their working hours more than fathers. However, when it comes to hourly wages, fathers see gains from working from home, while mothers do not, unless they switch employers. This suggests that women face weaker bargaining power compared to men when they remain with the same employer.

# 3. DATA

To analyze the gender wage gap in Germany from 2011 to 2022, I used the data from the Socio-Economic Panel (SOEP). The SOEP dataset, short for Sozio-oekonomisches Panel is a longitudinal household survey conducted in Germany since 1984. It is the largest and longest-running panel study in Germany, surveying approximately 30,000 individuals from 22,000 households every year. I worked with two key source files: pequiv.dta and pgen.dta, which I merged using person ID (pid) and survey year (syear). First, I reduced both datasets to include only the relevant variables that I needed for wage analysis. Second, I merged them, producing a combined dataset from 2011 to 2022. I then renamed the variables so they are easier to read and interpret (e.g., renaming e11101 to annual_work_hours, imaty to maternity_benefit, d11107 to number_of_children_in_HH, as well as all the industry codes, which I renamed according to their corresponding industry names) etc.

Next, I generated the key explanatory variables. Gender dummy was created as female = 1 if the person is a female, and 0 otherwise. Then, I constructed hourly wages as wageh = annual individual earnings (i11110) / annual hours worked (e11101), adjusted for inflation using the consumer price index (y11101), and finally transformed into logarithmic form (logwageh) as the main dependent variable. Marital status dummies were created from d11104 (marital status of individual), with the first category dropped as the reference group. Then the partnership variable was generated based on marital status dummies, assigning a value of 1 for individuals who are in a partnership, and 0 for those who were single, widowed, separated, or divorced. Industry dummies were created based on one-digit industry code e11106 (one-digit industry code of individuals). I created the variable educ_level by recoding the variable d11108 into three educational categories: 1 for “Less than High School”, 2 for “High School”, and 3 for “More than High School”. I restricted the sample to observations from the years 2011 to 2022 and to respondents aged 20-60. This excludes teenagers who are typically in education or apprenticeships and older individuals transitioning into (partial) retirement or with reduced hours. After this step, I saved the cleaned and prepared dataset.

To understand gender differences in observable characteristics, I computed means for men and women in Stata. The descriptive statistics shows important gender-specific differences.

In 2011 education level was slightly higher among women compared to men, suggesting that women had higher levels of education. Meanwhile men reported more full-time experience than women, whereas women had more part-time experience. This reflects traditional gender roles and labor market segmentation, with women more likely to engage in part-time employment due to childcare and household responsibilities. Unemployment experience is also higher among women compared to men, suggesting that women experienced longer or more frequent periods of unemployment. This may have long-term implications for wage growth and labor market attachment. Partnership status and the number of children in the household are relatively similar between genders. Interestingly, life satisfaction is reported to be slightly higher among women than men. Maternity benefit shows the most notable gender difference. This reflects the institutional design of maternity benefits, which primarily target women.
Industry differences are very evident. In agriculture, bank, insurance, mining, construction, manufacturing and transport men are more represented than women. These male-concentrated sectors tend to offer higher wages, which may contribute to the observed wage gap. In contrast, women are more present in trade. These industry-related differences are also visualized in Figure 2 where bar represents the industry share for female (grey) and male (blue). The most male dominant industry is manufacturing, followed by construction and transport, whereas females dominate the trade industry.

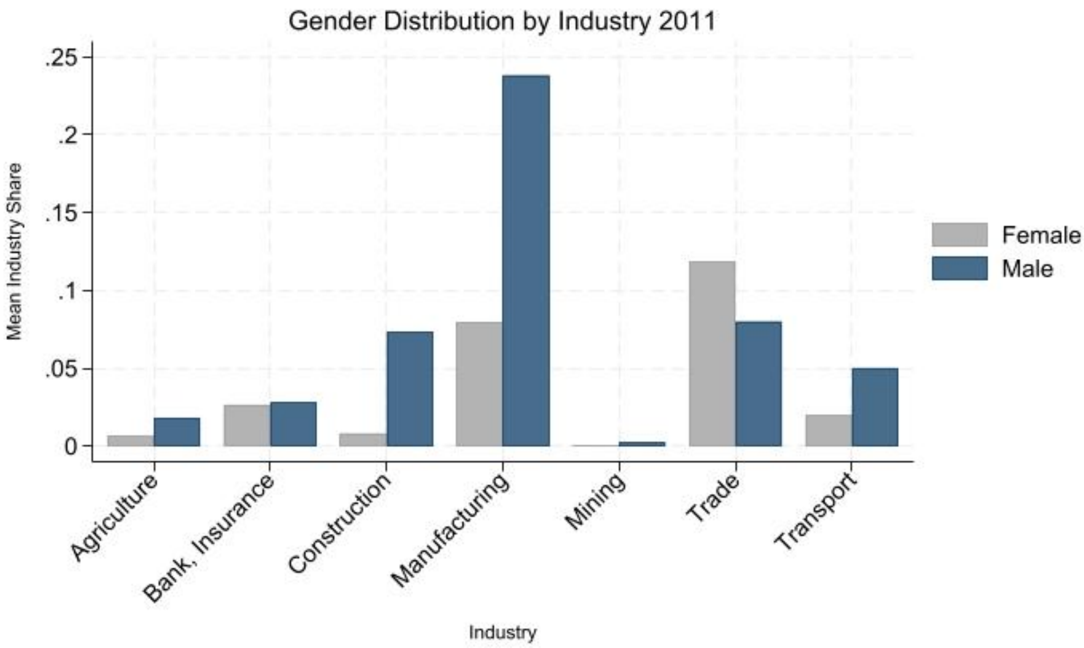


*Figure 2. Mean industry shares for men and women 2011.*
*Source: SOEP data, own calculations.*

In sum, the 2011 data clearly illustrate gendered patterns in education, experience and industries. These differences are likely to translate into wage differences and help explain the causes of the gender wage gap.

The dataset in 2022 shows that women again had a higher level of education than men, indicating that the trend of women achieving higher education observed in 2011 has continued into 2022. Men report higher full-time experience compared to women, whereas women continue to have more part-time and unemployment experience relative to men. The same pattern was also noticed in 2011. The share of individuals in a partnership and the number of children in the household is again similar across genders, indicating that gender gaps in labor market outcomes are unlikely to be driven by differences in family size alone but rather by how childcare responsibilities are distributed. Life satisfaction remains higher for women than for men, consistent with 2011. Men are more represented in manufacturing and construction while women remain concentrated in trade. Industries such as agriculture, bank, insurance, mining, and transport remain male-dominated, although their overall shares are small. These differences may contribute to the gender wage gap, as male-dominated sectors offer higher average wages. Figure 3 illustrates all previously mentioned industry-related differences.

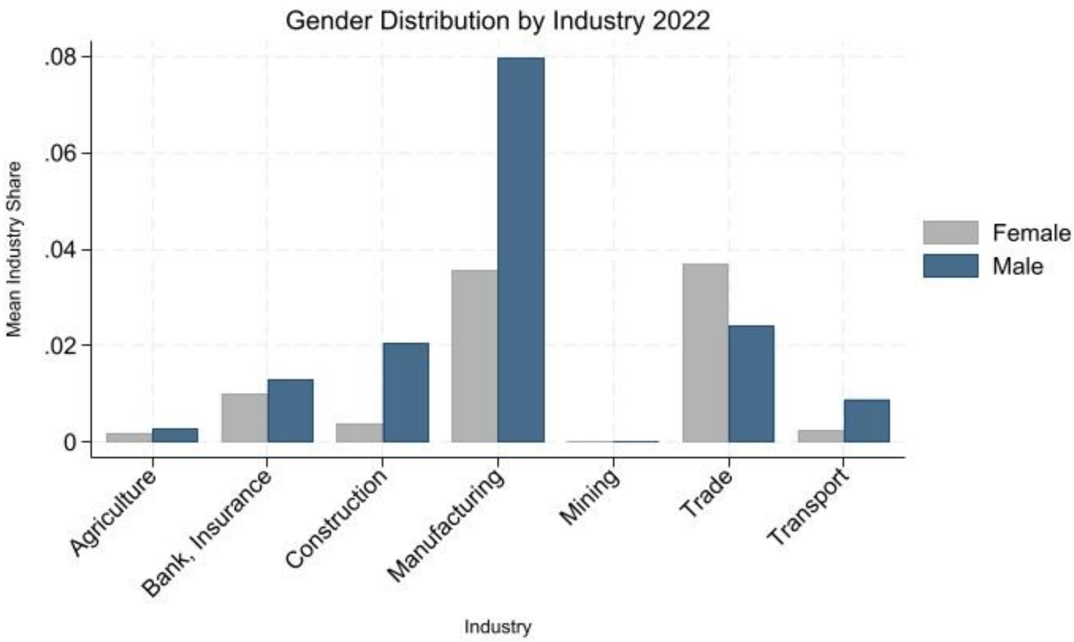


*Figure 3. Mean industry shares for men and women 2022.*
*Source: SOEP data, own calculations.*

In comparison with 2011, manufacturing had by far the highest mean industry share, by 2022, these mean shares declined although the sector remained male-dominated. Trade also showed relatively high mean shares in 2011, especially for women, but by 2022 both values fell, with women still maintaining a higher share. Construction and transport continued to be male dominated in both years, despite overall decreases in their mean shares. Conversely, banking and insurance have shown more balanced gender representation. Male dominance persists in construction, transport, and manufacturing, whereas women are more represented in trade.

## 4. METHODOLOGY

First, I estimate the raw gender wage gap by regressing the logarithm of real hourly wages on a gender dummy variable (female) for each year from 2011 to 2022. The variable is coded as 1 for women and 0 for men, so the estimated coefficient directly reflects the average wage difference between women and men without controlling for any additional characteristics.

Figure 4 below shows the evolution of the raw wage gap over time. The raw wage gap is the unadjusted difference in average wages between men and women, without accounting for any other characteristic. The results show a persistent and large negative coefficient throughout the entire period (2011-2022). As shown in the graph, the wage gap was largest in 2012, when the coefficient reached -0.23 log points. The gap remained stable at about -0.22 log points in the years 2013-2014, before narrowing slightly to around -0.20 log points in 2015 and around -0.18 log points in the years 2016-2019. During the COVID-19 period (2020-2022), the wage gap remained negative but declined further, reaching its lowest point of -0.15 log points in 2022. Overall, the raw wage gap decreased gradually over the period, with the widest gap observed in 2012 and the narrowest in 2022, which corresponds to a decrease of 0.08 log points.

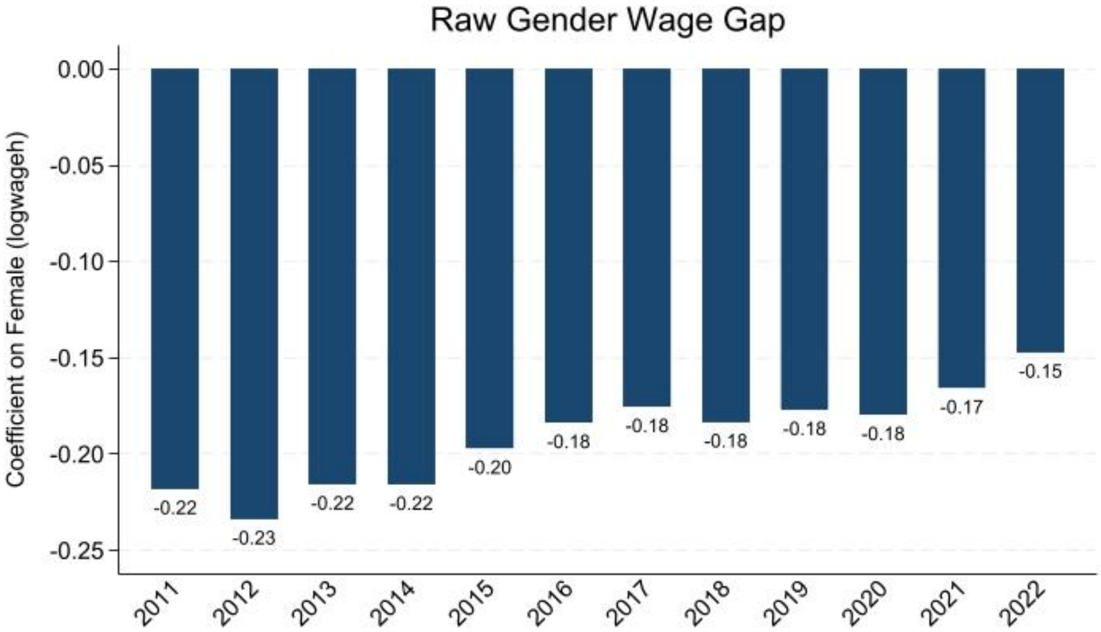


*Figure 4. Raw gender wage gap 2011-2022.*
*Source: SOEP data, own calculations.*

Then after adding all the explanatory variables, I ran a series of OLS regressions separately for each year from 2011 to 2022. In each regression, the dependent variable is the logarithm of real hourly wages, and the explanatory variables include education, experience (full-time, part-time, unemployment), industry, partnership status, number of children in the household, life satisfaction, and maternity benefits. This makes it possible to see how the corrected wage gap has changed from 2011 until 2022.

Figure 5 shows the corrected gender wage gap after including the explanatory variables from 2011-2022. The gap is largest at the beginning of the period -0.17 log points in 2011 and then declines steadily through the pre-COVID years, reaching -0.13 log points in 2012, -0.10 log points in 2013-2014, -0.07/-0.06 log points in 2015-2016. It reaches its smallest value in 2018 at -0.04 log points. After 2018 the pattern reverses modestly. The corrected gap is -0.05 log points in 2019, widens during the COVID-19 period to -0.08 log points in 2020 and -0.06 log points in 2021, and then rises further to -0.11 in 2022. Overall, the corrected wage gap narrows noticeably, hitting its minimum in 2018 before re-widening during the COVID-19 years, especially in 2020 and 2022 when it reached -0.11 log points. Interestingly in 2021 it decreases to -0.06 log points.


*Figure 5. Corrected gender wage gap 2011-2022.*

*Source: SOEP data, own calculations.*

## 4.1 OLS REGRESSIONS

Table 1 shows the results of the OLS regression analysis for 2011. These results show a gender wage gap of around 0.17 log points. Education has a significant and positive effect on wages of 0.35 log points. Part-time experience has a negative but insignificant effect on wages, as does unemployment experience.

Agriculture coefficient shows a negative and significant coefficient of approximately -0.34 log points, whereas manufacturing coefficient is positive and approximately 0.11 log points. Construction and trade show negative and significant coefficients of approximately -0.11 log points and -0.14 log points, respectively. Being in a partnership has a positive effect of approximately 0.20 log points, as well as life satisfaction which shows a coefficient of approximately 0.01 log points. Finally, receiving maternity benefits is associated with an extremely small but significant increase in wages. Overall, the regression model explains approximately 22.5% of the variation in log wages.

**Table 1: OLS Regression Results for 2011**

**Linear regression**

| | |
|---|---|
| Number of obs | **16,929** |
| F(18, 16910) | **264.15** |
| Prob > F | **0.0000** |
| R-squared | **0.2252** |
| Root MSE | **0.6595** |

| Variable | Coef. | Std. Err. | t | P> $\|t\|$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.1653*** | 0.0129 | -12.77 | 0.000 | [ -0.1907, -0.1399] |
| educ_level | 0.3458*** | 0.0091 | 37.66 | 0.000 | [ 0.3278, 0.3639] |
| fulltime_experience | 0.3738 | 0.1982 | 1.89 | 0.059 | [ -0.0148, 0.7628] |
| exp_ft_sq | -0.2369*** | 0.0686 | -3.45 | 0.001 | [ -0.3714, -0.1025] |
| parttime_experience | -0.2660 | 0.2004 | -1.33 | 0.184 | [ -0.6588, 0.1268] |
| exp_pt_sq | 0.4129*** | 0.1855 | 2.23 | 0.026 | [ 0.0494, 0.7766] |
| unemployment_experience | -0.1802 | 0.1432 | -1.26 | 0.208 | [ -0.4609, 0.1004] |
| agriculture | -0.3418*** | 0.0451 | -7.57 | 0.000 | [ -0.4303, -0.2535] |
| mining | 0.1494 | 0.1518 | 0.98 | 0.325 | [ -0.1482, 0.4467] |
| manufacturing | 0.1135*** | 0.0136 | 8.30 | 0.000 | [ 0.0867, 0.1404] |
| construction | -0.1095*** | 0.0210 | -5.23 | 0.000 | [ -0.1505, -0.0685] |
| trade | -0.1428*** | 0.0161 | -8.85 | 0.000 | [ -0.1744, -0.1112] |
| transport | 0.0007 | 0.0266 | 0.03 | 0.979 | [ -0.0514, 0.0528] |
| bank_insurance | 0.4139*** | 0.0244 | 16.95 | 0.000 | [ 0.3661, 0.4617] |
| partnership | 0.2097*** | 0.0113 | 18.57 | 0.000 | [ 0.1876, 0.2319] |
| number_of_children_in_HH | 0.0151*** | 0.0046 | 3.28 | 0.001 | [ 0.0024, 0.0206] |
| life_satisfaction | 0.0100*** | 0.0015 | 6.36 | 0.000 | [ 0.0078, 0.0122] |
| maternity_benefit | 0.0002*** | 0.0000 | 4.94 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.7204*** | 0.1395 | 12.33 | 0.000 | [ 1.4469, 1.9939] |

Results from OLS regression for the year 2011. Dependent variable is the logarithm of hourly gross wages. Significance levels: *p<0.1; **p<0.05; ***p<0.01

Figure 6 shows the effect of only significant variables on wages from the 2011 OLS regression with the dependent variable being the logarithm of real hourly wages. As shown in the graph, bank and insurance had the largest positive effect, followed by education. Even though women had higher levels of education in 2011, as shown in the descriptive statistics, they still faced wage penalties. This finding is consistent with Böheim et al. (2013), who demonstrate that women often earn less than men despite having more formal education, but have less work experience due to childbearing. On the other hand, agriculture had the highest negative effect on wages of approximately -0.34 log points, followed by trade -0.14 log points.

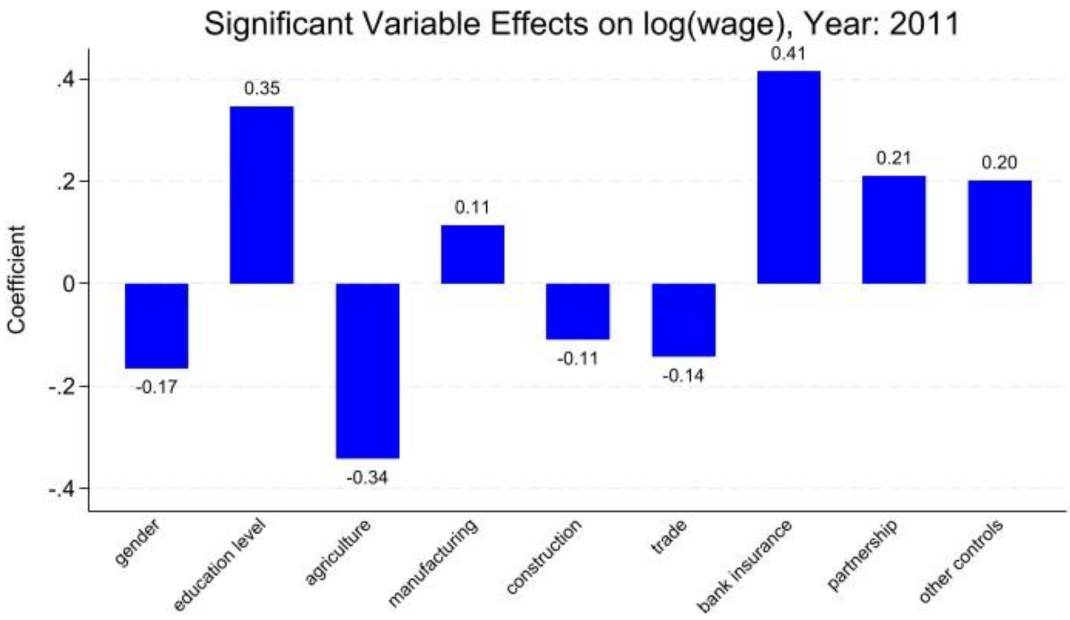


*Figure 6. Significant variables from the OLS Regression 2011*

*Source: SOEP data, own calculations.*

Table 5 reports the results of the OLS regression analysis for 2015. These results show a statistically significant gender wage gap of around 0.07 log points. Relative to earlier years, the coefficient is smaller, suggesting a decline in the gender wage gap. Education has a significant and positive effect on wages of approximately 0.3 log points.

Full-time experience has a positive and significant effect as we can see the coefficient is approximately 0.04 log points, while part-time experience shows a significant negative effect of approximately -0.15 log points. Unemployment experience also shows a negative and significant impact of -0.09 log points.

Industry differences continue to play an important role. Agriculture is negative, approximately -0.38 log points, whereas manufacturing shows a positive effect of 0.13 log points, followed by mining which shows a positive effect as well of 0.32 log points, and banking/insurance coefficient which is 0.35 log points. By contrast, construction approximately -0.06 log points and trade -0.13 log points, show significant negative effects, while transport (-0.03) log points remains small and insignificant.

Table 5: OLS Regression Results for 2015

**Linear regression**

| | |
|---|---|
| Number of obs | **14,908** |
| F(18, 14889) | **285.48** |
| Prob > F | **0.0000** |
| R-squared | **0.2816** |
| Root MSE | **0.6136** |

| Variable | Coef. | Std. Err. | t | P> $\|t\|$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0674*** | 0.0127 | -5.32 | 0.000 | [ -0.0923, -0.0426] |
| educ_level | 0.2880*** | 0.0091 | 31.60 | 0.000 | [ 0.2701, 0.3059] |
| fulltime_experience | 0.0436*** | 0.0121 | 3.59 | 0.000 | [ 0.0198, 0.0674] |
| exp_ft_sq | -0.0025* | 0.0013 | -1.90 | 0.058 | [ -0.0051, 0.0001] |
| parttime_experience | -0.1471*** | 0.0195 | -7.54 | 0.000 | [ -0.1853, -0.1089] |
| exp_pt_sq | 0.0655*** | 0.0060 | 10.81 | 0.000 | [ 0.0535, 0.0772] |
| unemployment_experience | -0.0934*** | 0.0095 | -9.81 | 0.000 | [ -0.1121, -0.0748] |
| agriculture | -0.3770*** | 0.0449 | -8.39 | 0.000 | [ -0.4650, -0.2889] |
| mining | 0.3208** | 0.1273 | 2.52 | 0.012 | [ 0.0712, 0.5704] |
| manufacturing | 0.1276*** | 0.0134 | 9.50 | 0.000 | [ 0.1013, 0.1539] |
| construction | -0.0576** | 0.0226 | -2.54 | 0.011 | [ -0.1020, -0.0132] |
| trade | -0.1314*** | 0.0158 | -8.31 | 0.000 | [ -0.1624, -0.1004] |
| transport | -0.0254 | 0.0242 | -1.05 | 0.293 | [ -0.0729, 0.0220] |
| bank_insurance | 0.3497*** | 0.0250 | 13.76 | 0.000 | [ 0.2999, 0.3995] |
| partnership | 0.1804*** | 0.0112 | 16.06 | 0.000 | [ 0.1584, 0.2024] |
| number_of_children_in_HH | 0.0131*** | 0.0049 | 6.34 | 0.000 | [ 0.0216, 0.0410] |
| life_satisfaction | 0.0252*** | 0.0036 | 7.07 | 0.000 | [ 0.0182, 0.0322] |
| maternity_benefit | 0.0000*** | 0.0000 | 2.97 | 0.003 | [ 0.0000, 0.0000] |
| _cons | 1.7517*** | 0.0483 | 36.30 | 0.000 | [ 1.6571, 1.8463] |

Results from OLS regression for the year 2015. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Being in a partnership has a positive impact on wages of 0.18 log points, while the number of children in the household has a small, yet significant and positive effect of 0.013 log points. Overall, the model explains 28.2% of the variation in log wages ($R^2 = 0.2816$), which is slightly higher than in previous years and suggests improved explanatory power. When it comes to the pay gap the results in 2015 show a pay gap of approximately -0.07 log points, meaning that it has decreased in comparison to previous years when the wage gap was -0.17 log points in 2011, -0.13 log points in 2012, -0.10 log points in 2013 and 2014. In comparison with 2011, wage gap decreased by approximately 0.10 log points.

Figure 7 illustrates the estimated effects of statistically significant variables on wages based on the 2015 OLS regression.

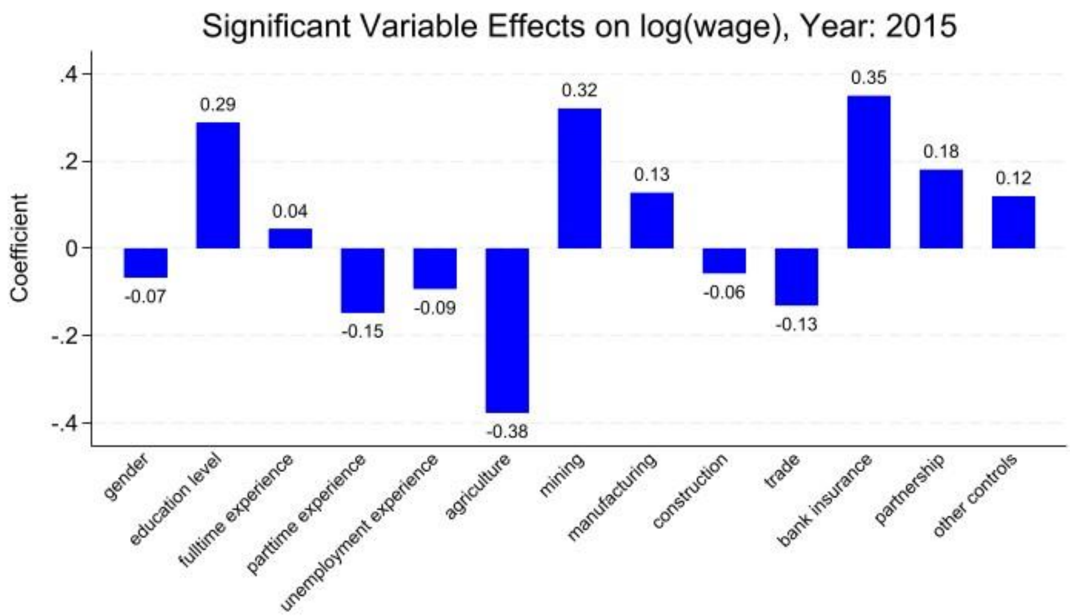


*Figure 7. Significant variables from the OLS Regression 2015.*
*Source: SOEP data, own calculations.*

As shown in the graph, bank and insurance had the largest positive effect, followed by mining and education. On the other hand, agriculture had the highest negative effect on wages of approximately -0.38 log points, followed by part-time experience -0.15 and trade -0.13 log points.

The results of the OLS regression for 2018 are reported in Table 8 in the Appendix. The estimates indicate a statistically significant gender wage gap of approximately 0.04 log points, which represents the lowest value observed over the study period. Education shows a positive and significant coefficient of approximately 0.3 log points. Full-time experience is also positive and significant, 0.05 log points. Part-time experience is associated with a small but significant negative effect of -0.03 log points. Whereas unemployment shows a negative and significant coefficient of -0.06 log points.

Agriculture is negatively associated with wages as we can see a negative and significant coefficient of -0.3 log points, while manufacturing shows a positive coefficient of 0.13 log points, as well as banking/insurance which shows a positive coefficient 0.4 log points. Also, construction and trade are significantly negative with a coefficient of -0.10 log points. Being in a partnership shows a positive coefficient of 0.18 log points. The number of children in the household also shows a positive coefficient of 0.02 log points. Life satisfaction is positively and significantly associated with log wages, approximately 0.04 log points.

Overall, the model explains about 30.6% of the variation in log wages ($R^2 = 0.3063$), which is higher than in previous years, suggesting improved explanatory power. The results for 2018 show a narrowing gender wage gap compared to previous years, in fact the lowest pay gap since 2011. Compared to 2011, the gender wage gap in 2018 decreased by 0.13 log points.

The gender wage gap began to widen again in 2019, reaching -0.05 (see Table 9 in Appendix). In 2019, the education coefficient was positive and statistically significant at approximately 0.3 log points, followed by the coefficients for banking and insurance 0.4 log points and manufacturing 0.1 log points. Part-time employment and unemployment showed negative and statistically significant coefficients of -0.04 and -0.08 log points, respectively. Agriculture as well showed a negative and significant coefficient of approximately -0.3 log points. The pay gap increased further in 2020. Table 10 in Appendix shows the results of the OLS regression for 2020, showing statistically significant gender pay gap of around 0.08 log points. Compared to 2018, the gender wage gap has increased approximately 0.04 log points which may be linked to disruptions in the labor market during the period of the pandemic.

Education has a significant positive effect of around 0.3 log points. Also, full-time experience has a significant and positive effect. The coefficient is 0.06 log points. Part-time experience is negative and insignificant. Unemployment experience shows a significant negative coefficient of approximately -0.06 log points. Agriculture coefficient is also negative, approximately -0.2 log points, manufacturing coefficient is significant and approximately 0.12 log points. Banking /insurance is also positive and statistically significant, approximately 0.4 log points. By contrast, construction and trade have significantly negative effects, -0.08 log points and -0.06 log points respectively. Being in a partnership has a positive and significant effect, approximately 0.20 log points, while the number of children in the household shows a small but significant positive effect of 0.02 log points. Life satisfaction has a small but positive coefficient of 0.02 log points. Overall, the model explains approximately 26.4% of the variation in log wages ($R^2 = 0.2644$), which is slightly lower than in 2018. The results highlight a reversal in the trend of the gender wage gap narrowing, with women facing a greater penalty in 2020 than in 2018. This could potentially reflect structural inequalities worsened by the shock of the pandemic. Nevertheless, education and industry continue to be the main factors influencing wages.

Figure 8 shows only the significant variables from OLS Regression in 2020. As shown in the graph, bank insurance had the largest positive effect, followed by education. On the other hand, agriculture has the highest negative effect followed by construction and trade.

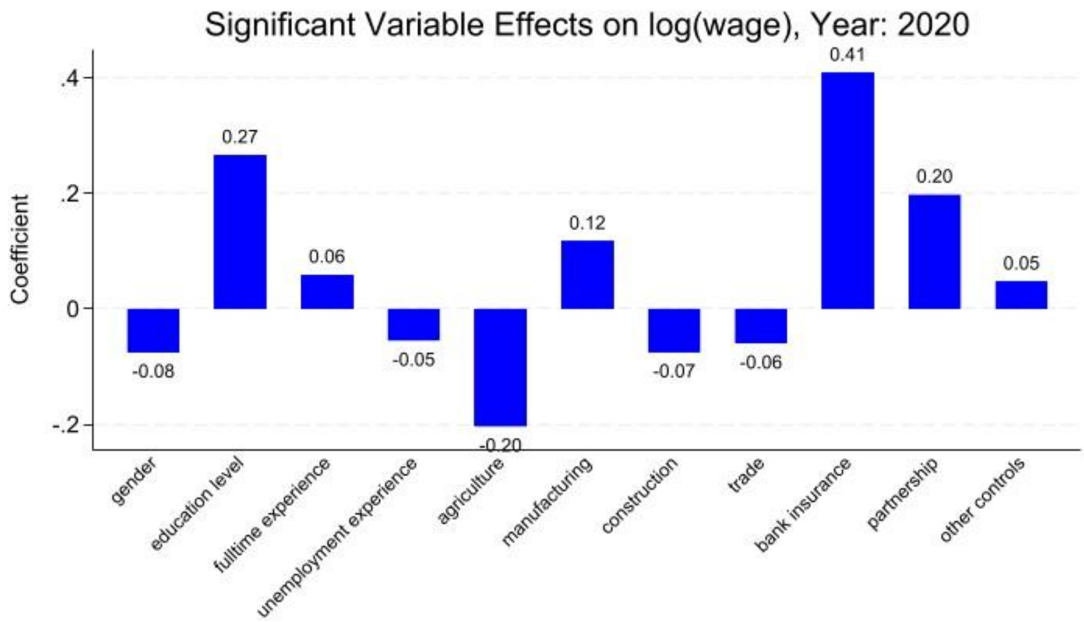


*Figure 8. Significant variables from the OLS Regression 2020.*

*Source: SOEP data, own calculations.*

However, the wage gap narrowed again in 2021, with the female coefficient decreasing to approximately -0.06 (see Table 11 in Appendix). This reduction indicates that the widening gap observed during the first year of the pandemic has been partially reversed. Education continues to have a significant and positive effect on wages, approximately 0.2 log points. Full-time experience also has a significant positive effect of 0.04 log points. By contrast, part-time experience is negative but statistically insignificant. Unemployment experience has a significant negative effect of about -0.05 log points. Agriculture has a negative and significant effect of -0.20 log points, as well as trade -0.14 log points, and transport -0.06 log points. On the other hand, banking and insurance show a positive wage effect on wages of 0.36 log points. Among the other controls, partnership status and life satisfaction have small but significant positive effects of approximately 0.02 log points, while the number of children is insignificant.

Table 12 presents the OLS regression results for 2022. The results show that, compared to men, women faced a wage penalty of -0.11 log points in 2022. This represents a sharp increase compared to 2021 (-0.06 log points), making 2022 one of the years with the widest gender wage gap in the observed period. This sudden reversal suggests that the disruptions caused by the pandemic may have had lingering and uneven effects on labor market outcomes, disproportionately disadvantaging women. Education remains a strong predictor of wages, however, the coefficient 0.11 log points is lower than in previous years, indicating a reduced return to education in log wage terms compared to earlier periods. The penalty for part-time experience continues to have a negative and significant effect of -0.03 log points. The effect of unemployment remains consistently negative of approximately -0.05 log points. Industry patterns continue to play an important role.

Agriculture shows a strong negative effect of -0.40 log points, as well as construction and trade which show a coefficient of -0.12 log points and -0.19 log points respectively. By contrast, manufacturing shows a positive effect of 0.06 log points and banking/insurance a coefficient of 0.33 log points. As in previous years, being in a partnership has a positive impact on wages of 0.19 log points. Number of children in the household has a small positive effect of 0.04 log points, while life satisfaction again shows a positive and significant effect on wages of approximately 0.02 log points. Maternity benefit is statistically insignificant.

Table 12: OLS Regression Results for 2022

**Linear regression**

| | |
|---|---|
| Number of obs | **14,186** |
| F(18, 14167) | **103.49** |
| Prob > F | **0.0000** |
| R-squared | **0.1077** |
| Root MSE | **0.7425** |

| Variable | Coef. | Std. Err. | t | P> $\|t\|$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.1077*** | 0.0140 | -7.67 | 0.000 | [ -0.1352, -0.0802] |
| educ_level | 0.1125*** | 0.0069 | 16.31 | 0.000 | [ 0.0990, 0.1261] |
| fulltime_experience | -0.0032 | 0.0049 | -0.66 | 0.508 | [ -0.0127, 0.0063] |
| exp_ft_sq | 0.0012*** | 0.0003 | 3.61 | 0.000 | [ 0.0006, 0.0019] |
| parttime_experience | -0.0261** | 0.0117 | -2.24 | 0.025 | [ -0.0490, -0.0033] |
| exp_pt_sq | 0.0071*** | 0.0017 | 4.27 | 0.000 | [ 0.0038, 0.0104] |
| unemployment_experience | -0.0460*** | 0.0030 | -15.16 | 0.000 | [ -0.0520, -0.0401] |
| agriculture | -0.4029*** | 0.0903 | -4.48 | 0.000 | [ -0.5794, -0.2265] |
| mining | -0.1189 | 0.3062 | -0.39 | 0.698 | [ -0.7191, 0.4813] |
| manufacturing | 0.0609*** | 0.0196 | 3.11 | 0.002 | [ 0.0225, 0.0994] |
| construction | -0.1169** | 0.0563 | -2.07 | 0.038 | [ -0.2273, -0.0065] |
| trade | -0.1944*** | 0.0278 | -6.98 | 0.000 | [ -0.2489, -0.1399] |
| transport | -0.1198* | 0.0654 | -1.83 | 0.067 | [ -0.2479, 0.0084] |
| bank_insurance | 0.3340*** | 0.0391 | 8.55 | 0.000 | [ 0.2574, 0.4106] |
| partnership | 0.1912*** | 0.0138 | 13.85 | 0.000 | [ 0.1642, 0.2183] |
| number_of_children_in_HH | 0.0430*** | 0.0072 | 5.91 | 0.000 | [ 0.0287, 0.0572] |
| life_satisfaction | 0.0154*** | 0.0044 | 3.48 | 0.001 | [ 0.0067, 0.0240] |
| maternity_benefit | 0.0000 | 0.0001 | -0.00 | 0.998 | [ -0.0001, 0.0001] |
| _cons | 2.6031*** | 0.0376 | 69.08 | 0.000 | [ 2.5292, 2.6770] |

Results from OLS regression for the year 2022. Dependent variable is the logarithm of hourly gross wages. Significance levels: *p<0.1; **p<0.05; ***p<0.01

The explanatory power of the model decreased considerably in 2022, with an $R^2$ of only 0.1077, much lower than in previous years, when it ranged from approximately 0.20 to 0.31. This suggests that the included variables explain less of the wage variation in 2022, which could reflect structural shifts in the labor market following the pandemic. In summary, the 2022 results suggest that the gender pay gap has widened considerably, that the returns to education and experience have decreased, and that the model's explanatory power has fallen. This leads to increased uncertainty and the need for new, unobserved factors that influence wage determination in the post-pandemic period.

Between 2020 and 2022, the gender wage gap evolved in a way that highlights the disruptive impact of the pandemic. In 2020, the wage gap was -0.08 log points, which was a significant increase when compared with 2018 (-0.04) log points and 2019 (-0.05) log points. This indicates that gender disparities were widening during the initial crisis period. Although the gender pay gap narrowed slightly in 2021, decreasing to -0.06 log points, this was only a partial recovery. By 2022, the corrected gender gap had widened again, reaching -0.11 log points, which is the highest level recorded after 2011 (-0.17) log points and 2012 (-0.13) log points. This increase indicates that the impact of the pandemic was not temporary but had lasting effects, worsening and reinforcing pre-existing inequalities. It shows how external shocks, such as the pandemic, disrupt progress in narrowing the gender pay gap.

Figure 9 shows the effect of the significant variables on wages from the 2022 OLS regression.

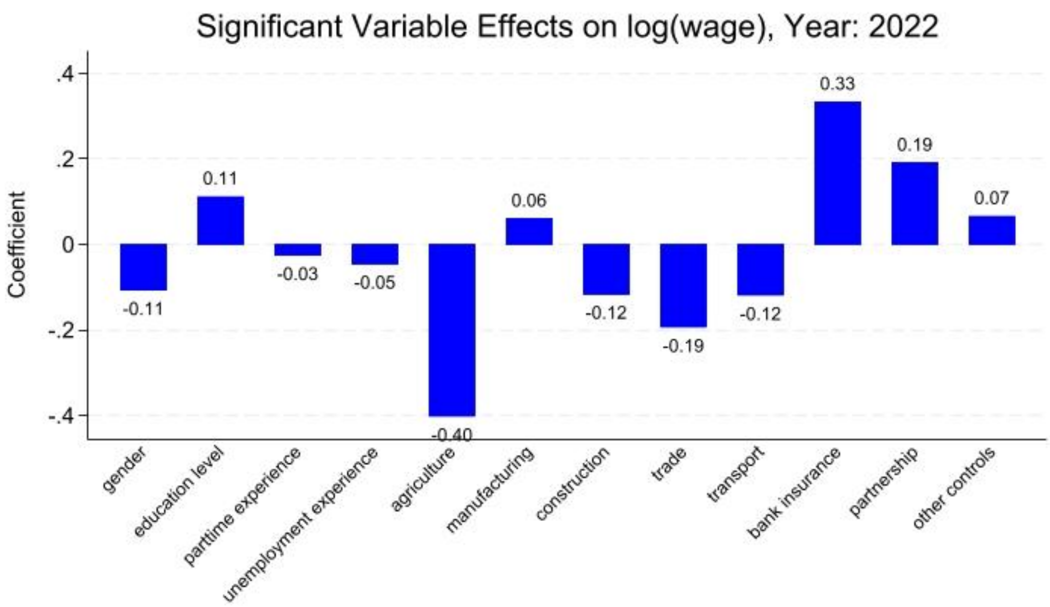


*Figure 9. Significant variables from the OLS Regression 2022.*

*Source: SOEP data, own calculations.*

As we can see from the graph, bank, insurance 0.33 log points, had the largest positive effect, followed by the partnership variable 0.19 log points. Education has a smaller positive effect than previous years. On the other hand, agriculture had the highest negative effect on wages -0.40 log points, followed by trade -0.19 log points.

Figure 10 compares the raw (uncorrected) and adjusted (corrected) gender wage gaps from 2011 to 2022. The red line corresponds to corrected wage gap whereas the blue line corresponds to the uncorrected wage gap. The uncorrected gap narrows from about -0.22 log points in 2011 to -0.15 in 2022, while the corrected gap remains consistently smaller, ranging from -0.17 log points in 2011 to -0.11 log points in 2022.

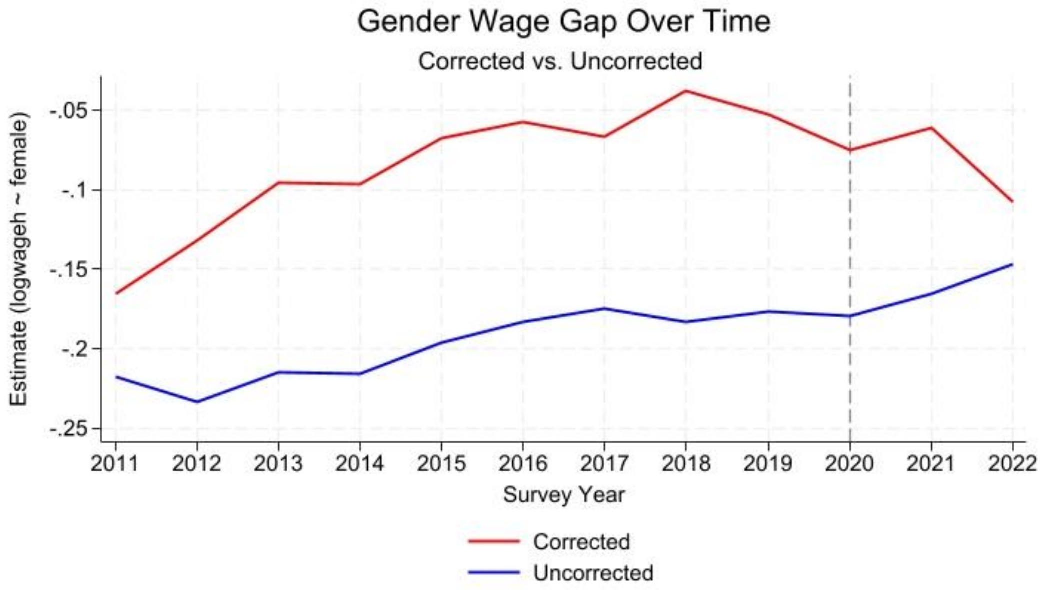


*Figure 10. Corrected vs Uncorrected wage gap 2011-2022.*

*Source: SOEP data, own calculations.*

The difference between uncorrected wage gap and corrected wage gap in 2011 is 0.05 log points, whereas in 2022 is 0.04 log points. In other years such as 2018 this difference is substantially larger, reaching 0.14 log points. The dashed vertical line marks the onset of the COVID-19 pandemic, after which differences in movement between corrected and uncorrected gap are visible. The corrected gap increases in 2020, slightly decreases in 2021 and then increases again in 2022 whereas the uncorrected gap decreases from 2020 until 2022. One explanation is that the COVID-19 pandemic affected men and women differently in terms of sectoral and occupational composition. Many women are employed in sectors such as hospitality, retail, and personal services, which were hit hardest in 2020 (Alon et al. 2020). The raw gap might have narrowed because COVID disproportionately pushed many low-wage women out of employment, which raised the average wages of those who remained in the workforce. However, when observable characteristics are controlled for, the corrected gap increases, indicating that women's relative position worsens. The decline in 2021 suggests that the corrected gender wage gap temporarily reduced as the labor market adjusted after the initial COVID shock, but the increase in 2022 indicates that this improvement was only temporary.

## 4.2 OAXACA-BLINDER

To complement the regression analysis, the Oaxaca-Blinder decomposition was applied for each year between 2011 and 2022 (Blinder, 1973; Oaxaca, 1973). This approach decomposes the average log wage differential into an explained component, capturing differences in observable characteristics between men and women, and an unexplained component. The explained part captures differences in factors such as education, labor market experience (full-time, part-time, and unemployment), industry, partnership status, number of children in the household, life satisfaction, and maternity-related benefits. The male wage structure is used as the reference group.

As a first step, the Blinder-Oaxaca model requires estimating separate wage equations for females (f) and males (m) using ordinary least squares (OLS):

$$Y_{if} = X_{if}\widehat{\beta_f} + u_{if} \qquad (1)$$

$$Y_{im} = X_{im}\widehat{\beta_m} + u_{im} \qquad (2)$$

Here, $Y$ denotes the log of hourly wages of an individual $i = 1,2,\dots,N$. $X$ is a vector of observed explanatory characteristics, $\hat{\beta}$ represents the estimated coefficient vector from the respective wage regression, and u is the error term. The explanatory factors are education, experience, industry, partnership, number of children in the household, life satisfaction and maternity benefit.

The difference in the means of wages can be expressed as:

$$\overline{Y_m} - \overline{Y_f} = \widehat{\beta_m}\left(\overline{X_m} - \overline{X_f}\right) + \overline{X_f}\left(\widehat{\beta_m} - \widehat{\beta_f}\right), \tag{3}$$

where the first term $\widehat{\beta_m}\left(\overline{X_m} - \overline{X_f}\right)$, represents the explained component, calculated using the male coefficients and the second term $\overline{X_f}\left(\widehat{\beta_m} - \widehat{\beta_f}\right)$, the unexplained part. I estimate the decomposition separately by year, which allows me to observe the evolution of the explained and unexplained components of the wage gap across the period 2011-2022.

In Table 13 I present the decomposition results of the gender wage gap in Germany from 2011 to 2022. In 2011, the average gender wage gap was 21.8 log points, which increased slightly to 23.3 log points in 2012 (a rise of approximately 1.6 log points). After 2012, the wage gap followed a generally downward trend, despite some small year-to-year fluctuations. It was 21.5 log points in 2014, 19.7 log points in 2015, and 18.3 log points in 2018, before falling further to 16.6 log points in 2021 and reaching 14.7 log points in 2022. Overall, between 2011 and 2022, the raw wage gap declined by about 7 log points, indicating a substantial narrowing of the gap over the observed period.

In 2011, differences in observable characteristics explained 11.3 log points, or about 52% of the total gap, while the unexplained part accounted for 10.5 log points (48%). The explained gap rose slightly until 2016 (17.3 log points) but then dropped sharply, amounting to only 7.6 log points by 2022. By contrast, the unexplained gap declined steeply until 2016, then started to rise again, reaching 7.4 in 2021 and 7.1 in 2022 (49% of the remaining gap). The decomposition shows that the decline in the gender wage gap was driven by different factors in different periods. From 2011 to 2016, the narrowing was mainly due to a strong decrease in the unexplained part of the gap, which fell from 10.5 to just 1.1 log points. Over the same period, the explained part increased, reaching a peak of 17.3 log points in 2016.

**Table 13: Gender wage decompositions, 2011–2022**

| Year | Wage gap | Difference over time | Explained gap | Difference over time | Unexplained gap | Difference over time |
|---|---|---|---|---|---|---|
| 2011 | 0.2177 | | 0.1130 | | 0.1047 | |
| 2012 | 0.2334 | 0.0157 | 0.1340 | 0.0210 | 0.0994 | -0.0053 |
| 2013 | 0.2153 | -0.0181 | 0.1545 | 0.0205 | 0.0608 | -0.0386 |
| 2014 | 0.2155 | 0.0002 | 0.1609 | 0.0064 | 0.0547 | -0.0061 |
| 2015 | 0.1968 | -0.0187 | 0.1618 | 0.0009 | 0.0349 | -0.0198 |
| 2016 | 0.1834 | -0.0134 | 0.1725 | 0.0107 | 0.0108 | -0.0241 |
| 2017 | 0.1751 | -0.0083 | 0.1319 | -0.0406 | 0.0431 | 0.0323 |
| 2018 | 0.1830 | 0.0079 | 0.1326 | 0.0007 | 0.0504 | 0.0073 |
| 2019 | 0.1767 | -0.0063 | 0.1317 | -0.0009 | 0.0450 | -0.0054 |
| 2020 | 0.1793 | 0.0026 | 0.1403 | 0.0086 | 0.0389 | -0.0061 |
| 2021 | 0.1655 | -0.0138 | 0.0912 | -0.0491 | 0.0743 | 0.0345 |
| 2022 | 0.1468 | -0.0187 | 0.0755 | -0.0157 | 0.0712 | -0.0031 |

Results from Blinder–Oaxaca decompositions.Dependent variable is the logarithm of hourly gross wages. Explanatory variables used in all decompositions are education, full time experience, part time experience, unemployment, partnership, number of children in the household, life satisfaction, maternity benefit.

After 2016, however, the pattern reversed; the explained component dropped sharply from 17.3 to 7.6 log points by 2022, while the unexplained component rose again to about 7.1 log points. Taken together, these results indicate that the early narrowing of the wage gap was primarily driven by a decline in the unexplained component, while the later reduction was due to a convergence in men's and women's observable characteristics.

Figure 11 shows the explained and unexplained wage gap from 2011 until 2022. The blue line represents the explained part, the orange line shows the unexplained part, whereas the dashed vertical line represents the onset of COVID-19 pandemic. The explained gap increased from 2011 to 2016, peaking in 2016 at about 0.17 log points, while the unexplained component declined to a minimum of roughly 0.01 log points in 2016. Between 2017 and 2019, the explained gap remained relatively stable at around 0.13 log points, while the unexplained part ranged from 0.04 to 0.05 log points. In 2011, as previously mentioned, observable characteristics explained about 52% of the wage gap, while the unexplained component accounted for the remaining 48%. The explained share had risen to almost 94% in 2016, with the unexplained share shrinking to only 6%. After 2020, however, the unexplained share increased again, reaching around 45% in 2021, whereas the explained share was 55%. During the onset of COVID-19 in 2020, the explained wage gap rose slightly to around 0.14 log points, while the unexplained gap declined to approximately 0.04 log points. However, from 2021 onwards, the explained gap dropped sharply, falling to about 0.07 log points by 2022, while the unexplained gap increased to nearly the same level, around 0.07 log points. This indicates that factors beyond observable characteristics became very important in shaping the gender wage gap in the COVID period. In the previous years, most of the gender wage gap can be attributed to differences in characteristics between men and women, such as work experience and industry. After the onset of COVID-19, the explained part declined while the unexplained part increased, suggesting that observable differences became less important, whereas unobservable or unmeasured factors gained significance. This shift may reflect unobserved characteristics that are not captured in the data or changes in the labor market induced by the pandemic.

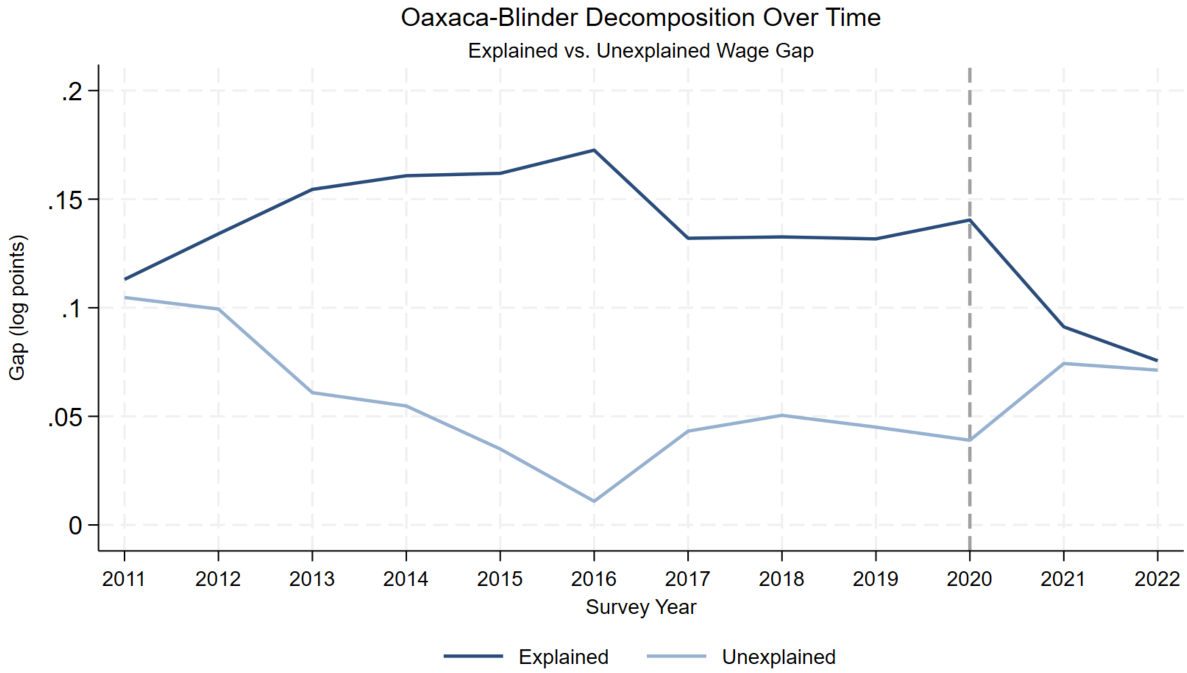


*Figure 11. Explained vs Unexplained Wage Gap, 2011-2022.*

*Source: SOEP data, own calculations.*

Figure 12 shows the explained component of the gender wage gap which is divided into three groups of observable characteristics: industry, experience (full-time employment, part-time employment, unemployment), and other characteristics. The explained component of the gender wage gap is primarily driven by differences in experience-related characteristics, which account for the largest share of observed wage differences over time. The industry component contributes positively but modestly to the explained gap in all years. This indicates that the unequal distribution of men and women across industries plays a secondary role compared to experience. On the other hand, other characteristics which include education, partnership status, number of children, life satisfaction, and maternity benefits contributes negatively in all years. The negative contribution of other characteristics indicates that women possess, on average, more favorable observable endowments in this category, which tend to reduce rather than widen the explained component of the gender wage gap. Taken together, the results indicate that the explained component of the gender wage gap is driven predominantly by differences in labor market experience, followed by industry. Over time, the explained component increases until the mid-2010s, peaks around 2016, and then gradually declines, with a noticeable reduction in the post-COVID period (2021-2022), reflecting a weakening role of observable characteristics in explaining the gender wage gap.

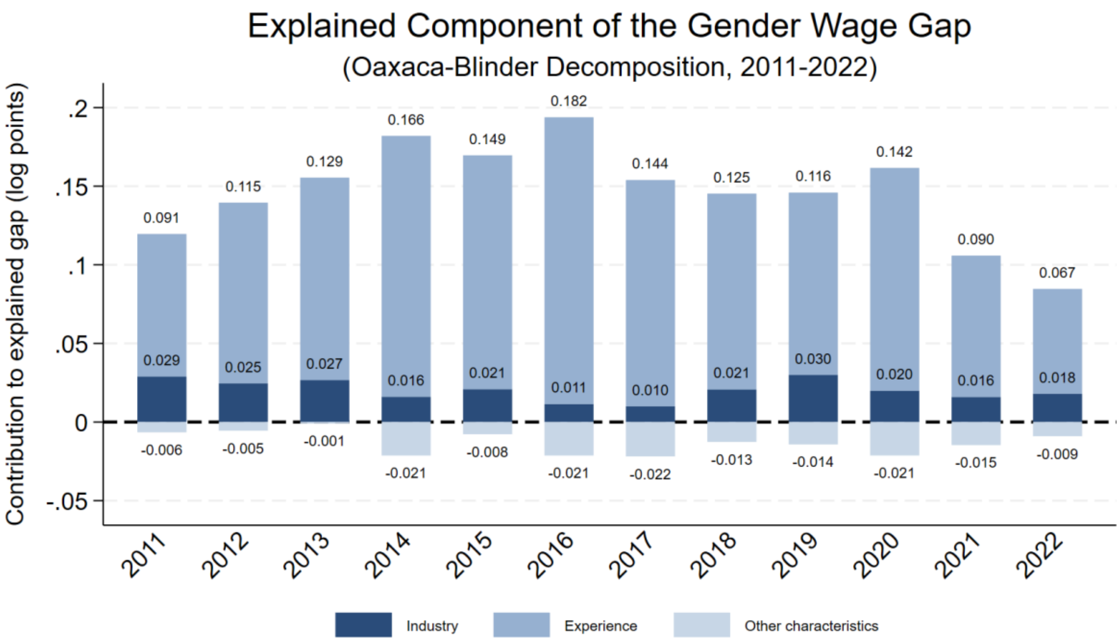


*Figure 12. Explained gender wage gap (Oaxaca-Blinder), 2011-2022.*

*Source: SOEP data, own calculations.*

Figure 13 presents the unexplained component of the gender wage gap, decomposed into contributions from industry, experience, and other observed characteristics over the period 2011-2022. The unexplained gap is dominated by other characteristics, particularly in 2011, 2013, 2016, and during the post-2020 period. Experience-related factors contribute negatively to the unexplained component in most years, indicating that differences in returns to experience tend to reduce unexplained wage inequality rather than exacerbate it. Industry effects remain small and close to zero over the entire period. Over time, the unexplained component shows considerable year-to-year variation, with relatively high levels in 2011 and a renewed increase in the post-COVID period (2020-2022), suggesting a strengthening of unexplained wage disparities following the pandemic.

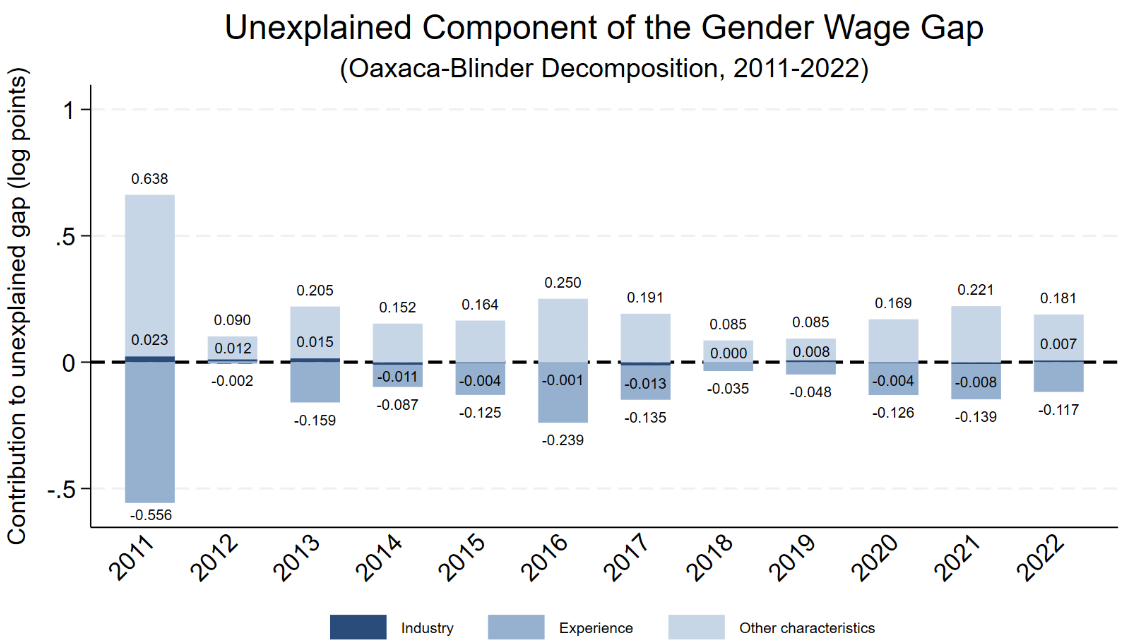


*Figure 13. Unexplained gender wage gap (Oaxaca-Blinder), 2011-2022.*

*Source: SOEP data, own calculations.*

# 5. CONCLUSION

This thesis examined the evolution of the gender wage gap in Germany between 2011 and 2022. The results show that, despite progress, wage differences between men and women remain a persistent feature of the German labor market. The descriptive analysis showed that men and women tend to have different education levels, levels of experience, and sectoral employment patterns. Women consistently achieved higher levels of education than men. They also accumulated more part-time and unemployment experience, while men had longer full-time experience. Men and women continued to be concentrated in different types of industries. Men continued to dominate in industries such as construction, manufacturing, and transport, while women were more dominant in trade. These structural differences provided an important background for the regression analysis, as they have a direct impact on wage outcomes.

The OLS regression results confirmed a steady, though uneven, narrowing of the raw gender wage gap over the decade, from around -0.22 log points in 2011 to -0.15 in 2022, a decrease in the raw wage gap of 0.07 log points. Once I add explanatory variables such as education, experience (full-time, part-time, unemployment), industry, partnership status, number of children in the household, life satisfaction, and maternity benefits, the corrected wage gap was substantially smaller, ranging from -0.17 log points in 2011 to -0.04 log points in 2018 which was also its lowest point. The outbreak of COVID-19 disrupted this trajectory. After 2020, the corrected gender wage gap began to widen again, rising to -0.08 log points in 2020 and peaking at -0.11 log points in 2022, which was the highest value since 2011- 2012. One possible explanation for this reversal can be that women were overrepresented in service sectors such as hospitality, retail, and personal care, which were hardest hit by lockdowns and restrictions. Many also faced career interruptions due to job losses or increased caregiving responsibilities at home. At the same time, the usual advantages of education and full-time work experience became weaker predictors of wages, and the overall model explained much less of the variation in 2022 than in earlier years. This suggests that the pandemic not only stalled progress but also introduced new uncertainties and unobserved influences that disproportionately affected women.

The Oaxaca-Blinder decomposition shows that the gender wage gap narrowed by about 7 log points between 2011 and 2022, but the drivers of this change shifted over time. In the first half of the period (2011-2016), most of the reduction came from a sharp fall in the unexplained component of the gap. After 2016, however, this trend reversed. The explained part of the gap declined, while the unexplained share rose again, accounting for nearly half of the remaining difference by 2022. The explained component of the gender wage gap is largely driven by differences in labor market experience, while the unexplained component is dominated by other characteristics.

Taken together, the results of this thesis highlight both progress and setbacks. Germany has made progress in narrowing the gender wage gap, but the fact that it widened again during the pandemic shows how fragile these gains really are. The progress achieved over many years can be set back very quickly when the labor market faces a major shock. In the end, reducing the gender wage gap is not only about improving economic outcomes but also about ensuring fairness and equal opportunities for future generations. True equality will require sustained effort and policies that go beyond individual characteristics to address the structural barriers that continue to hold women back. This study is limited until 2022 and therefore cannot capture the post COVID-19 effect in a longer term, which can be an interesting topic for future research.

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# 7. APPENDIX

**Table 2: OLS Regression Results for 2012**

**Linear regression**

| | |
|---|---|
| Number of obs | **16,393** |
| F(18, 16374) | **302.94** |
| Prob > F | **0.0000** |
| R-squared | **0.2666** |
| Root MSE | **0.6295** |

| **Variable** | **Coef.** | **Std. Err.** | **t** | **P> \|t\|** | **95% Conf. Interval** |
|---|---|---|---|---|---|
| female | -0.1324*** | 0.0126 | -10.53 | 0.000 | [ -0.1570, -0.1077] |
| educ_level | 0.3658*** | 0.0091 | 40.09 | 0.000 | [ 0.3479, 0.3837] |
| fulltime_experience | 0.0158 | 0.0355 | 0.44 | 0.657 | [ -0.0538, 0.0854] |
| exp_ft_sq | -0.0155* | 0.0080 | -1.93 | 0.053 | [ -0.0312, 0.0002] |
| parttime_experience | -0.4662*** | 0.0495 | -9.43 | 0.000 | [ -0.5632, -0.3693] |
| exp_pt_sq | 0.3297*** | 0.0311 | 10.61 | 0.000 | [ 0.2688, 0.3906] |
| unemployment_experience | -0.2032*** | 0.0258 | -7.88 | 0.000 | [ -0.2539, -0.1527] |
| agriculture | -0.3682*** | 0.0428 | -8.61 | 0.000 | [ -0.4523, -0.2845] |
| mining | 0.3536 | 0.2397 | 1.47 | 0.140 | [ -0.1166, 0.8238] |
| manufacturing | 0.1338*** | 0.0131 | 10.23 | 0.000 | [ 0.1082, 0.1594] |
| construction | -0.0939*** | 0.0210 | -4.49 | 0.000 | [ -0.1349, -0.0529] |
| trade | -0.1373*** | 0.0163 | -8.42 | 0.000 | [ -0.1692, -0.1056] |
| transport | 0.0122 | 0.0249 | 0.49 | 0.622 | [ -0.0365, 0.0620] |
| bank_insurance | 0.4250*** | 0.0245 | 17.34 | 0.000 | [ 0.3769, 0.4730] |
| partnership | 0.2045*** | 0.0108 | 18.91 | 0.000 | [ 0.1834, 0.2258] |
| number_of_children_in_HH | 0.0104*** | 0.0046 | 2.26 | 0.024 | [ 0.0039, 0.0219] |
| life_satisfaction | 0.0154*** | 0.0021 | 7.18 | 0.000 | [ 0.0112, 0.0196] |
| maternity_benefit | 0.0002*** | 0.0001 | 4.09 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.8044*** | 0.0463 | 38.96 | 0.000 | [ 1.7136, 1.8952] |

Results from OLS regression for the year 2012. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

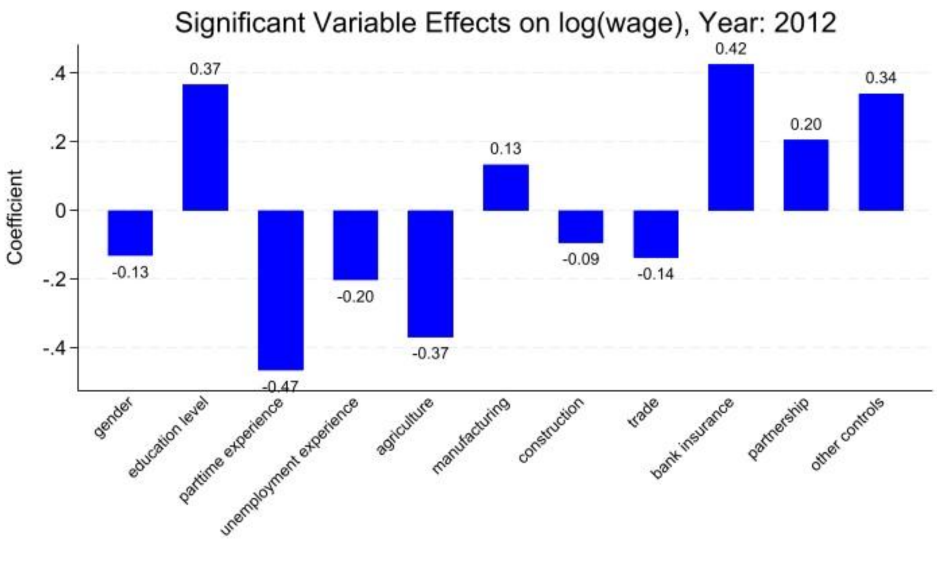


*Figure A1. Significant variables from the OLS Regression 2012.*

**Table 3: OLS Regression Results for 2013**

**Linear regression**

| | |
|---|---|
| Number of obs | **15,314** |
| F(18, 15295) | **309.49** |
| Prob > F | **0.0000** |
| R-squared | **0.2833** |
| Root MSE | **0.6160** |

| Variable | Coef. | Std. Err. | t | P> $\|t\|$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0954*** | 0.0129 | -7.37 | 0.000 | [ -0.1208, -0.0700] |
| educ_level | 0.3401*** | 0.0091 | 36.01 | 0.000 | [ 0.3216, 0.3586] |
| fulltime_experience | 0.0756*** | 0.0248 | 3.05 | 0.002 | [ 0.0271, 0.1243] |
| exp_ft_sq | -0.0116*** | 0.0038 | -3.06 | 0.002 | [ -0.0191, -0.0041] |
| parttime_experience | -0.3013*** | 0.0330 | -9.12 | 0.000 | [ -0.3661, -0.2365] |
| exp_pt_sq | 0.1809*** | 0.0150 | 12.08 | 0.000 | [ 0.1516, 0.2104] |
| unemployment_experience | -0.1202*** | 0.0187 | -6.43 | 0.000 | [ -0.1570, -0.0836] |
| agriculture | -0.2894*** | 0.0564 | -5.13 | 0.000 | [ -0.3999, -0.1788] |
| mining | 0.3873** | 0.1516 | 2.55 | 0.011 | [ 0.0901, 0.6844] |
| manufacturing | 0.1079*** | 0.0135 | 7.98 | 0.000 | [ 0.0813, 0.1343] |
| construction | -0.0656*** | 0.0216 | -3.03 | 0.002 | [ -0.1079, -0.0232] |
| trade | -0.1264*** | 0.0158 | -8.02 | 0.000 | [ -0.1578, -0.0956] |
| transport | 0.0065 | 0.0227 | 0.28 | 0.777 | [ -0.0423, 0.0553] |
| bank_insurance | 0.3887*** | 0.0243 | 15.98 | 0.000 | [ 0.3411, 0.4364] |
| partnership | 0.1939*** | 0.0109 | 17.65 | 0.000 | [ 0.1724, 0.2155] |
| number_of_children_in_HH | 0.0118** | 0.0047 | 2.49 | 0.013 | [ 0.0025, 0.0211] |
| life_satisfaction | 0.0289*** | 0.0033 | 8.93 | 0.000 | [ 0.0226, 0.0351] |
| maternity_benefit | 0.0004*** | 0.0001 | 6.68 | 0.000 | [ 0.0003, 0.0005] |
| _cons | 1.6255*** | 0.0569 | 28.52 | 0.000 | [ 1.5137, 1.7375] |

Results from OLS regression for the year 2013. Dependent variable is the logarithm of hourly gross wages. Significance levels: *p<0.1; **p<0.05; ***p<0.01

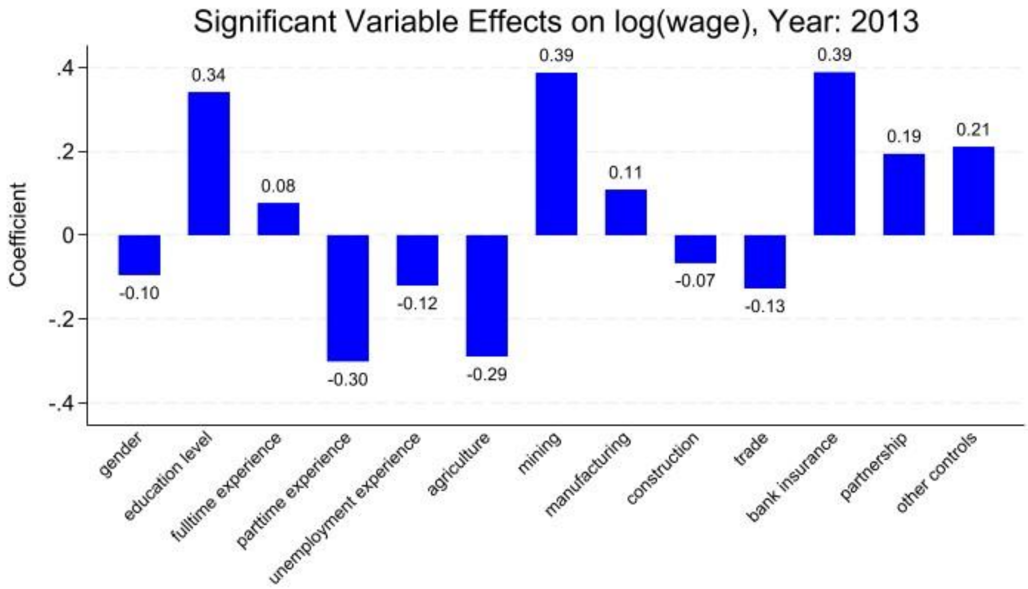


*Figure A2. Significant variables from the OLS Regression 2013.*

## Table 4: OLS Regression Results for 2014

**Linear regression**

| | |
|---|---|
| Number of obs | **16,119** |
| F(18, 16100) | **318.95** |
| Prob > F | **0.0000** |
| R-squared | **0.2894** |
| Root MSE | **0.6169** |

| Variable | Coef. | Std. Err. | t | P> \|t\| | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0962*** | 0.0122 | -7.88 | 0.000 | [ -0.1201, -0.0723] |
| educ_level | 0.2990*** | 0.0088 | 34.01 | 0.000 | [ 0.2813, 0.3158] |
| fulltime_experience | 0.0694*** | 0.0139 | 4.98 | 0.000 | [ 0.0421, 0.0968] |
| exp_ft_sq | -0.0053*** | 0.0020 | -2.70 | 0.007 | [ -0.0091, -0.0014] |
| parttime_experience | -0.1991*** | 0.0220 | -9.04 | 0.000 | [ -0.2422, -0.1559] |
| exp_pt_sq | 0.1109*** | 0.0083 | 13.30 | 0.000 | [ 0.0945, 0.1272] |
| unemployment_experience | -0.1005*** | 0.0115 | -8.73 | 0.000 | [ -0.1231, -0.0780] |
| agriculture | -0.2188*** | 0.0390 | -5.61 | 0.000 | [ -0.2952, -0.1423] |
| mining | 0.3646*** | 0.1381 | 2.64 | 0.008 | [ 0.0934, 0.6351] |
| manufacturing | 0.1044*** | 0.0132 | 7.84 | 0.000 | [ 0.0784, 0.1305] |
| construction | -0.1044*** | 0.0213 | -4.90 | 0.000 | [ -0.1461, -0.0625] |
| trade | -0.1654*** | 0.0159 | -10.41 | 0.000 | [ -0.1966, -0.1344] |
| transport | -0.0119 | 0.0220 | -0.54 | 0.588 | [ -0.0551, 0.0312] |
| bank_insurance | 0.3710*** | 0.0250 | 14.83 | 0.000 | [ 0.3220, 0.4204] |
| partnership | 0.1983*** | 0.0109 | 18.28 | 0.000 | [ 0.1774, 0.2199] |
| number_of_children_in_HH | 0.0233*** | 0.0047 | 5.85 | 0.000 | [ 0.0182, 0.0366] |
| life_satisfaction | 0.0239*** | 0.0031 | 7.36 | 0.000 | [ 0.0171, 0.0292] |
| maternity_benefit | 0.0002*** | 0.0000 | 5.90 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.6996*** | 0.0408 | 41.57 | 0.000 | [ 1.6195, 1.7798] |

Results from OLS regression for the year 2014. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

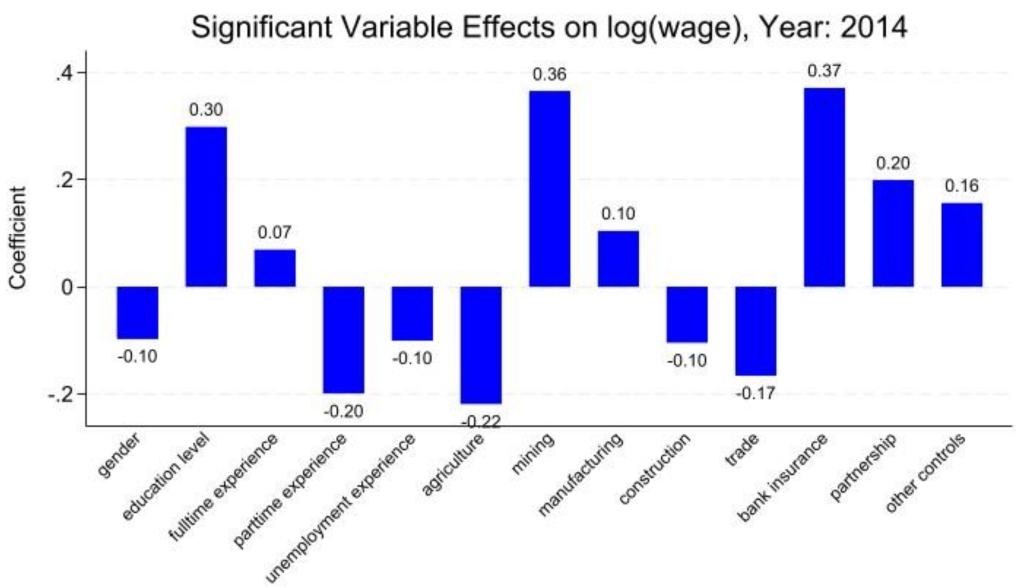


*Figure A3. Significant variables from the OLS Regression 2014.*

Table 6: OLS Regression Results for 2016

**Linear regression**

| | |
|---|---|
| Number of obs | **14,416** |
| F(18, 14397) | **312.64** |
| Prob > F | **0.0000** |
| R-squared | **0.3038** |
| Root MSE | **0.5985** |

| Variable | Coef. | Std. Err. | t | P>\|t\| | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0575*** | 0.0130 | -4.44 | 0.000 | [ -0.0830, -0.0321] |
| educ_level | 0.2788*** | 0.0088 | 31.79 | 0.000 | [ 0.2616, 0.2960] |
| fulltime_experience | 0.0543*** | 0.0087 | 6.22 | 0.000 | [ 0.0372, 0.0714] |
| exp_ft_sq | -0.0017** | 0.0008 | -2.01 | 0.045 | [ -0.0034, -0.0000] |
| parttime_experience | -0.0880*** | 0.0160 | -5.51 | 0.000 | [ -0.1193, -0.0567] |
| exp_pt_sq | 0.0424*** | 0.0040 | 10.49 | 0.000 | [ 0.0348, 0.0508] |
| unemployment_experience | -0.0722*** | 0.0068 | -10.61 | 0.000 | [ -0.0855, -0.0589] |
| agriculture | -0.3024*** | 0.0473 | -6.39 | 0.000 | [ -0.3951, -0.2096] |
| mining | 0.2486** | 0.1211 | 2.05 | 0.040 | [ 0.0111, 0.4861] |
| manufacturing | 0.1039*** | 0.0137 | 7.60 | 0.000 | [ 0.0771, 0.1307] |
| construction | -0.0890*** | 0.0227 | -3.93 | 0.000 | [ -0.1334, -0.0445] |
| trade | -0.1265*** | 0.0160 | -7.87 | 0.000 | [ -0.1580, -0.0950] |
| transport | -0.0273 | 0.0223 | -1.23 | 0.218 | [ -0.0710, 0.0162] |
| bank_insurance | 0.3654*** | 0.0271 | 13.47 | 0.000 | [ 0.3122, 0.4186] |
| partnership | 0.1692*** | 0.0116 | 14.63 | 0.000 | [ 0.1465, 0.1917] |
| number_of_children_in_HH | 0.0281*** | 0.0052 | 5.35 | 0.000 | [ 0.0177, 0.0384] |
| life_satisfaction | 0.0278*** | 0.0033 | 8.42 | 0.000 | [ 0.0213, 0.0343] |
| maternity_benefit | 0.0002*** | 0.0001 | 4.17 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.6935*** | 0.0410 | 41.30 | 0.000 | [ 1.6131, 1.7738] |

Results from OLS regression for the year 2016. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

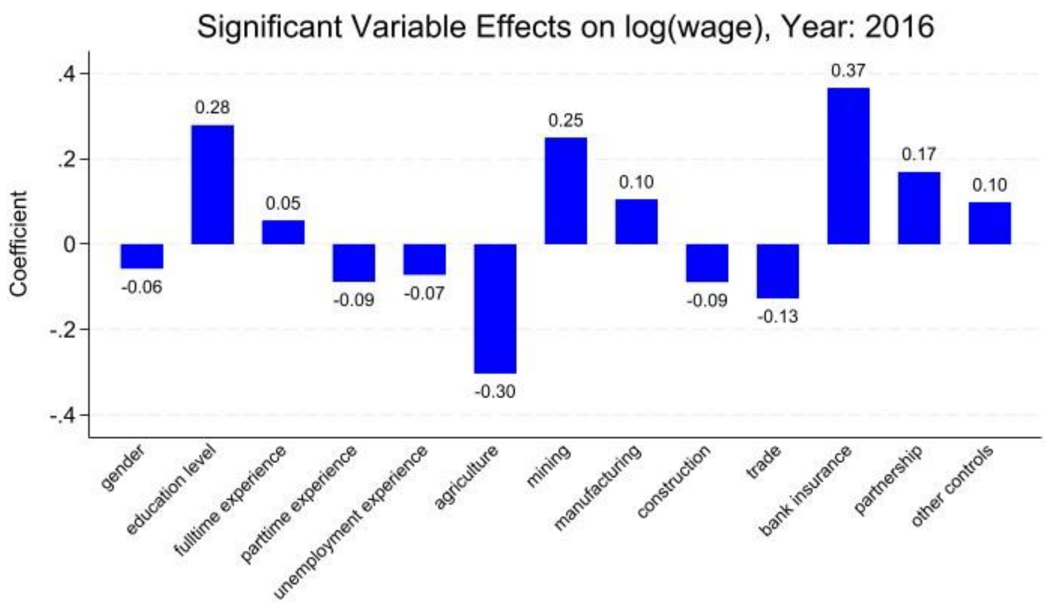


*Figure A4. Significant variables from the OLS Regression 2016.*

**Table 7: OLS Regression Results for 2017**

**Linear regression**

| | |
|---|---|
| Number of obs | **16,230** |
| F(18, 16211) | **330.01** |
| Prob > F | **0.0000** |
| R-squared | **0.2978** |
| Root MSE | **0.5893** |

| Variable | Coef. | Std. Err. | t | P> $\|t\|$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0666*** | 0.0116 | -5.74 | 0.000 | [ -0.0893, -0.0439] |
| educ_level | 0.2831*** | 0.0083 | 34.19 | 0.000 | [ 0.2669, 0.2994] |
| fulltime_experience | 0.0464*** | 0.0057 | 8.15 | 0.000 | [ 0.0353, 0.0576] |
| exp_ft_sq | -0.0018*** | 0.0006 | -3.04 | 0.002 | [ -0.0030, -0.0006] |
| parttime_experience | -0.0445*** | 0.0131 | -3.39 | 0.001 | [ -0.0702, -0.0187] |
| exp_pt_sq | 0.0241*** | 0.0030 | 8.10 | 0.000 | [ 0.0182, 0.0299] |
| unemployment_experience | -0.0679*** | 0.0039 | -17.27 | 0.000 | [ -0.0756, -0.0602] |
| agriculture | -0.3330*** | 0.0498 | -6.69 | 0.000 | [ -0.4306, -0.2356] |
| mining | 0.0708 | 0.0842 | 0.84 | 0.401 | [ -0.0943, 0.2359] |
| manufacturing | 0.1188*** | 0.0125 | 9.51 | 0.000 | [ 0.0943, 0.1433] |
| construction | -0.1276*** | 0.0214 | -5.96 | 0.000 | [ -0.1693, -0.0856] |
| trade | -0.1333*** | 0.0142 | -9.35 | 0.000 | [ -0.1611, -0.1052] |
| transport | -0.0493** | 0.0207 | -2.38 | 0.017 | [ -0.0900, 0.0086] |
| bank_insurance | 0.3762*** | 0.0230 | 16.34 | 0.000 | [ 0.3311, 0.4214] |
| partnership | 0.1730*** | 0.0101 | 17.12 | 0.000 | [ 0.1532, 0.1928] |
| number_of_children_in_HH | 0.0246*** | 0.0048 | 5.05 | 0.000 | [ 0.0150, 0.0342] |
| life_satisfaction | 0.0353*** | 0.0033 | 10.69 | 0.000 | [ 0.0288, 0.0419] |
| maternity_benefit | 0.0002*** | 0.0001 | 4.02 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.7035*** | 0.0351 | 48.56 | 0.000 | [ 1.6347, 1.7722] |

Results from OLS regression for the year 2017. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

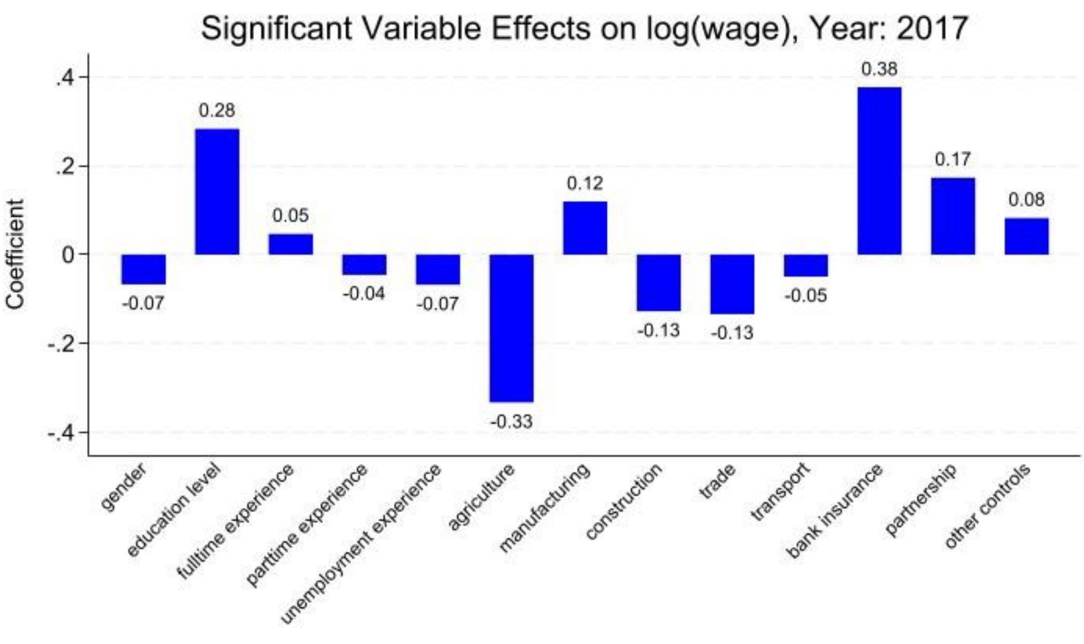


*Figure A5. Significant variables from the OLS Regression 2017.*

Table 8: **OLS Regression Results for 2018**

**Linear regression**

| | |
|---|---|
| Number of obs | **15,841** |
| F(18, 15822) | **350.92** |
| Prob > F | **0.0000** |
| R-squared | **0.3063** |
| Root MSE | **0.5946** |

| Variable | Coef. | Std. Err. | t | P> $\lvert t \rvert$ | 95% Conf. Interval |
|---|---|---|---|---|---|
| female | -0.0380*** | 0.0117 | -3.23 | 0.001 | [ -0.0610, -0.0150] |
| educ_level | 0.2664*** | 0.0080 | 33.12 | 0.000 | [ 0.2506, 0.2822] |
| fulltime_experience | 0.0549*** | 0.0053 | 10.44 | 0.000 | [ 0.0446, 0.0652] |
| exp_ft_sq | -0.0017*** | 0.0005 | -3.44 | 0.001 | [ -0.0026, -0.0008] |
| parttime_experience | -0.0262** | 0.0118 | -2.22 | 0.027 | [ -0.0495, -0.0030] |
| exp_pt_sq | 0.0186*** | 0.0022 | 8.16 | 0.000 | [ 0.0142, 0.0231] |
| unemployment_experience | -0.0561*** | 0.0036 | -15.72 | 0.000 | [ -0.0630, -0.0491] |
| agriculture | -0.2519*** | 0.0594 | -4.21 | 0.000 | [ -0.3692, -0.1346] |
| mining | 0.0922 | 0.1216 | 0.76 | 0.448 | [ -0.1461, 0.3304] |
| manufacturing | 0.1320*** | 0.0123 | 10.73 | 0.000 | [ 0.1079, 0.1562] |
| construction | -0.0996*** | 0.0214 | -4.66 | 0.000 | [ -0.1415, -0.0577] |
| trade | -0.0965*** | 0.0158 | -6.08 | 0.000 | [ -0.1277, -0.0654] |
| transport | -0.0244 | 0.0312 | -0.78 | 0.433 | [ -0.0856, 0.0367] |
| bank_insurance | 0.3992*** | 0.0265 | 15.08 | 0.000 | [ 0.3472, 0.4509] |
| partnership | 0.1817*** | 0.0104 | 17.49 | 0.000 | [ 0.1613, 0.2020] |
| number_of_children_in_HH | 0.0247*** | 0.0048 | 5.06 | 0.000 | [ 0.0152, 0.0343] |
| life_satisfaction | 0.0358*** | 0.0033 | 10.66 | 0.000 | [ 0.0292, 0.0424] |
| maternity_benefit | 0.0002*** | 0.0001 | 4.70 | 0.000 | [ 0.0001, 0.0003] |
| _cons | 1.6266*** | 0.0314 | 47.61 | 0.000 | [ 1.5588, 1.6926] |

Results from OLS regression for the year 2018. Dependent variable is the logarithm of hourly gross wages. Significance levels: *p<0.1; **p<0.05; ***p<0.01

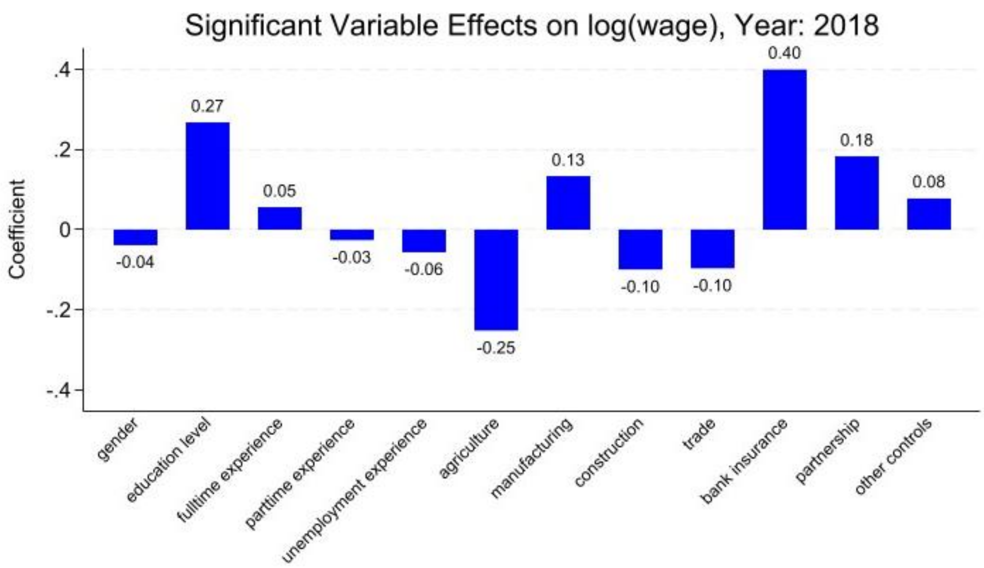


*Figure A6. Significant variables from the OLS Regression 2018.*

Table 9: **OLS Regression Results for 2019**

**Linear regression**

| | |
|---|---|
| Number of obs | **16,072** |
| F(18, 16053) | **318.23** |
| Prob > F | **0.0000** |
| R-squared | **0.2842** |
| Root MSE | **0.6522** |

| **Variable** | **Coef.** | **Std. Err.** | **t** | **P> $\|t\|$** | **95% Conf. Interval** |
|---|---|---|---|---|---|
| female | -0.0525*** | 0.0125 | -4.19 | 0.000 | [ -0.0771, -0.0279] |
| educ_level | 0.3025*** | 0.0087 | 34.61 | 0.000 | [ 0.2853, 0.3196] |
| fulltime_experience | 0.0112** | 0.0053 | 2.30 | 0.021 | [ 0.0017, 0.0215] |
| exp_ft_sq | -0.0000 | 0.0004 | -0.04 | 0.970 | [ -0.0008, 0.0008] |
| parttime_experience | -0.0410*** | 0.0112 | -3.66 | 0.000 | [ -0.0631, -0.0190] |
| exp_pt_sq | 0.0144*** | 0.0019 | 7.32 | 0.000 | [ 0.0105, 0.0182] |
| unemployment_experience | -0.0825*** | 0.0034 | -24.10 | 0.000 | [ -0.0892, -0.0758] |
| agriculture | -0.2773*** | 0.0529 | -5.24 | 0.000 | [ -0.3810, -0.1735] |
| mining | 0.0293 | 0.2210 | 0.13 | 0.894 | [ -0.4039, 0.4626] |
| manufacturing | 0.1489*** | 0.0136 | 10.88 | 0.000 | [ 0.1224, 0.1757] |
| construction | -0.0052 | 0.0249 | -0.21 | 0.836 | [ -0.0539, 0.0435] |
| trade | -0.0070 | 0.0175 | -0.39 | 0.694 | [ -0.0413, 0.0274] |
| transport | 0.0214 | 0.0381 | 0.56 | 0.576 | [ -0.0534, 0.0961] |
| bank_insurance | 0.4316*** | 0.0278 | 15.47 | 0.000 | [ 0.3766, 0.4866] |
| partnership | 0.1904*** | 0.0114 | 16.63 | 0.000 | [ 0.1679, 0.2128] |
| number_of_children_in_HH | 0.0249*** | 0.0052 | 4.77 | 0.000 | [ 0.0147, 0.0352] |
| life_satisfaction | 0.0377*** | 0.0038 | 9.76 | 0.000 | [ 0.0301, 0.0452] |
| maternity_benefit | 0.0000*** | 0.0000 | 2.94 | 0.003 | [ 0.0000, 0.0000] |
| _cons | 1.7890*** | 0.0386 | 46.29 | 0.000 | [ 1.7132, 1.8646] |

Results from OLS regression for the year 2019. Dependent variable is the logarithm of hourly gross wages. Significance levels: *p<0.1; **p<0.05; ***p<0.01

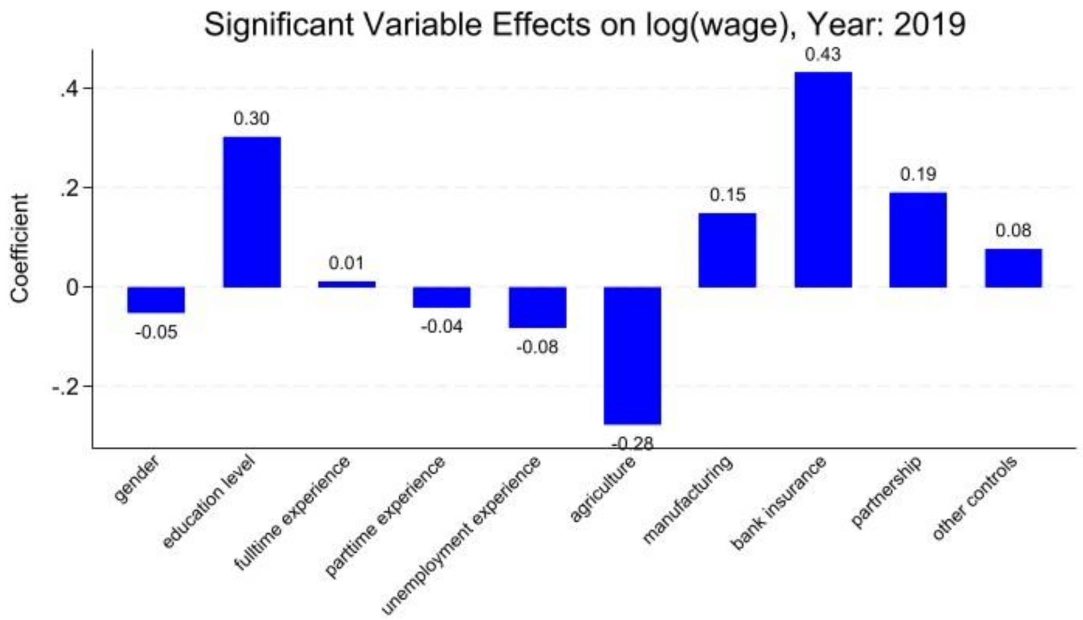


*Figure A7. Significant variables from the OLS Regression 2019*

## Table 10: OLS Regression Results for 2020

**Linear regression**

| | |
|---|---|
| Number of obs | **16,701** |
| F(18, 16682) | **323.82** |
| Prob > F | **0.0000** |
| R-squared | **0.2644** |
| Root MSE | **0.6693** |

| **Variable** | **Coef.** | **Std. Err.** | **t** | **P> $\|t\|$** | **95% Conf. Interval** |
|---|---|---|---|---|---|
| female | -0.0752*** | 0.0125 | -6.02 | 0.000 | [ -0.0998, -0.0507] |
| educ_level | 0.2662*** | 0.0079 | 33.82 | 0.000 | [ 0.2507, 0.2816] |
| fulltime_experience | 0.0587*** | 0.0046 | 12.67 | 0.000 | [ 0.0496, 0.0679] |
| exp_ft_sq | -0.0024*** | 0.0004 | -6.72 | 0.000 | [ -0.0031, -0.0017] |
| parttime_experience | -0.0030 | 0.0101 | -0.29 | 0.769 | [ -0.0229, 0.0169] |
| exp_pt_sq | 0.0105*** | 0.0016 | 6.42 | 0.000 | [ 0.0073, 0.0137] |
| unemployment_experience | -0.0551*** | 0.0027 | -20.03 | 0.000 | [ -0.0604, -0.0497] |
| agriculture | -0.2036*** | 0.0583 | -3.49 | 0.000 | [ -0.3179, -0.0894] |
| mining | -0.0727 | 0.1371 | -0.53 | 0.596 | [ -0.3415, 0.1961] |
| manufacturing | 0.1169*** | 0.0146 | 7.96 | 0.000 | [ 0.0882, 0.1457] |
| construction | -0.0749*** | 0.0255 | -2.93 | 0.003 | [ -0.1250, -0.0248] |
| trade | -0.0598*** | 0.0189 | -3.15 | 0.002 | [ -0.0970, -0.0226] |
| transport | -0.0290 | 0.0378 | -0.77 | 0.442 | [ -0.1033, 0.0451] |
| bank_insurance | 0.4085*** | 0.0314 | 12.99 | 0.000 | [ 0.3469, 0.4701] |
| partnership | 0.1976*** | 0.0115 | 17.08 | 0.000 | [ 0.1749, 0.2203] |
| number_of_children_in_HH | 0.0197*** | 0.0053 | 3.69 | 0.000 | [ 0.0092, 0.0302] |
| life_satisfaction | 0.0192*** | 0.0036 | 5.32 | 0.000 | [ 0.0121, 0.0263] |
| maternity_benefit | 0.0000*** | 0.0000 | 4.10 | 0.000 | [ 0.0000, 0.0001] |
| _cons | 1.8445*** | 0.0343 | 53.67 | 0.000 | [ 1.7771, 1.9118] |

Results from OLS regression for the year 2020. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

**Table 11: OLS Regression Results for 2021**

**Linear regression**

| | |
|---|---|
| Number of obs | **10,115** |
| F(18, 10096) | **139.03** |
| Prob > F | **0.0000** |
| R-squared | **0.2025** |
| Root MSE | **0.7092** |

| **Variable** | **Coef.** | **Std. Err.** | **t** | **P> $\|t\|$** | **95% Conf. Interval** |
|---|---|---|---|---|---|
| female | -0.0614*** | 0.0169 | -3.62 | 0.000 | [ -0.0946, -0.0282] |
| educ_level | 0.2149*** | 0.0109 | 19.65 | 0.000 | [ 0.1935, 0.2364] |
| fulltime_experience | 0.0401*** | 0.0061 | 6.54 | 0.000 | [ 0.0281, 0.0521] |
| exp_ft_sq | -0.0015*** | 0.0004 | -3.59 | 0.000 | [ -0.0023, -0.0006] |
| parttime_experience | -0.0055 | 0.0124 | -0.45 | 0.652 | [ -0.0299, 0.0187] |
| exp_pt_sq | 0.0063*** | 0.0018 | 3.47 | 0.001 | [ 0.0027, 0.0099] |
| unemployment_experience | -0.0542*** | 0.0035 | -15.29 | 0.000 | [ -0.0611, -0.0472] |
| agriculture | -0.2284*** | 0.0863 | -2.65 | 0.008 | [ -0.3975, -0.0593] |
| mining | 0.3055 | 0.3005 | 1.02 | 0.309 | [ -0.2836, 0.8947] |
| manufacturing | 0.0832*** | 0.0207 | 4.01 | 0.000 | [ 0.0426, 0.1233] |
| construction | -0.0420 | 0.0354 | -1.19 | 0.234 | [ -0.1113, 0.0273] |
| trade | -0.1378*** | 0.0279 | -4.94 | 0.000 | [ -0.1925, -0.0831] |
| transport | -0.0608*** | 0.0514 | -1.18 | 0.238 | [ -0.1616, 0.0040] |
| bank_insurance | 0.3629*** | 0.0363 | 9.98 | 0.000 | [ 0.2916, 0.4341] |
| partnership | 0.1960*** | 0.0155 | 12.64 | 0.000 | [ 0.1656, 0.2264] |
| number_of_children_in_HH | 0.0055 | 0.0075 | 0.74 | 0.457 | [ -0.0092, 0.0203] |
| life_satisfaction | 0.0201** | 0.0047 | 4.26 | 0.000 | [ 0.0108, 0.0294] |
| maternity_benefit | 0.0000*** | 0.0001 | 2.25 | 0.024 | [ 0.0000, 0.0000] |
| _cons | 2.1402*** | 0.0471 | 45.41 | 0.000 | [ 2.0478, 2.2326] |

Results from OLS regression for the year 2021. Dependent variable is the logarithm of hourly gross wages.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

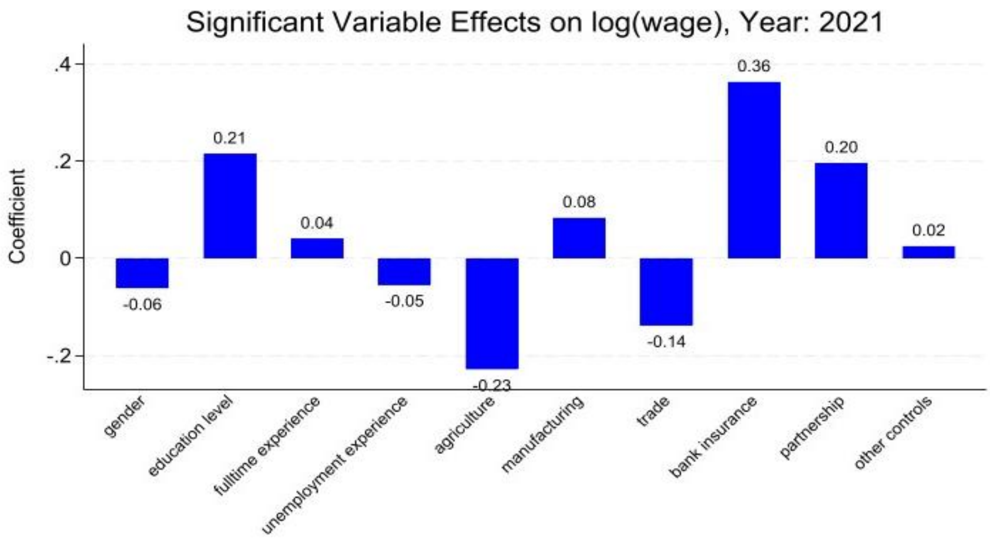


*Figure A8. Significant variables from the OLS Regression 2021.*