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A Time of Progress or Persistent Inequality? Assessing the Gender Wage Gap Post-2010

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ABSTRACT

Die Lohnunterschiede zwischen den Geschlechtern haben sich in den letzten Jahrzehnten erheblich verringert. In dieser Arbeit wird der Zeitraum nach 2010 anhand von Current Population Survey (CPS)-Daten untersucht. Wie die Analyse zeigt, hat sich der Trend der vergangenen Jahre nicht fortgesetzt, und in den letzten Jahren ist eine beunruhigende Stagnation zu beobachten. Darüber hinaus haben die Humankapitalvariablen bei der Erklärung der Unterschiede zwischen den Löhnen von Männern und Frauen an Kraft verloren. Die Variablen Gewerkschaftszugehörigkeit, Industrie und Beruf haben immer noch eine gewisse Erklärungskraft, die jedoch deutlich geringer als im 20. Jahrhundert ist. Diese Forschung soll einen Beitrag zu den Bemühungen um mehr Gerechtigkeit am Arbeitsplatz und zur weiteren Verringerung der Lohnunterschiede zwischen den Geschlechtern leisten.

TABLE OF CONTENTS

1. INTRODUCTION

The gender wage gap is a topic of concern in the field of economics and beyond, particularly in the past few years. Despite progress in narrowing the gap in previous decades, recent research suggests that there is still a significant gap between the wages of males and females in the United States, as well as in the rest of the world. This issue has received increasing attention, reflecting broader societal concerns about gender equality and fairness in remuneration. This thesis seeks to examine the gender wage gap after 2010 and identify the extent of the gap, trends over time, and potential explanations.

From a long-term point of view, a considerable reduction in the gender pay disparity has been observed in the United States and other economically advanced countries (Blau & Kahn, 2008). On the other hand, a short-term perspective shows no clear pattern (Blau & Kahn, 2017). This research builds on the influential paper by Blau and Kahn (2017), which provides a comprehensive synopsis of the gender wage gap and its explanations up until 2010. Since then, there have been significant changes in the labor market, policy landscape, and state and federal legislation. Therefore, it is still important to update our understanding of the gender wage gap and find the variable that could help explain this phenomenon more accurately. Figure 1 depicts real earnings ratios for hourly earnings (blue) and weekly earnings (green, dashed). It shows how much percentage of a man's wage a woman earns on average.

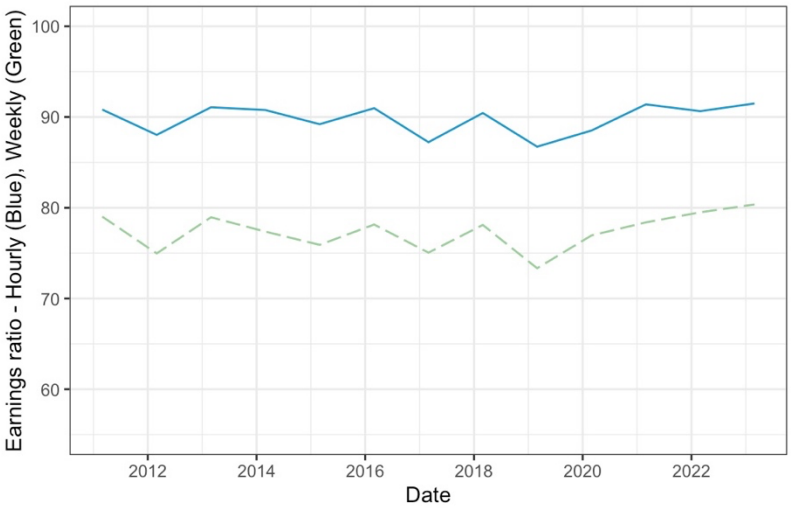

Figure 1. Female to male real earning ratios, hourly in blue, weekly in green dashed.
Source of the data: CPS data and historical consumer price index
Notes: Gross hourly and weekly wage in US dollars, deflated using the CPI (base year is 2011)

Supporting the importance of explaining the wage differences, according to the CPS data[1], women earn considerably less on average, and the ratio does not grow over time. Considering that women also work, on average, fewer hours than men, their weekly salary is even lower and, therefore, the gap is even wider.

Real wage rates for both genders are graphically illustrated separately in Figure 2. Despite the rise of real wages in both groups from 2011 to 2023, this picture nicely depicts the raw gap's persistence over the observed period. There has been no significant change over the past 12 years. The gap is not narrowing significantly and not opening wider. This thesis addresses the research question of how the gender wage gap evolved in the post-2010 era and how it compares to previous periods. It is crucial to recognize the main factors that drive the

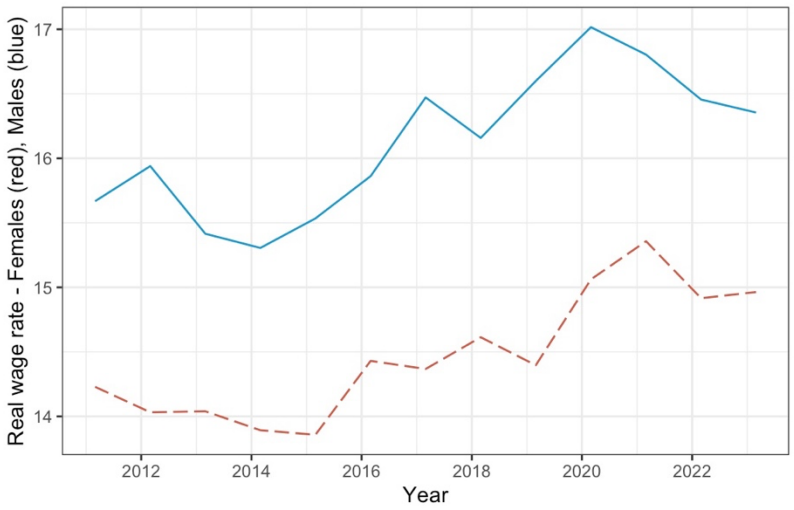

Figure 2. *The real wage rate for females is in red dashed and for males in blue.*
Source of the data: CPS data and historical consumer price index.
Notes: Gross hourly wage in US dollars, deflated using the CPI (base year is 2011)

gender wage gap and how these have changed over time. There also may be differences in different races, ethnicities, age groups, and other demographic characteristics. This research has important implications for policy and practice, as it can inform efforts to promote workplace equity and narrow the gender wage gap. By identifying the elements that contribute to the disparity and their relative importance, this research can help policymakers and employers develop targeted interventions to address the gap and promote gender equity. This thesis aims to examine the progress made in reducing the gender wage gap since 2010 and

[1] https://www.census.gov/data/datasets/time-series/demo/cps/cps-basic.2024.html#list-tab-1979780401

emphasize the importance of explaining it because, despite the efforts to address this problem, the gender wage gap remains.

I will conduct an empirical analysis using data from the Current Population Survey (CPS) to answer these questions. I will employ various econometric techniques to estimate the gender wage gap and its determinants, including OLS regression and decomposition methods. The thesis is organized as follows. In section 2, I begin with a summary of previous research papers on the gender wage gap. In the third section, I describe the data I use for this thesis, and in section 4, I do the empirical analysis. In the last section, number 5, I summarize my results and conclude.

2. Literature Review

Wedad Andrada Quffas emphasizes the importance of gender inequality topics in the paper "A Review of the History of gender equality in the United States of America." the Global Gender Gap Index Report confirms a correlation between the GDP per capita and gender inequality. Therefore, the gender pay gap is not only a discrimination issue but could be directly connected to the development of a country. In recent times, the most significant narrowing of the gender inequality gap was achieved in the economy and employment. On the other hand, despite the significant positive changes and entering women into the labor force more often than before, women still struggle with finding a first job, working full-time, and earning the same wage as the opposite sex. It may also be that women more often decide on a job that allows them to spend more time with their families. It opens debates about whether women choose to work part-time constantly more than men or if the risk-aversion of females could not cause the possible reason for the particular choice of a lower-paid job (Quffa, 2016).

Regarding wages, legislation in the United States does not allow differences between males and females, between races or colors. Everybody should be paid equally for the same job, but the reality of enacting is rather challenging. It is still noticeable that there is an ascendant of males over females at senior job levels. Therefore, it stands to reason that it is not possible to explain the gender wage gap only by human capital or the choice of part-time over full-time jobs (Quffa, 2016).

A step towards reducing gender inequality in the past was prohibiting wage discrimination between the sexes in 1963. The Equal Pay Act (EPA) ensures that employers cannot pay different wages to employees of different genders for the same work and under the same conditions. This prevents employers from discriminating against males and females in the workplace and provides them with equal protection (Quffa, 2016).

Blau and Kahn underline the seriousness of explaining gender inequality in several publications. Among the most notable is a paper titled "The Gender Wage Gap: Extent, Trends, and Explanations" (2017), which this master's thesis builds upon. The authors examine the comprehensive analysis of the gender wage gap, drawing on broad empirical evidence from various datasets and studies. They emphasize the persistence of the gap over time despite advancements in gender equality policies and increased female labor force participation. Blau and Kahn explain in detail the factors contributing to the inequality in wages of males and females, including differences in human capital investment, occupational segregation, and discrimination. They point out how education, job experience, and occupational choice affect the differences in earnings between men and women.

Moreover, the authors discuss the impact of minimum wage laws or collective bargaining on mitigating or worsening gender wage disparities. They provide critical insights into the complexities of this gender pay gap and how it impacts economic inequality and social welfare. They stress the need for ongoing research and policy efforts to address the underlying causes of the wage gap and foster more significant gender equity in the labor market.

For their analysis, Blau and Kahn used the Blinder-Oaxaca decomposition technique, which is likewise used in this thesis. They describe the unexplained part of the Blinder-Oaxaca decomposition as the estimate for discrimination, where workers with the same qualifications do not get equal pay. However, the unexplained gap may result from unmeasured variables such as productivity.

One of the principal findings of their research is, among other things, that women increased their human capital over the period from 1980 to 2010 and thus became, in fact, similar to males. While in the 80s, it was possible to explain a considerable part of the gender wage gap with variables such as education, work experience, race, or region of living, in 2010, only a tiny part. They describe these variables as human capital variables. Therefore, it became

more important to concentrate on other factors that may help to explain the gap. Blau and Kahn added controls for occupation, industry, and unionization to their model, thereby enabling them to clarify a more significant portion of the gender wage gap.

3. DATA

To conduct the analysis, I decided to work with Current Population Survey data or, shortly, CPS data. The survey samples around 60,000 occupied households each month from all 50 states of the United States of America and the District of Columbia. Participants are engaged in the study for four months, take an eight-month break, and then rejoin for another four months before exiting the sample eternally. This scheme provides a high level of consistency maintained between each consecutive month and throughout the entire year. It offers the additional advantage of enabling the continuous replenishment of the sample without overwhelmingly burdening the respondents. The CPS serves as the primary provider of labor force statistics for the United States population. The questionnaire for labor force participation is computerized and contains about 200 questions. However, by utilizing aggregate bound patterns that consider the responses to multiple questions, the survey ensures that respondents are posed with only a restricted number of self-related inquiries. The CPS samples data from households and their members that must be at least 15 years old and not in the Armed Forces. There is no upper bound for the age limit. However, the entries for ages above 85 years are top-coded. A reference person always answers questions for the whole household or, more precisely, for all eligible members. The Current Population Survey sample uses a probability-based sampling method to generate labor force characteristic estimates, including the civilian non-institutional population over 15 years old. In each state and the District of Colombia, samples are precisely modified to conditions that reign in the specific area. Eventually, around 60,000 households are chosen each month to represent the 824 sample areas[2].

For this analysis, the data for the month of March were chosen for the years from 2011 to 2023. March CPS data are widely used for different analyses as yearly data. The reason for

[2] The source for the information about CPS data is the webpage of the United State Census Bureau https://www.census.gov/programs-surveys/cps/technical-documentation/methodology.html, and U.S. Census Bureau, Current Population Survey Design and Methodology Technical Paper 77, October 2019.

selecting March data is that, unlike other moths, these always contain additional information about a household's annual income. Regrettably, this information is accessible only for whole households and not for individuals, which renders it unvalued or irrelevant to this research. To conduct the main analysis of this master thesis, the sample was restricted to specific criteria - it includes only full-time nonfarm wage and salary workers ages 25–64. The CPS data are censored. The variable for hourly wages is top-coded, meaning that the variable is limited at a specific upper bound. This is often done to handle extreme or outlier values that can disproportionately affect the results of an analysis. It is essential to deal with top coding when analyzing data. However, after checking the dataset, only very few observations were top-coded.

Table 1 summarizes the average hourly wages and usual weekly hours worked for full-time workers, separately for males and females. As Figure 1 suggests in section 1, women's hourly wage is, on average, lower over the whole observed period than men's. Moreover, females work fewer weekly hours on average, leading to a lower weekly and, thus, monthly or annual income.

TABLE 1

AVERAGE HOURLY WAGES AND USUAL WEEKLY HOURS, FULL-TIME WORKERS BY GENDER

	Men		*Women*	
Year	*Wage*	*Hours*	*Wage*	*Hours*
2011	*15.67*	*36.06*	*14.23*	*32.09*
2015	*15.53*	*36.80*	*13.86*	*32.67*
2019	*16.60*	*36.98*	*14.20*	*32.94*
2023	*16.41*	*36.93*	*14.96*	*33.52*

Notes: Gross hourly wage in US dollars, deflated using the CPI (base year is 2011)

Table 2 depicts unadjusted female-to-male log wage ratios for full-time workers. The mean log wage ratios are similar over the observed periods. The numbers are slightly below the 90 percent border. Higher ratios appear at the tenth percentile. The fiftieth and the ninetieth percentiles depict similar proportions as are on the means. The highest mean

percentile is for the year 2011, meaning that females earned, on average, 89.93 percent of the male wage this year. The most significant raw difference was observed in 2019, when females made only a scant 86 percent of male salaries.

TABLE 2

UNADJUSTED FEMALE/MALE LOG HOURLY WAGE RATIOS, FULL-TIME WORKERS

	Sample size					
Year	*Men*	*Women*	*Mean*	*Tenth percentile*	*Fiftieth percentile*	*Ninetieth percentile*
2011	*1733*	*1654*	*89.93%*	*94.44*	*89.40*	*90.00*
2015	*1723*	*1546*	*88.82%*	*90.00*	*88.75*	*89.19*
2019	*1614*	*1501*	*85.99%*	*87.50*	*88.62*	*82.35*
2023	*1201*	*1130*	*88.97%*	*93.33*	*88.41*	*85.71*

Notes: The sample comprises nonfarm wage and salary workers aged 25–64. Entries are exp(D), where D is the mean log wage of females, tenth, fiftieth, or ninetieth percentile log wage minus the corresponding log wage of males.

The means of some variables used for the analysis are summarized in Table 3 and Table 4. One of the variables that has mainly changed over time is the degree of education. According to the data from Blau and Kahn's publication (2017), women had, on average, less education in the 80s and 90s years of the last century. This has changed in the past few decades, and as the CPS data show, nowadays, women overjump men in the years of schooling. In particular, a more significant proportion of females get a higher educational degree than males. Logically, it leads to higher proportions of men with no high school diploma or degree. There have been no significant changes over time in the percentage of differences in education. However, the percentages of less educated people (no high school diploma or no degree) show a decreasing trend. On the other side, more and more people are interested in higher education degrees. In 2011, 13.79 percent of men did not finish high school and had only primary education. This proportion dropped to 9.66 percent in the 2023. A similar trend appears in women, too. The percentage of females with the lowest schooling decreased from 9.67 percent in 2011 to 5.93 percent in 2023.

Most of the population decides to finish their education with a high school diploma. Even though the percentage of men with only a high school diploma declined by 3.56 percent over the observed period and by women, a drop from 55.14 percent to 50.35 percent is

TABLE 3

SCHOOLING BY GENDER

Year	*Men*	*Women*	*Difference: Men–Women*
No high school diploma			
2011	*13.79%*	*9.67%*	*4.12%*
2015	*12.48%*	*7.63%*	*4.85%*
2019	*11.59%*	*7.13%*	*4.46%*
2023	*9.66%*	*5.93%*	*3.73%*
High school diploma			
2011	*61.51%*	*55.14%*	*6.37%*
2015	*59.49%*	*52.59%*	*6.90%*
2019	*57.13%*	*51.43%*	*5.70%*
2023	*57.95%*	*50.35%*	*7.60%*
Bachelor's or associate degree			
2011	*11.31%*	*15.66%*	*-4.35%*
2015	*11.26%*	*16.56%*	*-5.30%*
2019	*14.87%*	*19.99%*	*-5.12%*
2023	*15.24%*	*19.82%*	*-4.58%*
Advanced degree			
2011	*2.60%*	*4.17%*	*-1.57%*
2015	*3.48%*	*5.50%*	*-2.02%*
2019	*3.59%*	*5.53%*	*-1.94%*
2023	*4.00%*	*7.17%*	*-3.17%*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. High school diploma includes also individuals with some college education but without any degree. Advanced degree includes master's degree, professional school degree and doctorate degree. All differences are statistically significantly at 5% level.

observed, this type of education is still the leader among people's choices. As data show, studying at college or university is becoming more popular. In both gender groups, we see an increase of about 4 percent in bachelor's and associate degrees over the observed period, for advanced degree education decides the minor proportion of the population. It is 4 percent in the male group in 2023 and in the female group, 7.17 percent.

Table 4 presents the fraction of people working in managerial and professional occupations and collective bargaining coverage. Surprisingly, managerial and professional

occupations perform women markedly more often than men. The male fraction of workers registered faster growth in this sphere, from 13.56 percent in 2011 to 17.57 percent in 2023, which makes total growth by 4.01 percent. The female fraction falls behind in the speed of change, registering an increase of 2.37 percent. Regarding collective bargaining coverage, only around 8-10 percent of women are employed in occupations with collective bargaining. Men in the United States act more frequently in jobs with collective bargaining coverage. For example, in 2023, it was, on average, by 5.66 percent more than women.

TABLE 4

INCIDENCE OF MANAGERIAL OR PROFESSIONAL OCCUPATIONS AND COLLECTIVE BARGAINING COVERAGE BY GENDER

Year	*Men*	*Women*	*Difference: Men–Women*
Managerial and professional occupations			
2011	*13.56%*	*29.75%*	*-16.19%*
2015	*14.34%*	*31.18%*	*-16.84%*
2019	*18.40%*	*33.44%*	*-15.04%*
2023	*17.57%*	*32.12%*	*-14.55%*
Collective-bargaining coverage			
2011	*18.81%*	*9.43%*	*9.38%*
2015	*14.92%*	*9.64%*	*5.28%*
2019	*13.44%*	*8.59%*	*4.85%*
2023	*15.57%*	*9.91%*	*5.66%*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. All differences are statistically significant at 5% level.

According to the percentages presented in Tables 3 and 4, women have, on average, a higher degree of education than men and, more often, have a managerial or professional position. This could lead to the prediction that females should earn, on average, more than males, which is not valid, as shown in Table 2. Therefore, there must be another explanation for why there is gender inequality in wages and what should change to reach equal pay.

4. MODEL

For the empirical analysis of the gender wage gap at the mean, there is usually applied Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973; Neumark, 1988; Reimers, 1983;

Cotton, 1988; Oaxaca & Ransom, 1995). The gender wage gap is examined using this decomposition for four years: 2011, 2015, 2019, and 2023. The reason for choosing these years for the observation is the intent to resume Blau and Kahn's work (2017). In their paper "The Gender Wage Gap: Extent, Trends, and Explanations," they examined the gap in the period from 1980 up until 2010. The simple mean from Table 2 shows no clear pattern in the development of the gender wage gap. Unlike the period observed in the Blau and Kahn paper, where the unadjusted female /male log hourly wage ratios increase over time, the period from 2010 to 2023 shows relatively constant ratios. The only minor decrease was observed in 2019, emphasizing the importance of explaining the gender wage gap.

The first step in the Blinder-Oaxaca model is to estimate two wage regressions, one for females (f) and one for males (m), using ordinary least squares (OLS):

$$Y_{if} = X_{if}B_f + u_{if} \tag{1}$$

$$Y_{im} = X_{im}B_m + u_{im} \tag{2}$$

where Y is the log of hourly wages of an individual $i=1,2,...,N$, B is a vector of coefficients, X is a vector of explanatory characteristics, and u is an error term. The explanatory factors include Education, Age, Region, Race, Unionization, Industry, and Occupation. Education and Age are so-called Human Capital variables used for the first part of the analysis, together with the essential characteristics of Race and Region as explanatory variables (Blau & Kahn, 2017). The variable Age is supposed to replace a person's work experience, which is, unfortunately, not available for this dataset. The remaining explanatory variables are added to the model in the second part, labeled as Full Specification (Blau & Kahn, 2017). Unionization, industry, and occupation could help explain differences other than human capital and offer a broader view of the gender wage gap from new perspectives. Unionization is a dummy variable that represents whether a person is a labor union member. Industry is a categorical variable for fourteen categories of different industries, and the variable Occupation represents seven categories of occupations.

Since the OLS can be estimated with constant terms that produce zero mean, the difference in the means of wages can be decomposed as follows:

$$\bar{Y}_m - \bar{Y}_f = \beta_m\bar{X}_m - \beta_f\bar{X}_f = \beta_m\left(\bar{X}_m - \bar{X}_f\right) + \bar{X}_f(\beta_m - \beta_f) \tag{3}$$

where β_m is the OLS estimate of B_m and β_f is the OLS estimate of B_f. The first term on the right-hand side of the equation, $\beta_m(\bar{X}_m - \bar{X}_f)$, represents the influence of gender disparities in the explanatory variables, calculated using the male coefficients. The second component, $\bar{X}_f(\beta_m - \beta_f)$, represents the unexplained part of the decomposition. This differential pertains to the average female residual from the male wage equation. The decomposition is calculated separately for each of the four observed years.

The decomposition uses male coefficients and female means. To obtain the main result in Figure 3, the exponential of the unexplained part of the decomposition is taken, resulting in the female-to-male wage ratio. This is done separately, controlling for human capital and full specification variables. Indeed, these results represent the prediction of female wages using male characteristics compared to the actual female wage. The difference in the predicted and actual female wage may also be perceived as discrimination against women in the labor market.

As mentioned in section 3, top-coded data require special treatment. Instead of using OLS regressions in the decomposition, one should use the so-called Tobit regression or censored regression, introduced by J. Tobin (1958) and developed by Arthur Goldberg (1964). When the dependent variable is subject to censoring, as with hourly wage censored from above, it implies that observations with values at or above a certain threshold are all recorded as equal to that threshold. As a result, the actual value may either be precisely at the threshold or potentially higher. The analysis was done using both OLS and Tobit regressions. Since only a few observations were top-coded, the Tobit regression results were comparable to those of the OLS regression results. Therefore, only OLS results are presented in this thesis. For Tobit regression results, see chapter 9. Appendix.

5. RESULTS

The results are separately presented for each of the four observed periods: 2011, 2015, 2019, and 2023. There are always two decompositions for each year, one that only controls for human capital variables and one that controls for the full specification.

Table 5 lists the results of Human Capital Specification in 2011. The first two columns list coefficients β_m for males and β_f for females for each human capital variable. The further column lists the influences of gender disparities in the explanatory variables (log points), which is the difference in the male-female mean of the variable multiplied by the male coefficient for the corresponding variable. This term is also called the explanatory part of the Blinder-Oaxaca decomposition. The last column contains the percentage of the gender gap explained.

TABLE 5

Decomposition RESULTS FOR 2011 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2168*	*0.2613*	*0.0172*	*16.21*
Some college (no degree)	*0.2995*	*0.3230*	*-0.0047*	*-4.43*
Associate degree – occupational/vocational	*0.3964*	*0.4568*	*-0.0077*	*-7.26*
Associate degree-academic program	*0.3499*	*0.5135*	*-0.0091*	*-8.58*
Bachelor's degree	*0.3879*	*0.6537*	*-0.0169*	*-15.93*
Master's degree	*0.5963*	*0.7851*	*-0.0086*	*-8.11*
Professional school degree	*0.8123*	*1.2073*	*-0.0006*	*-0.57*
Doctorate degree	*-0.0425*	*1.0642*	*0.0001*	*0.09*
Region	*-0.2383*	*-0.1583*	*-0.0011*	*-1.04*
Race	*-0.3015*	*-0.1815*	*0.0046*	*4.34*
Age	*0.0074*	*0.0060*	*-0.0109*	*-10.27*
Total explained	-	-	*-0.0378*	*-35.63*
Total unexplained gap	-	-	*0.1439*	*135.63*
Total pay gap	-	-	*0.1061*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

The simple OLS regression shows that the variable representing Professional degree school has the most significant impact on the wages of both genders. In the male regression, the wage increases by 0.81 $ per hour if this is their highest education achieved. For females, it is roughly 1.21 $ per hour. On the other hand, the smallest coefficient is observed for the

variable Age, which means that years of experience in the labor market do not play an essential role in hourly earnings.

TABLE 6

Decomposition RESULTS FOR 2011 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1597*	*0.1688*	*0.0127*	*11.97*
Some college (no degree)	*0.2464*	*0.1711*	*-0.0039*	*-3.68*
Associate degree – occupational/vocational	*0.3135*	*0.2326*	*-0.0061*	*-5.75*
Associate degree-academic program	*0.2312*	*0.2413*	*-0.0060*	*-5.66*
Bachelor's degree	*0.2763*	*0.3980*	*-0.0120*	*-11.31*
Master's degree	*0.4497*	*0.4496*	*-0.0065*	*-6.13*
Professional school degree	*0.7097*	*0.6962*	*-0.0005*	*-0.47*
Doctorate degree	*0.0594*	*0.6738*	*-0.00004*	*-0.04*
Region	*-0.2282*	*-0.1731*	*-0.0010*	*-0.94*
Race	*-0.3369*	*0.0120*	*0.0024*	*2.26*
Age	*0.0050*	*0.0051*	*-0.0075*	*-7.07*
Unionization	*0.2032*	*0.1139*	*0.0191*	*18.00*
Industry	*-2.0381*	*-0.6083*	*0.0537*	*50.61*
Occupation	*-1.9596*	*-1.5977*	*0.0206*	*19.42*
Total explained	-	-	*0.0650*	*61.23*
Total unexplained gap	-	-	*0.0411*	*38.77*
Total pay gap	-	-	*0.1061*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

The unexpected finding is that most variables have negative signs of the effect of the gender gap in explanatory variables, leading to the negative total explained gap. This result suggests that the regressors negatively impact the pay gap despite better education or higher age, which typically helps explain why females are wage-discriminated. This leads to an explanation that improving women's education also leads to higher salaries. The positive outcome appears for the high school education degree dummy variable and contributes to the

gender pay gap of 16.21 percent. The doctorate degree also showed a positive outcome, with a negligible 0.09 percent. The last positive result of this table belongs to the variable *Race*, which explains 4.32 percent of the pay gap. As the overall explained percentage is negative, another factor must shed more light on this issue.

Table 6 lists results for the full specification for 2011, and additionally, it compares Table 5 for variables such as *Unionization*, *Industry*, and *Occupation*. Upon initial examination, it is evident that these variables contribute to explaining the gender wage gap, as we consistently observe positive signs for all of these three characteristics in the explained part of the gap. The most significant part is the *Industry*, which has an impact of more than 50 percent. This indicates that the professional field was the decisive factor in 2011 that made the most

TABLE 7

Decomposition RESULTS FOR 2015 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2498*	*0.2003*	*0.0188*	*15.86*
Some college (no degree)	*0.2573*	*0.2997*	*-0.0016*	*-1.35*
Associate degree – occupational/vocational	*0.3448*	*0.3904*	*-0.0025*	*-2.07*
Associate degree-academic program	*0.3678*	*0.3669*	*-0.0137*	*-11.54*
Bachelor's degree	*0.4390*	*0.5485*	*-0.0233*	*-19.63*
Master's degree	*0.3789*	*0.7395*	*-0.0075*	*-6.35*
Professional school degree	*0.3169*	*0.6971*	*-0.0004*	*-0.30*
Doctorate degree	*0.5964*	*0.7602*	*0.0005*	*0.42*
Region	*-0.1689*	*-0.0773*	*0.0004*	*0.32*
Race	*-0.1560*	*0.0100*	*0.0032*	*2.72*
Age	*0.0099*	*0.0056*	*-0.0117*	*-9.83*
Total explained	-	-	*-0.0377*	*-31.77*
Total unexplained gap	-	-	*0.1562*	*131.77*
Total pay gap	-	-	*0.1185*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

potent difference in wages between men and women. The variable Occupation contributes to explaining the gender differences with 19.42 percent. A similar proportion (18 percent) of the gap explains Unionization. The remaining human capital variables show results analogous to those in Table 5. They do not differ in the signs, and discrepant is only their proportion on the total explained part of the gap. In 2011, 61.23 percent of the gender wage gap was explained using full specification variables. We can observe results similar to those of the human capital specification for the simple OLS regression coefficients. Similarly, as in Table 5, the variable

TABLE 8

Decomposition RESULTS FOR 2015 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2455*	*0.1173*	*0.0185*	*15.59*
Some college (no degree)	*0.2338*	*0.1530*	*-0.0015*	*-1.23*
Associate degree – occupational/vocational	*0.2705*	*0.1818*	*-0.0019*	*-1.63*
Associate degree-academic program	*0.3105*	*0.1913*	*-0.0115*	*-9.75*
Bachelor's degree	*0.3611*	*0.3128*	*-0.0191*	*-16.15*
Master's degree	*0.2225*	*0.4187*	*-0.0044*	*-3.73*
Professional school degree	*0.3370*	*0.5596*	*-0.0004*	*-0.32*
Doctorate degree	*0.3857*	*0.3911*	*0.0003*	*0.27*
Region	*-0.1180*	*-0.1001*	*0.0008*	*0.65*
Race	*-0.0120*	*-0.0580*	*0.0008*	*0.63*
Age	*0.0085*	*0.0046*	*-0.0099*	*-8.36*
Unionization	*0.1782*	*0.1536*	*0.0094*	*7.94*
Industry	*-1.0012*	*-1.7404*	*0.0213*	*18.01*
Occupation	*-1.3393*	*-1.6603*	*0.0143*	*12.11*
Total explained	-	-	*0.0166*	*14.03*
Total unexplained gap	-	-	*0.1019*	*85.97*
Total pay gap	-	-	*0.1185*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

Professional school degree significantly impacts earnings. It is also not surprising that both *Industry* and *Occupation* influence hourly wages for both genders.

Results for 2015 are summed in Table 7 and Table 8, again, separately for Human capital specification and full specification. As expected, *Education, Region, Race,* and *Age* do not help explain the pay gap between genders, leading again to a negative total explained gap. Compared to 2011, this negative percentage dropped by a small amount to -31.77 percent. Variables mainly contributing to this negative explained gap are *Bachelor's degree, Associate degree - academic program,* and *Age*. Small changes in the OLS coefficients happened in 2015. A variable *Professional school degree* is not the one that has the most substantial impact on wages for both genders. A doctorate degree seems to be the key to an increase in salary in

TABLE 9

Decomposition RESULTS FOR 2019 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2346*	*0.1990*	*0.0169*	*11.23*
Some college (no degree)	*0.3102*	*0.2521*	*-0.0047*	*-3.14*
Associate degree – occupational/vocational	*0.2946*	*0.3107*	*-0.0008*	*-0.51*
Associate degree- academic program	*0.3329*	*0.3801*	*-0.0094*	*-6.26*
Bachelor's degree	*0.4266*	*0.5226*	*-0.0218*	*-14.47*
Master's degree	*0.5992*	*0.7166*	*-0.0109*	*-7.22*
Professional school degree	*0.7510*	*0.7373*	*-0.0011*	*-0.76*
Doctorate degree	*0.6588*	*0.6923*	*0.0002*	*0.15*
Region	*-0.1205*	*0.0074*	*0.0003*	*0.19*
Race	*-0.5883*	*-0.4201*	*0.0010*	*0.65*
Age	*0.0054*	*0.0037*	*-0.0073*	*-4.87*
Total explained	-	-	*-0.0377*	*-25.00*
Total unexplained gap	-	-	*0.1886*	*125.00*
Total pay gap	-	-	*0.1509*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

2015. We can also observe a nice increasing trend, especially for females, in coefficients representing education. The higher the education level, the higher the increase in hourly wage

The results of the full specification for 2015 are listed in Table 8. What is immediately apparent is the decrease in the explained gap, from 61.23 percent in 2011 to only 14.03 percent in 2015. This is mainly caused by a percentage drop in the explained gap for the three crucial variables – *Unionization*, *Industry,* and *Occupation*. Unionization explained only a scant 8 percent of the gender pay gap, which is 10 percent less compared to 2011. A significant decrease also happened in Industry, contributing to an explanation of only 18 percent in 2015

TABLE 10

Decomposition RESULTS FOR 2019 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2127*	*0.1296*	*0.0154*	*10.18*
Some college (no degree)	*0.2644*	*0.1334*	*-0.0040*	*-2.68*
Associate degree – occupational/vocational	*0.1857*	*0.1719*	*-0.0005*	*-0.32*
Associate degree-academic program	*0.2766*	*0.2026*	*-0.0078*	*-5.20*
Bachelor's degree	*0.3555*	*0.3356*	*-0.0182*	*-12.06*
Master's degree	*0.4927*	*0.4732*	*-0.0090*	*-5.94*
Professional school degree	*0.5459*	*0.5386*	*-0.0008*	*-0.55*
Doctorate degree	*0.5128*	*0.4596*	*0.0002*	*0.12*
Region	*-0.1160*	*0.0082*	*0.0004*	*0.29*
Race	*-0.3823*	*-0.2311*	*0.0003*	*0.18*
Age	*0.0049*	*0.0035*	*-0.0066*	*-4.38*
Unionization	*0.2210*	*0.0966*	*0.0107*	*7.10*
Industry	*-2.0469*	*-3.2292*	*0.0540*	*35.77*
Occupation	*-1.7212*	*-1.0487*	*0.0166*	*11.03*
Total explained	-	-	*0.0506*	*33.54*
Total unexplained gap	-	-	*0.1003*	*66.46*
Total pay gap	-	-	*0.1509*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

(compared to 50.61 percent in 2011). The smallest, but not negligible, change happened for Occupation, from 19.42 percent in 2011 to 12.11 percent in 2015.

Table 9 lists the 2019 results for the Human capital specification. Analogously to previous years, the percentage of explained gap appears with a negative sign, taking a value of -25 percent. With -14.47 percent, a *Bachelor's degree* still contributes the most to this, resulting in an overall negative gap. Less negative influence than in 2015 shows variables *Associate degree—academic program* and *Age.* OLS coefficients for 2019 in human capital specifications are similar to those in previous periods.

The 2019 results for the full specification are summarized in Table 10. The positive change is seen in the overall explained gap that rose to 33.54 percent, which is double compared to the

TABLE 11

Decomposition RESULTS FOR 2023 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1354*	*0.2262*	*0.0132*	*11.28*
Some college (no degree)	*0.1918*	*0.2841*	*-0.0041*	*-3.51*
Associate degree – occupational/vocational	*0.3237*	*0.3557*	*0.0004*	*0.35*
Associate degree-academic program	*0.1867*	*0.3172*	*-0.0069*	*-5.91*
Bachelor's degree	*0.3027*	*0.5365*	*-0.0139*	*-11.88*
Master's degree	*0.4133*	*0.5333*	*-0.0114*	*-9.78*
Professional school degree	*-0.0854*	*0.7253*	*0.0005*	*0.46*
Doctorate degree	*0.3961*	*0.4749*	*0.0009*	*0.74*
Region	*-0.1764*	*-0.0777*	*-0.0019*	*-1.61*
Race	*-0.3899*	*-0.1619*	*0.0036*	*3.06*
Age	*0.0054*	*0.0031*	*-0.0062*	*-5.28*
Total explained	-	-	*-0.0258*	*-22.08*
Total unexplained gap	-	-	*0.1427*	*122.08*
Total pay gap	-	-	*0.1169*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

previous period. Conversely, compared to the 2011 results for full specification, explained part of the gap dropped by almost half. The variable *Industry* remains the leader in the explanation. It explains more than 35 percent of the gap. The power of this variable could also be observed in simple OLS regression, where it leads on average to 3.23$ lower wages for women and to 2.05$ lower wages for men. Weaker still seems to be the O*ccupation* in explaining the pay gap, with 11 percent in 2019. The smallest portion of the explained gap comprises a *Doctorate degree, Region*, and *Race*, collectively contributing only approximately 0.6 percent to the explanation.

TABLE 12

Decomposition RESULTS FOR 2023 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1028*	*0.1432*	*0.0100*	*8.56*
Some college (no degree)	*0.1503*	*0.1428*	*-0.0032*	*-2.75*
Associate degree – occupational/vocational	*0.2163*	*0.2052*	*0.0003*	*0.24*
Associate degree-academic program	*0.0919*	*0.1347*	*-0.0034*	*-2.91*
Bachelor's degree	*0.2144*	*0.3280*	*-0.0098*	*-8.41*
Master's degree	*0.3557*	*0.3053*	*-0.0098*	*-8.42*
Professional school degree	*0.0131*	*0.4269*	*-0.0001*	*-0.07*
Doctorate degree	*0.2657*	*0.2904*	*0.0006*	*0.50*
Region	*-0.1300*	*-0.0323*	*-0.0015*	*-1.28*
Race	*-0.1758*	*-0.0769*	*0.0035*	*3.01*
Age	*0.0048*	*0.0032*	*-0.0055*	*-4.72*
Unionization	*0.1098*	*0.0413*	*0.0062*	*5.32*
Industry	*-2.1475*	*-1.8528*	*0.0333*	*28.48*
Occupation	*-0.9321*	*-1.0967*	*0.0045*	*3.89*
Total explained	-	-	*0.0250*	*21.43*
Total unexplained gap	-	-	*0.0918*	*78.57*
Total pay gap	-	-	*0.1169*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

The last observed period in this thesis is 2023. Results are listed in Table 11 for the Human Capital Specification and Table 12 for the Full Specification. Human capital results are similar to 2019. Minor changes in the effects of Bachelor's degree education were observed. In 2019, the impact of this variable on the gap was -0.0218 log points, which is -14.47 percent of the explained gap. In 2023, it was -0.0139 log points or -11.88 percent. The total explained gap using only human capital variables remains, not surprisingly, negative as in previous periods at -22.08 percent.

The full specification for the last observed period, 2023, explains 12.11 percent less of the gender gap than in 2019. The variables *Bachelor's degree* and *Master's degree* have the most significant unfavorable effect on the gap explanation, both with approximate negative 8.4 percent. Observed is also a drop in *Industry's* positive contribution to the explanation, from 35.77 percent in 2019 to 28.48 percent in 2023. Nonetheless, this represents an enhancement compared to 2015, when Industry accounted for only approximately 18 percent of the gap. Simple OLS regression coefficients also show that *Industry* caused lower salaries for both genders in 2023. It correlates with the 2.15$ decline in males' and 1.85$ in females' hourly pay.

Throughout the observed period, the positive effect of *Occupation* disappears. Initially, this variable could explain 19.42 percent of the gap, whereas it declined over time to 3.89 percent in 2023. To summarize the results, there is a significant change between the period before 2010, as observed in Blau and Kahn's study, and after 2010, as observed in this thesis. In the 20th century and at the beginning of the 21st, Human Capital variables explained quite a significant part of the wage gap. On the other hand, the pay gap used to be more marked than it is now.

In the past 13 years, females have become more educated and experienced, leading to a negative explained gap in the human capital specification. The Full specification remains positive, meaning that part of the gap could still be explained using variables such as *Industry*, *Occupation*, or *Unionization*. Figure 3 graphically illustrates the results better. It depicts female-to-male log wage ratios in three groups for each observed year. The grey bar represents the unadjusted ratio (calculated in Table 2), the light blue bar is adjusted for human capital specification covariates, and the dark blue bar is adjusted for the full specification covariates.

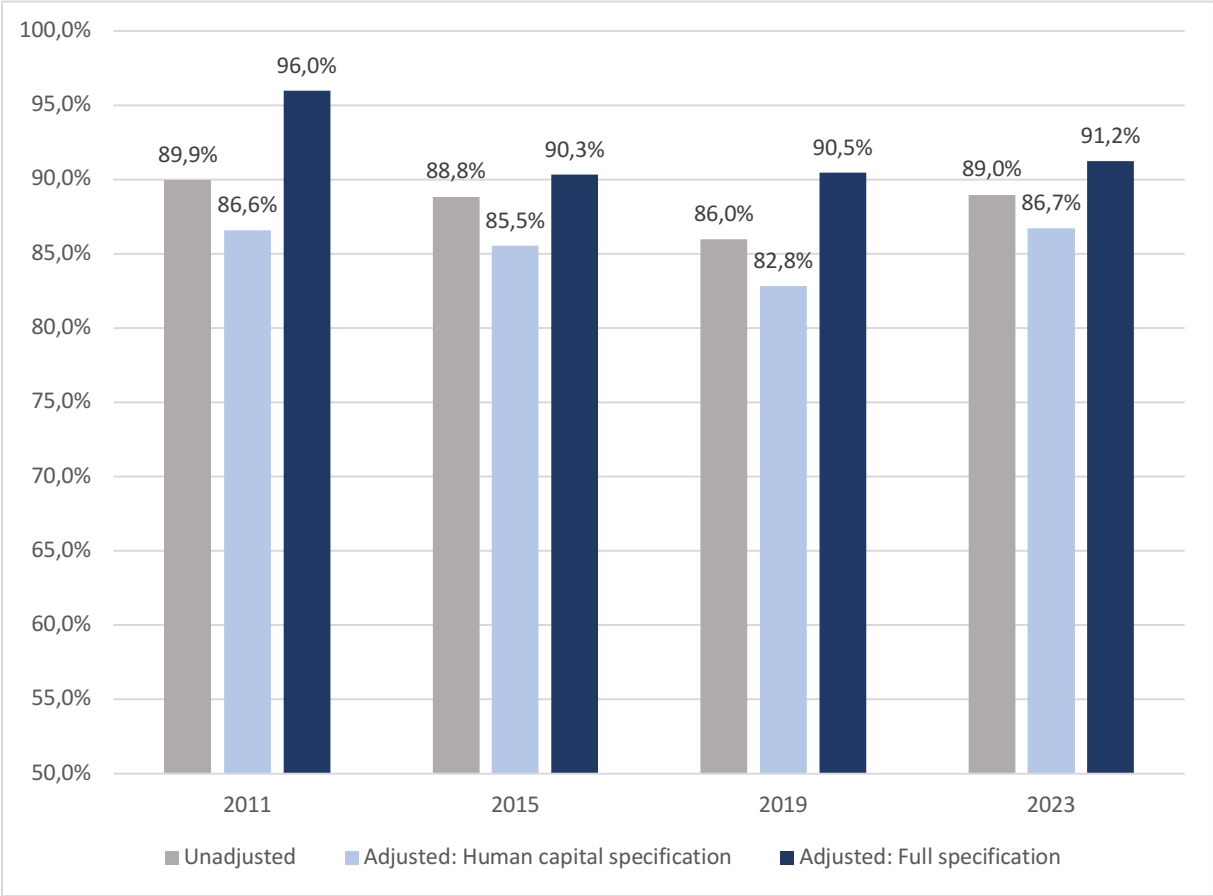

Figure 3. *Female-to-male log wage ratio. Unadjusted and adjusted for covariates*
Source of the data: CPS data

The ratios are computed as a percentage, where the log total pay gap's exponent is divided by the log explained pay gap's exponent (values are taken from the results in Tables 5-12).

The unadjusted female-to-male ratio slowly declined from 2011 to 2019 and grew marginally to 89 percent in 2023. Otherwise, the unadjusted ratio has no striking changes over the observed period. It came neither to some improvement nor some extreme worsening of the gap. The ratio adjusted for human capital variables did not vary much over the observed period. For every year, it reaches smaller percentage values than the unadjusted ratio, which was expected, considering the result in tables 5, 7, 9, and 11, where the explained gap had negative values. The adjusted full specification female/male ratio significantly declined between 2011 and 2015. Since then, this ratio has remained relatively constant, around 90-91 percent.

6. Factors Influencing the Gender Wage Gap

The analysis of CSP data has revealed a concerning trend, the diminishing effects of variables *Unionization*, *Industry*, and *Occupation,* when explaining the gender wage gap using Blinder-Oaxaca wage regression decomposition. Should this trend persist, in the future, these variables may lose explanatory power regarding the pay differences between males and females. Besides, even if it would explain some part, we observe that nearly 9% of the differential remains unexplained today. Consequently, there is a pressing need to identify additional measurable factors or an assortment of factors that could be helpful when explaining this gap. It also highlights the importance of continuous research and understanding of the gender wage gap issue, as the factors influencing it are dynamic and may change over time.

One of these factors could be switching jobs. 'Job turnover' or 'job mobility' refers to the deliberate decision of individuals to leave their current employment positions and seek new opportunities elsewhere. According to APD Pay Insights[3], job changers usually gain more than job stayers. Voluntary job turnover can enable individuals to negotiate higher salaries and better compensation packages. When considering job offers from prospective employers, candidates can leverage their skills, experiences, and market value to negotiate favorable salary terms. Admittedly, a pay rise is not the only motivation behind terminating employment. However, according to statista.com[4], it was the main reason for leaving a job in 2022 in the United States. In the context of the gender wage gap, if we could prove that males switch employers more often than females, this factor could be a reasonable explanation for this disparity.

Another often-discussed factor may be the labor force participation rate. Naturally, it is one of the critical assumptions for the analysis of wages since only employed people are able to participate in earning any income. According to Balu and Kahn's research conducted in 2017, historically, from the 50s of the 20th century to 2012, there was an increasing trend in women's employment rate. In contrast, among males, there was a decreasing employment rate. Interestingly, from 2012 to 2023, the rate remained roughly constant for both genders. The

[3] https://payinsights.adp.com
[4] https://www.statista.com/statistics/1310979/main-reasons-leaving-job-us/

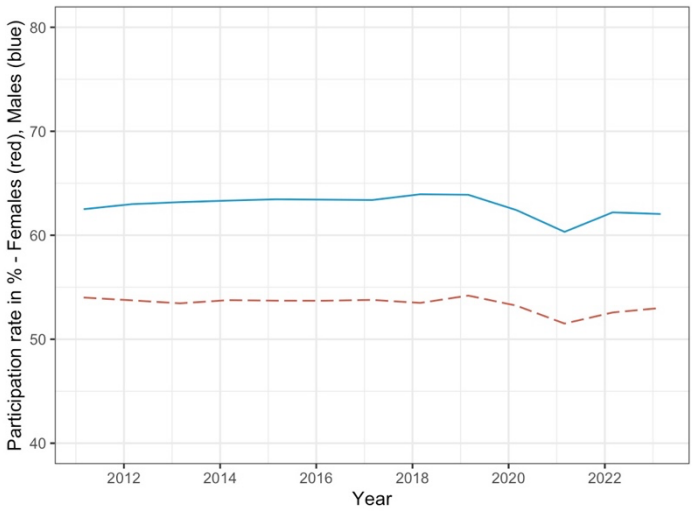

Figure 4. *The labor force participation rate in percent for females is in red dashed and for males in blue. Source of the data: CPS data*

women's participation is constantly around 53 percent, and in the men's group, it is, on average, 10 percent more. There was only one small drop in both groups in 2021, the year of the COVID-19 pandemic. Many businesses suffered during the lockdowns, especially in services, which the population could not use because of the ban on movement. As a result, several businesses closed down, and, naturally, the workforce was made redundant. For this reason, we can observe increased unemployment during the pandemic years and, therefore, reduced labor force participation rates.

Labor force participation may be meaningful in narrowing the gender wage gap. A higher female participation rate helps to reduce differences between genders and can challenge stereotypical gender roles. Increasing female participation could motivate other women to attempt higher education or to participate in the labor market. It also motivates institutions to create policies for better work-life balance, such as paid parental leave or establishing childcare facilities.

The next factor that may affect the gender wage gap is the ability to negotiate. As Kiesslin L. et al. (2024) have shown, women's expectations about their wages are lower than men's even before entering the labor market and participating in the labor force. Regarding wage negotiations, women usually start with more moderate wage demands than their reservation wage. The courage to negotiate comes with higher wage expectations, which may be, according to the findings of Kiesslin et al., driven by anticipation of gender discrimination. This suggests that addressing the gender wage gap requires encouraging women to negotiate

more assertively and creating supportive environments that mitigate the negative social consequences of negotiation. This is a crucial step in ensuring that women are not penalized for advocating for their worth in the workplace, and it can significantly contribute to narrowing the gender wage gap.

Claudia Goldin (2014) also pointed out that the gender pay gap may arise from occupation differences. It does not have to be only between occupation differences that have a share in the pay gap. Interestingly, equalizing wages within occupations may play a significant role in narrowing the gap. One of these issues might be disproportionally rewarding workers with higher weekly hours in terms of hourly wages. As shown in Table 1, females usually work fewer hours on average than males. If a man who works 48 hours a week compared to a woman who works 40 hours gets paid wage supplements for these 8 hours, his average hourly wage becomes higher, and thus the pay gap widens. Goldin (2014) suggests that further progress in narrowing the gap requires workplace changes that reduce the premium on long, inflexible hours, advocating for greater flexibility in work arrangements to reach more equality in opportunities and earnings for both genders.

7. Conclusion

The Current Population Survey data analysis reveals a disheartening trend - the gender wage gap has remained more or less unchanged from 2011 to 2023. While previous research, such as Balu and Kahn's work from 2017, showed promising improvements in gender pay equality and the narrowing of the gap from 1980, recent years have seen a troubling stagnation. As the results of this thesis suggest, human capital can no longer explain any differences between males' and females' wages. The variables of the so-called full specification still have some power of explanation. However, the difference between the unadjusted female-to-male log wage ratio and adjusted for covariates of the variables unionization, industry, and occupation is remarkably smaller than in the 20th century. This is due to the significant strides women have made in many areas - they are better educated than the opposite sex and have more years of experience than they had in the past. However, despite these advancements, the unexplained gender wage gap persists and has not narrowed in the past eight years, underscoring the urgent need for further research and action in this area.

The analysis focuses on the linear relationship between the log of hourly wages and explanatory variables. However, it does not examine nonlinear relations. Therefore, quadratic relationships were examined separately for males and females using simple OLS regressions. A very small negative but statistically significant quadratic relationship exists in the male regression in all four observed years: 2011, 2015, 2019, and 2023. On the other hand, in the female OLS regression, a small statistically significant negative effect was observed only for years 2015 and 2023. For the other two years, the estimate was insignificant. According to this finding, it may be hard to explain the gender wage gap if the relationship between the wage and explanatory variables is not always only linear.

As this thesis revealed, human capital variables are no longer the characteristics that help explain the pay gap between males and females. Previous research from Blau and Kahn (2017) found human capital variables helpful, as they interpreted a significant part of the wage gap, even in 2010. It is essential to mention that Blau and Kahn used data from the Panel Study of Income Dynamics (PSID), and this thesis analyzes the data from the Current Population Survey (CPS). Hence, the difference between the result of 2010 in Blau and Kahn's work and the result of 2011 in this thesis may lie in the different data used. To determine whether the data from a specific year would yield different results, the year 2006 was selected for additional analysis. The result was, however, similar to all other CPS data analysis results – the unadjusted female-to-male log wage ratio was 84.24 percent, the ratio adjusted for human capital variables was 81.74 percent, and the ratio adjusted for full specification variables was 89.62 percent. This finding emphasizes the need for further research to compare the results across different samples and deepen our understanding of the gender wage gap.

Policy measures have an essential influence on the gender pay disparity. Their role should be to help narrow the gap. Despite legislation that ensures that males and females receive equal pay for equal work, differences in working hours can still contribute to wage disparities. For instance, as was shown in Goldin's paper "A Grand Gender Convergence: Its Last Chapter (2014)," time flexibility at work might not be necessarily beneficial for those who work fewer hours. Although it enables a better work-life balance, on the other hand, more hours worked are disproportionally more rewarded. Wage Standardization may be another tool to increase pay equality. It ensures that pay is based on explicitly stated job responsibilities and skills, not gender or negotiation power.

Addressing the gender wage gap requires a versatile approach involving both policy interventions and cultural shifts that challenge traditional gender roles in the workforce. By supporting greater transparency, equality in opportunities, and support for work-life balance, we can move closer to gender wage equality.

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⇒ All Tables and Figures are based on the author’s calculations.

9. APPENDIX – TOBIT RESULTS

The Current Population Survey data are top-coded, meaning that values above a certain threshold are censored (for more information, see chapter 4. Model). This requires the usage of Tobit regression instead of simple ordinary least squares regression. The data were checked before analysis, and only very few observations were indeed top-coded. The whole analysis was done using this method to test whether the special treatment in the form of Tobit regression could impact the results. However, the results reveal only minor differences that are negligible. This suggests that the top-coding of the data and the use of Tobit regression did not significantly impact the findings of this research.

TABLE 13

Decomposition RESULTS FOR 2011 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2168*	*0.2613*	*0.0172*	*16.30*
Some college (no degree)	*0.2995*	*0.3230*	*-0.0047*	*-4.47*
Associate degree – occupational/vocational	*0.3964*	*0.4568*	*-0.0077*	*-7.31*
Associate degree-academic program	*0.3499*	*0.5135*	*-0.0091*	*-8.65*
Bachelor's degree	*0.3879*	*0.6537*	*-0.0169*	*-15.95*
Master's degree	*0.5963*	*0.7851*	*-0.0086*	*-8.09*
Professional school degree	*0.8123*	*1.2073*	*-0.0006*	*-0.55*
Doctorate degree	*-0.0425*	*1.0642*	*0.0000*	*0.03*
Region	*-0.2383*	*-0.1583*	*-0.0011*	*-1.06*
Race	*-0.4312*	*-0.1848*	*0.0046*	*4.34*
Age	*0.0074*	*0.0060*	*-0.0109*	*-10.34*
Total explained			*-0.0378*	*-35.75*
Total unexplained gap			*0.1436*	*135.75*
Total pay gap			*0.1058*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 14

Decomposition RESULTS FOR 2011 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1596*	*0.1688*	*0.0127*	*11.99*
Some college (no degree)	*0.2464*	*0.1711*	*-0.0039*	*-3.68*
Associate degree – occupational/vocational	*0.3133*	*0.2324*	*-0.0061*	*-5.78*
Associate degree-academic program	*0.2310*	*0.2410*	*-0.0060*	*-5.71*
Bachelor's degree	*0.2769*	*0.3985*	*-0.0120*	*-11.38*
Master's degree	*04495*	*0.4511*	*-0.0064*	*-6.09*
Professional school degree	*0.7095*	*0.7368*	*-0.0005*	*-0.48*
Doctorate degree	*0.0595*	*0.6733*	*0.00004*	*-0.04*
Region	*-0.2281*	*-0.1763*	*-0.0010*	*-0.92*
Race	*-0.3375*	*0.0122*	*0.0024*	*2.30*
Age	*0.0050*	*0.0051*	*-0.0075*	*-7.08*
Unionization	*0.2032*	*0.1130*	*0.0191*	*18.01*
Industry	*-2.0393*	*-0.6095*	*0.0538*	*50.84*
Occupation	*-1.9637*	*-1.5998*	*0.0205*	*19.38*
Total explained			*0.0649*	*61.36*
Total unexplained gap			*0.0409*	*38.64*
Total pay gap			*0.1058*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 15

Decomposition RESULTS FOR 2015 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2497*	*0.2002*	*0.0188*	*15.89*
Some college (no degree)	*0.2572*	*0.2997*	*-0.0016*	*-1.36*
Associate degree – occupational/vocational	*0.3448*	*0.3903*	*-0.0025*	*-2.08*
Associate degree-academic program	*0.3677*	*0.3668*	*-0.0137*	*-11.57*
Bachelor's degree	*0.4390*	*0.5485*	*-0.0233*	*-19.68*
Master's degree	*0.3776*	*0.7429*	*-0.0075*	*-6.35*
Professional school degree	*0.3169*	*0.7110*	*-0.0004*	*-0.30*
Doctorate degree	*0.5963*	*0.7602*	*0.0005*	*0.42*
Region	*-0.1692*	*-0.0793*	*0.0004*	*0.32*
Race	*-0.1558*	*0.0092*	*0.0032*	*2.72*
Age	*0.0099*	*0.0056*	*-0.0116*	*-9.85*
Total explained			*-0.0376*	*-31.82*
Total unexplained gap			*0.1559*	*131.82*
Total pay gap			*0.1182*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 16

Decomposition RESULTS FOR 2015 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2454*	*0.1172*	*0.0185*	*15.62*
Some college (no degree)	*0.2338*	*0.1530*	*-0.0015*	*-1.23*
Associate degree – occupational/vocational	*0.2704*	*0.1816*	*-0.0019*	*-1.63*
Associate degree-academic program	*0.3104*	*0.1911*	*-0.0115*	*-9.76*
Bachelor's degree	*0.3610*	*0.3127*	*-0.0191*	*-16.18*
Master's degree	*0.2215*	*0.4213*	*-0.0044*	*-3.72*
Professional school degree	*0.3370*	*0.5727*	*-0.0004*	*-0.32*
Doctorate degree	*0.3857*	*0.3910*	*0.0003*	*0.27*
Region	*-0.1182*	*-0.1020*	*0.0008*	*0.65*
Race	*-0.0118*	*-0.0587*	*0.0007*	*0.63*
Age	*0.0085*	*0.0046*	*-0.0099*	*-8.38*
Unionization	*0.1782*	*0.1534*	*0.0094*	*7.95*
Industry	*-1.0022*	*-1.7401*	*0.0213*	*18.03*
Occupation	*-1.3390*	*-1.6619*	*0.0144*	*12.14*
Total explained			*0.0166*	*14.06*
Total unexplained gap			*0.1016*	*85.94*
Total pay gap			*0.1183*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 17

Decomposition RESULTS FOR 2019 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2354*	*0.1991*	*0.0170*	*11.20*
Some college (no degree)	*0.3110*	*0.2521*	*-0.0048*	*-3.14*
Associate degree – occupational/vocational	*0.2946*	*0.3109*	*-0.0008*	*-0.51*
Associate degree-academic program	*0.3329*	*0.3802*	*-0.0094*	*-6.22*
Bachelor's degree	*0.4285*	*0.5231*	*-0.0219*	*-14.45*
Master's degree	*0.6065*	*0.7204*	*-0.0110*	*-7.27*
Professional school degree	*0.7917*	*0.7378*	*-0.0012*	*-0.79*
Doctorate degree	*0.6589*	*0.6923*	*0.0002*	*0.15*
Region	*-0.1177*	*0.0087*	*0.0003*	*0.19*
Race	*-0.5812*	*-0.4218*	*0.0010*	*0.64*
Age	*0.0054*	*0.0037*	*-0.0074*	*-4.87*
Total explained			*-0.0380*	*-25.07*
Total unexplained gap			*0.1897*	*125.07*
Total pay gap			*0.1517*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 18

Decomposition RESULTS FOR 2019 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.2131*	*0.1296*	*0.0154*	*10.15*
Some college (no degree)	*0.2649*	*0.1334*	*-0.0041*	*-2.67*
Associate degree – occupational/vocational	*0.1853*	*0.1718*	*-0.0005*	*-0.32*
Associate degree-academic program	*0.2763*	*0.2026*	*-0.0078*	*-5.17*
Bachelor's degree	*0.3569*	*0.3357*	*-0.0183*	*-12.04*
Master's degree	*0.4985*	*0.4761*	*-0.0091*	*-5.98*
Professional school degree	*0.5713*	*0.5388*	*-0.0009*	*-0.57*
Doctorate degree	*0.5117*	*0.4593*	*0.0002*	*0.11*
Region	*-0.1139*	*0.0093*	*0.0005*	*0.30*
Race	*-0.3751*	*-0.2325*	*0.0002*	*0.16*
Age	*0.0049*	*0.0035*	*-0.0066*	*-4.38*
Unionization	*0.2212*	*0.0963*	*0.0107*	*7.08*
Industry	*-2.1089*	*-3.2289*	*0.0548*	*36.16*
Occupation	*-1.7385*	*-1.0507*	*0.0163*	*10.78*
Total explained			*0.0510*	*33.61*
Total unexplained gap			*0.1007*	*66.39*
Total pay gap			*0.1516*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 19

Decomposition RESULTS FOR 2023 – HUMAN CAPITAL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1362*	*0.2260*	*0.0133*	*11.28*
Some college (no degree)	*0.1919*	*0.2841*	*-0.0041*	*-3.49*
Associate degree – occupational/vocational	*0.3254*	*0.3556*	*0.0004*	*0.35*
Associate degree-academic program	*0.1868*	*0.3171*	*-0.0069*	*-5.88*
Bachelor's degree	*0.3046*	*0.5372*	*-0.0140*	*-11.89*
Master's degree	*0.4203*	*0.5346*	*-0.0116*	*-9.89*
Professional school degree	*-0.0852*	*0.7253*	*0.0005*	*0.45*
Doctorate degree	*0.3959*	*0.4739*	*0.0009*	*0.74*
Region	*-0.1788*	*-0.0784*	*-0.0019*	*-1.62*
Race	*-0.3930*	*-0.1568*	*0.0036*	*3.04*
Age	*0.0054*	*0.0031*	*-0.0062*	*-5.27*
Total explained			*-0.0261*	*-22.17*
Total unexplained gap			*0.1436*	*122.17*
Total pay gap			*0.1175*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

TABLE 20

Decomposition RESULTS FOR 2023 – FULL SPECIFICATION

	Coefficients		*Effect of gender gap in explanatory variables*	
	Men	*Women*	*log points*	*Percent of gender gap explained*
Education	-	-	-	-
High school	*0.1037*	*0.1431*	*0.0101*	*8.59*
Some college (no degree)	*0.1502*	*0.1426*	*-0.0032*	*-2.74*
Associate degree – occupational/vocational	*0.2175*	*0.2051*	*0.0003*	*0.24*
Associate degree-academic program	*0.0917*	*0.1345*	*-0.0034*	*-2.89*
Bachelor's degree	*0.2155*	*0.3285*	*-0.0099*	*-8.41*
Master's degree	*0.3613*	*0.3064*	*-0.0100*	*-8.50*
Professional school degree	*0.0114*	*0.4265*	*-0.0001*	*-0.06*
Doctorate degree	*0.2637*	*0.2894*	*0.0006*	*0.49*
Region	*-0.1316*	*-0.0322*	*-0.0015*	*-1.28*
Race	*-0.1782*	*-0.0721*	*0.0035*	*3.00*
Age	*0.0048*	*0.0032*	*-0.0055*	*-4.72*
Unionization	*0.1105*	*0.0421*	*0.0063*	*5.32*
Industry	*-2.1425*	*-1.8457*	*0.0337*	*28.66*
Occupation	*-0.9450*	*-1.0996*	*0.0040*	*3.43*
Total explained			*0.0248*	*21.14*
Total unexplained gap			*0.0927*	*78.86*
Total pay gap			*0.1175*	*100.00*

Notes: The sample comprises full-time nonfarm wage and salary workers aged 25–64. The entries represent the difference between men and women in the indicated variables, multiplied by the male log wage coefficients for the current year associated with those variables. The total unexplained gap is the average female residual derived from the male log wage equation.

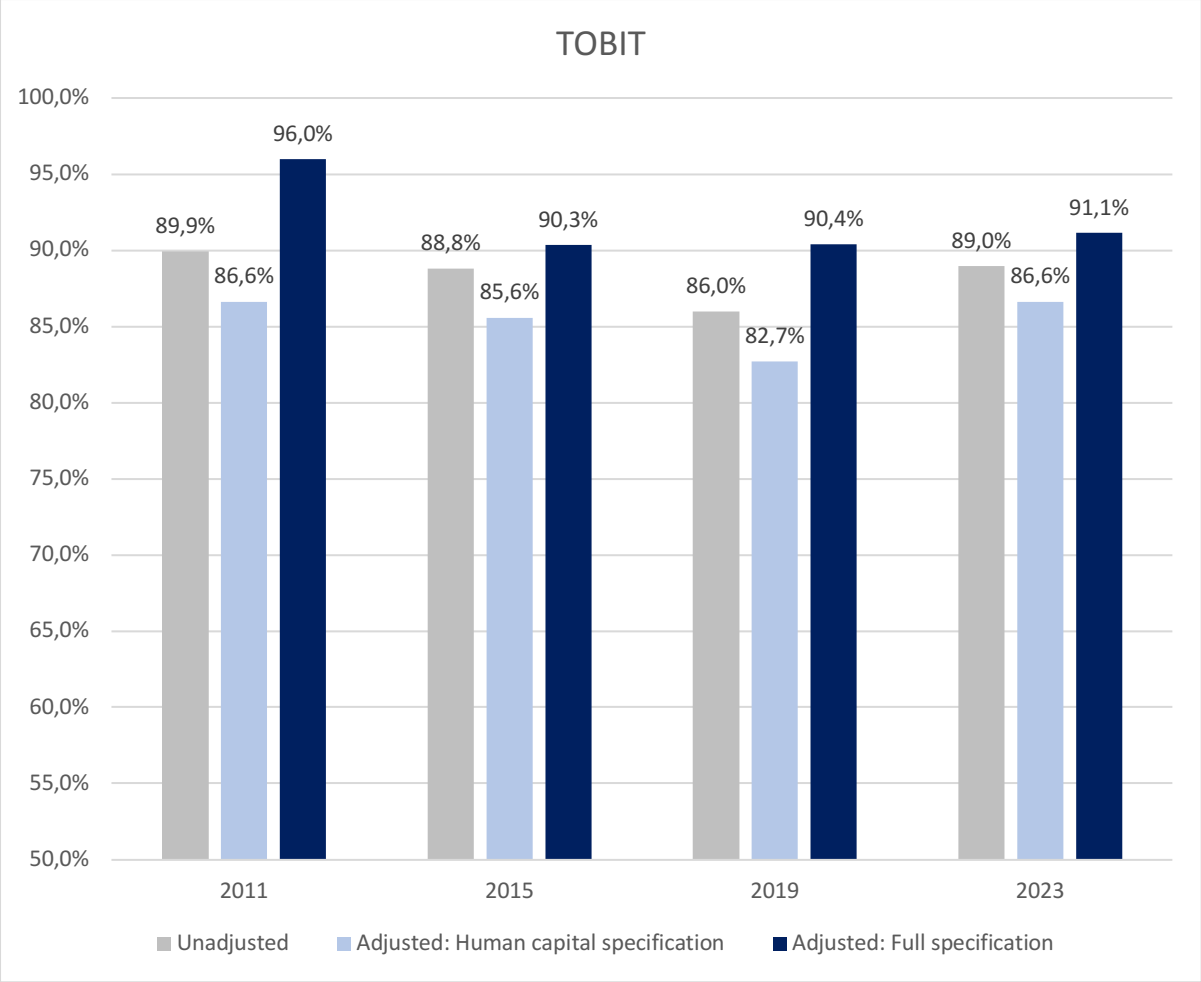

Figure 5. *Female-to-male log wage ratio using Tobit regression decomposition results. Unadjusted and adjusted for covariates.*
Source of the data: CPS data