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Analysing the gender wage gap

Empirical evidence from Germany and the United States

Linn Hildre Solem and Sajda Khadka

Supervisor: Astrid Kunze

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Abstract

The main objective of this thesis is to investigate the potential sources of the gender wage gap in Germany and the United States. For that purpose, we employ high quality microdata sets from the German Socio-Economic panel (SOEP) and IPUMS CPS. We use cross-sectional data for the years 1989 and 2019 to study a representative sample of full-time employees between the age of 25 to 64. By employing the Kitagawa-Oaxaca-Blinder (KOB) decomposition method (Kitagawa 1955; Oaxaca 1973; Blinder 1973) we estimate how much of the unadjusted gender wage gap in the countries is attributed gender differences in measured characteristics. Furthermore, by applying a Juhn, Murphy, and Pierce (JMP) (1991) decomposition we investigate how relative improvements in terms of characteristics and rising return to these characteristics affects the gender wage gap over time. The aim is to understand if increasing overall inequality counterbalances women's progress in the labour market and has a widening effect on the gender wage gap. Lastly, Blau and Kahn (1996) find that countries with more compressed wage distributions have smaller gender wage gaps. We investigate this by a JMP decomposition of the U.S.-German difference in the gender wage gap to understand if differences in return to characteristics is the most important contributor to international differences in the gender wage gap.

The results show that the gender wage gap declines in Germany and the United States between 1989 and 2019. The results from the KOB decomposition show that gender differences in observable characteristics in total no longer explain the gender wage gap for these countries in 2019. Gender differences in distribution by industry however continues to explain male-female wage disparities over the period studied. The JMP results show that changes in the return to characteristics negates some of the progress made by female workers over the period. Lastly, the most important factor for explaining the U.S- German difference in the gender wage gap is the relative differences in return to characteristics. This effect was however stronger in 1989 and reflects that the wage distribution in Germany have become more dispersed over the period of study and is thus more similar to that observed in the United States.

Keywords - Gender wage gap, wage inequality, decomposition, microdata

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1. Introduction

Women's labour force attachment has increased since their entrance into the labour market, and for most developed countries we have observed a decline in the gender wage gap since the 1970s. Yet, a persistent gender wage gap remains in most industrialized countries, with considerable international variations in the size of the gender wage gap (Kunze, 2018). The gender wage gap[1], for OECD countries with data, ranges from only 2.1 per cent in Belgium to 31.1 per cent in South-Korea (OECD, 2023). There are also considerable differences in the rate of convergence of male-female wages for different countries (Kunze, 2018).

Women have increased their labour force participation and have gained more lifetime labour force experience (Kunze, 2018). The educational attainment of women in some countries even surpasses that of men (Blau & Kahn, 2017). There has occurred a narrowing between the genders in terms of hours of work at home, occupational distribution by gender, and college majors (Goldin, 2014). Despite a narrowing between men and women in terms of labour market characteristics and participation, gender segregation by occupation and industry continues to be an important factor contributing to male-female wage disparities (Blau & Kahn, 2017; Blau & Winkler, 2018). Women are underrepresented in higher-paying fields and are more likely than men to work part-time (Kunze, 2018). Gender differences in college majors have also been found to contribute to wage disparities between college-educated men and women (Black et.al., 2008), and women continue to lag in the STEM[2] fields (Blau & Kahn, 2017).

Most industrialized countries have for the past decade seen an increase in wage inequality, measured as wage dispersion[3]. There has been a rise in the return received for skills and education (Autor, 2014). This has been driven by rising demand for skilled workers relative to unskilled workers. The cause of the rising demand for skilled workers is believed to be technological change. The effect of the technological change favouring skilled workers is referred to as skill-biased technical change (Acemoglu, 2002). The shifting demand is further

[1] Measured as the male-female difference in median earnings relative to the male median earnings (OECD, 2023).

[2] Science, technology, engineering, and mathematics

[3] The difference between high-wage workers and low-wage workers.

strengthened by low-skilled workers facing increased international competition from workers in low-wage countries (Autor, 2014). The effect of increased demand for skilled workers may affect the gender wage gap in multiple ways. Coupled with increased educational attainment amongst female workers, increased demand for highly educated workers can have a narrowing effect on the gender wage gap. On the other hand, assuming female workers will have less labour market experience than male workers due to more part-time work, the increased demand for skilled workers can have a widening effect on the gender wage gap.

While industrialized countries have seen a rise in wage inequality over the years, the level of wage inequality differs between countries. Wage-setting institutions impact the wage-structure and the overall wage inequality in a country. With wage-structure, we refer to the return received for labour market characteristics, like education and experience, and reward for employment in certain occupations and industries. Wage-setting institutions affect the level of wage compression within a country (Blau & Kahn, 2017). Strongly unionized economies with more centralized wage-setting institutions tend to have more compressed wage structures with lower overall wage dispersion (Blau & Kahn, 1996). Moreover, systems of wage compression that raise minimum pay levels narrow the gender wage gap in countries where the female wage distribution lies below the male wage distribution (Blau & Kahn, 2003).

While women have made progress in terms of labour market characteristics there is a persistent gender wage gap in most industrialized countries. We want to investigate further how much of the gender wage gap is explained by gender differences in observable labour market characteristics, like education and experience, and how much remains unexplained. To see more clearly how gender differences in characteristics impact the gender wage gap it is useful to compare earlier periods with today's situation. For that purpose, we focus our attention on the situation in 1989 compared to more recent times, 2019. Between these periods, most industrialized countries experienced rising wage inequality which might have impacted the gender wage gap in different ways depending on the labour market characteristics of female workers relative to male workers. Furthermore, we want to investigate how the convergence in male-female wages was impacted by increasing wage inequality, and if increasing returns to skills hurt or helped female workers. The development and size of the gender wage gap could be different across countries depending on wage-setting institutions and women's relative endowments of labour market characteristics. Germany has more centralized wage-setting institution compared to the United States, and these countries are therefore suitable candidates for comparing developments in the gender wage gap and cross-country differences in the gender wage gap (Blau & Kahn, 1996).

By applying two decomposition techniques we aim to investigate the gender wage gap in Germany and the United States in terms of factors contributing to wage disparities between male and female workers, developments in the gender wage gap amidst rising wage inequality, and finally differences in the gender wage gap across the two countries. We employ high-quality microdata sets from the German Socio-Economic panel (SOEP) and IPUMS CPS for the United States. In the first part of the empirical analysis, we decompose two cross-sectional samples for Germany and the U.S. in 1989 and 2019, to quantify how much of the gender wage gap is explained by gender differences in labour market characteristics. For the second part of the empirical analysis, we decompose the changes in the gender wage gap between 1989 and 2019 for both countries, to investigate how changes in the wage structure impact the gender wage gap. Lastly, the sources for international differences are investigated by decomposing the German-U.S difference in the gender wage gaps for 1989 and 2019. The aim is to answer the following research question:

What are the sources for the gender wage gap and convergence in male-female wages over time, and how can we explain cross-country differences in the gender wage gap?

1.1 Research questions

The objective of this thesis is to investigate how gender differences in labour market characteristics and the return to these characteristics contribute to gender differentials in wages. For this purpose, the empirical analysis is inspired by previous studies by Blau and Kahn (1996, 1997, 2017) which have analyzed the gender wage gap using similar approaches applied in this thesis. Blau and Kahn (2017) have looked at how human capital factors like educational attainment and job characteristics contributed to the narrowing of the gender wage gap between 1980 and 2010. Drawing on the study by Blau and Kahn (2017) we want to study how gender differences in observable characteristics contribute to male-female wage differentials with new data. For this purpose, we use two cross-sectional samples from 1989 and 2019 for Germany and the United States. Applying a Kitagawa-Oaxaca-Blinder decomposition method (Kitagawa 1955; Oaxaca 1973; Blinder 1973) we want to investigate the following question:

Research question 1: How much of the gender wage gap in Germany and the United States is explained by gender differences in observable characteristics?

For industrialized countries, we have observed a narrowing of the gender wage gap since the 1970s. This happened in a period when the overall wage inequality was rising. There are still international variations in the size of the gender wage gap (Kunze, 2018). Studies by Blau and Kahn (1996, 1997) have investigated how both gender differences in characteristics and the wage structure contributes to changes in the gender wage gap over time and cross-country differences in the size of the gender wage gap. We therefore want to investigate how changes in the wage structure impact the gender wage gap in Germany and the United States between 1989 and 2019, and if the gender wage gap in Germany is smaller due to a more compressed wage structure. Applying a Juhn, Murphy, and Pierce (1991) decomposition method we want to examine the following questions:

Research question 2: How do changes in gender differences in characteristics and the wage structure affect the development of the gender wage gap in Germany and the United States between 1989 and 2019?

Research question 3: Is the gender wage gap in the United States greater than in Germany, and can wage structure effects account for the difference?

1.2 Thesis structure

The remainder of the thesis is structured in the following way: chapter 2 presents background information on the gender wage gap including empirical evidence and economic explanations. In chapter 3, we outline the methodology applied in the empirical analysis, respectively the Kitagawa-Oaxaca-Blinder decomposition and the Juhn, Murphy Pierce decomposition. Furthermore, the empirical strategy employed in the thesis is outlined. Chapter 4 describes the data sources used to extract samples, the sample selection process, the harmonization process required for the empirical analysis and the variables included in the wage regression models. Finally, we present descriptive statistics on the U.S. and German samples. In chapter 5, the results from the Kitagawa-Oaxaca-Blinder decomposition and the Juhn, Murphy and Pierce decompositions are presented. Chapter 6 discusses the main findings and empirical strategy employed in this thesis. Lastly, the conclusion is presented in chapter 7.

2. Background on the gender wage gap

In this chapter, we present background and literature on factors contributing to wage disparities between male and female workers. We start by presenting Blau and Kahn's (1996, 1997, 2017) empirical findings. Their findings are presented to show how gender differences in labour market characteristics and the wage structure contribute to convergence in male-female wages over time and cross-country differences in the gender wage gap. Second, we outline the economical explanations and empirical evidence for male-female wage differentials. Lastly, we provide background information on Germany and the United States in terms of gender differences in characteristics, how the overall inequality has evolved in these countries and differences in wage-setting institutions.

2.1 Empirical evidence on the gender wage gap

The empirical analysis by Blau and Kahn (2017) investigates the convergence in the gender wage gap in the United States between 1980 and 2010. Using microdata from the Panel Study of Income Dynamics (PISD), they found that women's relative improvement in traditional human capital variables, occupational representation as well as increases in female union coverage contributed to a substantial convergence of the gender wage gap in the 1980s. Improvements in female human capital variables can be attributed to increased levels of job experience for women due to stronger labour force commitment and increased educational attainment for women relative to men. By 2010, human capital variables explained a smaller proportion of the gender wage gap in the aggregate, while selection into different occupations and industries continued to be an important explanation for male-female wage differentials in the United States. The unexplained gap converged from 21 per cent to 8 per cent in the 1980s. Blau and Kahn (2017) suggest this is due to a decline in labour market discrimination over the period and/or improvements in women's unobserved skills. The unexplained gap continued to constitute a substantial share of the total gender wage gap in 2010. Moreover, the unexplained gap declined relatively slower at the top of the wage distribution. While occupational segregation decreased, differences in occupational distribution by gender explained a greater proportion of the gender wage gap in 2010 compared to 1980. This suggests that labour market prices also impact the gender wage gap and imply an important role in the wage structure.

Blau and Kahn (1997) previously investigated this further using a decomposition methodology devised by Juhn et al. (1991). Here they decomposed the changes in the gender wage gap into a portion due to changes in gender differences in characteristics and a portion due to changes in labour market returns to these characteristics. They found that changes in the wage structure over time are likely to impact the gender wage gap. Despite unfavourable changes in the wage structure slowing women's progress in the 1980s, women managed to improve their labour market skills enough to counterbalance these adverse effects. Consequently, the gender wage gap declined substantially between 1979 and 1988, despite changes in the wage structure working in the opposite direction.

In addition to contributing to changes in the gender wage gap over time, differences in the wage structure might help to explain international differences in the gender wage gap. Countries differ with respect to their level of wage compression, and Blau and Kahn (1996) find that the wage structure is an important factor in explaining why the gender wage differentials in the United States are greater than of other industrialized countries. Using microdata sets on ten industrialized countries they find that the United States' higher levels of wage inequality place a larger penalty on lower-skilled workers and those employed in low-wage sectors. This contributes to an increase in the gender wage gap in the United States relative to the other countries in the study. In a detailed comparison of the United States and Sweden for 1984, they find that factors like gender differences in labour market qualifications or occupational status slightly favours US women relative to Swedish women. Yet, the gender wage gap is larger in the United States than in Sweden. It is suggested that the gender wage gap in the United States would be more equal to countries with smaller gender wage gaps, like Sweden if the wage structure was more similar.

2.2 Economic explanations and evidence on the gender wage gap

This section provides evidence and economical explanations for the existence of the gender wage gap. Blau and Kahn's (1996, 1997, 2017) findings suggest that both gender differences in characteristics and the wage structure is relevant for explaining changes in the gender wage gap over time and international variations in the size of male-female wage differentials. Women's relative improvements in human capital factors are an important reason for the observed convergence in the gender wage gap in the United States. Hence, a closer inspection of human capital theory and how it can contribute to wage disparities between men and women will be explained closer in the following. Moreover, gender segregation in occupations and industries continued to be an important explanation for the gender wage gap in the United States in 2010. This suggests that the persistence in labour market segregation accompanied by differences in return to favourable industries and occupations impacts the gender wage gap. Explanations for women's underrepresentation in high-paying male-dominated occupations are outlined in this section. Due to the persistence in the unexplained part of male-female wage differentials, a discussion of labour market discrimination as a potential source for the unexplained gap is necessary (Blau & Kahn, 2017). Lastly, Blau and Kahn's (1996, 1997) findings suggest that the overall wage structure might impact the gender wage gap across time and contribute to international variations in the size of the gap. Consequently, a discussion of why the wage structure contributes to the gender wage gap is needed.

2.3 Human capital investments

The human capital model (Mincer & Polachek, 1974) provides the major supply-side explanation for the gender wage gap. Individuals make decisions regarding human capital investments to increase productivity and thereby their wages in the future. Human capital investments include decisions about formal education and on-the-job training (Blau & Winkler, 2018). The traditional division of labour by gender in the family constraints women's investment in human capital (Blau & Kahn, 1999). Duchini and Van Effenterre (2022) investigated how the labour supply decisions of men and women were affected by an after-school reform in France. They find that men's labour supply decisions were not affected by the new reform. However, the new reform impacted the labour supply of women, indicating that institutional constraints were binding for the women in the study. This suggests that women are expected to have the primary responsibility of children. With lacking institutional infrastructure for childcare, women will demand more flexible work to meet these expectations. If women expect to have more intermittent work lives than men due to greater responsibility for childcare, this will disincentivize women to invest in human capital relative to men . Consequently, smaller investments in human capital will lower their wages relative to men. Moreover, for prolonged periods out of the workforce related to childbearing and childcare, human capital investments may depreciate (Mincer & Polachek, 1974). In addition, for periods outside of the labour force, individuals will forgo human capital accumulation from job experience or on-the-job training.

The human capital theory outlines how differences in human capital investments contribute to differences in wages received in the labour market. However, for men and women with equal levels of human capital, we still observe a pay gap (Blau & Kahn, 2017). Gender segregation in the labour market, on the other hand, is an important contributor to the gender wage gap. Men and women tend to work in different occupations with different reward structures.

2.4 Occupational segregation

The human capital theory also provides an explanation for the tendency of men and women to work in different occupations. Anticipating more discontinuous work lives, women might select female-dominated occupations with fewer requirements for human capital investments and lower wage penalties for periods outside the workforce (Blau & Winkler, 2018). If women have greater household responsibilities, this will constrain their ability to put in long work hours, travel extensively and relocate to new labour markets on short notice (Blau & Winkler, 2018). Hence, women might select occupations with greater temporal flexibility and more family-friendly characteristics. Goldin (2014) argues that many occupations have a nonlinear relationship between earnings and hours of work, and individuals in these occupations are disproportionately rewarded for working long hours and with less flexible work schedules. Consequently, if women consistently avoid these occupations this can contribute to male-female wage disparities.

In addition to the unequal distribution of men and women in different occupations, women tend to be underrepresented at the upper levels of the hierarchies at work (Blau & Winkler, 2018). Labour market segregation might reflect that men and women have different job preferences. Findings suggest that men and women differ with respect to psychological attributes and noncognitive skills. Women have been found to be more risk-averse and less competitive compared to men (Bertrand, 2011). As a result, women might shy away from occupations with competitive features applied to increase the performance of employees (Niederle & Vesterlund, 2007). However, Apicella et. al (2017) find no gender difference in the willingness to compete against one's own, previous score. If employees are incentivized by competing against each other and not with themselves, promotion criteria could be biased in favour of men. Hence, occupational segregation might reflect subtle institutional barriers. Other subtle barriers can include a lack of role models in male-dominated fields to alleviate negative stereotypes (Breda et. al., 2021) or access to informal networks (Cullen & Perez-Truglia, 2019) that advance their career progression. This suggests that subtle institutional barriers contribute to the gender wage gap.

2.5 Labour market discrimination

Labour market discrimination is another job barrier that can exclude women from certain occupations, slow women's upward career progression or contribute to lower wages in the labour market (Blau & Winkler, 2018). To understand why discriminatory behaviour persists in the labour market we differentiate between taste-based discrimination (Becker, 1971) and statistical discrimination (Phelps, 1972). It should be emphasized that labour market discrimination is different from societal discrimination (Blau & Wrinkler, 2018). Societal discrimination might influence women to make decisions that disadvantageously impact their status in the labour market. In a labour market setting, discrimination refers to the situation where equally productive or qualified workers are treated differently based on observable characteristics (Becker, 2010). However, labour market discrimination might indirectly reduce incentives for women to invest in human capital if women expect discriminatory behaviour in the labour market (Blau & Winkler, 2018).

In Becker's (1971) model, discrimination against female employees arises from preferences. Employers prefer candidates from their group when choosing between equally skilled and qualified candidates. The gender wage gap can then be attributed to female employees receiving lower earnings than comparable male employees to compensate for the antisocial preferences of the employer. Statistical discrimination happens in a labour market with uncertainty related to the behaviour and productivity of the employee. Group characteristics like gender are taken as a proxy for the productivity and reliability of the employee when sufficient data is unavailable (Phelps, 1972). Hence, past experiences with female workers, or even prejudice, will influence the predicted performance of women. For instance, mothers might be expected to be less productive due to anticipated main responsibility for household activities and children. Correll et al. (2007) find that mothers are perceived as less competent and penalized through lower recommended starting salaries, holding qualifications and job experience constant in a laboratory experiment. In an event study, Kleven et. al. (2018) find that the earnings and career prospects of women are negatively impacted by having children.

Human capital theory suggests that on-the-job training is an important investment that increases the future earnings of employers. Moreover, it might be valuable to secure entrance into higher-paying jobs (Blau & Winkler, 2018). Women receive less on-the-job training than men, and Royalty (1996) find that a major proportion of the gap is unexplained after controlling for the probability of worker turnover and other variables. There is also a gender difference in promotion rates, where studies have found that women have a lower probability of getting promoted (Blau & Devaro, 2007). Labour market discrimination might also help to explain why women are overrepresented in lower-paying occupations. In Bergmann's (1974) overcrowding model, labour market discrimination crowd women into certain occupations. This leads to an oversupply of labour for these occupations and depresses wages.

2.6 Wage structure and the gender wage gap

The human capital model and labour market discrimination imply an important role for the overall wage structure in explaining the size of the gender wage gap. The human capital model predicts that women will have less labour market experience, and on-the-job training, than men on average. Alternatively, labour market discrimination can contribute to gender differences in on-the-job training and thereby the relative levels of human capital. With higher returns to experience and more wage inequality, women that have below-average labour market characteristics will be penalized more harshly. This will increase the gender wage gap compared to more compressed wage structures. Analogously, if labour market discrimination or differences in human capital contributes to occupational segregation, and rents received in male-dominated occupations are higher than for female-dominated occupations, the gender wage gap will be larger (Blau & Kahn, 2000). If male-female wage differentials are associated with labour market segregation, more centrally determined wage-setting institutions may reduce the gender wage gap through smaller variations in wages across industries and firms (Blau & Kahn, 2003).

2.7 Germany and the United States

The Gender wage gap in Germany was 14.2 per cent as of 2020, which was a declined from 27.1 per cent in 1992 (OECD, 2023). The decline of the gender wage gap is due to women's increased labour force participation between 2001 and 2011, indicating that women became more attached to the labour market in this period. In addition, women increased their level of education attainment which contributed to rising income levels for women (Drechsel-Grau et al., 2022). Studies show that women and men in Germany tend to choose different fields of study. Weichselbaumer and Ransmayr (2022) found that the gender gap in fields of study is the greatest for engineering and natural sciences. In 2019, German women represented only 9 per cent of graduates from engineering, manufacturing and construction upper-secondary vocational programs in Germany, which is lower than the OECD average of 15 per cent (OECD, 2021).

Part-time work is another factor that is important for explaining the gender wage gap between male and female workers. The gap between men and women working part-time in Germany is among the highest in the EU (Bächmann et al., 2022). In 2019, 50 per cent of women were employed part-time compared to only 8 per cent of men (Ilieva & Wrohlich, 2022). Mini-jobs are a distinct type of job for the German labour market characterized by marginal employment contracts which are exempted from social security contributions and income tax. Mini-jobs which are more temporary jobs and lower-paid jobs has never played an important role for male workers as a primary job, while it represented a substantial share for women. During the period 2001-2016, the mini-job spike was much more pronounced for female worker than for male workers (Drechsel-Grau et al., 2022). In this period the median for women's wages was below the 25th percentile for men, while the 75th percentile for women was below the median for men. Women in Germany accumulate lower pension entitlements during their working life as they are more likely to work in lower-paid industries, are less represented in executive positions, work more part-time and take more time off from work (Statistisches Bundesmat, 2023).

Germany passed an equal pay policy in 1980 under the code of Civil procedure which was later than other countries like Australia and the United Kingdom which had begun to implement equal pay in 1969 and 1970 (Blau & Kahn, 1996). Income inequality in Germany started to rise tremendously during the 1990s and the early 2000s. After the Great Recession, there was a continuing trend of decreased income mobility. The trend of rising inequality in Germany started in the late 1980s for both men and women, but there were distinct gender differences in the evolution of inequality. Men experienced a greater increase in earnings inequality, particularly at the bottom of the distribution. After the Great Recession the inequality in earnings stabilized for those below the median. However, income inequality continued to grow for those above the median. For women, the bottom inequality was falling after 2009 while the top inequality increased. Overall, female earnings caught up with male earnings throughout most of the distribution between 2001 and 2016 and the top earners above the 90th percentile experienced the strongest growth in real earnings. Therefore, women's earnings inequality declined remarkably during this period (Drechsel-Grau et al., 2022).

The gender wage gap in the United States declined from 29.4 per cent in 1989 to 17 per cent in 2020 (OECD, 2023). The education gap between men and women saw a reversal between 1980 and 2011 as women gained more higher professional degrees of education (Blau & Kahn, 2017). However, a significant gap still exists in high-paid fields of science and technology, though women are now more represented in management and professional jobs. As of 2019, men are relatively more concentrated in higher-paying occupations such as financial investment analysis, computer and information systems managers, personal financial advisers, lawyers, and architectural and engineering managers (Center for American Progress, 2022). Female representation in STEM occupations increased from 8 per cent in 1970 to 27 per cent in 2019. The proportion of women employed in part-time work has remained fairly stable over the past five decades in the United Sates. In 2019, 23 per cent of employed women worked part-time in comparison to only 12 per cent of employed men (U.S. Bureau of Labour Statistics, 2021).

The United States was a world leader in implementing equal employment opportunity policies and passing and implementing antidiscrimination laws and regulations (Blau & Kahn 1996). Family and Medical Leave Act (FMLA) of 1993 allows eligible workers to take up to twelve weeks of unpaid parental leave. However, paid leave is firm voluntary. (Blau & Kahn, 2017). Autor (2014) found that an important explanation for rising inequality in the U.S. is the rising earnings gap between college and high school graduates which has more than doubled in the last three decades. In addition, there has been declining membership and bargaining power of

U.S. labour unions alongside fewer non-college employment opportunities due to technological advancement such as automation. Moreover, globalization has contributed to increased competition for U.S. manufacturers and U.S. workers, which has further reduced the bargaining power of unions. Intergenerational mobility is the lowest among all wealth democratic countries. While inequality has risen, mobility has stayed constant, further exacerbating intergenerational inequality.

The wage-setting institution in the United States is far less centralized than in other countries such as Sweden, Norway, Germany, and Austria (Flanagan et al. 1989). Moreover, the collective bargaining process is relatively more decentralized in the United States with a prominence of single-firm agreements. Furthermore, the U.S. government exerts minimal intervention in wage-setting (Flanagan et al. 1989). In Germany agreements between unions and employer representatives usually have a binding character for specific industries above a certain size (Drechsel-Grau et al., 2022). The United States have federal and state minimum wage legislation. However, the minimum wage is set at a relatively lower level by international standards (Blau & Kahn 1996). In Germany, a nationwide minimum wage of 8.50 euros was introduced in 2015 after collective bargaining negotiations pushed for higher wages. The minimum wage has been gradually increasing after 2015 (Drechsel-Grau et al., 2022). Wage dispersion is higher in the U.S. than in many other OECD countries. A much larger portion of the labour market is covered by unions in other OECD countries leading to more compressed wages compared to the United States (Blau & Kahn, 1996).

Based on the background information and empirical findings provided in this section, we expect to find a decline in the gender wage gap for both countries over the period due to increased human capital investments. Additionally, we expect gender differences in distribution across occupations and industries to contribute to the gender wage gap. However, we gender segregation in the labor market to explain less of the gender wage gap in 2019 compared to 1989. We also expect to find a rising return to skills due to skill-biased technical change, and rising inequality for both Germany and the United States. Moreover, we expect that this could have counterbalancing effects for progress made by women in terms of labor market characteristic. Due to a more centralized wage-setting institution in Germany, we expect more compressed wages in Germany to contribute to a smaller gender wage gap than in the United States.

3. Methodology

Simply quantifying the unadjusted gender wage gap in a country will reveal little about the sources of the gender wage gap. Men and women could differ in terms of human capital endowments, like education and experience, or other productivity-enhancing factors that are associated with wages. Moreover, the overall wage inequality might change over time or differ between countries as discussed in chapter 2. This can impact the returns to labour market characteristics like education and experience, or rents received from employment in different occupations and industries. In this chapter, we present the empirical strategy employed and the two decomposition methods applied in the empirical analysis, respectively the Kitagawa-Oaxaca-Blinder decomposition (Kitagawa 1995; Oaxaca 1973; Blinder 1973) and the Juhn, Murphy, and Pierce (1991) decomposition (hereafter the KOB and JMP decomposition).

3.1 Wage model specifications

In the empirical analysis, we want to estimate and decompose sources that contribute to wage differences between men and women. From chapter 2, we learn that gender differences in measurable labour market characteristics such as human capital endowments and selection into different occupations and industries are important for explaining gender differences in economic outcomes. Moreover, skill-biased technological change or crowding effects (Bergmann, 1974) could impact the rents received from employment in certain industries or occupations. We, therefore, estimate the male-female wage differentials conditional on these measurable labour market characteristics. For instance, human capital endowments are taken as a proxy for the observed productivity of the individual and controlling for differences allows for a comparison of wage differentials for equally productive workers (Kunze, 2008). We specify two different wage models to show the contribution of the added explanatory variables to male-female mean wage differentials. The first specification controls for human capital characteristics, education, and potential experience, while the full specification also includes indicator variables for industry and occupation. The two specifications and the interpretation of the included variables are presented below.

3.1.1 Human capital specification

In our empirical analysis, we are decomposing the predicted mean wage differentials between men and women using two different decomposition methods. For that purpose, we estimate separate wage regressions for men and women in Germany and the United States for 1989 and 2019. For individual i, we have the following model specification:

$$lnwage_i = \beta_0 + \beta_1 Education_i + \beta_2 Experience_i + \beta_3 Experince_i^2 + \epsilon_i \ (1.1)$$

The dependent variable is the estimated hourly logarithmic wage controlling for traditional human capital characteristics, years of education and years of labour market experience. In this model, an additional year of education increases log hourly wage by β_1 log points. Similarly, an additional year of experience increases log hourly wage by $\beta_2 + 2\beta_3 Experience$ log points.

3.1.2 Extended specification

The second specification allows us to estimate the effect of traditional human capital variables in addition to indicator variables for occupation and industry. We estimate the model, separately for men and women as:

$$\begin{aligned} lnwage_i = \beta_0 + \beta_1 Education_i + \beta_2 Experience_i + \beta_3 Experience_i^2 + \delta_r Industry_{r,i} \\ + \eta_d Occupation_{d,i} + \epsilon_i \ (1.2) \end{aligned}$$

For indicator variables included in the regression models, one category is omitted and serves as a reference category. Hence, the estimated coefficients of the indicator variables should be interpreted as the log point difference in wages between the omitted category relative to the other categories, keeping other factors constant. There are ten industry categories and ten broad occupational categories listed in the Appendix A2.

3.2 The Kitagawa-Oaxaca-Blinder decomposition

The KOB technique (Kitagawa 1955; Oaxaca 1973; Blinder 1973) allows us to decompose the estimated mean difference in wages between men and women into a proportion due to differences in measured (observable) characteristics and an unexplained component reflecting differences in unmeasured (unobservable) characteristics. This allows us to investigate how much the added explanatory variables, the measured characteristics, from the wage models specified in section 3.1 contributes to the gender wage gap in Germany and the United States. The unexplained part is commonly interpreted as a measure of labour market discrimination as it is not explainable by differences in observable characteristics (Becker, 1964). However, for this term to reflect labour market discrimination, all factors that determine the wage of an individual must be present in the wage regression and accurately measured (Cotton, 1988). Moreover, the measured variables should not be an outcome of discrimination themselves (Kunze, 2008). With data limitations or measurement errors, the residual component will reflect these omitted influences. Consequently, this term is more likely to reflect gender differences in unobserved characteristics, for instance, gender differences in ability or motivation that are not captured by the explanatory variables (Cotton, 1988).

In the following, equations describing the KOB decomposition are derived using similar notations as Blau and Kahn (2017). For year t, male (m) and female (f) wage regressions are estimated for individual i:

$$Y_m = X_m B_m + u_m \quad (2.1)$$

$$Y_f = X_f B_f + u_f \quad (2.2)$$

Equation 2.1 and 2.2 gives the relationship between wages and the added explanatory variables. The dependent variable is the log of hourly wages, denoted by Y. A vector of explanatory variables, X, represents the variables we control for. The explanatory variables we include are human capital characteristics as well as indicator variables for industry and occupation as explained in section 3.1. A vector of coefficients is indicated by B, and u represents the error term. Estimates of equations 2.1 and 2.2 enable us to compute the mean gender difference in wages that can be decomposed further.

Variables expressing mean values are indicated by a bar, and b_m and b_f are the estimated coefficients from the wage regressions, respectively B_m and B_f, using ordinary least squares (OLS). We can decompose the wage differential between men and women as:

$$\bar{Y}_m - \bar{Y}_f = b_m \bar{X}_m - b_m \bar{X}_f + b_m \bar{X}_f - b_f \bar{X}_f$$

$$= b_m(\bar{X}_m - \bar{X}_f) + \bar{X}_f(b_m - b_f) \quad (2.3)$$

The first term in the decomposition is the explained part of the gender wage gap, which is due to gender differences in measured characteristics ($\bar{X}_m - \bar{X}_f$) weighted by the male returns to these characteristics b. The second term gives us the residual component or unexplained part of the gender wage gap, which reflects gender differences in returns to characteristics ($b_m - b_f$) weighted by the mean of female characteristics $\bar{X}$.

3.3 The Juhn, Murphy and Pierce decomposition

The JMP-decomposition (1991) allows us to isolate the impact of changes in mean gender differences in labour market characteristics, and changes in the return to these characteristics to explain differences in the gender wage gap across time and countries. In this approach, gender differences in labour market characteristics and possibly labour market discrimination determine the percentile ranking of women in the male wage distribution. Simultaneously, the wage structure will determine the reward or penalty for having this position in the male wage distribution. To measure the overall wage structure in the country, male wage inequality is used. An important assumption for the JMP decomposition is that for male and female workers with the same percentile ranking, the same set of factors applies for determining their relative return to characteristics.

This methodology can be applied to decompose changes in the gender wage gap between two-time points or differences in the gender wage gap across two countries[4]. In the following equations, we illustrate the method for a decomposition across time. For a male worker i, in time j, we estimate the wage regression using ordinary least square (OLS):

$$Y_{ij} = X_{ij}B_j + \sigma_j\theta_{ij} \quad (3.1)$$

In equation 3.1, Y_{ij} represent the log of hourly wages. The explanatory variables and coefficients are expressed respectively by the vectors X_{ij} and B_j. We use the specification of the wage model displayed in section 3.1.2. The error term consists of the standardized residual

[4] See Blau and Kahn (1996;1997)

θ_{ij} which is the ranking of male or female workers in the residual male wage distribution, and the residual standard deviation σ_j of male wages for a given year. We can interpret the standardized residual as a measure for discrimination or unobserved characteristics that are important for determining economic outcomes. Similar to the KOB decomposition, the interpretation of the residual component as reflecting discrimination is problematic. The residual standard deviation of male wages expresses the residual male wage inequality after controlling for explanatory variables. Hence, for countries with more dispersed wage distributions the residual standard deviation σ_j will be larger than for countries with more compressed wage distributions.

We can express the gender gap in log wages for time j as:

$$D_j = Y_{mj} - Y_{fj} = \Delta X_j B_j + \sigma_j \Delta\theta_j \quad (3.2)$$

$$\Delta X_j = X_{mj} - X_{fj} \quad (3.3)$$

$$\Delta\theta_j = \theta_{jm} - \theta_{jf} \quad (3.5)$$

Where Y_{mj} and Y_{fj} are respectively the average male and female log of wages, and Δ indicates differences in male-female averages for the following variable. In equation 3.2 the gender wage gap is decomposed into two terms. The first term expresses gender differences in observable labour market characteristics weighted by the male return to these characteristics B_j. The second term expresses gender differences in percentile ranking weighted by the residual level of male wage inequality. The terms in equation 3.2 correspond to the two terms in the KOB- decomposition when using male coefficients as reference prices.

To explore the changes in the gender wage gap between two years, the following decomposition can be made using equation 3.2:

$$D_j - D_k = (\Delta X_j - \Delta X_k)B_k + \Delta X_j(\mathrm{B_j} - B_k) + (\Delta\theta_j - \Delta\theta_k)\sigma_k + \Delta\theta_j(\sigma_j - \sigma_k) \quad (3.6)$$

This first term is the "observed X's effect" and shows how changes in the observable characteristics of male and female workers affect the gender wage gap over time. For instance, a female worker's relative level of education will impact the gender wage gap in that country.

A declining gender wage gap over the period could therefore reflect a relatively higher level of educational attainment among female workers.

The second term, "the observed prices effect", shows how changes in the returns to the observed gender differences in labour market characteristics affect the gender wage gap over time. For instance, if female workers have less labour market experience than male workers, an increase in return to experience would have a widening effect on the gender wage gap.

The third term, the "gap effect", expresses how changes in the relative residual wage positions of men and women contribute to changes in the gender wage gap over time. Hence, this term gives the impact of relative changes in the female percentile ranking weighted by the residual male wage inequality in one year. For instance, if the gender differences in unobserved characteristics narrow over time this will contribute to a decline in the gender wage gap over the period.

Lastly, the fourth term shows the impact of changes in the residual wage inequality. This is termed the "unobserved prices effect" and reflects the impact of changes in the residual male wage inequality keeping the gender difference in unobserved characteristics constant. For instance, if the residual male wage inequality increases over time that would place a higher penalty on gender differences in unobserved characteristics and widen the gender wage gap.

Combining the first and third terms we get the total impact of observed and unobserved labour market characteristics. The total impact of the wage structure is captured by combining the second and fourth terms. As defined in the introduction the wage structure refers to the return to both observed and unobserved labour market characteristics and rents for employment in different occupations or industries. Employing this decomposition technique, we can therefore investigate how both labour market characteristics and overall wage inequality contributes to changes in male-female wage differentials over time or international differences in the gender wage gap.

3.4 Empirical strategy and identification

The empirical analysis for this thesis is divided into three parts. In the first part of the analysis, we use a KOB decomposition to estimate how much of the gender wage gap is explained by gender differences in labour market characteristics such as human capital factors and job characteristics. We compute the KOB decomposition using the Stata module *OAXACA* (Jann, 2008). We calculate four separate decompositions of the gender wage gap in Germany and the U.S. in 1989 and 2019, using estimates from two different wage models described in section 3.1.

We use the male coefficients as returns in the labour market instead of using coefficients from a pooled regression. Some have argued that estimated coefficients from a pooled regression would better resemble a non-discriminatory wage structure (Cotton 1988; Neumark 1988), than rewarding female characteristics using male coefficients. However, due to a lack of data on actual labour market experience in the samples we construct a variable containing the potential experience of men and women. Consequently, the female wage regression will give biased estimates of the female return to labour market experience due to measurement error. In turn, pooled regression estimates would then give biased counterfactual coefficients.

For the second part of the empirical analysis, we want to investigate how changes in the overall wage inequality in addition to changes in male and female labour market characteristics affect the gender wage gap in Germany and the United States between 1989 and 2019. For that purpose, we apply the JMP decomposition method to study the changes in the gender wage gap over time. The JMP method can also be applied to study cross-country differences in the gender wage gap. We, therefore, apply this method in the final part of the empirical analysis to investigate how country differences in the wage structure and relative gender differences in labour market characteristics contribute to cross-country differences in the gender wage gap for 1989 and 2019.

Male wage regressions are estimated for Germany and U.S. in 1989 and 2019 using the full specification found in section 3.1. We compute the JMP-decompositions using the Stata module *JMPIERCE2* (Jann, 2005). The inter-country changes in the gender wage gap between 1989 and 2019 are decomposed for both countries. Lastly, we decompose the cross-country difference in the wage gap between Germany and the US in 1989 and 2019.

Male estimates are used as reference coefficients (returns) and reference residual wage distributions for JMP decomposition. This implies that these coefficients and residual wage distributions are used as weights to determine the contribution of gender differences in observable characteristics. The year 1989 and the United States are respectively used as benchmarks for the intercountry decomposition of the changes in the gender wage gap over time and the cross-country decomposition of differences in the gender wage gap.

4. Data

In this chapter, we present and describe the data employed in the empirical analysis. We use cross-sectional data from two data-sources. First, the data-sources used to extract datasets for Germany and the United States are presented. Second, we outline the sample selection and harmonization of the variables included in the wage regression models. Finally, descriptive statistics on the final sample are presented at the end of the chapter.

4.1 Data sources

In this thesis, we are employing microdata sets from the Current Population Survey (CPS), the U.S. labour force survey, and the German Socio-Economic panel (SOEP), a longitudinal survey of private households in Germany. The empirical analysis covers cross-sectional samples for the years 1989 and 2019. This offers the opportunity to quantify the drivers of the gender wage gap in the two years. Moreover, it enables us to see the developments in male-female wage differentials between 1989 and 2019, factors contributing to changes over the period and cross-country variations in the gap.

Microdata for the United States is extracted from the IPUMS CPS database, which provides demographic information and employment data on an individual level (IPUMS, 2022). It harmonizes monthly microdata from the U.S labour force survey including the period from 1962 to 2021. The survey is administered by the U.S. Bureau of the Census and covers over 65,000 households. The database readily provides rich data for economic, social and health research.

SOEP provides longitudinal data on approximately 30,000 German citizens yearly for researchers worldwide (SOEP-Core, 2022). To receive the personal data, the researcher needs to sign a data distribution contract with the DIW in Berlin. The datasets provide information about the socioeconomic situation of the respondents, as well as information about behaviour, well-being, attitudes, and preferences. We employ SOEP-Core's latest wave version 37 in the empirical analysis. We use the $PEQUIV dataset from the SOEP Core vs 37 (waves A - BK = 1984 – 2020). Both data sources employed in the empirical analysis have collected valuable information about individual wages and characteristics that can be associated with differences in wage outcomes and are relevant for explaining the gender wage gap.

4.2 Sample selection

We select a representative sample of the working-age population following a similar approach as Blau & Kahn (2017). Two cross-sectional samples for 1989 and 2019 are selected from SOEP and IPUMS CPS. Firstly, we limit the samples to contain men and women in the age group 25-64 years, to capture the main work force in the population. Working individuals younger than 25 are believed to be combining work and studies and are therefore not representative of the workforce. The conclusion also holds for individuals older than 64. Furthermore, the samples are limited to include only full-time employees, defined as individuals working at least 35 hours per week. While wage differentials between men and women might be affected by gender differences in qualifications, they could also be affected by self-selection into full-time employment or part-time employment. Individuals that choose to work full-time might differ in terms of both measured and unmeasured characteristics compared to those that choose to work part-time. For instance, unobserved characteristics like ability or motivation could differ between part-time and full-time workers. Hence, we might introduce unobserved heterogeneity problems by including part-time workers. Observations with wages lower than 1 are also excluded to avoid negative log wage values. Finally, self-employed, and non-civilian workers are removed from the samples as they constitute special cases of the workforce. We are then left with a representative sample, which enables us to draw more accurate conclusions about the gender wage gap.

4.3 Harmonization of datasets and variable description

Since we are using data from two different data sources, harmonization of the variables is needed to perform the JMP decomposition. We have carefully studied the descriptions of the variables form the data sources before selecting the specific data variables. We harmonize the variables in terms of measurement and classification system for categories to generate a common system as we further study. In the following, we describe the variables included in the empirical analysis. Moreover, we outline the construction of variables needed for the empirical analysis, and harmonization efforts to ensure comparability between the datasets.

4.3.1 Dependent variable

The dependent variable for the regression models is the gross hourly log of wages. The logarithmic transformation of the wage variable allows for a percentage interpretation and comparing wage differentials across countries. We construct this variable for both samples using information about annual work hours and annual income. All income data are deflated to prices of 1989, using the Consumer Price Index (CPI). SOEP has no direct reporting of annual work hours, but constructs a variable using information about employment status, average number of work hours per week and number of months worked. We use a similar approach to construct a variable of annual work hours for the IPUMS CPS data extracted. IPUMS CPS contain a variable that reports the usual number of hours worked per week during the previous calendar year. Moreover, it has a variable that gives us the number of weeks that the respondent worked in the previous calendar year. This enables us to construct a variable that gives the annual work hours for an individual. Both IPUMS CPS and SOEP have not corrected for vacation or sick leave, which might create measurement errors in the calculated hourly wages by either overestimating or underestimating the annual work hours.

SOEP has a variable containing information about the annual income from wages or salary from the main job, as well as a variable containing information about income from secondary employment. By only taking the income from the main job, we create a consistent main salary income to calculate hourly wages. IPUMS CPS has a variable containing information about the annual income from salaried work received in the previous calendar year. We construct the log of hourly wage variable, $lnwage,$ by dividing the annual income by annual work hours.

4.3.2 Independent variables

Potential Experience

As discussed in section 3.3, both datasets lack information about actual labour market experience. We construct a variable for potential experience using the following approach:

$$\text{Potential experience} = \text{AGE} - \text{Years of education} - 6$$

This approach might create measurement errors, as women typically exhibit more intermittent labour force participation (Kunze, 2018). It is reasonable to think that both men and women would have periods outside of the labour market due to sickness, parental leave or job switching. Since women exhibit more intermittent labour market histories than men (Kunze, 2018) the potential experience calculated for women is more likely to be overestimated. Especially, since we have not corrected for the number of children each woman in the sample has given birth to. Correcting for the time out of work due to childbearing might improve the measurement error. Moreover, women in the United States and Germany work more part-time than men as addressed in sections 2.1 and 2.2. If one assumes that full-time workers accumulate more labour market experience than part-time workers this suggests that women on average would have less labour market experience compared to men. If the actual experience gap is larger than accounted for in the potential experience gap, we would overestimate the unexplained part of the gender wage gap. Moreover, a larger proportion of the gender wage gap would be accounted for by gender differences in characteristics. The variable, $Experience$, could therefore overstate the years of job experience for women.

Education

The SOEP dataset contains information about the years of education for individuals. This allows us to see how wages are impacted by an additional year of education in our wage regression model. Moreover, comparing cross-country differences in educational attainment might yield insight into the drivers of international differences and changes over time in the gender wage gap. We also need information about years of education to construct the potential experience variable. IPUMS does not have a variable for the individual number of years of education as SOEP does. However, it has information about educational attainment indicated by the type of education level for each individual. For example, it has various labels defined by categories such as grade 12 completed, bachelor's degree, associate, and professional degree. This allows us to construct a variable containing years of education by assigning each label a corresponding number of years of education.

Industry and Occupation

IPUMS CPS and SOEP use different classification schemes for their occupation and industry variables. The IPUMS uses the 1990 Census Bureau industrial classification system for the specific industry variable we have chosen to create our sample whereas the German SOEP uses 10 broad categories defined by a 1-digit industry code. For occupation classification, the IPUMS uses the 2010 Census Bureau occupation classification scheme for the specific occupation variable we have chosen. Whereas the German SOEP uses the ISCO-88 classification system.

We use the German SOEP classification systems for both industry and occupation as a base to create a common classification system. Therefore, to construct a common industry classification, we manually harmonize the IPUMS 1990 Census Bureau industrial classification system into the 1-digit industry code as per SOEP $PEQUIV Code book (SOEP Survey Papers 1082, 2022).

To harmonize the occupation categories, we use ISCO-08 as our base standard for the occupation classification system. We use Excel to manually harmonize the IPUMS detailed occupation categories into the broader classification system of ISCO-08 and later code it in STATA. We use ISCO-08 rather than ISCO-88 because it is the newer current version of the classification. The ISCO-08 classification system uses skill level and skill specialization to arrange occupations into groups. Hence, a category such as "professionals" could range from science and engineering professionals to musicians, singers and composers. Therefore, we cannot assume that all the occupations under one broad category are on a similar pay scale. See Appendix A2 for an overview of the occupational and industrial category codes.

4.4 Descriptive statistics

In this section, we present the summary statistics for the samples and variables used in the empirical analysis. We first present the development of wages and wage dispersion between 1989 and 2019 for male and female workers in Germany and the U.S. Lastly, the summary statistics on the dependent variables employed in empirical analysis are presented.

4.4.1 Wage statistics and wage distribution

Table 4.4.1. shows the development of the mean hourly wage, mean log of hourly wage, its standard deviation and mean percentile ranking of men and women in the male wage distribution. The statistics presented are in real value and cover both countries in their respective currencies for both years. We observe an increase in the log hourly wage for all groups apart from male workers in Germany. The log hourly wage for male workers is higher than their counterparts in both Germany and the United States in both years. Female workers in Germany on average earn 2.69 euros per hour less than men in 1989 and still earn 2.04 euros less than men in 2019. If we compare this with the United States, women on average earned 4.19 dollars less than men in 1989 and 3.67 dollars less compared to men in 2019.

Table 4.4.1: Wage Statistics 1989-2019, Germany and the U.S

	Germany				**U.S**			
	1989		**2019**		**1989**		**2019**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Hourly wage	10.9393	8.2402	12.5243	10.4846	14.1391	9.9478	17.5812	13.9126
Log hourly wage[a]	2.3179	2.0449	2.3543	2.2061	2.4871	2.1567	2.5974	2.3900
Standard deviation[b]	0.3668	0.3666	0.5859	0.5388	0.5813	0.5408	0.6859	0.6411
Mean wage rank[c]	0.5002	0.2785	0.5001	0.4237	0.6180	0.3309	0.6007	0.4090
Sample Size	2395	882	5367	2956	27199	19529	27045	22440

[a] Wages in Germany is in real gross euros/hour, and for U.S. it is in real gross dollars/hour. Wages in 2019 for both Germany and US are deflated to prices of 1989 basis using the CPI index calculator. [b] Standard deviation is calculated for the log hourly wage. [c] Mean wage rank is the average percentile ranking in the male wage distribution and is calculated based on log hourly wages.

Furthermore, we observe female workers in both countries moving up in the male wage distribution. Female workers in the U.S. increased their ranking from the 33^{rd} percentile in 1989 to 41^{st} percentile in 2019. In Germany, female workers improved their ranking in the male wage distribution from the 28^{th} percentile to the 42^{nd} percentile. Thus, female workers in Germany surpassed female workers in the U.S. with regards to percentile ranking in their respective male wage distributions in 2019 in contrast to 1989.

In Figure 4.4.1 and 4.4.2 below, we display the female-male wage differentials across three quartiles. We observe that the female workers have lower wages relative to men in all quartiles. For the United States, the wage differentials in the quartiles decrease over the period and most substantially for the 50^{th} percentile. In other words, female workers at the median have better closed the gap in terms of hourly wages. We observe a similar pattern in Germany and note that the decline in the 25^{th} and 75^{th} percentiles close the gap with modest decreases of 0.043 and 0.065 log points respectively (see Appendix A3). In comparison, the 50^{th} percentile closes the gap with 0.1332 log points. This is especially interesting given that the differences in the 25^{th} and 75^{th} percentile both were negative 0.2363 log points in 1989. In conclusion, the wage differences between men and women fall less at the top of the wage distribution for both countries over the period.

Figure 4.4.1. Difference across quartiles, Germany (Female-Male)

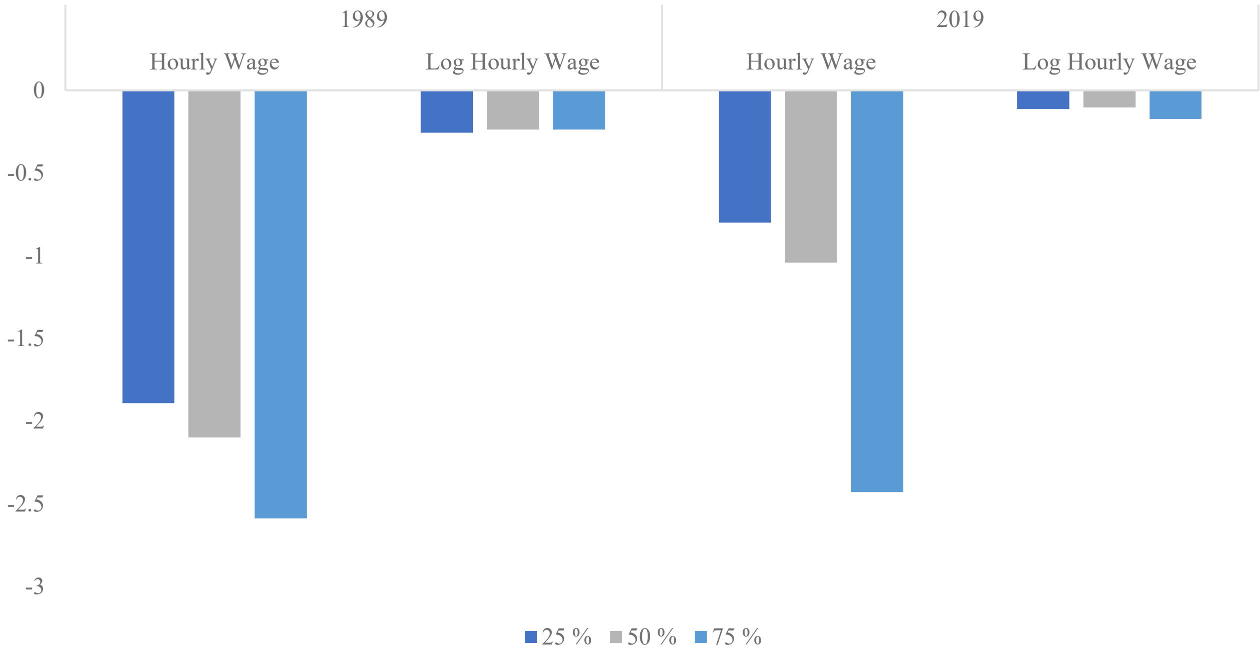
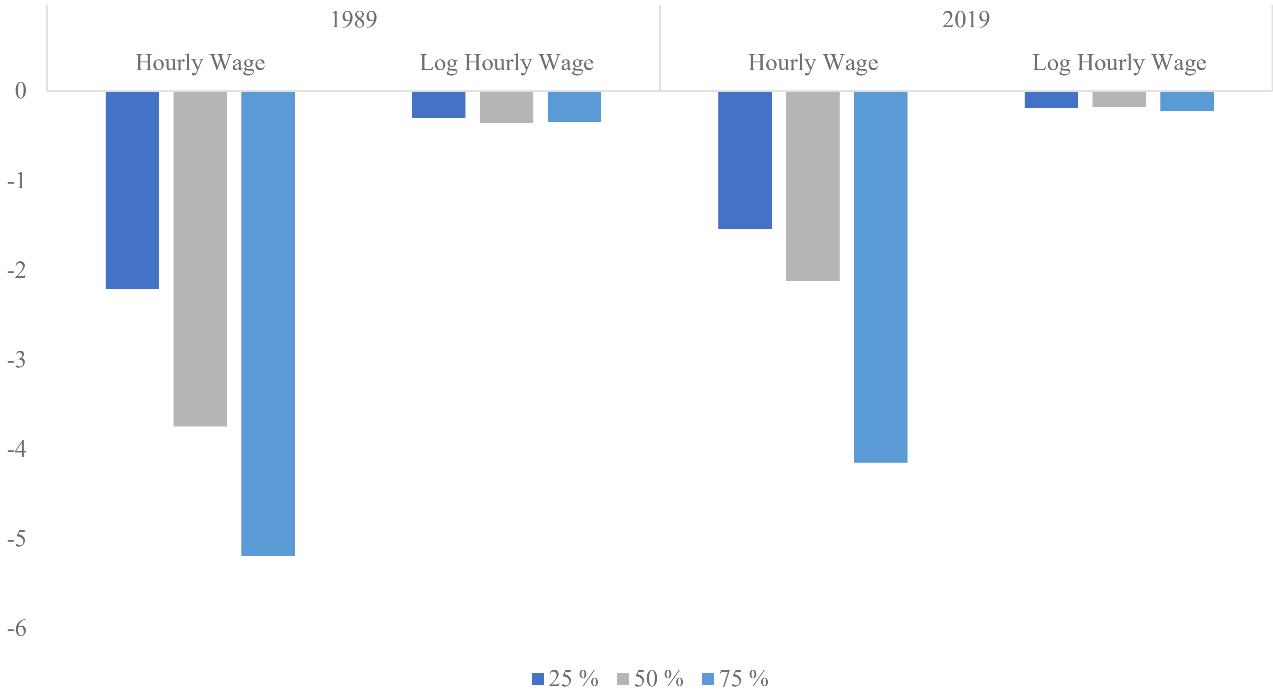


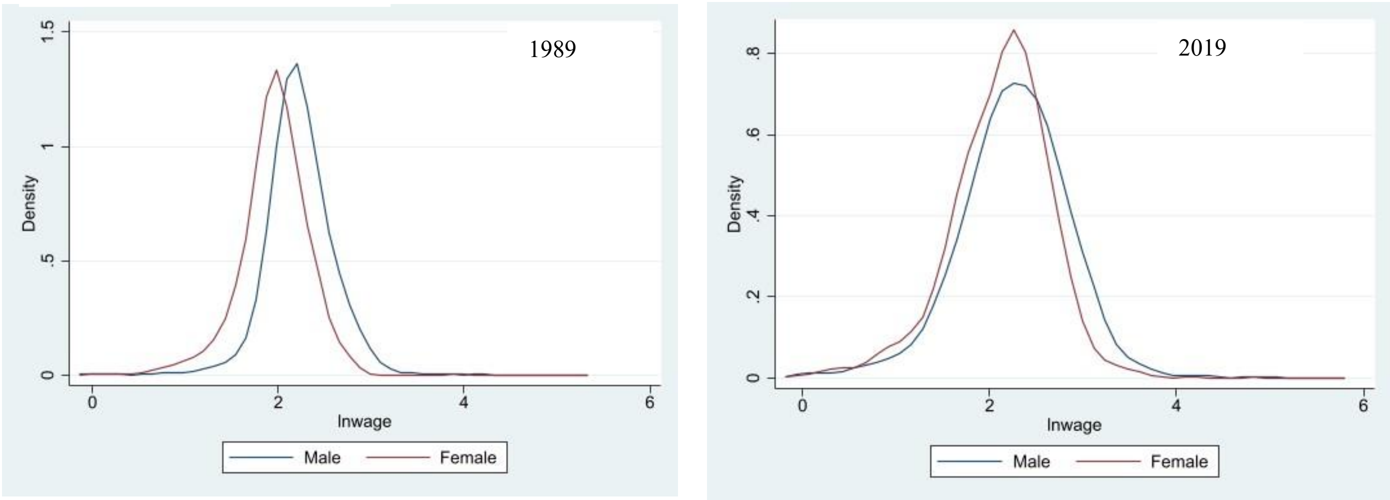
Figure 4.4.2. Difference across quartiles, U.S. (Female-Male)



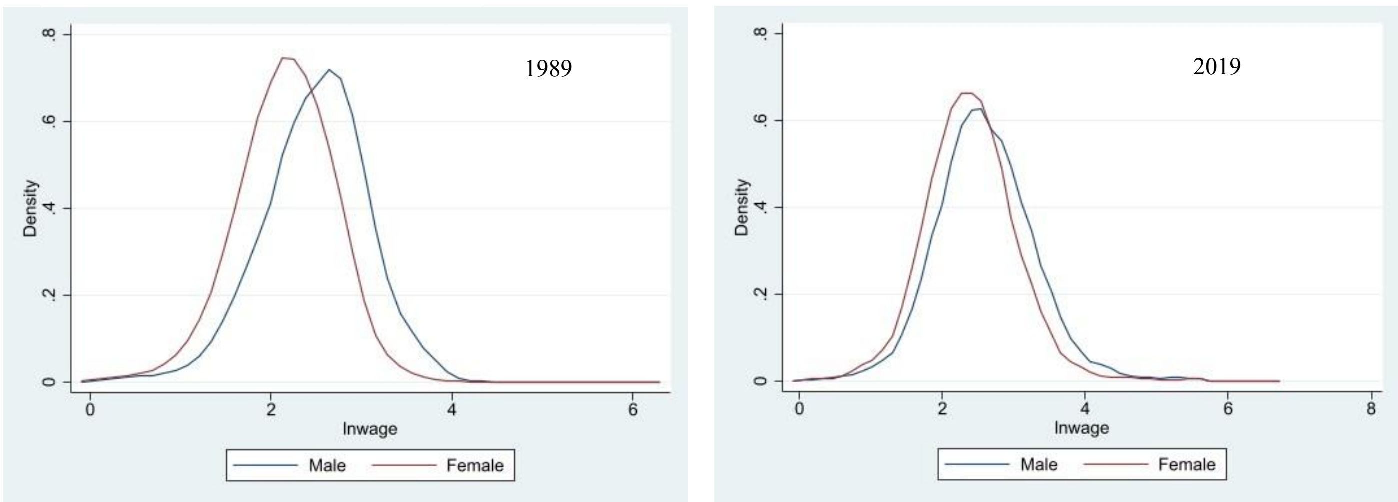
One consistent observation in Table 4.4.1 across all groups, is an increase in the standard deviation of log hourly wages, particularly for male and female workers in Germany where the standard deviations increase by 0.22 and 0.17 log points respectively. This indicates rising wage inequality in both countries over the period. This is consistent with the results in the kernel density Figures 4.4.3 and 4.4.4 given below. The figures display kernel density estimates of log hourly wages on a real dollar scale. This enables us to directly compare the wage distributions in the United States and Germany.

Figure 4.4.3. Kernel density distribution of the wage

Germany 1989- 2019



U.S. 1989- 2019



We can immediately observe that Germany had a more compressed wage distribution compared to the United States in 1989, indicating greater wage inequality in the United States. Furthermore, we see that the wages are more compressed in 1989 relative to 2019, indicating a development characterized by greater inequality. Moreover, comparing the female distribution to the male distribution over the period, it changes to become more similar to the male distribution in 2019.

4.4.2 Independent variables explaining the gender wage gap

Table 4.4.2 and 4.4.3 shows the mean values and standard deviation of education and potential experience. The statistics are presented to show how men and women in Germany and the U.S. compare in terms of education and experience and the development of these characteristics over time. Mean values and standard deviation for age are also presented in the tables. Since we construct a variable for the potential experience, the variation in terms of age and education in the sample is of importance.

In 1989, male and female workers in Germany have similar levels of education of approximately 11 years on average. Men do however have greater labour market experience compared to women, 24.6 and 22.2 years respectively. Since female and male workers have similar levels of education and men on average are older, the gap in experience is caused by an age gap. The younger female workforce may reflect that female participation in the labour market is a relatively new phenomenon. In 2019, we observe that female and male workers have similar levels of experience of approximately 26 years while the average female worker is older. The similar level of experience, therefore, reflects that women now have higher levels of educational attainment. In 2019, female workers have 13 years of educational attainment while men have 12 years.

In 1989, female and male workers in the U.S. have similar levels of educational attainment of 13 years on average. The gender gap in experience is negligible, and male and female workers have approximately 20.9 and 20.4 years of labour market experience respectively. In 2019, U.S. women are better than their counterparts in terms of years of education. However, female workers have less labour market experience on average. In 2019, women and men on average have 14.5 and 14 years of education respectively. Women have approximately 22.5 years of labour market experience on average while men have 23.8 years of labour market experience. Overall, the statistics show that men and women's human capital endowments, educational attainment, and labour market experience, are quite similar in both countries each year.

Table 4.4.2 Human Capital Variables 1989-2019, Germany

	1989				2019			
	Male		**Female**		**Male**		**Female**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age	41.7265	10.3989	39.0782	10.2966	44.7500	10.6812	45.2490	10.9083
Education	11.0818	2.5281	10.9274	2.5608	12.4607	2.9936	13.1803	2.7985
Experience	24.6447	10.9000	22.1508	11.1510	26.2893	10.6396	26.0687	11.3127
Experience^2	726.1213	563.0822	614.8617	538.0040	804.3048	563.8241	807.5085	577.2110

The sample size in 1989 is 2395 males and 882 females; in 2019 is 5367 males and 2956 females

Table 4.4.3 Human Capital Variables 1989-2019, U.S.

	1989				2019			
	Male		**Female**		**Male**		**Female**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Age	40.1186	10.1747	39.7468	10.0373	43.5460	10.7487	43.4089	10.8243
Education	13.2233	3.0020	13.3020	2.6426	13.909	2.753	14.4610	2.5989
Experience	20.8953	10.6908	20.4449	10.6811	23.637	11.153	22.9479	11.3724
Experience^2	550.9018	522.4191	532.0720	506.4130	683.106	560.489	655.9295	554.7723

The sample size in 1989 is 27199 males and 19529 females; in 2019 is 27045 males, and 22440 females

In Table 4.4.4 below, we report the distribution of male and female workers across industries and occupations. Note that the table does not show the fractions of female and male workers in an industry or occupation. In 1989, both female and male workers in Germany are highly concentrated in manufacturing and services. Following manufacturing and services, construction is the industry with the highest concentration of male workers. On the other hand, female workers are mostly concentrated in trade following the other two industries. By 2019, we observe shifts in the distribution of male and female workers across industries. Both male and female workers become even more concentrated in services. Consequently, the concentration of male and female workers in manufacturing, trade, and construction falls. In the United States, male and female workers are mostly concentrated in manufacturing, trade, and services in 1989. While male workers are mostly concentrated in the same industries in 2019, we observe a decline in manufacturing and an increase in services. Similarly, the concentration of female workers in manufacturing falls. Female workers are mostly concentrated in trade and services, which employes more than 50 per cent of the female workers. In general, we observe a shift from manufacturing towards services.

Studying the distribution of male workers across occupations in Germany in 1989, we observe a concentration in four main occupations. These are “craft and related trade workers”, “plant and machine operators and assemblers”, “technicians and associate professionals”, and “professionals”, in decreasing order of their concentration. This is consistent with the observation that male workers are concentrated in the manufacturing industries with a percentage of 47.9. Female workers are more dispersed, primarily across five occupations[5], mostly in “technicians and associate professionals”. In 2019, we observe shifts in the distribution of male workers across occupations relative to 1989. The share of male workers being employed in “craft and related trade workers” fell from 32 per cent to 13.5 per cent during this period. This shift in distribution seems to flow towards “professionals”, “technicians and associate professionals”, and “other” occupations. For female workers, we observe an increase in employment in “professionals”, “technicians and associate professionals” and “other” occupations, and a decrease in employment in “clerical support workers”. Again, we observe a shift towards services.

Compared to Germany, an interesting observation of the United States is the high employment rate among both male and female workers in managerial occupations in both years. In general, male workers in the U.S. are concentrated in “managers”, “professionals”, “technicians and associate professionals”, “craft and related trade workers”, and “plant and machine operators and assemblers” in 1989. Female workers are concentrated in fewer occupations, with “clerical

[5] Technicians and associate professionals, clerical support workers, service and sale workers, craft and related trade workers, and elementary occupations

support workers" employing 28 per cent of female workers. This is followed by "professionals" and "technicians and associate professionals". In 2019, the concentration of female workers in "clerical support workers" declines while it increases for "managers", "professionals" and "technicians and associate professionals". These four occupations employ 80 per cent of the female workforce in 2019. In comparison, 58 per cent of male workers are represented in these occupations in 2019. Male workers are more evenly distributed across occupations, with the highest concentration in "managers", "professionals", "technicians and associate professionals".

Table 4.4.4 Mean Industry and Occupation 1989-2019, Germany and the U.S.

	Germany				**US**			
	1989		**2019**		**1989**		**2019**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Industry								
Agriculture	0.0058	0.0023	0.0091	0.0051	0.0161	0.0065	0.017	0.0063
Energy	0.0167	0.0034	0.0000	0.0000	0.0239	0.0089	0.024	0.0061
Mining	0.0104	0.0000	0.0009	0.0003	0.0078	0.0014	0.004	0.0005
Manufacturing	0.4785	0.3673	0.2620	0.1272	0.2582	0.1692	0.153	0.0715
Construction	0.1102	0.0102	0.0656	0.0074	0.0978	0.0116	0.113	0.0158
Trade	0.0601	0.1156	0.0663	0.0809	0.1656	0.1490	0.152	0.1367
Transport	0.0685	0.0283	0.0341	0.0101	0.0654	0.0265	0.070	0.0276
Bank, Insurance	0.0284	0.0488	0.0281	0.0294	0.0552	0.1008	0.062	0.0867
Services	0.1687	0.3458	0.2458	0.3606	0.2085	0.4318	0.300	0.5528
Other	0.0526	0.0782	0.2881	0.3789	0.1015	0.0945	0.104	0.0961
Occupation								
Managers	0.0459	0.0181	0.0639	0.0551	0.1247	0.0957	0.153	0.1331
Professionals	0.1253	0.0794	0.1846	0.1847	0.1597	0.2039	0.208	0.2927
Technicians and Associate Professionals	0.1257	0.2222	0.1737	0.3150	0.1744	0.1752	0.164	0.2211
Clerical Support Workers	0.0735	0.1939	0.0676	0.1083	0.0543	0.2780	0.054	0.1604
Service and Sale Workers	0.0409	0.1168	0.0591	0.0896	0.0729	0.0939	0.083	0.0985
Skilled Agriculture, Forestry and Fishery Workers	0.0050	0.0023	0.0073	0.0030	0.0100	0.0029	0.011	0.0037
Craft and Related Trade Workers	0.3232	0.1202	0.1355	0.0244	0.1825	0.0309	0.147	0.0191
Plant and Machine Operators, and Assemblers	0.1545	0.0907	0.0850	0.0173	0.1370	0.0736	0.101	0.0270
Elementary Occupations	0.0676	0.1077	0.0525	0.0416	0.0845	0.0460	0.079	0.0444
Other	0.0384	0.0488	0.1709	0.1610	0.0000	0.0000	0.0000	0.0000

5. Empirical analysis of the gender wage gap

In this chapter, the results from the empirical analysis are presented. Section 5.1 reports the results from the KOB decomposition. Results from the JMP decomposition of the changes in the gender wage gap in Germany and the United States between 1989 and 2019 are reported in section 5.2. Lastly, we report the findings from a cross-country decomposition of the gender wage gap in Germany and the United States.

5.1 Results from the Kitagawa-Oaxaca-Blinder decomposition

In this section, we want to investigate the factors contributing to the gender wage gap in Germany and the United States. We first present the results from the KOB decomposition for Germany in 1989 and 2019. Next, we present the results for the United States in 1989 and 2019. Finally, we compare and summarize the findings for the Kitagawa-Oaxaca-Blinder decomposition.

Table 5.1.1 and 5.1.2 shows how the explanatory variables contribute to the observed male-female wage differentials for Germany and the United States. The decomposition results are based on wage regression estimates for men and women found in Appendix A4.1 and A4.2. The table displays the decomposition results for the two specifications defined in section 3.1. The full specification calculates the results of the decomposition for these years when adding industry and occupation variables to the wage regression model. The decomposition method allows us to investigate how much gender differences in human capital, industry and occupation characteristics explain the gender wage gap. However, directly comparing the decomposition results for 1989 and 2019 might be misleading as the return to the variables might have changed between the two years. This is something we will investigate further with the JMP decomposition in section 5.2. The contribution of each component is reported in log points and as a percentage of the total gender wage gap. The reported log points give the gender differences in mean values weighted by the corresponding male coefficients or returns for that year's wage regression.

5.1.1 KOB decomposition results for Germany: 1989 and 2019

Table 5.1.1 below, shows the results from the KOB- decomposition for Germany in 1989 and 2019. The results in the table are structured into panels (1) and (2), covering the two wage model specifications. In each panel, the contribution of each explanatory variable is shown separately. These are further aggregated to show the full effect of the variables and displayed as "Total explained". Its counterpart is the "Total unexplained". Together these parts represent the total gender wage gap.

Table 5.1.1 Decomposition of Gender Wage Gap, Germany: 1989 and 2019[a]

	1989		**2019**	
	log points (1)	% of Gender Wage Gap (2)	log points (3)	% of Gender Wage Gap (4)
(1) Human capital specification				
Education variables	0.0100	4 %	-0.0805	-54 %
Experience variables	0.0310	11 %	0.0122	8 %
Total explained	0.0410	15 %	-0.0683	-46 %
Total unexplained	0.2320	85 %	0.2165	146 %
Total gender wage gap	0.2730	100 %	0.1482	100 %
(2) Full specification				
Education variables	0.0064	2 %	-0.0581	-39 %
Experience variables	0.0286	10 %	0.0111	7 %
Industry variables	0.0228	8 %	0.0310	21 %
Occupation variables	0.0093	3 %	-0.0322	-22 %
Total explained	0.0670	25 %	-0.0363	-24 %
Total unexplained	0.2060	75 %	0.1965	133 %
Total gender wage gap	0.2730	100 %	0.1482	100 %

[a] based on German SOEP v37 (waves A - BK = 1984 - 2020)

The explained part: $b_m(\bar{X}_m - \bar{X}_f)$
The unexplained part: $\bar{X}_f(b_m - b_f)$
$\bar{X}_m$ *and* $\bar{X}_f$ are respectively mean values of female and male worker's characteristics, and b_m *and* b_f are male and female return to these characteristics.

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The human capital specification gives the effect of education and labour market experience in explaining the gender wage gap. In 1989, both education and experience contribute to widening the gender wage gap by respectively 0.01 and 0.031 log points. The widening effect reflects that men are relatively more endowed in terms of education and labour market experience which raises their wages compared to women. By 2019, the effect of education is reversed. Women now have higher educational attainments which raise their relative wage and therefore narrow the gender wage gap by 0.0805 log points. Experience still has a widening effect, but the magnitude has diminished to 0.0122 log points.

In panel 2, we observe that adding occupation-and industry- variables reduces the effect of human capital characteristics on the gender wage gap. This indicates that education and experience are associated with industry and occupation, and hence captures some of their effect. The association between the variables is stronger in 2019, and it is primarily limited to the education variable. We observe minimal changes in the effect of experience on the gender wage gap and its share of the total explained in both years. The effects when adding industry and occupation are reductions of 0.0024 and 0.0009 log points in 1989 and 2019, respectively.

While we observe a similar pattern for education in 1989 with a reduction of the impact of 0.0036 log points, the change is substantially higher in 2019 of 0.0224 log points. The total change of the impact of education both across years and the two specifications is multifaceted, but KOB-decomposition does not facilitate the separation of these. From one perspective, women have improved their levels of education over the period, but the total change is not only attributed to this factor. From the first equation displayed below Table 5.1.1, we observe that the gender difference in measured characteristics is weighted by a price component which refers to the male returns to characteristics. Changes in the return to education can be partially attributed to demand from industry and occupation due to technological change. Acemoglu (2002) argues that skill-biased technical change favours higher-skilled workers, which drives the rise in the return to education (see estimates in Appendix A4: Table A4.1). This effect has likely been reinforced through further technological changes since early 2000.

Proceeding to industry and occupation, we find that the composition of men and women across these contributes to the increase of the observed wage disparities in 1989. The distribution of men and women across industries contributes to raising the relative wage of men by 0.0228 log points, thereby making it the second most important factor for explaining the gender wage gap. Moreover, this impact increases to 0.031 log points in 2019. This is similar to the findings of Blau and Kahn (2017) who found that gender distribution by industry still was an important factor in explaining the gender wage gap in 2010. In contrast, the occupation variable does not follow the same pattern.

Gender differences in occupations explain a modest 0.0093 log points of the gender wage gap in 1989. However, in 2019 the gender differences in occupations favour women, which raises women's wages by 0.0310 log points. One might be tempted to conclude that this is due to the higher concentration of women in high-wage occupations. This is however not consistent with the findings regarding percentiles where it was concluded that the unadjusted gap decreases much less in the 75^{th} percentile, as compared to the 50^{th} percentile. A more probable cause could be the categories themselves. Although the categories are defined by skill level and specialization according to the standard, we observe a great deal of variation in the subcategories. For instance, primary school teachers and mechanical engineers are both grouped as "professionals". Given such disparities within the main categories and the fact that male returns are used as weights to calculate the effects, this might explain the puzzling result. On the other hand, other studies have used similar categories without reporting similar results.

The total gender wage gap has over the period declined from 0.2730 to 0.1482 log points. A key observation is in the components of the total gender wage gap, total explained and total unexplained. In line with the findings that the gender wage gap no longer is as well explained by the independent variables, the total explained part decreases from 0.0670 to negative 0.0363 log points in the full specification. Its counterpart, the total unexplained, decreases slightly from 0.2060 to 0.1965 log points.

5.1.2 KOB-decomposition results for the United States: 1989 and 2019

Table 5.1.2 reports the results of the KOB- decomposition for the United States in 1989 and 2019.

Table 5.1.2 Decomposition of Gender Wage Gap, United States: 1989 and 2019[a]

	1989		**2019**	
	log points (1)	% of Gender Wage Gap (2)	log points (3)	% of Gender Wage Gap (4)
(1)Human capital specification				
Education variables	-0.0069	-2 %	-0.0645	-31 %
Experience variables	0.0067	2 %	0.0096	5 %
Total explained	-0.0002	0 %	-0.0549	-26 %
Total unexplained	0.3306	100 %	0.2623	126 %
Total gender wage gap	0.3304	100 %	0.2074	100 %
(2)Full specification				
Education variables	-0.0049	-1 %	-0.0422	-20 %
Experience variables	0.0058	2 %	0.0088	4 %
Industry variables	0.0393	12 %	0.0174	8 %
Occupation variables	-0.0002	-0.1 %	-0.0358	-17 %
Total explained	0.0400	12 %	-0.0518	-25 %
Total unexplained	0.2904	88 %	0.2592	125 %
Total gender wage gap	0.3304	100 %	0.2074	100 %

[a] based on IPUMS-CPS

The explained part: $b_m(\bar{X}_m - \bar{X}_f)$
The unexplained part: $\bar{X}_f(b_m - b_f)$
$\bar{X}_m$ *and* $\bar{X}_f$ are respectively mean values of female and male worker's characteristics, and b_m *and* b_f are male and female return to these characteristics.

From the human capital specification, we observe that education already in 1989 had a narrowing effect on the gender wage gap of 0.0069 log points. This is consistent with the descriptive statistics that find that female workers had relatively higher levels of educational attainment compared to male workers. Experience on the other hand had a slight widening effect of 0.0067 log points. The direction of the variables' effect on the gender wage gap is the same in 2019, but their magnitude has changed. The effect of the education variable is however much greater than the effect of the experience variable, with negative 0.0645 compared to 0.0096. This is consistent with the observations on education and experience in section 4.4.1. The gap in experience increases during this time-period because the education gap has increased in favour of women. Consequently, female workers enter the labour market later than men and accumulate less labour market experience.

In the full specification, we observe similar results as for Germany. Including the industry and occupation variables reduces the effect of the human capital variables, especially for education. Similarly, we observe that the gender composition in occupations favours women and has a narrowing effect on the gender wage gap. Again, one should be careful to infer that women are not necessarily employed in higher-paid occupations. The result of the industry variable is more in line with expectations about labour market segregation across industries. The distribution of male and female workers across industries widens the gender wage gap with respectively 0.0393 and 0.0174 in 1989 and 2019.

The total gender wage gap declined by 0.123 log points between 1989 and 2019. Studying the development in the components of the total gender wage gap we observe a decrease in both. In 2019, the gender wage gap is no longer explained by gender differences in observed characteristics. The observed gender differences in characteristics contributes to narrow the gender wage gap by 0.0518 log points in 2019 in contrast to widening the gender wage gap by 0.0400 log points in 1989. The unexplained part of the gender wage gap declines from 0.2904 to 0.2592. In conclusion, due to the total explained having a negative effect on the gender wage gap in 2019, the gender wage gap is attributed to gender differences in unobserved characteristics.

5.1.3 Summary and Comparison KOB decomposition results

We observe a decline in the gender wage gap for both countries between 1989 and 2019. However, the gender wage gap in the United States is greater than that of Germany in both years. In addition to changes in the return to education, the narrowing of the gender wage gap can primarily be attributed to female workers' progress in terms of educational attainment relative to male workers. Gender differences in experience contribute to widening the gender wage gap, however, the effect is modest. In line with expectations, the composition of men and women across industries widens the gender wage gap in both countries. The effect is however decreasing over the period in the U.S., while it has been increasing in Germany. A puzzling observation is that the results show that the occupation variable narrows the gender wage gap in 2019 for both countries. This is contrary to expectations about the distribution of male and female workers across occupations from earlier studies[6]. As discussed, this could be a result of the broad classification of occupations disguising gender differences within sub-categories. The result of this can be an underestimation of the total explained part of the gender wage gap and an overestimation of the unexplained part. In addition to this uncertainty, while the gender differences in characteristics have changed between 1989 and 2019 for both countries, changes in the return to these characteristics are likely to be different between 1989 and 2019. From the descriptive statistics, we find evidence of rising inequality in both countries. Hence, the explanatory variables' effect on the gender wage gap can either reflect that women have improved their relative characteristics, or it can reflect that the return to observable characteristics has changed between 1989 and 2019.

5.2 Decomposition of changes in the gender wage gap

The Kitagawa-Oaxaca-Blinder decomposition shows that the gender wage gap declined between 1989 and 2019 for both Germany and the United States. However, the Kitagawa-Oaxaca -Blinder decomposition does not reveal how changes in the wage structure contributed to the narrowing of the gender wage gap, if there were any. The descriptive statistics suggest that there has been rising wage inequality over the period, which suggests that the return to characteristics has changed. This is in line with changing return to characteristics due to skill-biased technical change. By decomposing the changes in the gender wage gap for both countries, between 1989 and 2019, we can investigate how both changes in the wage structure and gender differences in human capital, industry and occupation characteristics contribute to the decline in the gender wage gap over time. Employing the Juhn, Murphy, and Pierce (hereafter JMP) decomposition, allows us to isolate the impact of changing returns on the gender wage gap. This is reflected in the wage structure component. The contribution of

[6] See Blau and Kahn (2017)

relative changes in human capital, industry and occupation characteristics on the gender wage gap is reflected in the "characteristic effect".

5.2.1 Germany, 1989-2019

In Table 5.2.1, we show the detailed JMP decomposition results for Germany between 1989 and 2019. The observed X's effect, observed prices, gap and unobserved prices are the different components of the decomposition and are organized row-wise. The observed X's reflect the effect of changes in relative endowments by gender on the gender wage gap and the effect of shifts in the gender compositions across occupations and industries. The observed prices show how changes in the wage structure, the male return to observed characteristics, affects the gender wage gap. The gap effect shows how changes in the female ranking in the residual male wage distribution contribute to changes in the gender wage gap. This position reflects unobserved characteristics, and this component then reflects how changes in gender differences in unmeasured characteristics affect the gender wage gap. Unobserved prices show how changes in the male returns to the unobserved characteristics affect the gender wage gap. In other words, this effect captures how changes in the level of residual male wage inequality impact the gender wage gap. Summarizing the observed X's effect and the gap effect, we get the total effect of changes in "characteristics" factors on the gender wage gap. Likewise, by summarizing the observed and unobserved prices effect, we get the total effect of changes in the wage structure on the gender wage gap.

Finally, the equations showing how these components are calculated are displayed below the table. The estimated wage regressions for men and women applied in the decompositions are found in Appendix A4. The Year 1989 is used as a benchmark, and the measured changes of the components in the decomposition are calculated relative to 1989.

Table 5.2.1 Decomposition of changes in the gender pay gap, Germany 2019-1989[a]

	Full specification
Observed X's	
All X's	-0.0893
Education variables	-0.0361
Experience variables	-0.0180
Occupation variables	-0.0258
Industry variables	-0.0094
Observed prices	
All B's	-0.0260
Education variables	-0.0284
Experience variables	0.0005
Occupation variables	-0.0157
Industry variables	0.0177
Gap	-0.0782
Unobserved Prices	0.0687
Sum characteristics	-0.1675
Sum wage structure	0.0427
Change in differential (D19 - D89)	-0.1248

[a]based on German SOEP v37 (waves A - BK = 1984 - 2020)

The observed X' s effect: $(\Delta X_{2019} - \Delta X_{1989})B_{1989}$

The gap effect: $(\Delta\theta_{2019} - \Delta\theta_{1989})\sigma_{1989}$

The unobserved prices effect: $\Delta\theta_{2019}(\sigma_{2019} - \sigma_{1989})$

ΔX is the mean male-female difference in observed characteristics, and B is the male return to characteristics. $\Delta\theta$ is the male-female difference in unobservable characteristics (or difference in percentile ranking in the residual male wage distribution). σ is the male return to unobserved characteristics.

In Table 5.2.1, we observe that the X's effect is negative 0.0893 log points, which indicates that it has a narrowing effect on the gender wage gap. Since 1989 is used as the benchmark, female workers in 2019 are in a more favourable position when compared to their male counterparts than they were in 1989. Concerning education, the gap between male and female workers has in absolute value increased. However, the educational gap is in favour of female workers in 2019 and has a narrowing effect of 0.0361 log points on the gender wage gap over the period. While experience in 2019 still has a widening effect on the gender wage gap[7], female workers in 2019 are in a more favourable position compared to their male counterparts than they were in 1989. The relative improvement in terms of experience has a narrowing effect of 0.0180 log points on the gender wage gap over the period. The effect of the relative change in the education variable is greater than that of the experience variable. The occupational and industry variables follow the same development. Shifts in the occupational distribution of male and female workers narrow the gender wage gap by 0.0258 log points. This indicates that women become more represented in the higher paying occupations of 1989 over the period. The changes in the distribution of men and women across industries also contribute to narrow the gender wage gap by 0.0094 log, which suggests that women become relatively more concentrated in the higher paying industries of 1989 in 2019. This effect is smaller than the narrowing effect of distributional shifts in occupation by gender.

The observed prices effect also contributes to reduce male-female wage differentials over the period, specifically by 0.0260 log points. Given the gender differences in observable characteristics in 2019, changes in return to these characteristics between 1989 and 2019 have a narrowing effect on the gender wage gap in total. However, when evaluating the changes in return to human capital, occupational and industry-characteristics separately we observe some differing effects on the gender wage gap. Over the period, the male return to education increases as seen from the regression results in the Appendix A4 Table A4.1. This is in line with the expectations about rising inequality over the period found in the kernel density figures in section 4.4. Since female workers in 2019 have relatively higher educational attainments than their male counterparts, the increase in return to education narrows the gender wage gap. Likewise, changes in the wage structure for occupations narrow the gender wage gap. This could be due to increasing returns in occupations where female workers are more concentrated in 2019 or decreasing returns for employment in occupations where male workers are more concentrated in 2019. Additionally, we cannot exclude the possibility that there is a combination of these forces at work. Proceeding to experience, the return has increased and the gender difference in this characteristic is weighted more heavily in 2019. Consequently, the experience variables have a widening effect on the gender wage gap. Similarly, changes

[7] From KOB-decomposition results for Germany.

in the return for employment in different industries widen the gender wage gap. The change in return cannot be decomposed further and similar reasoning as for occupation applies.

Proceeding to the gap effect, we observe that it decreases the gender wage gap by 0.0782 log points. This shows that female workers in 2019 improved their percentile ranking in the residual male wage distribution of 1989. We can interpret this effect to reflect that the gender differences in unobserved characteristics are declining over the period.

The unobserved prices effect works to widen male-female wage differentials over the period by 0.0687 log points. We can interpret this effect to indicate that the residual male wage distribution has become more dispersed over the period and that residual male wage inequality is rising. This is consistent with the results of the descriptive statistics, where we observe that the male wage distribution becomes more dispersed between 1989 and 2019. While female workers have improved their unobserved characteristics, a more dispersed residual male wage distribution in 2019 compared to 1989 penalizes more harshly gender differences in unobserved characteristics. In other words, rising returns to unobserved characteristics have a widening effect on the gender wage gap over the period since female workers are relatively less endowed with these unobserved characteristics.

Summarizing the observed X's effect and the gap effect, we observe that it has a narrowing effect on the gender wage gap of 0.1675 log points between 1989 and 2019. We interpret this as female workers relatively improving in terms of both measured and unmeasured characteristics over the period. On the other hand, the widening of the male wage distribution, and changes in the wage structure, have had a widening effect on the gender wage gap of 0.0427 log points over the period. Thus, the total on gender gap is negative 0.1248.

5.2.2 United States, 1989-2019

The JMP-decomposition results of the changes in the gender wage between 1989 and 2019 in the United States are reported in Table 5.2.2. The results displayed in the table follow a similar structure and interpretation to that of Table 5.2.1.

Table 5.2.2 Decomposition of changes in the gender pay gap, United States 2019-1989[a]

	Full specification
Observed X's	
All X's	-0.0476
Education variables	-0.0292
Experience variables	0.0037
Occupation variables	-0.0264
Industry variables	0.0043
Observed prices	
All B's	-0.0441
Education variables	-0.0062
Experience variables	-0.0007
Occupation variables	-0.0092
Industry variables	-0.0261
Gap	-0.0623
Unobserved Prices	0.0311
Sum characteristics	-0.1099
Sum wage structure	-0.0130
Change in differential (D19 - D89)	-0.1230

[a]Based on IPUMS CPS

The observed X' s effect: $(\Delta X_{2019} - \Delta X_{1989})B_{1989}$

The gap effect: $(\Delta\theta_{2019} - \Delta\theta_{1989})\sigma_{1989}$

The unobserved prices effect: $\Delta\theta_{2019}(\sigma_{2019} - \sigma_{1989})$

ΔX is the mean male-female difference in observed characteristics, and B is the male return to characteristics. $\Delta\theta$ is the male-female difference in unobservable characteristics (or difference in percentile ranking in the residual male wage distribution). σ is the male return to unobserved characteristics.

Similar to the decomposition results for Germany the observed X's effect is negative, indicating that female workers are in a relatively more favourable position in 2019 compared to 1989 in terms of observable characteristics. This contributes to narrowing the gender wage gap by 0.0476 log points over the period. The education gap in favour of female workers grows over the period. Weighted by male returns to education in 1989 this relative improvement in educational attainment narrows the gap by 0.0292 log points. Due to female workers' higher levels of educational attainment in 2019, the experience gap increases over the period. This is because the experience variable is constructed using the years of education and the age of the workers. The average male and female worker in the United States are the same age in 2019, resulting in women on average gaining less labour market experience from increased educational attainments. Consequently, this contributes towards widening the gender wage gap by 0.0038 log points. Shifts in the distribution of male and female workers across occupations and industries have differing effects on the gender wage gap. In contrast to Germany, female workers in the U.S. become more concentrated in the lower-paying industries of 1989. This widens the gender wage gap by 0.0043 log points over the period. Compositional changes in the distribution of male and female workers across occupations narrow the gender wage gap by 0.0264. This indicates that female workers in 2019 are more concentrated in higher-paying occupations of 1989 than female workers in 1989.

The observed prices effect is also negative and narrows the gender wage gap by 0.0442 log points over the period. While the return to education increases between 1989 and 2019[8], the return to experience slightly decreases This is beneficial for female workers in 2019 since they have relatively higher educational attainment and less experience than male workers. Changes in these returns narrow the gender wage gap 0.0504 log points in total. Similarly, we observe changes in the return of industries and occupations having a narrowing effect on the gender wage gap by respectively 0.0261 and 0.0092 log points.

Turning to the gap effect, we observe that it has a narrowing effect on the gender wage gap of 0.0624 log points. Similar to Germany, female workers in the United States have improved their percentile ranking in the residual male wage distribution of 1989. This indicates that male

[8] observed in the wage regressions in Appendix A.4

and female workers become more similar in terms of unobserved characteristics over the period.

Part of the convergence in male-female wages over the period is offset by a rise in the residual male wage inequality represented by the unobserved prices effect. This is consistent with the results in the descriptive statistics where we find that the male wage distribution becomes more dispersed over time. In other words, the return to unobserved characteristics increases and this widens the gender wage gap by 0.0312 log points.

Over the period, we observe a decline in the gender wage gap of 0.1230 log points. Both the wage structure and the "characteristics" effects contribute to narrowing the gender wage gap, with the "characteristics" effects contributing the most by 0.1099 log points to 0.0130 log points.

5.2.3 Summary and comparison of the JMP decomposition findings

The results in this section show that the gender wage gap decreases by approximately 0.12 log points in both countries. While descriptive statistics show higher wage inequality in both countries, we observe that only the wage structure effect in Germany has a widening effect on the gender pay gap.

5.3 Decomposition of the difference in gender wage gap: Germany and the United States

The decline in the gender differences in observed and unobserved endowments has had a narrowing effect on the gender wage gap in both countries. Over this period, we also observe that the wage structure changes, which is expected since the male wage distribution becomes more dispersed for both countries. While we observe a decline in the gender wage gap of approximately 0.12 log points for both countries, Germany has a consistently smaller gender wage gap compared to the United States. The results from the kernel density estimates in section 4 suggest that Germany has a more compressed wage distribution when compared to the United States in 1989. In this section, we, therefore, want to decompose the cross-country difference in the gender wage gap for 1989 and 2019. By decomposing the cross-country difference in the gender wage gap, we want to investigate if Germany's relatively smaller gender wage gap is caused by smaller gender differences in characteristics or its more compressed wage structure. For this purpose, we can apply the JMP method where we decompose the differences in the gender wage gap between two countries.

The JMP decomposition results for 1989 and 2019 are displayed in Table 5.3.1 below. The structure is the same as in Table 5.2.1 and 5.2.2. However, we now look at relative differences across countries and not across time. We use the United States as a benchmark and the results are to be interpreted relative to the United States. The observed X's effect gives the contribution of inter-country gender differences in human capital, industry and occupation characteristics to the international difference in gender wage weighted by the male workers' return to these characteristics in the United States. The observed prices effect gives the impact of international differences in return to observable characteristics weighted by gender differences in observable characteristics in Germany. The gap effect reflects how differences in the respective female ranking in residual male wage distribution contribute to international differences in the gender wage gap weighted by male returns to unobserved characteristics in the United States. Lastly, the unobserved prices effect reflects how country differences in residual male wage inequality contribute to international differences in the gender wage gap weighted by gender differences in unobservable characteristics in Germany.

Table 5.3.1 U. S - Germany differences in the gender wage gap: 1989 and 2019[a]

	Contribution to the Germany-U.S. Difference	Contribution to the Germany-U.S. Difference
	1989	**2019**
Observed X's		
All X's	0.0683	-0.0049
Education variables	0.0144	-0.0128
Experience variables	0.0233	-0.0011
Occupation variables	0.0212	0.0140
Industry variables	0.0093	-0.0049
Observed prices		
All B's	-0.0413	0.0084
Education variables	-0.0032	-0.0032
Experience variables	-0.0005	0.0034
Occupation variables	-0.0118	-0.0103
Industry variables	-0.0258	0.0185
Gap	0.0757	0.0007
Unobserved Prices	-0.1601	-0.0634
Sum characteristics	0.1440	-0.0042
Sum wage structure	-0.2014	-0.0550
Total (D_Germany - D_USA)	-0.0574	-0.0592

[a]Based on SOEP for Germany and IPUMS CPS for the United States

The observed X' s effect: $(\Delta X_{Germany} - \Delta X_{U.S.})B_{U.S.}$

The observed prices effect: $\Delta X_{Germany}(\mathrm{B}_{\mathrm{Germany}} - B_{U.S.})$

The gap effect: $(\Delta\theta_{Germany} - \Delta\theta_{U.S})\sigma_{U.S.}$

The unobserved prices effect: $\Delta\theta_{Germany}(\sigma_{Germany} - \sigma_{U.S.})$

ΔX is the mean male-female difference in observed characteristics, and B is the male return to characteristics. $\Delta\theta$ is the male-female difference in unobservable characteristics (or difference in percentile ranking in the residual male wage distribution). σ is the male return to unobserved characteristics.

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The total effect of the observed X's differs between 1989 and 2019. In 1989 the effect is positive indicating that relative gender differences in observed characteristics do not contribute to the U.S- German difference in the gender wage gap. By 2019, this effect has changed and relative gender differences in observed characteristics contribute to the U.S-German difference in the gender wage gap. When we investigate the different subcomponents, we see that the gender difference in terms of educational endowment favours female workers in the United States in 1989. The positive effect indicates that this should make the gender wage gap 0.0144 log points smaller in the United States compared to Germany. This is consistent with the descriptive statistics that show that female workers in the United States had higher educational attainments than their male counterparts, while female workers in Germany were less educated than male workers in 1989. While female workers in the United States still are more educated than female workers in Germany in 2019, female workers in Germany have relatively higher educational attainment than male workers. This relatively larger gender difference in endowments explains why Germany has a smaller gender wage gap by 0.0128 log points. We observe a similar pattern for the experience variables, where the experience gap is relatively smaller in the United States, and therefore contributes to reducing the U.S-German difference in the gender wage gap by 0.0233 log points. By 2019, the experience gap is relatively smaller in Germany and therefore contributes 0.0011 log points to the observed U.S.- German difference.

Turning to the industry and occupation variables, the effect of these variables is positive in 1989, indicating that they do not explain why the gender wage gap is greater in the United States. This indicates that female workers in the United States were relatively more concentrated in higher-paying industries and occupations compared to female workers in Germany. By 2019, female workers in the United States are still more represented in higher-paying occupations. However, shifts in the distribution of male and female workers across industries in Germany over the period contributed to a relatively higher concentration of female workers in higher-paying occupations. Consequently, this contributes to explaining 0.0049 log points of the U.S-German difference in the gender wage gap in 2019.

The observed prices effect changes from being negative in 1989 to becoming positive in 2019, and therefore this component does not explain why Germany has a relatively smaller gender wage gap in 2019. From appendix A4, we can observe that the male return to education is greater in the United States compared to Germany. Since the differences in male returns are weighted by the German gender differences in characteristics, this subcomponent explains 0.0413 log points of the U.S-German gap. Differences in return to experience and rewards for employment in certain occupations and industries all contribute to explaining the U.S.-German difference in the gender wage gap for 1989. By 2019, cross-country differences in return to observable characteristics no longer explain the relatively larger gender wage gap in the United States. This is mostly driven by differences in the relative return to employment in certain industries. Moreover, the return to experience is greater in Germany which places a higher penalty for less labour market experience.

The gap effect is 0.0757 log points in 1989 and declines to 0.0007 in 2019. This suggests that female workers in the U.S. are better positioned in the residual male wage distribution in 1989 than female workers in Germany. This indicates that the U.S. has a relatively smaller gender difference in unobservable characteristics and does therefore not explain the U.S.-German difference in the gender wage gap. By 2019, the difference in the difference has declined, which suggests that female workers in Germany have improved their ranking in the residual male wage distribution.

The unobserved prices effect is negative in 1989 and 2019 and respectively contributes 0.1601 and 0.0634 log points to the U.S.-German differences in the gender wage gap. This is consistent with the observation that the male wage distribution is considerably more dispersed in the United States compared to Germany in 1989. Therefore, gender differences in unobservable characteristics are more harshly penalized in the United States. Over the period, the male wage distribution in Germany becomes more dispersed, which would explain why the unobserved prices effect is smaller in 2019. In summary, the more compressed wage structure in Germany explained why the gender wage gap is smaller than in the United States.

In summary, we can observe that the gender differences in observed and unobserved endowments are relatively smaller in the United States in 1989. On the other hand, wage structure effects strongly favour German women, and contribute to explaining why Germany has a smaller gender wage gap than the United States in 1989. While the gender differences in observed and unobserved characteristics are relatively smaller in Germany in 2019, it is the cross-country differences in wage structure effects that are mostly attributable to the U.S.-German difference in the gender wage gap. Overall, these findings suggest that wage structure effects are most important in explaining why Germany has a smaller gender wage gap than the United States. However, we might note that the contribution of the wage structure effect is considerably smaller in 2019 compared to 1989.

6. Discussion

The purpose of this thesis has been to answer the research question: *What are the sources for the gender wage gap and convergence in male-female wages over time, and how can we explain cross-country differences in the gender wage gap?".* To answer this, we have investigated the gender wage gap in Germany and the United States for 1989 and 2019. Applying the KOB decomposition method we have investigated how much of the gender wage gap in Germany and the U.S., in 1989 and 2019, is explained by gender differences in characteristics. Moreover, employing the JMP decomposition method we focus on how both gender differences in characteristics and the wage structure has impacted the changes in the gender wage gap in Germany and the United States. Finally, we study how cross-country differences in in the wage structure and relative gender differences in characteristics impact the cross-country gender wage gap. In this section we will present and discuss the main findings of the empirical analysis.

6.1 Discussion of main findings and empirical strategy

First and foremost, the empirical analysis shows that the gender wage gap in both Germany and the United States have fallen over the period of study, respectively by 0.1248 and 0.1230 log points. In the KOB-decomposition we find that gender differences in measured characteristics in total no longer explain the gender wage gap in 2019, in both the human capital- and full-specification. In particular, women's relative improvements in educational attainments stand out as important for this development. The effect of education on the gender wage gap is expected since female workers have surpassed male workers in terms of educational endowments in 2019 and the returns to skills have been increasing. While the distribution of male and female workers across industries continues to explain the gender wage gap in 2019, its effect is declining in the U.S. and increasing in Germany. This is consistent with findings by Blau and Kahn (2017) who find that gender differences in distribution by industry continues to be important in explaining male-female wage disparities in 2010. The effect of occupational distribution by gender is however unexpected when compared to results in other studies (Blau and Kahn, 2017). We find that gender differences in occupation favours female workers in 2019 for both countries. Moreover, we find that the distribution of male and female workers across occupations already favoured female workers in the U.S. in 1989. Lastly, the KOB-decomposition reveals that the unexplained part of the gender wage gap has only decreased slightly, especially in Germany where it only declined by 0.0095 log points.

Further decomposition using JMP method reveals that the wage structure and the gender differences in characteristics work in opposite directions in Germany. While the changes in gender differences in characteristics have a narrowing effect on the gender wage gap, the changes in the wage structure have a widening effect. Female workers have relatively improved in terms of both observable and unobservable characteristics. However, adverse effects of increasing residual wage inequality negates some of the gains made by female workers. This is consistent with Blau and Kahn's (1997) findings that unfavourable changes in the wage structure slowed women's progress in the 1980s. Furthermore, the effect seems to have continued into our period of study. On the other hand, women managed to improve their labour market characteristics enough to counterbalance the adverse changes in the wage structure. In the United States, both the changes in the wage structure and gender differences in characteristics narrow the gender wage gap over the period. However, the majority of the decline in the gender wage gap is due to female worker's relative improvements in both observable and unobservable characteristics.

In the cross-country comparison the international difference in the gender wage gap changes by only 0.0018 log points between 1989 and 2019. What is interesting is how the components of the cross-country decomposition of the gender wage gap develops. In 1989, female workers in Germany were relatively less endowed in terms of characteristics compared to their male counterparts, than female workers in the United States. Isolated, this should have contributed to a smaller gender wage gap in the U.S. compared to Germany. However, the return to characteristics was higher in the United States leading female workers to be more harshly penalized for gender differences in characteristics. In 2019, the opposite is observed since the returns to characteristics in Germany has risen compared to the U.S. On the other hand, the gender differences in terms of characteristics are relatively smaller in Germany, which situates them in a more favourable position compared to female workers in the United States. Lastly, the results show that the unobserved prices effect on cross country differences in the gender wage gap declines between 1989 and 2019. This suggests that the wage structure in Germany and the United States are becoming more similar.

A key observation from the main findings is the modest decrease in the unexplained part of the gender wage gap when looking at the KOB-decomposition. An advantage of employing the JMP method is that it enables us to separate the characteristics effects and the wage structure effects. This gives us the opportunity to evaluate how relative improvements in women's human capital-and job characteristics has contributed to changes in the gender wage gap net of wage structure effects. The JMP show that female workers in both countries have improved in terms of unobservable characteristics that are important for economic outcomes. In the absence of adverse changes in the wage structure this would have contributed to a larger decline in the unexplained part of the gender wage gap. We observe that the decline in the unexplained part was smaller for Germany than the United States. The results from the kernel density estimates in chapter 4, show that the wage distribution in Germany changed quite drastically over the period compared to the wage distribution in the United States. In 1989, both male and female wages were considerably more compressed when compared to that of the United States. In 2019, the wages in Germany became more dispersed, and resembles more the wage distribution in the United States. This is consistent with the trend of rising inequality in Germany that started in the late 1980s. While the wage distribution in the United States also became more dispersed between 1989 and 2019, it is not as dramatic as for Germany. This might explain why the unobserved prices effect is smaller in the United States than in Germany, and why we see a larger decline in the unexplained part in the United States over the period.

While the KOB- and JMP- decomposition reveal factors contributing to the gender wage gap, the mechanisms for the observed outcomes in the gender wage still merit a discussion. We observe that both countries experienced a substantial decline in the unobserved gender differences in characteristics between 1989 and 2019 due to women's relative improvement in these characteristics. The relative improvements in women's unobserved characteristics are difficult to interpret because the root causes are unknown. It cannot be distinguished whether the change is due to changes in unobserved characteristics or change in discriminatory behaviour, if any. Our study shows that female workers have improved their observable characteristics. It is therefore plausible that progress in terms of observable characteristics, like increased levels of educational attainments also improved their levels of unobserved characteristics like problem solving skills, or time management skills that could have a positive impact on wages.

Considering the case of statistical discrimination, employers' expectations about female commitment might have changed between 1989 and 2019 because of increased labour force commitment among women. As a result, women's treatment in the labour market might have improved over the period due to updated expectations about their performance. While this could be a plausible reason for the decline, it requires that all factors that determine the wage of an individual is accurately measured and controlled for in the wage regression. This is highly unlikely to be the case, and we are therefore careful to suggest that the unexplained part of the gender wage gap reflect labour market discrimination. Men and women can differ on multiple characteristics that are unobservable, and difficult to control for. For instance, women and men have been found to differ in terms of risk-aversion and willingness to compete against others (Bertrand, 2011). Apicella et. al (2017) find that there is no gender difference in competition when competing against one's own, previous score. If competition amongst employees is used as a tool to increase employees' performance, and employees are rewarded for their performance this might lead to gender differences in wages. While such a workplace would be biased in favour of men, it is not labour market discrimination in the sense that equally productive or qualified workers are treated differently based on observable characteristics (Becker, 2010).

Returning to the unexplained part of the total gender wage gap, there are aspects of the empirical analysis than can introduce errors in this part. The way the experience variable is constructed can lead to measurement error in the variable. It is reasonable that both men and women would have periods outside of the labour market due to sickness, parental leave or job switching. Hence, it is likely that that the potential experience variable is overestimated. Moreover, female workers in Germany and the United States work more part-time compared to male workers. If one assumes that full-time workers accumulate more labour market experience than part-time workers, this suggests that women on average would have less labour market experience compared to men, and this will result in a biased estimate of the potential experience variable. This would lead to an underestimation of how much gender differences in experience contributes to the gender wage gap. Moreover, it would overestimate the unexplained part of the gender wage gap.

Another factor that could affect the unexplained part is the occupation variable. It is likely that this variable will lead to underestimation of how much of the gender wage gap is explained by gender differences in distribution by occupation. This is because the categories of the occupation variable are broadly defined, and there could be considerable variations in the distribution of male and female workers within a category. If for instance female workers are more concentrated in the lower paying occupations within the categories compared to men, we would underestimate the impact of gender differences in distribution by occupation. Although women have increased their educational levels, they are less represented in STEM fields. Black et. al. (2008) finds that gender differences in college majors contribute to wage differences between college-educated men and women. The occupation categories do not capture these nuances since for instance the "professionals" category ranges from primary school teachers to mechanical engineers.

With these limitations in mind there is opportunity for more empirical research on the topic. Further calibrations of the experience variable or inclusion of other variables can assist in better understanding the gender wage gap. Although it's out of scope for such an empirical analysis as this, a scrutiny of what leads women to work more part-time than men might yield interesting results. An underlying assumption of empirical analysis such as this, that keep part-time workers out of the sample, is that this makes the sample more representative. But if there are aspects of society that is leading women to work more part-time, we are assuming that these women are different from the women included in the study. Lastly, overall wage inequality yields interesting results in this analysis and some of these observations can already be made in the descriptive analysis. Dividing wages into percentiles we observe different changes over the years and and further study of this might reveal other details that might be missed otherwise.

7. Conclusion

In this thesis, we have analysed the gender wage gap in Germany and the United States using individual datasets from the German SOEP Core and IPUMS CPS. We have employed the Kitagawa-Oaxaca-Blinder decomposition method (Kitagawa 1955; Oaxaca 1973; Blinder 1973) to investigate how much of the gender wage gap in Germany and the United States is explainable by gender differences in observable characteristics. In addition, we have investigated changes in the gender wage gap over time as well as cross-country differences using the Juhn, Murphy, and Pierce (1991) decomposition method. This allows us to analyze how both gender differences in characteristics and wage structure effects contribute to the gender wage gap.

The results from the KOB decomposition show that the gender wage gap in Germany and the U.S. declined between 1989 and 2019. Furthermore, gender differences in observable characteristics in total no longer explain the gender wage gap in 2019 for both countries. In addition to changes in the return to education, the main cause for this decline is progress in female workers' educational attainment relative to male workers. For both Germany and the United States, the male advantage in terms of industrial distribution by gender continues to explain gender differences in wages for 2019. A puzzling result is that the distribution of men and women across occupations does not explain gender differences in wages for 2019 in both countries. We argue that this is due to aggregated data without enough detail. We also observe a modest decline in the unexplained part between 1989 and 2019. Hence, the majority of the gender wage gap in both countries remains unexplained.

The findings from the JMP decomposition method showed that reductions in gender differences in characteristics were most important for explaining the decline in the gender wage gap between 1989 and 2019 for both Germany and the United States. This is attributed to relative improvements in female workers' observed and unobserved characteristics. The results suggest that female workers in the United States and Germany would have made even further progress in terms of wage equality in the absence of rising inequality.

In the cross-country decomposition, the results show that the small change in the U.S.-German difference in the gender wage gap over the period hides considerably large changes in the different components. Germany has managed to narrow gender differences in characterises more than the United States in 2019, and this therefore explains partly why it has a relatively smaller gender wage gap. However, the rising wage inequality in Germany results in a decline in the differences in returns across the countries. Still, higher levels of wage inequality in the United States continue to be the most important reason why Germany has a relatively smaller gender wage gap.

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Appendix

A1 Variables

Table A1.1 Variables from IPUMS (KOB / JMP Decomposition)

US: IPUMS -CPS

Variables	Code/ Label	Description
Sample selection		
survey year	YEAR	
age	AGE	person's age at last birthday, previous year
sex	SEX	
population status	POPSTAT	whether the person is adult civilian, armed forces or child
employment status	EMPSTAT	whether part of labour force or currently unemployed
full time- part time	FULLPART	whether worked full or part time, previous year
earnings source	SRCEARN	whether the income is from wages and salary, self-employment, farm self-employment or working without pay
Regression dummies		
occupation[a]	OCC2010	2010 Census Bureau Occupation Classification System
industry[a]	IND1990	1990 Census Bureau Industrial Classification System
Auxillary variables		
weeks worked	WKSWORK1	number of weeks worked, previous year
education	EDUC	educational attainment, by the highest year of school or degree completed
work hours	UHRSWORKLY	hours worked per week if worked, previous year
wage and salary	INCWAGE	income from all salaried work annually, pretax, previous year

[a]Refer to IPUMS-CPS for more information about the variables

Table A1.2 Variables from SOEP (KOB / JMP Decomposition)

Germany: SOEP

Variables	Code/Label	Description
Sample selection		
age	D11101	current age
sex	D11102LL	
years of education	D11109	number of years of education completed at the time of survey, ranges from 7 to 18
employment level	E11103	full time, part time or unemployed
Regression dummies		
occupation	E11105	based on ISCO-99 occupation code
industry	E11106	10 broad categories based on 1 digit code
Auxilliary variables		
wage and salary	IJOB1	gross annual wages/ salary from the main job
annual work hours	E11101	constructed by SOEP using information on employment status, average number of hours worked, months worked; previous year

Table A1.3 Variables in Regression (KOB and JMP)[a]

Variables	Description
lnwage	logarithm of wages, dependent variable
education	number of years of education, independent variable
experience	potential expereince created by age and no. of years of education, independent variable
experience^2	potential squared experience, independent variable
industry dummies	10 broad categories, indicator variable
occupation dummies	10 broad categories, indicator variable

[a]for both the countries

A2 Industry and Occupation

Table A2.1 SOEP Industry Classification

SOEP code	SOEP classification
1	Agriculture
2	Energy
3	Mining
4	Manufacturing
5	Construction
6	Trade
7	Transport
8	Bank/Insurance
9	Services
10	Other

Source: SOEP Survey Papers Series D- Variable Descriptons and Coding;
SOEP-Core v37- Codebook for the $PEQUIC File 1984-2020

Table A2.2 SOEP Occupation Classification

ISCO Level	ISCO-08 Code	ISCO-08 Classification
1	1	Managers
1	2	Professionals
1	3	Technicians and Associate Professionals
1	4	Clerical Support Workers
1	5	Service and Sales Workers
1	6	Skilled Agricultural, Forestry and Fishery Workers
1	7	Craft and Related Trades Workers
1	8	Plant and Machine Operators, and Assemblers
1	9	Elementary Occupations
1	0	Armed Force Occupations

Table A2.3 Harmonized Occupation Classification System (Germany and the U.S.)

Occupation Code	**Harmonized Classification (Based on ISCO-08 Classification)**
1	Managers
2	Professionals
3	Technicians and Associate Professionals
4	Clerical Support Workers
5	Service and Sales Workers
6	Skilled Agricultural, Forestry and Fishery Workers
7	Craft and Related Trades Workers
8	Plant and Machine Operators, and Assemblers
9	Elementary Occupations
10	Not Specified

New harmonized occupation code recoded for both countries in STATA

A3 Wages

Table A3.1: Mean and Percentile Wages

		Male				Female			
		Mean	**25 %**	**50 %**	**75 %**	**Mean**	**25 %**	**50 %**	**75 %**
Germany 1989	Hourly Wage	10.9393	8.3885	9.9722	12.2369	8.2402	6.4957	7.8736	9.6478
	Log Hourly Wage	2.3179	2.1269	2.2998	2.5045	2.0449	1.8711	2.0635	2.2667
Germany 2019	Hourly Wage	12.5243	7.4957	10.6366	15.3321	10.4846	6.6958	9.5943	12.9028
	Log Hourly Wage	2.3543	2.0143	2.3643	2.7299	2.2061	1.9015	2.2612	2.5574
U.S. 1989	Hourly Wage	14.1391	8.4615	12.5000	17.6969	9.9478	6.25	8.75	12.5
	Log Hourly Wage	2.4871	2.1355	2.5257	2.8734	2.1567	1.8326	2.1691	2.5257
U.S. 2019	Hourly Wage	17.5812	8.7449	12.9231	20.3077	13.9126	7.2	10.8	16.1539
	Log Hourly Wage	2.5974	2.1685	2.5590	3.0110	2.3900	1.9741	2.3795	2.7822

A4 Regression Tables

Table A4.1 Regression Results: Germany (KOB/JMP Decomposition)

	1989				2019			
	Human capital specification		Full specification		Human capital specification		Full specification	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	0.0648***	0.0585***	0.0413***	0.0357***	0.112***	0.0951***	0.0808***	0.0690***
	(0.0027)	(0.0051)	(0.0037)	(0.0064)	(0.0021)	(0.0032)	(0.0025)	(0.0037)
Experience	0.0423***	0.0252***	0.0390***	0.0225***	0.0464***	0.0321***	0.0423***	0.0305***
	(0.003)	(0.005)	(0.0029)	(0.0048)	(0.0029)	(0.0035)	(0.0028)	(0.0033)
Experience^2	-0.0006***	-0.0003***	-0.0006***	-0.0003***	-0.0006***	-0.0004***	-0.0005***	-0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Industry	No	No	Yes	Yes	No	No	Yes	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes
Constant	1.043***	1.088***	1.347***	0.0174	0.241***	0.443***	0.841***	0.911***
	(0.049)	(0.0887)	(0.114)	(0.295)	(0.0451)	(0.0623)	(0.0875)	(0.151)
R^2	0.231	0.137	0.314	0.258	0.372	0.249	0.452	0.318
Observation	2395	882	2395	882	5367	2956	5367	2956

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A4.2 Regression Results: USA (KOB/JMP Decomposition)

	1989				2019			
	Human capital specification		Full specification		Human capital specification		Full specification	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	0.0874***	0.0953***	0.0617***	0.0600***	0.1168***	0.1204***	0.0763***	0.0832***
	(0.0011)	(0.0014)	(0.0013)	(0.0016)	(0.0014)	(0.0015)	(0.0017)	(0.0018)
Experience	0.0338***	0.0144***	0.0301***	0.0123***	0.0317***	0.0176***	0.0288***	0.0161***
	(0.0012)	(0.0013)	(0.0012)	(0.0012)	(0.0015)	(0.0014)	(0.0014)	(0.0014)
Experience^2	-0.0004***	-0.0001***	-0.0004***	-0.0001***	-0.0004***	-0.0002***	-0.0004***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Industry	No	No	Yes	Yes	No	No	Yes	Yes
Occupation	No	No	Yes	Yes	No	No	Yes	Yes
Constant	0.875***	0.700***	1.085***	1.208***	0.5297***	0.4044***	1.107***	1.0729***
	(0.0203)	(0.0252)	(0.0406)	(0.0602)	(0.0251)	(0.0273)	(0.0454)	(0.0672)
R^2	0.209	0.195	0.290	0.295	0.220	0.225	0.294	0.300
Observation	27199	19529	27199	19529	27045	22440	27045	22440

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

A5 Data Handling Experience

In this section, we summarize our experience of working with microdata of Germany and the United States. We are motivated to share this experience to help other students to use larger databases such as IPUMS CPS and SOEP for their research.

The IPUMS CPS is free for public use and has a friendly website user interface which allows us to select the variables required to create a sample for further research. It allows us to download, edit and extract the files to be further used in the statistical software. The online webpage has useful videos and information on easy guidance to use the database. Furthermore, we can also find detailed information on variables and sources in the webpage itself. It also has important documented codebooks and technical papers regarding the survey and samples. The IPUMS CPS website was easy to navigate and use for extracting individual data for the United States.

The German SOEP core study database is only available for researchers and provided only to the scientific community. We applied for the contract to have access to the database with the help of our supervisor, Astrid Kunze. We were assigned respective passwords and strict adherence to the data privacy guidelines to have access and extract data from the SOEP database. The SOEP webpages also have documents on codes, known as codebook and sample process of each database, which allowed us to get detailed information about each variable.

We used STATA for the empirical analysis. We used OAXACA and JMP STATA packages to perform the respective decomposition analysis. The process of selecting correct and consistent variables across countries and years was rigorous and we made manual use of excel to harmonize the variables. Since, we used large microdata sets, the process of data-handling was detail-oriented tasks prone to many small errors. We therefore dedicated a large part of our time checking, rechecking, and revising our samples and STATA codes to make our results free from minor yet significant errors. Our experience of working with large datasets has been rigorous, time-demanding, and challenging but it was very interesting and exciting to work with our own sample sets for analysing such an important topic as gender wage gap. We recommend other students to use both the IPUMS CPS and German Socio-Economic Panel (SOEP-Core) for their future research work.