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Beyond the Diploma: A Detailed Exploration of the Gender Wage Gap

An Empirical Analysis of the Gender Wage Gap among Graduates with Completed First-Stage Tertiary Education

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Abstract

A gender wage gap has been thoroughly documented, both in Norway and internationally. Prior studies have substantiated a significant wage discrepancy between genders among those holding an MBA, yet comprehensive research into this disparity across other graduate-level disciplines remains scarce. The purpose of this thesis is to fill this gap, by examining the wage gap, not only among business graduates, but also among medicine, law, and STEM graduates. To examine the gender wage gap in these four educational groups, we utilize cross-sectional register data from 2019, obtained from Microdata.no. Using recent high-quality data enables us to determine the severity of the graduate-level wage gap, and allows for an exploration of potential disparities between different educational groups.

Our analysis reveals a significant wage gap among graduate-level workers with educational backgrounds in medicine, law, STEM, and business fields. In this combined sample of graduate-level workers, we identified a raw wage gap of 15.39% and an adjusted wage gap of 7.98%. In comparison, the unadjusted wage gap in the general working population in Norway stood at 12.4% in 2019. Thus, our results suggest that the wage gap might be larger among those with a graduate-level degree than in the general working population.

We also uncover considerable gender wage gaps within the four educational groups. Moreover, our analysis reveals that the wage gap is substantially smaller among part-time workers than full-time workers. Additionally, we found that men enter the labor market with significantly higher wages than women, and that they have a significantly higher return on experience. At last, we found that the gender wage gap, at large, is greater among graduate-level workers than among undergraduate-level workers.

In this study, we confirm the existence of a wage gap between men and women at the graduate level in Norway. To successfully close the wage gap, we suggest several measures. First, additional research should be conducted to understand why men experience a higher return on experience. Moreover, we recommend initiatives to encourage more women to pursue full-time positions. The promotion of efforts to support and encourage women into senior roles, where compensation tends to be higher, could also contribute to narrowing the wage gap. Lastly, altering workplace structures and shifting societal expectations might further reduce segregation in the workforce.

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1 Introduction

1.1 Introduction

The gender wage gap has been extensively researched for several decades and remains an area of active and innovative research. In this thesis, we delve into the intricacies of the wage disparity between genders among individuals with tertiary education and provide new empirical estimates. Our primary focus is the wage gap in Norway, but we also review previous literature to identify internationally recognized explanations for the wage disparities between men and women. Nonetheless, we believe that a substantial part of our findings about the wage gap among the highly educated in Norway could be relevant to other countries, particularly other economically advanced nations.

In the period from 1980-2010, the gender pay gap has been narrowing (Blau and Kahn, 2017). In the same period, women have been increasing their relative labor market qualifications, particularly when it comes to education and experience. In the field of higher education, there are certain signs that gender segregation is declining (NOU2008:6). In Norway, the proportion of women in higher education has increased from 48.1% in 1980 to more than 60% in 2006. Women's choice of educational subjects has also changed, as an increasing number of women are studying economic and administrative subjects, medicine, as well as scientific or technical subjects.

Despite women's strides in labor market qualifications, a gender wage gap still persists. In Norway, the gender wage gap stood at 12.8% in 2021, indicating that women's wages on average make up 87.2% of men's wages (Grini and Fløtre, 2023). Moreover, women still remain underrepresented in high-status and high-earning roles, especially in financial and corporate sectors. In 2003, Norway passed a law requiring a minimum of 40% gender representation in the board of directors of public limited liability companies. While the qualifications and earnings gap of female board members improved after the reform, there's no evidence to suggest that an increase in female representation in boardrooms led to more recruitment or promotion of women within these firms, or to a more family-friendly work environment. Even though the quota system might have boosted the visibility of women in business, it didn't lead to significant improvements in average earnings or higher positions for women in the post-reform era (Bertrand et al., 2019).

Previously conducted research on the gender wage gap, have documented that not only gender segregation, but also other factors such as industry, sector, education, working hours, and occupation can contribute to explaining the gap. The challenge of comprehending the factors that contribute to wage disparities between genders, is however compounded when analyzing an entire population at large. The complexity arises from the variation in wage gaps across different professions, sectors, and educational levels in such diverse, heterogeneous samples (Meara et al., 2020). To enhance the precision of our analysis, we segment our sample of graduate-level individuals into smaller, more homogeneous educational groups: medicine, law, STEM, and business.

There are several reasons why we have chosen to examine the wage gap in these graduate-level educational groups. Numbers from Samordna Opptak (2019), show that studies within these four fields are highly popular, with law and business studies having the highest number of applicants in 2019. In 2023, healthcare was the educational area with by far the most applicants, whereas 1 in 5 of all applicants had at least one technology education in their application (Kunnskapsdepartementet, 2023). Furthermore, several of the educational fields in all four educational areas, are considered elite fields of education and require a relatively high grade point average (GPA) for entry. Studying these educational groups, thus allows us to focus on a highly ambitious group of men and women, with high earnings potential (Bütikofer et al., 2018).

This thesis seeks to advance the understanding of the wage gap in three key ways. First, we examine the wage gap among highly educated individuals in Norway. While Statistics Norway routinely provides wage statistics for the entire population, there is a paucity of research focusing specifically on highly educated individuals. This area warrants further studies to address broader issues of social equity and justice.

Second, we investigate the wage gap by dividing our sample into four educational groups. This approach allows us to provide new insights into how the gender wage gap manifests across the most popular fields of study in Norway. Prior research, such as the studies conducted by Brakstad and Sanner (2022) and Lyche and Stedje (2017), has primarily focused on individuals with an MBA. This has left an unexplored area surrounding individuals with other educational backgrounds, with different levels of gender segregation, experience and degrees of part-time employment. Our research aims to contribute fresh perspectives on this topic, especially in relation to fields that have a history of horizontal segregation.

Third, we investigate whether women can close the wage gap by acquiring more education. Despite its relevance, there is a dearth of research on this topic in Norway. By comparing the wage gaps among undergraduates and graduates, we aim to provide new insights into whether further education can help bridge the wage gap. In addressing these research topics, we aim to provide a comprehensive understanding of the wage gap in Norway among highly educated individuals, thus informing future research and policy-making.

1.2 Research Questions

This thesis aims to investigate gender-based wage disparities across four educational groups at the graduate level in Norway: medical educations, law, STEM (Science, Technology, Engineering, and Mathematics), and business. Our study uses the latest available data from 2019. Our primary objective is to quantify the extent of the gender wage gap among graduate-level professionals in Norway. Additionally, we aim to identify the factors contributing to this gap by examining the differences in characteristics between men and women. To achieve these objectives, we will address the following research questions:

Research Question 1: What is the magnitude of the gender wage gap among graduate-level professionals in Norway, and how does the wage gap vary across each educational group?

Research Question 2: What factors contribute to wage disparities among graduate-level professionals in each of the four educational groups, and how do these characteristics differ between men and women?

Research Question 3: Does attaining a graduate-level education, as opposed to an undergraduate degree, reduce the gender wage gap in Norway?

We will begin by examining the raw wage gap between men and women at the graduate level. Then, we will introduce various control variables to understand how the wage gap changes across different professions and sectors. Next, in research question 2, we will analyze how different characteristics explain the wage gap and how it varies across the four educational groups. We will also explore whether the wage gap changes over time. Finally, in research question 3, we will investigate if obtaining a graduate-level education can reduce the gender wage gap by comparing our four educational groups' wages at the graduate and undergraduate levels.

1.3 Limitations of the Study

For our study on the wage gap in Norway, we used Microdata.no, which is the national microdata platform for Norwegian and international research and analysis. We utilized cross-sectional data from 2019, which allowed us to obtain a snapshot of the population at a given time and identify associations and patterns. Cross-sectional data also enabled us to have a larger sample size than longitudinal studies, increasing the statistical power of our analysis.

However, cross-sectional data have limitations. It only provides information at a single point in time, which may not capture changes in the wage gap over a person's working life, and does not provide insights into trends. Additionally, cross-sectional studies cannot establish causation because data is collected only once, making it challenging to determine the sequence of events and the direction of causality.

While using cross-sectional data, we could establish the wage gap for people with identical experience, we could not be sure if this was due to different levels of experience or individual differences.Although conducting an analysis with panel data would allow us to collect the individual component in the model's error term, it requires all variables to have the same identification key, which our data does not have. Therefore, we have decided to use cross-sectional data for our analysis.

2 Background

This chapter provides a comprehensive review of previous studies on the gender wage gap in Norway and internationally for both men and women. We will present relevant theories that can explain why there is a wage gap between men and women with graduate education. Furthermore, we will delve into the findings on how the wage gap widens over time with more experience, how having children impacts gender and educational groups differently, how working part-time influences wages, and lastly, how profession and sector affect wages between different educational groups.

2.1 The Gender Wage Gap

2.1.1 The Wage Gap Internationally

The wage gap between men and women is a pervasive global issue, and numerous studies have consistently demonstrated that women tend to be paid less than men across various industries and educational levels. According to the International Labour Organization (ILO), women globally are paid approximately 20% less than men (ILO and WHO, 2022). The report from ILO and WHO further highlights that while factors such as education, working hours, occupational segregation, skills, and experience account for part of the gender pay gap, a significant portion can be attributed to gender-based discrimination.

Research conducted by Penner et al. (2023) reveals that women have achieved greater pay equality today compared to twenty years ago, with most countries, except Hungary, Slovenia, and the Czech Republic, making progress towards more equitable pay standards. Moreover, a study by the Organisation for Economic Co-operation and Development (OECD) indicates that the wage gap is typically wider among individuals with tertiary education compared to those with lower educational attainment. Additionally, the study finds that even in countries with high levels of women's labor force participation, women still earn less than men with similar educational backgrounds (ILO and WHO, 2022).

A gender wage gap also persist among those working part-time. A Canadian study conducted by Antonie, Gatto and Plesca (2020), found that male part-time workers earn a 5.4% wage premium over women's weekly wages, even after controlling for various characteristics related to productivity and demographics. The male part-time premium was much lower than the estimated 16.9% wage premium experienced by male full-time workers, implying that the wage gap is smaller among part-time workers (Antonie et al., 2020).

2.1.2 The Wage Gap in Norway

Norway is frequently praised as a global leader in gender equality; however, research indicates that Norway still struggles with a gender pay gap. Women in Norway earn less than men on average, even after controlling for factors such as experience and occupation. According to a recent study conducted by Penner et al. (2023), Norwegian women earned on average 20.6% less than men in 2018, after making basic adjustments for differences in age, education, and part-time status.

In Norway, wage inequality between men and women in the same job accounts for 35 to 40% of the total gender gap, while the remaining 60-65% is due to gender segregation in the labor market, with women and men receiving different wages for doing different work. However, the gender pay gap in Norway has narrowed over time. Based on annual wages, the gender gap decreased from 25% in 1997 to 20% in 2018. At the job level, the disparity in men's and women's average hourly wages decreased from 15 to between 8 and 9 percentage points over the same period (Engblad, 2022).

Different studies, do however provide widely different estimates of the gender wage gap. As opposed to Penner et al. (2023), Askvik (2020) found that in 2019, women in Norway earned on average 87.6% of a male wage, based on full-time equivalent monthly wage. This number represents a decrease from 83.3% in 2001, indicating a 4.3% decrease over the period from 2001 to 2019, as reported by Fløtre and Tuv (2022).

In 2020, women had a greater share of tertiary education than men in all age groups except for those aged 67 years or older. Approximately 60% of women between the ages of 25-29 and 30-39 had higher education, while only 40% of men in the same age group had education at this level (Nygård, 2021). This trend has contributed to reducing the wage gap between men and women. However, for the group with higher education, the wage gap has not changed much over the past 20 years. This is due to differences in preferences between men and women when choosing educational field (Kristoffersen, 2017).

For instance, women tend to select health and care-related educations. Kristoffersen (2017) also found that the wage gap is larger among those with a master's degree, than among those with a bachelor's degree.

Research has also established that the gender wage gap is partly due to differences in the professions and sectors that men and women work in. Labor market segregation occurs when men and women select different professions. Research also reveals that the private sector is male-dominated, with 60% of jobs, particularly those in the top 10% of wages. Conversely, women are overrepresented in the public sector, constituting 70% of the workforce (Fløtre and Tuv, 2022). In terms of graduate education, wages and deviation are higher in the private sector than in the public sector. Women in the public sector earn 87% of what men earn, whereas in the private sector, women earn only 76% of what men earn (Kristoffersen, 2017).

Roughly two out of four women and one out of four men work part-time, meaning they work less than 100 percent of full-time hours. In most age groups, nearly half of women work part-time, while it is mainly young or older men who opt for this work arrangement. There is no indication that part-time work in and of itself creates a gender pay gap, but full-time employees tend to have a higher pay level than part-time employees. This is primarily because part-time workers are employed in different occupations than full-time workers. When comparing pay between full-time and part-time employees in the same occupational group, only small differences are found. Thus, occupational choice is more important than whether one works full-time or part-time (Kristoffersen, 2017).

Research has also been conducted on the potential motherhood penalty on wages. Amongst others, Bütikofer, Jensen and Salvanes (2018) conducted a study on the impact of parenthood on the careers of women and men with graduate-level degrees in business, law, STEM, or medicine. Using Norwegian registry data, they found that the earnings penalty for mothers in professions with a nonlinear wage structure, such as MBAs and lawyers, is significantly greater than for mothers in professions with a linear wage structure. The gender gap pattern following childbirth is similar for those with an MBA or law degree, but contrasts sharply with the pattern for STEM and medicine graduates. The results suggest that women in professions with more nonlinear wage structures, such as those requiring MBA and law degrees, experience a larger and more persistent child earnings penalty of over 20% after ten years, compared to women in professions with a more linear wage structure, such as STEM and medicine (Bütikofer et al., 2018).

2.1.3 Wage Gap in Medical Professions, Law, STEM and Business

The wage gap is a significant and widely recognized issue in various professional fields, including in medical professions, law, STEM (science, technology, engineering, and mathematics), and business. Extensive research has been conducted to understand and address the disparities in earnings between men and women within these educational groups. In this section, we will explore previous studies that have examined the wage gap within each educational group.

2.1.3.1 Medical Professions

In the earlier parts of this chapter, we introduced research that confirmed a wage gap between men and women internationally and in Norway. Gender disparities in wages, are not confined to specific sectors, with the health sector also demonstrating wage differences that vary across its distinct fields. According to data released by the South-Eastern Norway Regional Health Authority, the wage gap is 8.9 percent among doctors, 3.8 percent among nurses, and 10.9 percent within the pharmacy sector (Eriksen, 2023). In line with these figures, a 2022 report by the International Labour Organization (ILO) uncovered an 8.1 percent wage gap in Norway's health and care sector (ILO and WHO, 2022).

Wage disparities uncovered in the health and care sector, are not exclusive to Norway, but exists internationally as well (ILO and WHO, 2022). In the global health and care sector women earn approximately 20 percent less than men. Upon controlling for the cluster effect, largely attributed to gender segregation, this wage gap narrows. The study further highlighted that the wage gap in the health and care sector is wider when compared to other non-health economic sectors. Key factors contributing to this gender pay gap, as identified in the report, include age, education level, and gender segregation across occupational categories.

2.1.3.2 Law

A study utilizing Norwegian registry data up until 2010 (Bütikofer et al., 2018), uncovered a distinct wage gap between men and women in business and law professions. It revealed that the wage disparity was significantly greater in these areas than in medical or STEM professions. The Institute for Social Research in Norway published a detailed report exploring wage disparities among lawyers. The findings indicated a clear wage gap between genders, which could be largely attributed to differences in organizational level after having children (Halrynjo et al., 2021). The study also found that men with more children were often in higher positions within the organization and were more likely to work in the private sector.

The sector in which one works, whether private or public, appears to have a significant impact on the wage gap. Upon controlling for experience and sector, the wage gap in the public sector in 2020 was only 4 percent, showing little variation when adjusting for children. The private sector presents a contrasting image. The wage gap in 2020 was a staggering 35 percent, a sharp increase from 15 percent in 2007. Among lawyers without children, women actually earned 107 percent of what men earned. However, introducing children into the equation dramatically changes the picture. For individuals with one child, the wage gap is 19 percent, but for those with two children, it expands to 27 percent. The disparity is even more startling for individuals with three children, where the wage gap soared to 63 percent (Halrynjo et al., 2021).

2.1.3.3 STEM

Over the last several decades, women have made substantial progress in diminishing the gender wage gap, yet disparities also persist within the STEM fields. One of the contributing factors to this disparity is the underrepresentation of women in STEM subjects and careers. For instance, women constitute roughly 37 percent of new entrants into tertiary-level science programmes, averaging across OECD nations, and merely about 24 percent of entrants into engineering, manufacturing, and construction programmes (OECD, 2017). Amplifying the presence of women in STEM is often proposed as a strategy to further reduce the overall wage gap between men and women within these sectors.

A study conducted by Michelmore and Sassler (2016) unearthed a significant wage gap among women employed in STEM professions. Their research revealed that white women in the STEM workforce earn approximately 84 cents for every dollar earned by their male counterparts. The disparity in human capital accumulation accounted for a large portion of this gender wage gap across numerous STEM occupations. However, even after accounting for demographic characteristics and human capital accumulation, a persistent wage gap was evident, underscoring the enduring challenge of gender wage disparity in STEM fields.

2.1.3.4 Business

In 2009, the Institute for Social Research conducted a study investigating the wage gap between men and women possessing an MBA degree in Norway. Commissioned by Econa, the Norwegian association for professionals and graduates in business and economics, the study revealed that men, on average, earn approximately 20 percent more than their female counterparts and typically occupy higher positions within organizational hierarchies (Halrynjo and Fekjær, 2020). The wage gap was largely attributed to occupational choices, with men predominating in higher-paying roles such as management positions, and more often working in the private sector. The significant wage gap was also apparent in median income calculations.

Further research into this subject has been conducted through various master's theses. For instance, a thesis by Lyche and Stedje (2017) proposed that MBA graduates often exhibit a non-linear wage structure, which can lead to a "wage penalty" for those working part-time or adopting more flexible work schedules. Given that women are more likely to deviate from standard working hours, this factor contributes to the wage gap. Another thesis by Brakstad and Sanner (2022) discovered a raw wage gap of 20.12 percent among individuals with an MBA in Norway. After controlling for variables such as experience, part-time work, profession, and sector, the wage gap reduced to 8.52 percent. The authors identified the differing returns on experience and workplace segregation as two key drivers of this wage gap.

2.2 How can the Wage Gap between Men and Women be Explained?

To accurately analyze the wage gap between men and women across different occupations, it's crucial to consider both the return on human capital and the issue of segregation in the workforce among individuals with equivalent human capital. As of recent data, women in OECD countries now attain more years of education than their male counterparts (OECD, 2017). Furthermore, the Global Gender Gap Report from 2022 affirms that women are significantly more likely to enroll in tertiary education than men (World Economic Forum, 2022). These findings suggest a relative increase in women's level of human capital compared to men's.

Occupational segregation refers to the overrepresentation or underrepresentation of a specific demographic group within a particular job category (Zhavoronkova et al., 2022). A study by Blau and Kahn (2017) found that occupation and industry, considered collectively, account for approximately half of the total gender wage gap (Blau and Kahn, 2017). Therefore, the forthcoming sections will delve into the theory of, amongst others, workforce segregation.

2.2.1 Human Capital

The theory of human capital is fundamental in discussions about wages. This theory encapsulates the value of knowledge, skills, education, and experience, all of which are crucial in determining an individual's wage potential. As proposed in Becker's Human Capital Theory, investments in education and skills development lead to enhanced productivity and, consequently, higher wages (Becker, 1964).

Education is a significant aspect of human capital. Research conducted by the OECD suggests that higher education levels generally correlate with increased earning potential, as advanced education often opens doors to specialized and higher-paying job opportunities (OECD, 2019). Similarly, acquiring specific, sought-after skills can boost an individual's market value, resulting in increased wages (World Economic Forum, 2020). Experience, another crucial component of human capital, also plays a vital role in wage determination. More seasoned professionals tend to command higher wages due to their refined skills and expertise.

2.2.1.1 Experience

The impact of work experience on wages, commonly assessed through wage progression, is substantial. Both the amount and the quality of work experience can contribute notably to one's wage growth. Statistics Norway's 2019 data suggests that wages increase with age, a common proxy for work experience, implying that wage enhancement typically accompanies an accumulation of work experience (Askvik, 2020). Furthermore, research indicates the importance of the quality of work experience; Topel and Ward (1992) discovered that job stability positively influences wage progression. Employees with longer job tenure tend to earn more due to the development of job-specific skills and knowledge, referred to as the job tenure effect.

Another study conducted by Stokke (2021) elucidates the progression of the gender wage gap in relation to work experience over the course of a career. Her findings suggest that the male wage premium is small upon entry to the labor market, but it increases rapidly throughout the early career before stabilizing. The return on experience is projected to be greatest earlier in one's working life and diminish over time (Blau and Winkler, 2018). This may suggest that the initial few years of employment have the most significant influence on career progression and wage trajectory.

2.2.1.2 Education

Education significantly contributes to human capital growth. A higher level of education generally equates to improved employment opportunities and increased earnings. Data from Statistics Norway (SSB) suggests that obtaining a master's or doctoral degree boosts average wages by approximately 25 percent (Bye, 2018). However, accurately determining the return on education can be challenging due to variations across different educational pathways, professions, and fields of study. Raaum, Aabø and Karterud (1999) determined that individuals with an MBA, or who are doctors, lawyers, or engineers, typically enjoy a higher return on education than teachers and healthcare workers.

2.2.2 Parenthood

The wage disparity between mothers and childless women has been well-documented in existing research. This disparity is often attributed to potential discrimination from employers, who may perceive mothers as less committed to their work, leading to disparities in hiring, promotion, and compensation (England, 2005). Moreover, women typically reduce their work hours and take maternity leave upon childbirth, resulting in a loss of valuable work experience - a key driver of wage growth (Staff and Mortimer, 2012).

On the other hand, men commonly experience a wage premium upon becoming fathers. This "fatherhood premium" is thought to stem from the traditional gender role expectation that fathers should enhance their breadwinning capacity (Hodges and Budig, 2010). This expectation often manifests in increased work hours and effort, particularly when their partners reduce work hours, thereby augmenting their earnings. This positive wage differential for fatherhood persists even after accounting for other influencing factors such as human capital, work hours, and effort (Lundberg and Rose, 2000).

The motherhood penalty and the fatherhood premium prevails in the general work force. However, the occurrence of a motherhood penalty or a fatherhood premium, might not be as prevalent in more homogeneous subdivisions of the labor force. A study conducted by Buchmann and McDaniel (2016) investigated this variation among highly educated professionals in 2010. They found that in traditionally male-dominated professions such as STEM, medicine, and law, women with children experienced a positive wage differential. In contrast, women in female-dominated professions continued to encounter a negative wage differential relative to non-mothers. For men, the fatherhood premium was evident across all highly educated groups.

2.2.3 Gender Segregation in the Labor Market

In our exploration of previous research, we have highlighted how variations in human capital can impact wages. Yet, this alone does not account for the entire wage gap, as wage disparities persist even when human capital between sexes is comparable. One critical factor behind this discrepancy is that women often pursue different fields of study, which subsequently leads to employment in different job sectors with varying returns on human capital. This phenomenon is known as gender segregation in the workforce, which comprises both horizontal and vertical forms of segregation.

2.2.3.1 Horizontal Segregation

Horizontal segregation in the labor market emerges when women and men are concentrated in different professions, industries, and sectors Barth, Reisel, Schøne and Østbakken (2017). Research from Jensberg, Mandal and Solheim (2012) revealed that this segregation within the Norwegian labor market is persistent, with diverse tendencies at various occupational levels. While the gender segregation across sectors has intensified, segregation within professions has seen a slight decrease.

Reisel (2014) elucidates that more women are now opting for professions traditionally dominated by men, indicating that career choices among tertiary-educated individuals are becoming increasingly gender-neutral. However, this trend is less evident among those with lower levels of education, who continue to choose careers in a gender-traditional manner. Women are often overrepresented in the public sector, while men are predominantly found in the private sector (Fløtre and Tuv, 2022).

Expanding the view to encompass educational choices, Charles and Bradley (2009) emphasize the impact of societal norms and expectations on these decisions. They argue that gendered socialization greatly influences the fields of study chosen by men and women, subsequently leading to occupational segregation.

2.2.3.2 Vertical Segregation

Vertical segregation, also known as hierarchical segregation, is a phenomenon wherein women and men occupy different positions within a professional hierarchy, with men typically occupying higher-level, better-paying roles and women more commonly found in lower-level, lesser-paying roles.

Cotter et al. (2001) argue that vertical segregation is an influential factor contributing to the gender wage gap. They suggest that although women's entry into the workforce and into various professional fields has increased, their ascension to top-tier positions has not kept pace. This "glass ceiling" effect limits women's earning potential, contributing to a persistent wage gap. Research by Blau and Kahn (2017) further underscores the persistence of vertical segregation, stating that even as horizontal segregation has somewhat lessened over time, vertical segregation remains significant, with women underrepresented in higher-ranking positions even within more gender-balanced or female-dominated fields.

2.2.4 Preferences and Career Choices

Gender disparities in occupational choices have been comprehensively explored, revealing that various factors such as societal norms, education, and personal preferences significantly shape these decisions. A study conducted by Su, Rounds, and Armstrong (2009) revealed that men tend to favor 'thing-oriented' fields such as engineering, computer science, and physical sciences, on average. In contrast, women predominantly prefer 'people-oriented' sectors such as healthcare, education, and social services. This study suggests that these vocational interest disparities persist across cultures and have remained consistent over the decades.

Furthermore, the impact of societal expectations and gender stereotypes on occupational choices cannot be disregarded. The OECD report "The Pursuit of Gender Equality: An Uphill Battle" (2017) elaborates on how societal norms and anticipations concerning 'suitable' occupations for each gender can steer educational and career decisions. Such stereotypes may discourage women from venturing into male-dominated fields and likewise deter men from female-dominated sectors (OECD, 2017).

The quest for work-life balance also plays a pivotal role in shaping occupational preferences. Several studies suggest that women, compared to men, are more inclined to prioritize jobs that facilitate a better work-life balance, chiefly due to traditional family responsibilities. A study by Leslie, Manchester, Park, and Mehng (2012) found that women, particularly those with children, were more prone to opt for jobs with flexible work arrangements to maintain an optimal work-life balance. Nonetheless, the study also underscored the potential career setbacks associated with such practices.

Several studies and reports have also established that women are more likely than men to work part-time (Blau and Kahn, 2017; OECD, 2017), possibly because women associate part-time work with lower work-to-family interference, better time management abilities, and greater life satisfaction (Duxbury et al., 2000). Another study provides suggestive evidence that the female selection into part-time work may be family related (Antonie et al., 2020).

Gender differences in preferences for competition-based compensation schemes can also provide insights into the gender wage gap. A lab experiment conducted by Niederle and Vesterlund (2007) demonstrated significant gender disparities in preferences when choosing between non-competitive and competitive compensation schemes, with women showing a tendency to shy away from competition. This aligns with the research findings of Flory, Leibbrandt, and List (2015), who observed that as compensation packages increasingly favored rewarding an individual's performance over their coworkers', the applicant pool exhibited a shift towards greater male dominance. These findings suggest that differences in preferences for competitive compensation schemes could contribute to the persistence of the gender wage gap.

3 Data

In this thesis, we aim to thoroughly investigate the wage gap across four different graduate-level educational groups in Norway, focusing on the disparities between them. Additionally, we aim to determine whether attaining a graduate-level education reduces the wage gap, as opposed to obtaining an undergraduate degree. To conduct our analyses, we have created two versions of our data set; one for graduate-level workers and one for undergraduate-level workers. In the analyses aimed at answering research question 1, we utilize the data set on graduate level workers. When analyzing the wage gap characteristics of each graduate-level educational group, we split the previously mentioned data set into four, based on educational field. At last, in the analysis aimed at answering research question 3, we utilize a data set that combines graduate- and undergraduate level workers. This set of data, is again split into four based on educational field.

3.1 Description of the Data Source

In order to examine the gender-based wage disparities in four different educational groups in Norway, we use a service called Microdata. This service provides access to accurate and unaltered register data through a collaboration between the Norwegian Agency for Shared Services in Education and Research (SIKT) and Statistics Norway (SSB) (Microdata, 2023a).

3.2 The Selection Process and Accompanying Data Sets

In this section, we will provide a comprehensive overview of the individuals that have been included and omitted from our data sets. Our data sets encompasses individuals with both undergraduate and graduate-level degrees, further divided into four educational categories: medicine, law, STEM, and business. A detailed description of the included educations can be found in table A2 in the appendix.

To determine the individuals' highest completed education, we have utilized educational codes provided in the Norwegian Standard Classification of Education (NUS2000). These NUS-codes are used to group people based on their educational activities and background

(SSB, 2023b). Specifically, our data set includes several of the individuals with NUS-codes starting with the digit six, indicating a first-stage tertiary education at the undergraduate level. We also include several of the individuals with NUS-codes starting with seven. Codes beginning with seven are assigned to individuals who have completed the first stage of tertiary education but at the graduate level. One exception to this rule is the code '641131', which corresponds to a four-year business study, the predecessor of the current five-year program. Therefore, this degree has been classified as a graduate-level education in our data set.

3.2.1 Description of the Selection Process and Data Sets

The data selection process is presented in detail in Table 3.1. The first section of the table outlines the selection of individuals with graduate-level degrees, while the second section describes the selection process for those with undergraduate-level degrees. The final sample used in the analyses consisted of 186,291 and 144,865 individuals with graduate- and undergraduate-level degrees, respectively.

Table 3.1: Data Set Selection for Wage Gap Analysis

	Number of observations	**Number removed**
Selection process for graduates		
(1) Population per 01.01.2019	5 328 209	
(2) Keep people who receive a wage	2 859 099	2 469 110
(3) Keep people with chosen educations	196 088	2 663 011
(4) Removes people older than 64	189 177	6 911
(5) Removes missing and "false" values	186 308	2 869
(6) Removes people who work in a foreign country	186 291	17
Final selection	**186 291**	
Selection process for undergraduates		
(1) Population per 01.01.2019	5 328 209	
(2) Keep people who receive a wage	2 859 099	2 469 110
(3) Keep people with chosen educations	209 577	2 649 522
(4) Removes people older than 64	202 631	6 946
(5) Removes missing and "false" values	144 872	57 759
(6) Removes people who work in a foreign country	144 865	7
Final selection	**144 865**	

This table illustrates the selection process for the graduate and undergraduate analysis, outlining the steps taken to exclude individuals with missing values for any of the variables. The process provides a breakdown of the initial number of observations available and the subsequent number of individuals removed at each step.

To arrive at this sample, we first imported data for all individuals residing in Norway as of January 1, 2019. We then filtered the data to include only those who received a wage. We then narrowed the sample further by only including individuals with the educational backgrounds listed in table A2 in the appendix. This reduced the sample to 196,088 and 209,577 individuals with graduate- and undergraduate-level degrees, respectively.

Since our study focuses on wages, we only included individuals who had completed their education by the spring of 2019, as wage data for these individuals was available from November 2019. We then removed individuals who were older than 64, which is the average retirement age in Norway (OECD, 2020). This further reduced the sample to 189,177 and 202,631 individuals with graduate- and undergraduate-level degrees, respectively.

To ensure data quality, we removed missing and "false" values from the data set. Finally, we excluded individuals who worked outside Norway from the sample, leaving us with a final sample of 186,291 and 144,865 individuals with graduate- and undergraduate-level degrees, respectively. We excluded individuals working outside of Norway to ensure that our study focuses solely on the situation within Norway.

3.2.2 The Proportion of Women in the Selection

Table 3.2 presents the proportion of women in four major fields of study, namely medicine, law, STEM (Science, Technology, Engineering, and Mathematics), and business, for both graduate and undergraduate levels. The table displays the number of individuals and women in each field, along with the percentage proportion of women in each field.

Table 3.2: Proportion of Women in Selection

	Number in selection	**Number of women**	**Proportion of women**
Graduate			
Medicine	32 035	18 932	59.10 %
Law	21 174	12 638	59.69 %
STEM	84 706	27 385	32.33 %
Business	48 377	21 287	44.00 %
Total	**186 291**	**80 242**	**43.07 %**
Undergraduate			
Medicine	15 983	12 477	78.06 %
Law	1 802	1 232	68.37 %
STEM	75 475	15 794	20.93 %
Business	51 605	27 804	53.88 %
Total	**144 865**	**57 307**	**39.56 %**

This table presents the distribution of women across educational groups within both the graduate and undergraduate samples.

At the graduate level, the proportion of women shows significant variation across fields, with the highest proportion in Medicine and Law (approximately 60%) and the lowest in STEM (around 32%). The overall proportion of women at the graduate level is 43.07%.

In the undergraduate selection, the proportion of women displays significant variation across fields, with the highest proportion in medical fields (over 78%) and the lowest in STEM (less than 21%). The overall proportion of women in the undergraduate selection is 39.56%.

The results indicate that women are underrepresented in STEM fields at both the graduate- and undergraduate level. In contrast, they are overrepresented in medical fields at the undergraduate level. Overall, Table 3.2 highlights the considerable variation in the proportion of women across different fields of study.

3.3 Wages in the Four Educational Groups

Table 3.3 presents the monthly wage statistics for the four educational groups in our dataset. These statistics are derived from a variable provided by Microdata. The variable represents the calculated monthly salary (in total) per full-time equivalent, and includes the agreed-upon monthly wage, as well as irregular additions and bonuses before tax (Microdata, 2023b). However, overtime pay is not included in the monthly salary. This exclusion is beneficial for the purpose of our analyses, as there will be no need to control for overtime hours. We also chose to use this variable because it allows for wage comparisons between full-time and part-time employees. For part-time employees, the monthly wage is recalculated to reflect what their earnings would be if they worked a full-time position.

Note that the Microdata variable is the same as the one used by Statistics Norway (SSB) when performing wage statistics. The variable is constructed on data from the a-ordning, which is a coordinated service used by employers to report information about income and employees to NAV, Statistics Norway, and the Norwegian Tax Administration (Skatteetaten, 2023). Our measurement time is set to November 2019: the same reference month that SSB has used when performing wage statistics since 2015 (SSB, 2023a).

We use the logarithm of full-time equivalent monthly wages as our dependent variable in all forthcoming analyses. Taking the logarithm of wages is a common practice in economics and statistics because it helps to address issues related to the distribution and interpretation of wage data. One of the main reasons logarithmic transformation is preferred, is that wage data frequently exhibit a right-skewed distribution, with a few high earners and many low earners. This distribution can create difficulties when analyzing the data, such as comparing wages across different groups or interpreting the effects of various variables on wages (Wooldridge, 2019).

By taking the logarithm of wages, we compress the distribution and reduce the impact of extreme values while preserving the relative differences in wages. The transformation also helps to make the data more symmetrical, which is frequently a desirable property for statistical analyses. Additionally, taking the logarithm of wages makes it easier to interpret the data in terms of percentage changes. For example, a 10% increase in wages corresponds to the same percentage increase in the logarithmic scale, regardless of the initial wage level.

Table 3.3: Full-Time Equivalent Monthly Wages across Educational Groups

	Men			Women		
	Average	Std.Dev	Median	Average	Std.Dev	Median
Graduate						
Medicine						
Wage	76 621	27 934	72 064	67 397	23 444	63 321
ln(wage)	11.18	0.36	11.19	11.06	0.33	11.06
Law						
Wage	71 757	29 827	63 431	60 646	22 458	54 553
ln(wage)	11.11	0.37	11.06	10.96	0.32	10.91
STEM						
Wage	71 810	29 234	65 075	60 432	23 395	54 742
ln(wage)	11.11	0.37	11.08	10.95	0.34	10.91
Business						
Wage	78 790	36 531	69 624	63 130	24 992	57 637
ln(wage)	11.18	0.42	11.15	10.99	0.34	10.96
Undergraduate						
Medicine						
Wage	46 496	14 016	43 750	42 487	9 261	42 083
ln(wage)	10.71	0.26	10.69	10.64	0.20	10.65
Law						
Wage	45 757	19 877	40 182	40 075	12 922	37 433
ln(wage)	10.66	0.35	10.60	10.56	0.27	10.53
STEM						
Wage	61 687	22 143	57 677	51 787	17 980	48 625
ln(wage)	10.97	0.34	10.96	10.80	0.32	10.79
Business						
Wage	61 109	26 935	54 167	49 784	18 031	45 774
ln(wage)	10.94	0.40	10.90	10.76	0.31	10.73

This table presents a comparison of full-time equivalent monthly wages, as of November 2019, for different educational groups under the age of 64. Distinct wage statistics, including average, standard deviation, and median values, are displayed for both men and women in graduate and undergraduate categories across our selected fields of study.

Table 3.3 presents descriptive statistics on the dependent variable, the logarithm of full-time equivalent monthly wages, along with absolute monthly wages. Including absolute wages allows us to better illustrate the differences between the four educational groups and provides an intuitive understanding of the wage statistics. However, it is worth noting that the numbers in the table are not entirely accurate because of the winsorization technique used in Microdata (Pedersen, 2021). This technique sets the 1 percent highest values to the 99th percentile and the 1 percent lowest values to the 1st percentile, which leads to an underestimation of the average and standard error, particularly for wages with long tails at the higher end. As a result, the average wage and average logarithmic wages may not match, but the median is not affected.

The table clearly shows that men have higher wages than women across all four areas of study, as well as across both educational levels. For instance, men with a graduate-level degree in medical fields earn an average wage of 76,621 NOK, while women in the same field earn an average wage of 67,397 NOK. The difference in the average wage between genders is naturally reflected in the logarithmic wage, with an average of 11.18 for men and 11.06 for women with medical backgrounds.

The median wage is also higher for men than for women across all fields of study and levels of education. We also note that the average wage is larger than the median wage for both genders, and across all fields of study and levels of education. This typically suggests that there is a positive skew in the wage distribution. In other words, there are relatively more individuals with higher wages that pull the average upward, while the majority of wage earners have lower wages. This situation often occurs when a subset of individuals have exceptionally high wages that significantly affect the average. These high earners can create a "tail" on the higher end of the wage distribution, pulling the mean higher than the median. Meanwhile, the majority of wage earners have lower wages, leading to a lower median.

Furthermore, the standard deviation is also higher for men than for women. This suggests that there is greater variability or dispersion in the distribution of male wages compared to female wages. In other words, male wages tend to vary more widely or exhibit greater differences among themselves than female wages. The wage statistics also shows that individuals with a graduate-level degree, on average, earn higher wages than individuals with an undergraduate-level degree, regardless of educational field. For instance, men with a graduate-level degree in business earn an average wage of 78,790 NOK, while men with an undergraduate-level degree in the same educational field earn an average wage of 61,109 NOK.

3.4 Explanatory Variables

In this subchapter, we provide an overview of the variables used in our analyses. We begin by discussing their content and how they were generated, followed by an explanation of their relevance to our research. Table 3.4 presents descriptive statistics for individuals with a graduate-level degree, as this is pertinent to research question 1 and 2, which examines factors contributing to wage disparities among graduate-level workers. Descriptive statistics for the independent variables of undergraduate-level workers, are not included, nor discussed, in this subchapter. This is because the main parts of our study is focused on graduate-level workers. Descriptive statistics on the independent variables of undergraduate-level workers, can however be found in table A4.1 in the appendix. A complete overview of all the variables used in our analyses, can be found in chapter A1 in the appendix.

Table 3.4: Descriptive Statistics of the Independent Variables (Graduate Level)

	Medicine		**Law**		**STEM**		**Business**	
	Men	Women	Men	Women	Men	Women	Men	Women
Work experience in years								
Experience	15.35	12.59	15.05	12.64	15.71	13.26	13.74	10.99
Experience^2	344.97	247.69	319.36	241.05	357.85	271.74	277.47	191.73
Children								
Number of children	1.26	1.27	1.11	1.10	1.06	1.05	1.20	1.15
Part-time (in %-proportions)								
Short part-time	24.28	20.14	6.55	6.11	4.34	7.24	5.35	6.24
Long part-time	5.95	8.67	2.92	3.55	2.92	7.36	2.17	4.67
Profession (in %-proportions)								
Managers	7.37	6.72	14.81	10.85	13.98	9.53	32.08	25.01
Professionals	85.39	84.82	74.32	76.85	55.88	60.63	38.11	45.77
Technicians and assoc. professionals	2.13	4.22	7.35	8.21	24.17	21.90	21.20	17.67
Clerical support workers	0.43	0.60	1.31	2.09	0.92	1.87	4.90	7.86
Other	4.69	3.65	2.21	1.99	5.04	6.06	3.71	3.70
Sector (in %-proportions)								
Publicly controlled enterprises	1.17	2.50	2.73	2.06	11.05	9.21	7.36	6.68
Privately controlled enterprises	23.51	23.57	40.36	27.33	68.42	53.97	58.30	48.68
Credit-granting enterprises	0.06	0.04	2.77	2.18	0.87	0.81	8.75	6.54
Other fin. enterprises	0.05	0.03	1.95	1.42	0.67	0.29	4.35	1.54
Insurance companies	0.17	0.03	2.77	3.27	0.58	0.68	1.83	1.52
General government	71.31	70.38	45.77	59.81	17.55	33.40	17.17	31.28
Non-profit institutions	3.56	3.22	3.07	3.54	0.73	1.50	2.09	3.64
Households	0.16	0.24	0.57	0.40	0.13	0.14	0.16	0.12

This table displays descriptive statistics of various independent variables, such as work experience, number of children, part-time status, profession, and sector affiliations for men and women across different graduate fields. Work experience is calculated by subtracting the graduation year from the year of measurement (2019). Short part-time employment refers to jobs with less than 50% employment rate, while long part-time comprises individuals employed between 50% and 100%. The categorization of professions follows the SSB standard STYRK-08, while the sector classifications adhere to the SSB standard for institutional sector grouping.

3.4.1 Work Experience

As depicted in table 3.4, we have constructed two separate independent variables for measuring work experience, one being *experience*, and the other being $experience^2$. The former, is calculated by subtracting the graduation year from the year of measurement (2019). For individuals with multiple degrees at the same educational level, we have used the number of years since their first completed degree.

It is important to note that our measure of experience does not account for time spent outside of the workforce, for instance due to sickness, maternity leave, or pursuing an additional degree. Thus, our approach may lead to an overestimation of our sample individuals' work experience. To address this issue, Brakstad and Sanner (2022) used the number of children as a proxy for maternity leave, and deducted a year of work experience per child for women. We, on the other hand, chose to a include the number of children as a separate independent variable for two reasons; Firstly, because we believe that Brakstad and Sanner's method of accounting for maternity leave may lead to an underestimation of women's work experience and an overestimation of men's work experience. Secondly, because we aim to conduct a separate analysis to examine whether the presence of children affects the wages of men and women differently.

Furthermore, to account for diminishing returns on experience, we have included experience squared ($experience^2$) as an independent variable. This recognizes that the relationship between wages and experience is not linear, and that each additional year of experience results in a smaller increase in wages than the previous year.

Table 3.4 displays that, on average, women have less work experience than men across all educational groups. Specifically, men in STEM have approximately 19% more experience, men in law have approximately 20% more, and men in medicine have approximately 22% more. However, the largest gap is observed among business graduates, where men have on average 25% more experience than their female counterparts. In the business field, the average work experience for men is 13.74 years, while for women it is 10.99 years.

3.4.2 Children

The next independent variable in table 3.4 is *children*. Unfortunately, Microdata does not offer a variable that measures the number of children per Norwegian resident. Instead, we had to use a Microdata variable that counts the number of children, no matter their age, who are residing in the family of at least one of their parents. It is important to note that children who have moved out of one/both of their parents' households are no longer registered as children of the individuals in our data set. Thus, the constructed *children* variable can only provide an indication of the actual number of children per individual in our data set. Considering our sample predominantly contains highly educated women, it's plausible that only a small proportion have children old enough to live independently. However, this approximation does come with inherent limitations, potentially leading to specification errors in the subsequent regression analyses.

When testing for gender disparities in the effect of having children in subchapter 5.2.3, we reduced our sample selection to individuals aged 45 or younger. We did this in order to reduce the errors that follow with the imprecise measurement of our *children* variable. Considering our sample predominantly contains highly educated individuals, it's plausible that only a small proportion have children old enough to live independently. The average number of children in the new sample of graduate level workers, is displayed in table 3.5 underneath. Moreover, the table presents the average number of children in each educational group, further broken down by gender.

Table 3.5: Average Number of Children for Graduate-Level Workers, Aged $\leq$ 45

	Medicine		**Law**		**STEM**		**Business**	
	Men	Women	Men	Women	Men	Women	Men	Women
Children								
Number of children	1.27	1.29	1.00	1.02	0.97	1.00	1.14	1.15

This table showcases the average number of children for graduate-level workers, aged 45 or less, in Medicine, Law, STEM, and Business. Please note, these statistics may be slightly lower than the actual due to the measurement methodology

Table 3.5 shows that within educational groups, men and women have a similar number of children, however there are slight variations across the different educational groups. Specifically, individuals with a graduate-level degree in the fields of law and STEM have the lowest average number of children, with approximately 1 child. Business graduates have the second highest average with approximately 1.15 children each, while individuals with a graduate-level degree in medical fields have an average of almost 1.3 children.

3.4.3 Part-time

We will now examine the next independent variable, part-time. This variable was created by using monthly reports from the "a-melding" that provide information about the percentage of employment. The measurement is set to November 2019. If an individual has multiple jobs, the percentage of employment for each job is added up. We have divided part-time work into short and long categories. Short part-time refers to jobs where the percentage of employment is less than 50%, while long part-time includes individuals working between 50% and 100%. Both of these variables are included in the forthcoming analyses, even though monthly wages are converted to full-time equivalent monthly wage.

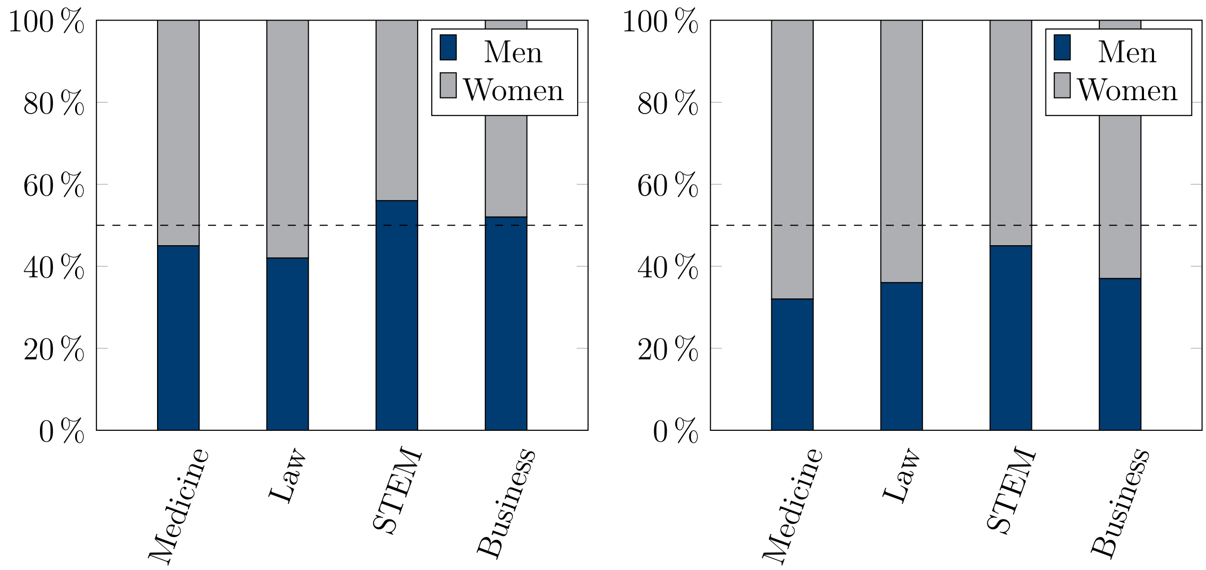
Table 3.4 displays the percentage of men and women working part-time in the four educational groups. From the table, we can read that 6.55% of men with a graduate-level degree in fields of law, work less than 50% of a full-time position, whereas 2.92% work between 50 and 100% of a full-time position. This means that the vast majority of men with a graduate-level degree in law work a full-time position (90.53%). The proportion of men with a graduate-level degree in fields of law working short- and long part-time, is highly similar to the corresponding proportions in STEM and business fields.

The proportions of short part-time workers are also quite similar across genders. However, the proportions of women in STEM and business fields who work less than 50% of a full-time position, are slightly larger than the corresponding proportions for men. The proportions of women who work long part-time, are also larger than the proportions of men who work long part-time across all four educational fields. This indicates that working long part-time is more prevalent among women.

Note that the group of individuals with a graduate-level degree in medical fields, stands out in terms of part-time work. Both men and women in this educational group have larger percentages of individuals working short- and long part-time compared to the other three educational groups. Among men in this group, 24.28% work less than 50% of a full-time position, while 5.95% work between 50% and 100% of a full-time position. For women with a degree in medical fields, 20.14% work less than 50% of a full-time position, and 8.67% work between 50% and 100% of a full-time position. As a result, the proportion of full-time workers is the lowest in medical fields. Specifically, 69.77% of men and 71.19% of women in this group are employed full-time.

Figure 3.1a displays the gender distribution among short part-time workers in each educational group. The figure shows that women make up 55% and 58% of short part-time workers with an educational background in medicine and law, respectively. Among short part-time workers with a graduate-level degree in STEM and business, there is a slightly higher proportion of men. Figure 3.1b, on the other hand, shows that women make up the majority of long part-time workers across all educational groups.

Figure 3.1: Gender Distribution among Short and Long Part-Time Workers



(a) Short part-time **(b)** Long part-time

These figures provide a visualization of the gender distribution among short- and long part-time workers with different educational backgrounds. Figure (a) represents those employed on a short part-time basis, defined as less than a 50% employment rate, whereas Figure (b) depicts individuals working on a long part-time basis, specified as having an employment rate between 50% and 100%

Table 3.6, on the other hand, displays the average monthly full-time equivalent wage of men and women with differing educational backgrounds, who work full-time (FT), short part-time (short PT) and long part-time (long PT). The table shows that the average wage of full-time employed men is higher than the average wage of full-time employed women across all four educational groups. Men who work part-time also have a higher average wage than that of women who work part-time. There is, however, one exception:

women in STEM who work long part-time have an average monthly wage that is slightly higher than that of their male equivalents. Another important notion, is that the gender disparities in average monthly wages are smaller among those working short- and long part-time, than among those working full-time.

Table 3.6: Average Full-Time Equivalent Monthly Wages of FT and PT Workers

	Men			Women		
	FT	Short PT	Long PT	FT	Short PT	Long PT
Graduate-Level						
Medicine						
Wage	80 616	66 235	66 776	69 475	61 782	61 726
ln(wage)	11.24	11.04	11.04	11.10	10.97	10.98
Law						
Wage	73 041	57 051	54 186	61 638	49 583	52 336
ln(wage)	11.13	10.88	10.84	10.98	10.75	10.82
STEM						
Wage	73 326	48 413	54 286	62 222	44 669	54 473
ln(wage)	11.14	10.72	10.84	10.98	10.65	10.85
Business						
Wage	82 041	51 973	56 931	65 161	45 698	51 994
ln(wage)	11.22	10.78	10.87	11.02	10.68	10.81

This table presents a comparison of average full-time equivalent monthly wages for working individuals under the age of 64, as of November 2019. The average wage is calculated for both men and women across four educational groups, further categorized based on whether they work full-time (FT), short part-time (Short PT), or long part-time (Long PT).

3.4.4 Profession

This subsection provides a detailed description of the independent variable, *profession*. As documented in the literature review, occupations can play a part in explaining the wage gap between men and women, as women tend to choose or be selected into different occupations than men. To gather data on the professions of our sample individuals, we used a Microdata variable called ARBLONN_ARB_YRKE_STYRK08. This variable provides occupational codes aligned with the codes in the STYRK-08 standard classification of occupations (Microdata, nda). The STYRK-08 classification is again based on the International Standard Classification of Occupations (Statistics Norway, 2011).

Furthermore, we set the time of measurement to November 2019, so that the reported monthly wage would match the reported occupational code. Like Brakstad and Sanner

(2022), we utilized the occupational codes provided by Microdata to create five different occupational groups; managers, professionals, technicians & associate professionals, clerical support workers, and others. Table A1.2 in the appendix, provides a complete overview of the occupational codes that were included in each of the five occupational groups.

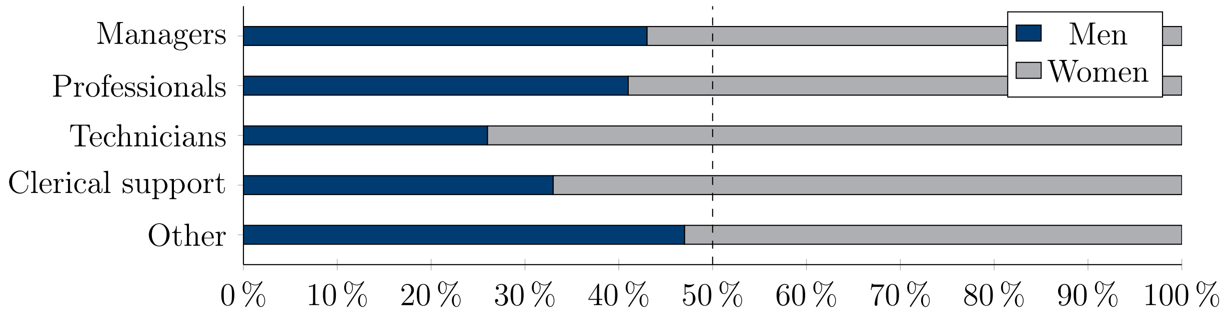
Table 3.4 provides information on how individuals of each gender are distributed across professions. Among those with a graduate-level degree in medical fields, a vast majority of men (85.39%) and women (84.82%) work as professionals. Managers emerge as the second-largest occupational category; 7.37% of men and 6.72% of women with a graduate-level degree in medical fields fall within this group. The remaining 7% of men and 8% of women work in the three other occupational categories.

Professionals is also the largest occupational category among those with a graduate-level degree in law; 74.32% of men and 76.85% of women with this educational background are categorised as professionals. Moreover, 14.81% of men and 10.85% of women are categorised as managers. The remaining 11% of men and 12% of women are spread out across the three remaining occupational categories.

Also among those with a graduate-level degree in STEM, the majority of men (55.88%) and women (60.63%) work as professionals. However, technicians & associate professionals is the second-largest occupational group, encompassing 24.17% of the men and 21.90% of the women with this educational background. Managers come in third, with 13.98% of the men and 9.53% of the women. The remaining 6% of men and 8% of women, belong in the two other occupational categories.

In the group of business graduates, both men and women are largely employed as professionals; 38.11% of men and 45.77% of women are included in this occupational category. Moreover, 32.08% of men and 25.01% of women are categorized as managers. Technicians & associate professionals encompass 21.20% of men and 17.67% of women, while the remaining 9% of men and 11% of women work in either of the two remaining occupational categories.

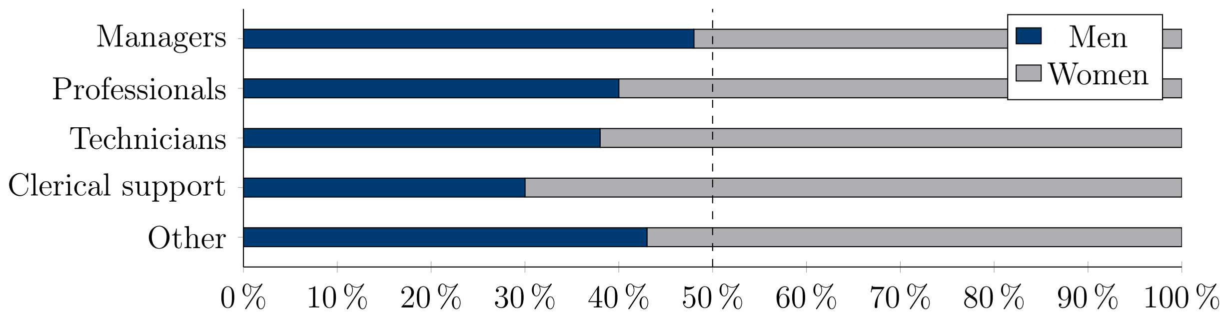
Figure 3.2: Medicine: The Gender Distribution within Occupational Groups



This figure presents the gender distribution within different occupational groups in the field of Medicine. The categorization of professions follows the SSB standard STYRK-08.

Figure 3.2 displays the gender distribution within occupational groups consisting of individuals with a graduate-level degree in medical fields. The table shows that women make up the majority in all occupational groups. The group of technicians & associate professionals has the highest proportion of women (74%), while other professions has the lowest (53%). Lastly, women make up 57% of all managers with a medical background.

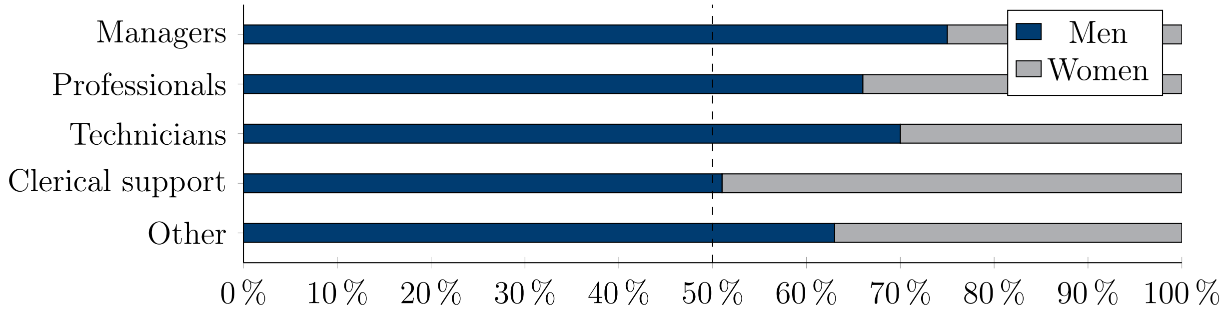
Figure 3.3: Law: The Gender Distribution within Occupational Groups



This figure presents the gender distribution within different occupational groups in the field of Law. The categorization of professions follows the SSB standard STYRK-08.

Figure 3.3 displays the gender distribution within occupational groups consisting of individuals with a graduate-level degree in law. This figure also shows an overrepresentation of women in all professions. The group of clerical support workers has the highest proportion of women with 70%, while managers have the lowest with 52% women.

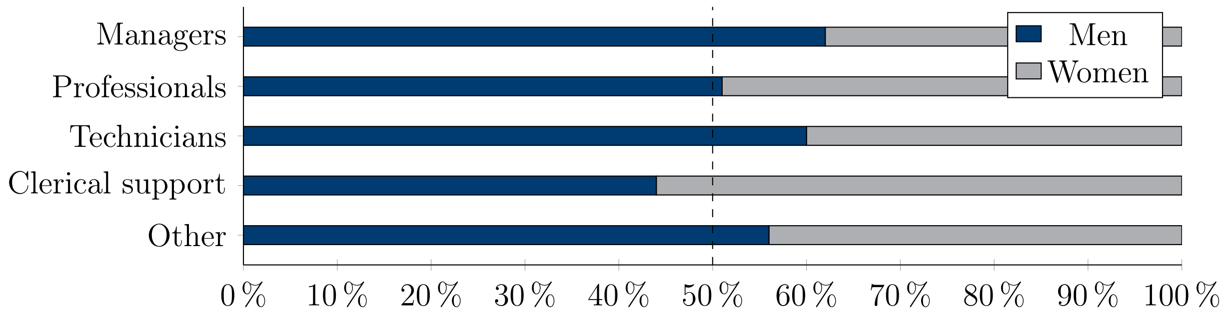
Figure 3.4: STEM: The Gender Distribution within Occupational Groups



This figure presents the gender distribution within different occupational groups in the field of STEM. The categorization of professions follows the SSB standard STYRK-08.

Figure 3.4 displays the gender distribution within occupational groups consisting of individuals with a graduate-level degree in STEM. The figure reveals an overrepresentation of men in all professions. The group of clerical support has the highest proportion of women with 49%, while Managers have the lowest with 25% women.

Figure 3.5: Business: The Gender Distribution within Occupational Groups



This figure presents the gender distribution within different occupational groups in the field of Business. The categorization of professions follows the SSB standard STYRK-08.

Lastly, figure 3.5 displays the gender distribution within occupational groups consisting of individuals with a graduate-level degree in fields of business. The figure reveals an overrepresentation of men in all professions except for clerical support. The group of clerical support has the highest proportion of women with 56%, while managers have the lowest with 38% women.

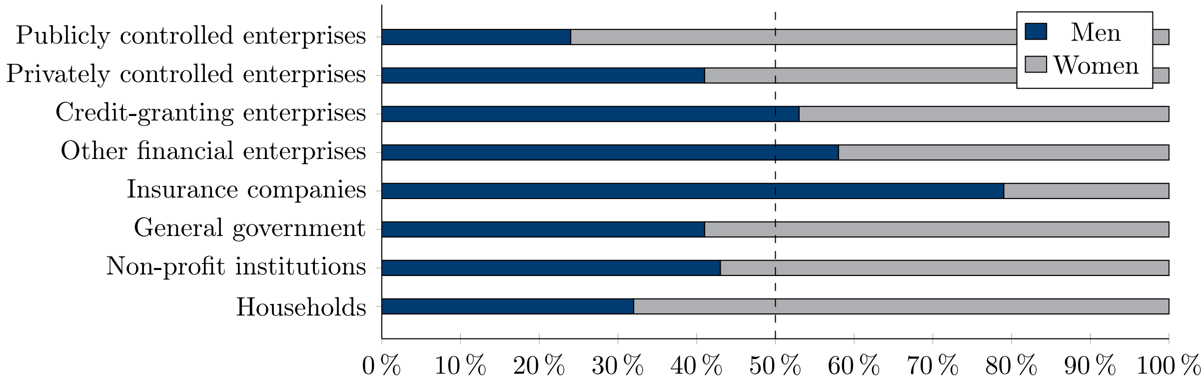
3.4.5 Sector

The final independent variable in our study is sector, which we obtained from employment statistics and is based only on the main employment relationship. The data was collected in November 2019, and we used the sector grouping standard employed by Statistics Norway for institutional sector grouping. Norway has nine sectors, and we excluded non-domestic sectors from our analysis. The sectors we analyzed include publicly controlled enterprises, privately controlled enterprises, credit-granting enterprises, other financial enterprises, insurance companies, general government, non-profit institutions, and households. A complete overview of what each sector includes can be found in table A1.3 in the appendix.

Table 3.4 displays the percentage of individuals employed in different sectors within each educational group. The table shows that the distribution of sectors varies across the four educational groups and genders. For example, in the medicine group, the majority of employees work in the general government sector, with 71.31% of men and 70.38% of women. Privately controlled enterprises are the sector with the second-highest employment, with 23.5% for both men and women. In the law group, the general government employs most men and women, with 45.77% of men and 59.81% of women. The second-largest sector is privately controlled enterprises, with 40.36% for men and 27.33% for women. The remaining 14% of men and 13% of women are distributed among the other six sectors.

For the STEM group, privately controlled enterprises are the largest sector, with 68.42% of men and 53.97% of women. General government is the second-largest sector, with 17.55% of men and 33.40% of women. The third-largest is publicly controlled enterprises, where the share of men is 11.05% and 9.21% for women. The remaining 3% of men and women are distributed among the remaining five sectors. Lastly, most people in the business profession work in privately controlled enterprises, with 58.30% of men and 48.68% of women. The second-largest group is general government, with 17.17% of men and 31.28% of women. The remaining 25% of men and 20% of women are distributed among the other six sectors. It is worth noting that for all groups, except medicine, women seem to be overrepresented in general government.

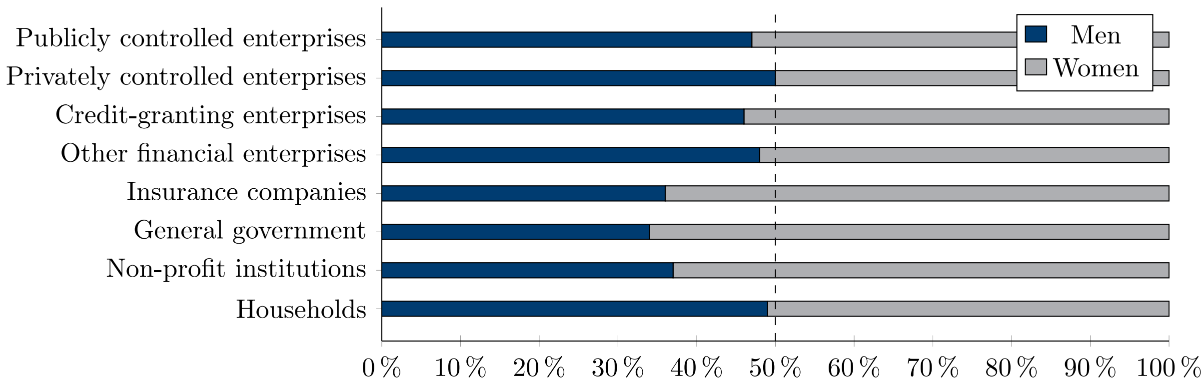
Figure 3.6: Medicine: The Gender Distribution within Sector Groups



This figure depicts the gender distribution across various sectors within the field of Medicine, utilizing the SSB standard for institutional sector grouping.

Figure 3.6 displays the gender distribution for each sector. Within medical professions, men are overrepresented in privately controlled enterprises, other financial enterprises, and insurance companies, while women dominate in the other sectors. In general government, the largest sector, women are overrepresented with 59%.

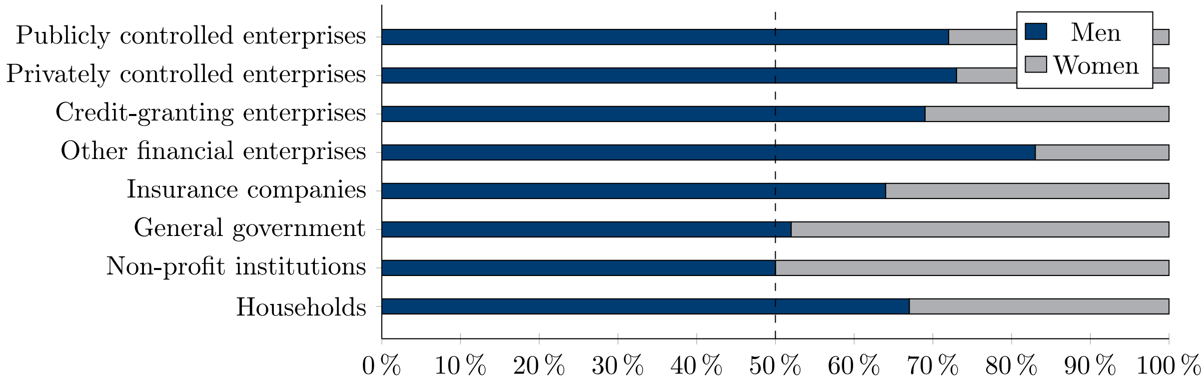
Figure 3.7: Law: The Gender Distribution within Sector Groups



This figure depicts the gender distribution across various sectors within the field of Law, utilizing the SSB standard for institutional sector grouping.

Figure 3.7 displays the gender distribution for each sector. In the field of law, women are overrepresented in all sectors except for privately controlled enterprises, where the gender balance is equal.

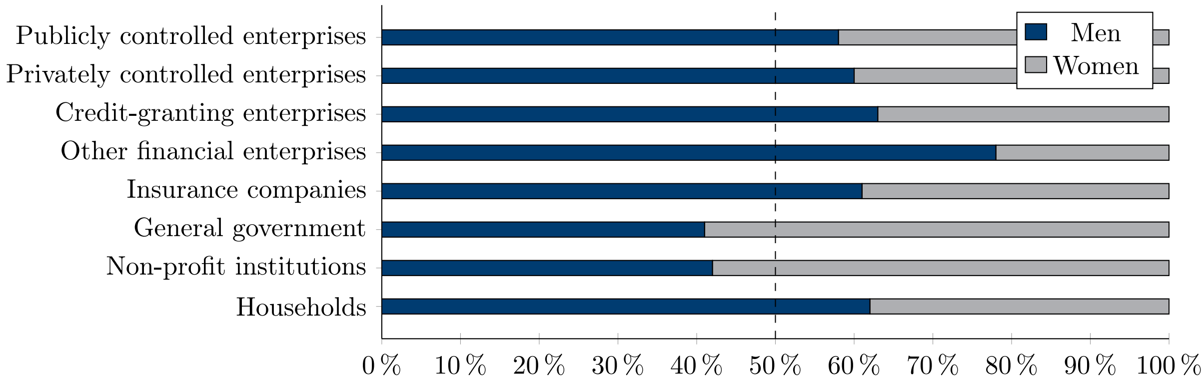
Figure 3.8: STEM: The Gender Distribution within Sector Groups



This figure depicts the gender distribution across various sectors within the field of STEM, utilizing the SSB standard for institutional sector grouping.

Figure 3.8 displays the gender distribution within STEM professions. Men are overrepresented in all sectors except non-profit institutions where the gender balance is equal. In the largest sector, *privately controlled enterprises*, the share of men is 73%.

Figure 3.9: Business: The Gender Distribution within Sector Groups



This figure depicts the gender distribution across various sectors within the field of Business, utilizing the SSB standard for institutional sector grouping.

Finally, Figure 3.9 presents the gender distribution within business professions. Men are overrepresented in all sectors except for general government and non-profit institutions, where the share of men is 41% and 42%, respectively. The largest sector, privately controlled enterprises, has a share of men at 60%.

4 Methodology

In this chapter, we will describe the methods we have used to answer our research questions. We will begin by explaining how we estimated the wage gap at the graduate level. Next, we will present our approach to estimating the wage gap within each educational group.

We will also describe our methods for examining the wage gap among part-time workers and in different professions and sectors, as well as testing for gender disparities in the return on experience and in the effect of having children. Finally, we will explain our method for estimating the effect of the educational level on the wage gap.

4.1 Estimating the Wage Gap at the Graduate Level

In this section, we will describe our approach to examining the wage gap among graduate-level workers in all four educational groups as a whole. Our methodology entails using various regression analyses. Specifically, we will be using log-linear models, which for us entails taking the logarithm of the dependent variable, wage. This approach allows us to interpret the results of the regression analyses in percentages rather than absolute numbers. Additionally, using log-linear models can mitigate the influence of outliers, particularly when dealing with positive monetary values such as wage (Wooldridge, 2019).

4.1.1 Estimating the Raw Wage Gap at the Graduate Level

To estimate the raw wage gap between male and female graduate-level workers, we will use a first-order linear model identical to that of Brakstad and Sanner (2022). Such a model will allow us to examine the linear relationship between a dependent variable and an independent variable (Keller, 2017). Our model examines the logarithmic wage of each individual i in November 2019, and is presented as follows:

$$\ln W_i = \beta_0 + \delta_0 Woman_i + \epsilon_i \tag{4.1}$$

In this model, the logarithmic wage serves as the dependent variable, while β_0 represents the y-intercept or constant term corresponding to the average wage of male individuals. The independent variable, on the other hand, is a dummy variable for *woman*. In statistics, a dummy variable is a variable that takes one of two possible values, typically 0 or 1

(Keller, 2017). A value of 1 indicates the presence of a specific condition, while a value of 0 indicates the absence of the condition. For our purposes, the independent variable takes the value of 1 if individual i is female and 0 otherwise.

Moreover, δ_0 is the coefficient for the independent variable and represents the average difference in the dependent variable for the group identified by the dummy variable. Thus, it indicates the percentage change in wages when individual i is female, thereby revealing the size of the raw wage gap. Finally, ϵ_i represents the error term that accounts for the difference between the actual wage and the predicted wage based on gender, thus capturing the effect of other factors that could potentially influence wages.

The coefficients of model (X) are estimated by applying the Ordinary Least Squares (OLS) method, using the following OLS-model:

$$\widehat{lnW_i} = \hat{\beta}_0 + \hat{\delta}_0 Woman_i \tag{4.2}$$

The estimates produced by the OLS method minimize the sum of squared residuals, resulting in the best-fitted straight line for our sample data. In the OLS-model presented above, $\widehat{lnW_i}$ represents the predicted wage, while the intercept, $\hat{\beta}_0$, represents the predicted wage when $Woman_i = 0$. Additionally, the coefficient $\hat{\delta}_0$ represents the predicted percentage change in wages when $Woman_i = 1$.

4.1.2 Estimating the Wage Gap with Control Variables at the Graduate Level

Going forward, we aim to estimate the wage gap among graduate-level workers when controlling for the independent variables mentioned in chapter 3.4. To accomplish this, we follow a similar approach to Brakstad and Sanner (2022) and gradually add our control variables to regression model 4.1. Our models do however differ, as we have taken a slightly different approach to control for work experience and children.

First, we examine the wage gap while controlling for differences in experience. We include the two experience variables, namely *experience* and *experience*^{2}, and obtain the regression model specified in equation 4.3. In this model, β_1 represents the percentage change in wage for each additional year of experience, holding all other factors fixed. Whereas β_2 captures the non-linear effect of experience on wages, thus accounting for diminishing returns on experience over time.

$$\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \epsilon_i \tag{4.3}$$

Next, we estimate the wage gap while controlling for the number of children residing in the household of individual i. To do so, we add the *children* control variable to the regression model, as presented in equation 4.4. In this updated regression model, β_3 represents the percentage change in wage for each additional child.

$$\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i + \epsilon_i \tag{4.4}$$

Going forward, we control for work time by adding the *short part-time* and *long part-time* dummies to the previous regression model, resulting in equation 4.5. The two work time dummies take on a value of 1 if their corresponding conditions regarding percentage employment, as described in subsection 3.4.3, are met. Together, the *short part-time* and *long part-time* dummies represent a nominal variable (*work time*) with three categories: short part-time, long part-time, and full-time. The full-time category serves as a reference category and is therefore omitted from the regression model.

Given that the wage variable captures the full-time equivalent wage, the wages of part-time workers are expressed as the wage they would have earned had they worked a full-time position. Thus, β_4 represents the percentage change in full-time equivalent wage, when individual i works less than 50% of a full-time position, holding all other factors fixed. Furthermore, β_5 represents the percentage change in full-time equivalent wage, when individual i is employed at a percentage ranging from between 50 and 100%, holding all other factors fixed.

$$\begin{aligned}\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i \\ + \beta_4 ShortParttime_i + \beta_5 LongParttime_i + \epsilon_i\end{aligned} \tag{4.5}$$

Next, we address differences in professions by incorporating the term $\gamma_p Profession_{p,i}$ into the regression model presented in equation 4.6. Here, $Profession_{p,i}$, denotes profession dummy p, whereas γ_p represents the coefficient for profession dummy p, indicating the percentage change in wage relative to the occupational reference group. As described in subsection 3.4.4, we operate with five different occupational groups; 1) *professionals*,

2) *managers*, 3) *technicians & associate professionals*, 4) *clerical support workers* and 5) *other professions*. Occupational group 1) was selected as the reference group, given that *professionals* is the largest occupational category across all four educational groups. Therefore, the regression model only includes dummies for occupational groups 2)-5).

$$\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i + \beta_4 ShortParttime_i + \beta_5 LongParttime_i + \gamma_p Profession_{p,i} + \epsilon_i \quad (4.6)$$

Finally, we control for sector as presented in regression model 4.7 In this model $Sector_{s,i}$ represents sector dummy s, while λ_s denotes the coefficient of sector s, which again indicates the percentage change in wage relative to the reference sector. In this model, we chose *privately controlled enterprises* as the reference sector and included the seven remaining sector category dummies in the regression.

$$\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i + \beta_4 ShortParttime_i + \beta_5 LongParttime_i + \gamma_p Profession_{p,i} + \lambda_s Sector_{s,i} + \epsilon_i \quad (4.7)$$

To gain a better understanding of the wage gap at the graduate level as well as within each educational group, we will apply regression models 4.1-4.7. Model 4.1-4.7 will be used to analyze the overall wage gap at the graduate level, while model 4.1 and 4.7 will be used to analyze the wage gap within each educational group separately.

4.1.3 Testing for Significance

In this section, we describe how we test the statistical significance of the wage gap coefficient, δ_0, and the β_j coefficients, where j corresponds to any of the remaining independent variables.

We conduct t-tests to assess whether the δ_0 coefficients significantly differ from 0. This helps us determine whether the estimated wage gap is statistically significant or not. The null-hypothesis, as shown in equation 4.8, states that the independent variable has no effect on the dependent variable. Thus, the null hypothesis states that a gender based wage gap does not exist.

$$H_0 : \delta_0 = 0 \quad (4.8)$$

On the contrary, the alternative hypothesis, as shown in equation 4.9, states that the δ_0

coefficient differs from 0. Thus, the alternative hypothesis implies that there is indeed a wage gap between men and women.

$$H_1 : \delta_0 \neq 0 \tag{4.9}$$

The same t-tests are used to determine whether the coefficients for our remaining independent variables, denoted by β_j, are significantly different from 0. The corresponding null hypothesis, as well as the alternative hypothesis, are shown in equation 4.10 and 4.11, respectively. If $\beta_j \neq 0$, there is sufficient evidence of a linear relationship between the independent variable, j, and the dependent variable, when the remaining independent variables are included in the model (Keller, 2017).

$$H_0 : \beta_j = 0 \tag{4.10}$$

$$H_1 : \beta_j \neq 0 \tag{4.11}$$

To determine the presence of a wage gap and the impact of the independent variables on the dependent variable, we start by selecting a significance level. When conducting regression analyses in Microdata, we are provided with p-values for both the δ_0 and β_j coefficients. We then compare these p-values to the selected significance level. If the p-value is lower than the selected level, we consider it small enough to reject the null hypothesis. However, if the p-value is higher than the selected level, we fail to reject the null hypothesis (Keller, 2017).

4.2 Estimating the Wage Gap in each Educational Group

To further investigate the wage disparities among medicine, STEM, law, and business graduates, we provide methods for examining whether the effect of our included independent variables on our dependent variable, the logarithm of *wage*, differs by gender.

4.2.1 Testing for Gender Disparities in the Return on Experience

We start by examining whether there are gender-based differences in the return on experience. We adopt a similar model to that of Brakstad and Sanner (2022) and Stokke (2021), which entails the use of interaction terms. Interaction terms are frequently used in multivariate analyses, to investigate whether the impact of an explanatory variable on the dependent variable, is contingent on a yet another explanatory variable (Wooldridge, 2019). For the purpose of this analysis, this implies examining whether the relationship between experience and wage is dependent on gender. The ensuing regression model is presented in equation 4.12

$$\begin{aligned}\ln W_i = \beta_0 + \delta_0 Man_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \delta_1 Man_i * Experience_i \\ + \delta_2 Man_i * Experience_i^2 + \beta_3 Children_i + \beta_4 ShortParttime_i \\ + \beta_5 LongParttime_i + \gamma_p Profession_{p,i} + \lambda_s Sector_{s,i} + \epsilon_i \quad (4.12)\end{aligned}$$

Given that we want to uncover whether men have a higher return on experience, we include the two following interaction terms: $Man_i * Experience_i$, and $Man_i * Experience_i^2$. If the corresponding coefficients, δ_1 and δ_2 are significant, and δ_1 is positive, it would imply that for each additional year of experience, the average male salary increases more than the average female salary, holding all other factors fixed. Note that model 4.12 also controls for the remaining independent variables mentioned in chapter 3.4

To uncover potential differences in wage development across educational groups, we estimate δ_1 and δ_2 for each of the four graduate level educational groups.

4.2.2 Testing for Gender Disparities in the Effect of Having Children

To test for potential gender-based differences in the effect of having children, we conduct a regression analysis based on regression equation 4.13. More specifically, this regression model examines whether the men in our sample of graduate-level workers experience a wage premium from having children.

$$\begin{aligned}\ln W_i = \beta_0 + \delta_0 Man_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i \\ + \delta_1 Man_i * Children_i + \beta_4 ShortParttime_i + \beta_5 LongParttime_i \\ + \gamma_p Profession_{p,i} + \lambda_s Sector_{s,i} + \epsilon_i \quad (4.13)\end{aligned}$$

The model includes a dummy variable for men, indicating that the constant term, β_0, represents the average logarithmic wage of women who do not have children. The coefficient for the variable representing children, β_3, tells us the change in the average logarithmic wage of women for each additional child. Thus, the average wage for women with one child is equal to $\beta_0 + \beta_3$. Note that we also control for experience, work time, profession, and sector to enhance the precision of our estimates.

To test for a potential male wage premium, we include the interaction term $Man_i * Children_i$, in our regression model. A positive and statistically significant δ_1 coefficient would suggest that for each additional child, the average male salary increases more than the average female salary, all else equal. The δ_1 coefficient is estimated for each of the four educational groups, in order to make comparisons across educational categories.

4.2.3 Estimating the Wage Gap among Part-Time Workers

We use model 4.14 to estimate the wage gap among part-time workers. The model includes a dummy variable for woman, dummy variables for part-time work, and the interaction terms $Woman_i * ShortParttime_i$ and $Woman_i * LongParttime_i$. Note that we also control for experience, children, profession, and sector.

$$\begin{aligned}\ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i \\ + \beta_4 ShortParttime_i + \beta_5 LongParttime_i + \delta_1 Woman_i * ShortParttime_i \\ + \delta_2 Woman_i * LongParttime_i + \gamma_p Profession_{p,i} + \lambda_s Sector_{s,i} + \epsilon_i \quad (4.14)\end{aligned}$$

The β_0 constant term represents the average logarithmic wage for men who work a full time position, whereas δ_0 indicates the percentage change in wages when individual i is female. Furthermore, the β_4 and β_5 coefficients indicate the change in the average wage for men working short part-time and long part-time, respectively. This implies that the average wage for men working short part-time, is equal to $\beta_0 + \beta_4$.

The coefficients corresponding to the two interaction terms, δ_1 and δ_2, indicate the change in the size of the wage gap when individual i belongs to the short part-time category and the long part-time category, respectively. To uncover potential differences in the size of the part-time wage gap, we estimate the size of δ_1 and δ_2 for each of the four graduate level educational groups.

4.3 Estimating the Effect of the Educational Level

In this section, we will describe our approach to estimating the effect of the educational level on the wage gap. To do so, we run a regression on the combined undergraduate and graduate sample. These two sample selections were elaborated on in subsection 3.2.1.

4.3.1 Estimating the Effect of Educational Level on the Wage Gap

We use regression model 4.15 to estimate the gender wage gap at different educational levels. Again, the logarithm of full-time equivalent wage is the dependent variable. We include a dummy for being a woman, and a dummy for having an undergraduate-level degree, as well as the interaction term $Woman_i * Undergraduate_i$. Note that in this regression model, graduate-level workers are used as a reference group. As with our previous models, we control for experience, children, work time, profession, and sector.

$$\begin{aligned} \ln W_i = \beta_0 + \delta_0 Woman_i + \beta_1 Experience_i + \beta_2 Experience_i^2 + \beta_3 Children_i \\ + \beta_4 ShortParttime_i + \beta_5 LongParttime_i + \gamma_p Profession_{p,i} + \lambda_s Sector_{s,i} \\ + \beta_6 Undergraduate_i + \delta_1 Woman_i * Undergraduate_i + \epsilon_i \end{aligned} \tag{4.15}$$

The coefficient for the interaction term, δ_1, tells us the percentage change in the size of the wage gap when individual i has an undergraduate-level degree. To uncover potential differences in the size of the wage gap across educational levels, we estimate δ_1 for each of the four educational groups.

5 Analysis of the Wage Gap

In this chapter, we will present the findings of our analyses aimed at answering our thesis statement. We will address one research question at a time and present our discoveries to achieve this. Firstly, we will examine the gender wage gap at the graduate level. Secondly, we will explore any educational disparities in the gender wage gap. Lastly, we aim to determine whether obtaining a graduate-level degree, compared to an undergraduate degree, reduces the gender wage gap in Norway.

5.1 Analysis of the Gender Wage Gap at the Graduate Level

Table 5.1 presents our estimates of the gender wage gap after controlling for various variables. Each column in the table, ranging from 1.1 to 1.6, corresponds to regression model 4.1 and 4.3-4.7, respectively. As presented in column 1.1, the estimated coefficient for women is significant at the 1% significance level, and implies that women in the fields of business, law, medicine, and STEM, on average earn 15.39% less than their male counterparts. This suggests that the raw wage gap among graduate level workers in these four educational fields as a whole, is 15.39%, with women earning 84.61% of what men do.

We then assess how the wage gap changes when introducing additional control variables. In column 1.2, we add controls for experience and experience squared, resulting in a reduced wage gap of 11.2%. However, the wage gap is still significant at the 1% level. The coefficients for *experience* and *experience*^{2} implies that there is a significant increase in wages for each additional year of work experience. Given the assumption of diminishing returns on experience, a person who has 1 year of experience will on average earn 3.74% more than a person with 0 years of experience, holding all other factors fixed. As established in Chapter 3, men tend to have more experience than women, leading to a reduction in the wage gap.

As we progress to column 1.3, we incorporate the number of children into the regression, leading to a marginal increase in the wage gap from 11.2% to 11.3%. The coefficient for *children* is statistically significant at the 1% level. What this implies is that the presence of each additional child has a positive influence on wages, yielding an increase of approximately 2.56%. In essence, every additional child correlates with a rise in the wages of an individual, suggesting that individuals with children may be perceived as more stable or responsible, traits that could be valued by employers.

Moving to column 1.4, we introduce control variables for both short and long part-time work. This addition leads to a further reduction in the wage gap, narrowing it down to 9.93%. Concurrently, it's revealed that part-time work—whether short or long—relates to considerably lower wages. This could potentially be explained by the characteristics of part-time jobs, which are typically associated with lower-responsibility roles within a firm, thereby commanding lesser compensation compared to full-time positions.

Next, we conduct a regression analysis based on regression model 4.6. The results of this regression are presented in column 1.5, and indicate a gender wage gap of 9.97% after introducing professions as independent variables. The coefficients suggest that managers have the highest wages, possibly due to greater job responsibilities. All else being equal, managers earn 21.16% more than professionals. Moreover, the disadvantage of working part-time decreases from around 23% to roughly 16%. This may be because part-time workers often hold lower-paid jobs. The return on experience also declines, as workers with more experience typically hold higher-paid positions. Similarly, the advantage of having a child decreases from 2.88% to 2.14%, possibly due to individuals with higher-paid positions having fewer children, given their professional ambitions.

Finally, in column 1.6, we introduce sector dummies, leading to a wage gap of 7.98%, which is significant at the 1% level after controlling for our full set of independent variables. Thus, women earn 92.92% of what men with the same experience, number of children, work time, profession, and sector do. Together, the independent variables included in the regression presented in column 1.6, explain 39.7% of the deviation in the logarithm of full time equivalent wage.

Table 5.1: Gender Wage Gap at the Graduate Level

	Dependent variable: Logarithm of wages					
	(1.1)	(1.2)	(1.3)	(1.4)	(1.5)	(1.6)
Woman	-0.1539***	-0.1120***	-0.1133***	-0.0993***	-0.0997***	-0.0798***
	(0.0018)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Experience		0.0381***	0.0339***	0.0329***	0.0291***	0.0282***
		0.(0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Experience^2		-0.0007***	-0.0006***	-0.0005***	-0.0005***	-0.0005***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children			0.0256***	0.0288***	0.0214***	0.0218***
			(0.0008)	(0.0008)	(0.0007)	(0.0007)
Short part-time				-0.2424***	-0.1615***	-0.1323***
				(0.0028)	(0.0027)	(0.0026)
Long part-time				-0.2281***	-0.1698***	-0.1597***
				(0.0037)	(0.0035)	(0.0034)
Managers					0.2020***	0.1822***
					(0.0021)	(0.0020)
Technicians and assoc. prof.					-0.0438***	-0.0821***
					(0.0020)	(0.0020)
Clerical support workers					-0.2368***	-0.2706***
					(0.0047)	(0.0046)
Other professions					-0.3839***	-0.3945***
					(0.0037)	(0.0036)
Publicly controlled enterprises						0.0964***
						(0.0028)
Credit-granting enterprises						0.1190***
						(0.0044)
Other financial enterprises						0.2353***
						(0.0064)
Insurance companies						0.0762***
						(0.0068)
General government						-0.0929***
						(0.0016)
Non-profit institutions						-0.0795***
						(0.0049)
Households						-0.2174***
						(0.0165)
Constant	11.1416***	10.7853***	10.7828***	10.8080***	10.8455***	10.8713***
	(0.0012)	(0.0021)	(0.0021)	(0.0020)	(0.0020)	(0.0021)
Observations	186 291	186 291	186 291	186 291	186 291	186 291
R2	0.0386	0.2354	0.2397	0.2813	0.3694	0.3970
Adjusted R2	0.0386	0.2354	0.2397	0.2813	0.3694	0.3970

Standard errors in parentheses

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The table above displays the regression results for estimating the wage gap among graduates in medical professions, law, STEM, and business. The analysis included individuals under 64 years of age and utilized 2019 data. The reference group comprises male professionals working full-time in privately-controlled enterprises with no children.

5.2 Analysis of Gender Wage Gap Determinants Across Educational Groups

In this subchapter, we will examine the disparities in the gender wage gap among medical, law, STEM, and business graduates. Such an investigation into the academic landscape yields a more nuanced understanding of how varying educational backgrounds might contribute to the existing graduate-level gender wage gap. We will also examine potential gender disparities in the return on experience. This will enable us to understand whether professional experience yields equal dividends across genders and educational groups. Next, we will investigate the differential wage effects experienced by men and women upon having a child. At last, we will examine the wage gap among those working part-time.

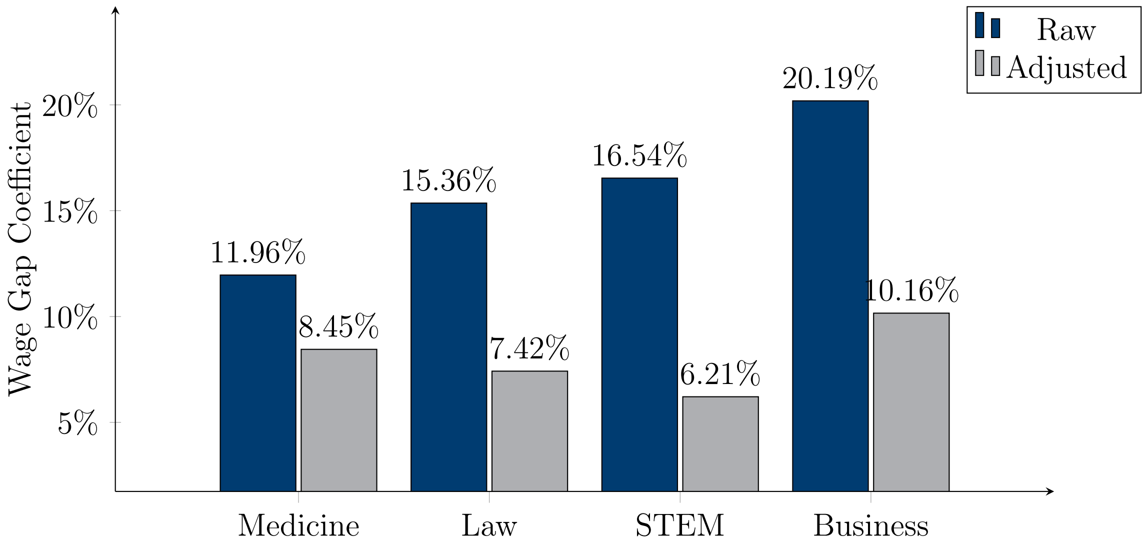
5.2.1 Disparities in the Wage Gap across Graduate-Level Educational Groups

To begin, we will examine the disparities in the gender wage gap among medicine, law, STEM, and business graduates. To do so, we conduct two regression analyses on each educational group, based on regression model 4.1 and 4.7. Regression model 4.1 estimates the raw wage gap, while regression model 4.7 estimates the adjusted wage gap. The complete regression results are presented in table A3.1 and A3.2 in the appendix.

Figure 5.1 shows notable variations in the raw and the adjusted wage gap across the four educational groups. The raw wage gap is smallest among those with a graduate-level medical education. In this group, women earn on average 11.96% less than their male counterparts. Meanwhile, law and STEM graduates experience similar unadjusted wage gaps of roughly 16%, whereas business graduates experience the highest gender wage gap of 20.19%.

Upon accounting for differences in experience, number of children, work hours, profession, and sector, the gender wage gap decreases in all educational groups. As a result, STEM becomes the educational group with the lowest gender wage gap, at 6.21%, while business still has the highest, at 10.16%. Within law and medical fields the adjusted wage gaps are at 8.45% and 7.42%, respectively.

Figure 5.1: Percentage Wage Gap: A Comparative Figure Analysis



This figure displays the raw and adjusted wage gap among medical, law, STEM, and business graduates. It includes individuals under the age of 64 and utilizes data from the year 2019. The reference group for each educational group consists of male professionals who work full-time in privately-controlled enterprises with no children.

Our analysis has shown that there is a wage gap between different graduate educations in Norway, even when controlling for factors such as experience, number of children, work time, profession, and sector.

5.2.2 Differences in Return on Experience

In this section, we examine the potential gender differences in the return on experience and how such differences could contribute to an increasing wage gap over the course of a working life. To achieve this, we conducted a regression analysis with two interaction terms, as described in subsection 4.2.1.

Table 5.2 shows that men enter the labor market with significantly higher wages than women. The estimated δ_0 coefficients reveal that, upon entry into the labor market, male graduates in the fields of medicine, law, STEM, and business have wage premiums of 4.56%, 4.11%, 1.93%, and 2.87%, respectively. It is worth noting that the male wage premium is relatively small at the beginning of the working life, especially among STEM and business graduates.

Table 5.2: The Return on Experience

	Logarithm of Wages			
	Medicine	Law	STEM	Business
Man	0.0456***	0.0411***	0.0193***	0.0287***
	(0.0083)	(0.0097)	(0.0046)	(0.0069)
Experience	0.0291***	0.0310***	0.0237***	0.0229***
	(0.0008)	(0.0010)	(0.0006)	(0.0008)
Experience^2	-0.0005***	-0.0005***	-0.0003***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Experience · Man	0.0069***	0.0071***	0.0058***	0.0112***
	(0.0011)	(0.0014)	(0.0007)	(0.0010)
Experience^2 · Man	-0.0002***	-0.0002***	-0.0001***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	10.7606***	10.8313***	10.8061***	10.8211***
	(0.0060)	(0.0064)	(0.0039)	(0.0056)
Observations	32 031	21 173	84 703	48 373
R2	0.3419	0.4362	0.5306	0.4273
Adjusted R2	0.3415	0.4357	0.5304	0.4271
Control for children	Yes	Yes	Yes	Yes
Control for work time	Yes	Yes	Yes	Yes
Control for profession	Yes	Yes	Yes	Yes
Control for sector	Yes	Yes	Yes	Yes

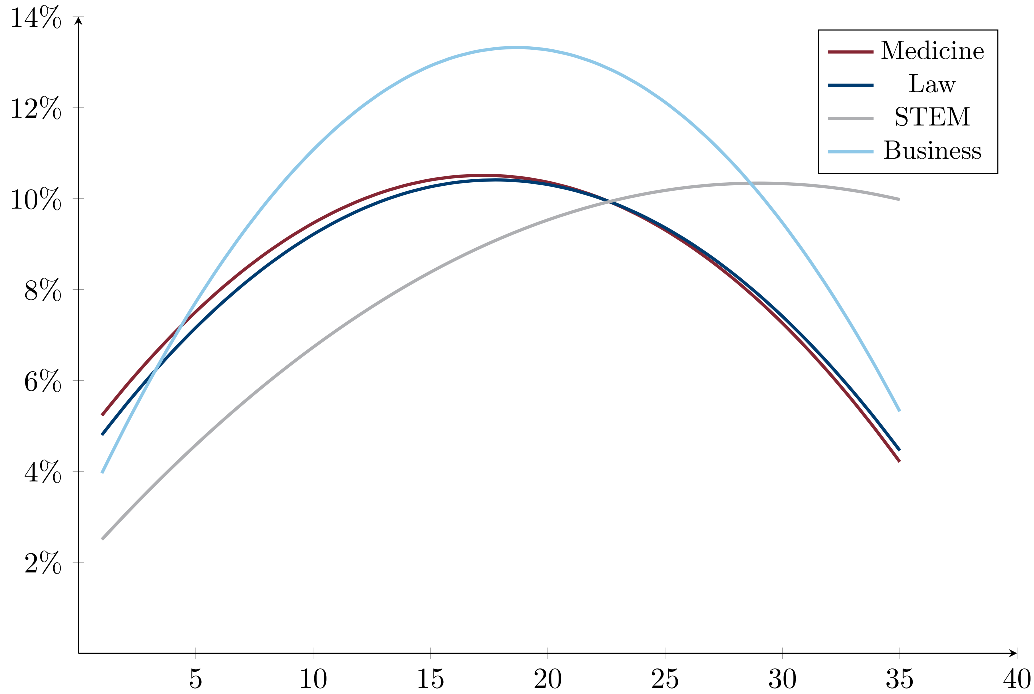
Standard errors in parentheses

$^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

This table displays the complete regression results used to test whether male and female medicine, law, STEM and business graduates have different return on experience. The analysis included individuals under 64 years of age and utilized 2019 data. The reference group is changed to women for easier interpretation of the male wage premium

However, the male wage premium continues to increase during the early-career across all four educational groups. As previously mentioned, male law graduates enter the labor market with a wage premium of 4.11%, whereas after 5 years of experience the male worker has a wage premium of 7.16%. This wage premium increases further to 9.21% after 10 years, and stabilizes after approximately 15 years of work experience. The evolution of the male wage premium among law graduates, as well as graduates in the three remaining educational fields, is displayed in figure 5.2. The figure shows that the male wage premium, as a result of differences in the return on experience, increases most rapidly among business graduates.

Figure 5.2: The Evolution of the Male Wage Premium



This figure illustrates the progression of the adjusted male wage premium across a span of 35 years of professional experience. The analysis encompasses individuals aged 64 and below, utilizing data from 2019.

Including a quadratic experience variable allows us to model the diminishing returns on experience in the labor market. This reflects the idea that each additional year of experience is generally associated with a higher wage, but that the wage increase obtained from each additional year of experience tends to decrease over time (Blau and Winkler, 2018). One might expect that the wage premium for work experience is higher for workers in their early years of employment (where they are gaining knowledge and their productivity is rapidly increasing) compared to later years (where additional experience might not contribute as much to productivity). Thereby, this approach allows us to capture the concept that the effect of an additional year of experience on wages changes as a worker gains more experience.

5.2.3 The Effect of Children on Wages

To estimate the effect of childen on wages, and more specifically examine whether the men in our sample experience a wage premium from having children, we conducted four regression analyses based on regression model 4.13, presented in subsection 4.2.2. The results of the regressions are presented in table 5.3 and visually displayed in figure

5.3. Note that these regression analyses have been run on a slightly altered sample of graduate-level workers (age $\leq$ 45), to minimize potential specification errors. This was elaborated on in subsection 3.4.2.

Table 5.3 shows that being male has a positive and statistically significant effect on earnings across all four educational groups. The coefficients for men range from 0.0406 for STEM to 0.0815 for Business, indicating that being male with no children is associated with a wage premium of between 4.06% and 8.15%.

Table 5.3: The Influence of Parenthood on Earnings Across Educational Groups

	Dependent variable: Logarithm of Wages			
	Medicine	Law	STEM	Business
Man	0.0667***	0.0498***	0.0406***	0.0815***
	(0.00583)	(0.00621)	(0.00284)	(0.00499)
Children	-0.0021	-0.0137***	-0.00231	0.0071***
	(0.00226)	(0.00286)	(0.00167)	(0.00251)
Man · Children	0.0117***	0.0319***	0.0263***	0.0310***
	(0.00332)	(0.00417)	(0.00193)	(0.00313)
Constant	10.8336***	10.9154***	10.9101***	10.9048***
	(0.01027)	(0.01115)	(0.00508)	(0.00688)
Observations	21 917	13 576	53 991	30 825
R2	0.3190	0.4393	0.4860	0.4373
Adjusted R2	0.3184	0.4385	0.4855	0.4370
Control for experience	Yes	Yes	Yes	Yes
Control for work time	Yes	Yes	Yes	Yes
Control for profession	Yes	Yes	Yes	Yes
Control for sector	Yes	Yes	Yes	Yes

Standard errors in parentheses

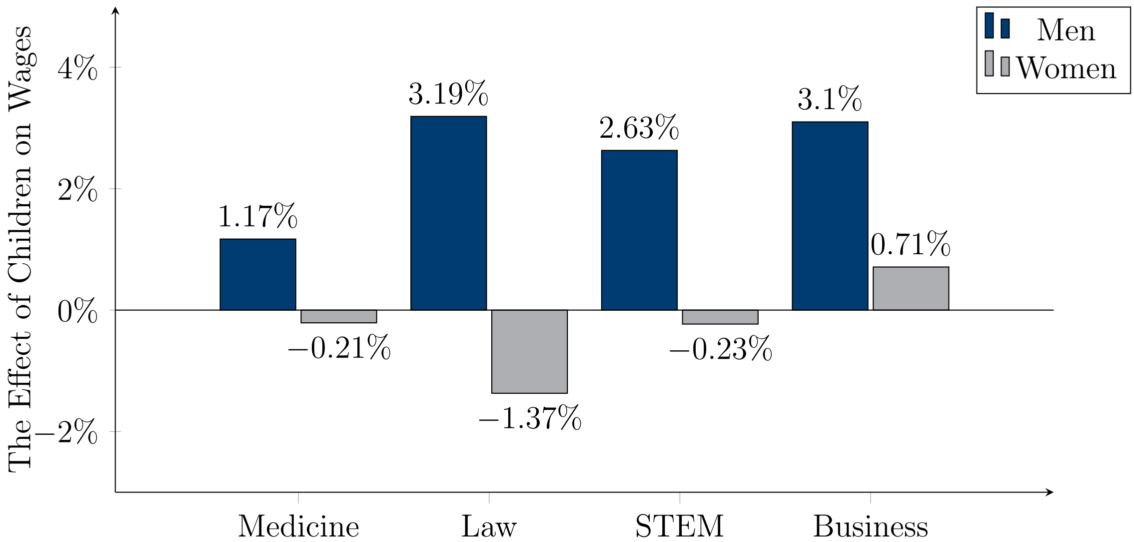
$^{*}\,p < 0.1$; $^{**}\,p < 0.05$; $^{***}\,p < 0.01$

This table displays the influence of parenthood on earnings across various graduate educational groups. The analysis encompasses individuals aged 45 and below and utilizes data from 2019.

The coefficient for children is negative among law graduates and positive among business graduates, indicating that having children is associated with lower wages for female law graduates but higher wages for female business graduates. The effect of having children is not statistically significant for female medicine and STEM graduates.

Furthermore, the coefficient for the interaction term is positive and statistically significant across all four educational groups, suggesting that the effect of having children on wages is greater for men than for women. The size of the effect ranges from 1.17% for male medicine graduates to 3.19% for male law graduates, indicating that the male wage premium becomes larger for each additional child.

Figure 5.3: The Fatherhood Premium/The Motherhood Penalty for Each Additional Child



This figure illustrates the premium or penalties associated with parenthood for each additional child. The analysis encompasses individuals aged 45 and below and utilizes data from 2019.

Overall our findings suggest that the average wage of female law graduates decreases for each additional child, holding all other factors fixed. On the other hand, the average wage of female business graduates, increases for each additional child, holding all other factors fixed. Men, who already experience a wage premium relative to women, experience an increase in this premium for each additional child. The size of the increase in the male wage premium is smallest among medicine graduates, and larger among STEM, law, and business graduates.

5.2.4 The Effect of Working Part-Time

To examine the wage gap among part-time workers, we conducted a regression analysis based on model 4.14, as described in subsection 4.2.3. The results, which are presented in table 5.4, show that full-time employed women with graduate level degrees in law earn 7.92% less than their male counterparts, while women in medicine, STEM, and business earn 11.02%, 7.04%, and 11.19% less, respectively.

Table 5.4: The Effect of Working Part-Time

	Logarithm of wages			
	Medicine	Law	STEM	Business
Woman	-0.1102***	-0.0792***	-0.0704***	-0.1119***
	(0.0040)	(0.0041)	(0.0021)	(0.0032)
Short Part-Time	-0.1948***	-0.2014***	-0.2052***	-0.3314***
	(0.0060)	(0.0121)	(0.0055)	(0.0089)
Long-Part-Time	-0.1726***	-0.2686***	-0.2051***	-0.2966***
	(0.0108)	(0.0176)	(0.0065)	(0.0136)
Short Part-Time·Woman	0.0917***	0.0412***	0.0670***	0.1182***
	(0.0080)	(0.0156)	(0.0081)	(0.0127)
Long Part-Time·Woman	0.0702***	0.0762***	0.0846***	0.1095***
	(0.0132)	(0.0219)	(0.0088)	(0.0172)
Constant	10.8458***	10.8951***	10.8448***	10.8903***
	(0.0059)	(0.0058)	(0.0025)	(0.0045)
Observations	32 031	21 173	84 703	48 373
R2	0.3441	0.4359	0.5308	0.4271
Adjusted R2	0.3437	0.4353	0.5307	0.4269
Control for experience	Yes	Yes	Yes	Yes
Control for children	Yes	Yes	Yes	Yes
Control for profession	Yes	Yes	Yes	Yes
Control for sector	Yes	Yes	Yes	Yes

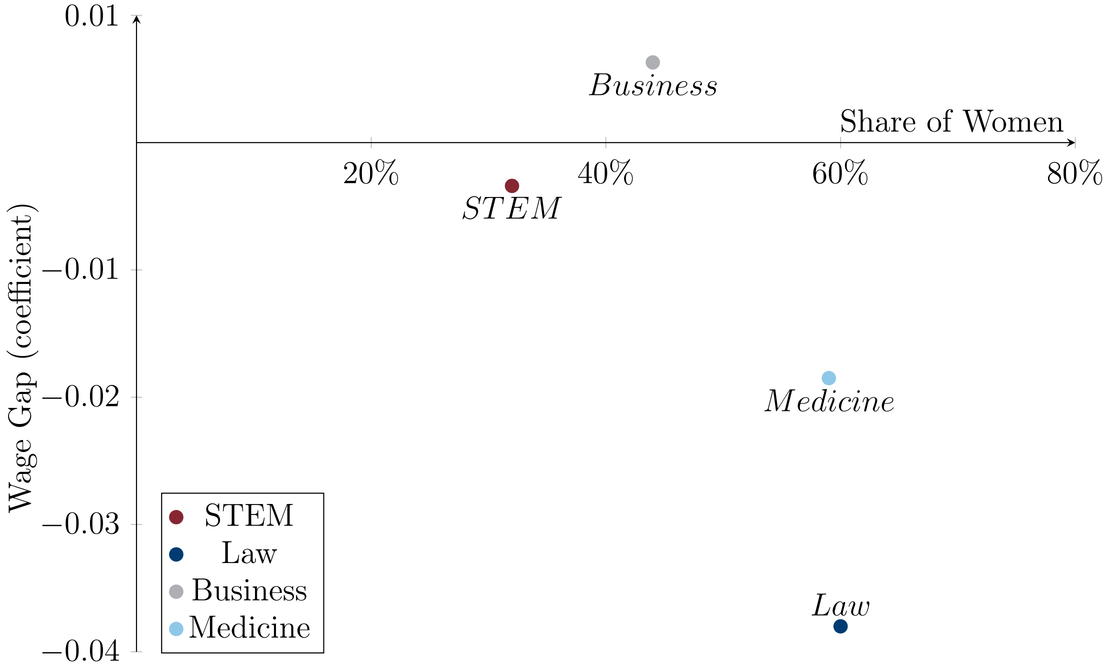
Standard errors in parentheses

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

In this table, we present the effect of part-time work across different educational groups. The analysis includes individuals aged 64 and below, utilizing data from 2019.

However, we found that the wage gap is significantly smaller among part-time workers. As depicted in figure 5.4, women with graduate level degrees in law, medicine, and STEM who work 50% or less of a full-time position, earn 3.80%, 1.85%, and 0.34% less than their male counterparts, respectively. Remarkably, female business graduates who work 50% or less of a full-time position, earn 0.63% more than their male counterparts. The figure also shows that among those who work between 0 and 50% of a full-time position, the wage gap tends to be larger in female-dominated educational groups.

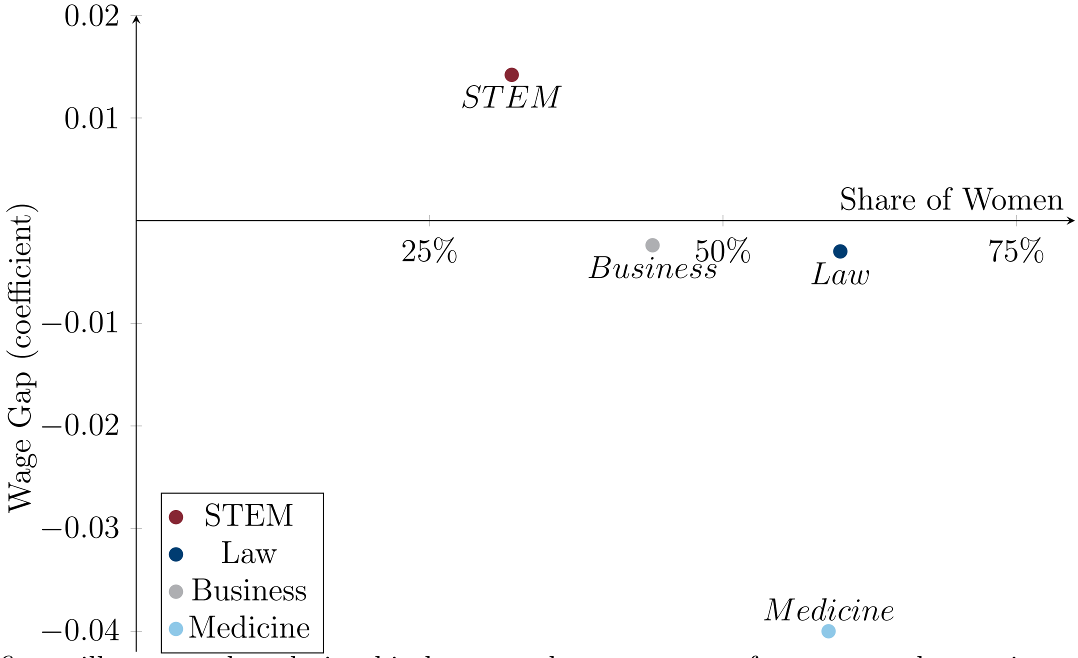
Figure 5.4: The Wage Gap among Short Part-Time Workers across Educational Groups



This figure illustrates the relationship between the percentage of women on the x-axis and the coefficient for women who work short part-time across four different educational groups. The analysis includes individuals aged 64 and below, utilizing data from 2019.

Furthermore, figure 5.5 shows that women with master's degrees in business, law, and medicine who work more than 50% of a full-time position earn 0.24%, 0.30%, and 4.00% less than men, respectively. However, in STEM, women who work longer part-time hours earn 1.42% more than part-time working men with a similar education.

Figure 5.5: The Wage Gap among Long Part-Time Workers across Educational Groups



This figure illustrates the relationship between the percentage of women on the x-axis and the coefficient for women who work long part-time across four different educational groups. The analysis includes individuals aged 64 and below, utilizing data from 2019.

5.3 Examining the Effect of Educational Level on The Wage Gap

In this subchapter, we examine whether women can narrow the wage gap by pursuing higher levels of education. Despite significant progress in academia and the workforce, women in Norway still encounter a persistent wage gap. We intend to explore whether attaining a graduate degree could further diminish this wage disparity. To do this, we compare individuals with similar educational backgrounds but different degree levels—specifically, those holding undergraduate degrees—to identify any disparities across our four educational groups, in comparison to our graduate sample.

5.3.1 The Wage Gap at the Undergraduate and Graduate-level

Next, we examine whether the wage gap varies across educational levels. To accomplish this, we performed a regression analysis based on model 4.15 as described in subsection 4.3.1. To conduct this specific analysis we pooled graduate and the undergraduate level samples and included a dummy for The regression results are presented in table 5.5 and depicted in figure 5.6.

Table 5.5: The Effect of the Educational Level on the Wage Gap

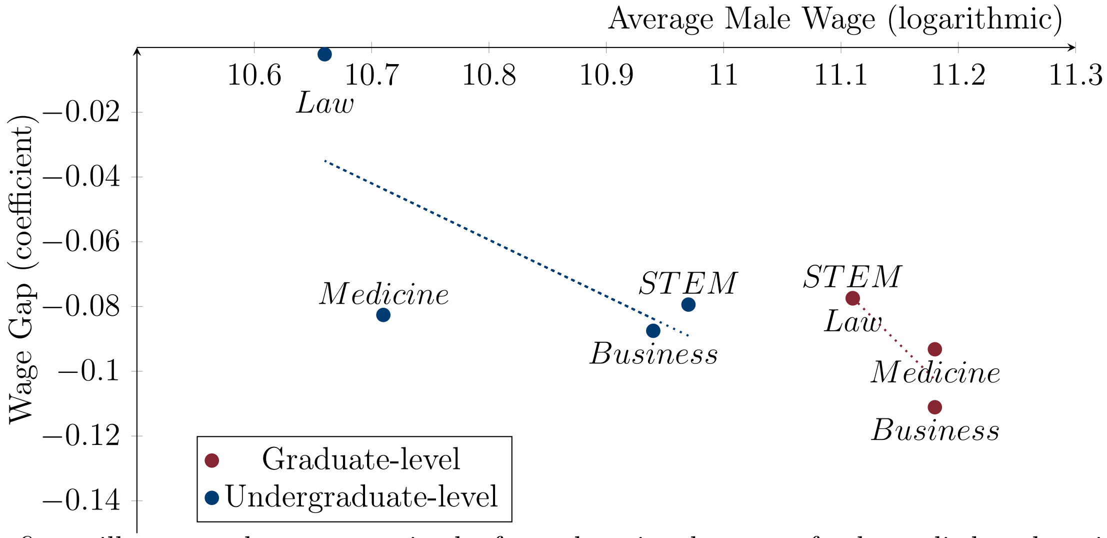
	Logarithm of Wages			
	Medicine	Law	STEM	Business
Woman	-0.0932***	-0.0775***	-0.0774***	-0.1111***
	(0.0032)	(0.0039)	(0.0020)	(0.0028)
Undergraduate	-0.3843***	-0.2106***	-0.1101***	-0.1905***
	(0.0054)	(0.0123)	(0.0016)	(0.0028)
Undergraduate·Woman	0.0106**	0.0754***	-0.0020***	0.0236***
	(0.0062)	(0.0143)	(0.0031)	(0.0039)
Constant	10.9108***	10.8912***	10.8619***	10.9131***
	(0.0046)	(0.0056)	(0.0020)	(0.0033)
Observations	48 011	22 972	160 181	99 980
R2	0.4902	0.4809	0.4966	0.4944
Adjusted R2	0.4900	0.4805	0.4965	0.4943
Control for experience	Yes	Yes	Yes	Yes
Control for children	Yes	Yes	Yes	Yes
Control for work time	Yes	Yes	Yes	Yes
Control for profession	Yes	Yes	Yes	Yes
Control for sector	Yes	Yes	Yes	Yes

Standard errors in parentheses
$^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

In this table, we estimate the effect of an undergraduate degree on wages, as well as the coefficient for the interaction between having an undergraduate degree and being a woman. The analysis includes individuals aged 64 and below and utilizes data from 2019.

Our analysis reveals that, at the undergraduate level, women with a degree in medicine earn 8.26% less than men with an equivalent degree. However, at the graduate level, this gap widens to 9.32%. Similarly, for law and business graduates, the wage gap is larger at the graduate level, with women earning 7.75% and 11.11% less than men, respectively. In contrast, for STEM graduates, the wage gap is smaller at the graduate level, with women earning 7.74% less than men, compared to 7.94% less at the undergraduate level. Overall, these findings suggest that the wage gap is larger at the graduate level than at the undergraduate level (except among STEM graduates). As can be seen from Figure 5.6, the gender wage gaps tend to be larger, the higher the average male wage.

Figure 5.6: The Wage Gap at Different Educational Levels



This figure illustrates the wage gap in the four educational groups, further split by educational level. The analysis includes individuals aged 64 and below, utilizing data from 2019.

6 Discussion

The aim of this thesis is to study the wage disparities between male and female graduate-level workers in Norway. To do so, we examined the size of the wage gap at the graduate level as a whole, however only including individuals with an educational background in medical, law, STEM or business fields. Moreover, we conducted analyses to uncover the size of the wage gap within each of the four aforementioned educational groups.

Additionally, we conducted analyses on how wage disparities develop throughout the career path. We also examined how the effect of having children differs between men and women, as well as the size of the wage gap among those working part-time. At last, we examined the size of the wag gap at different levels of first-stage tertiary education. In this chapter, we will discuss the main findings of these analyses, as well as the implications of our methodological approach.

6.1 Main Findings

6.1.1 The Wage Gap at the Graduate Level

The results of our analysis shows that there is a significant wage gap among graduate-level workers with an educational background in medicine, law, STEM and business fields. In this combined sample of graduate-level workers, we uncovered a raw wage gap of 15.39% and an adjusted wage gap of 7.98%. In comparison, the unadjusted wage gap in the general working population in Norway, was at 12.4% in 2019. Thus, our results suggest that the wage gap could be larger among those with a graduate-level degree, than in the general working population. However, to be able to establish statistical generalisability, further studies of the wage gap at the graduate-level as a whole should be undertaken.

Next we split the sample of graduate-level workers into four based on educational background, and conducted separate analyses on the wage gap within each educational group. The results show that among those with a graduate level degree in medical fields, the raw wage gap is estimated to 11.96%. Among individuals with an educational background in law, STEM and business, the raw wage gap is at 15.36%, 16.54% and 20.19%, respectively. Out of the four educational groups, business is the one with the highest average salary, and the one with the largest wage gap, with women earning 79.81% of a male wage. Given that wage disparities have been documented to be larger in the upper end of the income distribution, this finding was as expected.

After accounting for work experience, children, part-time work, profession and sector, the wage gap is reduced to 8.45%, 7.42% 6.21% and 10.16% among medicine, law, STEM and business graduates, respectively. Our analysis thus reveals that there are substantial differences in the wage gap across educational groups, even after accounting for different characteristics. Moreover, the adjusted wage gaps tend to be larger, the higher the average full-time wage of the educational group.

The adjusted wage gap is most pronounced among business graduates. A possible explanation can be linked to gender differences in the selection into competitive environments. As previously mentioned, men are more likely to prefer competitive compensation schemes (Niederle and Vesterlund, 2007), and to apply to jobs with more competitive compensation packages (Flory et al., 2015). Such competitive employment contracts are more likely to incorporate bonus- or other performance-based incentive schemes. Considering that our measure of full-time equivalent monthly wages encompasses irregular additions and bonuses, coupled with the plausibility that business graduates are more inclined to be offered competitive employment contracts, it appears reasonable that the adjusted wage gap is largest among business graduates.

6.1.2 Part-Time Employment

Furthermore, we found that working part time has a significantly negative effect on wages across all four educational groups. These findings coincide with the findings that constitute the vast majority of the literature on the gender wage gap. Moreover, we found that the wage gap is significant, yet substantially smaller among those working part-time than those working full-time. This finding applies to all four educational groups; Our analysis shows that women with graduate level degrees in law, medicine, and STEM who work 50% or less of a full-time position, earn 3.80%, 1.85%, and 0.34% less than their male counterparts, respectively. On the contrary, female business graduates who work 50% or less, earn 0.63% more than their male counterparts. In the category of individuals working between 50% and 100% of a full-time position, women with an educational background in fields of business, law and medicine, earn 0.24%, 0.30%, and 4.00% less than their male counterparts, respectively. Women in STEM who work between 50% and 100%, on the other hand, earn 1.42% more than their equivalent male counterparts.

In summary, the size of the part-time gender wage gaps are both negligible and highly similar across all four educational fields, suggesting that there are small earnings disparities between part-time working men and women at the graduate level. Given that individuals who work part-time on average earn less than those working full-time, it is unsurprising that the wage disparities are smaller among those working part-time. The fact that the gender wage gaps are smaller among those working part-time, can also be linked to the nature of part-time jobs, which are typically associated with lower-responsibility roles, thereby commanding lesser compensation compared to full-time positions. On the other hand, full-time positions might offer more diversity in the amount of work tasks and responsibilities.

6.1.3 Gender Disparities in the Return on Experience

Moreover, we found that men enter the labor market with significantly higher wages than women. The male wage premium upon entry into the labor market is largest among medicine graduates (4.56%) and smallest among STEM graduates (1.93%). The male wage premium upon entry into the labor market is estimated to 2.87% for business graduates. This finding is highly similar to that of Brakstad and Sanner (2022), who uncovered a corresponding male wage premium of 2.6% for business graduates. The small difference in our estimates is likely due to differences in the cut-off age of our samples. In comparison, Stokke (2021) found that Norwegian men on average have a wage premium of 3.5% upon entry into the labor market. Thus, it seems reasonable that our estimated male wage premiums upon entry into the labor market are scattered around this average.

We also found that men in all four educational groups have a significantly higher return on experience, even after controlling for children, work time, profession and sector. This implies that the male wage premium increases throughout the course of male careers, which consequently results in a larger gender wage gap. The progression of the male wage premium, as a result of differences in the return on experience, differs across educational groups, with the male wage premium increasing most rapidly among business graduates.

One plausible explanation is that experienced professionals are highly sought after in many business positions, particularly those that are fiercely competitive. The demand for such candidates can drive up the wages of individuals with more experience. Another potential explanation could be that skills and expertise developed over time, for instance in negotiation, strategic thinking, and leadership, may be highly valued and subsequently lead to higher wages. Furthermore, business positions often entail a higher degree of risk in terms of potential for failed ventures or financial losses. Higher wages might partly serve to offset this risk. Finally, business professionals often have a significant portion of their compensation linked to company performance or personal targets. As they accumulate experience, they may become more proficient at meeting or exceeding these targets, leading to increased compensation.

Conversely, male STEM graduates experience a lower return on their first 25 years of experience. One potential explanation could be the flat wage trajectories in some STEM fields. The accompanying rigid pay scales, will thereby result in slower wage growth over time. Additionally, rapid technological changes could render certain skills obsolete faster compared to fields like business. Therefore, the value of experience may wane if it's not paired with continuous learning and skill updates. Furthermore, a significant increase in wages within STEM fields may coincide with a transition into management or business-oriented roles, rather than remaining in purely technical positions. At last, compensation in business positions, could to a larger extent include performance-based components, such as bonuses or stock options. Providing this type of compensation, might be a less common practice in typical STEM positions.

6.1.4 Gender Disparities in the Effect of Having Children

In another analysis, we established that the effect of having children living in the house of either parent, has a substantially different effect on men and women's wages. Our findings suggest that for each additional child, the male wage premium increases by 1.17%, 2.63%, 3.10% and 3.19% for medicine, STEM, business and law graduates, respectively. On the contrary, having children has no significant effect on the wages of female graduates with an educational background in medical or STEM fields. Having a child does however have a significant negative effect on the wage of female law graduates, and a small but significant positive effect on the wage of female business graduates.

Similar to Buchmann and McDaniel (2016), we find a positive wage differential for fatherhood across all our graduate-level educational groups. However, our results differ in regards to the observed wage differential for women with children. This could potentially be due to differences in our models, differences in our samples, and differences in the definition of STEM, medicine, law and business groups. Whereas we divide individuals into these four groups based on educational background, Buchmann and McDaniel divide individuals into these groups based on their registered occupation. We can also not exclude that our results have been obscured by multicollinearity. We elaborate on this matter in subchapter 6.2.4.

6.1.5 The Wage Gap at the Undergraduate VS. Graduate Level

At last, we found that having an undergraduate-level degree, as opposed to a graduate-level degree, has a negative effect on the average wage across all educational groups, implying that the wages of graduate-level workers are higher than the wages of undergraduate-level workers. Moreover, the wage gap is significantly larger at the graduate level than at the undergraduate level in all educational groups except STEM. In the aforementioned educational group, the difference in the undergraduate and graduate-level gender wage gap is statistically significant, but very small. Additionally, the gender wage gaps at both educational levels tend to be more pronounced as the average male wage increases. This finding aligns with the pattern of larger wage disparities being observed at the higher end of the income distribution.

One possible explanation as to why the average male salaries are higher among graduate-level workers than undergraduate-level workers, can be linked to the types of job positions that are available to these two groups. It is plausible that undergraduate-level positions require less specialized knowledge and skills, resulting in relatively lower compensation compared to the positions offered to graduate-level candidates. Moreover, graduate-level workers have access to a broader range of job opportunities, which could lead to more diverse wage outcomes. This broader pool of available jobs may lead to instances where graduate-level women find themselves in job positions for which they are overqualified, thus contributing to the larger gender wage gap among graduate-level workers.

6.2 Discussion of the Main Findings and the Methodological Approach

In this subchapter we will discuss our findings in light of our methodological choices and approach. We will start by assessing our analysis of the wage gap at the graduate level, followed by a discussion of the analysis on the wage gap among part-time workers. Next, we emphasise some accuracy concerns in regards to our analysis on gender disparities in the return on experience, as well as our analysis on the effect of parenthood. At last we will assess our analysis of the wage gap at the graduate level vs. the undergraduate level.

6.2.1 The Wage Gap at the Graduate Level

Our analysis of the gender wage gap at the graduate level, revealed a raw (unadjusted) wage gap of 15.39%, and an adjusted wage gap of 7.98%. Given that we only include individuals with a graduate-level degree in medical, law, STEM and business fields in our analysis, our results can only provide an indication of the actual gender wage gap at the graduate level in Norway. In order to determine the actual gender wage gap at the graduate level, further studies should be undertaken on a sample of the Norwegian graduate-level population as a whole.

The reason why we only included individuals with a graduate-level degree in either of the four previously mentioned educational fields, was to investigate the gender wage gap within each educational group. By examining the wage gap in each of these four educational categories separately, we were able to enhance the precision of our estimates and to uncover potential differences in the wage gap across groups with varying educational backgrounds.

Furthermore, it is crucial to acknowledge that inaccuracies in the measurement of our independent variables, or the omission of relevant variables, can lead to either an overestimation or underestimation of the gender wage gap. A specific concern with our model relates to the measurement of full-time equivalent monthly wages, which includes irregular additions and bonuses. The fact that men, on average, receive significantly higher amounts in bonuses and irregular supplements per month (Gunnes, 2019), could potentially contribute to the observed higher average wage for men compared to women.

However, our model lacks the inclusion of controls for differences in received bonuses and additions. As a result, the estimated wage gap may be overestimated.

Our model also fails to consider demographic characteristics such as residence and workplace location. Geographical location is known to influence wage levels, making it sensible to include variables that account for this factor. At last, there are accuracy concerns regarding the measurement of our experience variable, which will be thoroughly discussed in subchapter 6.2.3.

6.2.2 Part-Time Employment

Our analysis has revealed that working part-time has a significant negative effect on wages across all four educational groups. Moreover, the gender wage gap is smaller among those working part-time, than among those working full-time. Our results also indicate that the size of the part-time gender wage gaps are both negligible and highly similar across all four educational fields. As previously discussed, this could potentially be attributed to part-time positions typically involving fewer job-related responsibilities or types of tasks that are often compensated at a lower rate. Given that our measure of full-time equivalent monthly wage includes bonuses and irregular supplements, it could also be attributed to part-time workers receiving less remuneration beyond the agreed upon monthly salary.

In this thesis, we define full-time workers as individuals who are employed at 100%, which in Norway corresponds to working 37.5 hours per week. Conversely, individuals working between 50% and 100% of a full-time position are classified as long part-time workers. Moreover, those who work less than 50% of a full-time position are categorized as short part-time workers. It is important to note that alternative definitions and classifications of full-time and part-time work may yield different estimates. The specific criteria used to define full-time work and group part-time workers can vary across studies. For instance, Antonie et al. (2020), defines full-time workers as individuals working 30+ hours a week, while individuals working less than 30 hours a week were defined as part-time workers.

To examine whether the impact of part-time work on wages differs based on the extent of part-time hours, we divided our part-time workers into two groups: short part-time and long part-time workers. As anticipated, we found that the negative effect of working part-time on wages is more pronounced when the employment percentage is below 50% of a full-time position. This pattern holds true across all educational groups, except for law graduates. Interestingly, among law graduates, the negative impact of working part-time on wages is greater for long part-time work compared to short part-time work. However, it is important to note that this result may be subject to bias due to the limited number of individuals with a graduate-level degree in law who work between 50% and 100% of a full-time position.

6.2.3 Gender Disparities in the Amount and Return on Experience

Our analysis reveals that male graduates in all four educational groups exhibit a significantly higher return on experience compared to their female counterparts. It is, however, important to keep in mind that we have employed potential experience as a proxy for actual experience. This could be somewhat problematic, because individuals who graduated at the same time will have the same potential experience, regardless of the actual duration of their work experience. Our proxy for experience fails to account for periods of unemployment, parental leave, illness, job transfers, or other absences from work that individuals in our sample may have experienced. This is unfortunate, given that absence from work could have a negative effect on wages.

Moreover, our experience variable does not account for the work history in the period between the completion of education and the time of measurement (November 2019). As a result, individuals who worked full-time at the time of measurement may have had previous periods of part-time employment earlier in their careers, and vice versa. This implies that the individuals in our sample may possess a greater or lesser amount of experience than what our experience variable is able to capture.

Other factors such as absence from work due to parental leave, could also affect the accumulation of work experience. In Norway, mothers take most of the parental leave, while fathers' parental leave largely follows the father's quota (Engvik and Pettersen, 2021). Consequently, it is reasonable to assume that the individuals in our sample may have less work experience than what is measured, and that the gender disparities in accumulated experience could potentially be larger than what is captured in our experience variable. It is also possible that gender disparities in the extent of absence due to illness, could affect the accumulation of experience. Given that absence due to illness is more common among women (Nossen, 2019), there could be larger gender differences in actual experience, than what our measurement of experience is able to capture.

In summary, this suggests that our estimate of the return on experience may not be entirely accurate. However, our estimated male wage premium among business graduates, is highly similar to that uncovered by Brakstad and Sanner (2022). Moreover, our findings are also similar to that of, Stokke (2021), who utilized actual, rather than potential, work experience. Consequently, there is foundation to conclude that male graduate level workers, in either of the four educational groups, have a higher return on experience than females.

6.2.4 Gender Disparities in the Effect of Having Children

To examine potential gender disparities in the effect of having children, we utilised a Microdata variable that counts the number of children, no matter their age, who are registered residents in the family of at least one of their parents. Microdata defines family as people who live in the same home and who are related to each other as spouses, registered partners, cohabitants and/or as parents and children. Thus, our measure of the number of children per individual is somewhat flawed. Instead of measuring the number of children per individual, our *children* variable measures the number of children registered as residing in the family of either or both of their parents. This implies that our *children* variable can only provide an indication of the actual number of children per individual in our data set. As previously described, the use of our constructed *children* variable could lead to noise and imprecise estimates. To reduce potential errors we reduced our sample to individuals aged 45 and younger, when running regression 4.13. By doing so we aimed to exclude older individuals who are more likely to have children who live independently.

Moreover, our estimates of the effect of having children, are somewhat difficult to interpret because age and number of children will presumably be correlated. We do not include controls for age, but we do however include controls for experience. Given that our measure of experience reflects the age of the our sample individuals, we presume that the number of children will be correlated with years of experience. Nevertheless, we still chose to include controls for experience given that the estimated effect of having a child would otherwise be overestimated. This will however, imply that our model could be affected by multicollinearity.

To detect potential multicollinearity, we conduct diagnostic tests that uncover the variance inflation factor (VIF) of all the independent variables included in each of the four regressions presented in table 5.3. Unsurprisingly, we find that the VIFs of *experience* and $experience^2$ are high across all educational groups. This is due to the fact that the experience^2 variable is a calculated by taking the logarithm of the experience variable. Moreover, the children variable, have VIFs ranging from between 1.98 in medicine and 3.32 in STEM. This suggests that there is multicollinearity between the children variable, and other variables included in our regression model. The VIFs of the interaction term between being male and having children are of the approximate same size.

Multicollinearity makes it challenging to disentangle the individual effects of the correlated variables. It becomes difficult to ascertain the specific impact of the number of children and the years of experience on the dependent variable, as their effects might overlap or interact. Multicollinearity also makes it challenging to interpret the coefficients of the interaction term accurately. Nevertheless, our estimates imply a significant fatherhood wage premium across all four educational groups. This finding is fortified in the vast majority of academic research on the effect of having children on wages. Thus, we consider it likely that a fatherhood premium exists, also within our sample of graduate-level workers. Given the plausible imprecision in our estimates, we will however exercise caution in determining the exact magnitude of the fatherhood premium among graduate-level workers.

6.2.5 The Wage Gap at the Undergraduate VS. Graduate Level

Our analysis of the gender wage gap at the undergraduate and graduate level, indicates that the gender wage gap is larger among graduate-level workers than among undergraduate-level workers in all of the studied educational groups, except for STEM. The results of this analysis, might however, be affected by the methodological issues we discussed in subchapters 6.2.1-6.2.4. Nevertheless, we still believe that our estimates will provide valuable insights into the effect of having an undergraduate-level degree vs. a graduate-level degree, and in determining the undergraduate- and graduate-level wage gaps across educational fields.

7 Conclusion

In this master's thesis we have thoroughly examined the gender wage gap among graduate-level workers in Norway, specifically focusing on workers with a degree in medical, law, STEM and business fields. Using high-quality register data and well established econometric methodologies, our study has brought new insights, while also acknowledging the complexities inherent in this topic. Consequently, we assess whether our findings are reasonable by comparing them with those of other studies.

Our findings reveal a significant wage gap among graduate-level workers with an educational background in medicine, law, STEM and business fields. In this combined sample of graduate-level workers, we uncovered a raw wage gap of 15.39%. In comparison, Askvik (2020), found that the raw wage gap in the general working population in Norway, was at 12.4% in 2019. Thus, our results suggest that the wage gap could be larger among those with a graduate-level degree, than in the general working population. The graduate-level gender wage gap is further reduced to 7.98% when we control for experience, children, work hours, profession and sector.

Next, we examined the potential differences in the gender wage gap within each of the four educational groups. Our findings indicate a raw wage gap of 11.96%, 15.36%, 16.54% and 20.19% among those with an educational background in medicine, law, STEM and business, respectively. After controlling for several characteristics, the wage gap is reduced to 8.45%, 7.42%, 6.21%, and 10.16% among medicine, law, STEM and business graduates, respectively. Consequently, our analysis reveals that there are substantial differences in the wage gap across the educational groups included in our sample.

Our study also reveals that part-time employment significantly reduces wages across all four educational groups. Moreover, the wage gap was substantially smaller among part-time workers than full-time workers. The gender wage gap among part-time workers were either small or negligible in all four educational groups. This suggests that wage disparities between part-time working men and women with graduate-level degrees are minimal across all four educational fields.

Additionally, we found that men enter the labor market with significantly higher wages than women. This finding suggests that there exists a male wage premium upon entry into the labor market. Our analysis also disclosed pronounced gender disparities in the return on experience, as male graduates across all four educational fields were found to reap a significantly higher return. Thus, the male wage premium continues to increase throughout the course of the professional career, which consequently results in a larger gender wage gap. The progression of the male wage premium, does however, display diverse patterns across the different educational groups. Specifically, male business graduates experience the most pronounced ascension in the wage premium, while STEM graduates experience a more moderate progression.

Our exploration of the gendered effect of parenthood revealed a significant fatherhood wage premium across all four educational groups. On the other hand, our estimates of the effect of motherhood, do not allow for an unambiguous interpretation of whether women experience a motherhood penalty. However, the results of our analysis on the gendered effect of parenthood warrants careful interpretation due to potential multicollinearity and limitations in the applied *children* variable.

Lastly, we found that having an undergraduate-level degree, as opposed to a graduate-level degree, has a negative effect on the average wage across all educational groups, implying that the wages of graduate-level workers are higher than the wages of undergraduate-level workers. Our analysis of the gender wage gap at the undergraduate and graduate level, also revealed that the gender wage gap is larger among graduate-level workers than among undergraduate-level workers in all of the studied educational groups, except for STEM. However, our findings generally imply that the attainment of a higher-level degree, in itself, does not contribute to reducing the gender wage gap.

In conclusion, this thesis has provided a comprehensive analysis of the gender wage gap among graduate-level workers in Norway, shedding light on its intricate dynamics. However, the complex nature of the issue underscores the necessity for additional research, incorporating more demographic characteristics and more accurately accounting for factors like experience and parenthood. Despite revealing persistent wage disparities, this research promotes further dialogue and action towards achieving wage equity in the workplace, serving as a stepping stone for future research and policy reform efforts.

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Appendix

A1 Variables

Table A1.1: Overview of Utilized Microdata Variables

Variable	**Name in Microdata**	**Description**
Registry Status	BEFOLKNING_STATUSKODE	Used to select residents per 01.01.2019
Gender	BEFOLKNING_KJOENN	Used to create gender dummies
Education	NUDB_BU	NUS-code for highest completed education. Used to create dummies for educational level and educational group
Age	BEFOLKNING_FOEDSELS_AAR_MND	Used to calculate the age of individual i
Year & Month of Graduation		
Graduate (NUS level = 7)	NUDB_AAR_FORSTE_FULLF_HOV	Time of completed education at major/ master's level
Undergraduate (NUS level = 6)	NUDB_AAR_FORSTE_FULLF_HOY	Time of completed undergraduate college education
	NUDB_AAR_FORSTE_FULLF_BACH	Time of completed education at bachelor's level
	NUDB_AAR_FORSTE_FULLF_CMG	Time of completed education at cand.mag level
Wage	ARBLONN_LONN_EKV_IALT	Full-time equivalent monthly wage. Also used to create lnWage
Experience		Calculated by subtracting the year of highest completed education from 2019. Also used to create Experience^2
Children	BEFOLKNING_BARN3_I_FAM	Number of children, regardless of age, who are registered residents in the family of at least one of the parents
Percentage employment	ARBLONN_ARB_STILLINGSPST	The agreed upon percentage employment
Short Part-Time		Dummy variable equal to 1 if percentage employment $<$ 50%
Long Part-Time		Dummy variable equal to 1 if 50% $\leq$ percentage employment $<$ 100%
Profession	ARBLONN_ARB_YRKE_STYRK08	Occupational codes. Used to create profession dummies
	ARBEIDSFORHOLD_PERSON	Coupling key used to connect a person to their work relationships
Sector	REGSYS_FRTK_SEKTOR_2014	Sector codes. Used to create sector dummies

This table displays the variables from Microdata that were utilized in this study, along with descriptions of their purpose.

Table A1.1 gives an overview of the Microdata variables that have been utilized in this study. It includes descriptions of their purpose and provides insights into how our variables were created and derived.

Table A1.2: Overview of the Professions included in each Occupational Group

Occupational Group	STYRK-08 Profession Codes
Managers	11 - Chief executives, senior officials and legislators
	12 - Administrative and commercial managers
	13 - Production and specialised services managers
	14 - Hospitality, retail and other services managers
Professionals	21 - Science and engineering professionals
	22 - Health professionals
	23 - Teaching professionals
	24 - Business and administration professionals
	25 - Information and communications technology professionals
	26 - Legal, social and cultural professionals
Technicians & Assoc. Professionals	31 - Science and engineering associate professionals
	32 - Health associate professionals
	33 - Business and administration associate professionals
	34 - Legal, social, cultural and related associate professionals
	35 - Information and communications technicians
Clerical Support Workers	41 - General and keyboard clerks
	42 - Customer services clerks
	43 - Numerical and material recording clerks
	44 - Other clerical support workers
Other Professions	
5) Service and sales workers	51 - Personal service workers
	52 - Sales workers
	53 - Personal care workers
	54 - Protective services workers
6) Skilled agricultural, forestry and fishery workers	61 - Market-oriented skilled agricultural workers
	62 - Market-oriented skilled forestry, fishery and hunting workers
7) Craft and related trades workers	71 - Building and related trades workers, excluding electricians
	72 - Metal, machinery and related trades workers
	73 - Handicraft and printing workers
	74 - Electrical and electronics trades workers
	75 - Food processing, woodworking, garment and other craft and related trades workers
8) Plant and machine operators, and assemblers	81 - Stationary plant and machine operators
	82 - Assemblers
	83 - Drivers and mobile plant operators
9) Elementary occupations	91 - Cleaners and helpers
	92 - Agricultural, forestry and fishery labourers
	93 - Labourers in mining, construction, manufacturing and transport
	94 - Food preparation assistants
	95 - Street and related service workers
	96 - Refuse workers and other elementary workers
0) Armed forces and unspecified	01 - Commissioned armed forces officers
	02 - Non-commissioned armed forces officers
	03 - Armed forces occupations, other ranks
	00 - Unspecified or unidentifiable occupations

This table presents the five occupational groups included in the study, constructed based on Statistics Norway's standard for the classification of professions, STYRK-08.

Table A1.2 lists the five occupational groups we included in this study (highlighted in bold), along with their corresponding inclusion of STYRK-08 codes. This table provides a detailed description of the specific codes encompassed within each occupational group, offering valuable insights into the classification of professions utilized in this study.

Table A1.3: Overview of the Sectors included in each Sector Group

Sector Category	**Sector Codes**
Non-financial corporations	
1) Publicly controlled enterprises	1110 - Public unincorporated enterprises, owned by central government
	1120 - Public incorporated enterprises, owned by central government
	1510 - Public unincorporated enterprises, owned by local government
	1520 - Public incorporated enterprises, owned by local government
2) Privately controlled enterprises	2100 - Private non-financial incorporated enterprises
	2300 - Private non-financial unincorporated enterprises
	2500 - Private non-profit institutions serving enterprises
Financial corporations	
3) Credit-granting institutions	3100 - Norges Bank
	3200 - Banks
	3500 - Mortgage companies
	3600 - Finance companies
	3900 - State lending institutions etc.
4) Other financial enterprises	4100 - Financial holding companies
	4300 - Mutual funds
	4500 - Alternative investment funds (AIF), except mutual funds
	4900 - Other financial enterprises, except insurance companies and pension funds
5) Insurance	5500 - Life insurance companies and pension funds
	5700 - Non-life insurance companies
General government	
6) General government	6100 - Central government
	6500 - Local government
Non-profit institutions	
7) Non-profit institutions	7000 - Non-profit institutions serving households
Households	
8) Households	8200 - Unincorporated enterprises within households
	8300 - Housing cooperatives etc.
	8500 - Employees, recipients of property income, pensions and social contributions, students, etc.
Rest of the world	
9) Rest of the world	9000 - Rest of the world

This table displays the standard classification of institutional sectors as defined by Statistics Norway.

Table A1.3 showcases SSB's standard classification of institutional sectors and provides a comprehensive overview of the sector codes associated with each of the nine sector categories. It is important to note that our sample selection process excluded individuals working outside of Norway, allowing us to focus specifically on sector groups 1) to 8).

A2 List of Educational Categories used in the Thesis (NUS2000)

The Norwegian Standard Classification of Education (NUS2000) is used to categorize individuals' educational background, and is widely used in Statistic Norway's own education statistics. Each educational category has six digits. The NUS-codes listed with only four digits, imply that we have included the full set of accompanying six-digit NUS-codes. We did this, in order to avoid listing all of the utilized NUS-codes.

Codes starting with 7 represent the first stage of tertiary education, graduate level. Codes starting with 6 also represent the first stage of tertiary education, but at the undergraduate level. One exception is NUS-code 641131, which is the predecessor of the five-year business and administration degree used today. Thus, individuals with this degree, were included in the sample of graduate level workers with a business degree.

Medical Educations: Graduate Level

Codes	*Education*
7631	Medicine
7632	Medicine, specialist training for doctors
7639	Medicine, other
7641	Odontology
7642	Dental care
7643	Dental technology
7644	Odontology, specialist training for dentist
7643	Dental technology
7644	Odontology, specialist training for dentist
7649	Dental health other
7651	Occupational therapy
7652	Physiotherapy
7653	Chiropractic
7659	Therapy, other
7661	Pharmacy
7662	Dispensing pharmacy

7663	Pharmacy, technology
7669	Pharmacy, other
7671	Veterinary science
7672	Veterinary nursing
7679	Veterinary medicine, other
755301	Optic science
755302	Visual pedagogy and visual rehabilitation

Medical Educations: Undergraduate Level

Codes	*Education*
6631	Medicine
6639	Medicine, other
6641	Odontology
6642	Dental care
6643	Dental technology
6649	Dental health
6651	Occupational therapy
6652	Physiotherapy
6653	Chiropractic
6659	Therapy, other
6661	Pharmacy
6662	Dispensing pharmacy
6663	Pharmacy technology
6669	Pharmacy, other
6671	Veterinary science
6672	Veterinary nursing
6679	Veterinary medicine, other
655301	Engineering programme, optics
655302	Engineering, optics, three-year
655303	Supplementary education for engineers, optics
655304	Bachelor's degree, optic
655305	Supplementary education, optics

Law Educations: Graduate Level

Codes	*Education*
7371	Study of law
7379	Law, other

Law Educations: Undergraduate Level

Codes	*Education*
6371	Study of law
6379	Law, other

Business Educations: Graduate Level

Codes	*Education*
7411	Business and administration
641131	Business and economics degree, four-year

Business Educations: Undergraduate Level

Codes	*Education*
6411	Business and administration (except 641131)

STEM Educations: Graduate level

Codes	*Education*
7513	Microbiology and cell biology
7514	Environmental and pollution studies
7515	Marine and freshwater biology
7519	Biology, other
7521	Physics
7522	Chemistry
7529	Physics and chemistry, other
7531	Mathematics
7532	Statistics
7539	Mathematics and statistics, other
7541	Information and computer technology
7542	Information modeling
7549	Information and computer technology, other
7551	Electrical and electronic subjects

7552	Mechanical subjects
7559	Electrical, electronic, mechanical and machine subjects

STEM Educations: Undergraduate level

Codes	*Education*
6513	Microbiology and cell biology
6514	Environmental and pollution studies
6515	Marine and freshwater biology
6519	Biology, other
6521	Physics
6522	Chemistry
6529	Physics and chemistry, other
6531	Mathematics
6532	Statistics
6539	Mathematics and statistics, other
6541	Information and computer technology
6542	Information modeling
6549	Information and computer technology, other
6551	Electrical and electronic subjects
6552	Mechanical subjects
6559	Electrical, electronic, mechanical and machine subjects, other

A3 The Wage Gap in Each of the Four Educational Groups

Table A3.1: The Adjusted Wage Gap in Graduate Level Educational Groups

	Dependent variable: Logarithm of wages			
	Medicine	Law	STEM	Business
Woman	-0.0845***	-0.0742***	-0.0620***	-0.1016***
	(0.003349)	(0.003904)	(0.001968)	(0.003074)
Experience	0.0321***	0.0343***	0.0275***	0.029***
	(0.000631)	(0.000779)	(0.000346)	(0.000554)
Experience^2	-0.0006***	-0.0006***	-0.0004***	-0.0005***
	(0.000018)	(0.000023)	(0.00001)	(0.000016)
Children	0.0028*	0.0082***	0.0185***	0.0226***
	(0.001562)	(0.001967)	(0.000931)	(0.001468)
Short part-time	-0.1439***	-0.1774***	-0.1765***	-0.2757***
	(0.004061)	(0.008034)	(0.004245)	(0.00662)
Long part-time	-0.1277***	-0.2200***	-0.1610***	-0.2300***
	(0.006276)	(0.010621)	(0.00445)	(0.008384)
Managers	0.1124***	0.1666***	0.1976***	0.2350***
	(0.006641)	(0.005946)	(0.002884)	(0.003659)
Technicians and assoc. prof.	-0.3012***	-0.1002***	-0.0384***	-0.0451***
	(0.009159)	(0.007362)	(0.00221)	(0.004247)
Clerical support workers	-0.3875***	-0.2189***	-0.3160***	-0.2195***
	(0.022742)	(0.014449)	(0.008186)	(0.006559)
Other professions	-0.3498***	-0.2947***	-0.4071***	-0.2342***
	(0.008478)	(0.013719)	(0.004268	(0.008422)
Publicly controlled enterprises	-0.0737***	0.0806***	0.1067***	0.0874***
	(0.012169)	(0.012805)	(0.003007)	(0.005965)
Credit-granting enterprises	0.2372**	0.1071***	0.1035***	0.0912***
	(0.102717)	(0.012568)	(0.009733)	(0.005779)
Other financial enterprises	0.1729*	0.0787	0.1683***	0.2555***
	(0.096816)	(0.015059)	(0.012219)	(0.008744)
Insurance companies	0.1992***	-0.0159	0.0743***	0.0874***
	(0.05321)	(0.011497)	(0.011538)	(0.011597)
General government	0.1620***	-0.2314***	-0.2308***	-0.1488***
	(0.004032)	(0.00427)	(0.00225)	(0.003786)
Non-profit institutions	0.2110***	-0.1200***	-0.2158***	-0.1777***
	(0.009523)	(0.010732)	(0.00917)	(0.009134)
Households	-0.1276***	-0.1797***	-0.2638***	-0.2802***
	(0.037825)	(0.026718)	(0.024641)	(0.041809)
Constant	10.8303***	10.8916***	10.8412***	10.8846***
	(0.005796)	(0.005764)	(0.002524)	(0.004517)
Observations	32 031	21 173	84 703	48 373
R2	0.341147	0.435367	0.529947	0.425702
Adjusted R2	0.340798	0.434913	0.529853	0.4255

Standard errors in parentheses

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The table above displays the regression results for estimating the wage gap among graduates in medical professions, law, STEM, and business. The analysis included individuals under 64 years of age and utilized 2019 data. The reference group comprises male professionals working full-time in privately-controlled enterprises with no children.

Table A3.2: The Raw Wage Gap in Graduate Level Educational Groups

	Dependent variable: Logarithm of wages			
	Medicine	Law	STEM	Business
Woman	-0.1196***	-0.1536***	-0.1654***	-0.2019***
	(0.004)	(0.00495)	(0.00272)	(0.0038)
Constant	11.1133***	11.111***	11.113***	11.1917***
	(0.00376)	(0.00382)	(0.00154)	(0.00252)
Observations	32 031	21 173	84 703	48 373
R2	0.02707	0.04337	0.04176	0.05487
Adjusted R2	0.02704	0.04333	0.04175	0.05485

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The table above displays the raw wage gap among individuals at the graduate level in medical professions, law, STEM, and business. The analysis included individuals under 64 years of age and utilized data from 2019.

A4 Descriptive Statistics of the Undergraduate Level

Table A4.1: Descriptive Statistics of the Independent Variables (Undergraduate Level)

	Medicine		Law		STEM		Business	
	Men	Women	Men	Women	Men	Women	Men	Women
Work experience in years								
Experience	12.09	12.26	8.3	6.21	17.41	15.94	16.51	14.45
Experience^2	245.02	242.27	147.96	97.01	449.46	386.59	404.22	321.74
Children								
Number of children	1.02	1.18	0.77	0.76	1.02	1.04	1.03	1.06
Part-time (in %-proportions)								
Short part-time	22.45	21.83	21.18	33.77	7.06	14.46	11.24	14.46
Long part-time	8.48	16.4	8.16	8.79	3.22	9.01	4.08	9.81
Profession (in %-proportions)								
Managers	8.14	4.12	7.97	4.61	13.08	7.65	24.34	13.57
Professionals	51.46	54.67	24.09	22.88	35.27	35.34	26.29	27.40
Technicians and assoc. professionals	23.87	25.95	25.82	25.38	37.36	35.72	28.98	30.85
Clerical support workers	1.68	2.30	11.61	17.78	2.07	5.33	9.27	16.56
Other	14.85	12.96	30.50	29.35	12.22	15.96	11.12	11.62
Sector (in %-proportions)								
Publicly controlled enterprises	1.63	1.79	4.69	2.42	9.84	7.48	4.66	3.68
Privately controlled enterprises	46.71	32.00	54.34	46.82	70.26	57.60	62.01	56.13
Credit-granting enterprises	0.20	0.18	6.77	5.72	0.81	1.08	8.94	6.75
Other fin. enterprises	0.00	0.00	2.60	1.05	0.42	0.41	2.18	1.09
Insurance companies	0.14	0.15	3.30	2.18	0.54	0.83	2.08	1.26
General government	45.19	61.04	25.35	36.83	17.09	30.41	17.63	28.24
Non-profit institutions	5.72	4.28	2.95	3.87	0.76	1.79	2.11	2.42
Households	0.40	0.55	0.00	1.13	0.27	0.39	0.39	0.43

This table displays descriptive statistics of various independent variables, such as work experience,number of children, part-time status, profession, and sector affiliations for men and women across different undergraduate fields. Work experience is calculated by subtracting the graduation year from the year of measurement (2019). Short part-time employment refers to jobs with less than 50% employment rate, while long part-time comprises individuals employed between 50% and 100%. The categorization of professions follows the SSB standard STYRK-08, while the sector classifications adhere to the SSB standard for institutional sector grouping.

A5 The Gender Wage Gap at the Undergraduate Level

Table A5.1: Gender Wage Gap at the Undergraduate Level

	Dependent variable: Logarithm of wages					
	(1.1)	(1.2)	(1.3)	(1.4)	(1.5)	(1.6)
Woman	-0.2124***	-0.1817***	-0.1822***	-0.1513***	-0.1415***	-0.1149***
	(0.0019)	(0.0016)	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Experience		0.0313***	0.0291***	0.0249***	0.0211***	0.0217***
		(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Experience^2		-0.0005***	-0.0004***	-0.0003***	-0.0003***	-0.0003***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Children			0.0181***	0.0190***	0.0144***	0.0137***
			(0.0008)	(0.0008)	(0.0007)	(0.0007)
Short part-time				-0.2280***	-0.1552***	-0.1328***
				(0.0025)	(0.0024)	(0.0023)
Long part-time				-0.2049***	-0.1531***	-0.1382***
				(0.0032)	(0.0030)	(0.0029)
Managers					0.2080***	0.1821***
					(0.0023)	(0.0023)
Technicians and assoc. prof.					-0.0228***	-0.0538***
					(0.0017)	(0.0017)
Clerical support workers					-0.1582***	-0.1990***
					(0.0031)	(0.0031)
Other professions					-0.2120***	-0.2262***
					(0.0025)	(0.0025)
Publicly controlled enterprises						0.0938***
						(0.0029)
Credit-granting enterprises						0.0198***
						(0.0039)
Other financial enterprises						0.1645***
						(0.0078)
Insurance companies						0.0353***
						(0.0072)
General government						-0.1314***
						(0.0017)
Non-profit institutions						-0.1155***
						(0.0052)
Households						-0.2004***
						(0.0115)
Constant	10.9532***	10.6326***	10.6267***	10.6854***	10.7373***	10.7644***
	(0.0012)	(0.0019)	(0.0020)	(0.0020)	(0.0021)	(0.0022)
Observations	144 865	144 865	144 865	144 865	144 865	144 865
R2	0.0817	0.3002	0.3027	0.3544	0.4386	0.4717
Adjusted R2	0.0817	0.3002	0.3027	0.3543	0.4386	0.4716

Standard errors in parentheses

$^{*} p < 0.1$; $^{**} p < 0.05$; $^{***} p < 0.01$

The table above displays the regression results for estimating the wage gap among undergraduates in medical professions, law, STEM, and business as a whole. The analysis included individuals under 64 years of age and utilized data from 2019. The reference group consists of male professionals working full-time in privately-controlled enterprises with no children.