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Exploring Gender Disparities in Sick Leave in Norway

A Descriptive Empirical Analysis

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Preface

I would like to thank the Frisch center and my supervisor Simon Bensnes and Martin Eckhoff Andresen for introducing me and guiding me in this project. The Frisch Center research projects are mainly funded by the Research Council of Norway, ministries and international organizations. Data received from Statistics Norway has been essential for the project and the paper.

All mistakes and shortcomings in this thesis are my own.

Abstract

The Norwegian welfare state payments to sick leave alone was NOK 49.19 billion in 2021(NAV, 2021). This accounted for over 1,5 percent of non-oil GDP in Norway (Statistisk sentralbyrå, 2022). It is essential to understand what drives sick leave for men and women in order to implement relative policy measures to lower these costs. In this thesis I present a descriptive analysis on the developments in sick leave for men and women in Norway in the period 2015-2021. I analyze the gender gap in sickness absence using individual-year data and a Blinder–Oaxaca decomposition. The gap is stable at roughly 3 pp each year. Most of it lies in the unexplained component; observable differences in age, education, children, and occupation account for only a small share. The explained share increases in 2020–2021, coinciding with the pandemic, but the unexplained component still dominates. These results indicate that time-varying or unobserved factors, rather than observed composition alone, largely drive the gender gap. The analysis is descriptive and does not claim causal effects.

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Chapter 1

Introduction

Norway is widely seen as a global frontrunner on gender equality, combining high female labor-force participation with generous family policies and strong worker protections. Yet, sickness absence remains elevated by international standards and displays a persistent gender gap (Køber & Lien, 2025). After a spike during the 2009/2010 swine influenza, sick leave in Norway was broadly stable from 2011 to 2019. With the onset of the COVID-19 pandemic in 2020, absence rose again and reached a new high in 2022. High absenteeism imposes significant fiscal and productivity costs. A recent NAV report documents the development of National Insurance expenditures and projects a further increase of approximately NOK 108 billion by 2033, underscoring the budgetary implications of sickness absence trajectories (NAV, 2025c). Over the past decade, the average sickness absence rates among working women in Norway have been approximately two to three percentage points higher than those of their male counterparts (sentralbyrå, 2025b). From an equality perspective, persistent gaps matter because higher absence can slow career progression and reduce access to leadership roles(Judiesch & Lyness, 1999).

The sources of this gap are debated. Part of it may reflect compositional differences, that women and men work in different occupations or face different family constraints. Many occupations, more frequently held by women, can involve higher physical or psychosocial exposures linked to illness or injury(STAMI, 2025). However, composition is unlikely to be the whole story. Even within the same occupational titles, task allocation, working conditions, and accommodations may differ by gender and life stage (e.g., pregnancy), leading to different "returns" of the same observed characteristics in terms of sick leave.

The main objective of this thesis is to describe associations between demographic indicators and occupation on sick leave for men and women in the period of 2015-2021. I use Norwegian administrative data for 2015–2021. I estimate linear regression models with Ordinary Least Squars, which provides insight on the contributions to sick leave percentage. Finally, I implement a classical twofold Blinder-Oaxaca decomposition for each year in the sample.This decomposition method quantifies the contributions of observable characteristics on the gender gap in sickness absence. I examine 31 different occupational categories, and characteristics: age groups, educational level, family status and number of children.

The decomposition separates the average gender gap into an explained component: which is what can be explained by men and women holding different jobs and having different levels of educations ect. The unexplained component is the part of the gap that emerges from men and women experiencing different "effects" of holding a job or higher education and sick leave.

Interpreted together, the regression results and the year-specific decompositions address a relevant question in understanding the gender gap: If women had the same observed characteristics as men, how much of the gender gap in sick leave could be explained? And how much of the remaining gap appears to stem from different returns to observable characteristics? How much smaller or larger would the gender gap be?

This thesis proceeds as follows: In chapter 2, I take a look at previous work on the topic. In chapter 3 I describe the institutional setting. Then, in chapter 4 I describe the data, define the sample and present the empirical strategy. Afterward, I present the results in chapter 5. First, the descriptive statistics, providing an updated picture of gender differences in sickness absence in Norway from 2015 to 2021. Secondly, the regression results and the findings from the classic Blinder-Oaxaca decomposition. Finally, I will discuss the results and conclude.

Chapter 2

Literature Review

In this part I will present an overview of previous work. Research on the topic of sick leave is evident in medicine, sociology and psychology. The three sections in this chapter explore previous work which has explored different hypothesis in regards to sick leave or the gender gap in sick leave. The first section links labor market participation to sickness absence rates. Furthermore, the second section explores how family responsibilities, including parenthood, impact sick leave among genders. The final section explores how cultural and normative expectations influence sickness absence, particularly focusing on individual characteristics that may not be observable. A general trend in previous literature is that they point to a lack of research on conditions only relevant to women in explaining the development in rates of absenteeism.

2.1 Compositional effects

Does higher labor force participation of women contribute to higher sickness leave? As more women enter into employment, are these women less fit to manage the strain of working? Or do women select into occupations with higher rates of sick leave?

Compositional effects of the Norwegian labor market have been pointed out as the main hypothesis for the large gap between genders (Kostøl & Telle, 2011). Sick leave seems to be related to female labor supply, as countries with high labor supply of women have a large gender gap in sick leave(Angelov et al., 2020). A study looking at disparities among working populations of 26 OECD countries find that occurrences of absenteeism and presenteeism are lower in countries with a high level of gender inequality in the labor market, especially in the countries with a high level of gender wage gap(Kwon, 2020). This suggests that high levels of equality in the labor market are associated with a larger gender gap in sick leave.

There is a gender divide in occupation. Women are still dominating many occupations that have been thought off as "female occupations", among them working within health care, cleaning, child care and cosmetology(STAMI, 2025). The combination of working a physical job and being exposed to emotional distress is what characterizes many occupations which are dominated by women (STAMI, 2025). In a report from STAMI, they find that women in health- and social-care jobs have around seventy percent greater risk of work-related sick-leave than men, with muscle-skeletal complaints, mental illness and pregnancy accounting for most lost days (STAMI, 2025). Moreover, NAV's review of register data confirms that, even after excluding pregnancy-related absences, women's sick-leave is still markedly higher; diagnoses such as depression, anxiety, migraine and chronic fatigue contribute substantially (NAV, 2024). Combination of different job strains, might be associated with higher leave for women than for men's leave within occupations that employ many women.

In Kostøl and Telle (2011), among the main reasons they point to, is composition effects; women choosing into occupations with higher levels of sick leave. In Mastekaasa and Olsen (1998) they explore if the gender difference in absenteeism is due to differences in the types of jobs typically occupied by men and women. More specifically, their hypothesis states that the gender difference in absenteeism will disappear after control for detailed occupation-workplace (o-w) combinations. They find that the differences found between men and women are more likely to reflect differences in general health and personality. On the other hand, Laaksonen et al. (2010) find that differences between occupations held by men and women accounted for half of the female excess in sick leave episodes lasting over 60 days.

A meta-analysis of publications on occupational health and work environment for women recently published in a report by The National Institute of Occupational Health (STAMI), summarizes findings from research published after 2010 for the Nordic countries. They look at how work environment factors: high emotional strain, demanding tasks, bullying, stress, threats and violence, hard physical work, heavy lifting or manual labor affects health of women and women's sick leave. In short, the findings indicate that several work environment factors affect women's health and illness, sick leave and participation in the workforce (STAMI, 2025). However, there is a lack of research of the effects on certain conditions that are only relevant for women: pregnancy and female reproduction, and life phases with hormonal influence.

2.2 Family responsibly and the double burden

Research shows that caregiving duties raise the risk of medically certified sick-leave. Employees who look after parents with care needs, use work absence, especially sick leave, more often than those without such duties (Gautun & Bratt, 2024).

The effect of parenthood and the degree of equality in the division of parental responsibilities between mothers and fathers can affect the burden of having children for men and women. Furthermore, the strain of family responsibility can be linked to sick leave. Previous studies have used number of children under the age of 16 as a proxy for "double burden" and find that there are no different effects for men and women (Mastekaasa, 2000). The tendencies in Norwegian households are that parents share many concrete care-taking responsibilities and domestic housework equally between them, however it is seldom that the father takes more responsibility (Smeby, 2017).

On the other hand, in Angelov et al. (2020) they estimate the effect of parenthood on the within-couple gender gap in paid sick leave, and find that as a result of parenthood, mothers more than double their sick leave compared to fathers. However, there is no corresponding effect on health measured by hospital stays. This might indicate that women take more responsibility in the caregiving role of young children. Moreover, in a panel from 2019-2022 in Sweden, mothers' attendance at pediatric appointments was 74 percent versus 44 percent for fathers, a 30-point gender gap that persisted even after video-conference visits were introduced(Mark et al., 2025).

There has been increased focus on women's role and responsibilities within the household going beyond what is normally captured in the "double burden" description. The double burden is closer to the description of the second shift: unpaid work domestic labor, such as cleaning and childcare. The third shift is defined as administrating the schedule of the family; coordinating child and parents activities, which has a practical, emotional, social and moral dimension (Smeby, 2017). Smeby (2017) finds that in couples who are considered equal in participation of paid labor and the second shift, mothers still perform the third shift alone, and it appears to even be positively correlated to equality within the other "shifts" (Smeby, 2017). Consequently, it may be essential to further investigate the differences in care-taking responsibilities between mothers and fathers.

2.3 Attitudes towards sickness absence

Many individual level characteristics might affect sickness absence, but are unobservable. A study from Finland explores the causal mechanisms between work related factors and sickness absence. Their findings show that the role of individuals unobserved characteristics can play a large role, and effects of work-related factors are likely overestimated when using traditional approaches (Hartikainen et al., 2022).

A survey experiment on male and female employed respondents in Norway from 2016, did not find substantial gender difference in either attitudes towards sickness absence or sickness absence norms. However, they point to some indications of more tolerant social norms of sickness absence for employees in gender-dominated occupations than for employees in gender-integrated occupations, but the pattern could be a result of the type of work attributed to these occupations (Løset et al., 2018).

Chapter 3

Institutional setting

3.1 The Norwegian Labor market

The labor market in Norway is characterized by high employment rates. Employment is particularly strong among women, as well as older and younger cohorts, when compared to many European countries. However, it is important to note that fewer women than men are employed, and a greater proportion of women work part-time. In fact, the share of part-time workers among women is significantly higher than among men (KUD, 2024).

The standard for employment in Norway emphasizes full-time permanent positions. While part-time work can serve as a pathway to include individuals currently outside the labor force, it also risks perpetuating traditional gender roles and contributing to income disparities between the genders (KUD, 2024). In 2023, approximately 70 percent of women and 76 percent of individuals aged 15 to 74 were participating in the workforce(sentralbyrå, 2025a). The presence of public policies aimed at facilitating equal labor market participation for men and women has been vital to the growing presence of women in employment(KUD, 2024). Key policies include paid parental leave, quotas for shared paid leave, extensive coverage of childcare facilities, rights to take leave when a child is ill, and flexible work hours.

In short, men and women are almost equally represented in the Norwegian labor market and women tend to work part-time more frequently than men.

3.2 National sickness absence benefit scheme

Norway, like numerous other European nations, has a national sickness absence benefit scheme. In this system, all employees have the right to receive pay while they are ill (Mæland & Pedersen, 2025). Registered leave, sick leave, is reported to the employer or the Norwegian Labor and Welfare administration (NAV) and provides the right to claim benefits.

Short periods of sick leave, up to three days, can be documented by the employee, for a maximum of 4 occurences per year. If the sick leave exceeds three days, one must receive documentation by a doctor, dentist, chiropractor, or manual therapist. Employers are obligated to maintain an employee's salary for the first 16 days of sick absence. After this period, wage costs are covered by the public health insurance system (Folketrygden). Sick leave benefits compensate yearly pay up to six times the basic rate of G; as per 2021, this was 638,394 NOK. You can only receive these benefits for up to one year (NAV, 2025a).

To be entitled to sick leave benefits from Folketrygden, one must be a member of Folketrygden or be a EU citizen working in Norway. One has to be employed for four weeks prior to the incident of sick leave absence. Furthermore, the employee must be under 70 years of age. For workers between 67-70, you are only permitted to receive the benefits for up to 60 days per year (Mæland & Pedersen, 2025).

Finally, the work must produce taxable income (NAV, 2025b). Individuals who are unable to work due to illness or injury have the right to receive the sick leave benefits. This also includes, among other special cases: when the individual is unable to work due to miscarriage or inability to work due to fertility treatment (Folketrygdloven, 1997). The National sickness benefit scheme in Norway is generous and compensates employees for the loss of income in episodes of sickness. However, it is not unusual that employers provide even more generous arrangements for their employees to ensure full compensation.

Chapter 4

Data, sample and empirical strategy

In this section I will describe the data sources and sample construction. In addition, I will describe the construction and definition of core variables. Also, the empirical strategy used to describe and decompose the changes in the gap in sickness absence between men and women.

4.1 Norwegian register data

In this thesis, the main data source is individual level register data from Norway in the period from 2015-2021. From 01.01 2015 SSB changed its method of documentation for producing labor market and wage statistics. The main source of information is A-meldingen, which is a report on income, employment, tax to institutions NAV, Skatteetaten and Statistics Norway (Berge et al., 2023). Therefore, the sample will cover the years from 2015 to 2021. This statistic is reported every month, and each dataset contains about 5,7 million observations.

To construct my employment and occupational measures, I observe individual level registered employment from Skatteetaten (A-meldingen) the first month of each year. For every employee information on income, employment and occupation is obtained. Occupation is defined in STYRK98. STYRK 98 is a occupational code with in total 7 digits(Statistisk sentralbyrå, 2016). By definition, occupation is characterized by certain characteristics that are present for a profession, without emphasis on education, title or sector(Statistisk sentralbyrå, 2011). The occupations are grouped in 10 main groups, as given in the occupational register described in table 4.1.

The sick leave registry is based on information from A-meldingen and a doctor prescribed leave registry. Information about the sickness absence is reported in quarterly datasets. The absence is aggregated to annual percentage leave by adding all the periods and adjusting it to the time-frame of the year. The measure of sick leave in the register data is number of workdays lost to self reported and medically certified sick leave. This variable is adjusted to the contracted work-percentage and disability. In that way, it measures the magnitude of leave for the person given their participation in the labor market (Statistisk sentralbyrå, 2000).

Code	Occupation Description
1	Administrative managers and politicians — Roles involving management and governance.
2	Academic professions — Jobs requiring advanced education and expertise.
3	College professions — Occupations needing specialized training from a college.
4	Office and customer service professions — Positions focused on administrative support and customer interactions.
5	Sales, service, and caring professions — Jobs involving direct customer engagement in retail, hospitality, or healthcare.
6	Agricultural, forestry, and fishing professions — Roles related to the primary production of food and natural resources.
7	Craftsmen and similar trades — Skilled manual labor positions in construction and artisan sectors.
8	Process and machine operators, transport workers, etc. — Jobs involving machinery operation and transportation tasks.
9	Professions with no education requirements — Roles not requiring formal educational credentials.
0	Military professions — Positions primarily related to military service, excluding civilian roles in defense.

Table 4.1: 10 main categories form the STRYK 98 Classification

The data from SSB does not capture self-employed workers or those who are in mandatory military service. In addition, it does not capture absence due to children's illness or leave for childcare in relation to birth.

Data on demographic information and educational level provide the classification of the persons educational level and registered date for highest completed educational level. The dataset contains observations from 1970 to 2024. In SSBs standard there are 9 different main categories: 0: No education/preschool education, 1: Primary school occupation, 2: secondary school education, 3: Upper secondary education ("grunnutdanning"), 4: Upper secondary education (final level), 5: Supplementary upper secondary education, 6: University and college education(lower level), 7: University and college education(higher level), 8: Doctoral education, 9: Not specified (Statistisk sentralbyrå, 2023).

Data on sociodemographic factors: family status and number of children are collected from register data on households in Norway. Partner status is indicated with 0:9, where 0 indicates if the individual is single, or single with children. 1-2 indicates married, and the following 3,5,6,7 and 8 indicates living with a partner, with children, either your own or the partners children.

4.2 Sample selection

This section outlines the criteria for sample selection. I begin with all individuals registered with positive income and contracted hours with at least one employer in A-ordningen in January of each year. To be included in the sample, an individual must have a defined occupation identifiable by an occupational code from STRYK 98. It is important to note that individuals may have multiple sources of income, resulting in several observations per year. To determine a single occupation for each individual per year, the occupation corresponding to the highest wage is selected as the individual's primary occupation. Individuals without a registered employer, lacking an occupational code, or categorized with an undefined occupation ("00") are excluded from the sample. Additionally, to be counted, an individual must have a contracted hours greater than 0 in January of that year. This criterion excludes individuals employed as temporary or on-call staff.

Furthermore, the analysis is limited to men and women aged 20 to 67, as the focus is on analyzing the sick leave percentage for those whose primary source of income is derived from employment. Table 8.1 and 8.2 in the appendix show the number of observations.

4.3 Variables

This study constructs a set of variables to capture working days, occupation, age, family status, education, and sick-leave outcomes. The motivation for selecting these variables is to observe if these observed characteristics have different associations for men and women's level of sick leave.

Occupations are grouped using the first two digits of STYRK-98, 31 occupational categories in total. This gives a broad grouping of occupations, however it is more detailed than the 10 main groups as refered to in table 4.1. Each category aggregates multiple specific occupations. For instance, I will refer to occupational code 32 in the following as health care occupations. However, this category captures nurse and occupational therapist as well as forest ranger and agronomist. Occupational code 51, captures caretaker and hairdresser as well as janitor and security guard. I include a full set of indicator variables for these 31 categories, the mapping is provided in the appendix (Table 8.3).

The sample comprises individuals aged 20–67. To flexibly model age, I define four non-overlapping age dummies covering the following intervals: A1: [20,32), A2: [32,44), A3: [44,56), and A4: [56,67]. Family status is captured with two elements. First, partnership status, originally coded using multiple register categories, is recoded into a binary indicator: partnered (married or registered partner) vs. single. Second, children are measured using the variable which records the number of children aged 0–17 at the family level. I construct mutually exclusive dummies for no child, one child, two children, and three or more children.

Education is measured as the highest completed level recorded for each individual as of 2021, following SSB's standard classification. I define four education dummies: (E1) completed primary school or lower; (E2) completed upper secondary (high school) or lower; (E3) completed lower university degree (e.g., bachelor); and (E4) completed higher university degree (master or PhD). Using the highest education as of 2021 implies a non-dynamic specification and may introduce bias for younger cohorts if their eventual educational attainment is overstated early in their careers. Yet, this is likely a very minor issue.

The dependent variable is the annual percentage absence due to sick leave, calculated in accordance with SSB's definition. Total sick leave within one year, the numerator of the sick leave percentage, is aggregated by summing registered leave from all quarter data. The numerator, lost days to sick leave (sfdagsvj), is defined as:

$$\text{Lost days to sick leave} = \text{days lost to sick leave} \times \text{position percentage} \times \text{degree of sick leave} \tag{4.1}$$

The measure of working days is calculated based on the percentage of a contracted position reported in A-meldingen. It represents the annual number of days an individual is expected to work. This measure serves as the denominator in the sick-leave percentage: 220*contracted work position/ 100.

The sick-leave percentage is then:

$$\text{Sick leave percentage} = (\text{days lost to sick leave} \div \text{contracted work days}) * 100 \tag{4.2}$$

By definition, sick leave percentage can take any value within the interval [0,100]. All individuals in the sample will have an outcome in sick leave.

In what follows, "sick leave" refers to this percentage measure unless otherwise stated. It is not weighted by employment, as it is already relative to the persons contracted work days, meaning that a person who has 100 percent sick leave is counted the same way regardless if the full contract of this person is full time or part time.

4.4 Empirical Approach

This section outlines the methodology employed to examine how the observable characteristics relate to sick leave for men and women. The main objective is to describe associations between demographic indicators and occupation on sick leave for men and women and how these change over time.

First, I will run multiple linear regression models separately for men and women. To further analyze the mean outcome differences between the two groups, I will employ the Blinder-Oaxaca decomposition, a widely recognized technique traditionally used to assess wage discrimination. This method decomposes the difference in outcomes for the two groups into an explained part; attributable to differences in observed characteristics, and an unexplained part; representing differences in returns or coefficients for the same characteristics, including the intercept. The unexplained portion may reflect variations in returns, unobserved factors, and model specification, though it should not be interpreted as causal.

4.4.1 Regression Model

To analyze the influence of education, age, family status, employment, and occupation on sick leave, I will estimate linear regression models. The same model specification will be applied to samples of men and women separately, in addition to presenting a pooled model. I aim to isolate the associations of specific variables, such as age, education level, family status, and occupation on sick leave. This approach allows for an examination of how changes in a variable, like education, correlates with sick leave rates while controlling for the confounding influences of other factors.

It is important to note that while this method clarifies individual relationships, it does not imply causation due to the complex interactions that exist among multiple variables. Moreover, certain variables, including occupation, may be endogenous. For example, a person with history of illness and thus sick leave may be forced to drop out of the labor force, work part time or change occupation. Additionally, unobservable characteristics such as abilities, motivation, and health could influence both employment intensity and absenteeism, potentially leading to omitted variable bias. I also acknowledge that occupational choices may be influenced by health and family conditions, suggesting that the coefficients for occupation may partially reflect the effects of prior health and decisions. I interpret my findings as descriptive associations rather than causal relationships.

The model specification will apply for females and males individually. In general, it can be expressed as follows:

$$Y_{it} \;=\; \beta_0 + \sum_{j=2}^{4} \alpha_j A_{j,it} + \sum_{k=2}^{4} \gamma_k E_{k,i} + \sum_{m=1}^{3} \delta_m C_{m,it} + \rho\, P_{it} + \eta_{\mathrm{occ}(i)} + \tau_t + u_{it}. \tag{4.3}$$

Outcome Y_{it} is sick leave for individual i in year t.

Reference categories (omitted) Age $A1$ (20–32), education $E1$ (primary/lowest), 0 children, single/not partnered, occupation is broker, analyst, advisor and consultant within various fields = 34, and base year = 2015). All coefficients are interpreted relative to these references.

Age

$$\sum_{j=2}^{4} \alpha_j A_{j,it} \;=\; \alpha_2 A_{2,it} + \alpha_3 A_{3,it} + \alpha_4 A_{4,it},$$

where $A_{2,it}$ = ages 32–44, $A_{3,it}$ = 44–56, $A_{4,it}$ = 56–67.

Education (time-invariant)

$$\sum_{k=2}^{4} \gamma_k E_{k,i} \;=\; \gamma_2 E_{2,i} + \gamma_3 E_{3,i} + \gamma_4 E_{4,i},$$

where $E_{2,i}$ = upper secondary school, $E_{3,i}$ = lower university, $E_{4,i}$ = higher university. Education has no time subscript.

Children

$$\sum_{m=1}^{3} \delta_m C_{m,it} \;=\; \delta_1 C_{it}^{(1)} + \delta_2 C_{it}^{(2)} + \delta_3 C_{it}^{(3)},$$

where $C_{it}^{(1)}$ = having one child, $C_{it}^{(2)}$ = two children, $C_{it}^{(3)}$ = three or more children.

Partner status P_{it} = partnered/married.

Fixed effects $\eta_{\mathrm{occ}(i)}$ are occupation fixed effects; τ_t are year fixed effects .

Intercept and error β_0 is the mean for the reference individual; u_{it} is the error term (standard errors typically clustered at the individual level).

The sign of the coefficient indicates an associated increase or decrease in sick leave percentage by β percentage points compared to a baseline scenario where the variable equals the reference levels.

I anticipate that sick leave is correlated with unobservable individual characteristics not included in this specification. These may include a history of illness, mental health conditions, personality traits, responses to illness, and social support. Additionally, lifestyle factors such as diet and fitness may affect overall health and subsequently influence the frequency of sick leave.

To address the individual correlation arising from these unobservable characteristics, I will employ a cluster-robust variance estimator. This method is employed because the error term of the observations are not independent. One individuals health outcome in one year does not have to be independent of the health outcome the following year.

With fixed effects for occupation and year, the remaining identification of coefficients relies on variation within occupations across years.

4.4.2 Blinder - Oaxaca Decomposition

This section draws inspiration from previous work Hlavac (2022). The Blinder-Oaxaca decomposition is a statistical method that decomposes differences in mean outcomes between two groups into a part that quantifies the group difference in the levels of explanatory variables and a part that quantifies the differences in regression coefficients(Hlavac, 2022). The method was first developed to examine linear relationships and that is also how it will be applied in this setting.

The results from the linear models discussed in the previous section provide the associated effects of observable characteristics and sick leave for men and women. However, I do not include the year fixed effects in the decomposition, so there is no subscript (t). Each decomposition is run within the respective year, from 2015-2021. Then, by applying the Blinder- Oaxaca decomposition it is possible to separate the explained and unexplained components of the gender gap in the sickness absence.

The twofold approach decomposes the mean difference in outcomes based on a given reference coefficients. In this application, the objective is to study components under the hypothetical scenario "if women were as men", without any implication of discrimination.

Groups are men (A) and women (B). The aim is to separate the gender gap in the average sick leave rate into two components. The explained component: the part which captures the differences between the groups in observed characteristics such as age, education, marital status, children and occupation. The unexplained part: differences in coefficients assessed at women's average levels of observables, including the intercept. This component may reflect disparities in returns as well as unobserved factors and model specification, but does not imply causation.

The decomposition can be expressed as follows:

$$\Delta\bar{Y} = \underbrace{(\bar{X}_{\mathrm{A}} - \bar{X}_{\mathrm{B}})\hat{\beta}^{*}}_{\text{explained}} + \underbrace{\bar{X}'_{\mathrm{A}}(\hat{\beta}_{\mathrm{A}} - \hat{\beta}^{*})}_{\text{unexplained A}} + \underbrace{\bar{X}'_{\mathrm{B}}(\hat{\beta}^{*} - \hat{\beta}_{\mathrm{B}})}_{\text{unexplained B}}. \tag{4.4}$$

Where the components are based on the result of linear regressions of observable characteristics on sick leave, for men and women separately.

Since I use men as the reference category, we have that:

$$\hat{\beta}^{*} = \hat{\beta}_{\mathrm{A}} \tag{4.5}$$

In this application, the second term (unexplained A) drops out, and the part that is unexplained is simply the difference between the coefficients of men and women valued with the reference coefficients from the regression on observations of men only.

The detailed contributions of the variables can be expressed as follows:

Explained:

$$(\bar{X}_{\mathrm{A}} - \bar{X}_{\mathrm{B}})'\hat{\beta}^{*} = (\bar{X}_{1\mathrm{A}} - \bar{X}_{1\mathrm{B}})\hat{\beta}_{1}^{*} + ... \tag{4.6}$$

Unxplained:

$$\bar{X}'_{\mathrm{B}}(\hat{\beta}_{\mathrm{B}} - \hat{\beta}^{*}) = \bar{X}_{1\mathrm{B}}(\hat{\beta}_{1\mathrm{B}} - \hat{\beta}_{1}^{*}) + ... \tag{4.7}$$

Estimation uncertainty

In R studio, the Oaxaca package reports bootstrapped standard errors of a specified number of sampling replicates. The specified number of resamples are randomly sampled with replacement from the set of observations. Decomposition estimates are calculated for each of the (B) resamples from the first step. Then, the bootstrapped standard error is the standard deviation of the (B) decomposition estimates from Step 2 (Hlavac, 2022).

This is done for all observations within one year. Bootstrapping with 100% of the observations means that the entire dataset is used, which is beneficial for producing accurate and stable estimates of the standard errors.

Chapter 5

Results

This chapter presents the results. First, I present descriptive tables of trends in sick leave and employment. This provides a basis for understanding the development of leave and what contributes to the gender gap. Then I will present the results of the regressions, which are to be interpreted as associations. Lastly, I will present the results of the Oaxaca-Blinder decomposition performed within each year of the sample. To review the the contributions of covariates in the decomposition, I present the results of the decomposition in 2021.

5.1 Descriptive statistics

As noted in the literature review, equal participation in the labor market may be associated with higher sick leave rates (Kwon, 2020). In addition, the job-strain in many "female-dominated" occupations may affect women more strongly then men when assessing health and absence (STAMI, 2025). This section aims to provide a comprehensive understanding of the interplay between gender representation and sick leave in the Norwegian labor market.

In the following descriptive statistics will be presented. First showing the general trends in gender in sick leave in Norway from 2015- 2021. Then, I will describe how gender composition within occupation has developed from 2015-2021, how sick leave has developed across occupation, and the development of the gender gap in sick leave within occupation.

5.1.1 General trends 2015-2021

Both men and women's sick leave increased in the period from 2015 - 2021 (Figure 5.1). This contributes to an overall increase in the level of sick leave in Norway. The annual average sick leave is also represented in Table 8.4 in the appendix.

An examination of the average sick leave at the occupational level (Table 8.5), reveals substantial disparities. The occupations with highest levels of leave are many health care occupations(32) and various service occupations (51), with over 7 percent annual average leave. Occupation 32 consists of largely health care professions, such as nurses and occupational therapists. Whereas occupation 51 also accounts for several health care occupations, and many other female dominated occupations: hairdresser, waiter, assistant in kindergarten. Additionally, occupation 91 has high levels of leave; this category includes cleaner/kitchen assistant, which are also occupations dominated by women. The occupations with low levels of leave are occupation 01, 12, 21, 31 and 33. These are capturing occupations in the military (01), politicians (11), leaders within public bureaucracy (12), civil engineers, engineers, scientific professions (21, 31) and teachers (33).

In Figure 5.2, the average annual levels of sick leave within occupational categories are plotted against female share of employment. The upward sloping pattern in this figure suggests that female-dominated occupations also tend to have higher rates of sickness absence. However, this is not the case for all occupations.

Development of average leave is mostly consistent across occupation. For 21 out of the 31 occupations, there are higher average sick leave in 2021 than in 2015 (Table 8.5). Occupation with the highest levels of leave in 2015 still dominate in 2021. This being occupation 22, 32, 51, 82, 83 and 91 (health care and service professions). Occupations with lowest leave in 2015 was for military, leaders in public bureaucracy, technologist ect, and engineers(01, 12, 21 and 31). For occupation with the lowest levels of leave in 2021, this was 01, 21, and teachers (33). In sum, the development in most occupations were towards higher levels of average annual sick leave in 2021.

5.1.2 Gender composition within occupations

The share of female employment across occupational groups are represented in Figure 5.4. The shares from 2015 and 2021 are represented for comparison. This comparison shows that women follow established patterns of employment in different occupations. Female dominated occupations include doctors, veterinarians, dentists and biologist (22), health care workers and nurses (32), teachers (33), service occupations (51) and cleaner, guards, kitchen- assistant (91). The occupations most dominated by men are 62,71,72, 81 and 83. These are: Lumberjack (62), skilled-labor in construction, groundwork, plumber (71), welder, meal worker, mechanic and electrician(72), offshore worker, skilled worker- woodwork/glass(81) and conductor, chauffeur, operator (83). Among the most gender neutral occupations are 23,25, 34 and 41: Workers in public administration, consultant/advisors in public and private sector (24), employees at university/ educational institutions (23), consultants/advisors/accountants/police officers(34) and clerks, workers in transportation and communication (41).

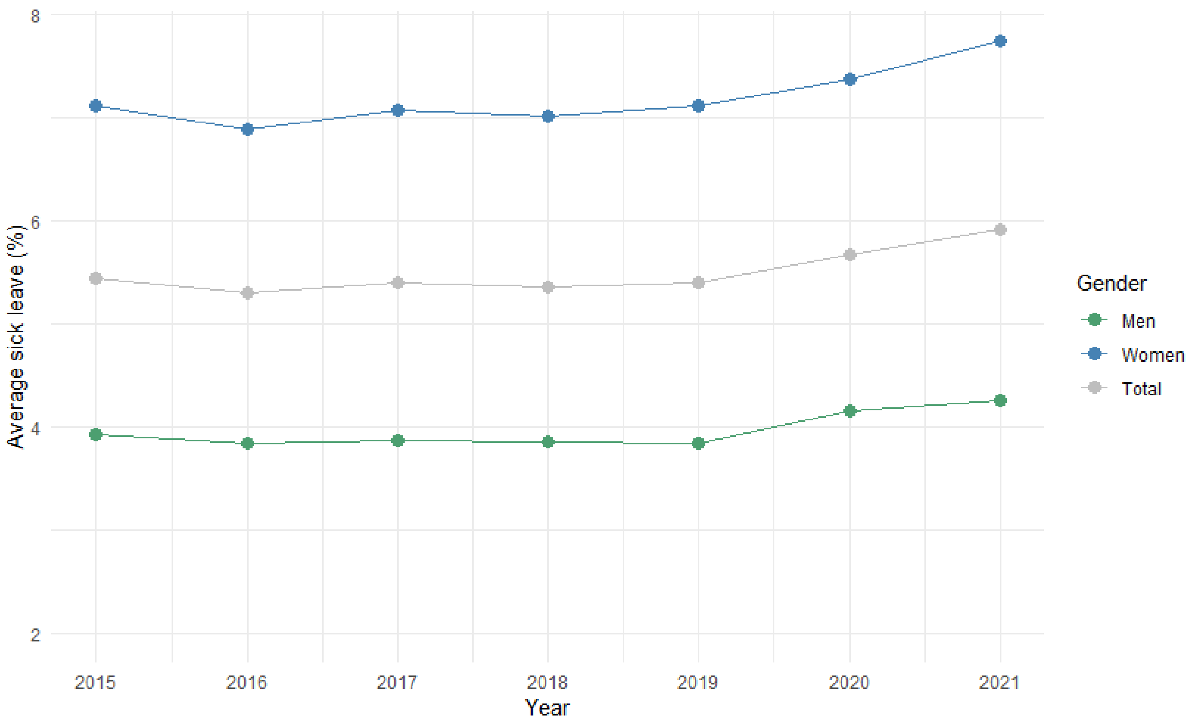

Figure 5.1: Annual average sick leave in Norway (2015-2021)

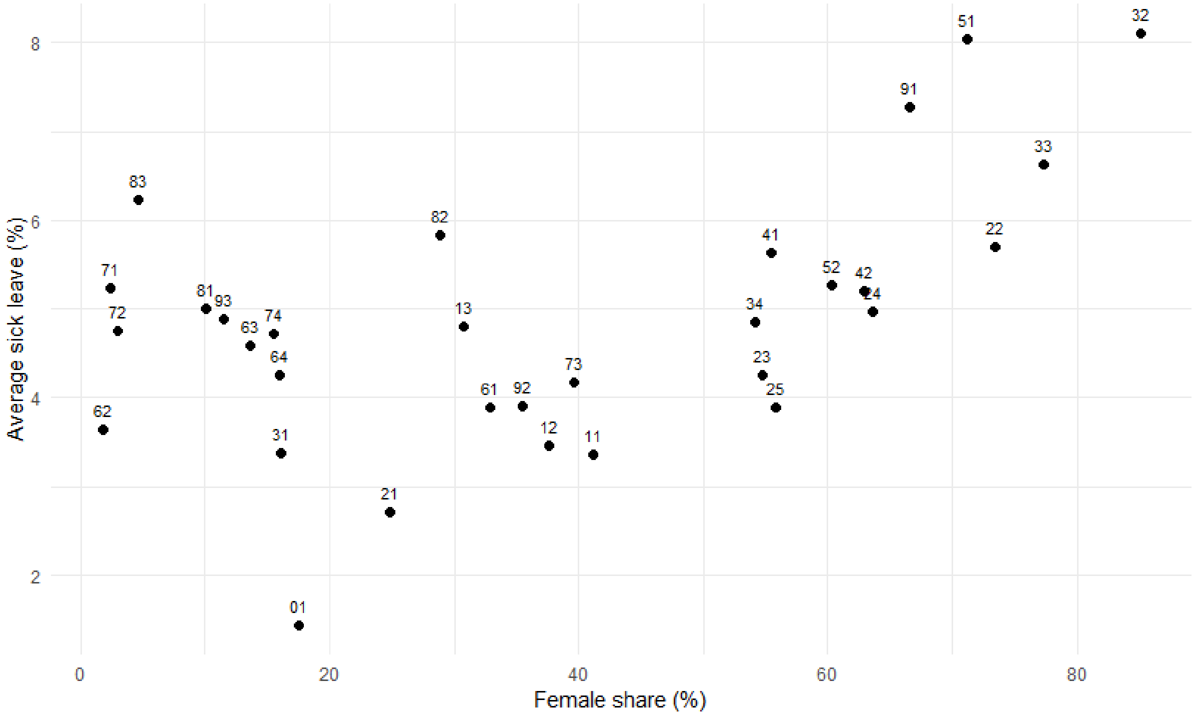

Figure 5.2: Average sick leave in occupational categories against the average share of female employment(the average across all years from 2015-2021)

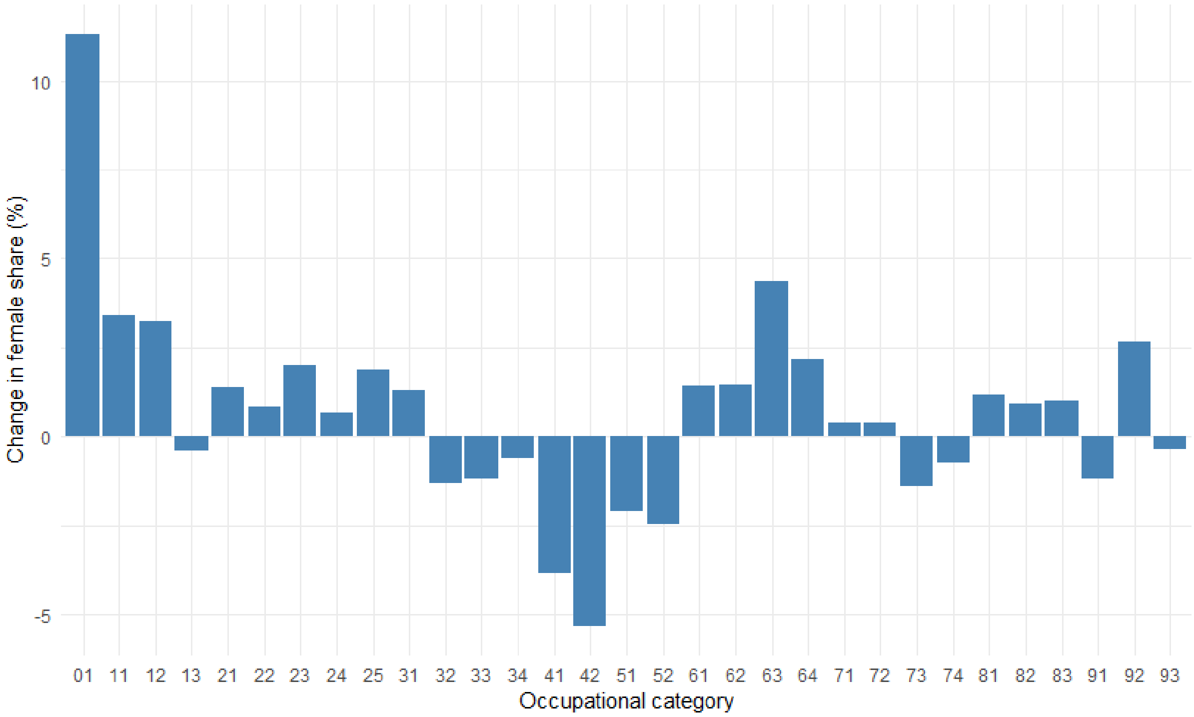

Figure 5.3: Relative change in female share within occupational categories from 2015 to 2021.

In the Table 5.3 , I show how the share of females within different occupations has changed from 2015 to 2021. Overall, the share of females across the different occupations appears stable. However, some occupations stand out. In occupational category 01, which includes positions within the military, the share of women has increased by 11 percent form 2015 to 2021. Other occupational categories with an increased female share are politicians and leaders/members of interest organizations(11), leaders/senior positions in bureaucracy on county/state level (12) and skilled workers- aquaculture and fish farming (63), with moderate changes in the relative female share ranging between 3.2 and 4.4 percent points.

It is notable that in many large occupational groups dominated by females, there has been a slight decrease in the share of women, most significantly in occupational category 42- service within hospitality ect. (over a 5 percent reduction), followed by categories 41, 52, and 51, which all capture traditional office work, sales and service. Also, moderate reduction in the female share of health care occupations with 1.33 pp reduction (32) and 1.2 pp reduction(91).

Changes in gender distribution across occupations may be relevant for understanding the development of differences in sickness absence between the genders. In particular, the increased share of women in occupational category 01, along with growth in other occupations associated with low levels of leave, might impact the overall differences in sick leave. However, these occupational groups employ few workers, hence the overall contribution will be small. At the same time, the slight decrease in the female share in several female-dominated occupations may signal some structural developments in employment. Moreover, it could suggest that the selection pattern of women get weaker over the time.

Based on the findings presented, the development in employment in occupations still very much follow "traditional" patterns. However, there is some movement in the occupation patterns of men and women.

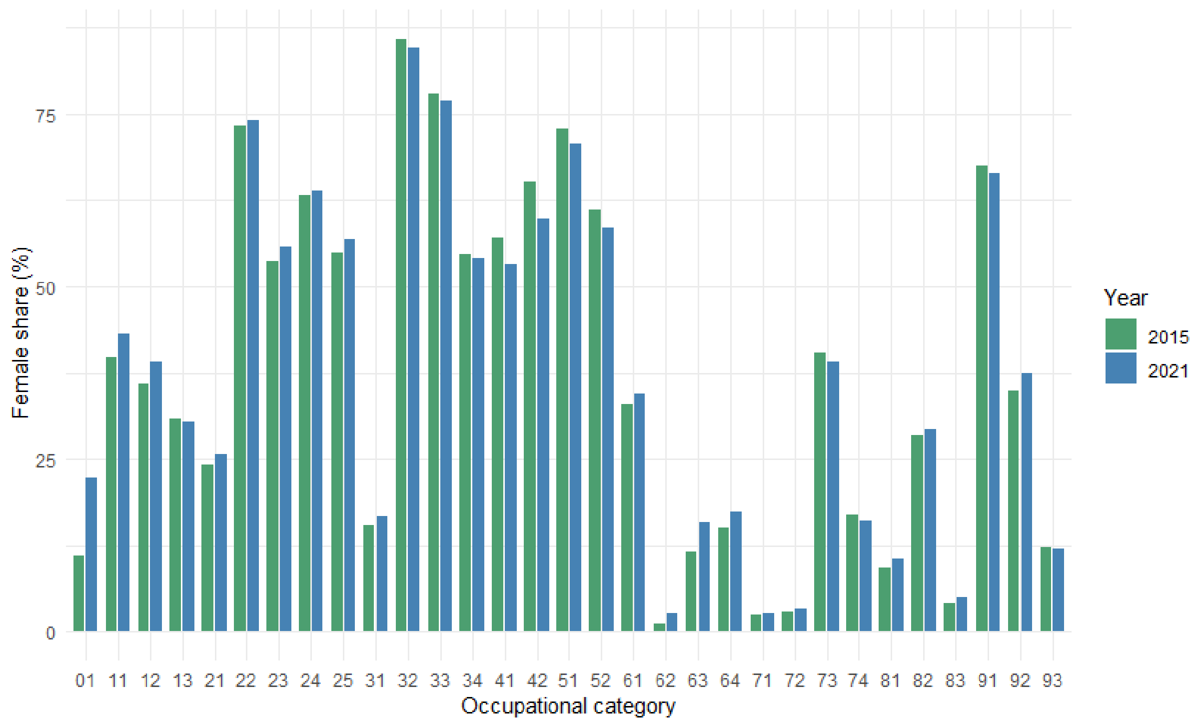

Figure 5.4: Female share in occupational categories, 2015-2021 comparison

5.1.3 Development of gender disparities in sick leave within occupations

For 18 out of 31 occupations the gender gap in sick increased from 2015- 2021 (Table 8.8). For 13 occupations, the sick leave gap remained at the same level, or tightened compared to what was the case in the base year. Examining the change from 2015 to 2021, the gender gap in sick leave was unchanged or reduced for occupations 01(military), 11(politicians) 62,63 and 64 (fishermen, skilled labor with fish farming and forestry). These occupations also experienced an increased share of women in employment(Table 5.3)

In other occupational categories that cover many health care occupations (22 and 32) there is relatively little change in the gender gap in sick leave before 2020, however it increases in years 2020/2021. The average leave of workers in occupation 22 and 32 increased in 2021. The gender gap in sick leave appears to widen more in female dominated occupations and more so in the years 2020 and 2021. This might relate to a change in the strain of working within health care during a pandemic. Furthermore, it could predict women were more affected by the shock of the pandemic.

It should be borne in mind that the occupational codes cover a broad range of specific occupations, and that men and women might sort into different specific occupations within one "code" which follows from the classification (Table 8.3). That the gap in sick leave for men and women develop differently in different occupations might also relate to differences in unobserved characteristics between men and women who hold different occupations. However, it might also reflect that changes in the job stain of holding the occupation affects men and women differently. In short, sick leave increased across large occupational categories from 2015 to 2021. At the same time, the gender gap in sick leave widened 18 out of 31 occupations.

5.2 Regression results

In the following I will present the results of the regressions, which are to be interpreted as associations. The reference individual in both models is 20-32 years (A1), working in occupational category which represents broker, analyst, advisor and consultant within various fields(occ 34), has highest completed education of primary education (E1), is single and has no children in the year of 2015. The results are presented in two tables, demographic and year estimates in Table 5.1 and all occupation estimates are presented in Table 8.7.

There is a large baseline gender gap. Intercept for men is 3.74 pp and for women it is 7.11 pp (Table 5.11) . The intercept can be interpreted as the average sick leave of a man/women who has the characteristics of the reference individual. Difference in intercepts all else being equal, translates into women have 3,37 pp higher sick leave then men.

Age is associated with higher sick leave for both men and women. For men, relative to the base category, sick leave is increasing with 1.3 percent in group for 32-44 years , with 2 pp. in the age group 44-56 and almost 3 pp. for 56- 67 years. For women, sick leave is associated with older age, increasing with 2 percent in group for 32-44 years, with 1.6 in the age group 44-56 and 2.1 for 56- 67 years relative to the base category. The increase to the 56-67 age group has the strongest association for both genders, slightly steeper for men at the highest age group.

Higher education is associated with lower sick leave, and more so for women than for men. For men, completing high school (E2) is associated with a reduction in sick leave by -1.5 pp, lower higher education(E3) with -3.2 and upper higher education (E4) with -2.5 pp. In the case of women, the relationship is -1 pp for (E2), -4.2 pp (E3) and -2.8 pp (E4). These associations imply that women gain a stronger protection against leave from higher education.

The effect of the first child on sick leave is associated with higher leave for mothers than for fathers. Relative to having no children for men, having one child relates 0.04 percentage points higher sick leave. For women, relative to having no children, having one child predicts 1.3 percent point higher sick leave. Having two children compared to the base category is associated with -0.1 pp for men and 0.08 pp increase in sick leave for women. Finally, having three or more children predicts 0.08 pp increase in leave for men and -0.1 pp decrease in sick leave for women.

Having one child captures going from zero to one child, and it can be biological differences driving the difference between men and women. One child may capture the effect of having younger children and pregnancy related sick leave, such that the coefficients bundle selection and timing. Indeed, mothers and fathers who progress to have more children, may be healthier, have higher/more stable income, and women who experience large health complications with pregnancy may choose not to have any more children. Accordingly, coefficients are descriptive and may partly capture timing and selection and does not capture the causal effect of having children.

Conditional on all other characteristics, having a partner is associated with lower sick leave. Having a partner or being married is associated with - 0.2 pp for men. For women having a partner or being married lowers sick leave with around -0.5 pp. Conditional on everything else, the effect of partner relates stronger to sick leave for women.

The occupation associated with the highest change in percentage leave with respect to the reference occupation (34), is the same for both genders (Table 8.7). Coefficient on occupation 32 (covers many health care occupations) is associated 2.4 percent higher leave for men, and 3.1 pp higher leave for women. The occupations where this relationship has the strongest negative association compared to the reference category is for occupations within the military (occ 01). Here the associated leave for men is - 1 pp and - 3.8 pp for women.

Occupations where the associated effect on sick leave for women and men are different are occupations 52, 74 and 42. These are: sales representative/ assistant and retail worker(52), tailor, carpenter, butcher, baker and pastry chef (74). Rental agent, travel agent, receptionist, service worker (42). All above has a negative association with sick leave for women, whereas the relationship for men is higher leave in comparison to the reference occupation broker, analyst, advisor and consultant within various fields (34). One possible explanation for this might be, that men and women are employed in different roles within these broad occupation codes.

Year fixed effects are stronger for women than for men. These results indicate that after controlling for all observable characteristics the unexplained leave of women in the model predicts higher leave with time. The year dummies could then represent time varying factors that are not included in the model become stronger for women. This is consistent with the findings in the descriptive part, which showed that the gender gap in sick leave increased for 18 out of 31 occupations between 2015 and 2021, and particularly from 2020-2021. The difference in year effect in 2020/2021 could indicate that the pandemic may have disproportionately affected men and women. However, it does not explain the stronger year fixed effects in the years prior to 2020.

Variable	**Estimate for Men**	**Estimate for Women**
(Intercept)	3.735*** (0.0300)	7.106*** (0.0422)
A2 (32–44)	1.284*** (0.0146)	1.976*** (0.0219)
A3 (44–56)	1.979*** (0.0159)	1.605*** (0.0218)
A4 (56–67)	2.965*** (0.0192)	2.102*** (0.0252)
E2 (completed high school)	-1.521*** (0.0230)	-1.023*** (0.0307)
E3 (completed lower university degree)	-3.224*** (0.0236)	-4.173*** (0.0345)
E4 (completed higher university degree)	-2.451*** (0.0225)	-2.783*** (0.0312)
One child	0.039* (0.0156)	1.297*** (0.0207)
Two children	-0.118*** (0.0167)	0.0790*** (0.0230)
Three children	0.0804*** (0.0243)	-0.0910*** (0.0341)
Married/partnered	-0.1725*** (0.0140)	-0.5240*** (0.0178)
Year 2016	-0.102*** (0.0140)	-0.160*** (0.0188)
Year 2017	-0.088*** (0.0150)	0.029 (0.0202)
Year 2018	-0.106*** (0.0151)	-0.015 (0.0202)
Year 2019	-0.104*** (0.0152)	0.099*** (0.0204)
Year 2020	0.193*** (0.0155)	0.371*** (0.0207)
Year 2021	0.249*** (0.0155)	0.740*** (0.0210)
Year FE	Yes (ref.= 2015)	
Occupation FE	Yes (ref.= 34)	
Std. errors	Clustered at person level	
Observations	15,274,895	
R^2	0.02277	
Adjusted R^2	0.02276	

Notes: Entries are estimates with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table 5.1: OLS regression results for men and women.

5.3 Decomposition results

I perform a twofold decomposition for each year from 2015 to 2021 individually. Consequently, the results of the decomposition should be interpreted as the explained and unexplained components of the gender gap in sick leave for each specific year. Table 5.2 shows the result of the decompositions. Total differences in sick leave increased from the reference year to the pandemic year of 2021. In 2015 the total gap was 3.146 percentage points between men and women, and in 2021 it was 3.497 pp. This means, in comparison to the base year (2015) the gap in sick leave was 0.35 pp larger in 2021. This indicates that, overall, the gap in sick leave between men and women widened.

Total gender gap in sick leave is above three percent consistently across the years in my sample. The results of the decomposition indicate that the unexplained component accounts for almost all of the total difference in sick leave between men and women. The explained component has increased slightly over the years in the sample, accounting for a larger proportion of the total gender gap. The share of the explained part accounts for around 0-2 percent of the overall gender gap in the first four years of the sample (2015-2019). Moving from 2019 forward, the share of the explained component increases. Although the explained part in the decomposition has increased in relative terms , still within each year the share of the explained part of sick leave is very moderate.

Without further investigation into dynamics across years, the results do not explain the dynamic pattern of what contributes to the parts in the decomposition across years, as the year results are simply results of given endowments and returns within that year. However, as I will return to, I will briefly look into this by examining the effect of health care occupations.

Year	Explained	Unexplained	Total	Share of explained (%)
2015	-0.058	-3.088	-3.146	1.84
2016	-0.014	-3.01	-3.024	0.46
2017	-0.022	-3.15	-3.172	0.69
2018	-0.051	-3.10	-3.151	1.62
2019	-0.094	-3.12	-3.214	2.92
2020	-0.167	-3.02	-3.187	5.23
2021	-0.27	-3.227	-3.497	7.73

Table 5.2: Main results from yearly decomposition (2015-2021)

5.3.1 Contributions in 2021

In the following, the results of the twofold Blinder-Oaxaca decomposition in 2021 will be interpreted in order to closer examine the contributions of each observable characteristic to the explained and unexplained part (Table 8.8). In 2021, the explained component of the gender gap in sick leave is - 0.27 pp. In plain terms, this means that differences in observed characteristics can account for 0.27 of the difference in sick leave between men and women. Again, relative to the total gap in sick leave this explained difference can only account for about 7.7 percent points of the total gender gap.

The results of the decomposition shows that the biggest contributor to the explained part is occupational composition (Table 8.7 in). Meaning that women are more concentrated in occupations that, under men's coefficients, are associated with higher sick leave. And, women could be less represented in occupations that have a negative association with sick leave than the reference occupation (34). There are negative contributions from several occupation codes, occupation 32= -0.25, 22= - 0.05, 51=-0.43, 91= -0.02. As noted, these occupations are some of the occupations with the highest shares of women at the same time as they are associated with higher sick leave then the reference occupation. Moreover, there are negative contributions from male dominated occupations as well, including occupation 01: -0.045 pp and occ. 31: -0.05.

Given men's returns, the sum of compositional differences in employment raises women's predicted sick leave relative to men. In aggregate, this pattern can reveal that men are more employed in lower-absence occupations, so occupational sorting alone makes the observed gender difference in sick leave wider. This is consistent with the findings in the descriptive part. However, the contribution is very moderate.

Children and education have small contributions in the explained component. For education, the contribution of the highest educational level (E4) is small but positive, 0.4pp, meaning women's actual education profile, evaluated using men's returns would predict slightly more sick leave than men's. As noted in the regression results, women "gain" more protection form higher education than men. If women were as men in regards to protection from higher education, they would have more leave.

For children, the net explained effect is about -0.03 pp, implying that women's family composition (e.g., having children) contributes very modestly to their higher predicted leave under men's coefficients. One child has -0.03 pp, which implies it contributes in very little degree to the explained part. Partner status explained contribution is + 0.034 pp, which slightly offsets the gap. In other words, based on observed partnering patterns alone (holding returns fixed at men's), women would be predicted to take a little more leave everything else equal.

Turning to the unexplained component, which reflects different coefficients or returns and unobserved factors, the dominant contributor is the intercept, which accounts for -3.2 pp. The intercept captures the baseline gap for a reference individual when all covariates are at their reference categories. A large negative intercept suggests that, even before accounting for specific characteristics, there is a substantial baseline difference in women's predicted sick leave relative to men for that reference profile, and/or that there are unmeasured factors or model structure contributing to this baseline.

	Explained		Unexplained	
Variable	contribution	SE	contribution	SE
(Intercept)	0.0000		−3.2234	0.0986
A2 (32–44)	−0.0013	0.0015	−0.2489	0.0158
A3 (44–56)	−0.0045	0.0012	0.3140	0.0135
A4 (56–67)	0.0092	0.0012	0.1080	0.0102
E2 (completed high school)	−0.1332	0.0083	−0.1882	0.0363
E3 (completed lower university degree)	0.0738	0.0183	0.0873	0.0109
E4 (completed higher university degree)	0.4300	0.0094	0.0299	0.0177
One child	−0.0278	0.0012	−0.2295	0.0095
Two children	−0.0036	0.0007	−0.0679	0.0103
Three children	−0.0003	0.0001	−0.0091	0.0057
Married/partnered	0.0034	0.0004	0.1728	0.0348
Occupation FE	Included (coefficients by occupation in Appendix).			

Notes: Coefficients are percentage points. Explained = $(\bar{X}_A - \bar{X}_B)\beta_A$. Unexplained = $(\alpha_A - \alpha_B) + \bar{X}_B(\beta_A - \beta_B)$. A=Men, B=Women. Standard errors (SE) from the Oaxaca output.

Table 5.3: Twofold Blinder- Oaxaca decomposition, 2021

Beyond the intercept, the most important unexplained movements come from how children "pay off" differently for women versus men. If women were assigned men's returns to children, their predicted sick leave would be about 0.31 pp lower (approximately −0.23 for one child, −0.07 for two, −0.009 for three). This reveals having children is associated with a larger increase in sick leave for women than for men. In other words, the same family situation seems to translate into more absence for women, which could reflect differences in caregiving responsibilities.

Education's unexplained effects are mixed across levels, but sum to about −0.13 pp. That means if women had men's education returns, they would be predicted to take somewhat more sick leave. This could again indicate that higher education yields different occupational pathways or health-related behaviors for women versus men, even at the same education level.

Partner status moves in the opposite direction +0.173 pp. This suggests women benefit more from being partnered than men do in ways that reduce sick leave or, phrased differently, if we imposed men's returns to partnership on women, their predicted sick leave would be higher. This might reflect differences in division of care that mitigate absences for partnered women more than for partnered men. Differences in returns by age (A2 −0.249, A3 +0.0314, A4 +0.108) leave around -0.11, so age is not a major driver either way.

Unexplained differences in returns to specific occupation codes are small compared with the explained effect from occupational sorting. Which indicates that it is less about men and women experiencing different returns within the same occupation and more about the fact that they work in different jobs to begin with that contributes to the large gap.

In short, the explained component of the decomposition from 2021 show that if men and women had the same observed composition (age, education, children, occupation), holding men's beta's fixed, the men–women difference would change by -0.27, which means the actual composition pushes women's sick leave up relative to men. The unexplained component show that if we keep women's endowments but give women men's returns and intercept, women's predicted sick leave would be 3.2 pp lower. In total, women would have almost 3.5 percentage points lower leave if they "were as men" in 2021.

5.3.2 Exploring time trends

In the following section, I will explore one potential reason for the increased contribution of explained factors to the gender gap in sick leave observed from 2015 to 2021. This section will explore whether the explained component is driven by a divergence between observational characteristics of men and women, or that given the same level of difference in endowments, the association between this endowment and sick leave becomes stronger for men. I will look at this by examining the contribution of working within occupation 22, 32 and 51 (female dominated occupations that capture health care).

That a larger proportion of the total gender gap in sick leave is accounted for in the explained component can suggest that (1) a more substantial proportion of the difference in sick leave can now be accounted for by the observed characteristics in the model, (2) that the differences in observed characteristics of men and women have increased in such a way that women are more exposed to take sick leave by their composition, (3) or that given the same levels of endowments as previously, men also experience higher returns of these effects, (4) combinations of these. I aim to further investigate the time trend and contributions of the endowment effects and coefficient effects.

What drives the changes?

1. Changes in the composition gap contribute to the changes in the explained part over time.

2. Changes in returns (coefficients) to those characteristics change over time.

(1) can be formulated as follows:

$$Composition \;=\; (\bar{\mathbf{X}}_m - \bar{\mathbf{X}}_f)_t' \, \boldsymbol{\beta}_{m,2015} \tag{5.1}$$

(2) can be formulated as follows:

$$Coefficients = \; (\bar{\mathbf{X}}_m^{2015} - \bar{\mathbf{X}}_f^{2015})' \, \boldsymbol{\beta}_{m,t} \tag{5.2}$$

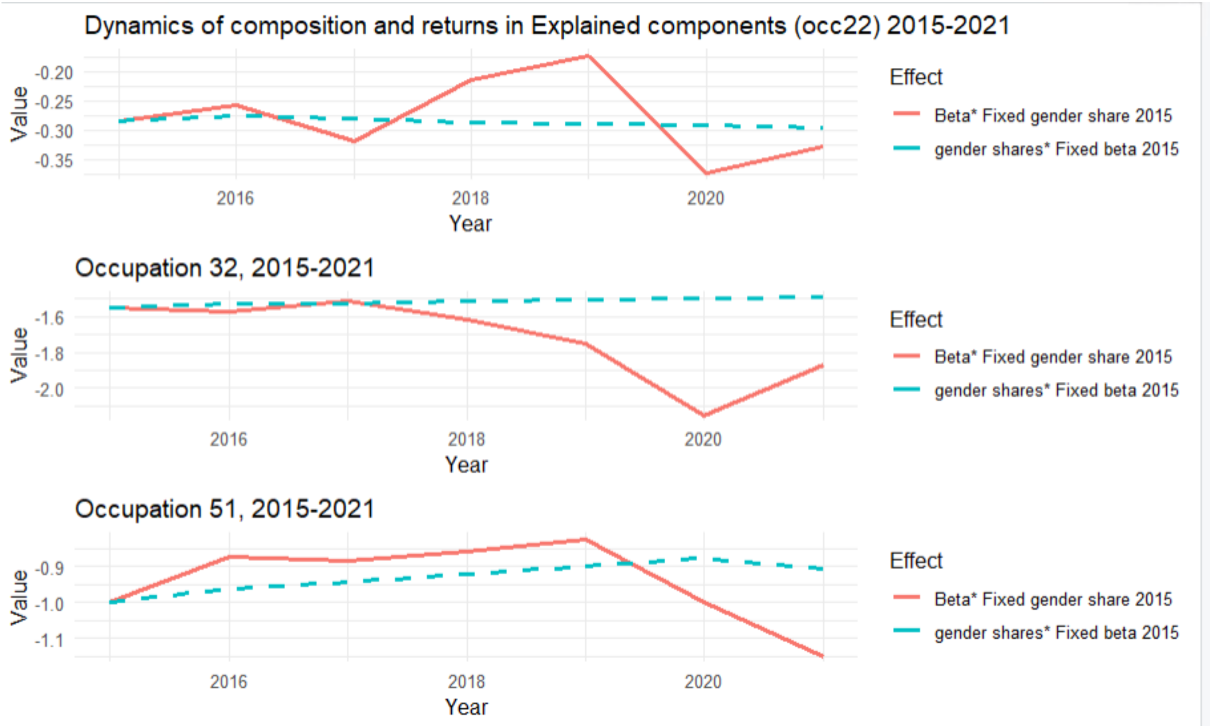

Figure 5.5: Dynamics of composition and returns in explained components(2015-2021)

To test the contribution if (1) I allow difference between the endowment level changes over time, and keep returns constant at 2015 level. To examine the effect of (2) I keep endowment constant at 2015 level and let returns vary with time.

Developments in the explained component

Development of (1) and (2) in health care occupations 22, 32 and 51(Figure 5.5) show that (2) are providing stronger contributions in the explained part. It appears that, men's associations between health care occupations and sick leave become stronger (the coefficients of men become increasingly positive) So that the explained part becomes more negative could imply that the associated relationship of working within health care occupations for men on sick leave increases after 2019.

Chapter 6

Discussion

The descriptive statistics reveal an unequal distribution of men and women across various occupations. This disparity likely influences the average job strain experienced by each gender, potentially contributing to the observed gender gap in sick leave. Nonetheless, the results from the decomposition analysis indicate that differences in observed characteristics account for only a small portion of the overall gap in sick leave across all years.

From 2015 to 2021, the gender gap in sick leave has widened, as confirmed by the decomposition results. A significant portion of this gap can be traced back to the unexplained part and the intercept associated with female. Regression analysis performed on men and women separately indicates that women exhibit stronger year-fixed effects. This suggests that women may be disproportionately associated with unobservable factors not captured in the model.

Interestingly, the explained component of the gender gap has increased. It constitutes a larger portion of the total gap than one might anticipate, given some of the trends in selection patterns illustrated in Table 5.3. To gain a deeper understanding of the reasons behind this rise in the explained component, a comprehensive analysis of all observables in the model, as discussed under *developments in the explained component*, would be beneficial. I was only able to analyze this for three occupational groups. These occupational groups were selected based on findings form the descriptive statistics. A comparative analysis across additional groups would provide further insights into the dynamics at play.

As discussed in the literature review previous research have shown a link between workplace factors and women's health (STAMI, 2025). The results of the decomposition in this thesis indicate that men and women are unevenly distributed across occupations only contribute to a small portion in the overall gender gap in sick leave. Again, the occupational categories that are used to classify occupation in this paper are broad categories, and cannot fully be expected to account for occupation in the sense which is intended. As within one occupational category, men and women might be unevenly distributed across specific occupations. This might then also affect the workplace strains they are exposed to, and subsequently their associated sick leave.

As noted, Mastekaasa (2000), find that the association between children and sickness absence is weak, particularly for married people of both genders. The findings therefore provide little support for role overload/conflict theories in explaining sick leave. In this thesis, findings from the simple models employed to study the association of family (among other observable characteristics) indicate that there are stronger associations for women then men, when going from 0 to one child on sick leave, everything else equal. This might indicate that women take more leave when having small children, or experiences more health complications in relation to birth or pregnancy (with second child). This is more consistent with the findings of Angelov et al. (2020) and that mothers take a more dominant role in child care as in Mark et al. (2025). Nevertheless, the aspects of female reproduction and hormonal influence are yet largely unexplored in relation to women's sick leave, and would need to be explored further in order to fully understand this dynamic.

Chapter 7

Conclusion

In this paper, the general trends in sick leave across 31 different occupational categories from 2015-2021 have been examined. In addition, gender composition and disparities in sick leave have been explored within these occupational categories. With linear regression, the associated relationship between observable characteristics and sick leave have been assessed for men and women. Finally, I have conducted a decomposition of sick leave.

I find that if women "were as men", women's sick leave would be over 3 percent lower in all years from 2015-2021. I find that, the fact that men and women are employed in different occupations only very moderately can explain the difference in sick leave between men and women. Equivalently, differences in other observable characteristics such as age, education, number of children and partner status also do not provide an explaination why there is such a large sick leave gap between men and women. That men and women have different associated relationships between occupation, children, age and sick leave also have low contributions in explaining the gap. This signals the existence of other factors, potentially including differences in overall health, societal expectations, family responsibilities that particularly affect women and/or model limitations.

As noted, I evaluate the sick leave gap using men's associated relationship between occupation, children (ect.) and sick leave as the reference level. I evaluate this difference within every year from 2015-2021 and find that the sick leave gap increases. The majority of this gap remains unexplained in all years. However, at the same time, the fact that men and women are employed in different occupations and have differences in other observable characteristics explain slightly more of this gap. I suggest that this might be a consequence of men's relationships in observed characteristics and leave becoming stronger, when I assess the development in health care occupations. In plain words, all else being equal, men also take more leave in the later years of the sample than in 2015.

There are several reasons why it is crucial to keep investigating the sick leave gap, including understanding the underlying factors contributing to the disparity between men and women. Payments to sick leave are costly for the Norwegian welfare state. It is essential to understand what drives sick leave for men and women in order to implement relevant policy measures to lower these costs. In addition, understanding why sick leave is elevated for women is important for gender equality.

I acknowledge that the models I have used in this thesis have several limitations. However, they are designed for description, not identification. Unobserved factors may correlate both with gender and sick leave percentage in the linear specification in the Blinder-Oaxaca decomposition, which means that the magnitude and allocation of the explained and unexplained components are also not causal.

Future work could use finer occupational measures than the 31 categories that were assessed in this study. This would provide a more accurate description of how differences in occupation affect the sick leave gap. Moreover, it would be meaningful to gain insight in overall health and biological differences between men and women to fully understand the gender gap in sick leave.

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Chapter 8

Appendix

8.0.1 Balance

Number of unique observations	Number of individuals with 7 observations
3,264,231	1,283,363

Table 8.1: Balance

Year	Observations
2015	2,032,330
2016	2,312,799
2017	2,343,579
2018	2,381,222
2019	2,424,208
2020	2,454,135
2021	2,424,065

Table 8.2: Total Number of Observations Across Years

8.0.2 Occupational codes

Occupational code	Description
01	Positions in the military.
11	Elected politician, board member/leader of political organizations, chair/member (interest organizations).
12	Chief, director, leader, senior at city/district/division/county level (county doctor).
13	Director, chief, chairman, general manager, manager (private enterprise, primarily fewer than 10 employees).
21	Meteorologist, chemist, geologist, physicist, mathematician, programmer, IT/data consultant/responsible/leader. Architect, civil engineer (senior/system/over).
22	Biologist, biology, botany and zoology, doctor, dentist, veterinarian, specialty nurse, pharmacist.
23	Positions at university/college/high school.
24	Advisor, consultant (economics and social science, public administration), various advisors and consultants (public and private).
25	Auditor, business consultant, positions in HR, consultant/analyst (marketing/sales), legal professions, economist, sociologist, political scientist, historian, psychologist, author/publishing, artist, pastor.
31	Engineer (construction, machinery, chemistry, petroleum, IT, senior), technician/engineer (electrical power, petroleum), project manager/construction manager (electronics/construction), various photographer/sound technician, crew on ships, captain/pilot.
32	Engineer, agronomist, inspector, optician, occupational therapist, nurse, physiotherapist, social worker.
33	Teacher, lecturer, instructor, educator.
34	Broker/analyst/advisor/consultant (finance, insurance, real estate), salesperson/sales consultant, purchaser, consultant/advisor (bank), employee (marketing and advertising), auditor, economist, caseworker, police officer, social worker, graphic designer, sports coach, librarian.
41	Secretary, office worker, finance/accounting worker, warehouse and logistics worker, air/port/traffic/railway - leader/controller/assistant, mail carrier, librarian.
42	Service worker (debt collection, travel agency, rental), receptionist (hotel), switchboard operator.
51	Cook, waiter, barista, serving, child/school assistant/employee, environmental worker, healthcare assistant, caretaker, ambulance worker, hairdresser, cosmetologist, funeral consultant, janitor, security guard.
52	Salesperson, clerk, store employee.
61	Gardener, farmer (cereals, dairy, livestock), farm operation.
62	Forest worker, lumberjack.
63	Skilled worker (aquaculture and fish farming).
64	Skipper, fisherman.
71	Bricklayer, worker in concrete and groundwork, skilled worker (construction), plumber, chimney sweeper.

Continued on next page

Occupational code	Description
72	Welder, sheet metal worker, diver, blacksmith, aircraft/car/machine/industrial mechanic, electrician.
73	Maker (instruments, watches), silversmith, ceramicist, photographer.
74	Tailor, carpenter and furniture carpenter, butcher, bakery and confectionery.
81	Offshore worker in the oil/gas industry, skilled worker - wood/glazier
82	Production/operator - plastics, metals, ammunition, food industry.
83	Conductor, driver, crane operator, ship/boat mechanic/operator.
91	Cleaner, guard, kitchen assistant.
92	Helper (agriculture, forestry, aquaculture).
93	Helper, handyman (construction and building/warehouse/industry).

Table 8.3: Translated STYRK 98 Codes and Descriptions

8.0.3 Results

Year	2015	2016	2017	2018	2019	2020	2021
Total	5.45	5.31	5.40	5.36	5.40	5.67	5.90
Men	3.93	3.85	3.87	3.86	3.85	4.16	4.27
Women	7.12	6.90	7.08	7.01	7.11	7.37	7.74

Table 8.4: Annual average sick leave in Norway, 2015–2021

Occupation code	2015	2016	2017	2018	2019	2020	2021
01	1.9400	1.2200	1.3100	1.3100	1.3000	1.4300	1.5000
11	3.6700	3.2500	3.0900	3.1300	3.3200	3.3300	3.4300
12	3.2000	3.3400	3.3500	3.4700	3.5200	3.5700	3.5500
13	4.6800	4.6000	4.6800	4.7300	4.8100	5.2400	4.8300
21	2.5900	2.6500	2.7200	2.7500	2.7500	2.6700	2.8300
22	5.4400	3.5600	5.4900	5.6000	5.6100	6.0900	6.3500
23	4.2900	3.9900	4.2800	4.3800	4.3700	4.4400	4.6300
24	4.9100	4.9000	5.0000	4.9900	5.1300	4.9100	4.9600
25	3.7900	3.8600	3.9800	3.9000	3.9200	3.8600	3.9400
31	3.2700	3.3000	3.4000	3.3900	3.3000	3.3900	3.5700
32	7.7300	7.7000	7.7900	7.7900	8.0600	8.6400	9.0300
33	3.6000	6.1000	3.0500	3.3700	3.4200	2.4900	2.6300
34	4.8300	4.7100	4.8500	4.8400	4.9300	4.8600	4.9900
41	5.6900	5.5000	5.5800	5.5600	5.5500	5.7000	5.8300
42	5.3300	5.0400	5.1400	5.1900	5.2700	4.9500	5.4400
51	8.1400	7.6800	7.8200	7.7000	7.7800	8.8200	8.8300
52	5.0700	4.8700	5.9100	5.1200	5.8200	5.7400	5.8300
61	3.8700	3.4900	3.6500	3.9700	4.0000	4.1000	4.8200
62	3.3100	3.6400	3.6800	4.1000	3.2400	3.8500	3.7000
63	4.4900	4.6500	4.3400	4.2400	4.3400	4.6300	4.9300
71	4.2700	4.3100	4.1200	4.1600	4.2200	4.2200	4.2100
72	4.7000	4.6600	4.6600	4.5700	4.4800	5.0100	5.2400
73	4.3700	4.0700	4.2500	4.0400	4.1200	4.0700	4.2100
74	5.1900	4.7700	4.5100	4.4700	4.3200	4.7100	5.0200
81	4.7500	4.8800	4.9700	4.4900	4.6800	5.0100	5.5600
82	6.0100	5.7700	5.7100	5.3100	5.5200	5.8800	6.3500
83	6.5000	6.2600	5.9600	5.9000	5.8900	6.5400	6.5900
91	7.8000	7.1700	7.7200	6.9800	6.9200	7.1400	7.7100
92	5.0500	3.0600	3.7000	3.3600	4.0300	4.1700	4.3100
93	5.1600	4.7400	4.7500	4.5400	4.4900	5.0300	5.5100

Table 8.5: Development in average sick leave by occupation (2015–2021)

Occupation code	2015	2016	2017	2018	2019	2020	2021
01	2.2600	0.9400	0.5100	0.5600	0.4700	0.3800	0.3000
11	1.9000	1.4200	1.4700	1.3700	1.4200	1.5400	1.9000
12	2.2600	2.3000	2.2800	2.2600	2.3600	2.3000	2.5000
13	2.4200	2.5300	2.4400	2.2400	2.4600	2.7400	2.7400
21	2.2600	2.4000	2.5400	2.5900	2.3800	2.2000	2.4600
22	3.6500	3.6500	5.5500	3.8600	3.9400	3.9000	4.4000
23	2.7200	2.6000	2.8000	2.8600	2.9800	2.9600	3.1400
24	2.9300	3.0400	3.1600	3.1900	3.2400	3.1000	3.1200
25	2.6400	2.8000	2.8700	2.7300	2.7700	2.6500	2.8800
31	2.0200	1.9800	2.2500	2.1600	2.1400	1.8500	2.0200
32	3.5000	3.4600	3.6000	3.4700	3.4800	3.5600	4.3600
33	3.2300	3.4600	3.4700	3.5000	3.7000	3.9000	4.5000
34	3.2900	3.1500	3.2900	3.2000	3.3000	3.1500	3.3700
41	1.6600	1.5500	1.9100	1.7400	1.7000	1.4200	1.4200
42	2.7000	2.0800	2.5000	2.6800	2.5200	1.8700	2.7300
51	3.8000	3.7100	3.7600	3.6300	3.7700	3.9200	4.0500
52	2.6300	2.4300	2.6600	2.6800	2.6600	2.7100	3.0100
61	2.0500	1.5400	1.6300	1.8600	2.0200	1.5800	2.0700
62	4.8000	4.0500	0.7000	0.3100	1.5400	−0.7600	2.6300
63	2.8100	2.1000	2.3100	1.2000	1.7400	1.5600	2.1700
64	−0.8900	−2.9100	−1.9900	−3.6100	−4.0700	−2.7600	−3.4300
71	4.3500	3.9100	3.6000	3.6900	4.0000	3.8300	3.4800
72	4.0700	3.8300	3.8300	3.6500	3.7000	3.4600	3.8800
73	1.8300	2.0900	2.0100	2.4700	2.3100	2.0600	1.7800
74	2.1100	1.7800	2.5200	1.7800	1.5500	2.3000	2.6000
81	2.9900	2.1000	2.6200	2.2800	2.2600	2.0700	2.6000
82	3.0200	2.9300	2.9900	2.8500	2.9000	2.5300	3.0600
83	3.5000	3.5900	4.2000	3.8300	4.0300	3.6200	3.9000
91	2.6700	2.4200	2.5400	2.3500	2.6200	2.4000	2.4400
92	0.1600	0.7400	1.4100	2.1300	0.4900	0.0900	0.2500
93	2.3300	1.7900	2.1300	1.6900	1.4300	1.3100	1.4000

Table 8.6: Gender gap in sick leave, difference in average annual sick leave by occupation (2015–2021)

Variable	Men: Estimate	Men: Std. Error	Women: Estimate	Women: Std. Error
occ = 01	−1.0080	0.0291	−3.8020	0.0688
occ = 11	−0.6813	0.0998	−1.7340	0.1490
occ = 12	−0.9811	0.0230	−1.3800	0.0349
occ = 13	0.1434	0.0392	−0.5044	0.0658
occ = 21	−0.6556	0.0228	−0.8713	0.0441
occ = 22	0.5986	0.0474	1.4280	0.0450
occ = 23	0.3031	0.0373	0.5476	0.0469
occ = 24	0.0382	0.0400	0.1756	0.0440
occ = 25	−0.3777	0.0299	−0.5519	0.0390
occ = 31	−0.1235	0.0242	−0.0731	0.0339
occ = 32	2.4160	0.0615	3.1440	0.0380
occ = 33	1.1860	0.0403	1.7400	0.0354
occ = 41	1.0900	0.0334	−0.7986	0.0371
occ = 42	0.4927	0.0675	−0.4896	0.0686
occ = 51	2.0690	0.0281	2.1730	0.0288
occ = 52	0.5423	0.0285	−0.2531	0.0331
occ = 61	0.5393	0.0976	−0.9711	0.1467
occ = 62	0.2293	0.1845	−1.5970	1.3700
occ = 63	0.9768	0.0980	−0.3012	0.2909
occ = 64	1.5070	0.3770	−3.0350	1.2640
occ = 71	2.1010	0.0309	2.0620	0.1794
occ = 72	1.4370	0.0285	1.5510	0.1494
occ =73	−0.2319	0.0990	−1.7740	0.1503
occ = 74	1.6820	0.0594	−0.2556	0.1319
occ = 81	1.0810	0.0428	0.0982	0.1348
occ = 82	1.3580	0.0428	0.6978	0.0776
occ = 83	2.1540	0.0353	2.6340	0.1600
occ = 91	2.1060	0.0490	0.8942	0.0454
occ = 92	1.4050	0.2671	−1.3240	0.2994
occ = 93	1.7850	0.0525	0.3006	0.1445
Year FE	Yes (ref.= 2015)			
Std. errors	Clustered at person level			
Observations	15,274,895			
R^2	0.02277			
Adjusted R^2	0.02276			

Notes: Entries are estimates with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.001, 0.01, and 0.05 levels, respectively.

Table 8.7: OLS regression results for occupation on sick leave for men and women.

Variable	Explained contribution	SE	Unexplained contribution	SE
(Intercept)	0.0000	0.0000	−3.2234	0.0993
A2 (32–44)	−0.0013	0.0116	−0.2489	0.0169
A3 (44–56)	−0.0045	0.0011	0.0314	0.0160
A4 (56–67)	0.0092	0.0011	0.1084	0.0131
E2 (completed high school)	−0.1533	0.0087	−0.1882	0.0340
E3 (completed lower university degree)	0.0738	0.0201	0.0873	0.0101
E4 (completed higher university degree)	0.0403	0.0109	0.0298	0.0193
One child	−0.0278	0.0013	−0.2290	0.0089
Two child	−0.0040	0.0006	−0.0680	0.0096
Three child	−0.0003	0.0001	−0.0090	0.0056
Married/Partnered	0.0034	0.0004	0.1730	0.0320
occ = 01	−0.0450	0.0013	0.0479	0.0020
occ = 11	−0.0006	0.0001	0.0018	0.0007
occ = 12	−0.0395	0.0018	0.0414	0.0069
occ = 13	−0.0077	0.0021	0.0164	0.0047
occ = 21	−0.0480	0.0043	0.0275	0.0075
occ = 22	−0.0478	0.0025	−0.0132	0.0017
occ = 23	−0.0053	0.0007	−0.0029	0.0025
occ = 24	0.0024	0.0016	0.0020	0.0022
occ = 25	0.0097	0.0012	0.0080	0.0034
occ = 31	−0.0522	0.0071	0.0641	0.0095
occ = 32	−0.2470	0.0005	−0.0157	0.0019
occ = 33	−0.1512	0.0043	−0.0240	0.0025
occ = 41	0.0072	0.0008	0.0932	0.0050
occ = 42	0.0010	0.0006	0.0039	0.0012
occ = 51	−0.4295	0.0098	−0.0357	0.0082
occ = 52	−0.0068	0.0020	0.0260	0.0051
occ = 61	−0.0005	0.0003	0.0038	0.0013
occ = 62	0.0000	0.0021	0.0038	0.0020
occ = 63	0.0008	0.0015	0.0038	0.0021
occ = 64	−0.0005	0.0006	0.0015	0.0007
occ = 71	0.1615	0.0217	0.0112	0.0223
occ = 72	0.1667	0.0241	−0.0033	0.0261
occ = 73	−0.0016	0.0002	0.0048	0.0009
occ = 74	−0.0009	0.0023	0.0232	0.0035
occ = 81	0.0178	0.0063	0.0166	0.0075
occ = 82	0.0194	0.0023	0.0108	0.0042
occ = 83	−0.1555	0.0015	−0.0357	0.0165
occ = 91	−0.0240	0.0024	0.0243	0.0028
occ = 92	−0.0002	0.0000	0.0016	0.0040
occ = 93	−0.0011	0.0039	0.0370	0.0026

Notes: Coefficients are percentage points. Explained = $(\bar{X}_A - \bar{X}_B)\beta_A$. Unexplained = $(\alpha_A - \alpha_B) + \bar{X}_B(\beta_A - \beta_B)$. A=Men, B=Women. Standard errors (SE) from the Oaxaca output.

Table 8.8: Twofold Blinder–Oaxaca decomposition, 2021