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# Master Thesis

# at BI Norwegian Business School

by Sara Skjelbred and Ida Johansen Andreassen

# - The Gender Pay Gap in Leadership Positions in Norway -

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This master thesis is the final component of the study programme MSc in Business with a major in Economics at BI Norwegian Business School. Throughout the research process, the investigation has proven captivating yet challenging. Valuable insight and a comprehensive understanding of the nature of the gender pay gap in leadership positions have been acquired. This research intends to stimulate further understanding of wage disparities and serve as an inspiration for future research.

We extend our gratitude to our supervisor Ingrid Huitfeldt for the opportunity of participating to her project #326391: "The Gender Pay Gap: Firms, Children, and Unpaid Work", granted by the Research Council of Norway. Huitfeldt and the project team have offered support and guidance throughout this academic journey. Their expertise, encouragement and valuable feedback have played a crucial role in shaping the quality and possible impact of this thesis.

Abstract

Our hypothesis posits that the magnitude of the gender pay gap may be exaggerated because such representations typically fail to account for individual and group characteristics[1]. The escalating wage disparity with advancing age and experience implies that the most substantial gender pay gaps are likely to occur in leadership roles.

We use employee-employer data to compare women and men in the same firm and occupation. We do not intend to establish any causal relationship between gender and wage. Instead, our findings indicate a correlation between these variables. Upon controlling for individual characteristics, the gender pay gap is most pronounced in the private sector at 32.9%, compared to 21.6% in the public sector. Introducing firm and occupational fixed effects reduces the gap to 13.5% and 7.7% in the private and public sectors. Thus, firm and occupational traits explain 59.0% of the wage disparity in the private sector and 64.4% in the public sector[2]. A significant part of the remaining annual wage variance is linked to contracted hourly wages rather than contracted hours. Upon accounting for individual characteristics, the annual wage difference among executives is 27.4% in the private sector and 16.6% in the public sector. The gender pay gap in leadership roles is smaller than among all workers, countering prior statistical reports. Our research also finds a slight decrease in the gender pay gap between 2015 and 2020.

Our results substantiate the fact that there is a gender pay gap but also amplify that a large part of it is due to firm and occupational characteristics. While it is well-documented that more women work part-time, this discrepancy becomes minimal once group characteristics are considered. Simultaneously, our findings indicate that the widest gender pay gap is observed among all workers rather than specifically among leadership roles. Compared to broader statistics, this wage discrepancy could be attributed to our modifications and controls for individual and group characteristics.

[1] In our thesis, individual characteristics include age and education, while group characteristics include firms and occupations.
[2] Refer to section 1.0 Introduction – calculates the contribution of firm and occupational characteristics to wage disparity.

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## 1.0 Introduction

The gender pay gap, the earnings difference between men and women, was at an average of 14.1% across Europe in 2020 among employees. Although Norway is one of the wealthiest countries in the world in terms of GDP, it ranked 16$^{th}$, with women earning 13.4% less than men in the same year (Eurostat Statistics Explained, 2022). In 2021, Norwegian women made up 87.9% of men's average monthly wages (Statistics Norway, 2022a), which represents a difference of 12.1%. The gender pay gap becomes evident as individuals enter the labour market and continue to widen by age and work experience (Schøne, 2004, p.8)[3]. The monthly pay gap among leaders in all sectors and industries was 17.7% in 2021 (Statistics Norway, 2022b). Previous studies show significant overall gender pay gaps but no differentiation between managers, leading to the possible weakness of comparing top managers to line managers. Consequently, we assume that the gender pay gap amongst leaders may be exaggerated due to comparisons across dissimilar hierarchical positions and different individual characteristics, such as age and education. To investigate this hypothesis, we must analyse on the same premises which form the foundation for our research question: *"Are women's wages lower than men's wages in leadership positions, if all else is equal? If so, what mechanisms may contribute to the gender differences in the labour market?"*

To probe our research question, it is essential to account for individual and group characteristics. Consequently, we adjust for variables like age and education and integrate fixed effects pertaining to firm and occupation[4]. Three key challenges underpin the answers to these questions. First, the acquisition of employee-employer data, which links workers' identity numbers to their respective firms. This linkage allows wages from the firms to be connected to each individual and their characteristics. Second, the gender difference in wages may be associated with unobservable factors such as productivity and preferences. Third, the classification of leaders is crucial to compare on the same basis. Our thesis addresses these challenges using employee-employer data from Statistics Norway, thoroughly discussing emerging weaknesses and identifying areas for future

[3] Refer to Appendix A - section A1. When does the gender pay gap occur?
[4] In our thesis, individual characteristics include age and education, while group characteristics include firms and occupations.

research. Our dataset encompasses observations from the entire population in the period 2015 to 2020 in Norway. We cannot fully account for all unobservable elements, but employing fixed effects for firm and occupation allows us to identify some of these variables. Using fixed effects helps eliminate time-invariant unobserved characteristics within firms and occupations. These may be wage negotiation skills, job responsibilities or work culture, among others. To navigate the challenge of defining leaders, we adopt two different classification systems[5].

The key findings substantiate previous research to a large extent. We observe that the largest gender pay gap among all workers is in the private sector, with 32.9% compared to 21.6% in the public sector, after controlling for individual characteristics. When accounting for the time-constant differences in firms and occupations through fixed effects, the gender pay gap decreases to 13.5% in the private sector and 7.7% in the public sector. Hence, firm and occupational characteristics account for 59.0% $\left(\frac{(32.9\%-13.5\%)}{32.9\%}\right)$ of the wage discrepancy in the private sector and 64.4% $\left(\frac{(21.6\%-7.7\%)}{21.6\%}\right)$ in the public sector. A substantial portion of the remaining yearly wage variation is not attributed to significant disparities in contracted hours but rather to contracted hourly wages. It is previously highlighted[6] that more women work part-time than men, but there is only a slight difference when having the same characteristics. The yearly wage difference among executives is 27.4% in the private sector and 16.6% in the public sector when accounting for individual characteristics. Compared to all workers, we find that the smallest gender pay gap is among leadership positions. This contradicts the statistics and previous articles, which suggest the opposite pattern. This may be due to the fact that the statistics include employed people, regardless of industry affiliation and working hours (Statistics Norway, 2022a), while we do several modifications and control for individual characteristics. Our findings also reveal a marginal reduction in the gender pay gap from 2015 to 2020.

Our results reinforce the ongoing presence of the global phenomenon, the 'Glass Ceiling'[7], emphasising the importance of policies aimed at shattering the invisible

[5] Refer to section 3.2.1. workers sample, which explains how leaders are defined.
[6] Refer to Appendix A – section A1. Theoretical background
[7] Refer to Appendix A - section A2. Females in leadership positions.

barrier (Matsa & Miller, 2010). Albrecht et al. (2001) found evidence of a glass ceiling hindering women from reaching the top of the labour market. They also found that the gender pay gap was the highest at the top of the wage distribution. The article is based on Swedish data from 1998. Newer research substantiates the same findings. Huitfeldt et al. (2022) identify a strong connection between internal hierarchy and individual wages. They found that average log wages increase almost linearly with the hierarchy level. Due to this, we assumed that the highest gender pay gap would be among leaders. Contrary, our results find the opposite.

Our findings also enrich the limited literature on the gender pay gap on the same premises. Penner et al.'s (2022) ground-breaking article received global recognition for its contributions, underlining the significance of gender pay gap research. They estimate the gap for individuals aged 30-55 in 15 countries, including Norway. They find evidence that occupational and firm characteristics are essential in explaining gender pay differences. We use their article as a starting point for our research by reproducing their models. One of the authors, Are Skeie Hermansen, provided insights and information[8], which gave a close approximation of their results, with minor discrepancies due to slight variations in the data. Hence, the models established were used as a fundament for our analysis. In contrast to Penner et al.'s (2022) article, which employed a fixed effect of full-time versus part-time status, our model estimates the impact of contracted hours and contracted hourly wage. This enables us to avoid potential biases associated with assuming that wage differences are attributable to contracted hours. We also widened the data selection and included the whole labour force in Norway. Further, we extend by incorporating leaders. We hope to enrich Penner et al.'s (2022) recognised results through our research.

## 2.0 Research Design

The goal is to estimate the gender pay gap in leadership positions controlling for individual and group characteristics. This can be formulated by the following regression model:

[8] Due to certain ambiguities, communication was established with the author, Are Skeie Hermansen, professor of sociology at the University of Oslo, to seek clarification.

$$y_i = \alpha + \delta female + \beta X_i + \varepsilon_i$$

where $y_i$ denotes the outcome for the individual $i$. The dependent variable includes the natural logarithm of (1) yearly wage, (2) contracted hours and (3) contracted hourly wage. Changing the variables to natural logarithms is motivated by examining growth rates rather than absolute levels, which is often more insightful and meaningful for comparative purposes. Considering multiple dependent variables gives a more comprehensive analysis to capture different aspects of wage disparity between genders. Incorporating several outcomes enables us to distinguish whether contracted hours explain differences in yearly wages. The intercept is represented by $\alpha$. Gender differences are captured by the dummy variable $female$, which is 1 when the individual is a woman and 0 otherwise. The coefficient of interest related to the variable is $\delta$. The vector of the independent variables age, age$^2$ and education ($X_i$) is related to the coefficient $\beta$. Age$^2$ is included in the data to account for potential non-linear relationships between age and the outcome. This enables the model to account for potential variations that may arise as individuals age. Lastly, $\varepsilon_i$ denotes the residual, representing all the variables omitted from the regression model. The error term also includes the unobservable variables that can explain the outcome.

To identify and understand the gender pay gap, we use the OLS estimator to estimate the baseline model (1), which is the model described above. Additionally, the second model (2) analyses within-firm differences. It is the baseline model plus the fixed effect of firms ($\lambda_f$). This is advanced to account for time-invariant distinctions across various companies that could potentially influence the gender pay gap. Firms differ in various aspects, such as their size, industry, culture, and human resource. These characteristics can impact wage structures and gender pay disparities. The third model (3) analyses the within-occupation differences. It is the baseline model, plus the fixed effect of occupational code ($\gamma_o$), which controls for differences across professions. Different occupations have distinct characteristics that can impact wages, such as skills, requirements, experience levels and responsibilities. The fourth model (4) is the baseline model with the inclusion of both the fixed effect of firm and occupation ($\lambda_f + \gamma_o$) to account for variations in wage at both the firm and occupational levels. Each model estimates all the years combined (2015 to 2020) with different samples for sector and hierarchical ranks[9]. Afterwards, we explore in greater depth by looking into the development year by year.

The goal is to estimate a regression model that is the best-fitting line to minimise the discrepancy between the observed data points and the predicted values. The ordinary least square (OLS) estimator is a widely used statistical method for estimating the parameters of a linear regression model. It seeks to find the values of the coefficients that minimise the sum of the squared residuals to achieve this goal (Wooldridge, 2019, p. 27). Our OLS estimates will not reflect the causal effect of gender on output but instead a correlation between the dependent- and independent variables[10].

## 3.0 Data and Sample

### 3.1 Data

The analysis is based on employee-employer data provided and obtained by Statistics Norway. A detailed overview of the variables used can be found in Appendix B.

The employee data is based on the national identity number sourced from "Sentralkontoret for folkeregistrering" (Statistics Norway, n.d.a). From this source, gender and age can be extracted. Education information is sourced from the "Nasjonal utdanningsdatabase (NUDB)". This dataset encompasses details regarding an individual's ongoing education and their highest attained level of education (Statistics Norway, 2020a).

The employer data is mainly sourced from "a-ordningen", which collects information from various authoritative databases (Statistics Norway, 2020b). The data is submitted every month from the companies. This makes it possible to connect an individual's identity number to their respective firm. This registry contains comprehensive information about wage earners. Firms and establishments are also included in the database, each with its unique organisation number. The establishments provide a higher level of precision, as two individuals can be employed by the same firm but have distinct establishments based on their

[9] Refer to section 3.2 Sample
[10] Refer to section 4.0 Assessing OLS-estimator

location or industry (Statistics Norway, 2014). We use establishment in our data but refer to it as firm, as this term is more commonly used in the vernacular. Finally, the registry includes data on occupational codes. This is based on classification from Statistic Norway. Choosing STYRK-98 rather than STYRK-08 is due to compatibility with existing data and previous studies based on this classification system[11]. Furthermore, the more detailed 7-digit code is employed, as our investigation is limited to Norway, and that we do not need to account for cross-country comparisons.

The data used in this research span from 2015 to 2020, with a yearly frequency. The limitation in 2015 is due to a modification in the register employed by Statistics Norway for wage collection (Statistics Norway, 2020c). Additionally, access to the education variable after 2020 was not available. Hence, the dataset is restricted from 2015 to 2020. In this period, there were monthly observations of wages, which have been aggregated to yearly frequency. This removes any seasonal effects and makes it more manageable to work with in the statistical software STATA. After compiling the data, the selection contains 12 395 429 observations.

## 3.2 Sample

### *3.2.1 Workers sample*

Our sample includes individuals within the age range of 15 to 74, representing the Norwegian labour force. We exclude individuals' missing an establishment or occupation and exclusively use data exceeding the threshold of 1G. The threshold of 1G is the basic amount in the national insurance scheme, serving as fundamental for calculating all benefits within the scheme. Including this limitation ensures that the individuals in the sample are affiliated with the labour market. This yields a referral sample of 2 793 581 individuals, referred to as all workers in our analysis.

Secondly, we incorporate leaders in two ways: as executives and CEOs. Executives are categorised by occupation. The Norwegian Tax Administration defines executives by occupational codes starting with the number 1. Managers that use most of their time in joint production or have the responsibility for few

[11] Refer to Appendix B – section B1. Fundamental variables for measuring the gender pay gap

employees should not be categorised with occupational code starting with number 1 (Skatteetaten, 2020). Jørgen Sandberg wrote his master's thesis about the development of executive wages in Norway (Sandberg, 2021, p.18). His empirical study defined executives using STYRK-08, specifically category one within the 4-digit code. This substantiates the decision to use occupational code and category one. When controlling the upgrade from STYRK-98 to STYRK-08, it is observed that most occupational codes exist in both systems, albeit with different categorisations within each subgroup. Table 1 shows the old and updated classifications of leaders, as seen below.

**Table 1.** Classification of leaders in STYRK-98/STYRK-08

| Code | STYRK-98 | STYRK-08 |
|---|---|---|
| 1XXX | Administrative leaders and politicians | Leaders |
| 11XX | Politicians and top executives in public administration and interest organisations | Politicians and top executives |
| 12XX | Leaders in large and medium-sized companies | Administrative and commercial leaders |
| 13XX | Leaders in small companies | Managers of units for goods production and service provision |
| 14XX | | Hospitality, retail and other services managers. |

Notes: The standard occupation categorisation STYRK-98 and the upgraded STYRK-08 by Statistics Norway are commonly used to separate different occupations in Norway. Both are based on the international standard from the International Standard Classification of Occupation (ISCO).

Some may argue that certain codes, such as board members and politicians, should be excluded. Additionally, there might be instances where individuals are classified as managers, despite their contribution to joint production. The process of classification is inherently time-consuming and should strive for objectivity.

Hence, the executive variable is based on the definition from The Norwegian Tax Administration and the previously mentioned thesis. The sample consists of 337 205 executives in total.

CEO is determined using “Enhetsregisteret”, a register that assigns distinct codes to various job positions. In this context, DAGL classifies as CEO (Statistics Norway, 2019). It is possible to define CEOs based on either STYRK-98 or STYRK-08 by using categories 12 and 13. However, this approach necessitates a manual examination of the occupational codes to differentiate CEOs from top management and board members. Therefore, “Enhetshetsregisteret” is chosen as the defining criterion for CEOs. There is a total of 135 293 CEOs in the sample.

The categorisation of leaders into executives and CEOs imposes limitations on the models we can employ in our investigation of leadership. Since executives are determined based on occupational code, including a fixed effect of occupation would lead to perfect multicollinearity. Similarly, when considering CEOs, it is important to note that each firm has only one CEO at a time (either female or male). Including the fixed effect of the firms would limit the results to only those firms that experienced changes from female to male CEO or vice versa during the research years. Therefore, we only incorporate the baseline model when we compare all workers to executives and CEOs. The second model with a fixed effect of firms is used to compare all workers to executives.

### *3.2.1 Sector sample*

The starting point was to investigate both sectors combined and then the public sector and private sector separately. There were 1 237 685 people in the public sector, while 1 772 524 were in the private sector. Previous research suggests that women are overrepresented in the public sector, while more men are in the private sector (Statistics Norway, n.d.b.). The latter also has the highest-paid jobs, with men filling the top positions (Fløtre & Tuv, 2022). This substantiates that we examine the results related to the private sector in greater depth.

## 3.3 Descriptive statistics

The dataset consists of 2 793 581 people in total. Of those are, 47% females and 52% men. Table 2 highlights the number and distribution of employers for all workers, executives and CEOs based on sector. Our data selection substantiates that there are more women in the public sector than in the private sector and more men than women in the private sector. The selection contains the same patterns as previous research[12], implying that the data is a good foundation for further investigating the gender pay gap.

**Table 2**. Number of people in data selection based on sector

| | Total num. | Women | Men |
|---|---|---|---|
| *All workers* | | | |
| Both sectors | 2 793 581 (100%) | 1 316 132 (47%) | 1 477 449 (53%) |
| Public sector | 1 237 685 (100%) | 806 285 (65%) | 431 400 (35%) |
| Private sector | 1 772 524 (100%) | 622 757 (35%) | 1 149 767 (65%) |
| *Executives* | | | |
| Both sectors | 337 205 (100%) | 124 378 (37%) | 212 827 (63%) |
| Public sector | 101 419 (100%) | 55 351 (55%) | 46 068 (45%) |
| Private sector | 242 665 (100%) | 71 668 (30%) | 170 997 (70%) |
| *CEOs* | | | |
| Both sectors | 135 293 (100%) | 31 570 (23%) | 103 725 (77%) |
| Public sector | 12 809 (100%) | 5 290 (41%) | 7 519 (59%) |
| Private sector | 123 212 (100%) | 26 477 (21%) | 96 735 (79%) |

Notes: The numbers refer to the maximum in the period 2015 to 2020. They may not add up due to mobility across sectors and firms during the period.

Our sample comprises a total of 265 794 firms and 6171 occupational codes. The proportion of private and public firms fluctuates based on the time of measurement due to mobility during the period[13]. The ample number of firms and occupations underscores the diverse combination of group characteristics, potentially elucidating the gender pay gap. We have integrated fixed effects into our analysis to accommodate these group-specific attributes[14].

[12] Refer to Appendix A - section A1. When does the gender pay gap occur?
[13] Refer to Appendix C – Table C3 showing the number of firms and occupations in the data selection based on sector.
[14] Refer to Appendix B – Section B3. Managing group-specific differences.

## 4.0 Assessing OLS Estimator

The phrase "correlation does not imply causality" is widely used in statistics. In the subsequent section, we expound upon its connection to the ordinary least squares (OLS) estimator and its relevance to our research. Furthermore, we accentuate the underlying assumptions for employing the OLS estimator.

### 4.1 Correlation vs causality

The OLS estimator can identify the relationship (correlation) between variables but does not establish the direction of causality. Consequently, when estimating a regression model, the cause-and-effect relationship between the variables remains undetermined (Price et al., 2015). Thus, it is not possible to conclude that gender is the cause of wage disparities. However, examining the presence of a correlation between the variables is feasible.

### 4.2 Efficiency of OLS: Best linear unbiased Estimator (BLUE)

The OLS estimator derives from the Gauss-Markov theorem, which states that under certain assumptions, the OLS is the best linear unbiased estimator (BLUE). This means the smallest variance among all linear unbiased estimators and that it is more likely to give an estimate close to the actual value than any other linear unbiased estimator (Wooldridge, 2019, p. 118).

Jeffrey Wooldridge (2019) presents five assumptions in his book: (1) Linear in parameters[15], (2) Random sampling[16], (3) No perfect collinearity[17], (4) Zero conditional mean and (5) Homoscedasticity. If the zero conditional mean assumption (4) fails, then OLS will be biased, so the Gauss-Markov theorem fails. In the presence of heteroskedasticity, failure of assumption (5), OLS no longer has the smallest variance among linear unbiased estimators (Wooldridge, 2019, p. 119). Therefore, these are the two assumptions that will be discussed further.

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[15] Perfect linearity assumption is flexible and allows variables to be transformed or manipulated arbitrarily while maintaining linearity (Wooldridge, 2019, p. 103). This allows for capturing the non-linear relationship of age ($age^2$) and incorporating logarithms of the dependent variables.

[16] Random sampling implies that the observations should be independent. Autocorrelation is common in time series data and thus violates the independence assumption (Wooldridge, 2019, p. 103). This is accounted for by employing robust standard errors.

[17] Perfect multicollinearity is rarely a practical problem, and the assumption does allow the independent variables to be correlated, just not perfectly correlated (Wooldridge, 2019, pp. 103-104). STATA also omits variables to account for multicollinearity problems.

*4.2.1 Zero conditional mean*

The zero conditional mean assumption signifies that the expectation of the error term must be equal to zero. In other words, the average estimation error must be zero for different combinations of the independent variables (Wooldridge, 2019, p. 105).

$$E(u|x_1, x_2, \dots, x_k) = 0$$

This assumption is valid as long as the regression model includes an intercept (Wooldridge, 2019, p. 108).

*4.2.2 Homoscedasticity*

Homoscedasticity means that the variance of the residuals is constant and finite for all observations (Wooldridge, 2019, p. 111).

$$Var(u|x_1, x_2, \dots, x_k) = \sigma^2$$

If homoscedasticity is not satisfied, there is heteroscedasticity in the error term. The error term is often heteroscedastic in empirical studies, leading to biased estimation of the dependent variable. We cluster the observations in STATA to account for heteroscedasticity.

## 5.0 Result on the Gender Pay Gap

This section addresses the first part of our research question: "Are women's wages lower than men's wages in leadership positions, if all else is equal?". Moreover, potential weaknesses and improvements will be discussed in section 6. While only the key finding of our analysis will be elaborated upon herein, the rest of the results are available in Appendix C.

### 5.1 Main results

*5.1.1 Firm- and occupation characteristics account for 65.4% of the pay gap*

We first investigated all workers and found that the gender pay gap is present in the data selection. Table 3 presents estimates of the coefficient female for outcomes $y_i = Log\ of\ yearly\ wage,$ $\log of\ contracted\ hours$ & $\log of\ contracted\ hourly\ wage$ for all workers based on sector. Figure 1 plots

the coefficient of being a female for the gender pay gaps for all workers based on sector.[18] The wage difference is 31.3% in both sectors in baseline (model 1) and 10.8% after controlling for fixed effects of firm and occupation (model 4).
The largest pay gap is in the private sector, with 32.9% in model 1 and 13.5% in model 4. Comparing it to the public sector, there is a gender pay gap of 21.6% in model 1 and 7.7% in model 4.

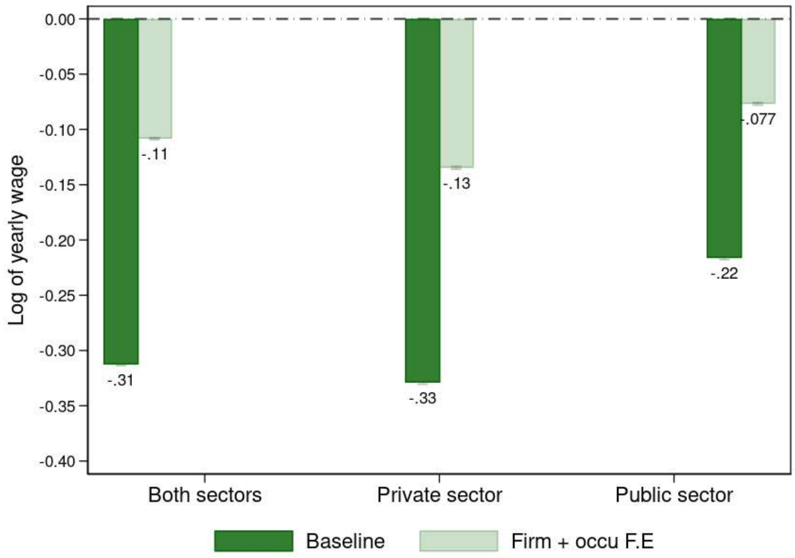


**Figure 1.** Gender wage differences for all workers based on sectors

Notes: The figure plots the coefficient of being a female for the outcome $y_i = \log of\ yearly\ wage$ in the years 2015 to 2020 combined. The "Baseline" (model 1) controls for age, age$^2$ and education, while the "Firm + occu F.E" (model 4) includes the fixed effect of firm and occupation.

Further, we are looking into the private sector. Figure 2 plots the coefficient of being a female for the gender pay gaps for all workers in the private sector[19]. Table 3 and Figure 2 show that the gender pay gap in the private sector reduces when accounting for time-invariant distinctions across various firms and occupations. When controlling for individual characteristics, the wage difference is 32.9% (model 1). When adjusting for the fixed effect of the firm, it reduces to 21.2% (model 2). When adjusting for the fixed effect of occupation, it drops to 15.9% (model 3). Lastly, when including both the fixed effect of firm and occupation, it reduces to 13.5% (model 4).

[18] Refer to Appendix C - Figure Ca plots the coefficient of being a female for all workers based on the sector for all the dependent variables (model 1 and model 4).
[19] Refer to Appendix C - Figure Cb plots the coefficient of being a female for all workers based on the sector for all the dependent variables (model 1, model 2, model 3 and model 4).

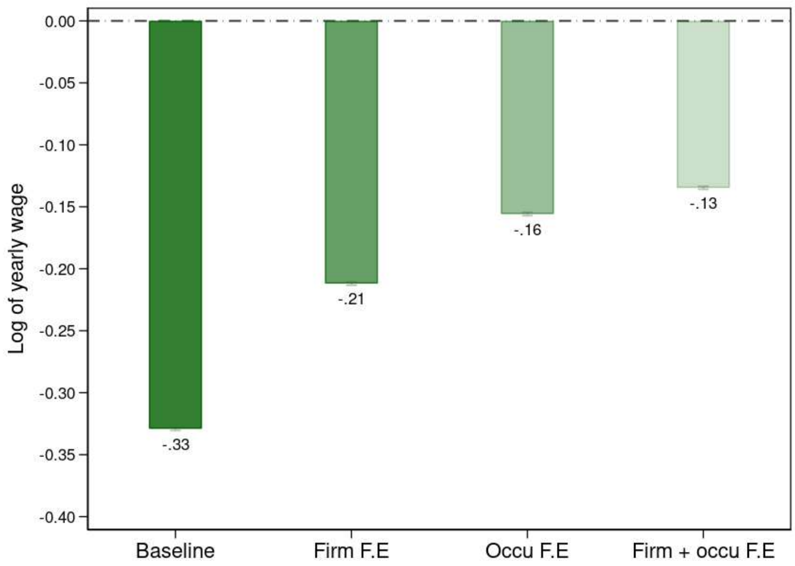


**Figure 2**. Gender wage difference for all workers in the private sector

Notes: The figure plots the coefficient of being a female for the outcome $y_i = \log of\ yearly\ wage$ in the years 2015 to 2020 combined. The "Baseline" (model 1) controls for age, age$^2$ and education. The "Firm F.E" (model 2) adds the fixed effect of firm to model 1. In the "Occu F.E" (model 3), the fixed effect of occupation is added to model 1. The "Firm + occu F.E" (model 4) includes the fixed effect of both firm and occupation to model 1.

Drawing from Table 3 and using the formula $\frac{(model\ 1 - model\ 4)}{model\ 4}$, it is evident that firm- and occupation characteristics account for 65.5% $\left(\frac{(31.3\% - 10.8\%)}{31.3\%}\right)$ of the gender wage gap in both sectors: 59.0% in the private sector $\left(\frac{(32.9\% - 13.5\%)}{32.9\%}\right)$ and 64.4% $\left(\frac{(21.6\% - 7.7\%)}{21.6\%}\right)$ in the public sector. This substantiates that group characteristics contribute to explaining the gender wage gap. When women and men select similar paths in terms of firm and occupation, it seems like a large part of the gender wage gap diminishes. The remaining wage disparity is explored in the context of differences in contracted hours and hourly wages.

### *5.1.2 Minimal impact of contracted hours on the remaining pay gap*

Table 3 reveals that the yearly wage gap is a cumulative function of the disparities in contracted hours and contracted hourly wage. To illustrate this, women and men employed in the same private firm, sharing the same occupational code, exhibit negligible differences in contracted hours (-2.2%). However, their contracted hourly wages significantly diverge (-11.3%). Consequently, this yields a remaining yearly wage gap of 13.5% (2.2%+11.3%) in the private sector.

Figure 3 presents the coefficient associated with being a female for both contracted working hours and hourly wage across sectors for all workers. Upon inclusion of firm and occupation fixed effects, The difference in contracted hours is comparable in both sectors, registering 2.2% in the private sector and 2.7% in the public sector. The disparity in contracted hourly wage, however, exhibits greater variation. After accounting for group characteristics, the contracted hourly wage gap stands at 11.2% in the private sector and 4.9% in the public sector.

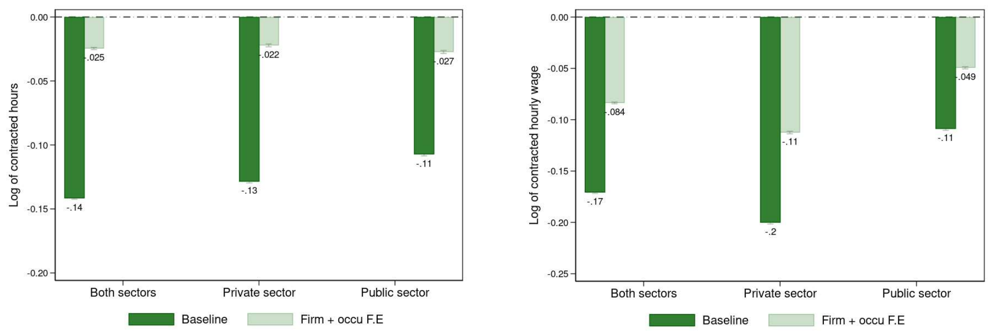


**Figure 3.** Gender difference in contracted working hours and contracted hourly wage based on sectors

Notes: The figure plots the coefficient of being a female for the outcome $y_i = \log of\ contracted\ hours$ & $\log of\ contracted\ hourly\ wage$ in the years 2015 to 2020 combined. The "Baseline" (model 1) controls for age, age$^2$ and education, while the "Firm + occu F.E" (model 4) includes the fixed effect of firm and occupation

Drawing from Table 3 and using the formula $\frac{(model\ 1 - model\ 4)}{model\ 4}$, it is evident that firm- and occupation characteristics account for 82.4% $\left(\frac{(14.2\% - 2.5\%)}{14.2\%}\right)$ of the variance in contracted hours in both sectors. In more detail, these characteristics explain 74.8% $\left(\frac{(10.7\% - 2.7\%)}{10.7\%}\right)$ in the public sector and 82.9% in the private sector $\left(\frac{(12.9\% - 2.2\%)}{12.9\%}\right)$. Similarly, these characteristics account for 50.9% $\left(\frac{(17.1\% - 8.4\%)}{17.1\%}\right)$ of discrepancies in contracted hourly wage in both sectors: 54.1%$\left(\frac{(10.9\% - 5.0\%)}{10.9\%}\right)$ in the public sector and 43.5% in the private sector $\left(\frac{(20.0\% - 11.3\%)}{20.0\%}\right)$. These findings highlight that the remaining gender pay gap is due to different contracted hours rather than contracted hourly wages. Despite the trend of more women working part-time than men[20], the difference is minimal when controlling for group characteristics.

[20] Refer to Appendix A – section A1. Theoretical background

**Table 3**. Gender gap based on sector for all workers

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | |
| Both sectors | - 0.313 | - 0.178 | - 0.130 | - 0.108 |
| | ***(0.001) | *** (0.001) | *** (0.000) | *** (0.000) |
| Public sector | - 0.216 | - 0.131 | - 0.098 | - 0.077 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Private sector | - 0.329 | - 0.212 | - 0.156 | - 0.135 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| $y_i$ = *Log of contracted hours* | | | | |
| Both sectors | - 0.142 | - 0.042 | - 0.040 | - 0.025 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| Public sector | - 0.107 | - 0.030 | - 0.039 | - 0.027 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Private sector | - 0.129 | - 0.050 | - 0.040 | - 0.022 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| $y_i$ = *Log of contracted hourly wage* | | | | |
| Both sectors | - 0.171 | - 0.135 | - 0.090 | - 0.084 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| Public sector | - 0.109 | - 0.101 | - 0.054 | - 0.050 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Private sector | - 0.200 | - 0.162 | - 0.116 | - 0.113 |
| | ***(0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | | | | |
| Individual characteristics | YES | YES | YES | YES |
| Firm F.E | NO | YES | NO | YES |
| Occupation F.E | NO | NO | YES | YES |

Notes: Table shows the coefficient of being a female for the outcomes $y_i$ in the years 2015 to 2020 combined. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. In the third model (column 3), the fixed effect of occupation is added to model 1. The fourth model (column 4) includes the fixed effect of both firm and occupation to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

*5.1.*3 Leaders exhibit a lower gender pay gap compared to all workers

Given that the most significant pay gap is in the private sector, this will be the further focus. Subsequent investigations will examine leaders compared to all workers. This inquiry begins with exploring the baseline model (model 1) applicable to all workers, executives, and CEOs before incorporating firm-specific fixed effects (model 2) for all workers and executives. For this analysis, we utilise Figure 4 for the private sector and data from Table 4.

Table 4 presents estimates of the female coefficient for all the outcomes for all workers, executives and CEOs differentiated by sector. In the private sector, the baseline model (model 1) demonstrates a 32.9% lower yearly wage for women than men across all workers. This gender wage gap diminishes slightly for executive roles, with females earning 27.4% less than their male counterparts - an improvement of 5.5% (32.9%-27.4%) from all workers. A similar pattern is observed for female CEOs, with a wage gap of 29.7%, denoting a 3.2% (32.9%-29.7%) improvement compared to all workers. This analysis does not suggest that leadership positions command lower wages; rather, it illustrates that the wage gap persists, albeit slightly diminishing, as one ascends the hierarchical ladder.

Figure 4 elucidates estimates of the female coefficient for the gender pay gaps among all workers, executives, and CEOs within the private sector[21]. The graph highlights a persistent wage difference across the entire sample, with the pay gap showing a tendency to diminish as one ascends the hierarchical ladder. However, substantial yearly wage disparities persist. Upon considering firm-specific fixed effects (model 2), a wage gap of 21.2% exists for all workers and is marginally lower at 20.5% for executives. Figure 4 does not include firm fixed effects for CEOs. Based upon the baseline model, it is likely that a significant gender wage gap also exists among CEOs when including the fixed effect of firms. However, the exact magnitude cannot be determined from Figure 4. Differences across firms, such as size, industry, and culture, may impact the salary level. All of the above implies that firm characteristics are crucial when determining the gender pay gap.

[21] Refer to Appendix C - Figure Cc plots the coefficient of being a female for all workers (model 1-model 4), executives (model 1-2) and CEOs (model 1) based on the sector for all the dependent variables.

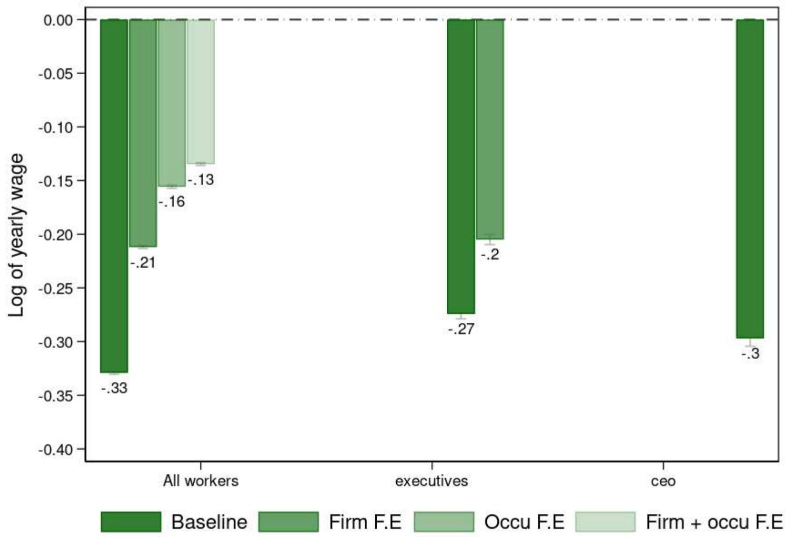


**Figure 4.** Gender wage difference for all workers, executives, and CEOs in the private sector.

Notes: The figure plots the coefficient female for outcome $y_i = \log of\ yearly\ wage$ in 2015-2020 combined. The "Baseline" (model 1) controls for age, age$^2$ and education. The "Firm F.E" (model 2) adds the fixed effect of firm to model 1. In the "Occu F.E" (model 3), the fixed effect of occupation is added to model 1. The "Firm + occu F.E" (model 4) includes the fixed effect of both firm and occupation to model 1.

Figure 5 shows estimates of the coefficient female for contracted hours and contracted hourly wage for all workers, executives, and CEOs in the private sector. The figure reveals no severe difference in contracted hours for women and men in executive positions. In contrast, the contracted hourly wage determines the most significant part of the observed wage disparities.

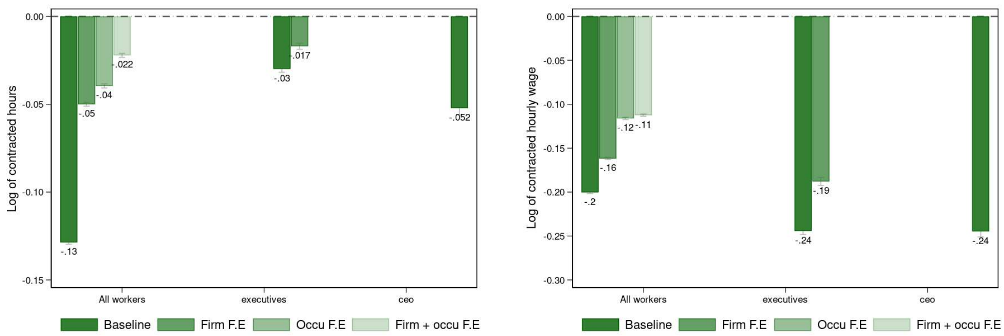

**Figure 5.** Gender difference in contracted working hours and contracted hourly wage for all workers, executives, and CEOs in the private sector.

Notes: The figure plots the coefficient female for the outcome $y_i = \log of\ contracted\ hours$ & $\log of\ contracted\ hourly\ wage$ in 2015 to 2020 combined. The "Baseline" (model 1) controls for age, age$^2$ and education. The "Firm F.E" (model 2) adds the fixed effect of firm to model 1. In the "Occu F.E" (model 3) the fixed effect of occupation is added to model 1. The "Firm + occu F.E" (model 4) includes the fixed effect of both firm and occupation to model 1.

**Table 4**. Gender gap based on sector for all workers, executives, and CEOs

| | All workers | | Executives | | CEOs |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 1 | Model 2 | Model 1 |
| $y_i$ = *Log of yearly wage* | | | | | |
| Both sectors | - 0.313 | - 0.178 | - 0.264 | - 0.163 | -0.285 |
| | ***(0.001) | *** (0.001) | *** (0.002) | *** (0.002) | *** (0.004) |
| Public sector | - 0.216 | - 0.131 | - 0.166 | - 0.100 | -0.211 |
| | *** (0.001) | *** (0.001) | *** (0.002) | *** (0.002) | *** (0.009) |
| Private sector | - 0.329 | - 0.212 | - 0.274 | - 0.205 | -0.297 |
| | *** (0.001) | *** (0.001) | *** (0.002) | *** (0.002) | *** (0.004) |
| $y_i$ = *Log of contracted hours* | | | | | |
| Both sectors | - 0.142 | - 0.042 | - 0.019 | - 0.012 | -0.047 |
| | *** (0.000) | *** (0.000) | *** (0.001) | *** (0.001) | *** (0.002) |
| Public sector | - 0.107 | - 0.030 | - 0.009 | - 0.005 | -0.026 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.005) |
| Private sector | - 0.129 | - 0.050 | - 0.030 | - 0.017 | -0.052 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.002) |
| $y_i$ = *Log of contracted hourly wage* | | | | | |
| Both sectors | - 0.171 | - 0.135 | - 0.245 | - 0.151 | -0.238 |
| | *** (0.000) | *** (0.000) | *** (0.002) | *** (0.002) | *** (0.003) |
| Public sector | - 0.109 | - 0.101 | - 0.158 | - 0.096 | -0.186 |
| | *** (0.001) | *** (0.001) | *** (0.002) | *** (0.002) | *** (0.008) |
| Private sector | - 0.200 | - 0.162 | - 0.244 | - 0.188 | -0.244 |
| | ***(0.001) | *** (0.001) | *** (0.002) | *** (0.002) | *** (0.003) |
| | | | | | |
| Individual characteristics | YES | YES | YES | YES | YES |
| Firm F.E | NO | YES | NO | YES | NO |
| Occupation F.E | NO | NO | NO | NO | NO |

Notes: Table shows the coefficient of being a female for the outcomes $y_i$ in the years 2015 to 2020 combined. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

*5.1.4 Marginal decrease of gender pay gap from 2015 to 2020*

Further, we delve into the evolution of the gender pay gap for all workers, executives, and CEOs from 2015 to 2020. Tables C13 to C21 in Appendix C outline the regression estimates for the development segmented by sector. The tables indicate a progressive annual reduction in the gender pay gap, with an approximate decrease of one percentage point annually for all workers, as observed in the baseline model (Model 1) across both sectors. The public sector predominantly drives this trend. Figure 6 explicitly visualises the temporal trajectory of the gender pay gap in the private sector for all workers. When the firm fixed effects (Model 2) are controlled for, the gender wage gap among all workers in the private sector exhibits a similar annual reduction of nearly one percentage point.

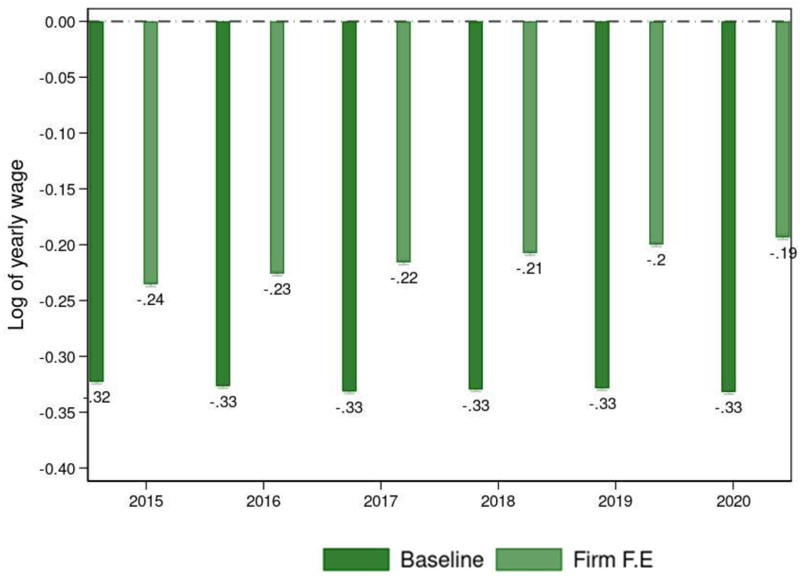


**Figure 6.** Gender wage difference development in private sector for all workers

Notes: The figure plots the coefficient female for the outcome $y_i = \log of\ yearly\ wage$ from the year 2015-2020 separately for all workers in the private sector. The "Baseline" bar (model 1) controls for age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1.

Figure 7 demonstrates the gender pay gap development in the private sector for executives (left panel) and CEOs (right panel). The baseline model (model 1) presents minimal variation over the years for all workers, executives, and CEOs within the private sector. However, when controlling for the fixed effect of firm (model 2), a marginal decline in the pay gap is observed for executives, with a decrease of approximately two percentage points from 2015 to 2020 in total.

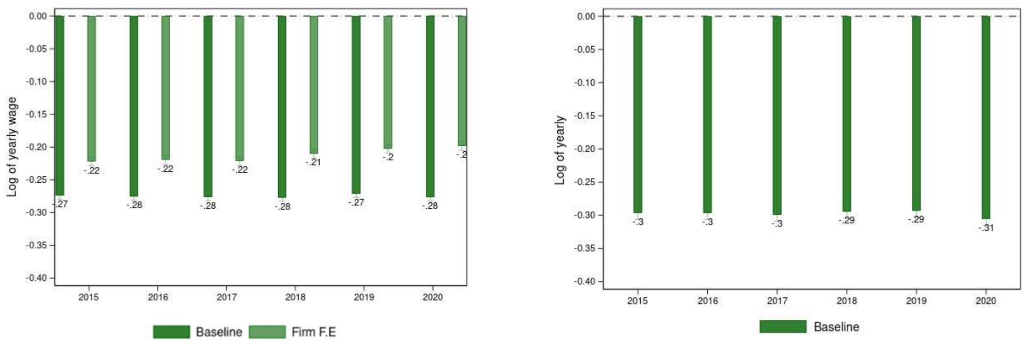


**Figure 7.** Gender wage difference development in private sector for executives and CEOs.

Notes: The figure plots the coefficient female for the outcome $y_i = \log of\ yearly\ wage$ from the year 2015-2020 separately for executives (left panel) and CEOs (right panel) in the private sector. The "Baseline" bar (model 1) controls for age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1.

Even after accounting for firm and occupational fixed effects, evidence of a persistent gender pay gap is present. While there has been a slight reduction in wage disparities from 2015 to 2020 for all workers, the wage gap for executives and CEOs has remained largely constant. The model could benefit from further refinements that might elucidate the remaining unexplained gender pay gap within specific firms and occupations.

## 6.0 Discussion on Weaknesses of the Models

For every research, it is vital to recognise the weaknesses of the study. This research is no exception. It is essential to identify and examine these potential shortcomings to fully appreciate the applicability and validity of the findings. The following sections will outline and discuss the primary weaknesses encountered during the research process.

### 6.1 Omitted variables

Omitted variables refer to relevant factors or variables not included in the analysis but that could have influenced the relationships or outcomes under investigation (Wilms et al., 2021, p.3). Consequently, the results and conclusions presented should be interpreted cautiously, recognising that the full extent of the model's explanatory power may not have been captured. Further, we will discuss potential implications and considerations related to the presence of omitted variables.

### *6.1.1 Actual hours*

Including actual hours as opposed to contracted hours could help explain wage differences. Some argue that the variable can be used to measure productivity. On the other hand, a worker can be effective without necessarily being efficient. Efficient means producing the desired result without wasting resources, while effective means producing a result even if it takes some unnecessary resources, such as materials, time or energy (Oxford Languages, n.d.). Due to this, measuring actual working hours include some challenges:

(1) Many modern workplaces offer flexible work arrangements such as flextime and remote work. These arrangements allow employees to have more control over their schedules and work outside traditional office hours. Tracking and measuring actual working hours becomes complex when employees have the freedom to adjust their schedules based on personal preferences or specific job demands. Some employees may also often take breaks or experience interruptions such as meetings, phone calls and emails during working hours. Some interruptions may be non-work related, such as personal phone calls and socialising with colleagues. These interruptions temporarily shift focus away from direct productivity. Measuring actual working hours requires accounting for these interruptions and determining the amount of time spent on productive work versus non-productive activities and work-related and non-work-related activities.

(2) There is a big difference between contracted and actual working hours. In some industries or occupations, employees may regularly work beyond their standard hours, known as overtime. However, these additional hours often go unrecorded for various reasons, such as informal agreements, cultural norms, or employees' reluctance to report overtime. Employees may do work-related tasks without reporting the time. As a result, measuring actual working hours becomes difficult when significant portions of work time are not officially accounted for.

The presence of actual working hours could explain wage differences due to an employee working more or less compared to others. Including an overtime variable could solve this problem, but as previously mentioned, actual overtime hours also prove to be hard to measure accurately.

### *6.1.2 Paid hourly overtime*

Paid hourly overtime could explain wage variations. In some industries, overtime is part of the employment contract and included in the contracted hourly wage. The main rule is that the overtime supplement must be paid as an addition to the fixed payment. For some employees, it is still the case that the overtime allowance is included in the fixed salary (Codex, n.d). In these cases, they have higher wages due to the included contracted overtime pay. Therefore, including paid overtime would account for these variations. Including paid overtime would require actual working hours as a variable to see whether the variations are due to hours or wages. The difficulties regarding measuring actual working hours lead to difficulties in measuring paid overtime.

### *6.1.3 Work experience*

Work experience can be a potential explanation for wage differences for individuals in the same positions in the same firms. Work experience can be defined in various ways, such as total years of employment, experience within a specific field or industry, or experience in a particular job role. These differing definitions create challenges in comparing and analysing consistently across diverse individuals or groups. Obtaining comprehensive and accurate data can also pose difficulties, as employers might lack complete records of employees' past work experience, while individuals may not consistently report their entire work history. Individuals may face career interruptions such as parental leave, unemployment or career transitions. These non-linear career trajectories make it difficult to accurately capture and measure work experience, especially when comparing individuals from varying backgrounds and circumstances. Work experience also may not capture an individual's skills or qualifications.

## 6.2 Classification of leaders

The classification of leaders generates potential weaknesses in gender pay gap research. Definitions can be subjective and open to interpretations. The classification of a leader can vary across organisations, industries and contexts. As mentioned, this research defines leaders in two different ways, namely executives and CEOs, respectively, using STYRK-98 and "Enhetsregisteret"[22]. Classifications may vary across studies or disciplines, making it challenging to compare findings across studies or draw definitive conclusions.

By using category one of STYRK-98 to define executives, there may be a possibility of including occupational codes that are not representative of analysing the gender pay gap within firms and occupations for leaders. This can lead to misleading results. For example, category one includes board members who are not always seen as a firm leader. Some may be board members across several firms, and an additional board member's salary may be next to their primary income. There is a possibility of removing occupational codes manually, but this would diminish the objectivity of this research. Consequently, the classification is substantiated by previous studies. Additionally, not identifying the hierarchal rank within the leadership samples enables the weakness of comparing a line manager to a top manager. Our models do not include the fixed effects of occupation since this would lead to multicollinearity, and the classifications we employ do not rank leadership positions.

Similarly, the classification of CEOs sourced from "Enhetsregisteret" have potential weaknesses. Neither the fixed effect of firm nor occupation is included in the model. If we only include the fixed effect of occupation, we would be comparing across firms with the possibility of comparing the wage of a CEO with 1000 employees to another with 10 employees. Generally, a more prominent firm would have the possibility to provide higher wages due to higher profits. On the other hand, including the fixed effect of the firms would limit the results to only those firms that experienced changes from female to male CEO or vice versa during the research years.

## 7.0 Possible Mechanisms for the Gender Pay Gap

This section aims to answer the second part of the research question: "What mechanisms may contribute to the gender differences in the labour market?" While identifying the exact causes of gender wage disparities proves elusive, it is within our reach to shed light on the potential mechanisms that may explain the remaining gender pay gap found in our research. The presence of a gender pay

[22] Refer to Appendix B - section B2. Our data.

gap can be due to discrimination, preferences and/or productivity (The Council Of Economic Advisors, 1998).

### 7.1 Discrimination

Gender discrimination involves unequal treatment based on gender (Stanford University, n.d.), manifesting in various ways in the labour market. Women may face barriers to career advancement, limited access to leadership positions, and lower wages compared to their male counterparts, despite having similar qualifications and experience. Occupational segregation, where specific industries and professions are dominated by one gender, can limit opportunities and perpetuate gender-based pay disparities.

Globally, 178 countries possess discriminatory laws that prevent women's participation in the labour market and economy on equal terms with men. In 2021, 23 countries amended their laws to strengthen gender equality in the economic sphere. Many countries still have different laws for men and women, determining whether women have access to work, start businesses, own land, or receive an inheritance (FN-Sambandet, 2022).

In Norway, known for its gender equality commitments, workplace gender discrimination still persists (Statistics Norway, 2018). However, few sources suggest the gender pay gap is due to discrimination. The government have implemented robust gender equality policies and legislation to foster equal opportunities and fair treatment in the workplace (OECD, 2021). The Equality and Anti-Discrimination Act (Lovdata, n.d.) provides legal protection against gender-based discrimination. This Act is also regulated through "Arbeidsmiljøloven" (Arbeidstilsynet, n.d.). Government initiatives aim to challenge gender stereotypes, promote diversity and inclusion, and create equal opportunities for all genders. Organisations in Norway are encouraged to implement diversity and inclusion policies, promote awareness, and provide training to ensure fair and equitable practices. Additionally, individuals who believe they have experienced discrimination can file complaints or seek legal recourse through the court system (Regjeringen, 2023).

### 7.2 Preferences

While various factors contribute to gender wage disparities, individual preferences are crucial in shaping career choices, job selection, and work-related decisions. These preferences may stem from societal expectations, personal interests, or traditional gender roles. Studies have shown that women, on average, tend to prioritise work-life balance, job flexibility, and non-monetary benefits. At the same time, men may be more inclined towards career advancement and higher-paying positions (Council of Economic Advisers, 2015). These divergent preferences can result in differences in occupational choices, working hours, and job sectors, contributing to variations in wage between genders.

Men and women may have different career aspirations and interests. Specific industries or professions may be traditionally dominated by one gender, leading to variations in wage. For example, women are more likely to choose careers in fields such as education and healthcare, which typically have lower average wages than male-dominated sectors like engineering or finance (Council of Economic Advisers, 2015). Earlier research (Fernandez-Mateo & Fernandez, 2016, p. 3636) also discusses women choosing not to apply for the same jobs as men in fear of discrimination. The Council of Economic Advisors (2015) discusses whether women end up in different positions due to preferences or discrimination and the implications for this. They state, "In many situations, the line between discrimination and preference is ambiguous" (Council of Economic Advisers, 2015). Further, they discuss that if the differences are due to preferences, they should be accounted for. On the other hand, if men and women choose different jobs because of discrimination, industry and occupation should not be included in the models (Council of Economic Advisers, 2015).

Our research aims to account for individual choices by including the fixed effects of both firm and occupation, thus focusing on men and women who share similar individual and group characteristics. While these characteristics can account for a significant portion of the gender pay gap, a residual gap persists. Variations in contracted hours contribute minimally to this remaining gap, with the majority stemming from differences in contracted hourly wages. This discrepancy could be attributed to differential wage negotiation strategies. Previous studies indicate that men are more inclined to negotiate for higher salaries and promotions than women

(Council of Economic Advisers, 2015). This divergent negotiation behaviour could foster wage disparities, as men may secure higher wages, despite occupying identical positions as their female counterparts.

### 7.3 Productivity

Productivity may serve as a contributory factor to wage disparities (U.S Bureau of Labor Statistics, n.d.). An employee who exhibits higher productivity levels may earn higher wages. Similarly, the quality of work delivered can contribute to gender-based wage differentials.

Measuring productivity can be challenging due to several reasons. Productivity is not easily quantifiable or measurable in certain roles or industries, especially those involving creative or knowledge-based work (Chew, 1988). Employees often perform various tasks and responsibilities, making it difficult to isolate and attribute productivity to a specific individual. The complexity of job roles and mutual dependence on job tasks leads to a challenge in accurately measuring individual contributions. External factors such as organisational support, resource availability, and external constraints can significantly impact an employee's productivity. This results in difficulties when isolating the impact of individual performance from external influences. Additionally, the complexity of assessing productivity in real-time also enhances the difficulties. The effects of an employee's productivity may not be immediately visible. Productivity gains or losses may take time to become apparent.

Nevertheless, previous research that only focuses on specific industries or firms has included productivity as a variable. They measure the output of services or products produced, calculated by the number of units produced per hour or the value of goods manufactured per employee (Chew, 1988). If an employee produces exceptionally well compared to others, they may be compensated through a higher salary. The efficiency of an employee can, as a result of this productivity measurement method, have a substantial impact on wages. There is only a minority of firms that can measure productivity, as above. Therefore, there is a need for a productivity measure enabling comparison among all firms and industries, but this proves challenging.

## 8.0 Concluding Remarks

In conclusion, this master thesis sheds light on the complexities and mechanisms contributing to the gender pay gap. The primary findings largely corroborate existing research. The most substantial gender pay gap is observed in the private sector, with firm and occupational characteristics explaining 65.4% across both sectors. After accounting for fixed effects, variations in yearly wage are not significantly linked to disparities in contracted hours but instead tied to contracted hourly wages. While the gender pay gap among leaders is smaller than among all workers, it remains a persistent issue as individuals ascend the hierarchical ladder.

While the findings provide valuable insights, some areas warrant further investigation. Therefore, to explain more of the gender pay gap, the following recommendations are put forth for future research.

- Categorise leaders hierarchically to investigate the gender pay gap within each rank.
- Investigate CEOs with the same firm characteristics.
- Include experience as a variable.
- Account for productivity.
- Investigate and rank non-executives.

The underlying factors behind gender pay disparities are not yet comprehensively grasped, and there is still ambiguity surrounding the extent to which the gender pay gap can be attributed to discrimination, preferences, or productivity.

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Appendix A: Theoretical Background

**Section A1. When does the gender pay gap occur?**

The nature of the gender pay gap in the workforce is complex and beyond just a few factors. There is a need to identify when the problem arises to understand the underlying mechanisms. The stereotypic career path begins with studying and ends with retirement. Hence, the investigation will delve into gender pay inequality within career ladders, explicitly focusing on Norway.

*Primary- and Upper Secondary School*

All public schools in Norway are government-funded. Primary school, which is mandatory, starts at the age of 5 and ends at 15. Girls leave primary school with higher grades than boys in all subjects except physical education (Statistics Norway, 2022c). Further, at the age of 15-18, people continue to upper secondary education, which is voluntary, but a requirement to obtain higher education. According to data from Statistics Norway (2022d), the percentage of high school students who completed their studies within 5 or 6 years, depending on the study programme, was 80.4% from 2015 to 2021. Of these accomplished graduates, 55.6% were female.

*Higher education*

In 1980, 11.3% of the population obtained education at university. Of those were, 57.1% men and 42.9% women. The main difference was the length of education. Shorter education contained approximately half of each gender, while the longer consisted of only 14.8% of women. Compared to 2021, 36.0% of the population graduated an increase of over triple the original per cent. Of those were 56.3% women and 43.7% men, the opposite of 1980. There were still approximately half of each gender for shorter educations. For the more extended education, women stood for 48.9% (Statistics Norway, 2022e).

Highly educated parents are often associated with a higher likelihood of students completing their education (Statistics Norway, 2017). Of those who enrolled from 2013 to 2021, only ⅔ finished their degree. Additionally, 72.2% of all the women that enrolled in these years graduated, compared to 58.9% of all men. If we look at the period from 1995 to 2003, we see the same pattern (Statistics Norway, 2022f). In other words, education does not seem to be the problem regarding the gender pay gap, substantiating further investigation of educational choice in the following paragraphs.

*Moving into the labour market*

The Norwegian labour force encompasses individuals aged 15 to 74, comprising 72.1% of the total population in 2021. The proportion of unemployed individuals in the labour force stood at 4.4% (Statistics Norway, 2022g). Men had an average monthly salary of 53.710 NOK, whereas women had an average monthly salary of 47.190 NOK, representing a difference of 12.1% less for women than men (Statistics Norway, 2022a). Regarding the type of employment, there will be a differentiation between full-time and part-time jobs. Of all working women, 46% had a part-time job, compared to 25% of working men in 2021. On average, females work 2-4 hours less every week, but there are some exceptions. For academic workers, women are employed 1.5 hours less per week than men. Further, female leaders are only 0.1 hours below men (Fløtre & Tuv, 2022). Women work more part-time during their studies than men. The same occurs for women taking care of small children. If adjusting for this, full-time working men had an average of 55.210 NOK, while women had 49.490 NOK. The gap is 10.4%, which is still a significant difference (Statistics Norway, 2022a).

Women are also overrepresented in the public sector, while more men are in the private sector. Women dominate 70.1% of the public sector, while only 36.5% of the private sector (Statistics Norway, n.d.b.). The latter sector also has the highest-paid jobs. Men fill the top positions with the highest salaries. If adjusting for this, the gap reduces dramatically from 12.1% to 3.8%. That is a natural reason for the gender pay gap (Fløtre & Tuv, 2022). Analysis point to the return on education, which is higher in the private sector than in the public sector.

The gender pay gap also varies across industries. There are some female-dominated industries, such as nursing and care. Others are highly male-dominated, such as construction (Bruun, 2022). When we look at the studies from the United States between 2020 and 2021, the most significant gap was in "finance & insurance", "agencies & consultancies", and "health care". The industries that had the smallest gap were "arts, entertainment & recreation", "real estate & rental/leasing", and "construction". This gap may be due to women dominating the industries with the highest gaps or females choosing to enter these industries. These facts show that industry is essential to keep in mind when researching the gender pay gap (Smith, 2022).

*Starting a family*

Studies show that workers are usually between 25-40 years old in the parent phase. At this age, the wage gap increases the most (Regjeringen, 2008, p. 177). Research shows that employed women with children have lower hourly wages than those without children (Regjeringen, 2006, p. 32). For men, the tendency is the opposite. Men with children have higher hourly wages than men without children (Regjeringen, 2008, p. 179). Women take more maternity leave when they give birth than men (Askvik, 2020). As of 2019, the proportion of fathers who took at least full paternity leave during the child's first three years was 62% (Gram, 2021). After giving birth, women often take full parental leave and work part-time to have time for the family. Contrary, men's working hours are not affected much by family situations. When mothers are away from work, they may lose valuable professional experience and skills development.

*Line manager to top position*

Statistics Norway published 12 indicators for gender equality in 2010. While there has been progress in all areas, two particular aspects have undergone the most significant changes over time. That is the ratio between the genders in higher education, as mentioned earlier, and the distribution among leaders. In 2008, the percentage of female managers stood at 32%, while in 2019, it rose to 37% (Gram, 2021). The difference grows when climbing the career ladder from middle manager to senior manager. CORE's top management barometer shows that in the 200 largest companies in Norway, 25% of executives are women. In the same companies, 86% of men are in the highest position, CEO (CORE, 2020, pp. 1-4). The monthly pay gap among leaders in all sectors and industries was 17.7% in 2021. Men had an average monthly pay of 79.960 NOK and women at 65.790 NOK. Compared to 2015, the gap was at 20.5%, which shows a decrease in the difference (Statistics Norway, 2022a).

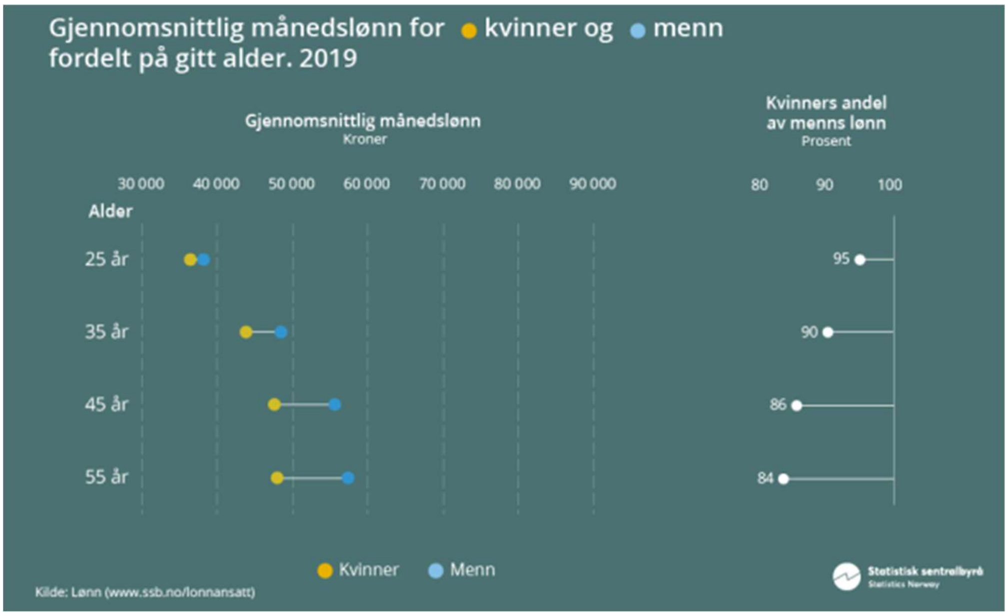



*Image 1. Average monthly salary for women and men. (Askvik, 2020).*

To sum up, the average monthly salary and wage gap increase by age (refer to image 1). It is worth mentioning that the average salary is greatly affected by the "extreme values" at the end of the distribution. Therefore, it may be appropriate to look at the median instead of the mean (Fløtre & Tuv, 2022). All the above play a part in understanding the gender pay gap, carrying varying weight in their impact.

**Section A2. Females in leadership positions**

*The phenomenon "The Glass Ceiling"*

Marilyn Loden first mentioned the Glass ceiling phenomenon in 1978. Loden discussed women's difficulties when moving to higher roles in a male-dominated corporate hierarchy. Women who entered the workforce during the 1980s were unable to advance beyond a certain management level (Kagan, 2022). At the time, it was common to say that women at the childbearing age were less motivated and disciplined than men. After childbirth, women were perceived as less capable of working because of mommy duties (Fritscher, 2017). The focus on the differences has increased over the years, and numerous research has been conducted to study the mechanisms contributing to the phenomenon.

Legal policies, such as the "anti-discrimination law" of 2007 and the gender quota on executive boards, have been implemented to help women balance family and work life. These help encourage and motivate women to apply for leadership positions. Despite these initiatives, women are still vastly underrepresented in the decision-making part in all sectors (Hanzes & Babic, 2021, p.2). The European Women on Boards (EWOB) network provides a Gender Diversity Index, which monitors the progress of women's participation across over 600 listed corporations in Europe. Women only account for 7% of CEO positions (EWOB, n.d). This share equals female CEOs in only 50 out of 668 companies, an insignificant increase compared to 42 in 2020. The female-led companies have twice as many women in leadership positions as in all the other companies researched (EWOB, n.d.).

A Pew Research Center (2015) study identified two primary challenges: first, women are held to higher standards than men, and second, many businesses are not ready to hire women. Other common obstacles include family responsibilities, limited access to the same networks as men, and that women biologically are less likely to ask for promotions (Pew Research Center, 2015). All of the above may influence the underrepresentation of women in leadership positions. There has been a slight growth in the percentage of female leaders throughout the years, but they still occupy a drastically smaller percentage of these roles (WEOB, n.d.). The barriers associated with the Glass Ceiling are often unspoken and vary across countries and cultures. Women may face restrictions imposed by societal norms rather than explicit corporate policies. Research indicates that diverse groups make better decisions than homogeneous ones (McKinsey & Company, 2020), highlighting the benefits of eliminating the Glass Ceiling for companies. To break the glass ceiling, one must overcome the barriers set to prevent women's access to advancement.

*Breaking "The Glass Ceiling"*

The phenomenon of the Glass Ceiling has received significant attention in academic research as a prominent factor contributing to the gender pay gap. Earlier research investigates the drivers and the impact of policies implemented to "break" the Glass Ceiling.

Bertrand et al. (2018) conducted a study titled "Breaking the Glass Ceiling," which explores the barriers women encounter in attaining top leadership positions on a global scale. The research identifies factors such as slower promotion rates for equally qualified women, career interruptions due to childbirth and family responsibilities, and underrepresentation of females in industries more likely to lead to top positions. The study investigates potential solutions such as gender quotas and supportive organisational cultures with mentoring programs and transparent hiring processes. The authors found that gender quotas for corporate boards did not result in significant changes in female representation for top positions, except for the women who managed to enter the boardrooms. However, they find that organisational culture and leadership support are essential for creating an inclusive environment that enables women to succeed and advance in their careers.

Matsa and Miller's (2010) article "A Female Style in Corporate Leadership? Evidence from Quotas" also investigates the impact of gender quotas on corporate boards, particularly on corporate decisions. The study focuses specifically on the effects of Norway's gender quota policy. In 2004, Norway implemented a law requiring 40% of the boards to be women due to the almost total absence of female representation (Teigen, 2015, p. 9). Matsa and Miller demonstrate that this policy effectively increased female representation on corporate boards without negatively affecting firm performance. However, the research refutes the idea of a distinct "female style" of leadership and emphasises the long-term positive effects of quotas on gender diversity in corporate leadership.

Kunze and Miller's (2017) research "Women Helping Women" explores the concept of women supporting and promoting each other in the workplace. Based on a sample of 4 000 private companies in Norway, the research reveals that policies aimed at increasing female representation in corporate leadership can have spill-over benefits for women in lower ranks. Female supervisors provide more developmental support and contribute to a more inclusive work environment. They conclude that gender-inclusive policies help to maximise the impact of women helping women in breaking through barriers.

Fernandez-Mateo & Fernandez's (2016) article "Bending the Pipeline? Executive Search and Gender Inequality in Hiring for Top Management Jobs" brings attention to the possible contribution of headhunting firms to the persistence of gender inequality in leadership positions. The study investigates how recruitment firms may contribute towards gender inequality and whether they can help bend the pipeline. The authors highlight the importance of addressing biased practices, increasing transparency, and fostering collaboration between organisations and headhunting firms to achieve greater gender equality in top management.

In summary, Bertrand et al. (2018) propose two solutions for breaking the Glass Ceiling within companies: gender quotas and supportive organisational cultures. Matsa and Miller (2010) studied the effect of gender quotas, while Kunze & Miller (2017) studied women supporting other women. Fernandez-Mateo & Fernandez (2016) highlight a solution outside the company: the contribution of headhunting firms to promote women to top management positions. The findings collectively indicate that the Glass Ceiling is very much alive, which substantiates the importance of investigating the gender pay gap in leadership positions while considering the specific level of position.

Appendix B: Data

**Section B1. Fundamental variables for measuring the gender pay gap**

This section aims to provide an explanation of the variables that are previously used to explain wage differences. Each subsection offers different ways of measuring the variables.

*Wage*

The definition of wage is a "fixed, regular payment earned for work or services" (Oxford Languages, n.d.). There is a substantial variation in the definition, resulting in many ways of measuring wages. Statistics Norway (2022a) defines it as an allowance from the employer to the employee based on agreed working hours. Gender egalitarianism is often measured by salary. This measurement is substantiated by Statistic Norway (2023a), which uses yearly salary as one of the 12 indicators for gender equality in Norway.

There are primarily three ways to measure salary: yearly, monthly or hourly.
All numbers related to wages at Statistics Norway (2020c) are before taxes and built on data from "a-ordningen". Their primary measurement is monthly wages, including agreed wages, irregular salary supplements and bonuses. Agreed monthly wages are the predetermined salary and serve as a core component of the employee's total compensation. Irregular salary supplements are compensation related to specific responsibilities or non-standard working hours, while bonuses are not necessarily related to a task. Yearly wages are the aggregate of the monthly wages. Paid overtime is not included in the wages above but is published in separate statistics (Statistics Norway, 2023b). Hourly wages refer to the amount of money an employee earns per hour and are typically specified in employment contracts or agreements set by the employer or established through collective bargaining agreements.

*Gender*

Gender is commonly included as a dummy variable. The gender is sourced from the national identity number; the ninth digit indicates sex. Even numbers indicate women and uneven men.

*Age*

The age of the Norwegian labour force includes individuals from 15-74 (Statistics Norway, 2023c). The age is found in a person's birth number.

*Education*

The International Standard Classification of Education (ISCED) is the official framework for international comparisons of education systems. The system was developed in 1976 by the United Nations Educational, Scientific and Cultural Organization (UNESCO) and was revised in 1997 and 2011. There are differences in the duration of each education level across countries, which can be problematic.

The classification is listed below (The World Bank, n.d.a.):

- ISCED 0 = Early childhood education
- ISCED 1 = Primary education
- ISCED 2 = Lower secondary education
- ISCED 3 = Upper secondary education
- ISCED 4 = Post secondary non-tertiary education
- ISCED 5 = Short-cycle tertiary education
- ISCED 6 = Bachelor's degree or equivalent tertiary education level
- ISCED 7 = Master's degree or equivalent tertiary education level
- ISCED 8 = Doctoral degree or equivalent tertiary education level

Statistics Norway implemented the Norwegian classification system of education (NUS) for the first time in 1970. This classification system has since been revised in 1973, 1989 and 2000. NUS2000 includes Norwegian education codes as well as corresponding codes from ISCED (Statistics Norway, 2016) (Statistics Norway, 2023d).

*Occupation*

The standard occupation categorisation STYRK-98 or the upgraded STYRK-08 by Statistics Norway is commonly used to separate different occupations in Norway. Both are based on the international standard from the International Standard Classification of Occupation (ISCO). Specific work tasks decide the occupation code. The main rule is that all employees doing the same duties should have the same occupation code (Skatteetaten, 2020). The complete code can be a maximum of 7 digits, but using 1, 2, 4 and 7-digit codes is common.

The first number of the code ranges from 0-9 and separates the field of work:

- 0XXX: Military professions and unspecified
- 1XXX: Administrative leaders and politicians
- 2XXX: Academic professions
- 3XXX: Higher education professions
- 4XXX: Office and customer service
- 5XXX: Sales, service, and care
- 6XXX: Agricultural, forestry and fishing.
- 7XXX: Craftsmen and similar professions
- 8XXX: Process and machine operator, transportation worker and other
- 9XXX: Professions that do not require education

The first number also indicates the competence level, meaning:

- 0,1 and 9: No specific competence level.
- 2: Competence corresponding to a minimum of 2-4 years of college
- 3: Competence corresponding to a minimum of 1-3 years of college
- 4-8: Competence corresponding to primary and elementary school.

Further, the different numbers separate into different levels. The second number is the sub-major, the third is the minor, and the fourth is the unit (Statistics Norway, 2011).

*Firm*

The organisational number is a unique 9-digit number assigned by the Central Coordinating Register for Legal Entities in Norway. Each firm has a unique organisation number. You can not find direct information from the organisation number (Statistics Norway, n.d.b). However, it connects to different authoritative registers, making extracting information more efficient (Statistics Norway, 2015). Importantly, a firm and an establishment have different serial numbers, meaning an employee will always register with two different serial numbers.

**Section B2. Our data**

**Table B2a.** Variables in data selection based on type, source and measurement

| Variable | Source | Measurement |
| --- | --- | --- |
| *Outcome variables* | | |
| Yearly wage | A-ordningen | Aggregated from the monthly wage |
| Contracted hours | A-ordningen | Agreed working hours per week |
| Contracted hourly wages | A-ordningen | $\frac{yearly\ wage}{(weekly\ contracted\ hours * 52\ weeks)}$ |
| *Baseline variables* | | |
| Female | National identity number | The dummy variable catches the effect of being a woman versus a man.<br>• If the female variable=1, the individual is a woman.<br>• If the female=0, the individual is a man. |
| Age | National identity number | Generated by subtracting the birth year from the year of observation. |
| $Age^2$ | National identity number | Generated by raising the age to the power of 2. |
| Education | Nasjonal utdannings-database (NUDB) | Four education dummy variables divide education into four levels based on ISCED:<br>• Educ1: ISCED level 0-2<br>• Educ2: ISCED level 3-5<br>• Educ3: ISCED level 6<br>• Educ4: ISCED level 7-8 |
| *Fixed effect variables* | | |
| Establishment | A-ordningen | Each establishment has a unique organisation number. Each individual's identity number is connected to their respective establishment. |
| Occupational code | A-ordningen | 7-digit occupational codes based on STYRK-98 |

Notes: Based on the fundamentals that were previously in studies used when examining the gender pay gap

## Section B3. Managing group-specific differences

*Perfect experiments*

A perfect gender pay gap experiment would ideally be a randomised controlled trial, where gender is the only variable systematically manipulated (Price et al., 2015). The participants would have equal backgrounds, qualifications, and experience, eliminating any potential confounding factors related to these variables. Further, the perfect experiment would involve identical job positions or tasks performed by both female and male participants, ensuring equal opportunities for performance and advancement. By comparing the treatment and control groups, researchers could determine the causal effect of gender on pay outcomes, isolating the gender pay gap from other potential factors. It is essential to note that conducting a perfect gender pay gap experiment is practically impossible due to ethical considerations, legal constraints, and the complexities of manipulating gender as an independent variable. As a result, real-world research on gender pay gaps typically relies on observational studies.

*Observational studies*

Observational studies systematically document behaviour without manipulation or control, generating a comprehensive natural characterisation of an individual, group, or setting (Ming, A, 2021). Observational studies can be either cross-sectional, where data is collected at a single point in time, or longitudinal, where data is collected over an extended period (Institute for Work and Health, 2015). These studies, which can be either cross-sectional or longitudinal, establish associations between variables but do not confirm causality due to potential confounding factors and biases (Institute for Work and Health, 2015). Confounding variables can obscure the true relationship between the studied variables. Confounding variables are factors associated with both the exposure and the outcome of the interest. Selection biases may also arise as participants are not randomly assigned.

Achieving complete control over all potential variables is an unattainable objective in research, making the presence of hidden variables a persistent challenge that can contaminate research outcomes. This contamination, known as omitted variable bias, can compromise the validity and accuracy of the results.

However, fixed effects models offer a means to address omitted variable bias by examining changes within specific groups over time.

*Fixed effects*

Fixed effects are a technique utilised in regression analysis to account for individual or entity-specific differences that remain constant over time. The technique allows for controlling individual or group-specific factors by adding a specific term in the regression that represents each person or group separately. Incorporating fixed effects isolates the changes happening within each individual or group, thus focusing on understanding the relationship between variables over time without being influenced by factors that stay the same for each person (Farkas, 2005).

This approach is practical when analysing the effects of time-varying variables while controlling for individual-specific factors. Including fixed effects in the statistical analysis allows researchers to control for these factors and focus on the relationship between variables, addressing potential biases and obtaining more accurate estimates. In other words, it helps understand how other variables impact the outcomes while considering individual or group-specific factors (Farkas, 2005).

Using fixed effects can be beneficial because it helps address omitted variable bias. Omitted variable bias occurs when relevant variables are excluded from the analysis, leading to biased or inaccurate estimates. By including fixed effects, researchers can account for the unobserved heterogeneity across individuals or groups and obtain more reliable estimates of the relationship between variables (Farkas, 2005).

Appendix C: Results

**Table C1.** Observations in data selection

| | Total obs. | Women | Men |
|---|---|---|---|
| *All workers* | | | |
| Both sectors | 12 395 429 | 5 828 613 | 6 566 816 |
| Public sector | 5 239 371 | 3 501 340 | 1 738 031 |
| Private sector | 7 156 058 | 2 327 273 | 4 828 785 |
| | | | |
| *Executives* | | | |
| Both sectors | 1 278 746 | 454 739 | 824 007 |
| Public sector | 378 542 | 207 182 | 171 360 |
| Private sector | 900 204 | 247 557 | 652 647 |
| | | | |
| *CEOs* | | | |
| Both sectors | 493 967 | 109 370 | 384 597 |
| Public sector | 43 782 | 18 373 | 25 409 |
| Private sector | 450 185 | 90 997 | 359 188 |

Notes: The numbers refer to the maximum in the period 2015 to 2020. They may not add up due to mobility across sectors and firms during the period.

**Table C2.** Number of people in data selection

| | Total num. | Women | Men |
|---|---|---|---|
| *All workers* | | | |
| Both sectors | 2 793 581 | 1 316 132 | 1 477 449 |
| Public sector | 1 237 685 | 806 285 | 431 400 |
| Private sector | 1 772 524 | 622 757 | 1 149 767 |
| | | | |
| *Executives* | | | |
| Both sectors | 337 205 | 124 378 | 212 827 |
| Public sector | 101 419 | 55 351 | 46 068 |
| Private sector | 242 665 | 71 668 | 170 997 |
| | | | |
| *CEOs* | | | |
| Both sectors | 135 293 | 31 570 | 103 725 |
| Public sector | 12 809 | 5 290 | 7 519 |
| Private sector | 123 212 | 26 477 | 96 735 |

Notes: The numbers refer to the maximum in the period 2015 to 2020. They may not add up due to mobility across sectors and firms during the period.

**Table C3.** Number of firms and occupations in data selection

| Sector | Firms | Occupations |
|---|---|---|
| Both sectors | 265 794 | 6 171 |
| Public sector | 194 477 | 4 854 |
| Private sector | 73 988 | 5 688 |

Notes: The numbers refer to the maximum in the period 2015 to 2020. They may not add up due to mobility across sectors and firms during the period. The numbers for occupations do not add up due to existence of several occupations in both in public- and private sector separately. Firm refers to all establishments. Occupation refers to the 7-digit code.

**Table C4.** Regression estimates for all workers in both sectors.

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | |
| age | 0.088 | 0.077 | 0.065 | 0.061 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.555 | -0.363 | -0.155 | -0.097 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.382 | -0.272 | -0.098 | -0.059 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.213 | -0.131 | -0.077 | -0.050 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.313 | -0.178 | -0.130 | -0.108 |
| | *** (0.001) | *** (0.001) | *** (0.000) | *** (0.000) |
| | | | | |
| $y_i$ = *Log of contracted hours* | | | | |
| age | 0.045 | 0.037 | 0.036 | 0.033 |
| | *** (0.001) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.120 | -0.052 | 0.014 | 0.027 |
| | ***(0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.096 | -0.043 | 0.003 | 0.015 |
| | *** (0.000) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.057 | -0.013 | -0.024 | -0.015 |
| | *** (0.000) | *** (0.000) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.142 | -0.042 | -0.040 | -0.025 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |

| $y_i$ = *Log of contracted hourly wage* | | | | |
|---|---|---|---|---|
| age | 0.043 | 0.040 | 0.030 | 0.028 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.434 | -0.311 | -0.169 | -0.124 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.286 | -0.229 | -0.101 | -0.075 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.157 | -0.118 | -0.053 | -0.035 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.171 | -0.135 | -0.090 | -0.084 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | | | | |
| Individual characteristics | YES | YES | YES | YES |
| Firm F.E | NO | YES | NO | YES |
| Occupation F.E | NO | NO | YES | YES |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for all workers in both sectors. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. In the third model (column 3) the fixed effect of occupation is added to model 1. The fourth model (column 4) includes the fixed effect of both firm and occupation to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C5**. Regression estimates for all workers in public sector.

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | |
| age | 0.074 | 0.069 | 0.057 | 0.055 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.575 | -0.468 | -0.115 | -0.099 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.411 | -0.364 | -0.084 | -0.071 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.201 | -0.158 | -0.063 | -0.050 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.216 | -0.131 | -0.094 | -0.077 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | | | | |
| $y_i$ = *Log of contracted hours* | | | | |
| age | 0.045 | 0.039 | 0.033 | 0.032 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.227 | -0.148 | 0.019 | 0.027 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.171 | -0.085 | 0.008 | 0.019 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.058 | -0.007 | -0.023 | -0.015 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.107 | -0.030 | -0.039 | -0.027 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

| $y_i$ = *Log of contracted hourly wage* | | | | |
|---|---|---|---|---|
| age | 0.029 | 0.030 | 0.024 | 0.023 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.347 | -0.320 | -0.134 | -0.126 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.240 | -0.279 | -0.091 | -0.090 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.143 | -0.151 | -0.040 | -0.036 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.109 | -0.101 | -0.054 | -0.050 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | | | | |
| Individual characteristics | YES | YES | YES | YES |
| Firm F.E | NO | YES | NO | YES |
| Occupation F.E | NO | NO | YES | YES |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for all workers in public sector. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. In the third model (column 3) the fixed effect of occupation is added to model 1. The fourth model (column 4) includes the fixed effect of both firm and occupation to model 1. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C6**. Regression estimates for all workers in private sector

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | |
| age | 0.095 | 0.082 | 0.070 | 0.064 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.594 | -0.276 | -0.174 | -0.093 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.415 | -0.188 | -0.109 | -0.051 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.238 | -0.102 | -0.088 | -0.049 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.329 | -0.212 | -0.156 | -0.135 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | | | | |
| $y_i$ = *Log of contracted hours* | | | | |
| age | 0.046 | 0.037 | 0.038 | 0.034 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.084 | 0.004 | 0.012 | 0.027 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.064 | -0.005 | 0.001 | 0.014 |
| | *** (0.001) | *** (0.001) | * (0.001) | *** (0.001) |
| educ_3 | -0.062 | -0.023 | -0.025 | -0.016 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.129 | -0.050 | -0.040 | -0.022 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

| $y_i$ = *Log of contracted hourly wage* | | | | |
|---|---|---|---|---|
| age | 0.049 | 0.045 | 0.032 | 0.030 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.510 | -0.280 | -0.186 | -0.120 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.351 | -0.183 | -0.110 | -0.065 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.176 | -0.079 | -0.064 | -0.033 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.200 | -0.162 | -0.116 | -0.113 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | | | | |
| Individual characteristics | YES | YES | YES | YES |
| Firm F.E | NO | YES | NO | YES |
| Occupation F.E | NO | NO | YES | YES |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for all workers in private sector. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. In the third model (column 3) the fixed effect of occupation is added to model 1. The fourth model (column 4) includes the fixed effect of both firm and occupation to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C7**. Regression estimates for executives in both sectors.

| | Model 1 | Model 2 |
|---|---|---|
| $y_i$ = *Log of yearly wage* | | |
| age | 0.104 | 0.079 |
| | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.497 | -0.253 |
| | *** (0.003) | *** (0.004) |
| educ_2 | -0.395 | -0.227 |
| | *** (0.002) | *** (0.003) |
| educ_3 | -0.196 | -0.098 |
| | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| Female | -0.264 | -0.163 |
| | *** (0.002) | *** (0.002) |
| | | |
| $y_i$ = *Log of contracted hours* | | |
| age | 0.023 | 0.016 |
| | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.043 | -0.006 |
| | *** (0.001) | *** (0.001) |
| educ_2 | -0.034 | -0.009 |
| | *** (0.001) | *** (0.001) |
| educ_3 | -0.019 | -0.004 |
| | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| female | -0.019 | -0.012 |
| | *** (0.001) | *** (0.001) |
| | | |
| $y_i$ = *Log of contracted hourly wage* | | |
| age | 0.081 | 0.063 |
| | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.454 | -0.247 |
| | *** (0.003) | *** (0.003) |
| educ_2 | -0.361 | -0.218 |
| | *** (0.002) | *** (0.003) |
| educ_3 | -0.177 | -0.094 |
| | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| female | -0.245 | -0.151 |
| | *** (0.002) | *** (0.002) |

| | | |
|---|---|---|
| Individual characteristics | YES | YES |
| Firm F.E | NO | YES |
| Occupation F.E | NO | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for executives in both sectors. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C8**. Regression estimates for executives in public sector

| | Model 1 | Model 2 |
|---|---|---|
| $y_i$ = *Log of yearly wage* | | |
| age | 0.092 *** (0.001) | 0.070 *** (0.001) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.390 *** (0.008) | -0.276 *** (0.007) |
| educ_2 | -0.331 *** (0.004) | -0.268 *** (0.004) |
| educ_3 | -0.197 *** (0.003) | -0.117 *** (0.003) |
| educ_4 | 0 (omitted) | 0 (omitted) |
| female | -0.166 *** (0.002) | -0.100 *** (0.002) |
| $y_i$ = *Log of contracted hours* | | |
| age | 0.030 *** (0.001) | 0.023 *** (0.001) |
| age-squared | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.055 *** (0.005) | -0.023 *** (0.005) |
| educ_2 | -0.048 *** (0.002) | -0.030 *** (0.003) |
| educ_3 | -0.023 *** (0.001) | -0.005 *** (0.001) |
| educ_4 | 0 (omitted) | 0 (omitted) |
| female | -0.009 *** (0.001) | -0.005 *** (0.001) |
| $y_i$ = *Log of contracted hourly wage* | | |
| age | 0.063 *** (0.001) | 0.048 *** (0.001) |
| age-squared | -0.001 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.335 *** (0.007) | -0.254 *** (0.007) |
| educ_2 | -0.283 *** (0.004) | -0.238 *** (0.004) |
| educ_3 | -0.175 *** (0.003) | -0.112 *** (0.002) |
| educ_4 | 0 (omitted) | 0 (omitted) |
| female | -0.158 *** (0.002) | -0.096 *** (0.002) |

| | | |
|---|---|---|
| Individual characteristics | YES | YES |
| Firm F.E | NO | YES |
| Occupation F.E | NO | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for executives in public sector. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C9**. Regression estimates for executives in private sector

| | Model 1 | Model 2 |
|---|---|---|
| $y_i$ = *Log of yearly wage* | | |
| age | 0.109 | 0.082 |
| | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.569 | -0.236 |
| | *** (0.004) | *** (0.004) |
| educ_2 | -0.463 | -0.206 |
| | *** (0.003) | *** (0.004) |
| educ_3 | -0.214 | -0.082 |
| | *** (0.004) | *** (0.003) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| female | -0.274 | -0.205 |
| | *** (0.002) | *** (0.002) |
| | | |
| $y_i$ = *Log of contracted hours* | | |
| age | 0.023 | 0.015 |
| | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.034 | 0.001 |
| | *** (0.002) | (0.002) |
| educ_2 | -0.023 | -0.001 |
| | *** (0.001) | (0.001) |
| educ_3 | -0.016 | -0.002 |
| | *** (0.001) | ** (0.001) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| female | -0.030 | -0.017 |
| | *** (0.001) | *** (0.001) |
| | | |
| $y_i$ = *Log of contracted hourly wage* | | |
| age | 0.087 | 0.067 |
| | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) |
| educ_1 | -0.535 | -0.237 |
| | *** (0.004) | *** (0.004) |
| educ_2 | -0.439 | -0.205 |
| | *** (0.003) | *** (0.003) |
| educ_3 | -0.198 | -0.080 |
| | *** (0.003) | *** (0.003) |
| educ_4 | 0 | 0 |
| | (omitted) | (omitted) |
| female | -0.244 | -0.188 |
| | *** (0.002) | *** (0.002) |

| | | |
|---|---|---|
| Individual characteristics | YES | YES |
| Firm F.E | NO | YES |
| Occupation F.E | NO | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for executives in private sector. The baseline model (column 1) controls for age, $age^2$ and education. These are referred to as individual characteristics. The second model (column 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C10**. Regression estimates for CEOs in both sectors

| | Model 1 |
|---|---|
| $y_i$ = *Log of yearly wage* | |
| age | 0.103 |
| | *** (0.001) |
| age-squared | -0.001 |
| | *** (0.000) |
| educ_1 | -0.461 |
| | *** (0.006) |
| educ_2 | -0.355 |
| | *** (0.005) |
| educ_3 | -0.140 |
| | *** (0.005) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.285 |
| | *** (0.004) |
| | |
| $y_i$ = *Log of contracted hours* | |
| age | 0.028 |
| | *** (0.001) |
| age-squared | -0.000 |
| | *** (0.000) |
| educ_1 | -0.038 |
| | *** (0.003) |
| educ_2 | -0.016 |
| | *** (0.002) |
| educ_3 | -0.018 |
| | *** (0.002) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.047 |
| | *** (0.002) |
| | |
| $y_i$ = *Log of contracted hourly wage* | |
| age | 0.075 |
| | *** (0.001) |
| age-squared | -0.001 |
| | *** (0.000) |
| educ_1 | -0.423 |
| | *** (0.005) |
| educ_2 | -0.339 |
| | *** (0.004) |
| educ_3 | -0.123 |
| | *** (0.005) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.238 |
| | *** (0.003) |

| | |
|---|---|
| Individual characteristics | YES |
| Firm F.E | NO |
| Occupation F.E | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for CEOs in public sector. The baseline model (column 1) controls for age, $age^2$ and education. These are referred to as individual characteristics. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C11**. Regression estimates for CEOs in public sector

| | Model 1 |
|---|---|
| $y_i$ = *Log of yearly wage* | |
| age | 0.126 |
| | *** (0.004) |
| age-squared | -0.001 |
| | *** (0.000) |
| educ_1 | -0.561 |
| | *** (0.025) |
| educ_2 | -0.459 |
| | *** (0.014) |
| educ_3 | -0.201 |
| | *** (0.012) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.211 |
| | *** (0.009) |
| | |
| $y_i$ = *Log of contracted hours* | |
| age | 0.036 |
| | *** (0.003) |
| age-squared | -0.000 |
| | *** (0.000) |
| educ_1 | -0.128 |
| | *** (0.015) |
| educ_2 | -0.082 |
| | *** (0.007) |
| educ_3 | -0.023 |
| | *** (0.005) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.026 |
| | *** (0.005) |
| | |
| $y_i$ = *Log of contracted hourly wage* | |
| age | 0.090 |
| | *** (0.003) |
| age-squared | -0.001 |
| | *** (0.000) |
| educ_1 | -0.433 |
| | *** (0.021) |
| educ_2 | -0.377 |
| | *** (0.012) |
| educ_3 | -0.178 |
| | *** (0.010) |
| educ_4 | 0 |
| | (omitted) |
| female | -0.186 |
| | *** (0.008) |

| | |
|---|---|
| Individual characteristics | YES |
| Firm F.E | NO |
| Occupation F.E | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for CEOs in public sector. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C12**. Regression estimates for CEOs in private sector

| | Model 1 |
|---|---|
| $y_i$ = *Log of yearly wage* | |
| age | 0.103<br>*** (0.001) |
| age-squared | -0.001<br>*** (0.000) |
| educ_1 | -0.448<br>*** (0.006) |
| educ_2 | -0.342<br>*** (0.005) |
| educ_3 | -0.129<br>*** (0.006) |
| educ_4 | 0<br>(omitted) |
| female | -0.297<br>*** (0.004) |
| | |
| $y_i$ = *Log of contracted hours* | |
| age | 0.028<br>*** (0.001) |
| age-squared | -0.000<br>*** (0.000) |
| educ_1 | -0.030<br>*** (0.003) |
| educ_2 | -0.008<br>*** (0.002) |
| educ_3 | -0.016<br>*** (0.003) |
| educ_4 | 0<br>(omitted) |
| female | -0.052<br>*** (0.002) |
| | |
| $y_i$ = *Log of contracted hourly wage* | |
| age | 0.075<br>*** (0.001) |
| age-squared | -0.001<br>*** (0.000) |
| educ_1 | -0.418<br>*** (0.010) |
| educ_2 | -0.334<br>*** (0.005) |
| educ_3 | -0.113<br>*** (0.005) |
| educ_4 | 0<br>(omitted) |
| female | -0.245<br>*** (0.003) |

| | |
|---|---|
| Individual characteristics | YES |
| Firm F.E | NO |
| Occupation F.E | NO |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ in the years 2015 to 2020 combined for CEOs in private sector. The baseline model (column 1) controls for age, age$^2$ and education. These are referred to as individual characteristics. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C13**. Regression estimates for development for all workers in both sectors

| | | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|
| *$y_i$ = Log of yearly wage* | | | | | | | |
| Model 1 | | | | | | | |
| | age | 0.085 | 0.089 | 0.090 | 0.090 | 0.090 | 0.088 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.538 | -0.543 | -0.551 | -0.554 | -0.558 | -0.572 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_2 | -0.371 | -0.378 | -0.383 | -0.380 | -0.379 | -0.389 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_3 | -0.206 | -0.207 | -0.213 | -0.214 | -0.215 | -0.216 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | -0.333 | -0.321 | -0.313 | -0.309 | -0.306 | -0.296 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | | |
| | age | 0.074 | 0.076 | 0.077 | 0.078 | 0.079 | 0.078 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.378 | -0.364 | -0.357 | -0.357 | -0.354 | -0.355 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_2 | -0.287 | -0.275 | -0.269 | -0.266 | -0.262 | -0.261 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_3 | - 0.129 | -0.125 | -0.130 | -0.130 | -0.129 | -0.127 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | -0.194 | -0.188 | -0.181 | -0.174 | -0.169 | -0.162 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

$y_i = Log\ of\ contracted\ hours$

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Model 1 | | | | | | | |
| | age | 0.040 | 0.041 | 0.046 | 0.046 | 0.047 | 0.048 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | age-squared | -0.000 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.122 | -0.115 | -0.117 | -0.117 | -0.123 | -0.126 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_2 | -0.093 | -0.093 | -0.095 | -0.095 | -0.097 | -0.102 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_3 | -0.048 | -0.052 | -0.058 | -0.059 | -0.059 | -0.062 |
| | | *** (0.001) | *** (0.001) | (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | -0.142 | -0.143 | -0.147 | -0.143 | -0.141 | -0.135 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | | |
| | age | 0.033 | 0.034 | 0.038 | 0.037 | 0.039 | 0.039 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.068 | -0.058 | -0.051 | -0.049 | -0.050 | -0.046 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_2 | -0.048 | -0.046 | -0.043 | -0.042 | -0.042 | -0.042 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_3 | -0.006 | -0.009 | -0.013 | -0.014 | -0.015 | -0.016 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | 0.045 | -0.045 | -0.044 | -0.041 | -0.038 | -0.035 |
| | | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

$y_i$ = *Log of contracted hourly wage*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.045 | 0.047 | 0.044 | 0.045 | 0.043 | 0.040 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.001 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.416 | -0.428 | -0.433 | -0.437 | -0.435 | -0.446 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.278 | -0.286 | -0.288 | -0.285 | -0.282 | -0.286 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.158 | -0.155 | -0.155 | -0.155 | -0.156 | -0.153 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.191 | -0.177 | -0.166 | -0.166 | -0.165 | -0.161 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | |
| age | 0.041 | 0.042 | 0.040 | 0.041 | 0.040 | 0.039 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.310 | -0.306 | -0.306 | -0.308 | -0.304 | -0.309 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.239 | -0.230 | -0.226 | -0.223 | -0.220 | -0.219 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.123 | -0.117 | -0.117 | -0.115 | -0.115 | -0.111 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.149 | -0.144 | -0.138 | -0.133 | -0.131 | -0.126 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for all workers in both sectors. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C14**. Regression estimates for development for all workers in public sector

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.079 *** (0.000) | 0.074 *** (0.000) | 0.076 *** (0.000) | 0.076 *** (0.000) | 0.076 *** (0.000) | 0.075 *** (0.000) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.563 *** (0.002) | -0.561 *** (0.002) | -0.571 *** (0.002) | -0.573 *** (0.002) | -0.576 *** (0.002) | -0.579 *** (0.002) |
| educ_2 | -0.406 *** (0.001) | -0.405 *** (0.001) | -0.411 *** (0.001) | -0.410 *** (0.001) | -0.407 *** (0.001) | -0.407 *** (0.001) |
| educ_3 | -0.203 *** (0.001) | -0.200 *** (0.001) | -0.202 *** (0.001) | -0.200 *** (0.001) | -0.198 *** (0.001) | -0.193 *** (0.001) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.235 *** (0.001) | -0.229 *** (0.001) | -0.219 *** (0.001) | -0.214 *** (0.001) | -0.209 *** (0.001) | -0.194 *** (0.001) |
| Model 2 | | | | | | |
| age | 0.067 *** (0.000) | 0.069 *** (0.000) | 0.070 *** (0.000) | 0.070 *** (0.000) | 0.071 *** (0.000) | 0.070 *** (0.000) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.469 *** (0.002) | -0.461 *** (0.002) | -0.463 *** (0.002) | -0.465 *** (0.002) | -0.468 *** (0.002) | -0.463 *** (0.002) |
| educ_2 | -0.365 *** (0.001) | -0.358 *** (0.001) | -0.361 *** (0.001) | -0.361 *** (0.001) | -0.361 *** (0.001) | -0.356 *** (0.001) |
| educ_3 | -0.158 *** (0.001) | -0.153 *** (0.001) | -0.157 *** (0.001) | -0.158 *** (0.001) | -0.158 *** (0.001) | -0.152 *** (0.001) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.145 *** (0.001) | -0.140 *** (0.001) | -0.135 *** (0.001) | -0.128 *** (0.001) | -0.125 *** (0.001) | -0.118 *** (0.001) |

$y_i = Log\ of\ contracted\ hours$

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Model 1 | | | | | | | |
| | age | 0.043 *** (0.000) | 0.044 *** (0.000) | 0.045 *** (0.000) | 0.045 *** (0.000) | 0.046 *** (0.000) | 0.047 *** (0.000) |
| | age-squared | -0.000 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| | educ_1 | -0.228 *** (0.002) | -0.224 *** (0.002) | -0.225 *** (0.002) | -0.224 *** (0.002) | -0.230 *** (0.002) | -0.230 *** (0.002) |
| | educ_2 | -0.165 *** (0.001) | -0.168 *** (0.001) | -0.1718 *** (0.001) | -0.171 *** (0.001) | -0.173 *** (0.001) | -0.175 *** (0.001) |
| | educ_3 | -0.053 *** (0.001) | -0.056 *** (0.001) | -0.0589 *** (0.001) | -0.059 *** (0.001) | -0.059 *** (0.001) | -0.061 *** (0.001) |
| | educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| | female | -0.121 *** (0.001) | -0.117 *** (0.001) | -0.1119 *** (0.001) | -0.105 *** (0.001) | -0.098 *** (0.001) | -0.092 *** (0.001) |
| Model 2 | | | | | | | |
| | Age | 0.038 *** (0.000) | 0.039 *** (0.000) | 0.039 *** (0.000) | 0.039 *** (0.000) | 0.040 *** (0.000) | 0.040 *** (0.000) |
| | age-squared | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| | educ_1 | -0.153 *** (0.002) | -0.148 *** (0.002) | -0.148 *** (0.002) | -0.147 *** (0.002) | -0.151 *** (0.002) | -0.143 *** (0.002) |
| | educ_2 | -0.081 *** (0.001) | -0.082 *** (0.001) | -0.085 *** (0.001) | -0.086 *** (0.001) | -0.087 *** (0.001) | -0.085 *** (0.001) |
| | educ_3 | 0.001 (0.001) | -0.002 (0.001) | -0.085 *** (0.001) | -0.009 *** (0.001) | -0.011 *** (0.001) | -0.013 *** (0.001) |
| | educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| | female | -0.038 *** (0.001) | -0.035 *** (0.001) | -0.031 *** (0.001) | -0.028 *** (0.001) | -0.025 *** (0.001) | -0.023 *** (0.001) |

$y_i = Log\ of\ contracted\ hourly\ wage$

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.029 | 0.030 | 0.030 | 0.031 | 0.030 | 0.027 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.336 | -0.338 | -0.346 | -0.350 | -0.345 | -0.349 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_2 | -0.241 | -0.238 | -0.240 | -0.239 | -0.234 | -0.233 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.150 | -0.144 | -0.143 | -0.142 | -0.139 | -0.132 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.114 | -0.112 | -0.107 | -0.109 | -0.110 | -0.103 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | |
| age | 0.030 | 0.030 | 0.030 | 0.031 | 0.031 | 0.029 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.315 | -0.313 | -0.316 | -0.319 | -0.316 | -0.320 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_2 | -0.284 | -0.276 | -0.276 | -0.275 | -0.274 | -0.272 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.159 | -0.151 | -0.151 | -0.149 | -0.146 | -0.139 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.107 | -0.105 | -0.104 | -0.100 | -0.099 | -0.095 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for all workers in public sector. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C15**. Regression estimates for development for all workers in private sector

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.093 | 0.096 | 0.097 | 0.097 | 0.097 | 0.094 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.586 | -0.587 | -0.588 | -0.591 | -0.595 | -0.611 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_2 | -0.411 | -0.416 | -0.415 | -0.409 | -0.409 | -0.421 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.001) | *** (0.001) |
| educ_3 | -0.216 | -0.224 | -0.238 | -0.241 | -0.245 | -0.254 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.323 | -0.327 | -0.331 | -0.330 | -0.329 | -0.332 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | |
| age | 0.078 | 0.081 | 0.082 | 0.082 | 0.083 | 0.082 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.295 | -0.281 | -0.269 | -0.268 | -0.264 | -0.270 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_2 | -0.210 | -0.196 | -0.184 | -0.179 | -0.174 | -0.177 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_3 | -0.099 | -0.097 | -0.100 | -0.101 | -0.101 | -0.102 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.235 | -0.226 | -0.216 | -0.207 | -0.200 | -0.193 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

$y_i = Log\ of\ contracted\ hours$

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.039 | 0.041 | 0.047 | 0.047 | 0.049 | 0.048 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.079 | -0.077 | -0.081 | -0.083 | -0.089 | -0.093 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.059 | -0.060 | -0.061 | -0.064 | -0.066 | -0.071 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_3 | -0.046 | -0.053 | -0.064 | -0.066 | -0.065 | -0.071 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.106 | -0.118 | -0.136 | -0.135 | -0.137 | -0.135 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | |
| age | 0.030 | 0.032 | 0.037 | 0.037 | 0.039 | 0.038 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.010 | -0.003 | 0.005 | 0.007 | 0.006 | 0.008 |
| | *** (0.001) | * (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_2 | -0.013 | -0.010 | -0.003 | -0.003 | -0.002 | -0.004 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | ** (0.001) | *** (0.001) |
| educ_3 | -0.018 | -0.021 | -0.024 | -0.025 | -0.022 | -0.023 |
| | *** (0.001) | *** (0.001) | (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.050 | -0.051 | -0.052 | -0.049 | -0.046 | -0.043 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

| $y_i$ = *Log of contracted hourly wage* | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.053 *** (0.000) | 0.055 *** (0.000) | 0.049 *** (0.000) | 0.050 *** (0.000) | 0.048 *** (0.000) | 0.045 *** (0.000) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.507 *** (0.002) | -0.510 *** (0.002) | -0.507 *** (0.002) | -0.507 *** (0.002) | -0.506 *** (0.002) | -0.518 *** (0.002) |
| educ_2 | -0.352 *** (0.002) | -0.356 *** (0.002) | -0.353 *** (0.002) | -0.346 *** (0.001) | -0.343 *** (0.001) | -0.350 *** (0.001) |
| educ_3 | -0.170 *** (0.002) | -0.172 *** (0.002) | -0.174 *** (0.002) | -0.174 *** (0.002) | -0.180 *** (0.002) | -0.183 *** (0.002) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.217 *** (0.001) | -0.208 *** (0.001) | -0.196 *** (0.001) | -0.195 *** (0.001) | -0.192 *** (0.001) | -0.197 *** (0.001) |
| Model 2 | | | | | | |
| age | 0.048 *** (0.000) | 0.049 *** (0.000) | 0.045 *** (0.000) | 0.045 *** (0.000) | 0.044 *** (0.000) | 0.044 *** (0.000) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.285 *** (0.002) | -0.278 *** (0.002) | -0.274 *** (0.002) | -0.275 *** (0.002) | -0.271 *** (0.002) | -0.278 *** (0.002) |
| educ_2 | -0.197 *** (0.002) | -0.186 *** (0.002) | -0.180 *** (0.002) | -0.176 *** (0.002) | -0.172 *** (0.002) | -0.173 *** (0.002) |
| educ_3 | -0.081 *** (0.002) | -0.076 *** (0.002) | -0.076 *** (0.002) | -0.076 *** (0.002) | -0.079 *** (0.002) | -0.079 *** (0.002) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.185 *** (0.001) | -0.175 *** (0.001) | -0.164 *** (0.001) | -0.158 *** (0.001) | -0.154 *** (0.001) | -0.150 *** (0.001) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for all workers in prvate sector. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C16**. Regression estimates for development for executives in both sectors

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.104 | 0.105 | 0.105 | 0.104 | 0.104 | 0.103 |
| | *** (.0008487) | *** (.000843) | *** (.0008447) | *** (.0008369) | *** (.0008368) | *** (.0008791) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.496 | -0.489 | -0.487 | -0.494 | -0.495 | -0.512 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_2 | -0.386 | -0.389 | -0.391 | -0.391 | -0.394 | -0.406 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_3 | -0.197 | -0.193 | -0.192 | -0.189 | -0.194 | -0.198 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.275 | -0.270 | -0.266 | -0.265 | -0.261 | -0.256 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| Model 2 | | | | | | |
| age | 0.084 | 0.086 | 0.085 | 0.084 | 0.083 | 0.083 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.275 | -0.268 | -0.259 | -0.263 | -0.257 | -0.252 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) |
| educ_2 | -0.236 | -0.235 | -0.235 | -0.233 | -0.228 | -0.226 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_3 | -0.100 | -0.101 | -0.101 | -0.096 | -0.095 | -0.095 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.179 | -0.175 | -0.176 | -0.169 | -0.163 | -0.157 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |

$y_i$ = *Log of contracted hours*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.022 | 0.024 | 0.023 | 0.023 | 0.023 | 0.023 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.038 | -0.040 | -0.042 | -0.040 | -0.043 | -0.052 |
| | *** (0.002) | *** (.0024288) | *** (.0023633) | *** (.002368) | *** (.002343) | *** (.0025419) |
| educ_2 | -0.031 | -0.032 | -0.034 | -0.031 | -0.033 | -0.042 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_3 | -0.018 | -0.018 | -0.0198 | -0.019 | -0.018 | -0.023 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.001) | *** (0.002) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.022 | -0.020 | -0.021 | -0.019 | -0.016 | -0.015 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| Model 2 | | | | | | |
| age | 0.015 | 0.018 | 0.017 | 0.016 | 0.016 | 0.015 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.002 | -0.008 | -0.008 | -0.008 | -0.009 | -0.007 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_2 | -0.008 | -0.012 | -0.013 | -0.009 | -0.009 | -0.010 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_3 | -0.002 | -0.003 | -0.005 | -0.005 | -0.004 | -0.005 |
| | *** (0.002) | *** (0.002) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.014 | -0.012 | -0.012 | -0.010 | -0.010 | -0.009 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of contracted hourly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.082 | 0.081 | 0.082 | 0.081 | 0.080 | 0.080 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.457 | -0.449 | -0.445 | -0.453 | -0.452 | -0.459 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_2 | -0.355 | -0.357 | -0.356 | -0.360 | -0.361 | -0.364 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_3 | -0.179 | -0.175 | -0.172 | -0.170 | -0.175 | -0.175 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.253 | -0.250 | -0.245 | -0.247 | -0.245 | -0.240 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| Model 2 | | | | | | |
| age | 0.070 | 0.068 | 0.068 | 0.068 | 0.067 | 0.067 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.273 | -0.261 | -0.251 | -0.255 | -0.248 | -0.245 |
| | *** (0.006) | *** (0.006) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) |
| educ_2 | -0.228 | -0.223 | -0.222 | -0.224 | -0.219 | -0.216 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_3 | -0.098 | -0.098 | -0.096 | -0.0914967 | -0.0908504 | -0.089747 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.165 | -0.165 | -0.163 | -0.158 | -0.153 | -0.147 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.002) | *** (0.002) | *** (0.002) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for executives in both sectors. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C17**. Regression estimates for development for executives in public sector

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.094 | 0.093 | 0.095 | 0.093 | 0.091 | 0.088 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.402 | -0.378 | -0.373 | -0.382 | -0.395 | -0.394 |
| | *** (0.010) | *** (0.011) | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.011) |
| educ_2 | -0.326 | -0.326 | -0.325 | -0.329 | -0.325 | -0.328 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) |
| educ_3 | -0.201 | -0.200 | -0.195 | -0.192 | -0.190 | -0.188 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.004) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.174 | -0.171 | -0.171 | -0.168 | -0.168 | -0.159 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| Model 2 | | | | | | |
| age | 0.074 | 0.075 | 0.076 | 0.072 | 0.074 | 0.069 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.313 | -0.295 | -0.279 | -0.277 | -0.272 | -0.270 |
| | *** (0.011) | *** (0.011) | *** (0.011) | *** (0.010) | *** (0.011) | *** (0.011) |
| educ_2 | -0.267 | -0.269 | -0.276 | -0.277 | -0.269 | -0.263 |
| | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| educ_3 | -0.120 | -0.119 | -0.122 | -0.121 | -0.115 | -0.115 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.114 | -0.110 | -0.109 | -0.107 | -0.105 | -0.096 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |

$y_i = Log\ of\ contracted\ hours$

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.029 *** (0.002) | 0.032 *** (0.002) | 0.031 *** (0.002) | 0.030 *** (0.002) | 0.028 *** (0.002) | 0.028 *** (0.002) |
| age-squared | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.058 *** (0.007) | -0.049 *** (0.007) | -0.054 *** (0.008) | -0.057 *** (0.008) | -0.054 *** (0.007) | -0.057 *** (0.008) |
| educ_2 | -0.044 *** (0.003) | -0.044 *** (0.003) | -0.053 *** (0.003) | -0.047 *** (0.003) | -0.049 *** (0.003) | -0.052 *** (0.003) |
| educ_3 | -0.023 *** (0.002) | -0.022 *** (0.002) | -0.024 *** (0.002) | -0.022 *** (0.002) | -0.022 *** (0.002) | -0.021 *** (0.002) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.012 *** (0.002) | -0.009 *** (0.002) | -0.010 *** (0.002) | -0.008 *** (0.002) | -0.007 *** (0.002) | -0.007 *** (0.002) |
| Model 2 | | | | | | |
| age | 0.022 *** (0.002) | 0.029 *** (0.002) | 0.024 *** (0.002) | 0.023 *** (0.002) | 0.023 *** (0.002) | 0.022 *** (0.002) |
| age-squared | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.022 *** (0.009) | -0.019 *** (0.009) | -0.021 *** (0.008) | -0.022 *** (0.008) | -0.028 *** (0.009) | -0.031 *** (0.009) |
| educ_2 | -0.022 *** (0.004) | -0.028 *** (0.004) | -0.037 *** (0.004) | -0.031 *** (0.004) | -0.029 *** (0.004) | -0.031 *** (0.004) |
| educ_3 | -0.004 *** (0.003) | -0.001 *** (0.003) | -0.005 *** (0.002) | -0.007 *** (0.002) | -0.006 *** (0.002) | -0.007 *** (0.002) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.009 *** (0.002) | -0.005 *** (0.002) | -0.001 *** (0.002) | -0.002 *** (0.002) | -0.004 *** (0.002) | -0.005 *** (0.002) |

$y_i$ = *Log of contracted hourly wage*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.065 *** (0.002) | 0.060 *** (0.002) | 0.064 *** (0.002) | 0.063 *** (0.002) | 0.063 *** (0.002) | 0.061 *** (0.002) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.344 *** (0.010) | -0.329 *** (0.010) | -0.318 *** (0.011) | -0.325 *** (0.010) | -0.341 *** (0.010) | -0.338 *** (0.010) |
| educ_2 | -0.282 *** (0.005) | -0.282 *** (0.005) | -0.272 *** (0.005) | -0.282 *** (0.005) | -0.276 *** (0.005) | -0.276 *** (0.005) |
| educ_3 | -0.178 *** (0.004) | -0.177 *** (0.004) | -0.171 *** (0.003) | -0.170 *** (0.003) | -0.168 *** (0.003) | -0.167 *** (0.003) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.162 *** (0.003) | -0.163 *** (0.003) | -0.161 *** (0.003) | -0.160 *** (0.003) | -0.161 *** (0.003) | -0.152 *** (0.003) |
| Model 2 | | | | | | |
| age | 0.052 *** (0.002) | 0.045 *** (0.002) | 0.051 *** (0.002) | 0.050 *** (0.002) | 0.050 *** (0.002) | 0.047 *** (0.002) |
| age-squared | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.001 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) | -0.000 *** (0.000) |
| educ_1 | -0.291 *** (0.011) | -0.276 *** (0.011) | -0.259 *** (0.011) | -0.255 *** (0.011) | -0.244 *** (0.012) | -0.238 *** (0.011) |
| educ_2 | -0.245 *** (0.006) | -0.241 *** (0.006) | -0.239 *** (0.006) | -0.246 *** (0.006) | -0.239 *** (0.006) | -0.231 *** (0.006) |
| educ_3 | -0.116 *** (0.004) | -0.118 *** (0.004) | -0.117 *** (0.004) | -0.114 *** (0.004) | -0.108 *** (0.004) | -0.107 *** (0.004) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.105 *** (0.003) | -0.105 *** (0.003) | -0.108 *** (0.003) | -0.105 *** (0.003) | -0.101 *** (0.003) | -0.091 *** (0.003) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for executives in public sector. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C18**. Regression estimates for development for executives in private sector

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| *$y_i$ = Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.110 *** (0.001) | 0.111 *** (0.001) | 0.110 *** (0.001) | 0.109 *** (0.001) | 0.110 *** (0.001) | 0.109 *** (0.001) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.582 *** (0.005) | -0.567 *** (0.005) | -0.561 *** (0.005) | -0.562 *** (0.005) | -0.562 *** (0.005) | -0.572 *** (0.005) |
| educ_2 | -0.468 *** (0.004) | -0.462 *** (0.004) | -0.459 *** (0.005) | -0.455 *** (0.004) | -0.459 *** (0.004) | -0.465 *** (0.004) |
| educ_3 | -0.217 *** (0.004) | -0.209 *** (0.005) | -0.210 *** (0.005) | -0.205 *** (0.005) | -0.213 *** (0.005) | -0.220 *** (0.005) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.274 *** (0.003) | -0.276 *** (0.003) | -0.276 *** (0.003) | -0.277 *** (0.003) | -0.271 *** (0.003) | -0.277 *** (0.003) |
| Model 2 | | | | | | |
| age | 0.089 *** (0.001) | 0.090 *** (0.001) | 0.089 *** (0.001) | 0.088 *** (0.001) | 0.086 *** (0.001) | 0.087 *** (0.001) |
| age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| educ_1 | -0.258 *** (0.007) | -0.253 *** (0.007) | -0.241 *** (0.007) | -0.245 *** (0.007) | -0.241 *** (0.007) | -0.237 *** (0.007) |
| educ_2 | -0.219 *** (0.005) | -0.217 *** (0.005) | -0.213 *** (0.005) | -0.210 *** (0.005) | -0.208 *** (0.005) | -0.207 *** (0.005) |
| educ_3 | -0.085 *** (0.005) | -0.087 *** (0.005) | -0.084 *** (0.005) | -0.075 *** (0.005) | -0.077 *** (0.005) | -0.078 *** (0.005) |
| educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| female | -0.222 *** (0.004) | -0.219 *** (0.004) | -0.221 *** (0.004) | -0.210 *** (0.004) | -0.203 *** (0.003) | -0.198 *** (0.004) |

$y_i$ = *Log of contracted hours*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.022 | 0.023 | 0.023 | 0.023 | 0.023 | 0.022 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.032 | -0.033 | -0.032 | -0.031 | -0.033 | -0.040 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_2 | -0.024 | -0.024 | -0.022 | -0.021 | -0.022 | -0.029 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_3 | -0.015 | -0.014 | -0.015 | -0.015 | -0.014 | -0.022 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.030 | -0.029 | -0.033 | -0.029 | -0.027 | -0.031 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| Model 2 | | | | | | |
| age | 0.013 | 0.015 | 0.015 | 0.014 | 0.014 | 0.014 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | 0.004 | -0.004 | -0.002 | -0.001 | -0.002 | 0.002 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_2 | -0.001 | -0.006 | -0.003 | 0.000 | -0.000 | -0.000 |
| | *** (0.002) | *** (0.002) | * (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_3 | -0.000 | -0.004 | -0.004 | -0.002 | -0.001 | -0.002 |
| | *** (0.002) | ** (0.002) | ** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.017 | -0.015 | -0.021 | -0.016 | -0.015 | -0.013 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |

$y_i$ = *Log of contracted hourly wage*

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Model 1 | | | | | | | |
| | age | 0.088 *** (0.001) | 0.088 *** (0.001) | 0.087 *** (0.001) | 0.087 *** (0.001) | 0.086 *** (0.001) | 0.086 *** (0.001) |
| | age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| | educ_1 | -0.550 *** (0.005) | -0.534 *** (0.005) | -0.529 *** (0.005) | -0.531 *** (0.005) | -0.529 *** (0.005) | -0.532 *** (0.005) |
| | educ_2 | -0.444 *** (0.004) | -0.437 *** (0.004) | -0.437 *** (0.004) | -0.434 *** (0.004) | -0.437 *** (0.004) | -0.435 *** (0.004) |
| | educ_3 | -0.202 *** (0.005) | -0.195 *** (0.004) | -0.194 *** (0.005) | -0.190 *** (0.004) | -0.199 *** (0.004) | -0.198 *** (0.004) |
| | educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| | female | -0.244 *** (0.003) | -0.246 *** (0.003) | -0.244 *** (0.003) | -0.248 *** (0.003) | -0.245 *** (0.003) | -0.246 *** (0.003) |
| Model 2 | | | | | | | |
| | age | 0.075 *** (0.001) | 0.075 *** (0.001) | 0.074 *** (0.001) | 0.073 *** (0.001) | 0.072 *** (0.001) | 0.073 *** (0.001) |
| | age-squared | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) | -0.001 *** (0.000) |
| | educ_1 | -0.262 *** (0.007) | -0.249 *** (0.007) | -0.239 *** (0.007) | -0.244 *** (0.007) | -0.240 *** (0.006) | -0.239 *** (0.007) |
| | educ_2 | -0.218 *** (0.005) | -0.211 *** (0.005) | -0.210 *** (0.005) | -0.210 *** (0.005) | -0.207 *** (0.005) | -0.207 *** (0.005) |
| | educ_3 | -0.085 *** (0.005) | -0.083 *** (0.005) | -0.079 *** (0.005) | -0.073 *** (0.005) | -0.077 *** (0.005) | -0.075 *** (0.005) |
| | educ_4 | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) | 0 (omitted) |
| | female | -0.205 *** (0.004) | -0.204 *** (0.004) | -0.201 *** (0.004) | -0.194 *** (0.004) | -0.188 *** (0.003) | -0.185 *** (0.004) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for executives in private sector. The baseline model (model 1) controls for age, age$^2$ and education. The second model (model 2) adds the fixed effect of firm to model 1. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C19**. Regression estimates for development for CEOs in both sectors

| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.104 | 0.107 | 0.104 | 0.104 | 0.103 | 0.100 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.468 | -0.465 | -0.453 | -0.460 | -0.457 | -0.465 |
| | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) |
| educ_2 | -0.363 | -0.361 | -0.351 | -0.352 | -0.352 | -0.349 |
| | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| educ_3 | -0.139 | -0.142 | -0.138 | -0.141 | -0.137 | -0.142 |
| | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.288 | -0.287 | -0.289 | -0.284 | -0.281 | -0.289 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.004) | *** (0.004) | *** (0.005) |
| $y_i$ = *Log of contracted hours* | | | | | | |
| Model 1 | | | | | | |
| age | 0.028 | 0.029 | 0.028 | 0.028 | 0.028 | 0.026 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.040 | -0.039 | -0.035 | -0.035 | -0.041 | -0.041 |
| | *** (0.005) | *** (0.005) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.005) |
| educ_2 | -0.017 | -0.014 | -0.015 | -0.014 | -0.019 | -0.017 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |
| educ_3 | -0.019 | -0.013 | -0.015 | -0.016 | -0.018 | -0.026 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.047 | -0.044 | -0.052 | -0.047 | -0.045 | -0.047 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) |

$y_i = Log\ of\ contracted\ hourly\ wage$

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.076 | 0.078 | 0.076 | 0.076 | 0.076 | 0.074 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.428 | -0.426 | -0.418 | -0.425 | -0.415 | -0.424 |
| | *** (0.008) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) |
| educ_2 | -0.346 | -0.347 | -0.336 | -0.337 | -0.334 | -0.332 |
| | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| educ_3 | -0.120 | -0.129 | -0.123 | -0.124 | -0.119 | -0.115 |
| | *** (0.007) | *** (0.007) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.241 | -0.242 | -0.238 | -0.237 | -0.236 | -0.242 |
| | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for CEOs in both sectors. The baseline model (model 1) controls for age, age$^2$ and education. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

**Table C20**. Regression estimates for development for CEOs in public sector

| | | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|---|
| *$y_i$ = Log of yearly wage* | | | | | | | |
| Model 1 | | | | | | | |
| | age | 0.121 | 0.132 | 0.123 | 0.130 | 0.125 | 0.125 |
| | | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| | age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.552 | -0.551 | -0.538 | -0.559 | -0.586 | -0.582 |
| | | *** (0.031) | *** (0.033) | *** (0.032) | *** (0.031) | *** (0.031) | *** (0.033) |
| | educ_2 | -0.443 | -0.451 | -0.450 | -0.462 | -0.466 | -0.461 |
| | | *** (0.018) | *** (0.017) | *** (0.018) | *** (0.018) | *** (0.018) | *** (0.018) |
| | educ_3 | -0.185 | -0.204 | -0.198 | -0.204 | -0.208 | -0.203 |
| | | *** (0.015) | *** (0.015) | *** (0.015) | *** (0.015) | *** (0.015) | *** (0.015) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | -0.221 | -0.215 | -0.222 | -0.221 | -0.201 | -0.206 |
| | | *** (0.012) | *** (0.012) | *** (0.012) | *** (0.012) | *** (0.012) | *** (0.012) |
| *$y_i$ = Log of contracted hours* | | | | | | | |
| Model 1 | | | | | | | |
| | age | 0.035 | 0.039 | 0.038 | 0.041 | 0.029 | 0.032 |
| | | *** (0.004) | *** (0.004) | *** (0.005) | *** (0.005) | *** (0.004) | *** (0.005) |
| | age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| | educ_1 | -0.100 | -0.143 | -0.133 | -0.133 | -0.122 | -0.137 |
| | | *** (0.018) | *** (0.024) | *** (0.023) | *** (0.024) | *** (0.021) | *** (0.021) |
| | educ_2 | -0.076 | -0.069 | -0.077 | -0.087 | -0.086 | -0.099 |
| | | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.010) |
| | educ_3 | -0.017 | -0.024 | -0.020 | -0.023 | -0.024 | -0.031 |
| | | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.008) | *** (0.007) | *** (0.007) |
| | educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| | female | -0.026 | -0.025 | -0.028 | -0.030 | -0.022 | -0.023 |
| | | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) |

$y_i$ = *Log of contracted hourly wage*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.086 | 0.093 | 0.085 | 0.089 | 0.095 | 0.094 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.006) | *** (0.005) | *** (0.006) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.452 | -0.408 | -0.404 | -0.426 | -0.464 | -0.444 |
| | *** (0.027) | *** (0.030) | *** (0.032) | *** (0.031) | *** (0.028) | *** (0.029) |
| educ_2 | -0.367 | -0.382 | -0.372 | -0.375 | -0.379 | -0.362 |
| | *** (0.015) | *** (0.016) | *** (0.015) | *** (0.015) | *** (0.015) | *** (0.016) |
| educ_3 | -0.168 | -0.180 | -0.178 | -0.181 | -0.184 | -0.172 |
| | *** (0.014) | *** (0.013) | *** (0.013) | *** (0.013) | *** (0.013) | *** (0.013) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.195 | -0.190 | -0.194 | -0.192 | -0.178 | -0.183 |
| | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.010) | *** (0.011) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for CEOs in public sector. The baseline model (model 1) controls for age, age$^2$ and education. Standard errors are clustered in person. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$,*** $p < 0.01$

**Table C21**. Regression estimates for development for CEOs in private sector

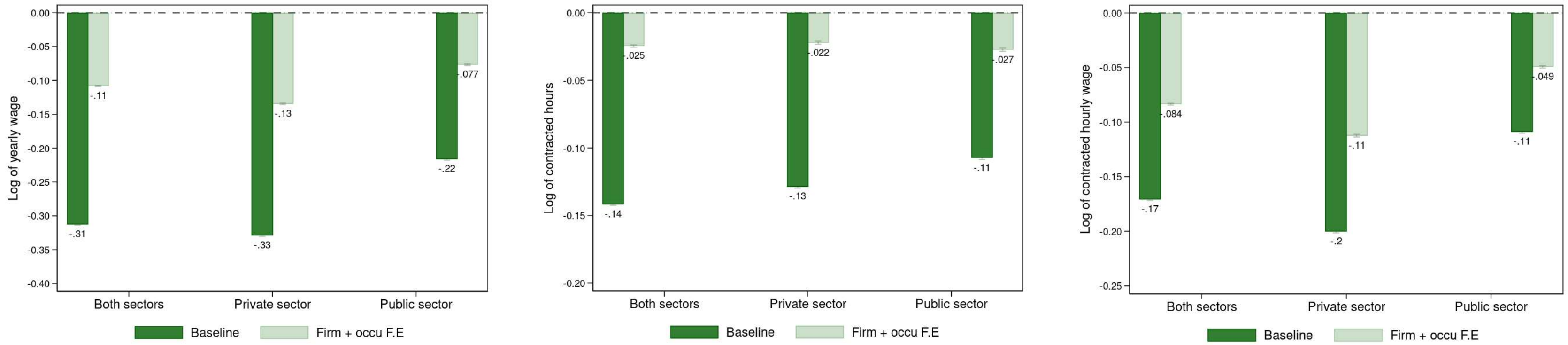
| | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|---|
| $y_i$ = *Log of yearly wage* | | | | | | |
| Model 1 | | | | | | |
| age | 0.104 | 0.106 | 0.104 | 0.103 | 0.103 | 0.099 |
| | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) | *** (0.002) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.458 | -0.453 | -0.440 | -0.446 | -0.441 | -0.448 |
| | *** (0.009) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) |
| educ_2 | -0.354 | -0.349 | -0.338 | -0.338 | -0.337 | -0.332 |
| | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) |
| educ_3 | -0.130 | -0.131 | -0.127 | -0.129 | -0.124 | -0.132 |
| | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.007) | *** (0.008) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.297 | -0.297 | -0.299 | -0.295 | -0.293 | -0.306 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) |
| $y_i$ = *Log of contracted hours* | | | | | | |
| Model 1 | | | | | | |
| age | 0.028 | 0.029 | 0.028 | 0.028 | 0.028 | 0.026 |
| | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.001) |
| age-squared | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.033 | -0.030 | -0.026 | -0.027 | -0.033 | -0.030 |
| | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) | *** (0.005) |
| educ_2 | -0.012 | -0.007 | -0.007 | -0.007 | -0.011 | -0.007 |
| | *** (0.004) | * (0.004) | ** (0.004) | * (0.004) | *** (0.004) | * (0.004) |
| educ_3 | -0.019 | -0.010 | -0.014 | -0.015 | -0.016 | -0.025 |
| | *** (0.004) | ** (0.004) | *** (0.004) | *** (0.004) | *** (0.004) | *** (0.005) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.052 | -0.048 | -0.056 | -0.051 | -0.050 | -0.054 |
| | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.003) | *** (0.004) |

$y_i$ = *Log of contracted hourly wage*

| | | | | | | |
|---|---|---|---|---|---|---|
| Model 1 | | | | | | |
| age | 0.076 | 0.077 | 0.076 | 0.075 | 0.075 | 0.073 |
| | *** (0.002) | *** (0.002) | *** (0.001) | *** (0.001) | *** (0.001) | *** (0.002) |
| age-squared | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 | -0.001 |
| | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) | *** (0.000) |
| educ_1 | -0.425 | -0.423 | -0.414 | -0.419 | -0.407 | -0.418 |
| | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) | *** (0.008) |
| educ_2 | -0.344 | -0.343 | -0.331 | -0.331 | -0.326 | -0.325 |
| | *** (0.007) | *** (0.007) | *** (0.006) | *** (0.006) | *** (0.006) | *** (0.006) |
| educ_3 | -0.111 | -0.120 | -0.113 | -0.114 | -0.107 | -0.106 |
| | *** (0.008) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) | *** (0.007) |
| educ_4 | 0 | 0 | 0 | 0 | 0 | 0 |
| | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) | (omitted) |
| female | -0.245 *** | -0.248 | -0.243 | -0.244 | -0.243 | 0.251 |
| | (0.005) | *** (0.005) | *** (0.005) | *** (0.004) | *** (0.004) | *** (0.005) |

Notes: Table shows coefficient of the independent variables for the outcomes $y_i$ from the years 2015 to 2020 separately for CEOs in private sector. The baseline model (model 1) controls for age, $age^2$ and education. Standard errors are clustered in person. Stars indicate significance levels: * p < 0.1, ** p < 0.05,*** p < 0.01

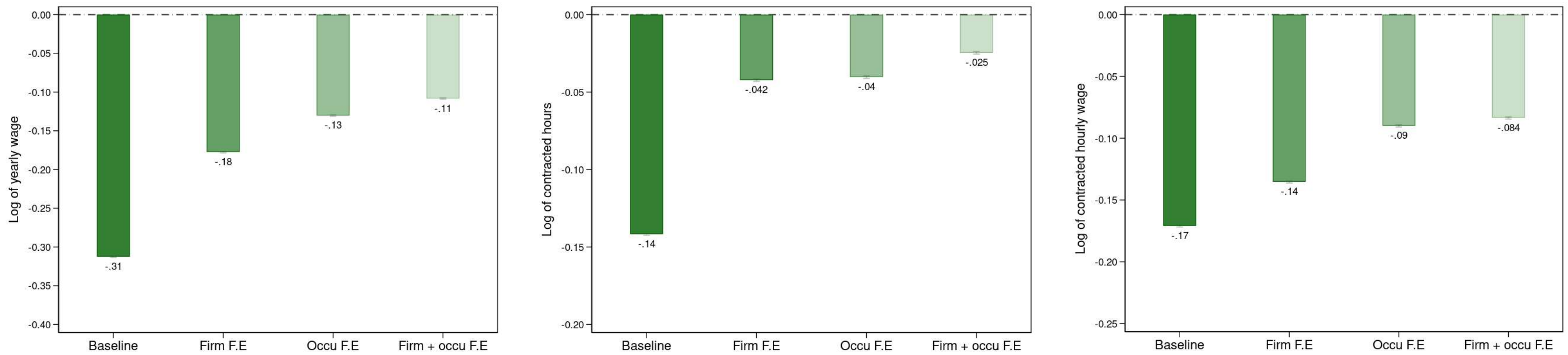
**Figure Ca.** Gender gap for all workers (model 1 and model 4)



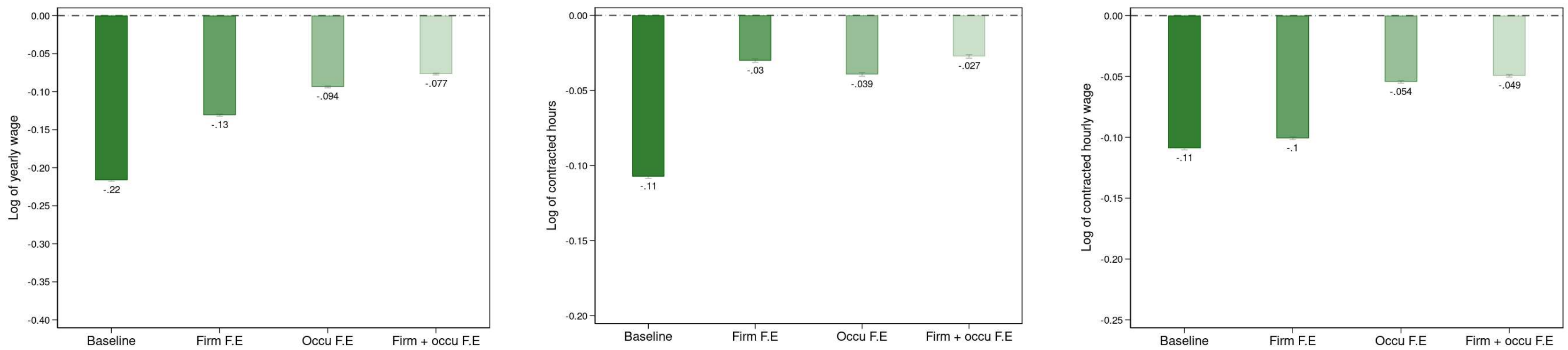

Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, $\log of\ contracted\ hours$, $\log of\ contracted\ hourly\ wage$, in the years 2015 to 2020 combined, for all workers. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education, while the "Firm + occu F.E" bar (model 4) includes the fixed effect of firm and occupation

**Figure Cb.** Gender gap for all workers (model 1, model 2, model 3 and model 4)

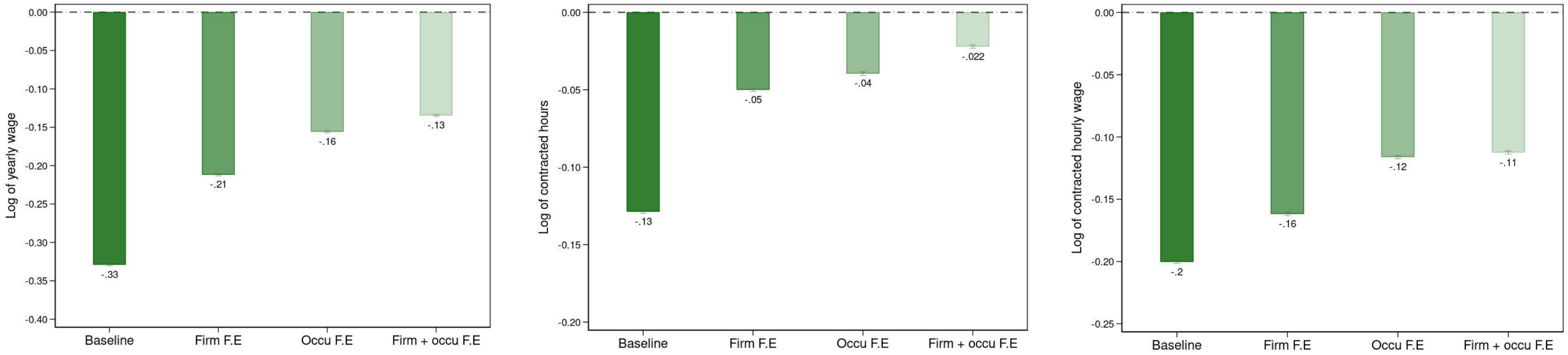
*Both sectors*




*Public sector*



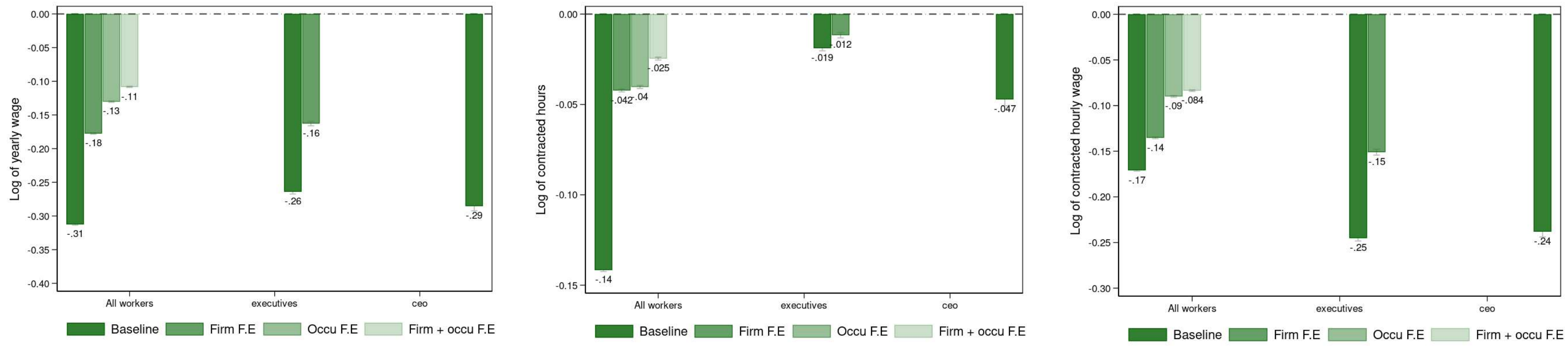
*Private sector*



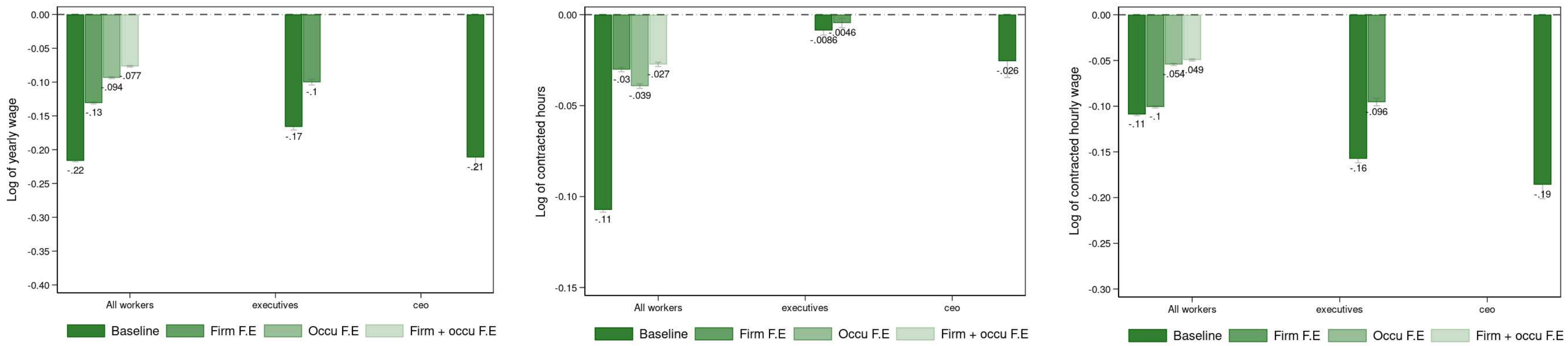

Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, $\log of\ contracted\ hours$, $\log of\ contracted\ hourly\ wage$, in the years 2015 to 2020 combined, for all workers. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1. In the "Occu F.E" bar (model 3) the fixed effect of occupation is added to model 1. The "Firm + occu F.E" bar (model 4) includes the fixed effect of both firm and occupation to model 1.

**Figure Cc.** Gender gap for all workers, executives and CEOs

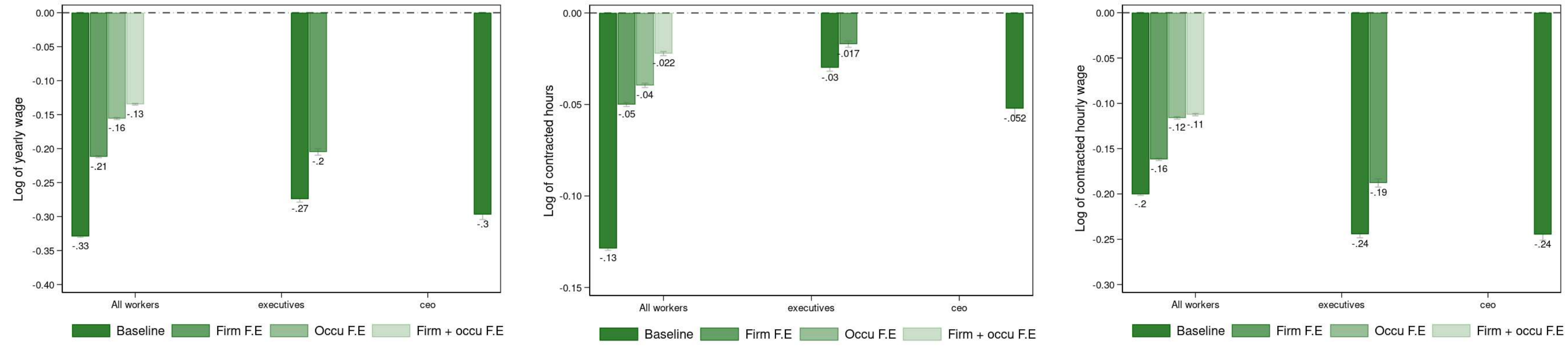
*Both sectors*




*Public sector*



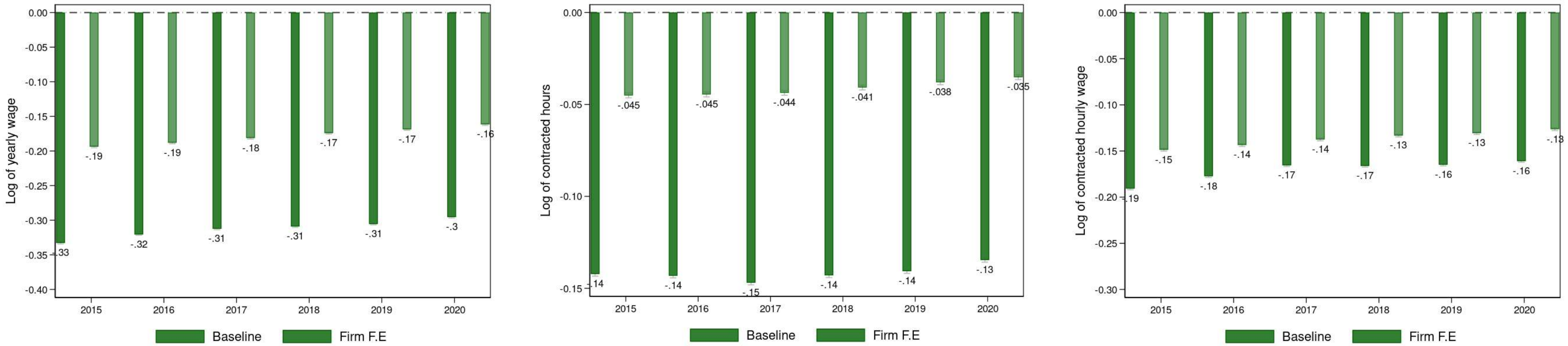
*Private sector*



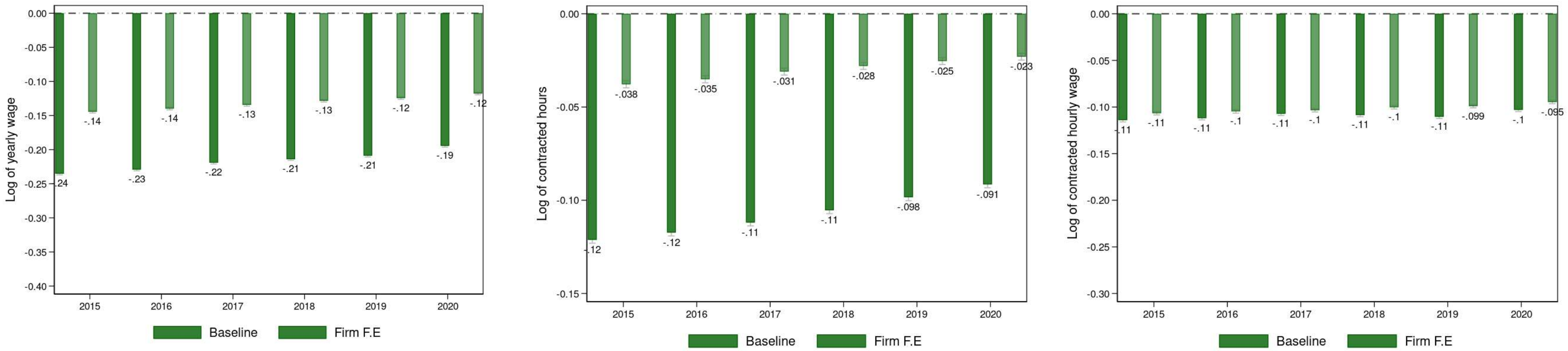

Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, $\log of\ contracted\ hours$, $\log of\ contracted\ hourly\ wage$, in the years 2015 to 2020 combined, for all workers. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1. In the "Occu F.E" bar (model 3) the fixed effect of occupation is added to model 1. The "Firm + occu F.E" bar (model 4) includes the fixed effect of both firm and occupation to model 1.

**Figure Cd.** Gender gap development for all workers

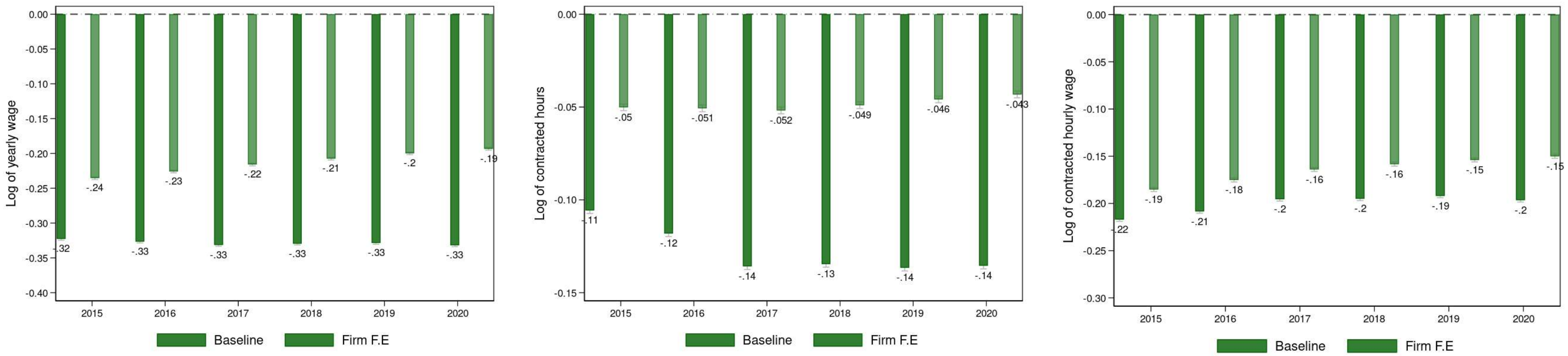
*Both sectors*




*Public sector*



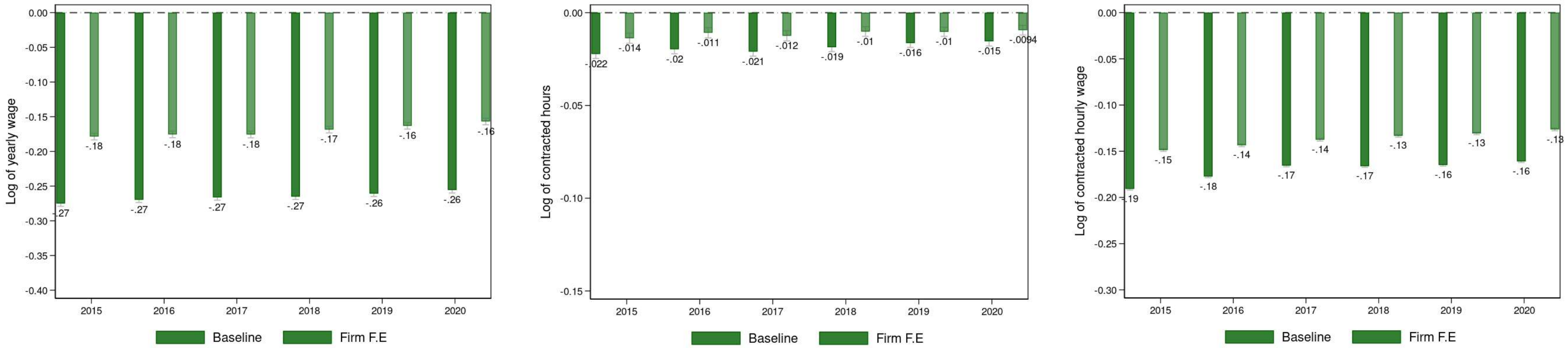
*Private sector*



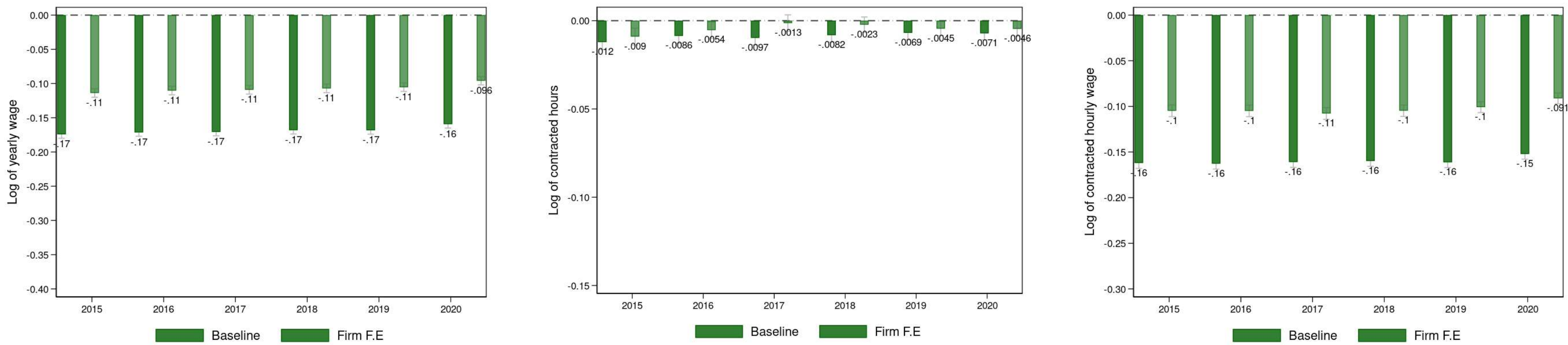

Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, $\log of\ contracted\ hours$, $\log of\ contracted\ hourly\ wage$, in the years 2015 to 2020 separately, for all workers. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1.

**Figure Ce.** Gender gap development for executives

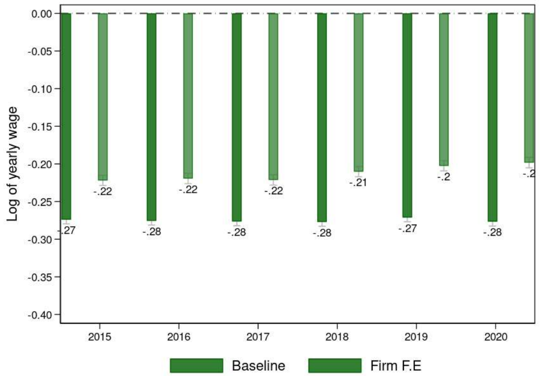
*Both sectors*

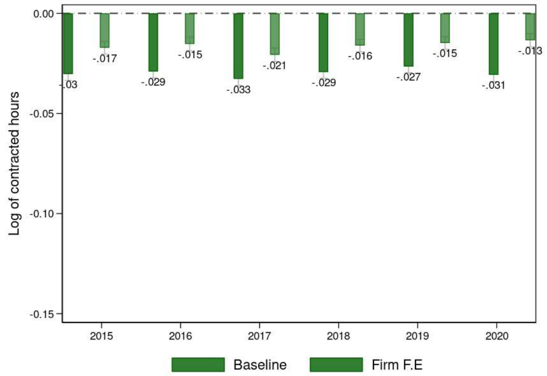


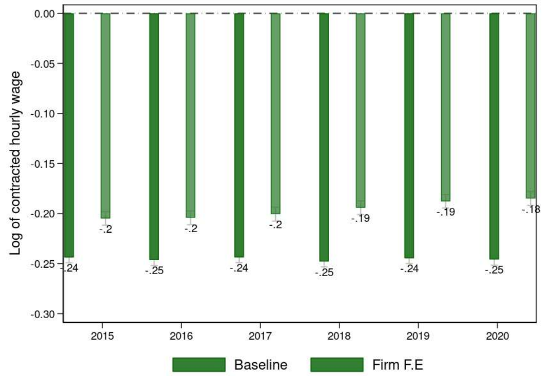

*Public sector*



*Private sector*



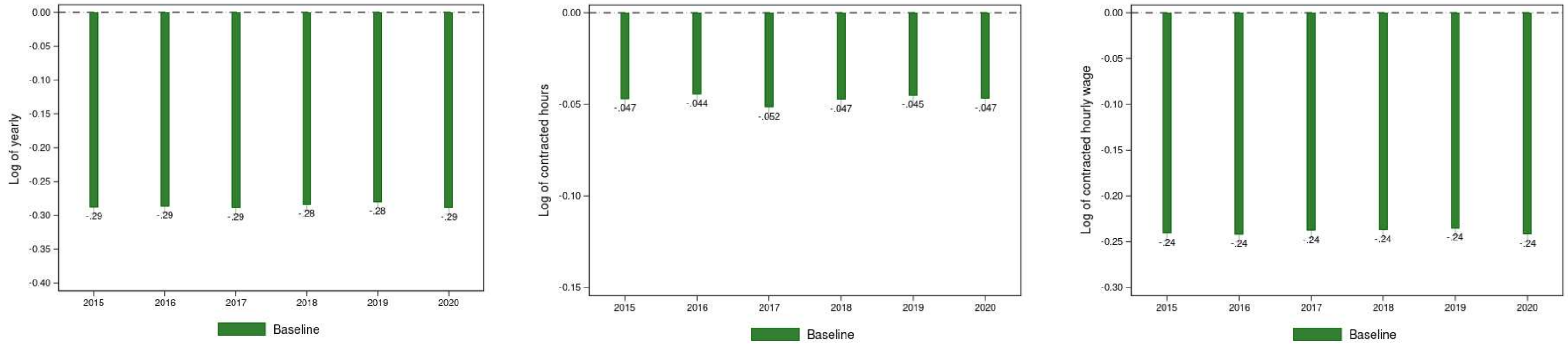



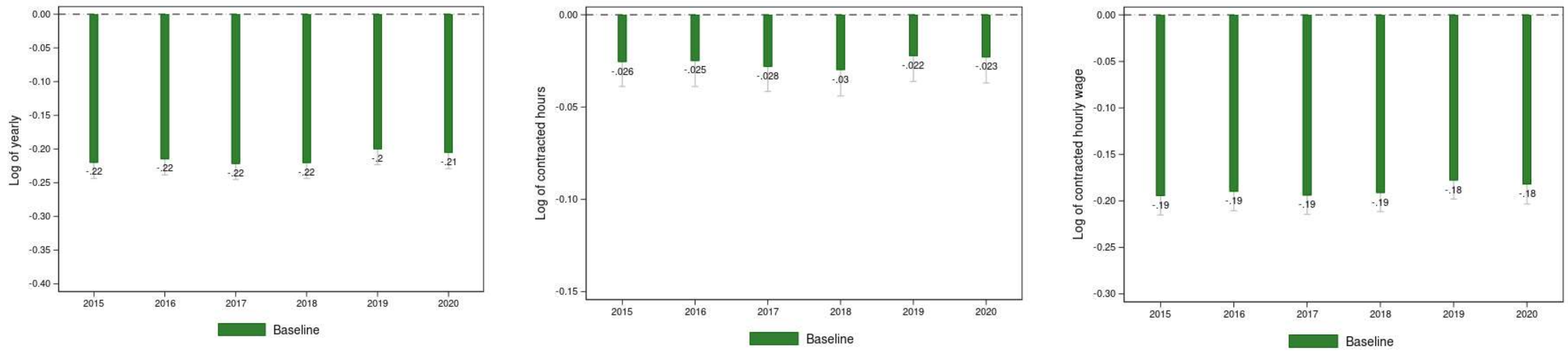

Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, $\log of\ contracted\ hours$ , $\log of\ contracted\ hourly\ wage$, in the years 2015 to 2020 separately, for executives. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education. The "Firm F.E" bar (model 2) adds the fixed effect of firm to model 1.

**Figure Ce.** Gender gap development for CEOs

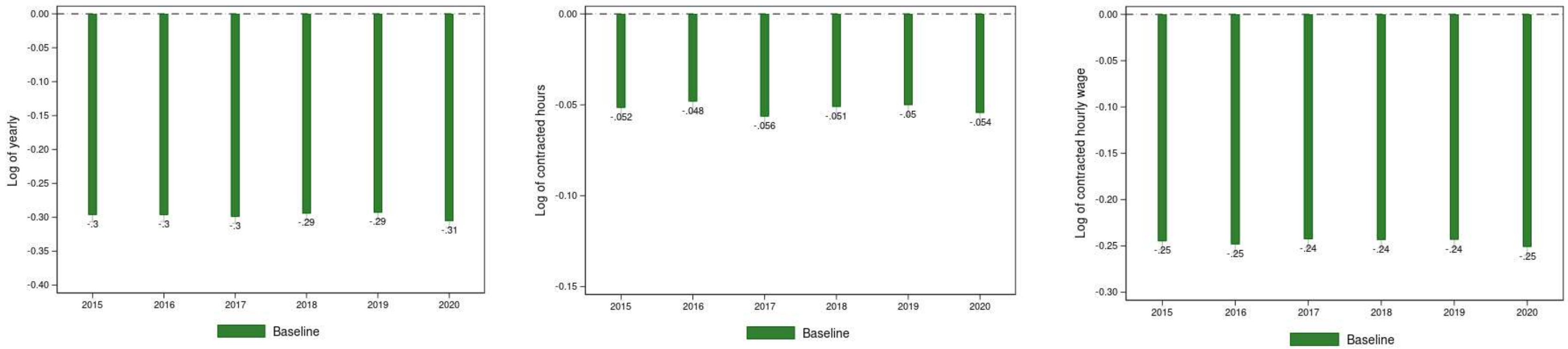
*Both sectors*




*Public sector*



*Private sector*




Notes: The figure plots the coefficient of being a female for the outcome $y_i = log\ of\ yearly\ wage$, log $of\ contracted\ hours$ , log $of\ contracted\ hourly\ wage$, in the years 2015 to 2020 separately, for CEOs. The "Baseline" bar (model 1) controls for gender, age, age$^2$ and education.

## Appendix D: STATA code

```
/*******************************************************************************

THE GENDER PAY GAP IN LEADERSHIP POSITIONS
	- Based on framework of Penner et. al (2022) in Norway
	- Extend the framework to give investigate leaders
	- Year from 2015 - 2020
	- Age is based on labour force 15 - 74
	- Education is based on 8-category ISCED for education
	- Occupation is based on 7-digit STYRK-98

	Created: 2023/06/3 by Sara Skjelbred & Ida Andreassen

*******************************************************************************/

use "/ssb/stamme01/gap/projects/masterdegree/data2.dta",clear

***(1) PREPARING DATA

keep if year>=2015
drop if year==2021

* Investigate workers in establishments
drop if missing( arb_stillingspst_innrapp )
drop if arb_stillingspst_innrapp==0
drop if missing( plant )
drop if missing( occu_4_d )

* Only people higher than 1G in 2018 (not higher or equal, gives different result)
keep if wagelevel>96883

* Generating new variables
gen ln_wagelevel=ln(wagelevel)
gen x_age2 = x_age^2
gen ln_hours=ln(hours)
gen hourly_wage=wagelevel/(hours*52)
gen ln_hourly_wage=ln(hourly_wage)
gen executive = inlist(substr(occupation,1,1),"1")

* Installing package - Gives opportunity to do multiple fixed effects
ssc install reghdfe

save "/ssb/stamme01/gap/projects/masterdegree/data2_10.dta", replace
global master /ssb/stamme01/gap/projects/masterdegree/
use $master/data2_10, clear

***(2) GENDER GAP FOR ALL WORKERS

***...IN BOTH SECTORS

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person)
eststo both_lnwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person)
eststo both_lnwage_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person)
eststo both_lnwage_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person)
eststo both_lnwage_m4

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person)
eststo both_hours_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person)
eststo both_hours_m2
```

```
* Setting model 3 - Fixed effect of occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(occu_7_d)
cluster(person)
eststo both_hours_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person)
eststo both_hours_m4

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person)
eststo both_hwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person)
eststo both_hwage_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person)
eststo both_hwage_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person)
eststo both_hwage_m4
***...IN PUBLIC SECTOR

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==0
eststo public_lnwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if private==0
eststo public_lnwage_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person), if private==0
eststo public_lnwage_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==0
eststo public_lnwage_m4

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==0
eststo public_hours_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if private==0
eststo public_hours_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(occu_7_d)
cluster(person), if private==0
eststo public_hours_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==0
eststo public_hours_m4

** y = log of contracted hourly wage
*Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==0
eststo public_hwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person), if private==0
eststo public_hwage_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person), if private==0
eststo public_hwage_m3
```

```
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==0
eststo public_hwage_m4

***... IN PRIVATE SECTOR

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==1
eststo private_lnwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if private==1
eststo private_lnwage_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person), if private==1
eststo private_lnwage_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==1
eststo private_lnwage_m4

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==1
eststo private_hours_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if private==1
eststo private_hours_m2
* Setting model 3 - Fixed effect of occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(occu_7_d)
cluster(person), if private==1
eststo private_hours_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==1
eststo private_hours_m4

** y = log of contracted hourly wage
*Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if private==1
eststo private_hwage_m1
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person), if private==1
eststo private_hwage_m2

* Setting model 3 - Fixed effect of occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(occu_7_d) cluster(person), if private==1
eststo private_hwage_m3
* Setting model 4 - Fixed effect of establishment and occupation
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant
occu_7_d) cluster(person), if private==1
eststo private_hwage_m4

***(3) GENDER GAP FOR EXECUTIVES

***...IN BOTH SECTORS

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1
eststo both_lnwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1
eststo both_lnwage_m2_executive

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1
```

```
eststo both_hours_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1
eststo both_hours_m2_executive

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1
eststo both_hwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person), if executive==1
eststo both_hwage_m2_executive

***...IN PUBLIC SECTOR

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==0
eststo public_lnwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1 & private==0
eststo public_lnwage_m2_executive
** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==0
eststo public_hours_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1 & private==0
eststo public_hours_m2_executive

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==0
eststo public_hwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person), if executive==1 & private==0
eststo public_hwage_m2_executive

***...IN PRIVATE SECTOR
** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==1
eststo private_lnwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1 & private==1
eststo private_lnwage_m2_executive

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==1
eststo private_hours_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, absorb(plant)
cluster(person), if executive==1 & private==1
eststo private_hours_m2_executive

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if executive==1 & private==1
eststo private_hwage_m1_executive
* Setting model 2 - Fixed effect of establishment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
absorb(plant) cluster(person), if executive==1 & private==1
eststo private_hwage_m2_executive
```

```
***(4) GENDER GAP FOR CEOS

***...IN BOTH SECTORS

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1
eststo both_lnwage_m1_ceo

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1
eststo both_hours_m1_ceo

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1
eststo both_hwage_m1_ceo

***...IN PUBLIC SECTOR

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==0
eststo public_lnwage_m1_ceo

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==0
eststo public_hours_m1_ceo

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==0
eststo public_hwage_m1_ceo

***...IN PRIVATE SECTOR

** y = log of yearly wage
* Setting model 1 - Basic adjustment
reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==1
eststo private_lnwage_m1_ceo

** y = log of contracted hours
* Setting model 1 - Basic adjustment
reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==1
eststo private_hours_m1_ceo

** y = log of contracted hourly wage
* Setting model 1 - Basic adjustment
reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
cluster(person), if role_dagl==1 & private==1
eststo private_hwage_m1_ceo

***(5) GENDER GAP DEVELOPMENT FOR ALL WORKERS, EXECUTIVES AND CEOs

***...IN BOTH SECTORS

** y = log of yearly wage

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if year == `y'
	eststo both_lnwage_m1_year`y'
}
```

```
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if year == `y'
        eststo both_lnwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if executive==1 & year == `y'
        eststo both_lnwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if executive==1 & year == `y'
        eststo both_lnwage_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if role_dagl==1 & year == `y'
        eststo both_lnwage_m1c_year`y'
}

** y = log of contracted hours

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if year == `y'
        eststo both_hours_m1_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if year == `y'
        eststo both_hours_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if executive==1 & year == `y'
        eststo both_hours_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if executive==1 & year == `y'
        eststo both_hours_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if role_dagl==1 & year == `y'
        eststo both_hours_m1c_year`y'
}

** y = log of contracted hourly wage

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if year == `y'
        eststo both_hwage_m1_year`y'
}
```

```
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if year == `y'
	eststo both_hwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if executive==1 & year == `y'
	eststo both_hwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if executive==1 & year == `y'
	eststo both_hwage_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if role_dagl==1 & year == `y'
	eststo both_hwage_m1c_year`y'
}

***...IN PUBLIC SECTOR

** y = log of yearly wage

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & year == `y'
	eststo public_lnwage_m1_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & year == `y'
	eststo public_lnwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_lnwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_lnwage_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & role_dagl==1 & year == `y'
	eststo public_lnwage_m1c_year`y'
}

** y = log of contracted hours

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
	cluster(person), if private==0 & year == `y'
	eststo public_hours_m1_year`y'
}
```

```
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & year == `y'
	eststo public_hours_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
	cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_hours_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_hours_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
	cluster(person), if private==0 & role_dagl==1 & year == `y'
	eststo public_hours_m1c_year`y'
}


** y = log of contracted hourly wage

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & year == `y'
	eststo public_hwage_m1_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & year == `y'
	eststo public_hwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_hwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	absorb(plant) cluster(person), if private==0 & executive==1 & year == `y'
	eststo public_hwage_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==0 & role_dagl==1 & year == `y'
	eststo public_hwage_m1c_year`y'
}


***...IN PRIVATE SECTOR

** y = log of yearly wage

* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
	reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
	noabsorb cluster(person), if private==1 & year == `y'
	eststo private_lnwage_m1_year`y'
}
```

```
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & year == `y'
        eststo private_lnwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_lnwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_lnwage_m2e_year`y'
}
* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_wagelevel x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if private==1 & role_dagl==1 & year == `y'
        eststo private_lnwage_m1c_year`y'
}

** y = log of contracted hours

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if private==1 & year == `y'
        eststo private_hours_m1_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & year == `y'
        eststo private_hours_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_hours_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_hours_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hours x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female, noabsorb
        cluster(person), if private==1 & role_dagl==1 & year == `y'
        eststo private_hours_m1c_year`y'
}


** y = log of contracted hourly wage

* All workers
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if private==1 & year == `y'
        eststo private_hwage_m1_year`y'
}
```

```
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & year == `y'
        eststo private_hwage_m2_year`y'
}

* Executives
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_hwage_m1e_year`y'
}
* Setting model 2 - Fixed effect of establishment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        absorb(plant) cluster(person), if private==1 & executive==1 & year == `y'
        eststo private_hwage_m2e_year`y'
}

* CEOs
* Setting model 1 - Basic adjustment
forv y = 2015/2020 {
        reghdfe ln_hourly_wage x_age x_age2 x_ed1 x_ed2 x_ed3 x_ed4 x_female,
        noabsorb cluster(person), if private==1 & role_dag1==1 & year == `y'
        eststo private_hwage_m1c_year`y'
}

***(6) FIGURES AND PLOTS
ssc install coefplot
set scheme s1mono

** Figure 1 - Gender gap for all workers (model 1 and model 4)
coefplot ///
        (both_lnwage_m1, aseq("Both sectors")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (both_lnwage_m4, aseq("Both sectors")  bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        (private_lnwage_m1, aseq("Private sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (private_lnwage_m4, aseq("Private sector") bcolor(dkgreen%25)
        barwidth(0.15) bargap(0) ) ///
        (public_lnwage_m1, aseq("Public sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (public_lnwage_m4, aseq("Public sector") bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        , legend(order(2 "Baseline" 4 "Firm + occu F.E") region(lc(none) fc(none))
        rows(1)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black)) ///
        name(basic, replace)

coefplot ///
        (both_hours_m1, aseq("Both sectors")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (both_hours_m4, aseq("Both sectors")  bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        (private_hours_m1, aseq("Private sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (private_hours_m4, aseq("Private sector") bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        (public_hours_m1, aseq("Public sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (public_hours_m4, aseq("Public sector") bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        ,  legend(order(2 "Baseline" 4 "Firm + occu F.E") region(lc(none) fc(none))
        rows(1)) ///
         ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.20, angle(horizontal) format(%9.2f) labsize(small))
        ///
```

```
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black)) ///
        name(basic, replace)

coefplot ///
        (both_hwage_m1, aseq("Both sectors")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (both_hwage_m4, aseq("Both sectors")  bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        (private_hwage_m1, aseq("Private sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (private_hwage_m4, aseq("Private sector") bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        (public_hwage_m1, aseq("Public sector")  bcolor(dkgreen) barwidth(0.15)
        bargap(0) ) ///
        (public_hwage_m4, aseq("Public sector") bcolor(dkgreen%25) barwidth(0.15)
        bargap(0) ) ///
        ,  legend(order(2 "Baseline" 4 "Firm + occu F.E") region(lc(none) fc(none))
        rows(1)) ///
         ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.25, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black)) ///
        name(basic, replace)

** Figure 2 - Gender gap for all workers (model 1, model 2, model 3 and model 4)

* ... in both sectors

coefplot ///
        (both_lnwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30) bargap(0)
        ) ///
        (both_lnwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (both_lnwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (both_lnwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25) barwidth(0.30)
        bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (both_hours_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30) bargap(0)
        ) ///
        (both_hours_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (both_hours_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (both_hours_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25) barwidth(0.30)
        bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.20, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (both_hwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30) bargap(0)
        ) ///
        (both_hwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
```

```
        (both_hwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (both_hwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25) barwidth(0.30)
        bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.25, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

* ... in public sector

coefplot ///
        (public_lnwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (public_lnwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (public_lnwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (public_lnwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (public_hours_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (public_hours_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (public_hours_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (public_hours_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.20, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (public_hwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (public_hwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (public_hwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (public_hwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.25, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

* ... in private sector

coefplot ///
        (private_lnwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (private_lnwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
```

```
        (private_lnwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (private_lnwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (private_hours_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (private_hours_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (private_hours_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (private_hours_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.20, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

coefplot ///
        (private_hwage_m1, aseq("Baseline")  bcolor(dkgreen) barwidth(0.30)
        bargap(0) ) ///
        (private_hwage_m2, aseq("Firm F.E")  bcolor(dkgreen%75) barwidth(0.30)
        bargap(0) ) ///
        (private_hwage_m3, aseq("Occu F.E")  bcolor(dkgreen%50) barwidth(0.30)
        bargap(0) ) ///
        (private_hwage_m4, aseq("Firm + occu F.E")  bcolor(dkgreen%25)
        barwidth(0.30) bargap(0) ) ///
        , ciopts(lcolor(gs12) recast(rcap) ) ///
        vertical keep(x_female) recast(bar)  ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.25, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) ///
        aseq swapnames ///
        coeflabels(, labsize(medsmall)) leg(off) format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))

** Figure 3 - Gender gap for all workers, executives and CEOs

* ... in both sectors

coefplot ///
        (both_lnwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (both_lnwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (both_lnwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (both_lnwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (both_lnwage_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (both_lnwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12) bargap(0)
        ) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
```

```
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (both_hours_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (both_hours_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (both_hours_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (both_hours_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (both_hours_m1_executive, aseq("executives") bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (both_hours_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12) bargap(0) )
        ///
         , vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (both_hwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (both_hwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (both_hwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (both_hwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (both_hwage_m1_executive, aseq("executives") bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (both_hwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12) bargap(0) )
        ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

* ... in public sector

coefplot ///
        (public_lnwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (public_lnwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (public_lnwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (public_lnwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (public_lnwage_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (public_lnwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
         , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
```

```
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (public_hours_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (public_hours_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (public_hours_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (public_hours_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (public_hours_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (public_hours_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12) bargap(0)
        ) ///
         , vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (public_hwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (public_hwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (public_hwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (public_hwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (public_hwage_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (public_hwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12) bargap(0)
        ) ///
         , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

* ... in private sector

coefplot ///
        (private_lnwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (private_lnwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (private_lnwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (private_lnwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (private_lnwage_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
```

```
        (private_lnwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_lnwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (private_hours_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (private_hours_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (private_hours_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (private_hours_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (private_hours_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (private_hours_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        , vertical keep(x_female) recast(bar)  ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

coefplot ///
        (private_hwage_m1, aseq("All workers")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        (private_hwage_m2, aseq("All workers")  bcolor(dkgreen%75) barwidth(0.12)
        bargap(0) ) ///
        (private_hwage_m3, aseq("All workers")  bcolor(dkgreen%50) barwidth(0.12)
        bargap(0) ) ///
        (private_hwage_m4, aseq("All workers")  bcolor(dkgreen%25) barwidth(0.12)
        bargap(0) ) ///
        (private_hwage_m1_executive, aseq("executives") bcolor(dkgreen)
        barwidth(0.12) bargap(0) ) ///
        (private_hwage_m2_executive, aseq("executives")  bcolor(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_ceo, aseq("ceo")  bcolor(dkgreen) barwidth(0.12)
        bargap(0) ) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E" 6 "Occu F.E" 8 "Firm + occu F.E")
        region(lc(none) fc(none)) rows(1))  ///
        name(test, replace)

** Figure 4 - Gender pay gap development for all workers, executives, and CEOs

** ... in both sectors

* y = log of yearly wage

coefplot ///
```

```
        (both_lnwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_lnwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_lnwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
```

```
        (both_lnwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_lnwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hours

coefplot ///
        (both_hours_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_hours_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
```

```
        (both_hours_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_hours_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hours_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hourly wage

coefplot ///
        (both_hwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
```

```
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_hwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (both_hwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (both_hwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

** ... in public sector

* y = log of yearly wage

coefplot ///
        (public_lnwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
```

```
        (public_lnwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (public_lnwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (public_lnwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1c_year2018 , aseq("2018

        ") swapnames color(dkgreen) barwidth(0.12) bargap(0)) ///
```

```
        (public_lnwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_lnwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of yearly",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hours

coefplot ///
        (public_hours_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (public_hours_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
```

```
        (public_hours_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (public_hours_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hours_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hourly wage

coefplot ///
        (public_hwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (public_hwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)
```

```
coefplot ///
	(public_hwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
	(0.12) bargap(0)) ///
	(public_hwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	, vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
	wage", size(medsmall)) ///
	ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
	///
	yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
	ciopts(lcolor(gs12) recast(rcap) ) ///
	aseq swapnames format(%9.2g) ///
	addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
	///
	legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
	///
	name(yearly, replace)

coefplot ///
	(public_hwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(public_hwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	, vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
	wage", size(medsmall)) ///
	ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
	///
	yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
	ciopts(lcolor(gs12) recast(rcap) ) ///
	aseq swapnames format(%9.2g) ///
	addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
	///
	legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
	name(yearly, replace)

** ... in private sector

* y = log of yearly wage

Coefplot ///
	(private_lnwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
```

```
	(private_lnwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	, vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
	size(medsmall)) ///
	ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
	///
	yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
	ciopts(lcolor(gs12) recast(rcap) ) ///
	aseq swapnames format(%9.2g) ///
	addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
	///
	legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
	///
	name(yearly, replace)

coefplot ///
	(private_lnwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
	barwidth(0.12) bargap(0)) ///
	, vertical keep(x_female) recast(bar) ytitle("Log of yearly wage",
	size(medsmall)) ///
	ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
	///
	yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
	ciopts(lcolor(gs12) recast(rcap) ) ///
	aseq swapnames format(%9.2g) ///
	addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
	///
	legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
	///
	name(yearly, replace)

coefplot ///
	(private_lnwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	(private_lnwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
	barwidth(0.12) bargap(0)) ///
	, vertical keep(x_female) recast(bar) ytitle("Log of yearly",
	size(medsmall)) ///
	ylabel(0.00(-0.05)-0.40, angle(horizontal) format(%9.2f) labsize(small))
	///
```

```
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hours

coefplot ///
        (private_hours_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (private_hours_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
```

```
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (private_hours_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hours_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hours",
        size(medsmall)) ///
        ylabel(0.00(-0.05)-0.15, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

* y = log of contracted hourly wage

coefplot ///
        (private_hwage_m1_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (private_hwage_m1e_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1e_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1e_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1e_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
```

```
        (private_hwage_m1e_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1e_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2015 , aseq("2015") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2016 , aseq("2016") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2017 , aseq("2017") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2018 , aseq("2018") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2019 , aseq("2019") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m2e_year2020 , aseq("2020") swapnames color(dkgreen%75)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline" 4 "Firm F.E") region(lc(none) fc(none)) rows(1))
        ///
        name(yearly, replace)

coefplot ///
        (private_hwage_m1c_year2015 , aseq("2015") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1c_year2016 , aseq("2016") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1c_year2017 , aseq("2017") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1c_year2018 , aseq("2018") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1c_year2019 , aseq("2019") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        (private_hwage_m1c_year2020 , aseq("2020") swapnames color(dkgreen)
        barwidth(0.12) bargap(0)) ///
        , vertical keep(x_female) recast(bar) ytitle("Log of contracted hourly
        wage", size(medsmall)) ///
        ylabel(0.00(-0.05)-0.30, angle(horizontal) format(%9.2f) labsize(small))
        ///
        yline(0, lpattern(dash_dot)) xlabel(,labsize(small)) ///
        ciopts(lcolor(gs12) recast(rcap) ) ///
        aseq swapnames format(%9.2g) ///
        addplot(scatter @b @at, ms(i) mlabel(@b) mlabpos(6) mlabcolor(black))
        ///
        legend(order(2 "Baseline") region(lc(none) fc(none)) rows(1))  ///
        name(yearly, replace)

*** (6) DESCRIPTIVE STATISTICS - counting observations and numbers of people
count
egen group_person=group(person)
sum group_person
egen group_person_female=group(person) if x_female==1
sum group_person_female
egen group_person_male=group(person) if x_female==0
sum group_person_male

egen group_person_privat=group(person) if private==1
sum group_person_privat
egen group_person_privat_female=group(person) if private==1 & x_female==1
sum group_person_privat_female
egen group_person_privat_men=group(person) if private==1 & x_female==0
sum group_person_privat_men

egen group_person_public=group(person) if private==0
sum group_person_public
egen group_person_public_female=group(person) if private==0 & x_female==1
sum group_person_public_female
egen group_person_public_men=group(person) if private==0 & x_female==0
sum group_person_public_men

egen group_person_role_dagl=group(person) if role_dagl==1
sum group_person_role_dagl
egen group_person_role_dagl_female=group(person) if role_dagl==1 & x_female==1
```

```
sum group_person_role_dagl_female
egen group_person_role_dagl_men=group(person) if role_dagl==1 & x_female==0
sum group_person_role_dagl_men

egen group_person_executive=group(person) if executive==1
sum group_person_executive
egen group_person_executive_female=group(person) if executive==1 & x_female==1
sum group_person_executive_female
egen group_person_executive_men=group(person) if executive==1 & x_female==0
sum group_person_executive_men
```