Reconsidering Union Wage Effects

A Distributional Approach

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Abstract

This thesis has revisited the role of union membership, collective agreements and establishment union density for wage levels and dispersion in the period 2004-2011. To investigate the wage effect from these three covariates, two different approaches are presented in this thesis. Pooled OLS and FE estimates are reported to investigate the wage effects on the mean, and unconditional quantile regression to investigate the distributional effects of these covariates. These estimates will be informative of how union membership, collective agreements and establishment level union density is rewarded on the mean, and the heterogeneous wage effects across the distribution of wages. A decomposition of the union non-union wage gap is reported to identify what factors that can/cannot explain this wage gap.

Using panel data rich with worker and establishment characteristics, pooled OLS suggest a union membership premium of 8,3 %. Controlling for unobserved individual effects, the union wage effect is in the range of 12,7 % to 13,6 %. Pooled OLS suggest that the wage effect of collective agreements is -1,7 % while different FE models estimate a wage effect in the range of -3,4 % to 2 %. Variation in establishment level union density is not associated with a significant wage effect, except where establishment fixed effects are used; Here, a 10 % increase in union density is associated with a -0,2 % reduction to yearly wage.

There is evidence of interaction between union membership and union density. Union membership yields an additional wage premium of up to 6,4 % through union density. The effects of union membership and union density are different across sectors and bargaining schemes. In the private sector covered by collective agreements, the membership premium disappears with the inclusion of an interactive term between membership and union density. In the non-covered private sector and the public sector, a membership premium in the range of 4,5 % and 7,6 % remains when interactive terms are included.

Results following recentered influence function regression indicate the very heterogeneous returns to union membership and union density across the distribution of wages. Treating the sample population with union membership yields big wage premiums at the median and below, and negative premiums at the 72th percentile and above. The effects of union density across the distribution of wages follow a similar trend. Manipulating the distribution of union density yields positive wage effects at the median and below, and negative effects above the 77th percentile. The distributional effects of collective agreements remains unidentified, as confidence intervals are

large and point estimates are not significantly different from zero for most of the wage distribution.

The decomposition analysis suggest that unions reduce wage dispersion in the left tail of the wage distribution. For the median and above, differences in the composition of observables can fully account for differences in inequality across union membership. In the left tail, the wage structure effect is larger than the composition effect.

Contents

1 Introduction

The effects of unionization on wage levels and dispersion is an age-old question, dating back as far as Adam Smith. He wrote about union membership and its effect on wage dispersion in his 1776 Wealth of Nations. Nowadays, the median labour economist believes the union non-union wage gap to be about 15 % for the US labour market [1], and most textbooks on labour economics put the union wage gap in the range of 10-20 %[2].

Point estimates of the union wage gap for the Norwegian labour market are hard to come by. Some researchers have conditioned their estimates on establishments covered by collective agreements, and found that union membership increases wages only through establishment union density (Barth, Raaum & Naylor, 2000)[3]. OLS estimates from 1988 suggest a male union earnings gap of about 10.2 %[4]. Others have found an establishment union density wage premium of 6.7 % in the Norwegian manufacturing industry[5] and no significant return to individual membership, consistent with the findings by Barth et al.. Newer research inspecting the intra-gender union wage differential finds no significant wage premium associated with union membership, if anything, the membership premium from the Norwegian labour market was found to be negative, although small in magnitude[6]. Other researchers of the Norwegian labour market has turned their attention to union membership, density and collective agreements at the establishment level, or in the context of efficiency measures[7, 8]. Although some evidence on the wage effects from individual membership exist, the effects of membership, union density and collective bargaining on the distribution of wages in Norway has not been examined in recent times.

In the anglo-saxon literature, that dominates the research on the union wage gap, several identification strategies has been suggested and deployed to better understand the relationship between unionization and wage inequality[9, 10, 11, 12, 13].

Amongst researchers investigating the relationship between wage inequality and union coverage, David Card is one of the most frequently sited. He used survey data to analyze the effect of union membership on female and male wage inequality from the mid-1970s to early 1990s. Card found that the decline in union membership in his research period could account for 15-20 % of the increase in overall wage inequality for men. He also found that, for men, the "...difference in trends in union membership between the public and private sectors can explain 50-80 % of the slower growth of wage inequality in the public sector" relative to the private[14]. Cards' evidence suggest that unions tend to raise wages more for those with relative low observable skill in the US labour market, a finding that has been confirmed by several other researchers.

The old school approach to identify the wage effect of union membership is to formulate a Mincer wage equation, modelling wage as a function of relevant covariates and a union dummy. Identifying the union wage premium then becomes a matter of inspecting the sign and magnitude of the union dummy coefficient. However, ordinary least square estimates are only insightful for identifying treatment effects on the mean. Conclusions reached in the canonical literature suggest that union membership yields large wage premiums for low earners, while the union premium is negligible or negative for high earners.

To identify the wage effects of union membership, establishment level density and collective agreements on distributional statics beyond the mean, quantile regression has been suggested by several researchers in recent times[15, 16]. This framework allows for identification of the partial effect of continuous and binary variables on different distributional statics such as quantiles, gini-coefficint and more.

During the early 2000s,the quantile regression framework was also extended to decomposition methods. Machado and Mata (2005) sought to decompose changes in wage distributions into covariates that explained the increase in wage dispersion in Portugal from 1986 to 1995 by way of quantile regression. They found that increased educational levels during the period contributed to greater wage inequality. Machado and Mata constructed counterfactual distributions to identify the density of wages in 1995, keeping the distribution of covariates at the 1986 level. With this, they provided a way of extending the much-used Oaxaca-Blinder decomposition to distributional statics beyond the mean[17].

In this thesis, estimates following OLS-, FE- and unconditional quantile regression (UQR) are reported to identify how the Norwegian labour market rewards union density, individual membership and collective bargaining on the mean, and on 99 quantiles of the wage distribution. UQR estimates draw heavily on the methods proposed by Firpo, Fortin & Lemieux (FFL) in their paper "Unconditional Quantile Regression"[15]. The quantile regression framework is especially interesting, as I am not aware that it has been used to assess the wage effects from unionization and wage bargaining in the Norwegian labour market. A formal decomposition analysis using recentered influence functions is also reported with the purpose of identifying the contribution of covariates to the union non-union wage gap.

This thesis is structured as follows: Chapter 2 gives an overview of the union literature. Here, some of the most important books and papers on unions and their effect on wages are presented. There is an overweight of papers that explain the relationship between unionization and wage inequality, especially those using a quantile regression framework. In chapter 3, the methodology used for this thesis is presented. The main object of this chapter is to give an introduction to quantile regression. This includes the assumptions needed for inference, interpretation of the coefficients and the differences in the two main approaches. The decomposition framework is also covered in this chapter, both the simple decomposition and the method used for this thesis. In chapter 3, the underlying wage models are also presented. Descriptive statistics from the Norwegian labour market are presented in chapter 4. The data used for analysis is also presented here. Descriptive statistics are compared with the sample means in the data to get a view of how representative the data is to the Norwegian labour market. In chapter 5, the results are presented. The implication of the results will also be discussed throughout this chapter. In chapter 6, the conclusion is presented. This chapter will conclude on the most significant results, which results are the strongest, possible shortcomings of the results and what researchers could do different in the future.

2 Overview of the Literature

2.1 Background

The 1950s mark the beginning of the evidence driven approach to labour economics. Several new papers were written on the subject of unions. At this time, well-known economists believed that unions increased income inequality. One of these authors was Nobel price winner Milton Friedman, he wrote in a 1962 paper that when unions gain bargaining power they force up wages within an industry. This in turn creates unemployment for workers in a specific industry, and they would need to look for work elsewhere. The large flow of unemployed into different industries force down the wages. As unions were generally strongest amongst groups of relative high income, they would capture a larger share of the labour market rents compared to the working class. An increase in the union participation rate would create more dispersed wages, i.e. higher wage inequality both within and between industries[18].

The view that unions create more dispersion in wages was not shared by all scholars at the time. Reynolds and Taft, two economists working at Yale, concluded that the net effect of unionization reduced wage inequality. They argued that the standard wage rates negotiated by the unions created less wage dispersion, certainly within an industry[19]. In this time period, evidence of unions and wage dispersion was largely based on speculation and theoretic predictions until the availability of micro data became salient the 1970s.

2.2 First Wave of Empirical Studies

As micro data became easier to come by, several papers published in the late 1960s and early 1970s sought to identify possible distributional effects of unionization by using improved micro-data. s. Rosen and Johnson & Youmans are examples of researchers that found that unions compressed the wage structure by raising the wages of workers with relative low skill[20, 21]. Ashenfelter found that unions also played a contributing role in decreasing the black-white wage gap[22].

In 1980, Richard Freeman used establishment level data to measure unions' effect on the wage gap between white-collar and blue-collar workers. His most important finding was that union membership decreased within industry inequality, especially in manufacturing industries. In addition to decreasing the white-collar and blue-collar wage gaps, the within industry effect of unions more than made up for the negative between industry effect associated with union membership[23]. This paper is of historic importance, as it is the first to convincingly prove the inequality-reducing effect of unions. For this reason, Freeman is still cited in papers interested in unions and wage inequality.

2.3 Second Wave of Empirical Studies

In 1984, Freeman revisited unions in his and Medoff's book "What do unions do", using micro data to confirm that wage inequality was lower in union covered industries when controlling for between-individual heterogeneity by applying individual fixed effects. Their belief was that unions play two roles in the labour market. As mentioned earlier, unions are believed to create between industry wage inequality, this effect is undesirable from society's point of view. The other side of the coin is that unions decrease wage dispersion within an industry and provide a platform for workers to voice their discontent and improve conditions in the workplace, known to us now as the "union voice effect"[24]. When their research was expanded with longitudinal data from the 1980s, they concluded that the decline in unionization observed in the late 1980s could account for roughly 20 % of the increase of male wage inequality in the US. Similar conclusions were made by Card (2001) and Gosling & Machin (1995)[25, 14, 26].

Until the early 1990s, studies considering the relationship between unions and inequality were largely focused on men in the private sector, most researchers did not allow for heterogeneity between workers. In 1997, DiNardo & Lemieux used a reweighing technique to inspect the relationship between union membership and the dispersion of wages for American and Canadian men in 1981 and 1988. They found that unions reduced the variance of male wages by 6 % in the US in 1981, and by 3 % in 1988. In Canada, unions reduced the variance of male wages by 10 % in 1981 and 13 % in 1988. They conducted a decomposition analysis and concluded that unions lower the variation in wages both within and between groups, with the largest effect being found within skill groups[27].

A year later, Bell & Pitt used the same method to analyze possible impacts of a declining unionization rate on the growth in wage inequality in the UK. They found that between 10-25 % of the increase in male wage inequality can be explained by the reduction in the unionization rate observed in their research period[28]. A similar conclusion was reached by Machin[29]. Most all researchers during the 1990s were in agreement that unions play an important role in reducing wage inequality.

In another frequently cited paper on the relationship between unions and wage inequality, Card (2001) analyzed the effect of union membership for both the private and public sector in 1973-1974 and 1993. When comparing trends in the union wage gaps by skill groups, he found that unionization affected the private and public sector similarly. In the public sector, Card estimated that unions reduced the variance of male wages by 12 % in 1973-1974 and 16 % in 1993. In the private sector, the decline in unionization during the research period could explain 36 % of the increase in male wage inequality, as measured by the variance of wages. Unions effect on female wage inequality were all close to zero, this is also influenced by the fact that female union participation rates were stable during the research period[14].

Similarly, Gosling & Lemieux (2001) were also particularly interested in the effect of union across genders. They used data from the US and UK between 1983 and 1998. Using the reweighing method proposed by DiNardo, Fortin & Lemieux, they found that the equalizing effects of unions were much smaller for women when compared with men. Corresponding to the conclusion Card reached years earlier, they found that changes in unionization rate had little or no effect on female wage inequality[26].

A handful of researchers have also investigated the role of unions for wage inequality in the Norwegian labour market. Lawrence Kahn used Norwegian micro data in the period 1987-1991 to investigate the relationship in Norway. He found that though the distance between the top and the middle of the wage distribution increased similarly to other OECD countries, unions could account for significant compression on the left tail of the wage distribution. Any supply or demand conditions were ruled out, as these trends were similar to the other OECD countries in Kahns sample[30].

2.4 Going Beyond the Mean: Studies With a Quantile Regression Approach

Several of the above-mentioned papers gives insightful evidence of unions effects on inequality within and between industries on the mean. Recently, a large effort has gone into identifying union wage effects on distributional statics other than the mean. In this context, quantile regression has been suggested as a useful tool for quantifying effects at different points of the wage distribution. An important contribution to the union literature in the context of quantile regression is Gary Chamberlains 1994 chapter "quantile regression, censoring, and the structure of wages". Chamberlain used the method pioneered by Koenker and Bassets in 1978 to measure changes in returns to schooling as well as union wage effects for different quantiles of the wage distribution. He found that the union wage effect was fairly uniform across quantiles for young workers but observed a decline in the effect for older workers. Chamberlain reports a monotonically decreasing union wage effect from 0.36 for the 10th percentile to 0.09 at the 90th percentile of the conditional wage distribution[31].

Firpo, Fortin & Lemieux (FFL) first introduced the concept of unconditional quantile regression in their 2008 paper "Unconditional Quantile Regression" (UQR). This statistical tool provides a simple way of estimating effects of a binary treatment variable on different distributional statics, without conditioning the wage distribution on covariates. In their paper, they provide an empirical application of UQR. Income data from the US current population survey in the period 1983-1985 was used to study the impact of union membership on male log wages. They also include results from OLS estimates as well as conditional quantile regression for the sake of comparability between the different approaches. Using UQR, FFL finds that the union wage premium was 0.195 for the 10th percentile, 0.337 for the median and -0.135 for the 90th percentile of the wage distribution. The OLS estimate of the union wage premium was 0.195, and their CQR model reports that the premium was 0.288 for the 10th percentile, 0.195 for the median and 0.088 for the 90th percentile.

The point estimates in FFL demonstrate that the union wage effect was highly non-monotonic across the wage distribution, contrary to Chamberlains results. These results also provide an insight to why the conditional quantile approach might not be best suited when the unconditional distribution og wages is the static of interest[15].

As seen above, FFL report positive union wage premiums for the whole conditional distribution, while the union premium turn negative at the 85th percentile of the unconditional distribution. FFL argues that this is due to conditioning the distribution on covariates. At first glance, one would expect the results from a CQR to be similar to a UQR, but these estimates provide some evidence to the hypothesis that negative effects at the top end of the distribution are averaged away when conditioning on covariates.
Furthermore, FFL provide results following both a RIF-logit, RIF-OLS and a RIF-NP specification and show that these models provide similar results. From this, they conclude that using a linear model specification provides accurate results, at least for this application.

FFL revisited their approach in 2018. Here they not only provided estimates for the treatment effect of union membership across the wage distribution using UQR, but also used this approach to decompose the wage distribution into the wage structure and composition effect. With this, they effectively provide a way of extending the much-used Oaxaca-Blinder type decompositions to distributional statics such as quantiles and variance[13, 32]. In the context of decomposing the contribution of union membership on wage inequality, the results of RIF-regressions are usually interpreted as an infinitesimal change in the distribution of covariate on the outcome variable. However, for most applications, a small change in the distribution of unionization is not interesting from a policy perspective, or feasible from an econometric perspective. For policy applications, interest lies in identifying distributional effects of changing the union dummy from zero to unity for the whole sample, holding the wage structure constant. This effect can be obtained by a simple rewriting of the composition effect in the standard OB-decomposition. In practice, this is often done by obtaining coefficients on covariates for union members as well as for non-union individuals and treating union members with the returns to characteristics that prevails for non-union individuals or vice versa.

FFL also extended their 2008 analysis by providing RIF-regression results from inequality measures such as variance of log wages and gini-coefficients for the US in the periods 1988-1990 and 2014-2016. They show that union coverage reduces variance of log wages by 0.075 in 1988-1990 and 0.04 in 2014-2016, with estimated variance of log wages being respectively 0.341 and 0.418. These results are significant at the 1 % level and provide further proof of Freeman's 1984 conclusion that union coverage reduces variance of log wages for the US labour market. They report that unions contribute to a reduction of the gini-coefficient by 0.067 (gini estimate 0.330) in 1988-1990 and by 0.039 (gini 0.396) in 2014-2016. Marital status, education level, potential experience and sector affiliation were also significant in explaining differences in variance of log wages and variation in intra-group gini-coefficients. Furthermore, their results from decomposition analysis show that de-unionization in the period 1990-2014 could account for about 25 % of the increase in the 50-10 wage differential. Thee results are in line with results obtained by Freeman, Card and DiNardo that observed a similar trend in roughly the same period.

2.5 Studies Using Establishment Level Data

Controlling for selection into unions and collective bargaining is difficult. In recent years, several researchers have opted to investigate the wage effects of unionization at the establishment level. This approach does not identify the individual effect of union membership, but wage effects on the mean of wages within an establishment. Individual or household level data suffer from the fact that selection into unions on the basis of unobservables cannot be fully accounted for. Instead attention is turned to the effects of unionization within establishments.

In 2004, DiNardo & Lee used establishment level data to estimate the effects of unions on business survival, employment, wages and productivity in the period 1984-2001. In this paper, they apply a regression discontinuity design to explore differences between employer outcomes for those businesses where unions won the election by a small margin, compared to those where unions lost the election by a small margin. They find small impacts on all outcome variables, including the union wage effect. The null of less than 2 % short term union wage effect could not be ruled out, and the long term effect of winning the election was not significantly different from zero several years after the election[27]. DiNardo & Lee argue that these results are consistent with similar literature that use establishment-level data[33, 34]. These results could also be explained by productivity measures if only the most productive firms are affected by unionization[1]. When using individual level data, union wage premiums are usually reported in the range of 15-20 percent, DiNardo & Lee highlights the weakness of using household or individual level data due to selection problems. However, DiNardo and Lee are answering a different question than those studies that utilize individual level data, that is, they are trying to figure out how much more an employer must pay when their firm becomes unionized. Furthermore, they note that their paper should not be interpreted to show that unions have no effect on workers or their wages and point to the different channels in which unions may improve conditions for workers. These channels include providing job security, conflict resolution and other policies that improve working conditions at the establishment or industry level. The paper from DiNardo and Lee serves as a reality-check for all researchers investigating the effects of unions by using individual level data, and underlines the importance of utilizing controls for establishment level effects.

As recent as 2020, Barth et al. used an IV approach to identify effects of changes in establishment level union density on productivity and wages for the Norwegian labour market in the period 2001-2012. They exploit an increase of the tax deduction from union membership, and find this to be a valid instrument, as the increase in tax deduction led to higher unionization rate. In their paper, they report that an increase in union density of 1 % is associated with an increase in firm productivity of 1.7 %. The paper identifies a positive wage effect from union density; A 1 % increase in density was associated with a 1 % - 1.5 % increase in wage levels when controlling for skill groups, unobserved worker effects and establishment level value added per worker[8]. Barth et al. offers several explanations for how the unions may affect productivity. First, there is a possibility of positive or negative

[1] If productive establishments are affected by unionization to a higher extent than less productive establishments, this implies that selection is not fully accounted for whenever establishment level data is used.

selection into unions. Then there is the possibility that a union non-union wage gap provide incentive for workers to invest in their own human capital, or for the employer to invest in their workers. They also argue that the "union voice effect", introduced by Freeman and Medoff in 1984 could explain unions effect on wage levels and productivity. This effect is the theoretical presumption that unions have the opportunity to voice the concerns and knowledge of the workers to management in a more efficient way than the workers could do on their own, thereby increasing efficiency. In a non-perfect competition scenario, unions may also be able to capture some of the employer rents, increasing efficiency if employment fluctuation, seasonality or sub-optimal capital investment is a problem. Barth et al. finds evidence of rent-sharing.

Others have also suggested that unions bolster efficiency through bargaining efficiency wages, where excess hiring is eliminated. Efficiency wages also has the added benefit of increasing worker satisfaction and could possibly relegate shirking, although bargaining wages above market rate can increase unemployment and between-sector inequality.

2.6 Individual Union Wage Effects in the Norway

A well-known paper investigating individual premiums from union membership and establishment union density in Norway is the 2000 paper "Union wage effects: Does membership matter?" (Barth, Raaum & Naylor, 2000). In this paper, matched employer-employee data is used to identify wage effects of unionization for both workers and establishments. Barth et al. hypothesize that union wage differentials could be explained by omitted establishment level characteristics. Considering only establishments covered by collective agreements, they find that establishment level union density is associated with significant wage premium, while the individual membership wage premium disappears when control for union density is added. By only considering establishment where wages are determined at least partly by collective bargaining, they solve problems of heterogeneity of wage effects across bargaining regimes.

Barth et al. point to three main interpretations of the wage differential arising from individual membership. First, union members might be favored for promotions and other higher paying jobs when compared to non-members. This seems a plausible explanation whenever the union is lobbying to have their members instituted to administrative positions and higher paying jobs in general. Secondly, union membership could be correlated to unobserved characteristics that are positively correlated with wage. Thirdly, the union wage differential could be explained by omitted establishment level controls.

This argument makes a lot of sense if establishment characteristics such as union coverage within establishment is a main driver for the union wage differential. BRN argues that establishment level union density is an important predictor of wage, as high degree of unionization increase the bargaining power of unions. High degree of unionization within establishment also improves the relative effectiveness of strikes, go-slows and other tools available to disgruntled workers. Whenever union density is low, the effectiveness of these tools is limited, as the same degree of coordination and mutual interest might not be present when workers in general are not organized. They conclude that the wage effect from individual union membership works through union density, meaning that the union wage effect is a pure public good increasing in establishment level union density. Barth et al. does not state that there is no union wage effect, but that membership in itself cannot explain the union wage gap. They underline that the relationship between individual membership and within-establishment union density is a more important predictor of individual wage[3].

This 2000 paper features a good research setting, good data and interesting discussions. Therefore, some of the results obtained from OLS- as well as FE-regressions in this thesis are compared to the results obtained by Barth, Raaum & Naylor. However, it should be noted that the research setting and data material in their paper is drastically different from what has been used in this thesis. The methodologies and models are also quite different. In other words, differing results should not be interpreted as conflicting.

3 Methodology

In this thesis, a number of identification strategies has been applied to identify the effects of collective bargaining, individual union membership and union density on wage levels and dispersion. Estimates following pooled OLS, fixed effect regression, unconditional quantile regression and recentered influence function decomposition are reported to this end. The purpose of this chapter is to give some background on these approaches. In section 3.1, the wage models used for pooled OLS and FE estimates are presented. Section 3.2 is a brief introduction to quantile regression. Section 3.3 contains the assumptions needed for unconditional quantile regression, and the decomposition framework. Section 3.4 and 3.5 gives background on the methodology of conditional and unconditional quantile regression. In section 3.6, the simple Oaxaca-Blinder decomposition is presented as well as the decomposition approach used for this thesis.

3.1 Pooled OLS- and FE-Models

To get a first impression of the relationship between union membership, collective agreements, establishment level union density and wages, pooled OLS estimates are reported. The natural logarithm of yearly wages, Y are modelled as:

$$\ln y_{it} = \alpha + \beta T_{it} + \lambda C_{jt} + \delta D_{jt} + \theta X_{it} + \varphi_t + \varepsilon_{it} \tag{1}$$

T_{it} is a union membership dummy, active whenever individual i is member of a union. C_{jt} is a collective agreement dummy and D_{jt} is establishment union density, both of these varies over time with establishment $j \in J$. The parameters β, λ and δ are the ones of interest for this thesis. X is a vector of time-variant covariates; Potential experience, potential experience squared, weekly work hours, part-time employment dummy, public sector dummy, administrative position dummy, manual labour dummy, metropolitan workplace dummy[2], establishment size in four levels, dummy indicating high rate of highly educated individuals within establishment, 22 two-digit industry code dummies and time-invariant characteristics: Gender, education attainment in four levels, immigration status and parental educational attainment. φ_t denotes 11 year fixed effects, included to account for common time trends.

Pooled OLS regression will yield consistent and unbiased estimates of the union wage effect provided the conditional mean independence assumption holds. However, in the context of wage regression, there is no reason to believe that this assumption holds. Union membership is not assigned

[2]These are establishments located in Trondheim, Oslo, Stavanger or Bergen.

at random, there is a strong possibility that there are unobservables correlated with union membership and with significance in predicting wages. If unobserved effects within entities are correlated with covariates of interest, OLS will yield biased and possibly inconsistent estimators. The Hausman test that these unobservables are appropriately modelled by a random effect estimator is rejected.

For these reasons, a FE regression becomes more attractive. With fixed effect models, often referred to as the within-estimator, only variation within entities (individuals, years, industries, establishments etc..) is considered. Time-invariant characteristics drops out, as these are captured by fixed effects. Within-regression also allows researchers to consider variation within entities at different levels of the labour market. This means that FE regression allows for autocorrelation within entities. As the presence of both autocorrelation and heteroskedasticity cannot be ruled out, all models cluster their standard errors around 3-digit industry codes. The choice of clustering standard errors at this level follow from the presumption that this is the most aggregated level of the labour market in which one would expect unobserved characteristics to be correlated between entities[3]. The models used for FE estimation is:

$$\ln y_{it} = \alpha + \beta T_{it} + \lambda C_{jt} + \delta D_{jt} + \theta X_{it} + \varphi_t + \mu_i + \varepsilon_{it} \tag{2}$$

In this model, the time dimension present in the panel data is utilized. Individual fixed effects, μ_i, are included to account for selection issues. Here, X is a vector of the same time-variant characteristics as above. There is also the strong possibility that unobservable characteristics within different level of the labour market are correlated with union membership, collective agreements and union density. To account for this, variation within entities are further restricted with inclusion of fixed effects for 2-digit industry codes (aggregated), 3-digit industry codes (less aggregated) and establishment identifier.

$$\ln y_{it} = \alpha + \beta T_{it} + \lambda C_{jt} + \delta D_{jt} + \theta X_{jt} + \varphi_t + \mu_i + \gamma_j + \varepsilon_{it} \tag{3}$$

Here, time-invariant industry/establishment fixed effects, γ_j, are included. The subscribt j denotes three levels of the labour market. This model has been run with 22 fixed effects for 2-digit industry codes, 780 fixed effects for 3-digit industry codes and 168983 establishment fixed effects.

[3](Abadie, Athey, Imbens & Woolridge, 2017) see[35]. There is otherwise no reason for choosing 3-digit industry code for clustering. There remains a possibility that standard errors should be clustered around several dimensions. Having used several cluster variables, correcting for residual correlation only at the 3-digit industry level proved reasonable.

3.2 Introduction to Quantile Regression

The methodology of quantile regression is divided in two approaches, conditional and unconditional quantile regression. These frameworks have been used to identify distributional effects of union membership, education in labour economics, and has also gained traction in other fields such as health- and educational economics[36, 37]. The purpose of the following chapter is to give a brief explanation of these approaches, their differences, similarities and applications. In the end of the chapter, the approach used for this thesis is described.

The **conditional** quantile regression framework is seeks to identifying the impact of covariates on the distribution of the outcome variable, conditional on relevant covariates. The **unconditional** framework is used whenever researchers wish to identify the effect of a covariate on a distribution while defining the distribution pre-regression. With the relationship between union membership and wage as an example, one might expect that union membership affects predicted wages differently at different points of the distribution of wage, education, age etc.. Quantile regression can be used to assess the distributional effects of union membership, collective agreements and union density. The term quantile regression was first introduced by its inventors, Koenker and Basset in 1978.

To demonstrate the differences between conditional and unconditional quantile regression, some notation is needed. Let Y be the outcome variable of interest, and $F_Y(y) = Pr(Y \leq y)$ be the cumulative distribution function of Y for the population. In this thesis, interest lies in identifying the effect of manipulating the distribution of a binary covariate T on the distribution of wages. Let T be a categorical variable indicating union membership for individual i. Denote $q_\tau(y)$ as the τth quantile of the distribution of wages. As inference relies on manipulating the distribution of covariates, some strong assumptions are needed.

3.3 Assumptions

Identifying the effect of union membership on different points of the distribution of wages requires the formulation of a counterfactual. To see how the distribution of wages changes from an increase in union participation, or rather, an increase to the probability of union membership, the counterfactual scenario is one in which the probability of membership is higher than is observed in-sample. One can only observe the distribution of wages for union members or non-members, hence the distribution of wages when the whole sample are union members is never observed.

Some examples of useful counterfactuals in the context of labour economics include: What labour market returns would union members get were they compensated as non-members? How would the wage distribution of those who are not union members look like if they were members of a union? These questions belong to a part of econometric literature commonly referred to as treatment effects. As an exercise like this requires the formulation of a counterfactual, the methodology is closely related to the program evaluation literature. To change the probability of union membership above what is observed in-sample, some assumptions are needed.

3.3.1 Ignorability or Unconfoundedness

Let (X, T, ϵ) follow a joint distribution.
For all x in X, ε is independent of T given $x = X$.

This assumption states that the distribution of unobservable characteristics is the same across union members and non-members when conditioned on observable characteristics[4]. The ignorability assumption is a very strong one. Certainly in the case of union membership, as there are unobservable characteristics that determine union membership and has significance in predicting wages. Union membership is not random, and cannot fully be predicted on the basis of observable characteristics. As an example; whenever the ignorability assumption is invoked, coefficients from OLS can be interpreted as the average treatment effects (ATE), as assignment to treatment is independent of unobservables. If ignorability does not hold, OLS estimates will only ever provide researchers with the average treatment effect on the treated (ATT)[5].

This paper deals with possible selection problems by introducing multi-way time-invariant fixed effects to account for unobserved heterogeneity between individuals. Using within-estimators while invoking ignorability assumption is somewhat of a contradiction. However, one could also argue that the assumption of ignorability only holds whenever multi-way fixed effect are applied.

3.3.2 Overlapping Support: Strong Ignorability

For all x in X, $Pr(X) = Pr[T = 1|x = X] < 1$ and $Pr[T = 1] > 0$

[4]Parameters of interest θ and δ are omitted for this chapter. T denotes union membership, and other variables of interest are omitted for simplicity.

[5]In this chapter, individual fixed effects are included in the vector X. The ignorability assumption is needed as the possibility that individual fixed effects does not fully control for selection into unions cannot be ruled out.

This assumption states that there is an overlap in observable characteristics across union members and non-members. This assumption is not particularly restrictive. The ignorability assumption combined with overlapping support is often called strong ignorability, a term first coined by Rosenbaum and Rubin in 1983[38]. Strong ignorability allows identification of the ATE of union membership across the wage distribution.

3.4 Conditional Quantile Regression

Let $Q_\tau(y|x)$ for $\tau \in (0,1)$ be the τth quantile of the distribution of wages, y, conditional on a vector X of covariates. A simple linear model of the conditional median can be formulated as:

$$Median\,(y|x) = m\,(T, x, \beta_{\tau=0.5}, \theta_{\tau=0.5}) \tag{4}$$

The subscript on the coefficient indicates the quantile of interest, and serves as a reminder that the coefficients are dependent on the relevant quantile of the outcome variable. If the model is correctly specified, $E(y|x) = m(x, \beta_o)$ where β_o is the true population parameter. As shown by Koenker and Basset in 1978[39], the least absolute deviation estimator(LAD) of β solves the minimization problem:

$$\min_{\beta\in\Theta} \frac{1}{N}\sum_{i=1}^{N} |y_i - m(T_i, x_i, \beta_{\tau=0.5}, \theta_{\tau=0.5})| \tag{5}$$

If Θ is compact, and $m(\cdot)$ is continous over Θ for each x. The LAD provides a consistent estimator for the conditional median, which is a special case of quantile regression[40]. To find estimates from other parts of the outcome distribution, the quantiles are assumed linear in their parameters. An intercept is also introduced:

$$Q_\tau(y_i|x_i) = \alpha_o(\tau) + \beta_o(\tau)T_i + \theta_o(\tau)x_i \tag{6}$$

As the population quantile is a continuous, real-valued function in a closed domain, when $q(\tau)$ is the τth quantile of y_i, then $q(\tau)$ solves the problem:

$$\min_{q\in\mathbb{R}} E\left\{(\tau\mathbb{1}\left[y_i - q \geq 0\right] + (1-\tau)\mathbb{1}\left[y_i - q < 0\right]) \cdot |y_i - q|\right\} \tag{7}$$

Where $\mathbb{1}[\cdot]$ is an indicator function, active whenever the statement in the bracket is true. The function:

$$c_\tau(u) = (\tau\mathbb{1}[u \geq 0] + (1-\tau)\mathbb{1}[u < 0]) \cdot |u| = (\tau - 1[u < 0]) \cdot u \tag{8}$$

(8) is the called the asymmetric absolute loss function or the "check function". When the quantile of interest corresponds to the median, the check function is the absolute loss divided by two, and is symmetric about zero. As showed before, the median minimizes the absolute error. It follows from this that the conditional quantile minimizes the check function, conditional on x_i. With this established, estimates of different quantiles besides the median can be found by minimizing:

$$\min_{q \in \mathbb{R}, \beta \in \mathbb{R}^{\mathbb{K}}} \sum_{i=1}^{N} c_\tau(y_i - \alpha - \beta T_i - \theta_i x_i) \tag{9}$$

Following this procedure, coefficients of observables can be interpreted as returns to characteristics in the labour market at different points of the conditional wage distribution. In the case of a binary covariate T, the quantile regression coefficient is given by $\beta_\tau = F^{-1}_{y|T=1,x=\bar{x}}(\tau) - F^{-1}_{y|T=0,x=\bar{x}}(\tau)$ Where $\bar{x}$ represents the sample means of characteristics, corresponding to the quantile of interest. This CQR coefficient is used to identify effects of a heterogeneous treatment, meaning that the treatment of union membership can vary between quantiles of the wage distribution. Under this framework, the effect of changes to covariates are called quantile treatment effects (QTE). However, this relies on weak or sometimes strong independence assumption. In other words, selection into union is fully accounted for by assumption. In a real-world application, this assumption may or may not hold, but is crucial for inference.

With OLS, one can generally go from $E[y_i|x] = E[y_i]$ by the law of iterated expectation. This is a property of the expectation operator that does not hold in the case of quantiles. Therefore, $F^{-1}_{y|T=1,x=\bar{x}}(\tau) = q_{y|T=1,x=\bar{x}}(\tau) \neq q_y(\tau)$. In other words, the τth quantile of the conditional distribution is generally not the same as the τth quantile of the unconditional distribution. The only case where β is a consistent estimator of the effect of union membership on the unconditional distribution, is the one where all conditional distributions are affected by the increased union membership equally, amounting to a pure parallel shift for every covariate.

When distributional statics are conditioned on covariates, one usually cannot discern where in the outcome distribution an individual will end up. As an example; Condition on education, an individual that has low education might still be a top earner in their quantile of education attainment, therefore this individual would end up at the right tail of the conditional distribution of wages, as apposed to the bottom part of the unconditional distribution.

Conditional quantile regression became a popular approach for investigating distributional statics during the 1990s. Notably, Buchinsky used the framework to investigate women's returns to schooling and across the distribution of wages[41].

3.5 Unconditional Quantile Regression

Having somewhat established the main points of quantile regression, and discussed some of the shortcomings of CQR when one wants to define quantiles before performing regression, attention is turned to unconditional quantile regression. There several ways of obtaining the effect of a treatment on the unconditional quantile. The first approach, is to use coefficients from the CQR to obtain the unconditional effect by integrating out the conditioning covariates. Firpo, Fortin & Lemieux (FFL) also show that the effect of a covariate on a conditional quantile of the outcome distribution, can be found by identifying all the unconditional quantiles of Y and reweighting their conditional counterparts (Similar to Machado & Mata, 2005). This approach requires the use of nonparametric techniques and can be difficult to implement. As such, a description of this approach will not be covered in this thesis.

The second approach is to use influence functions (IF), as suggested by FFL. Influence functions is a tool used for robust estimation, first developed by Hampel et al in 1981[42]. These functions are used to identify the influence of a single observation to a number of distributional statics such as quantiles. The influence function can identify the change in the distribution of outcome following small manipulation of the distribution of covariates. These manipulations can be as small as an infinitesimal data contamination with any given characteristics[6], or as big as treating the whole sample with union membership (setting the probability of union membership to unity). FFL suggest adding the statistic of interest back to the influence function, to yield a recentered influence function (RIF). In the case of quantiles, the influence function is given as:

$$IF(Y; q_\tau, F_Y) = \frac{\tau - \mathbb{1}\{Y \leq q_\tau\}}{f_Y(q_\tau)} \tag{10}$$

Adding the population quantile back to this static, the RIF is obtained as:

$$RIF(Y; q_\tau, F_Y) = q_\tau + \frac{\tau - \mathbb{1}\{Y \leq q_\tau\}}{f_Y(q_\tau)} \tag{11}$$

[6]In statistics, influence functions are often used to infer how the mean changes from removing or adding a single observation without having to re-calculate the mean.

The RIF can be computed by estimating the sample quantile, q_τ, the density of Y, $f_Y(q_\tau)$, using kernel method and an indicator dummy variable, $\mathbb{1}\{Y \leq q_\tau\}$, active whenever the outcome variable is smaller than q_τ.

The effect of a small change in the distribution of a covariate of interest can be estimated in several ways. In this thesis, OLS regression is performed with the RIF as the dependent variable. This is the simplest approach and is consistent so long as $Pr\left[Y > q_\tau | X = x\right]$ is linear in x. FFL proves that the conditional expectation of the RIF, modeled as a function of covariates:

$$E[RIF(Y; q_\tau, F_Y)|T, X = x] = m_\tau(x, T) \tag{12}$$

Can be used to infer effects of a small shift in the distribution of a covariate on the unconditional quantile of Y. This follows from the assumption that the conditional density function is unchanged from manipulation of X. Hence the unconditional quantile treatment effect can be identified under the restrictive assumption that the conditional expectation of the RIF can be modelled as a linear function of covariates:

$$E_x E[RIF(Y; q_\tau, F_Y)|T = t, X = x] = q_\tau \tag{13}$$

By definition of the RIF. In the case of quantiles, one can obtain the partial effect of a covariate on the unconditional distribution of outcome as:

$$E_x \left(\frac{dm_\tau(x, T)}{dx} \right) \doteq UQPE \tag{14}$$

This is the key identification solution and is interpreted as the effect of a marginal shift in the distribution of covariates on the τth unconditional quantile of Y, keeping everything else constant. In simpler terms, the unconditional quantile partial effect (UQPE) identifies the change to the distributional static associated with a small shift in the distribution of covariates. This UQPE is used to interpret the effect of union density on the unconditional quantiles.

The partial effects of manipulating the distribution of union membership and collective agreement coverage are also an area of interest for this thesis. However, as these covariates are categorical by nature, manipulating these imply changing the probability of union membership to unity for the whole sample. This effect can be interpreted as the unconditional quantile treatment effect (UQTE), and can be calculated as:

$$E\left[Pr\left[Y > q_\tau | T = 1\right]\right] - E\left[Pr\left[Y > q_\tau | T = 0\right]\right] \doteq UQTE \tag{15}$$

Interpreting the change in union membership as a probability is somewhat non-intuitive, although technically correct. Manipulating the distribution of a categorical variable implies changing it to unity, and since density is obtained by Kernel methods, this manipulation should be interpreted as a change to the probability of union membership or collective bargaining. With this approach researchers can get an impression of the treatment effect from union membership and collective bargaining for different quantiles of the distribution of wages.

However, this approach is not infallible. Several researchers have showed that this method does **not** identify the partial effect of a binary covariate on unconditional quantiles, or other features of the distribution of wages for that matter[43]. C. Rothe show that the UQPE is only partially identified when the underlying empirical model has more than one covariate. In addition to this, the unconditional partial effect of a covariate is only identified with the strong assumption of exogenous regressors. With this in mind, point estimates should be taken with a grain of salt. In this authors belief, point estimates of the treatment effects of union membership on the distribution of wages will give an impression of the heterogeneous effects of union membership. From a theoretical point of view, the collective bargaining and union membership wage premium is expected to be negative for the right tail of the wage distribution, and positive for the left tail of the distribution. This is due, in part, to the possibility that high skilled individuals could negotiate higher returns to their characteristics in a decentralized bargaining scheme[44]. There are also historical reasons to expect union membership to be more important for workers with relative low skills (i.e. wages).

3.5.1 RIF-OLS Model

For the unconditional quantile regression estimates, a multi-way fixed effect model similar to the ones above are run, with the RIF as the dependent variable:

$$RIF(Y; q_\tau, F_Y) = \alpha + \beta T_{it} + \lambda C_{jt} + \delta D_{jt} + \theta X_{jt} + \varphi_t + \mu_i + \gamma_j + \varepsilon_{it} \quad (16)$$

Year-, individual- and 3-digit industry code fixed effects are applied, as establishment level fixed effects are very restrictive. As quanile regression requires the estimation of densities and population quantiles in the first stage to obtain the recentered influence function, the literature advises the use of bootstrapped standard errors. Producing bootstrapped standard errors is computationally intensive for a sample of this size. Having tested the model for different quantiles of the wage distribution both with and without bootstrapped standard errors, cluster-robust standard errors proved sufficient[7].

[7]Some researchers suggest that bootstrapping standard errors for RIF-OLS might not be necessary in large samples[45].

3.6 Decomposition Method

As shown, RIF-regression provides a way of analyzing the effect of changes to a covariate on the outcome variable of many distributional statics. Like shown in the paper by FFL, the union wage premium is highly non-monotonic across the unconditional distribution of wages.

However, these results does not tell us explicitly how union membership affects wage inequality. Although they do give first evidence of how union membership affects different part of the wage distribution, this could simply be a feature of the labour market, and does not serve as proof of the presumed inequality-reducing effects of union membership and collective bargaining. In order to explore the effects of these covariates on wage inequality, a RIF-OB-decomposition has been run. In this section, an introduction of the Oaxaca-Blinder decomposition method of decomposing the mean group gap into a structural and a composition effect will be presented. This framework is extend to include other statics beyond the mean.

The decomposition methodology has been widely used in social sciences since its inception in 1973 by Ronald Oaxaca. Several extensions to the simple OB-decomposition has been developed, and as such, I will only cover the simple case, as well as the method applied for this thesis. The decomposition methodology used in this thesis was first proposed by FFL in 2007, and builds on the reweighing strategy proposed by DiNardo, Fortin and Lemieux in 1996. As such, this method could be seen as a hybrid of RIF-regression decomposition and reweighing decomposition in DiNardo. Their framework allows for detailed decomposition of the union non-union differentials into the wage structure and composition effect. To motivate this exercise, the simple OB-decomposition is presented first.

3.6.1 The Simple Decomposition

Oaxaca and Blinder developed their decomposition framework motivated by exploring the factors contributing to the wage differential between men and women as well as blacks and whites[46, 47]. Dividing the wage distribution into two groups, Y_0 denotes the wage in group 0 and Y_1 the wage in group 1[8]. As an individual can only belong to one of these groups, only one of these wages are observed for an individual. The observed wage can be written as $Y = Y_1 \cdot T + Y_0 \cdot (1 - T)$ where $T = 1$ if the individual belongs to group 1, or $T = 0$ if she belongs to group 0. Under assumption of linearity, the wage

[8] I omit subscripts indicating individual and year for this section. Note that Y denote the natural logarithm of yearly wages, but kept as Y for simplicity.

function can be written as:

$$Y_T = \alpha + \beta_T X + \varepsilon_T \tag{17}$$

The overall mean wage differential is denoted as Δ_O^μ. This overall differential can be divided into the wage structure effect, Δ_S^μ, and the composition effect, Δ_C^μ. Averaging over X, the overall wage differential can be written as:

$$\begin{aligned}
\Delta_O^\mu &= E[Y_1|T=1] - E[Y_0|T=0] \\
&= E[E\left(Y_1|X,T=1\right)] - E[E\left(Y_0|X,T=0\right)] \\
&= E[X_1|T=1]\beta_1 + E[\varepsilon_1|T=1] - \left(E[X_0|T=0]\beta_0 + E[\varepsilon_0|T=0]\right)
\end{aligned}$$

Under the conditional independence assumption $E[\varepsilon_T|T=t]=0$, and the expression reduces to:

$$\begin{aligned}
\Delta_O^\mu &= E[X|T=1]\beta_1 - E[X|T=0]\beta_0 \\
\Delta_O^\mu &= E[X|T=1]\left(\beta_1 - \beta_0\right) + \left(E[X|T=1] - E[X|T=0]\right)\beta_0 \\
\Delta_O^\mu &= \Delta_S^\mu + \Delta_C^\mu
\end{aligned} \tag{18}$$

The first term in (18) is the wage structure effect, it gives the part of the wage differential that can be explained by different returns to characteristics between the two groups. The second term is the composition effect, and gives us the part of the overall wage gap that arise due to difference in characteristics between the groups. When this method was first proposed, the structure effect was called the unexplained part of the wage differential, and can to some extent be interpreted as wage discrimination, as this component cannot be explained by observable characteristics.

In practice, the simple OB-decomposition is easy to implement by performing OLS regression, replacing β_T with the obtained coefficients and $E[X|T=t]$ with the sample means for each group. Doing this for every covariate of interest provides a way of dividing the contribution of a single covariate to the composition and wage structure effect.

3.6.2 Shortcomings

The simple OB-decomposition suffers some major shortcomings. First, the contribution of a single covariate to the structure effect, given by $E[X|T=1](\beta_1 - \beta_0)$ is sensitive to what group is used as the reference group. Another weakness is that consistent estimates of the wage structure and composition effects relies on the assumption that the conditional expectation is linear in the choice of groups. Keeping in mind that the counterfactual of interest when applying the simple OB-decomposition is what wage would prevail if group 1 were compensated by the wage structure of group 0. However, if linearity does not hold, the term $E[X|T=1]\beta_0$ would not correctly identify this counterfactual. With the mean decomposition somewhat established, the decomposition method used for this thesis is described in the next section.

3.6.3 RIF-OB Decomposition

To determine how differences in characteristics and differences in returns to these characteristics influence the overall difference in wage, a counterfactual scenario must be constructed. In the context of quantiles, one suggestion is to run separate RIF-regressions for both groups and identify a linear counterfactual where mean characteristics of any unconditional quantile are given the estimated coefficients from the apposing group according to:

$$\begin{aligned} v_1 &= E\left[RIF\{Y, v\left(F_{Y|T=1}\right)\}\right] = \bar{T}_1\hat{\beta}_1 \\ v_0 &= E\left[RIF\{Y, v\left(F_{Y|T=0}\right)\}\right] = \bar{T}_0\hat{\beta}_0 \\ v_C &= \bar{X}_1\hat{\beta}_0 \end{aligned} \tag{19}$$

This approach, although valid, suffers the same shortcomings as the linear decomposition in the previous section. Union membership is not observed for both groups, and as such, the linearity assumption may not hold. To correct for this, another strategy has been suggested by DiNardo, Fortin & Lemieux.

By using RIF-regression in combination with a reweighing strategy, the contribution of relevant covariates to intra-group differences in inequality measures such as gini-coefficients, 90-10 differential, variance differential etc. can be decomposed. In the case of a binary covariate such as union status, this reweighting procedure allows for dividing each covariate to the wage structure and composition effect[9, 10]. In this section, a brief explanation of the procedure is presented.

Assume there is a joint conditional distibution function that captures the relationship between wage, Y, relevant covariates, X, and union membership, T, which is the cathegorical variable which the decomposition will be estimated over. The conditional cumulative distribution is given by:

$$F_{Y|T=t} = \int F_{Y|X,T=t} dF_{X|T=t} \tag{20}$$

The conditional cumulative distribution function is used to estimate the gap in the distributional static:

$$\begin{aligned}\Delta v_O &= v_1 - v_0 = v\left(F_{Y|T=1} - F_{Y|T=0}\right)\\ \Delta v_O &= v\left(\int F_{Y|X,T=1}\cdot dF_{X|T=1}\right) - v\left(\int F_{Y|X,T=0}\cdot dF_{X|T=0}\right)\end{aligned} \tag{21}$$

Differences in the distributional static come from differences in the distribution of X and diffences in the relationship between Y and X. Compared to the simple OB-decomposition, this is equivalent to differences in the mean of covariates between the two groups, and the difference in the OLS coefficients between the groups.

This decomposition still relies on the linearity assumption in order to correctly identify the counterfactual
$F_{Y|X,T=1}\cdot dF_{X|T=0} \doteq F^C_{Y|T}$
The counterfactual is never observed, but the reweighing procedure allows using the observed distribution of covariates in $F_{X|T=0}$, multiply it with a reweighing factor $\omega(X)$, so that it becomes an approximation of the observed distribution $F_{X|T=1}$, hence:

$$F^C_{Y|X,T=t} = \int F_{Y|X,T=0}\cdot dF_{X|T=1} \cong \int F_{Y|X,T=0}\cdot dF_{X|T=0}\cdot\omega(W) \tag{22}$$

This reweighing factor is obtained from Bayes rule:

$$\begin{aligned}\omega(W) &= \frac{dF_{X|T=1}}{dF_{X|T=0}} = \frac{dF_{T=1|X}dF_X}{dF_{T=1}}\cdot\frac{dF_{T=0}}{dF_{T=0|X}dF_X}\\ &= \frac{dF_{T=0}}{dF_{T=1}}\cdot\frac{dF_{T=1|X}}{dF_{T=0|W}} = \frac{1-P}{P}\cdot\frac{P(T=1|X)}{1-P(T=1)|X}\end{aligned} \tag{23}$$

With P being the proportion of people in group 1, and $P(T = 1|X)$ is the conditional probability that an individual belongs to group 1, often referred to as a propensity score. This propensity score is obtained through a logit or probit model. With this approach, the counterfactual static in (2) can be estimated using a linear model of the reweighed least squares in:

$$v_C = E[RIF\{(y, v(F^C_Y)\}]) = \bar{X^C}\hat{\beta}_C \tag{24}$$

Yielding a four fold decomposition:

$$\Delta v = \bar{X}_1(\hat{\beta}_1 - \hat{\beta}_C) + (\bar{X}_1 - \bar{X}_C)\hat{\beta}_C + (\bar{X}_C - \bar{X}_0)\hat{\beta}_0 + \bar{X}_C(\hat{\beta}_C - \hat{\beta}_0) \tag{25}$$

The two first terms of (24) corresponds to the wage structure effect and the last two terms are the composition effect. The first term is called the pure wage structure effect, and gives the returns that prevails in group 1, were they compensated like the reweighted wage structure function of group 0. The second term i used to assess the the quality of the reweighting strategy, if an appropriate logit model is specified, this term should go to zero. Term three is the pure composition effect, and gives insight to how group 0 would be compensated if they had the characteristics as the reweighted sample. The last term can be informative of erroneous model specification.

3.6.4 RIF-OB Model

For the purpose of decomposition analysis, a simple logit model was run to obtain propensity scores:

$$Pr(T = 1|X = x_{it}) = \alpha + \lambda C_{it} + \delta D_{jt} + \theta X_{it} + \varphi_t + \varepsilon_{it} \tag{26}$$

Where X is a vector of covariates; Educational attainment, potential experience, public sector dummy, part-time dummy, year dummies, firm size and 2-digit industry dummies.

4 Descriptive Statistics and Data

This section contains descriptive statistics from the Norwegian labour market, and from the data used for analysis.

4.1 The Norwegian Labour Market

4.1.1 Collective Bargaining Coverage

As with the rest of the Nordic countries, collective bargaining coverage in Norway is high. Around 72 % of Norwegian workers are covered by collective bargaining as of 2014[48]. For comparison, 90 % of the wage determination is set by collective bargaining in Sweden[49]. As with most European countries, workers in Norway do not need to be member of a union to benefit from the collective bargaining regime, as wages are set at an industry level. Because of this, collective bargaining reaches every worker in establishments that have collective wage bargaining regardless of individual membership status.

In the private sector, collective bargaining covers 57 % of the workers as of 2014. The salience of collective bargaining in the Norwegian labour market is an interesting characteristic for researchers interested in union wage effects. As collective wage determination reaches all workers in an establishment that follows collective agreements, one could predict that the presence of collective agreements is more important for wage levels than individual membership. A union membership premium may still be present, if union workers are first in line for promotions, get to know people working in administrative positions, get access to courses organized by the unions etc.. There is also the possibility of selection into unions based on unobserved characteristics, which to some extent can be controlled for with multi-way fixed effects.

4.1.2 Union Membership

Union membership in Norway is somewhat lower than collective bargaining coverage. Union membership rates have been relatively stable around 50 % in the period 2004-2014. More people are covered by collective bargaining than are members of a union. This is interesting, as there might be incentives to free-ride whenever collective agreements are present. If collective bargaining yields a positive wage premium, while individual membership does not, workers in the covered sector that are not members of a union can be said to be free-riders, as they benefit equally from the collective wage setting. This hypothesis has been rejected for the US labour market[50], but has not been an area of interest for Norwegian researchers.

4.1.3 Establishment Union Density

Establishment union density in the Norwegian labour market are estimated on the basis of survey data from 8019 establishments. Union density in the private sector was estimated at 38 % in the private sector and 81 % in the public sector[48] (FAFO, 2014). In other words, union density is much higher in the public sector compared to the private.

4.2 Data

The empirical analysis utilizes matched employer-employee data, drawn from rich registry data in the period 1993-2014 which I have been given access to by Statistics Norway. This includes micro-data from the employer-/employee-registry (AA-registeret), AFP registry, folkeregisteret, educational statistics and tax registry.

To obtain data on individual union membership, the fact that union membership in Norway is partly tax deductible is exploited. Every worker who report tax deduction for union membership are coded as members of a union. Union tax deductions are described as an opt-out scheme[9], therefore these data are measured with relatively little error[51].

The sample is drawn from folkeregisteret, a registry of every Norwegian citizen dating back to 1900. Adult wage takers aged 25-50 in 2004 are included and observed for 11 years. This yields a sample of 4.734.040 observations with a total of 535.640 individual wage takers. Individuals who died or moved out of Norway during this period are excluded from the sample population, as are individuals coded as unemployed or out of the work force. Wokers earning less than 10.000 NOK per year or more than 10 million per year are also excluded from the sample[10]. As attrition is assumed non-random, the panel dimension is somewhat unbalanced, with the median observation being observed 10 times during this period. There is a total of 8.088 individuals only observed once, these are dropped from all the models except the pooled OLS model. In total, 5 % of the sample is observed 3 times or less, and 25 % of the sample population is observed 8 times or less.

[9] The unions and employers are supposed to report these deduction to the tax authoroties.

[10] This restriction is made to trim outliers. Most observations below 10.000 have negative wages. Less than 200 observations have a reported income above 10 million NOK.

4.2.1 Union Membership, Density and Collective Agreement Coverage

The union membership rate is monotonically increasing from 55,3 % in 2004 to 70,6 % in 2014. This somewhat contrasts the FAFO report mentioned above. There are three main reasons for this; First, only wage takers are observed. There are no unemployed persons in this sample population. This is one reason for the high union membership rate. Secondly, all observations that do not change union status during the research period are dropped for simplicity. A high fraction of these are never members of a union, and as such, the union membership rate is higher in-sample when compared to labour market statistics. The third reason is that union membership is correlated with age. As wage takers aged 25-50 in 2004 are included, union membership becomes more salient as the sample population gets older.

Union density is defined as the sum of union members within an establishment divided by every worker in the establishment minus one. In other words, one worker is left out of the mean, to better capture union density as an establishment characteristic. In-sample establishment level union density is monotonically increasing from 56,8 % in 2004 to 65 % in 2014. Correlation between age and union density is the only explanation that can be offered for this trend. However, these data are in relative correspondence with statistics from the labour market. Collective wage bargaining is also increasing during the research period, from 73,9 % in 2004 to 78,7 % in 2014. This is somewhat high compared to statistics from FAFO. The most likely explanation for this is that the sample captures individuals with a strong affiliation to the labour market, where the presence of collective agreements is more likely. Dropping individuals that does not change union membership status also explain the large fraction of establishments with collective bargaining. In table 1, it is

Table 1: Sample characteristics in private and public sector

	Private sector	Public sector
Individuals	55.6 %	44.4 %
Collective agreement coverage	57.9 %	100 %
Union membership	57.8 %	74.7 %
Establishment union density	47.2 %	79.8 %

apparent that the data captures a larger share of public sector workers than what is expected. Almost 45 % of the sample population works in the public sector, while statistics from SSB show that 34 % of Norwegian workers are in the public sector. The largest 2-digit industry in the data is the health service industry, about 26 % of the sample population works in health services. This is somewhat high, as OECD statistics show that 20 % of the Norwegian workers work in the health services.

4.2.2 Wages, Employment and Sample Means

Wage data are gathered from the Statistics Norways wage statistics. These record yearly pre-tax wages with no significant error. Yearly wages are CPI-adjusted for 2015 prices in order to make meaningful inference when exploiting the time-dimension of the data. Not having an efficiency measure of workers in terms of hourly wage somewhat weakens the empirical analysis. Attempts at getting a good measure of hourly wage proved difficult, as working hours are reported with significant measure error.

Worker characteristics are captured in registry data from different sources, the sample means by union membership are displayed in table 2:

Table 2: Sample means of characteristics by union status

	Union	Non-union
Yearly wage	466.822	443.074
ln(Yearly wage)	12,937	12,81
Female	54,8 %	48,5 %
Education (years)	13,73	13,17
Potential Experience	22,24	21,47
Immigrant	8,7 %	9,1 %
Administrative Position	4,7 %	8,2 %
Manual Labour	15,3 %	16,5 %
Weekly Hours	33,42	32,98
Part-time Employment	12,8 %	19,9 %
Collective Agreements	85,6 %	60,4 %
Public Sector Employment	51,4 %	31,3 %
High Skilled Establishment	2,7 %	2,2 %

5 Results

In this chapter, the results of pooled OLS, FE regression, RIF regression and RIF-OB decomposition are presented. These estimates will give insights to how union membership, collective agreements and union density is rewarded on the mean, and on 99 quantiles of the distribution of wages. In section 5.1, pooled OLS and FE estimates are reported to identify the wage effect of union membership on the mean. In 5.2 controls for collective agreements and establishment union density is added. Section 5.3 introduces an interactive model, this model features two interactions: One with union membership and collective agreements, and one with membership and union density. The purpose of the interactive model is to identify the relationship between union membership and important workplace characteristics. This interactive model is also applied on samples restricted to the public sector, the private sector covered by collective agreements and the private sector not covered by collective agreements. The purpose of this exercise is to inspect heterogeneous effects of union membership and union density across sector and bargaining scheme. In section 5.4 results from RIF-OLS regression are presented. RIF-OLS results will give insight to the heterogeneous effects of unionization and bargaining across 99 quantiles of the distribution of wages. In 5.5 the results from the detailed decomposition of union non-union differences in income inequality is presented. The purpose of this exercise is to inspect differences in wage inequality for union members and non-members, and to identify which factors contribute to these differences. The obtained results are discussed throughout this chapter, but the conclusion is preserved for chapter 6.

5.1 Union Wage Effect

To get a clear view of how union membership is rewarded in the Norwegian labour market, a pooled OLS model is run. To account for selection into unions from unobservables, variation in yearly wages are restricted in four stages, introducing time-invariant individual-, 2-digit industry-, 3-digit industry- and establishment level fixed effects. The hypothesis that random effects (RE) capture individual level effects adequately is rejected, hence the choice of a FE estimator. The results from pooled OLS and FE regression can be seen in table 3. Only point estimates of the wage effect from union membership is presented.

Pooled OLS estimates suggest that the wage premium associated with union membership is about 9 %. The estimates from pooled OLS feature variation in individual wages between and within individuals. To account for the possibility of selection into unions based on unobservable characteristics,

Table 3: Union wage effects

	(1)	(2)	(3)	(4)	(5)
Union Membership	0.0833***	0.128***	0.126***	0.125***	0.120***
	(0.0077)	(0.0071)	(0.007)	(0.007)	(0.0073)
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	Yes
2-Digit Industry FE	No	No	Yes	No	No
3-Digit Industry FE	No	No	No	Yes	No
Establishment FE	No	No	No	No	Yes
Adjusted R^2	0.460	0.708	0.709	0.712	0.737
Within R^2	0.432	0.173	0.169	0.164	0.154
N	4734040	4725952	4725952	4725947	4702287

Standard errors in parentheses
Model (1) - Pooled OLS
Model (2)-(5) linear fixed effects models
Coefficients given in log of yearly real wage
Standard errors clustered around 3-digit industry code
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

time-invariant individual fixed effects are applied in column (2)-(5). The FE estimates suggest that union members enjoy a wage premium in the range of 12,7 % to 13,7 %. This indicates that when wage variation between individual is considered, pooled OLS estimates of the union wage effect are downward biased. This is a bit surprising, as it is generally accepted (for the US labour market) that the wage effect from unionization is upward biased in the case of omitted variable bias[52]. Jakubson (1991) was one of the first researchers to use time-invariant individual fixed effects to measure the union wage premium. He found that the conventional cross-section estimate of the union wage premium at 20 % was reduced to 5 % - 8 % with the inclusion of individual fixed effects[11].

As can be seen in table 3, the more restrictive the model, the smaller the union wage effect. In column (5), only variation within an establishment is considered, this yields a wage effect from union membership of about 12,7 %. That is the wage effect of an individual that changes union status within an establishment.

A union wage effect of 13 % can be considered a very high estimate in the Norwegian labour market. Newer research from Norway suggest that

[11] In a large part of the anglo-saxon literature, the effect of union membership denotes the effect of collective agreements, as trade unions bargain wages only at the establishment level.

the individual wage effect from union membership is much smaller in magnitude. The importance of using establishment level controls is also underlined. Therefore, control for collective agreements and establishment level union density is added in the next section.

5.2 Union Wage Effects: Controlling for Collective Agreements and Establishment Union Density

In the Norwegian labour market, wages are often set at an industry level. About 70 % of the Norwegian labour market are covered by collective agreements. These are agreements between workers' interest organizations and employers interest organization. Collective agreements cover working conditions, pay ladders and overtime pay schemes, and as such are detrimental to wage levels. For this reason, it is an important control for researchers interested in predicting Norwegian wages. The same model as in table 3 is run with the inclusion of collective agreements control.

Table 4: Union wage effects: Controlling for Collective Agreements

	(1)	(2)	(3)	(4)	(5)
Union Membership	0.0859***	0.126***	0.125***	0.125***	0.121***
	(0.0076)	(0.0071)	(0.0071)	(0.0072)	(0.0073)
Collective Agreement	-0.0176*	0.0198***	0.0105***	0.0052	-0.0353***
	(0.0097)	(0.0065)	(0.0037)	(0.0033)	(0.0059)
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	Yes
2-Digit Industry FE	No	No	Yes	No	No
3-Digit Industry FE	No	No	No	Yes	No
Establishment FE	No	No	No	No	Yes
Adjusted R^2	0.460	0.708	0.709	0.712	0.737
Within R^2	0.432	0.173	0.169	0.164	0.154
N	4734040	4725952	4725952	4725947	4702287

Standard error in parentheses
Model (1) - Pooled OLS
Model (2)-(5) linear fixed effects models
Coefficients given in log of yearly real wage
Standard errors clustered around 3-digit industry code
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As can be seen in table 4, controlling for collective agreements does not affect the union membership premium significantly. Pooled OLS suggest that collective agreements is associated with a 1,7 % wage penalty, although this estimate is only significant at the 10 percent level.

When individual fixed effects are included, the wage effect of collective bargaining changes sign. Accounting for unobserved indivudual effects (column 2), changing collective bargaining status is associated with a 2 % increase in individual wage. However, when 3-digit industry fixed effect is applied, there is no significant return to collective agreements, and with establishment fixed effects the effect is negative at -3,5 %. Inspecting variation in collective agreements within establishment, it is apparent that few establishment change bargaining scheme during the research period. As establishments feature low within-variation in collective agreement status, this estimate might be sensitive to outliers and misspecification errors.

There is a possibility that high wage individuals may select themselves into establishments that does not feature collective bargaining. High skill individuals might get better returns to their characteristics under a decentralized bargaining scheme[44]. There is some support for this hypothesis, as the collective agreement coefficient is negative for pooled OLS, and positive in column (2)-(4).

In column (5), collective agreements are associated with a negative and large in magnitude effect on individual wage. An hypothesis is that changing to a collective bargaining scheme comes at a cost, and that workers take a share of this cost at least in the short term. However, the change of signs and magnitude leaves no more than speculation of the role of collective agreements for individual wages.

A prediction in the union literature for the Norwegian labour market, is that establishment level union density is a hugely important covariate for variation in wages. Therefore, control for union density is included in table 5. As establishment union density is somewhat collinear with union membership in small establishment, a leave-one-out measure of union density is defined as the sum of union members in an establishment, divided by the number of employees excluding worker i. Hence, an establishment with two employees, where one of them is a member of a union, union density is coded as 1 (100 %).

As can be seen in table 5, controlling for establishment union density does not affect the membership premium or the collective bargaining premium. The union density estimate is not significantly different from zero for any specifications except where establishment level fixed effects are applied. The inclusion of union density does not significantly increase the explanation power of the model or reduce the mean square error of any of the models. In column (5), changing union density from zero to unity is associated with a 2,3 % reduction of wages. This is a somewhat surprising result, as the wage

Table 5: Union wage effects: Controlling for Collective Agreements and Union Density

	(1)	(2)	(3)	(4)	(5)
Union Membership	0.0868***	0.125***	0.125***	0.125***	0.121***
	(0.0075)	(0.0073)	(0.0072)	(0.0072)	(0.0072)
Collective Agreement	-0.0161	0.0174***	0.0097***	0.0053	-0.0319***
	(0.0114)	(0.0049)	(0.0031)	(0.0035)	(0.0059)
Union Density	-0.0056	0.0086	0.003	-0.0005	-0.0229***
	(0.0173)	(0.0077)	(0.0055)	(0.0045)	(0.0033)
Year FE	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	Yes	Yes
2-Digit Industry FE	No	No	Yes	No	No
3-Digit Industry FE	No	No	No	Yes	No
Establishment FE	No	No	No	No	Yes
Adjusted R^2	0.460	0.708	0.709	0.712	0.737
Within R^2	0.432	0.173	0.169	0.164	0.155
N	4734040	4725952	4725952	4725947	4702287

Standard error in parentheses
Model (1) - Pooled OLS
Model (2)-(5) linear fixed effects models
Coefficients given in log of yearly real wage
Standard errors clustered around 3-digit industry code
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

effect from establishment union density is well documented to be positive and significant for the Norwegian labour market[3].

5.3 Model With Interactive Effects

To get a better view of the effects of establishment union density on individual wages, an interactive model is implemented. Barth et al. (2000) conclude that union membership is a pure public good, increasing in union density. This seems a reasonable assumption, as high union density could improve the bargaining power of the unions, and the effectiveness of strikes, go-slows, overtime bans and other resources available only to workers in establishments that are characterized by a high fraction of union members. They argue that the absence of workplace characteristics, not differences in wage data, is the driving reason for the positive wage premiums found by researchers before them[53, 4]. This hypothesis has been confirmed also for the US labour market[50]. Budd et al. (2000) argues that to capture the overall wage effect of union membership, researchers should distinguish the effect across collective bargaining coverage.

In this thesis, controls for workplace characteristics such as union density and firm size are implemented. Heterogeneous effects of union membership and union density across sectors and collective agreement coverage are reported. A preliminary test of the stability of the union membership estimate across sector and coverage is resoundingly rejected[12]. This is clear evidence that the effects of union membership and union density differs across sector and collective bargaining coverage.

Table 4 suggest that variation in union density and collective bargaining is not in itself significant/important in explaining variation in yearly wages. However, the prediction in Barth et al. is that union membership becomes more effective wherever union density is salient. An interactive model is introduced to get a better view of the relationship between individual membership and establishment union density.

$$\ln y_{it} = \alpha + \beta T_{it} + \lambda C_{jt} + \delta D_{jt} + \theta X_{jt} + \rho T_{it} C_{jt} + \pi T_{it} D_{jt} + \varphi_t + \mu_i + \gamma_j + \varepsilon_{it}$$

The interactive model includes an interactive term between membership and union density, $T_{it}D_{jt}$ as well as membership and collective agreements, $T_{it}C_{jt}$. ρ will measure the effect of changing union status in the presence of collective agreement, or changing collective agreement status in the presence of union membership[13]. π will measure the wage effect of changing union status in an establishment with non-zero union density, or the effect of changes to union density in the presence of union membership. β, λ and δ will be referred to as

[12]Test following FE regression, similar to a Chow-test, but allowing for multiple intercepts.

[13]Within a 3-digit industry code.

the “flat” wage effect of union membership, collective agreements and union density respectively. 3-digit industy fixed effects are applied, as establishment level fixed effects might be too restrictive.

The results from this model are reported in four stages. Table 6 shows results from the interactive model on the whole sample. In table 7, only full-time public sector workers are considered, table 8 features private sector workers covered by collective bargaining and in table 9, private sector workers not covered by collective bargaining are considered:

Table 6: Union wage effects: Introducing interactions

	(1)	(2)	(3)	(4)
Union Membership	0.125***	0.108***	0.108***	0.0895***
	(0.0072)	(0.0073)	(0.0068)	(0.0093)
Collective Agreement	0.0054	-0.004	-0.0045	0.0107**
	(0.0035)	(0.0065)	(0.0063)	(0.005)
Union Density	-0.0009		0.0018	-0.0331***
	(0.0045)		(0.0038)	(0.0099)
Membership · Collective		0.0221**	0.0222**	-0.0011
		(0.0101)	(0.01)	(0.007)
Membership · Density				0.062***
				(0.0135)
Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
3-Digit Industry FE	Yes	Yes	Yes	Yes
Within R^2	0.164	0.165	0.165	0.165
N	4725947	4725947	4725947	4725947

Standard errors in parentheses
Coefficients in log of yearly wage
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

As can be seen in table 6, there is an immediate drop in the union membership premium when interactions between collective agreements and membership is introduced in (2). Column (2) indicates that union membership yields an additional wage premium of 2,2 % when a collective agreement is present.

Including control for union density in (3) does not change the union premium or the interaction between membership and collective agreements. When interaction between union membership and union density is introduced, the membership premium drops to 9,4 %. A large and significant effect from the membership-density interaction appears. Union membership yields an additional yearly wage premium of 6,2 % when every worker in the 3-digit industry code is member of a union. The total effect of changing membership status in an industry with full coverage with respects to both collective bargaining and union density is 13,8 %. The explanation power of our model is not affected by the inclusion of interactive term, but the mean square error is reduced by a fair amount.

The results from the interactive model shows that the relationship between union membership and union density is indeed explaining a significant amount of the variation in yearly wages. However, not much insight into the role of collective bargaining for individual wages is gathered from this exercise. In column (2) it is the interaction between membership and collective agreements that is important, while in column (4), it is the presence of collective agreements that has significance in explaining variation in individual wages. In any case, the relationship between membership and union density is more important for explaining variation in wages than collective agreements.

5.3.1 Conditioning on Full-time Employment by Sector and Bargaining Regime

The sample population for the estimates in table 3-5 are not restricted, and as shown the union wage effects are larger in magnitude than what one might expect for the Norwegian labour market. In the paper by Barth et al. they condition their estimates on workers covered by collective agreements. Conditioning estimates on sectors and collective agreements makes sense, as wage setting is likely to be different between sectors and bargaining scheme. To investigate the heterogeneous effects of union membership and union density, the interactive model has been run for full-time workers across sectors and bargaining schemes. As wage setting is different for workers covered by collective agreements as apposed to those who are not, the new sample features a more homogeneous wage formation. Results from this exercise can be seen in table 7, 8 and 9.

5.3.2 Public Sector

For full-time workers in the public sector, the flat membership premium is in the range of 7,6 % to 11,9 %. In column (2), control for establishment union density is included, this does not affect the membership estimate, and union density does not seem significant in explaining variation in individual wages for the public sector. Introducing an interaction between membership and density, the membership premium drops to 7,6 %. Here, the flat premium associated with an increase in union density is negative, but still not significantly different from zero. Changing union status in the public sector in a workplace featuring high union density is associated with a large additional wage premium. The total membership premium in a 3-digit industry where

Table 7: Union wage interactions: Full-time workers in the public sector

	(1)	(2)	(3)
Union Membership	0.113***	0.113***	0.0731***
	(0.0113)	(0.0113)	(0.0147)
Union Density		0.0057	-0.0271
		(0.0057)	(0.0181)
Membership · Density			0.0515**
			(0.0244)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
3-Digit Industry FE	Yes	Yes	Yes
Within R^2	0.170	0.170	0.170
N	1826428	1826428	1826428

Standard errors in parentheses
Coefficients in log of yearly wage
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

every worker is a union member is 13,3 %. This indicates a large wage premium associated with union membership in the public sector. Workers enjoy an additional membership wage premium up to 5 % related to the degree of union density.

5.3.3 Private Sector Covered by Collective Agreements

Table 8: Union wage interactions: Full-time workers in the private sector covered by collective agreements

	(1)	(2)	(3)
Membership	0.0354***	0.0358***	0.00582
	(0.003)	(0.003)	(0.0048)
Union Density		-0.0042	-0.0346***
		(0.0047)	(0.008)
Membership · Density			0.0535***
			(0.0093)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
3-Digit Industry FE	Yes	Yes	Yes
Within R^2	0.0829	0.0829	0.0834
N	1249349	1249349	1249349

Standard errors in parentheses

Coefficients in log of yearly wage

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the private sector covered by collective agreements, the benefits of being a union member are significantly smaller than in the public sector. Column (1) indicates a 3,6 % membership premium. Introducing control for establishment union density does not significantly change this estimate. When the interactive term is introduced, the individual membership premium disappears. Column (3) indicates that union membership in itself is not important in explaining wages, but that it is the interaction between membership and union density that matters. Union membership yields a wage premium up to 5,5 % related to union density. Table 8 also indicates that union density is associated with a wage penalty up to -3,4 %. These results are somewhat surprising. Whenever union density increases by 10 %, yearly wages drop by 0,35 %. However, union membership yields a wage premium related to union density up to 5,5 %. In the private sector covered by collective bargaining, there is no wage effect from union membership in itself. However, the membership premium works though establishment union density. This is consistent with the findings in Barth et al. (2000).

5.3.4 Private Sector not Covered by Collective Agreements

Table 9: Union wage interactions: Full-time workers in the private sector not covered by collective agreements

	(1)	(2)	(3)
Membership	0.0407***	0.0395***	0.0437***
	(0.0037)	(0.0035)	(0.0041)
Union Density		0.0067*	0.0144***
		(0.0038)	(0.0055)
Membership · Density			-0.0135**
			(0.0065)
Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
3-Digit Industry FE	Yes	Yes	Yes
Within R^2	0.0678	0.0678	0.0678
N	818545	818545	818545

Standard errors in parentheses
Coefficients in log of yearly wage
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For the private sector not covered by collective agreements, there is a significant membership premium in all tree specifications. In column 1, union membership is associated with a 4,1 % wage premium. Adding control for union density, this effect is somewhat reduced. Column 2 indicates that union density is associated with a flat wage premium of about 0,7 %. This effect is not very large as it denotes the effect of changing union density from zero to unity. A flat union density premium is consistent with the hypothesis that unions can increase the wage of their members by capturing rents from establishments. Surprisingly, when introducing the interactive term, the membership premium jumps by 0,4 % and union density premium jumps by almost 1 %. The interactive term indicates that changing union status in the presence of high union density has a negative effect on yearly wages. This result is somewhat non-intuitive, and is not at all consistent with existing literature. Drawing conclusions on the effects of union density for the Norwegian labour market on the basis of table 9 would be unwise. However, the presence of a union membership wage premium in the non-covered private sector is somewhat confirmed, although it is unlikely that this effect is point identified.

5.4 RIF-OLS Regressions

The purpose of this section is to inspect how manipulation of the distribution of union membership, collective bargaining and union density affects different quantiles of the distribution of yearly yearly wage. The sample population is restricted to full-time workers. In table 10, results from the FE model is compared to the RIF-OLS results for 5 quantiles of the wage distribution:

Table 10: FE- and RIF-OLS Estimates: Conditioned of Full-time Employment

	FE	10th	25th	Median	75th	90th
Union Membership	0.0780***	0.269***	0.0903***	0.0239***	-0.0116***	-0.0330***
	(0.0073)	(0.0303)	(0.0073)	(0.0032)	(0.0034)	(0.0043)
Collective Agreement	0.0059*	-0.0312*	-0.0095*	0.0077**	0.0148***	0.0230**
	(0.0034)	(0.0163)	(0.0057)	(0.0031)	(0.0037)	(0.01)
Union Density	0.0049	0.0339***	0.0333***	0.0118***	-0.0091**	-0.0497***
	(0.0041)	(0.0125)	(0.0054)	(0.0032)	(0.0044)	(0.0089)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
3-Digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.767	0.513	0.620	0.662	0.678	0.662
Within R^2	0.144	0.108	0.0946	0.0363	0.0147	0.00871
N	3993192	3993192	3993192	3993192	3993192	3993192

Standard errors in parentheses
Conditioned on full-time employment
Results from OLS and RIF-OLS for the 10th, 25th, Median, 75th and 90th percentile of the distribution of log of real yearly wage
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 displays the heterogeneous effects of union membership across the wage distribution. In the 10th percentile of the distribution, manipulating union status to unity for the population quantile is associated with a 31 % increase in yearly wage! For the 25th percentile, this effect drops dramatically to about 9 %. Treating the median with union membership is associated with a 2,4 % wage increase. At the 75th percentile, the treatment effect associated with union membership is -1,2 % , and drops monotonically to the 99th percentile, ending at at -5 %. Inspection of the within R^2 shows that the model has far more explanation power for the lower quantiles than the higher quantiles. In other words the model is a better fit for the left side of the wage distribution.

The initial presumption that the effect of collective agreements would be somewhat similar to the effect of union membership is shown to be erroneous. If collective agreements reduce dispersion of wages, one would think that treating the sample with collective bargaining would yield positive effects for the left tail of the distribution. That does not appear to be the case; Changing collective bargaining status is associated with large negative wage effects for the left tail of the distribution, however these are only significant at the 10 percent level. At the median and above, collective bargaining is associated with a positive wage premium in the range of 0,7 % to 2,3 %.

The effect of establishment level union density is somewhat monotonically decreasing in quantiles of the wage distribution. In other words, increasing union density by a small amount for the whole sample is associated with a positive wage premium up to the median, and a negative premium for the 75th percentile and above.

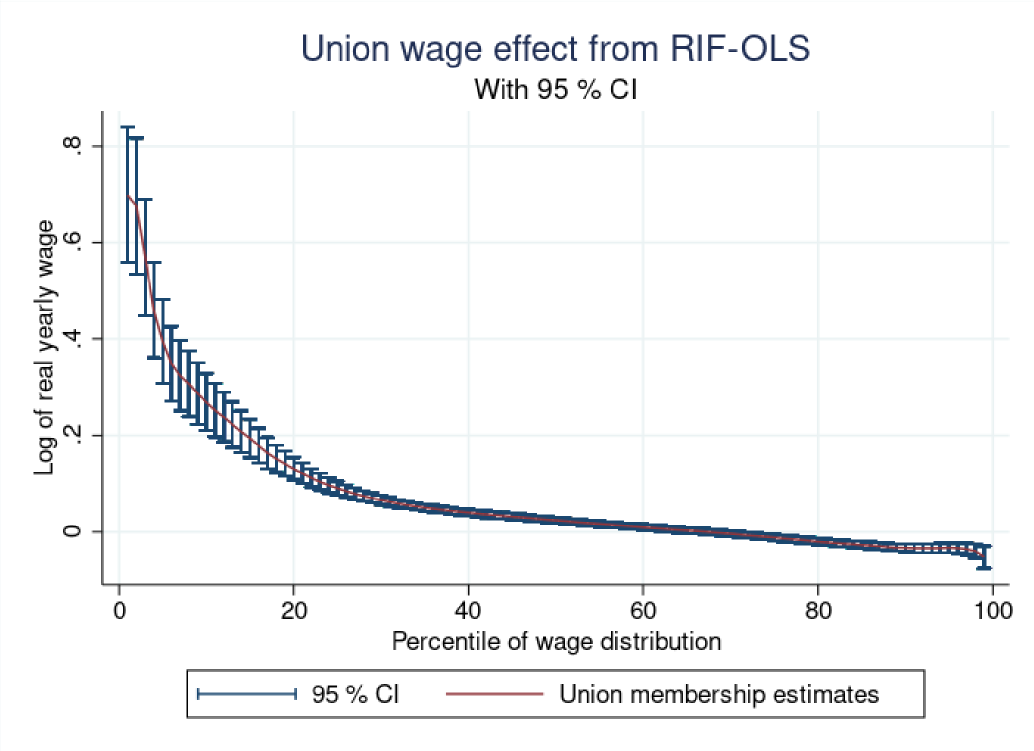

Figure 1: Union wage premium for 99 quantiles of the distribution of log(yearly wage)

These figures are drawn from RIF-OLS regression for 99 quantiles of the distribution of wages. For the bottom 10 percentiles of the distribution of wages, the wage effects associated with union membership are huge. Changing the union status to unity for the first three percentiles is associated with a wage increase of well above 60 %. The results from the first quantiles must be taken with a grain of salt. It is unlikely that the unconditional quantile treatment effects of union membership are of this magnitude, most likely the coefficients capture students, long time sick-leavers or individuals on sick leave which are coded as full-time workers that get permanent employment, go back to work etc. However, even if 20 quantiles are disregarded, there are staggering differences in the union premium across the distribution of wages. Treating the 72th percentile and above with union membership is associated with a negative premium. Due to the big effects in the left tail of the distribution, it is not easy to see the magnitude of the negative effects, but for the 95th quantile and above, the effect is in the range of -3 % to -5 %. In figure 2, the collective bargaining premium from 99 quantiles of the wage distribution are drawn. Interestingly, the wage effect of collective agreements are negative

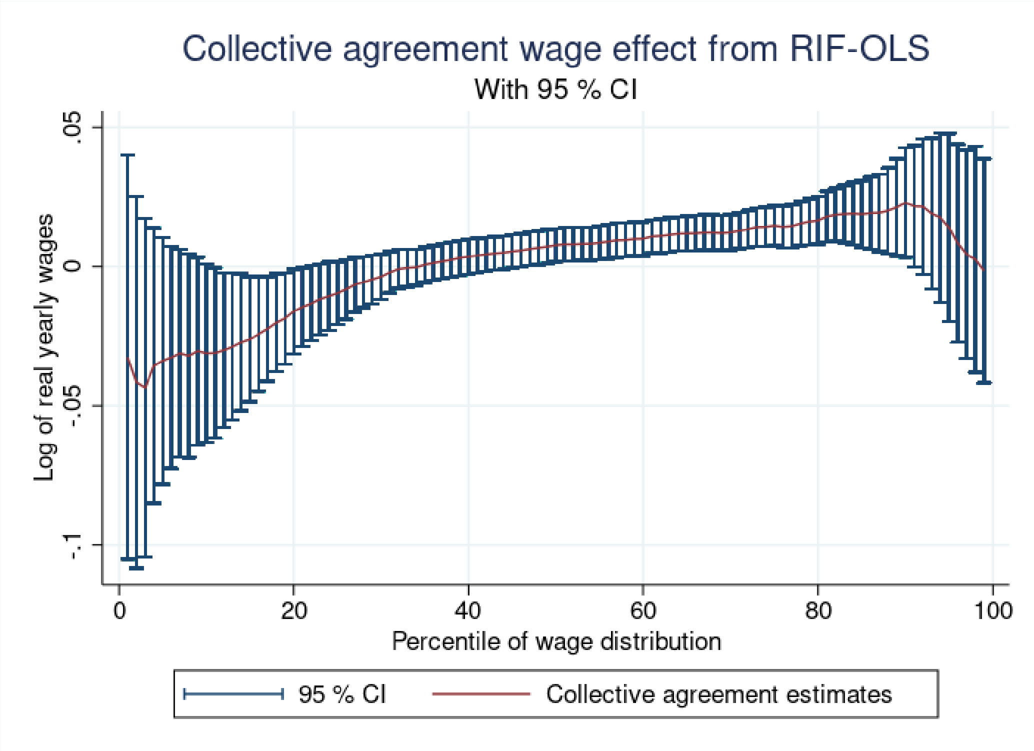

Figure 2: Collective agreements wage premium for 99 quantiles of the distribution of log(yearly wage)

for the left tail of the wage distribution, and positive for the right tail. This trend is not at all expected. However, the effect of treating the sample to collective bargaining is not significantly different from zero for most of the distribution. Figure 2 does not yield any meaningful insights to the role of collective agreements for the distribution of wages.

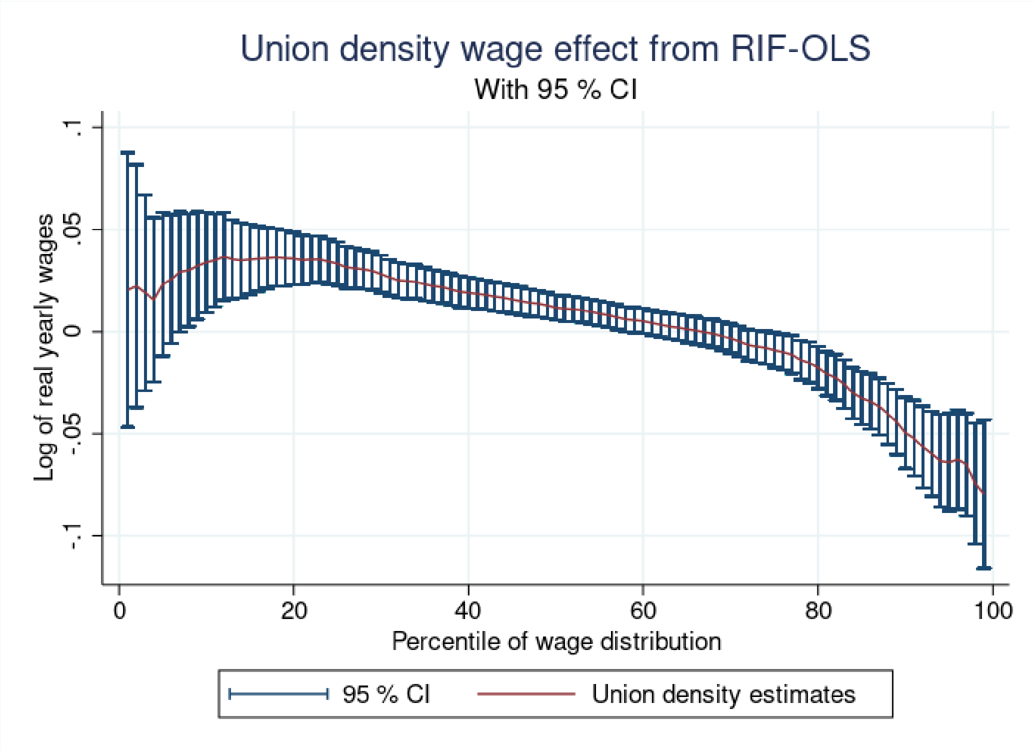

Figure 3: Union density wage premium for 99 quantiles of the distribution of log(yearly wage)

Figure 3 tells a more interesting story. The negative relationship between the union density premium and quantiles of the wage distribution is apparent. For the 77th percentile and above, a small manipulation of the distribution of union density is associated with a negative and significant wage effect. For the 90th percentile and above, a small increase to union density gives a negative wage effect in the range of -5 % to -8 %. Union density is only beneficial up to the 60th percentile of the wage distribution. For the left tail of the distribution, the confidence intervals are large and the null of no wage effects from union density cannot be rejected. Figure 3 indicates that the median and below benefit from being treated to a higher degree of establishment union density, while high earners get a wage punishment from manipulation of the distribution of union density.

5.5 Results of OB-Decomposition

The results from RIF-OLS show that union membership, union density and possibly collective bargaining can have large distributional effects. This section investigates the possible distributional effects of independent variables to see what characteristics are important for explaining the wage gap between union members and non-members; And if differences in the returns to these characteristics can explain the union non-union wage gap. To this end, OB decomposition using recentered influence function regression is reported. The counterfactual scenario is constructed using the reweighting strategy by FFL; Obtaining propensity scores from the observed distribution of covarites from union members, and manipulate the union distribution of covariates by weighted regression. To motivate this exercise, the cumulative distribution for union members, non-members and the counterfactual scenario are drawn in figure 4:

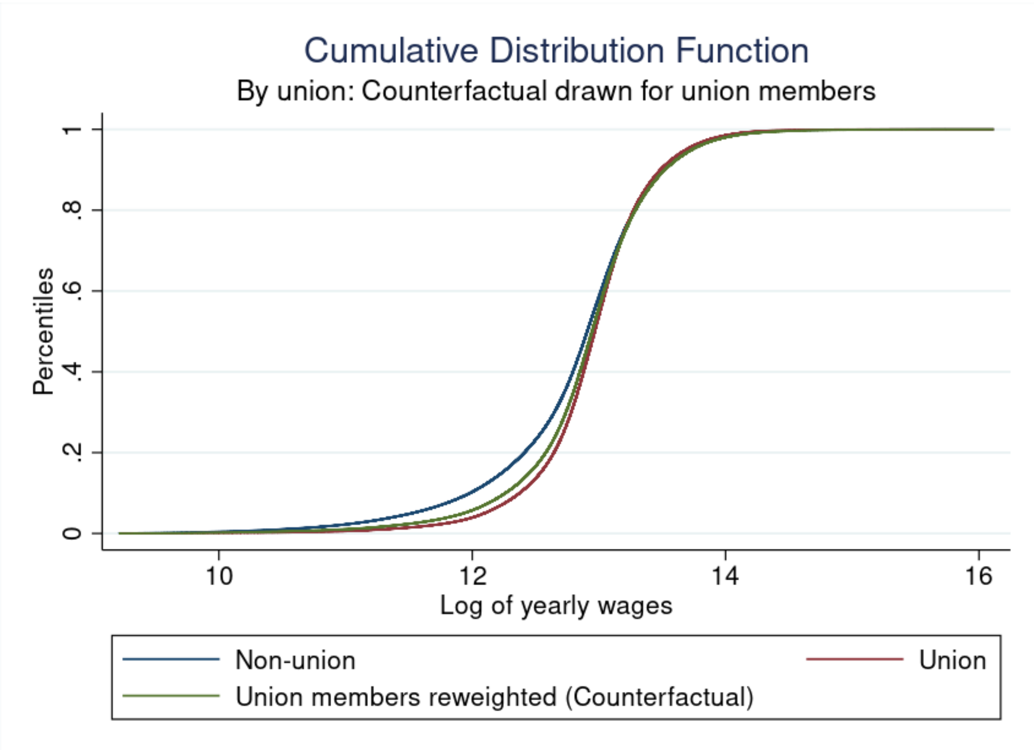

Figure 4: Cumulative distribution function for union members, non-union members and union members reweighted by propensity score.

Figure 4 indicates that the wage structure of union members is more compressed than for non-members. This is especially valid in the left tail of the distribution. The counterfactual scenario is one in which union members are treated with the predicted returns for non-union individuals. As figure 4 demonstrates, treating union members with non-union returns yields a CDF featuring more dispersion in wages, especially for the left tail of the distribution. This serves as preliminary evidence that unions compress the wage distribution in the left tail by offering more evenly spread returns to characteristics. Results following detailed decomposition of the 90th-10th quantile union non-union wage differential, 90th-50th differential, 50th-10th differential, gini differential and variance differential are displayed in table 11. These results are quite extensive, therefore only key figures are reported.

Table 11: RIF-OB Decomposition

	90th-10th	90th-50th	50th-10th	Gini x 100	Var(wage)
Overall					
Union members	1.112	0.519	0.593	24.89	0.254
	(39.31)	(495.77)	(30.63)	(736.71)	(28.56)
Counterfactual	1.260	0.602	0.683	28.01	0.331
	(52.05)	(417.41)	(38.02)	(487.84)	(30.61)
Non-members	1.528	0.602	0.962	30.79	0.458
	(41.68)	(417.41)	(34.14)	(594.78)	(27.81)
Total difference	0.416	0.083	0.333	5.899	0.205
	(15.08)	(54.32)	(21.70)	(110.12)	(16.08)
Total compositon	0.147	0.083	0.090	3.115	0.077
	(7.05)	(61.11)	(8.16)	(68.70)	(9.71)
Total wage structure	0.269	0.000	0.243	2.784	0.127
	(9.53)	(0.14)	(13.72)	(39.56)	(8.25)
Total composition effect					
Total	0.147	0.083	0.090	3.115	0.077
	(7.05)	(61.11)	(8.16)	(68.70)	(9.71)
Pure compositon	0.134	0.072	0.083	2.342	0.055
	(7.18)	(80.60)	(8.05)	(68.78)	(8.36)
Specification error	0.014	0.0105	0.007	0.773	0.022
	(0.72)	(8.14)	(0.92)	(19.02)	(3.00)
Detailed composition effect					
Potential experience	-0.017	-0.013	-0.004	-0.524	-0.007
	(-3.39)	(-20.66)	(-1.48)	(-25.53)	(-4.29)
Education	-0.011	-0.008	-0.001	-0.226	-0.004
	(-2.21)	(-13.47)	(-0.53)	(-28.18)	(-2.61)
Collective bargaining	0.051	0.036	0.015	1.076	0.019
	(4.27)	(42.17)	(3.35)	(35.54)	(4.93)
Part-time employment	0.033	0.002	0.032	0.448	0.008
	(8.01)	(6.27)	(8.12)	(51.97)	(2.95)
Specification error					
Potential experience	0.018	0.120	-0.095	1.837	0.016
	(0.26)	(9.18)	(-2.12)	(3.98)	(-0.82)
Collective bargaining	0.076	0.070	0.007	1.412	0.017
	(2.24)	(26.99)	(0.61)	(17.08)	(1.59)
Total wage structure effect					
Total	0.269	0.000	0.243	2.784	0.127
	(9.53)	(0.14)	(13.72)	(32.56)	(8.25)
Reweighting error	-0.004	-0.018	-0.013	0.293	-0.001
	(-0.56)	(-25.85)	(-2.09)	(10.18)	(-0.44)
Purely unexplained	0.273	0.019	0.255	2.491	0.129
	(10.04)	(8.49)	(15.96)	(28.10)	(8.44)
Detailed wage structure effect					
Potential experience	-0.093	-0.092	-0.008	-4.230	0.056
	(-0.86)	(-4.07)	(-0.11)	(-4.50)	(1.15)
Education	-0.095	-0.049	-0.055	-2.472	-0.037
	(-2.29)	(-7.11)	(-2.87)	(-8.04)	(-1.39)
Collective bargaining	0.067	0.027	0.038	1.487	0.033
	(3.25)	(7.95)	(2.81)	(11.75)	(2.98)
Weekly hours	-0.268	-0.082	-0.151	-3.307	-0.217
	(-3.92)	(-16.44)	(-2.32)	(-14.75)	(-4.69)
Reweighting error					
Education	-0.007	-0.005	-0.002	-0.175	-0.003
	(-3.74)	(-22.35)	(-3.79)	(-19.63)	(-3.49)

z-static in parentheses

The results of the detailed decomposition can be read in table 11. Every wage inequality measure is higher for non-unionized workers as compared to union workers. Non-union wage inequality is 13,7 % to 44,5 % higher than for union members. Unexpectedly, the 90th-50th quantile union wage differential is the smallest, while variance of yearly wages is the highest. Comparison between the 90th-50th and the 50th-10th differential gives evidence that unions compress wages to a larger extent in the left tail of the wage distribution than for the right. The decomposition fits the data best for the 50-10 union wage differential and the 90-10 differential, as specification error is small in magnitude, keeping results from RIF-OLS regression in mind, this is not surprising.

5.5.1 Composition Effect

The composition effect can be interpreted as the difference in inequality measures between non-union and union members that can be explained by differences in observed characteristics between the two groups. Differences in characteristics can account for between 27 % and 100 % of the between-group inequality differences. Inequality as measured by the 90-50 differential can be fully accounted for by differences in characteristics[14]. This implies that union non-union differences in wage inequality at the top end of the distribution arise due to differences in observable characteristics such as education and part-time employment.

For every other inequality measure, differences in characteristics cannot account for the intra-group inequality difference. The composition of observables accounts for only 27 % of the union non-union inequality-difference as measured by the 50-10 wage differential. This implies that in the left tail of the wage distribution, differences in returns to characteristics account for significantly larger share of the total differential. Part-time employment has the biggest contribution to the composition effect as measured by the 50-10. Every inequality measure indicates that increasing education and potential experience for union workers would decrease intra-group inequality, although this effect is small in magnitude.

It is not unexpected that education can not account for a large share of the composition effect, as education attainment does not differ significantly for non-union and union members. The salience of collective agreement coverage for union workers explains a significant share of the intra-group inequality. On first look, differences in collective agreement coverage seems to create between-group inequality. This effect is smallest for variance of wages, which

[14]Not accounting for specification error and reweighting error.

is expected as the presence of collective agreements should reduce variance of wages significantly from a theoretical point of view.

Specification error in the composition effect is significantly different from zero for the 90-50-, gini-coefficent- and variance-differential (although small in magnitude for the variance measure). This is a bad sign, and implies the RIF model does not fit the data very well for these inequality-measures, or rather, that the RIF does not provide a good approximation of the true value of the quantiles. The detailed specification error suggest that erroneous model specification can possibly account for the "inequality-increasing" effect of collective bargaining as measured by variance of wages and the 50-10 wage differential. Accounting for specification error, increasing the collective agreement coverage for union members reduce wage inequality as measured by intra-group differences in the 90-10, 90-50 and 50-10 wage differential.

5.5.2 The Wage Structure Effect

Differences in returns to observable characteristics can account for a large share of the union non-union inequality differential as measured by the 90-10, 50-10, gini and variance. Inspecting the detailed wage structure effect, it becomes clear that if union members were compensated like non-union individuals with respects to education, weekly work hours and potential experience, intra-group wage inequality would be significantly reduced. This is a finding that is consistent with results from other countries[16]. The reweighting error is significantly different from zero for the 90-50, 50-10 and gini differential. This suggests that the logit model used for obtaining the reweighting factor does not fit the data very well and the counterfactual might not be well defined for these inequality measures. Accounting for reweighting error does not significantly affect the magnitude of education attainments contribution to the wage structure effect.

5.5.3 Overall Decomposition

Overall, the detailed decomposition suggest that the composition of observable characteristics can fully account for union non-union wage inequality at the median and above. For the left tail of the wage distribution, differences in observables can not account for a large share of the difference in wage inequality. From the 10th percentile to the median, the wage structure can explain a larger share of the differences in inequality than the composition of covariates. Although specification error is significant and somewhat large in magnitude, there is weak evidence that collective bargaining reduce wage inequality. A significant driver for the union non-union wage gap is that non-union individuals seems to get higher returns to their characteristics at the median and below. Improvements to education and potential experience reduces this gap. As both specification error and reweighting error is significantly different from zero for several of the inequality measures, these results should not be interpreted to point identify the contribution of covariates to the wage structure or composition effect. However, the estimate may give an indication of the main drivers behind the union non-union differential. As the decomposition is done over union status, this analysis should not be interpreted to mean that union membership is the driver for differences in inequality measures. Rather, this decomposition gives insight to what factors contribute to the union non-union differentials. Identifying the contribution of union membership to wage inequality over time would be an interesting exercise for future research.

6 Conclusion and Discussion

Having investigated the role of union membership, collective agreements and union density for wage levels and wage dispersion in the Norwegian labour market, some conclusions can be drawn. A union wage gap in the range of 9 % - 13 % is reported from the simple wage model. Having controlled for union density, and interaction between membership, density and collective bargaining, the hypothesis that the union wage premium works through establishment union density for workers in the private sector covered by collective agreements is confirmed. This is in line with other research from the Norwegian labour market[3]. However, in both the non-covered private sector and the public sector, the interaction between union density and membership cannot fully account for the union wage gap. This suggests that the union wage premium is present wherever significant heterogeneity in wage setting is allowed. The results in this thesis somewhat differs from newer research on the Norwegian labour market, there are several reasons for this. In this thesis, a large data-set is used, with very few restrictions on the data. Firstly, the union wage premiums may be upward biased from individuals that change union status in the presence of large jumps to individual wage. Inspection of the RIF-OLS estimates somewhat confirms this suspicion, as unreasonably large partial effects of union membership are present in the left tail of the wage distribution. Secondly, there is a possibility that the heterogeneous wage settings are not appropriately controlled for, this might also bias the estimates. Lastly, it remains a possibility that selection into unions based on unobservables are not fully accounted for by applying multi-way fixed effects.

However, several theoretical explanations can be offered for a union wage gap. Unions could bolster the effectiveness of bargaining tools such as strikes and go-slows. This hypothesis is strengthened by the positive relationship between union membership and union density. Union members might also be first in line to promotions, as unions and union representatives prefer to promote their own members. There are also additional channels in which union members are preferred for promotion: they might get in a position to meet management through union meetings, conflict resolution or other channels. In addition to this, union members might get access to lectures, re-education, courses etc. not available to non-members. There is also a possibility that establishments are able to capture rents on their workers in the absence of collective bargaining, and/or union density.

The role of collective agreements for explaining variation in individual wages remains unidentified. In three of the individual fixed effects model, a wage premium from collective agreements in the range of 0,5 % to 2 % are reported. However, applying establishment fixed effects yield a large negative wage effect from collective bargaining. There is a possibility that changing bargaining scheme within an establishment comes at a cost. Either changing bargaining scheme is costly in the short run, or the large negative effects of changing wage setting for the right tail of the within-establishment wage distribution far outweighs possible positive effects for the median worker. The frequent change of signs[15] for the collective bargaining estimates from both OLS and UQR regression leaves no more than speculation on the role of collective bargaining for both wage levels and inequality.

Results following RIF-OLS indicate very heterogeneous effects of both union membership and union density across the distribution of wages. Being treated to union membership yields large wage premiums for the left tail of the distribution and negative wage effects are reported for 72th percentile and above. This points to the possibly large inequality-reducing effect of union membership and establishment level union density, while the inequality reducing effects of collective bargaining remains unidentified. There is also support for the hypothesis that union membership, union density and collective bargaining is of less importance for explaining variation in individual wages in the right tail of the wage distribution.

Having investigated the union non-union differential by way of RIF-OB decomposition, wage inequality is significantly lower for union members as compared to non-members. Differences in characteristics between these two groups can account for a large share of the between-group differential when individual wages are high. At the median and below, differences in the

[15] Although the magnitude of these estimates are always small.

compositon of covariates are of less importance. There is strong evidence that differences in returns to characteristics can account for a significant share of the difference in inequality between union members and non-members. The results of the decomposition also indicate that unions compress the wage structure in the left tail of the wage distribution. For the right tail of the wage distribution, unions has small effects on wage dispersion.

As estimates on the wage effects from unionization suffer from bias and might not appropriately correct for selection issues, researchers interested in these effects would be wise to use instrument variables as suggested by Barth et. al. (2020) in the future.

The large positive wage premiums present in this thesis suggest that identification of the individual wage premium from union membership is worth a revisit by researchers far more experienced than myself. Unconditional quantile regression shows that the wage effects from unionization are drastically different across the distribution of wages. The large distributional effects are not captured by mean regression, therefore the quantile regression framwork also offer an interesting approach for future research on the Norwegian labour market.

For researchers interested in the relationship between union membership and wage inequality, decomposing the contribution of union membership to inequality over time could be an area of interest. The contribution of union membership to wage inequality over time was not presented in this thesis as the panel dimension is not suited for such an analysis[16].

[16] A cross-sectional approach would be better suited. The main interest in this thesis was to find factors that contributed to the union non-union wage differentials.

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