UiT THE ARCTIC UNIVERSITY OF NORWAY

School of Business and Economics

Unemployment rate, Labor-Market and Sickness-absence

How the unemployment affects sickness-absence in Troms County. An Empirical analysis

Espen Berthung

Master's thesis in Economics, September 2018

Abstract

This thesis investigates how the unemployment rate affect the sickness-absence in Troms county. For doing so, we set up a model that investigates the *causal* relationship between labor market tightness and workers absence behavior and the cyclical selecting of employees with bad health during different states of the business cycle. We take advantage of over 230,000 recorded sickness-absences and measures their transition from sickness back to work. Since job-security laws differs in labor-market, we choose to focus on the respected government-, municipality- and private sectors. The results indicate significant differences between the sectors, especially between private and public sector. Key findings are that: (1) The average health condition for public workers fluctuates more with the business cycle compared to private workers. (2) Lower economic activity during a spell sequence increases the risk of losing the job, however, this risk is significantly less shared in the public sector. (3) The propensity for claiming sick increases during lower economic activity. However, the "threshold" for claiming sick is significantly lower for municipality and government workers compared to private workers. Conclusion; The high level of sickness-absence in Troms county can to some degreed be explained by the large share of public workplaces.

Key words: Business cycle condition, labor-market tightness, economic downturns, survival analysis

Table of content

List of Figures

List of Tables

Introduction

The purpose of this paper is to investigate the relationship between the unemployment and sickness-absence in Troms county. More precisely, how the unemployment rate affect sickness-absence duration, with the focus on different sectors. Previous findings in this field show that there tend to be a negative relationship between these two measurements, see Leigh (1985). These findings indicate that the unemployment rate creates a procyclical sickness-absence. In simple terms, the presence of procyclical absenteeism implies when the economy is going well, and unemployment rate is low, workers exhibit longer and more frequent absence spells. The same principles apply vice versa. Why is this interesting? From an economic perspective, "the tide lifts all boats" is an argument widely used for economic growth. However, there seem to be negative consequences with respect to sickness absence that follows economic upturns.

The widespread of sickness absence in Norway is substantial. According to Det Kongelige Finansdepartementet (2017) the sick-pay scheme exceeded 41 billion NOK in 2017. Loss of efficiency, productivity and health care expenditures are costly for companies and governments. Among the monetary costs and financial expenditures stands the negative consequences for individuals. Goodman and Atkin (1984) summarizes the negative consequences for individuals as follows; lost payments, increased accidents, less disciplined actions (e.g. not performing work tasks) and changed job-perceptions. Hence, increased knowledge for governments, policymakers and companies may increase efficiency and human health with respect to sickness absence.

Industrial psychologists and business management researchers have been devoting considerable attention to absenteeism. Yet, it is only relatively recently that the topic has received the same amount of scholarly attention from economists. In so doing the inverse relationship between unemployment rates and sickness-absence was observed (see e.g. (Leigh, 1985); (Audas & Goddard, 2001);(Askildsen, Bratberg, & Nilsen, 2005);(Arai & Thoursie, 2005) Previous papers show that job-security and financial incentives, e.g. sickness-payment, have an impact on sickness-absence behavior. (see , (Buzzard & Shaw, 1952); ((Røed & Zhang, 2003); (T. A. Barmby, Orme, & Treble, 1991);(Olsson, 2009)). But these two factors alone can't explain the complexity of sickness-absence.

The existing literature differentiate between two main channels that may contribute to procyclical absenteeism. The first is the ***selection effect*.** This concept assumes that the available workforce has individuals that are differently exposed to sickness. Those who are more exposed to sickness are therefore more absent. When the business cycle is increasing, the economy needs more available workforce. That's is, the *selecting effect* arises if employment behavior of people with bad health is especially cyclical. This demand for workforce pulls the more sickness-prone workers inside the labor-market and creates the procyclical pattern we observe. Literature define them as *marginal workers*, see Arai and Thoursie (2005). Further, in economic downturns the more sickness-prone workers are the first to be selected out. E.g. the marginal worker, see Leigh (1985).

The second channel concerns the ***causal effects*** that influence *worker's absence behavior*. The literature summarizes three sub-channels for how different labor-market tightness may causally affect the *absence behavior of workers*. Thereby create this procyclical pattern[1]. First, there is an *incentive effect*. When the macroeconomic conditions are good – that is, jobs are safe and new jobs are easily found – the potential cost of being caught shirking is low. Further, when the unemployment rate is dropping, workers become less fearful of losing their jobs and more inclined to be absent, e.g. lowering threshold for claiming sick. (see(Leigh, 1985); (T. Barmby, Sessions, & Treble, 1994)).

Second, there is a *stress effect*. Tighter labor-market conditions impact the health of workers directly, see (Ruhm, 2003). A higher demand for product and services gives a more stressful workplace, resulting in more stress and accidents for workers.

And third is the *monitoring effect*. A decreased unemployment rate yields a less available workforce, and thus it is more difficult obtaining replacements for absent workers. In good times, firms increase monitoring and other health promoting activities for preventing absenteeism.

The two main channels are not mutually exclusive explanations, but economic theory cannot tell which of the effects that prevails or dominates in a given region at a given point in time. This is an empirical question.

The argument for focusing on the different sectors bases on the high share of government and municipality workplaces in Troms and different job-security laws towards them. There exist two main laws that govern the Norwegian labor-market. E.g. "Statsansatteloven" and the Working Environment Act. Where the former yields stronger job-security for its employed in the government sector.

[1] Absence assumptions in this field of economics bases from the first paper that investigates this relationship. Different papers describe the assumptions differently, while they have the same origin. For more info, see the introduction from (Leigh, 1985)

Further, theory from literature regarding job-security can be summarized as follows; Employment protection can affect sickness rate in different ways. First is the *behavior effect*, where weaker job-security results in increasing risk of redundancies. The employees have an incentive for continue working instead of reporting sick and risk being laid off. This is quite similar to the *incentive effect,* while the *behavior effect* could mitigate or reinforce the *incentive effect.* Whether the *behavior effect* reinforce or mitigate, depends on the state of business cycle. Second, sickness rate can be affected by a *compositional effect.* Weaker employment protection can lead to more redundancies of sickness prone workers. Thereby mitigate average sickness at the workplace, Olsson (2009).
Adding the aspect of job-security are of interest since it could provide a clearer explanation for the high level of sickness-absence

Previous findings from Johansson and Palme (2002) with Swedish data from 1990-1991, find that the increased cost of being absent caused the decreased absence rate, rather than a higher unemployment rate. More recently, similar result have been reported from Arai and Thoursie (2005) and Askildsen et al. (2005) . Their results indicate that procyclical variations are a response of a behavior change from the stable workers. However, Nordberg and Røed (2009) results indicate that *workers absence behavior* is affected by the *incentive effect* and *stress effect*. Further, they find evidence of the *selecting effect*, that health status among workers are negatively related to the business cycle.

This paper complements existing literature and research by studying job-security and the procyclical effects with improved data. The improvements in the data are the knowledge of where the transition goes for individuals after ending a spell sequence. All individuals are observed at work the following month. Further, we have the inclusion of short time spells. Previous papers like Nordberg and Røed (2009) and Askildsen, Bratberg and Nilsen (2005) uses absence spells only exceeding two weeks. They are defined as long-term spells, and in the present dataset they only cover 42% of all absence spell. The last 58% are short-term spells. This analysis considers all spells from 1 to 365 days. The inclusion of short-term will yield more precise measurements and reflect the absent workers better.
For analyzing, we make us of a parametric Weibull model. This model measures time to events, or in this case, from sickness to work. Previous papers used a non-parametric model that yields larger standard error, and therefore less precise estimates.

Since workers diseases are unknown[2], we are conditioning the unemployment rate at the time of entry into an absence spell. This is for capturing unobserved cyclical heterogeneity among workers entering the spells, e.g. the *selecting effect.* Further, we use labor-market developments during absence spells for capturing the *causal effects* that could influence absence behavior of workers. This is further discussed in the section of identification strategy and estimation.

This analysis shows that sickness-absences in Troms county have a cyclical respondence to labor-markets changes. A tighter labor-market, equally to economic upturns yields longer absence-duration. Different *causal effects* created by changes in the labor-market are observed, and we find significant differences between the respected sectors.

The organization of the reminder is structured as follows. Section 2 presents some empirical literature. Section 3 describes the data used in this analysis. Section 4 presents the method, Section 5 presents the identification strategy and estimation process. Section 6 presents the results and interpretation, while section 7 concludes

Empirical Literature

Absenteeism alone have been investigated numerous times with the Neoclassical approach for explaining it. It bases on individuals labor-supply and firms labor-demand decisions when maximizing their utility. See Allen (1981), T. Barmby, Sessions, and Treble (1994) and (T. Barmby, Orme, & Treble, 1995; Coles & Treble, 1993)

The first paper investigating the relationship unemployment rate and absenteeism was done by Leigh (1985). He used individual data from the Panel Study of Income Dynamics together with industry unemployment rates and found support for *incentive* and *selecting* mechanisms in the United States. Ruhm (2003) used in his paper microdata rom the National Health Interview Surveys for the 1972-1981 period. Ruhms' major findings are the existence of a counter-cyclical variation in physical health, and the most exposed are individuals in prime-working age, employed persons and males. More recently, Arai and Thoursie (2005) tested the procyclical pattern in Sweden. They analyzed aggregate industry-region panel data from 1989 to 1999 in which marginal workers were represented with temporary contracts and stabile workers with permanent contracts. When investigating the correlation between sick rates and the share of temporary contracts they found that temporary workers had lower sick-

[2]. Due to time limitations the approval process for diagnosis was above 6 months. Since this is a master thesis we did not consider this option.

rates – that is, a negative correlation – implying that the incentive effect dominates. However, using temporary contracts as a proxy for the *selecting effect* have several shortcomings. First, they don't differentiate on who enters a short-term contract. The heterogeneity is potentially huge. Second, "short-term" is not defined in terms of length, and people with poor health could easily push themselves through a month of work for the economic incentive[3]. Meanwhile, Askildsen et al. (2005) try to distinguish between the two channels in Norway. Using a panel of Norwegian register data on long-term sickness absences. Their results suggest that procyclical variations in sickness absence is caused by stable workers and not by marginal workers. In a related paper, Nordberg & Røed (2009) use a comprehensive multivariate mixed proportional hazard model to examine the transition from absence to work resumption and absence to rehabilitation. Their results suggest that both effects are present in their data. However, a limitation with both these studies is that they only observe absences longer than two weeks, therefore, do not consider short-term absences. Moreover, Nordberg & Røed (2009) do not report which effect that have the largest impact.

Regarding *job-security*, in the Italian paper from Ichino and Riphahn (2005), they use weekly observations for 858 individuals in a Italian bank. The individuals are eligible for job-protection after 12 weeks of work. They measure the probability of being absent and find that the probabilities increased substantively after 12 weeks. In the Swedish paper written by Olsson (2009) he investigated how decreased job-security impacted sickness absence. Olsson exploited the exemption in the Swedish Employment Act, that gave employers the possibility to exempt two workers from the seniority rule during layoffs. He finds that the exemption decreased sickness absence by more than 13%. He further state that this is due to an absence behavior effect, that is equal to *causal effects.*

This paper is closely related to Nordberg and Røed (2009) and makes an effort in complementing and help further research, by improved data, within this field of economics. A more detailed description follows the Data and Method section.

[3] Olsson used the Swedish Employment Security Act from 2001 for demonstrating the impact job-security have on absence behavior. "*especially for shorter spells among male workers that hold permanent contracts*" (Olsson, 2009)

The Data

We use data collected by the Norwegian Labor and Welfare Directorate (henceforth, Arbeids og Velferdsdirektoratet) which contains all absence spells in Troms county, lasting from 1 to 365 days, between January 2010 and December 2017. The argument for restricting length of absences to 365 days is the financial arrangements. Norwegian workers who are eligible for sick-pay, have the right to 100% financial cover the first year of sickness absence. After one year of sick-pay, individuals are transferred to work assessment allowance that covers 66% of previous income. Hence, a potential financial motive is reduced after one year. The sample consist of 230428 recorded absence spells in and all spells required a medical certificate. Further, individuals have their unique ID number and are followed their whole sickness period before returning to work. This feature ensures that all individuals are observed in work the following month after ending a spell sequence. This feature is not present in the paper for Nordberg and Røed. Instead they infer that work resumption has occurred when sickness benefits are exhausted[4]. Some of absence-spells starts before the last one ended. These overlapping absences are merged into one spell. Absence spells lasting longer than 365 days have been removed from the sample. This ensures that right-censoring is not present in the analysis.

The dependent variable is absence length where units are in days, stretching from 1 to 365 days. The explanatory variables are used because they are believed to influence sickness absence. They can be divided into three types of explanatory variables, the demographic variables, the geographical variables and labor-market variables. The demographic variables are profession, sex, sector, age and level of sickness leave, also known as graded sick-leave. The main purpose is investigating how the labor-market conditions affect the sickness absence, However, the demographic factors are quite basic and few, and with 230428 events, overfitting is not an issue[5]. The geographical variable is the restriction to Troms county. The labor-market variables are the unemployment rate and two *changes in unemployment rate* variables, that are discussed later. The remainder of this section gives a deeper explanation regarding the explanatory variables.

[4] Nordberg and Røed are aware of this feature. For further information, view footnote 5 at page 209. Nordberg, M. and K. Røed (2009). "Economic Incentives, Business Cycles, and Long-Term Sickness Absence." Industrial Relations: A Journal of Economy and Society **48**(2): 203-230.

[5] One "rule of thumb" for avoiding overfitting is a ratio of 1/10 with respect to covariate and events.

Demographic Variables
Individuals in the data are from 20 to 59 years old. Rather than being a continuous variable, age is represented with eight dummy variables. Each dummy variable has a categorical interval of five years. There exists a rising absent-trend with respect to age for both sexes. Workers above 59 years old is therefore excluded from the sample. The argument is that older individuals are more exposed to sickness and could give biased results.
There are nine different profession groups. Each profession is represented with their own dummy variable, see table 1 for more info.

Sex is presented as a dummy variable. Difference between the sexes are not of interest, since previous papers have shown that women are more absent than men. However, including the sex variable are important because it can explain much of the variation that are observed.

Graded sick-leave and full-time sick-leave is treated as two dummy variables. Graded sick-leave is a tool for keeping workers connected to the workplace and ensure a smoother transition from being absent to be back at work. Its purpose is reducing individual's sickness absence. The definition for Graded sick leave in this analysis is being part time sick between 20% and 99% of your working capability. The specific limit of 20% are set since individuals under 20% are not eligible for sick payments. By including this variable in the analysis, we can control that these individuals have in fact decreased their sickness duration. No further emphasizing will be done with this factor. There exist three different sectors, they are labeled private-, municipality- and government sector. Each are represented with their own dummy variable.

Geographical Variable and Restriction
The geographical factor that restricts this analysis to Troms county are interesting for two reasons. First is the procyclical absenteeism that is observed. Troms county have a relative low unemployment rate and a high degree of sickness absence compared to other counties in Norway. According to NAV (20.12.2017) the registered sick leaves for the 3. quarter of 2017 in Troms county was 6%. While the average for Norway the same period was 5.4%. In January 2018 Troms county had the lowest unemployment rate in Norway with 1.7%. The average unemployment rate at the same time for Norway was 2.6%, NAV (29.06.2018). Second is the high degree of public workplaces, that is government sector and private sector. The public sector in Troms county is relatively large compared to private sector. In this dataset public sickness absences represent 51% of all observed spells. Previous papers have stated that job-security impact absences. As mentioned, there exists two laws in Norway that govern the labor markets, that is, "Statsansatteloven" and the Working Environment Act,

where the former yields higher job-security. Since the government sector follows "Statsansatteloven", where municipality together with private-sector follows "The Working Environment Act" we expect different absence behavior among the workers. View table 2 for a quick summary of absence duration for the three sectors. The table show that municipality have the longest median sickness length. While private sector has the longest average and the government sector has the shortest average. The reason for reporting the average and median is the skewed distribution of duration. Numbers are in days. Hence, analyzing if job-security impacts the *causal* and *selecting-effects*, are of interest.

As stated, male and female differences are not emphasized. However, notice that the majority in the samples are women. This majority of women could potentially influence the results in sectors where men are out-numbered. For further information, view table 2 at the end of the section.

Labor-Market Variables

The labor-market variables are represented in the analysis with the unemployment rate and two difference variables that are discussed later. We use the unique number of unemployed individuals in Troms county. For identifying the state of the business cycle the unemployment rate is used as a proxy. A *high business cycle* state is associated with a *tight-labor market*, since this yields less available jobs. Further, the level of unemployment and the change in unemployment is used for identifying unobserved health status among workers entering the spell, this is later discussed in the identification section. The unemployment rate is collected from SSB and are seasonal adjusted with the X-12 ARIMA method for avoiding the effect of seasonality. The period of observation is characterized by a down-trending unemployment rate, that is equal to a tighter labor market and a higher business cycle. By having one main trend in the level of unemployment could be a drawback. Individuals can adapt to higher demands, and more stressful times that follows a tighter labor-market. This could impact the *causal effect* and *selecting effect*, see **Feil! Fant ikke referansekilden.**.

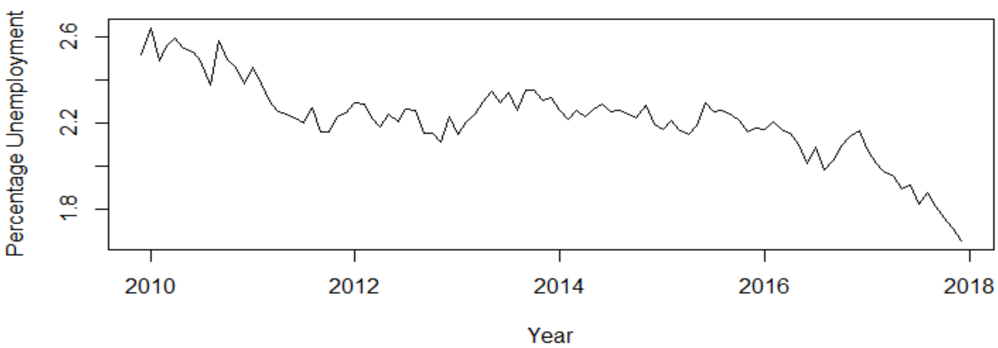

Figure 1 Unemployment rate developments

Table 1
Descriptive Statistics

Number of absences and their percentage		
	Number of observed absences	Percentage of total data
All absences	230428	100
Men	90435	39.3
Women	139993	60.7
Age		
20-24	24530	10.6
25-29	29352	12.7
30-34	30072	13
35-39	30692	13.3
40-44	32981	14.3
45-49	31038	13.4
50-54	27165	11.8
55-59	24598	10.7
Professions		
Military	4346	30.3
Administrative leaders and Politicians	10715	1.8
Academics	43403	4.6
College professions	38887	18.8
Office administration	13623	16.8
Sales and Service proffesions	70004	5.9
Farmers and Fishermans	1640	0.7
Craft Mans	18358	7.9
Machine, transportation and Process	14314	6.2
Cleaner and assistants	15138	6.5
Sectors		
Government	44442	19.3
Municipality	73732	32.0
Private	112254	48.7
Graded sick leave	52505	22.7
Full time	177932	77.3

Table 2
Characteristics of sectors

	Number of absence spells		Numbers in days		
	Men	Women	Median	Average	Total
Sectors					
Government	12724	31718	11	33.52	44442
Municipality	12572	61160	12	36.92	73732
Private	65139	47115	11	37.10	112254
Total Data	90435	139993	11	36.34	230428

Method

The Choice of Statistical Method

The argument for using "time to event" analysis relies on the data distribution and the ability of modeling worker-behavior as the macroeconomic environment changes. Since the data don't contain any form of censoring, a standard regression procedure could be used. However, this may be an insufficient solution since (1) the sickness distribution is highly positive skewed with a long tail the right, se figure 2 in appendix; (2) the probability of surviving past a point in time is of more interest than the event itself; and (3) the hazard function in survival analysis can give more information of failures than normal regression. Further, we are interested in what affects the time until an event occurs. In this case, how labor-market conditions affect the length of absenteeism. Based on this, we turn to the branch of survival analysis.

Surival Analysis

Survival analysis is the study of time to event and the factors that influences them. Survival analysis is known as event history analysis in social science and reliability analysis in engineering. A survival endpoint can refer to both a positive and negative event. Examples of studies with survival outcomes are clinical trials, animal experiments and engineering reliance where they focus on time until death, progression, destruction or transition.

Parametric versus Non-Parametric
At first, a semi-parametric cox proportional hazard model was created, similar to the multivariate mixed proportional hazard model Nordberg and Røed (2009) used. For testing the proportionality assumption, a Schoenfeld residual test was used. The low p-values indicated violation of the proportional hazard assumption for the covariates. Therefore, a parametric approach is preferred. According to Bradburn, Clark, Love, and Altman (2003) a parametric approaches is more efficient when used properly since they give smaller standard errors[6]. Further, the first objective is specifying a distribution that fits the variation in sickness duration. Several distributions were tested to see which gave the best fit. For comparing the distributions, the log likelihood and Akaike criterion was used. The result is reported in table 3.

Table 3 Log-likelihood and AIC results

	Distributions				
	Exponential	Weibull	Gauss	Logistic	Extreme
Log likelihood	-1040258	-1008882	-1277451	-1220510	-1381274
AIC	2080566	2017815	2554954	2441075	2762599

Using the highest log likelihood- and lowest AIC value, the Weibull distribution is selected for further computations. The last diagnostic check if survival times do follow a Weibull distribution, is known as log(-log(survival) plot. According to Moore (2016) this is mathematically defined as $y_i = \log[-\log(\hat{S}(t_i)]$. Where y_i is plotted against log (t_i), further, a straight line is fitted through the points. If the points fall along the straight line its' concluded that survival times could be modeled using a Weibull distribution. The resulting plot is shown in figure 3 in appendix. Except from one outlier and a few converging dots, the survival time show a close agreement with a Weibull distribution. According to Moore (2016) An alternative to the proportional hazard model is the Weibull model that also have the features of an Accelerated failure time model. Conclusion; the Weibull distribution was selected for further computations.

[6]The difference between non-parametric and parametric models is assuming that the hazard ratio follows a statistical distribution when a parametric proportional hazard model is fitted to the data, while the cox model does not follow this constraint. Except from this, the two methods are equal, with same interpretation of the hazard ratio. (Clark, Bradburn, Love, & Altman, 2003)

The Weibull Model

In survival analysis, the cumulative distribution function is given by $F(t) = pr(T \leq t), 0 < t < \infty$, and is right continuous. Further, the probability density function is $f(t) = -\frac{-d}{dt}S(t)$ or $f(t) = \frac{d}{dt}F(t)$ and is the rate of change of CDF. The hazard function relates to the survival function and PDF by the formula $h(t) = \frac{f(t)}{S(t)}$, and Moore (2016) defines a survival distribution mathematically as;

$$f(t) = S(t) * h(t) \quad (1)$$

Where the S(t) is the survival function and h(t) is the hazard function. The Weibull distribution have Survival function $S(t) = e^{-\lambda t^{\alpha}}$ and Hazard function $h(t) = \alpha\lambda t^{\alpha-1}$, with the parameters shape (α) and scale (λ). The relationship between S(t) and h(t) is clearly defined by the calculus formula $h(t) = \frac{-d}{dt}[\log S(t)]$. If either S(t) or h(t) is known, the other is automatically determined, see Clark et al. (2003) . Therefore, with this is mind, the hazard rate is specified as

$$h(t,z) = \lim_{\delta t \to 0} \frac{P(t \leq T \leq t + \delta t | T \geq t, z)}{\delta t} \quad (2)$$

Where t is spell duration, T is time of events, z is a vector of covariates. According to this formula, the hazard depends now on observed time-varying and time-invariant characteristics.

In the vector z, some of the included covariates are age, profession, county and sex. The labor-market conditions are present by the unemployment rate.

According to Bradburn et al. (2003) when survival times follows a Weibull distribution it can be shown that an accelerated failure time model can be used for modeling survival times. According to Carroll (2003) Accelerated Failure-Time models examine survival time through a log-linear model. This ensures that the treatment effects are expressed in terms of a relative increase or decrease in survival time. For simplicity, the distribution of time to event of, T, as a function of a single covariate is given by

$$\log(T) = \beta_0 + \beta_z + \sigma\epsilon \quad (3)$$

That is the basic structure of a Weibull regression model, where σ is shape, and ϵ have an extreme value distribution. This is also known as an Accelerated Failure Time model, since the covariates effect on time scale is multiplicative, they therefore accelerate survival times Moore (2016). One property of the AFT model, if the covariate is effective, the AFT coefficient will be positive. This means that the covariate gives longer survival time. If the covariate is not effective it decreases survival time and the AFT coefficient will be negative. In terms of measuring absence duration, our view of the coefficient will be of the opposite site. A negative coefficient yields shorter absence spell and therefore decreases absence duration. That is a sign of improved health among workers. For measuring the magnitude of accelerated failure time constants, they need to be transformed to acceleration factors. This is done by taking the exponential of each covariate. That is e^{β_n}, where β represents the coefficient. This acceleration factors are either larger or smaller than 1. A factor larger than one increases failure time, and a factor less than one decreases failure time. Or similar, a factor larger than one increases absence duration where a factor smaller than 1 decreases absence duration. For viewing the magnitude in days, these acceleration factors need to be multiplied with either the median or mean survival time of the sample.

Identification Strategy and Estimation

A problematic aspect in survival analysis is the presence of unobserved heterogeneity among individuals. The same applies in this analysis, especially since information regarding diagnoses are unknown[7]. Shorter absences are associated with less serious diseases and longer absences with more serious diseases, for more information view Sundell (2018).
The purpose of this paper is to investigate how the unemployment affect sickness-absence duration. To do this we need to separate the potential *causal effect* from the observationally similar *selecting effect*.

As stated, the *selecting effect* arises if employment behavior of people with poor health is especially cyclical. In this thesis, I choose the same strategy as Nordberg and Røed (2009).That is, separating the *causal effects* by conditioning on labor market conditions at the time workers enters a sickness spell. We therefore condition on two labor market variables, the level of unemployment and the change in unemployment at the time of entry into sickness

[7] Due to long processing time, diagnosis was not considered for this master thesis

absence. Like in Nordberg and Røed (2009) the coefficients of these two variables are thus meant to measure the cyclical variation in unobserved health condition among those who enter sickness absence. That is, capturing the seriousness of diseases among workers who enters a spell sequence. Further, I call these two variables as entry variables. Labor-market developments during the absence spell are included to capture the *causal effects.*

The *causal effects* are difficult to measure. The optimal solution would be having a more direct proxy when measuring. For instance, how much money have been invested in health promoting activities the least years. If the *incentive-*, *stress- and monitoring effects* are not strongly present, it could be a response of mitigation from each-other. However, due to lack of data we must rely on the assumption that the change in unemployment during absence used as a proxy for causalities and cyclical health is a good enough indicator.

As mentioned, different job-security laws towards the labor-market could influence sickness-absence. This was the argument for investigating the sectors.

In Norway, it is well known that different sectors have different magnitudes of sickness duration. We are therefore interested in investigating if there exist different absence behavior among workers, and employment behavior of people with poor health within the different sectors.

For investigating how the state of business cycle affect the sickness-absence duration within different sectors, we make interaction terms with the dummy variables and labor-market variables. Each sector is represented with its own dummy variable and then interacted with the labor-market variables. This approach allows workers within the sectors to react differently with the changes in the labor-market.

The coefficients show how the sectors respond to changes in the labor-market.

Since the government sector follows «Statsansatteloven» that provides stronger job-security we expect longer absences for this sector. That is, the *incentive effect* is mitigated since workers are less afraid of losing their jobs. Further, municipality sector and government sector consist of non-profit organizations. For instance, hospitals, nursing homes, police department and the State Highways Authority. These jobs are, in theory, risk free for bankruptcy. Workers are therefore less afraid that their absence could interrupt the survival of the workplace. This could mitigate the *incentive effect* for going back to work. Private sector consists of profit organizations and have weaker job-security, we therefore expect the *incentive effect* to be dominating in this sector.

As previously mentioned, this sample contains both short-term and long-term spells. Previous papers from Norway did not have this opportunity. Papers as Nordberg and Røed

(2009) and Askildsen et al. (2005) uses spells lasting from 14 to 365 days. Only viewing long-term absences may be a drawback, and both papers argues that short-term spells may be more financially motivated. However, short-term absences may also be viewed as more acceptable among employers when workers consider a sickness absence[8]. Previous papers only using long-term absences thus faced a more biased result regarding heterogeneity. Individuals that have a less serious disease tends to return early to work, leaving behind individuals with more serious diseases. By including the short-term absence spell, we get a more complete picture of absence duration.

From 2010 to 2017 there were no institutional changes in the sickness insurance system that could biased the results. The Working Environment Act govern the Norwegian labor market for private and the municipality sector. Its purpose is securing a work environment that gives a healthy and meaningful working situation, see chapter 1, (sosialdepartementet, LOV-2005-06-17-62). This act was realized in 2005 and have been updated several times. There have been no major changes in the act that could potential affect the *causal effects*. However, year 2001 was the beginning for "IA-avtalen", that is "Inkluderende Arbeidsliv Avtalen" or "Including Working Agreement" Regjering (25.01.2017). The agreement was updated 4.march 2014 and aims at increasing follow-up actions of sick individuals and increasing their activity level, one tool is the usage of graded sick leave, (Regjering, 25.01.2017). This could potentially affect the *causal effects* for sickness absence behavior. Graded sick-leave have a rising trend in the data, this could potentially interrupt the results.

The estimation is completed in two steps. First, we do a regression model with no interaction terms. This is a simple model where we investigate how the business cycle conditions impact the general sickness-absence. Next step is creating a more realistic model with interaction terms between the labor-market variables and the respected sectors. This approach allows workers absence-duration within the sectors to react differently with the changes in the labor-market.

The results are given in the following section.

[8] An analysis of sickness absence across income quantiles from Germany show that rich people constantly take a moderate number of sick days. For more info see page 22 the Conclusion section fomr Schön (2015)

Results

Before proceeding to the results, we do a quick brief for how to interpret and expect the results. Be aware that one unit increase in the labor-market variables is equal to a worsening business cycle.

Regarding the *causal effect* (Leigh, 1985), we look at the coefficients from the change in unemployment during absence spells. Recall that the *stress effect Ruhm (2003)* would lead to shorter absence spell when unemployment rises. The argument is that lower economic activity during absence spells results in less stressed workers. The presence of an *incentive effect* would also yield shorter absence. The increase in unemployment during absence would shorten the spell. The argument relies on the foundation of absence theory. If lower economic activity increases the probability of being laid-off, then you have an incentive for going back to work. Since you fear the risk of being laid-off. Lower economic activity during absence should therefore decrease the spell.

According to theory stated in the introduction, *monitoring effect (Audas & Goddard, 2001)*with other health promoting activities, increases during good times for avoiding absence. In contrast, during bad times *monitoring* are decreasing, one argument is that employers will avoid the increased costs from *monitoring* during bad times. We therefore expect the *monitoring effect* to be less dominating in this situation.

The *selection effect* is measured with the two entry variables. The coefficients for the two entry variables gives indications for the cyclical variation in unobserved health among entrants. From theory, we expect the threshold for claiming sick during bad times to increase. That is, we expect the coefficient for the change in unemployment before entry to sick-leave to be positive, this indicates that more serious diseases enter the spells.

One unit increase in the level of unemployment rate is equal to a bad, but stable, business cycle condition. We therefore expect the coefficient to be negative. Meaning that average health among workers are inversely related to the level of unemployment rate.

With respect to workers within different sectors we expect different absence behavior. The argument is that higher job-security could reveal a lower *incentive effect* for going back to work when sick.

The Results are presented in the following table.

Table 4 Regression Results

Variables	No interactions	Interactions
Men	0.007	0.007
	(0.006)	(0.006)
Reference group age (40-44 years)		
20-24	-0.261***	-0.260***
	(0.011)	(0.011)
25-2 9	-0.107***	-0.107***
	(0.010)	(0.010)
30-34	-0.061***	-0.060***
	(0.010)	(0.010)
35-39	-0.048***	-0.047***
	(0.010)	(0.010)
45-49	0.071***	0.071***
	(0.010)	(0.010)
50-54	0.128***	0.128***
	(0.010)	(0.010)
55-59	0.227***	0.226***
	(0.011)	(0.011)
Part time sick leave	1.548***	1.548***
	(0.006)	(0.006)
Reference group(Private)		
Government	-0.214***	0.129
	(0.008)	(0.097)
Municipality	-0.128***	0.118
	(0.007)	(0.084)
Reference group (Private)		
Change in unemployment rate during absence	-0.081***	-0.087***
	(0.001)	(0.001)
Government*Change in unemployment during absence		0.011***
		(0.002)
Municipality*Change in unemployment during absence		0.013***
		(0.002)
Change in unemployment rate before entry	0.058***	0.061***
	(0.001)	(0.002)
Government*Change in unemployment before entry		-0.009***
		(0.004)
Municipality*Change in unemployment before entry		-0.006**
		(0.003)
The level of unemployment rate	-0.414***	-0.348***
	(0.027)	(0.032)
Municipality*The level of unemployment rate		-0.110***
		(0.038)
Government*The level of unemployment rate		-0.155***
		(0.044)
Constant	150.209***	149.836***
	(4.039)	(4.041)
Observations	230,428	230,428
Log likelihood	-976,334.700	-976,301.700
Chi2	84,686.030*** (df=24)	84,751.940*** (df=30)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses. Both *models include* group fixed effects

The setup of this table is for making it simpler to differentiate between the entry variables and labor-market developments during absence in the more realistic model.

Recall that the coefficients are accelerated failure time constant, AFT. A negative AFT coefficient indicates a higher hazard rate, this decreases the length of survival, that is equivalent to decreasing the absence-spell. The standard errors are extremely low. This show that we are not worried for statistical uncertainty.

We start out by viewing the simple model where we look at how the labor-market variables affect sickness absence.

We begin by viewing how the *causal effects* unfold during sickness absence.

The change in unemployment during absence is negative (-0.081) and highly significant. This indicates that lower economic activity during absence spells tend to shorten the spells. By theory this indicates that the *incentive effect* dominates. That is, lower economic activity during absence spells gives the worker an incentive for going back to work. The worker is controlled by the fear of losing the job.

Now looking at the entry variables for capturing the *selection effect.* First variable is the change in unemployment at entry, the coefficient is positive (0.058) and significant. This indicates that when unemployment increases, less healthy workers enter sickness absence. Further, we interpret this as when the economic activity decreases, workers increase their "threshold" for claiming sick, resulting in less healthy entrants.

Second, we have the level of unemployment at entry. This coefficient is negative (-0.414) and significant and by far the greatest in magnitude among the labor-market variables. This negative coefficient indicates that the unemployment decreases absence spells. Indicating that the average health status among entrants improves when the business cycle decreases. This suggest that the *selection effect* dominates.

When we look at the indicator variables for the different sectors, we see that the coefficient for government sector is negative (-0.214) and significant. For municipality sector the coefficient is negative (-0.128) and significant. indicating that workers in the government- and municipality sector has shorter absence spells, and that the average health improves more compared to workers in the private sector. These sectors are significantly different from the private sector[9].

Now moving over to the more realistic model where we allow workers within different sectors to interact with changes in the labor-market. We begin with the indicator variables for the sectors. The coefficient for government is positive (0.129), and for municipality it is positive (0.118.), However, they are no longer significant. We interpret this that the absence behavior between sectors is differing because sick absent workers react differently on labor-market conditions.

Further, we look at the coefficient for the interaction terms. beginning with change in unemployment during absence for viewing how the *causality effects* unfold. As expected, the coefficient for private workers, that is the reference group, is negative (-0.87) and significant. This coefficient decreases the absence spell, indicating that the *incentive effect* dominates. Further, we look at the interaction term during absence for government workers. The coefficient is positive (0.011) and significant. This variable shortens the absence spell, but by a less amount compared to private workers. We see the same applies for the Municipality variable. The coefficient is positive (0.013) and significant. indicating that this variable shortens the absence spell but by a less degree compared to the reference group. This indicates that the *incentive effect* is less dominating for government- and municipality workers compared to private workers. This suggest that the *behavior effect* from job-security mitigate the *incentive effect* for Municipality and Government workers. Lower economic activity during absence spell tends to shorten the spell. Indicating that the workers are afraid of losing their job, however, the results also indicates that municipality- and government workers don't share the same fear of losing their job, and results in longer sickness-absence

Lets' look at the entry variables that capture unobserved cyclical variation among entering workers. We begin with the private variable that are the reference group. The coefficient for change in unemployment is as expected, positive (0.061) and significant. This coefficient indicates that the variable increases the spell and that unobserved cyclical variation has worsened. By word, lower economic activity before entering a spell tend to lengthen the spell, yielding less healthy workers entering into sickness-absence. This indicates that the *threshold* for claiming sick have increased, since a worse health condition is justified for

[9] A new regression was conducted with municipality sector as reference group. This was for investigating if there was significant differences between municipality and government sector. The result showed that they were statistically different from each other, for more info view table 8.

being absent when labor-market worsens.
Moving on to the coefficient for the interaction term between government and change in unemployment rate before entry. This coefficient is negative (-0.009). This increases the absence spell but by a less amount compared to the private variable. We see similar results for the municipality variables with a negative coefficient of (-0.006). It indicates that unobserved cyclical variation among government and municipality entrants have worsened, but less worsened compared to private workers. That is, lower economic activity before entering decreases the spell, less healthy individuals are entering. When comparing the coefficients, this indicates that the *"threshold"* for claiming sick is lower for government and municipality workers compared to private workers.

Finally, we investigate how the level of unemployment interacts with the workers in different sectors. We start with private workers that is the reference group. This coefficient is negative (-0.348) and significant. Indicating that the average health status among entrants improves during higher levels of the unemployment rate. Next is the interaction with the government variable, this coefficient is negative (-0.155) and significant. This increases absence duration and by a greater amount compared to private workers. Viewing at the municipality interaction we see similar results. The coefficient is negative (-0.110) and significant. This coefficient indicates that absence duration for municipality workers increases by a greater amount than private workers. We interpret the results that average health status among workers entering the spell improves during higher levels of unemployment. The *selection effect* is therefore dominating. Further, these results indicate that average health condition among municipality workers and government workers fluctuates more with changes in labor-market tightness compared to private workers. This suggest that the *compositional effect* from job-security dominates. Weaker employment protection leads to more redundancies of sickness prone workers. This leaves behind more healthy workers with an average health that fluctuate less with the state of business cycle. At last we change the reference groups in the more realistic model, the coefficients indicate that there are statistical differences between private and municipality workers and between private and government workers, but not significance differences between government and municipality workers.

Interestingly, according to the results, men are not statistically different from women with the positive coefficient (0.007). Further, the coefficient for age are as expected. When workers get older they tend to have longer absence spells. Hence, age affect absenteeism negatively.

The coefficient for part time sick leave is positive (1.548) and significant. This indicates that individuals that are part time sick have longer absence spells than those who are full time sick. The part time sick leave has no decreasing effect of absence spells. This could be a paradox since graded sick leave as a tool was expected to decrease the absence spell.

Remember the formula for finding the acceleration factor. That is e^{β_i}, where β_i represents some accelerated failure time coefficient. For finding how one unit increase in unemployment rate affect the sickness absence in days, we do the following. $e^{-0.348}$ *median of the respected variable. The results are in table 5.

Table 5 How sectors react to changes in the unemployment rate

Sectors	Medium days	Average days	β_i	e^{β_i}	$e^{\beta_i} * median$	$e^{\beta_i} * average$
Private	11	37.10	-0.348	0.7060	7.7	26.19
Municipality	12	36.92	-0.458	0.6325	7.5	23.35
Government	11	33.52	-0.503	0.6047	6.6	20.26

From the table we see that one percent increase in the unemployment rate decreases the absence spells. For the private sector it decreases the median by 3.3 days. For municipality sector it decreases by 4.5 days, and for government sector it decreases the median with 4.4 days.

Concluding Remarks

In this thesis we have investigated the relationship between the unemployment and sickness absence in Troms county. The observation period lasted from 2010 to 2017 where we observed 230428 transitions from sickness-absence back to work. We have set up a Weibull survival model that investigates the *causal* relationship between labor market tightness and workers absence behavior and the cyclical *selecting* of employees with bad health during different states of the business cycle. Our key findings are from the more realistic model and are as follows:

The sickness-absence in Troms are to a high degree procyclical. The unemployment has a *causal* impact on workers sickness-behavior. Lower economic activity during absence spells, tend to shorten the spell. This result indicates the workers absence behavior are driven by the *incentive effect.* Workers have an *incentive* for going back to work in fear of losing the job. However, this fear is less shared by workers from the municipality- and government sector. Their behavior results in longer absences in their respected sector compared to private sector.

Unobserved cyclical variation entering an absence-spell, tend to worsen during lower economic activity before entering. Less healthy individuals enters the spell during lower economic activity. This indicate that “threshold” for claiming sick have increased. However, the “threshold” for claiming sick are significantly lower in the municipality and government sector.

At last the level of unemployment. This variable decreases the absence spell, indicating that during higher levels of unemployment, that is equally to economic downturns, improves the average health status among entering workers. The *Selecting effect* dominates and pushes less healthy individuals out of the labor-market. Further, we see that average health status among municipality and government workers fluctuates more with business cycle conditions compared to private workers. The *compositional effect* is dominating, indicating that sickness prone workers have been laid-off in the private sector. Leaving behind workers with an average health status that are less affected by business cycle fluctuations. These results support the findings from Nordberg and Røed (2009) with respect to cyclical employment behavior and causal effects. However, by adding the aspect of job-security we find significant differences between the sectors.

By combining the above findings, the results suggest that the high share of government and municipality workplaces can to some degree explain why sickness-absence is substantial in Troms county.

Acknowledgements

I wish to express my gratitude to my supervisor Professor Mikko Moilanen. I want to thank him for his patient, advices and support towards finishing this thesis. To my family, thanks for the support during my education and for believing in me. At last I wish to send a special thanks to my study friend Martin Iver. Thanks for all the help, discussions and arguments we have had over the last years.

References

Allen, S. G. (1981). An empirical model of work attendance. *The Review of Economics and Statistics*, 77-87.

Arai, M., & Thoursie, P. S. (2005). Incentives and selection in cyclical absenteeism. *Labour Economics, 12*(2), 269-280.

Askildsen, J. E., Bratberg, E., & Nilsen, Ø. A. (2005). Unemployment, labor force composition and sickness absence: a panel data study. *Health economics, 14*(11), 1087-1101.

Audas, R., & Goddard, J. (2001). Absenteeism, seasonality, and the business cycle. *Journal of Economics and Business, 53*(4), 405-419.

Barmby, T., Orme, C., & Treble, J. (1995). Worker absence histories: a panel data study. *Labour Economics, 2*(1), 53-65.

Barmby, T., Sessions, J., & Treble, J. (1994). Absenteeism, efficiency wages and shirking. *The Scandinavian Journal of Economics, 96*(4), 561-566.

Barmby, T. A., Orme, C. D., & Treble, J. G. (1991). Worker absenteeism: An analysis using microdata. *The Economic Journal, 101*(405), 214-229.

Bradburn, M. J., Clark, T. G., Love, S., & Altman, D. (2003). Survival analysis part II: multivariate data analysis–an introduction to concepts and methods. *British journal of cancer, 89*(3), 431.

Buzzard, R. B., & Shaw, W. J. (1952). An analysis of absence under a scheme of paid sick leave. *British journal of industrial medicine, 9*(4), 282.

Carroll, K. J. (2003). On the use and utility of the Weibull model in the analysis of survival data. *Controlled clinical trials, 24*(6), 682-701.

Clark, T., Bradburn, M., Love, S., & Altman, D. (2003). Survival analysis part I: basic concepts and first analyses. *British journal of cancer, 89*(2), 232.

Coles, M. G., & Treble, J. G. (1993). The price of worker reliability. *Economics Letters, 41*(2), 149-155.

Det Kongelige Finansdepartementet. (2017). *Statens inntekter og utgifter*. Retrieved from https://www.statsbudsjettet.no/Statsbudsjettet-2017/Satsinger/?pid=73005#hopp.

Goodman, P. S., & Atkin, R. S. (1984). Effects of absenteeism on individuals and organizations.

Ichino, A., & Riphahn, R. T. (2005). The effect of employment protection on worker effort: Absenteeism during and after probation. *Journal of the European Economic Association, 3*(1), 120-143.

Leigh, J. P. (1985). The effects of unemployment and the business cycle on absenteeism. *Journal of Economics and Business, 37*(2), 159-170.

Moore, D. F. (2016). *Applied survival analysis using R*: Springer.

NAV. (20.12.2017). Stabilt sykefravær i Troms [Press release]. Retrieved from https://www.nav.no/no/Lokalt/Troms/Pressemeldinger/stabilt-sykefrav%C3%A6r-i-troms--531491

NAV. (29.06.2018). Fortsatt lav ledighet i Troms [Press release]. Retrieved from https://www.nav.no/no/Lokalt/Troms/Pressemeldinger/fortsatt-lav-ledighet-i-troms

Nordberg, M., & Røed, K. (2009). Economic Incentives, Business Cycles, and Long-Term Sickness Absence. *Industrial Relations: A Journal of Economy and Society, 48*(2), 203-230.

Olsson, M. (2009). Employment protection and sickness absence. *Labour Economics, 16*(2), 208-214.

IA-avtalen 2014-2018, (25.01.2017).

Ruhm, C. J. (2003). Good times make you sick. *Journal of health economics, 22*(4), 637-658.

Røed, K., & Zhang, T. (2003). Does unemployment compensation affect unemployment duration? *The Economic Journal, 113*(484), 190-206.

Schön, M. (2015). Unemployment, sick leave and health.

sosialdepartementet, A.-o. (LOV-2005-06-17-62). *Work environment act, LOV-2017-06-16-51* Retrieved from https://lovdata.no/dokument/NLE/lov/2005-06-17-62.

Sundell, T. (2018). *Utviklingen i sykefraværet, 4. kvartal 2017*. Retrieved from ARBEIDS- OG VELFERDSDIREKTORATET/ STATISTIKKSEKSJONEN https://www.nav.no/539720/sykefrav%C3%A6rsstatistikk%287%29

Appendix

The following section contains lift and figures used during the analysis. For making it easier to read the thesis, all

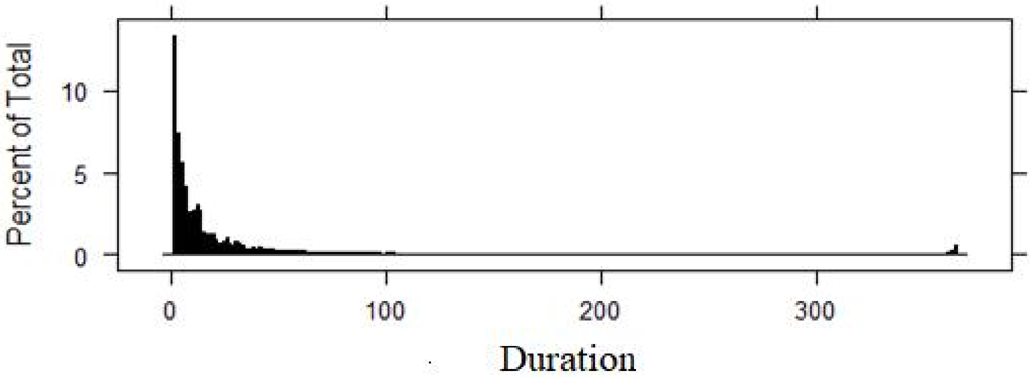

Figure 2 Sickness-absence distribution

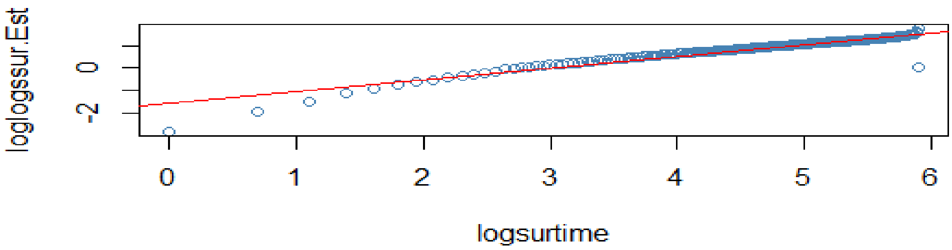

Figure 3 Log of survival times

Table 6 Working variable names

KjonnMenn	Male
Yrke 0	Military
Yrke 1	Administrative leaders and Politicians
Yrke 2	Academics
Ykre 3	College professions
Yrke 4	Office administration
Yrke 5	Sales and Service proffesions
Yrke 6	Farmers and Fishermans
Yrke 7	Craft Mans
Yrke 8	Machine, transportation and Process
Yrke 9	Cleaner and assistants
Sektor_1	Government sector
Sektor_2	Municipality sector
Sektor_4	Private sector
Aldergr1	Age 20-24
Aldergr2	Age 25-29
Aldergr3	Age 30-34
Aldergr4	Age 35-39
Aldergr5	Age 40-44
Aldergr6	Age 45-49
Aldergr7	Age 50-54
Aldergr8	Age 55-59
Ledighetsnivå.x	Unemployment rate
Månedlig_chg_ledige	Unemployment rate at Entry
Spell_chg	Unemployment rate during absence
gradertFulltid	Full time sickleave

Table 7 Regression of simple model

Model without interaction

	Value	Std. Error	z	p
(Intercept)	1.49e+02	4.04e+00	36.81	< 2e-16
year	-7.20e-02	1.98e-03	-36.30	< 2e-16
kjonnMenn	6.63e-03	6.32e-03	1.05	0.29
yrke0	-9.10e-02	2.03e-02	-4.48	7.3e-06
yrke1	3.72e-03	1.33e-02	0.28	0.78
yrke2	-8.90e-02	8.35e-03	-10.66	< 2e-16
yrke3	-7.00e-02	8.21e-03	-8.53	< 2e-16
yrke4	-1.43e-01	1.20e-02	-11.95	< 2e-16
yrke6	1.79e-01	3.14e-02	5.71	1.1e-08
yrke7	-1.12e-02	1.14e-02	-0.98	0.33
yrke8	2.16e-01	1.24e-02	17.41	< 2e-16
yrke9	9.45e-02	1.13e-02	8.35	< 2e-16
aldergr1	-2.61e-01	1.08e-02	-24.06	< 2e-16
aldergr2	-1.07e-01	1.01e-02	-10.64	< 2e-16
aldergr3	-6.05e-02	9.96e-03	-6.08	1.2e-09
aldergr4	-4.77e-02	9.88e-03	-4.83	1.4e-06
aldergr6	7.07e-02	9.85e-03	7.18	7.0e-13
aldergr7	1.28e-01	1.02e-02	12.52	< 2e-16
aldergr8	2.27e-01	1.05e-02	21.58	< 2e-16
sektor_kode1	-2.14e-01	8.23e-03	-26.03	< 2e-16
sektor_kode2	-1.28e-01	6.92e-03	-18.52	< 2e-16
gradertgradert	1.55e+00	6.37e-03	243.09	< 2e-16
ledighetsnivå.x	-4.14e-01	2.71e-02	-15.27	< 2e-16
månedlig_chg_ledige	5.75e-02	1.33e-03	43.14	< 2e-16
spell_chg	-8.14e-02	8.35e-04	-97.49	< 2e-16
Log(scale)	2.19e-01	1.46e-03	150.32	< 2e-16

Table 8 Regression more realistic model

	Value	Std. Error	z	p
(Intercept)	148.28826	4.04095	36.70	< 2e-16
year	-0.07184	0.00198	-36.23	< 2e-16
kjonnMenn	0.00681	0.00633	1.08	0.28147
yrke0	-0.08852	0.02031	-4.36	1.3e-05
yrke1	0.00297	0.01332	0.22	0.82333
yrke2	-0.09002	0.00836	-10.76	< 2e-16
yrke3	-0.06931	0.00822	-8.43	< 2e-16
yrke4	-0.14317	0.01200	-11.93	< 2e-16
yrke6	0.17874	0.03140	5.69	1.3e-08
yrke7	-0.01162	0.01145	-1.01	0.31016
yrke8	0.21536	0.01242	17.34	< 2e-16
yrke9	0.09407	0.01130	8.32	< 2e-16
aldergr1	-0.26005	0.01083	-24.00	< 2e-16
aldergr2	-0.10744	0.01010	-10.64	< 2e-16
aldergr3	-0.06032	0.00996	-6.06	1.4e-09
aldergr4	-0.04748	0.00988	-4.81	1.5e-06
aldergr6	0.07075	0.00985	7.18	6.8e-13
aldergr7	0.12752	0.01021	12.49	< 2e-16
aldergr8	0.22629	0.01051	21.54	< 2e-16
sektor_kode1	0.12877	0.09745	1.32	0.18637
sektor_kode2	0.11839	0.08425	1.41	0.15996
ledighetsnivå.x	-0.34817	0.03220	-10.81	< 2e-16
månedlig_chg_ledige	0.06117	0.00191	32.08	< 2e-16
spell_chg	-0.08732	0.00114	-76.41	< 2e-16
gradertgradert	1.54809	0.00637	243.12	< 2e-16
sektor_kode1:ledighetsnivå.x	-0.15450	0.04377	-3.53	0.00042
sektor_kode2:ledighetsnivå.x	-0.10988	0.03783	-2.90	0.00367
sektor_kode1:månedlig_chg_ledige	-0.00947	0.00358	-2.65	0.00816
sektor_kode2:månedlig_chg_ledige	-0.00646	0.00302	-2.14	0.03245
sektor_kode1:spell_chg	0.01093	0.00223	4.90	9.4e-07
sektor_kode2:spell_chg	0.01301	0.00184	7.07	1.6e-12
Log(scale)	0.21898	0.00146	150.29	< 2e-16

Table 9 Checking significance between sectors

	Value	Std. Error	z	p
(Intercept)	1.49e+02	4.04e+00	36.77	< 2e-16
year	-7.20e-02	1.98e-03	-36.30	< 2e-16
kjonnMenn	6.63e-03	6.32e-03	1.05	0.29
yrke0	-9.10e-02	2.03e-02	-4.48	7.3e-06
yrke1	3.72e-03	1.33e-02	0.28	0.78
yrke2	-8.90e-02	8.35e-03	-10.66	< 2e-16
yrke3	-7.00e-02	8.21e-03	-8.53	< 2e-16
yrke4	-1.43e-01	1.20e-02	-11.95	< 2e-16
yrke6	1.79e-01	3.14e-02	5.71	1.1e-08
yrke7	-1.12e-02	1.14e-02	-0.98	0.33
yrke8	2.16e-01	1.24e-02	17.41	< 2e-16
yrke9	9.45e-02	1.13e-02	8.35	< 2e-16
aldergr1	-2.61e-01	1.08e-02	-24.06	< 2e-16
aldergr2	-1.07e-01	1.01e-02	-10.64	< 2e-16
aldergr3	-6.05e-02	9.96e-03	-6.08	1.2e-09
aldergr4	-4.77e-02	9.88e-03	-4.83	1.4e-06
aldergr6	7.07e-02	9.85e-03	7.18	7.0e-13
aldergr7	1.28e-01	1.02e-02	12.52	< 2e-16
aldergr8	2.27e-01	1.05e-02	21.58	< 2e-16
sektor_kode4	1.28e-01	6.92e-03	18.52	< **2e-16**
sektor_kode1	-8.60e-02	7.94e-03	-10.83	< **2e-16**
gradertgradert	1.55e+00	6.37e-03	243.09	< 2e-16
ledighetsnivå.x	-4.14e-01	2.71e-02	-15.27	< 2e-16
månedlig_chg_ledige	5.75e-02	1.33e-03	43.14	< 2e-16
spell_chg	-8.14e-02	8.35e-04	-97.49	< 2e-16
Log(scale)	2.19e-01	1.46e-03	150.32	< 2e-16

Table 10 Testing significance between sectors in the realistic model

	Value	Std. Error	z	p
(Intercept)	148.40665	4.03955	36.74	< 2e-16
year	-0.07184	0.00198	-36.23	< 2e-16
kjonnMenn	0.00681	0.00633	1.08	0.2815
yrke0	-0.08852	0.02031	-4.36	1.3e-05
yrke1	0.00297	0.01332	0.22	0.8233
yrke2	-0.09002	0.00836	-10.76	< 2e-16
yrke3	-0.06931	0.00822	-8.43	< 2e-16
yrke4	-0.14317	0.01200	-11.93	< 2e-16
yrke6	0.17874	0.03140	5.69	1.3e-08
yrke7	-0.01162	0.01145	-1.01	0.3102
yrke8	0.21536	0.01242	17.34	< 2e-16
yrke9	0.09407	0.01130	8.32	< 2e-16
aldergr1	-0.26005	0.01083	-24.00	< 2e-16
aldergr2	-0.10744	0.01010	-10.64	< 2e-16
aldergr3	-0.06032	0.00996	-6.06	1.4e-09
aldergr4	-0.04748	0.00988	-4.81	1.5e-06
aldergr6	0.07075	0.00985	7.18	6.8e-13
aldergr7	0.12752	0.01021	12.49	< 2e-16
aldergr8	0.22629	0.01051	21.54	< 2e-16
sektor_kode4	-0.11839	0.08425	-1.41	**0.1600**
sektor_kode1	0.01038	0.10447	0.10	**0.9208**
ledighetsnivå.x	-0.45804	0.03633	-12.61	< 2e-16
månedlig_chg_ledige	0.05471	0.00235	23.29	< 2e-16
spell_chg	-0.07430	0.00147	-50.38	< 2e-16
gradertgradert	1.54809	0.00637	243.12	< 2e-16
sektor_kode4:ledighetsnivå.x	0.10988	0.03783	2.90	0.0037
sektor_kode1:ledighetsnivå.x	-0.04462	0.04694	-0.95	**0.3417**
sektor_kode4:månedlig_chg_ledige	0.00646	0.00302	2.14	0.0324
sektor_kode1:månedlig_chg_ledige	-0.00301	0.00383	-0.79	**0.4322**
sektor_kode4:spell_chg	-0.01301	0.00184	-7.07	1.6e-12
sektor_kode1:spell_chg	-0.00208	0.00242	-0.86	0.3894
Log(scale)	0.21898	0.00146	150.29	< 2e-16

The most important r-studio codes

Some of the most important codes used in r-studio are listed here.

##Modelerring uten interaksjoner

```
fit1 <-  survreg(Surv(lengde) ~ year + kjonn + yrke + aldergr + sektor_kode + gradert +
ledighetsnivå.x + månedlig_chg_ledige + spell_chg, data = navdata, dist = "weibull")

summary(fit1)
```

###Changing reference group for checking significance

```
table(navdata$sektor_kode)
navdata$sektor_kode <- relevel(navdata$sektor_kode, ref = "2")
```

##Still no interaksjoner

```
fit1 <-  survreg(Surv(lengde) ~ year + kjonn + yrke + aldergr + sektor_kode + gradert +
ledighetsnivå.x + månedlig_chg_ledige + spell_chg, data = navdata, dist = "weibull")

summary(fit1)
```

##Significantly different

##Modelleringer med interaksjoner

```
fit2 <- survreg(Surv(lengde) ~ year + kjonn + yrke + aldergr + sektor_kode*ledighetsnivå.x +
sektor_kode*månedlig_chg_ledige + sektor_kode*spell_chg + gradert, data = navdata, dist =
"weibull")

Summary(fit2)
```

##Changing reference group for checking significance

```
table(navdata$sektor_kode)
navdata$sektor_kode <- relevel(navdata$sektor_kode, ref = "2")

fit2 <- survreg(Surv(lengde) ~ year + kjonn + yrke + aldergr + sektor_kode*ledighetsnivå.x +
sektor_kode*månedlig_chg_ledige + sektor_kode*spell_chg + gradert, data = navdata, dist =
"weibull")

Summary(fit2)
```

##Still significantly different from privat, men government og municipality are not different
##from each other in their interactions variables. They have equal behavior