UiT The Arctic University of Norway

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Geographical Variation of the Impact by the Covid-19 Pandemic in Norway

How much has the covid-19 pandemic affected excess mortality and excess decline in employment in Norway on a geographical level in 2020?

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Foreword

This master thesis marks the end of my master's degree in economics at the school of business and economics at the University of Tromsø - The Arctic University of Norway. I would like to thank all lecturers for everything they have taught me, and the fellow students for all the great experiences along the way.

I would like to express my gratitude to my supervisor associate professor Even Soltvedt Hvinden, for giving me excellent advice while still giving me the chance to make the thesis my own. I am very thankful for the interesting conversations and fun I had working together with Hvinden. Hvinden showed great interest in the thesis, and was of great help and motivation during the whole process.

I would also like to thank friends and family for the encouragement and advice during my period as student.

Abstract

This thesis investigates the geographical variation of excess mortality and excess decline in employment, during the covid-19 pandemic in Norway. The data were collected from Statistics Norway and The Norwegian Labour and Welfare Administration. The method tells you how much the present value are greater or lesser, compared to previous years. Excess mortality and decline in employment were measured at a municipality, and county levels respectively. I found no evidence of effect on excess all-cause mortality, but sign of effect on excess decline in employment. The results showed evidence of geographical differences, were Oslo had the most dominant results regarding decline in employment. The thesis can be used as preliminary results for policy makers for future events, and can be used as a guideline to reproduce the investigation with present up to date data. The method used is straightforward, but makes it easier to reproduce and compare with other similar investigations.

Keywords:

Pandemic, Mortality, Layoffs, Excess mortality and Excess decline in employment

Contents

1 Introduction 1

2 Theory 3
- 2.0.1 Mortality and employment rate . . . 3
- 2.0.2 Excess mortality and excess decline in employment . . . 4
- 2.0.3 Why look at all-cause deaths rather than official Covid deaths? . . . 4
- 2.0.4 Why look at a municipality and or county level? . . . 5
- 2.0.5 Why employment, and not unemployment? . . . 5
- 2.0.6 Hypothesis . . . 6

3 Method 7
- 3.0.1 Excess mortality, excess decline in employment . . . 7
- 3.0.2 Statistical calculations . . . 8
- 3.0.3 Data . . . 9
- 3.0.4 Descriptive data analysis . . . 9

4 Results 11
- 4.0.1 Excess Mortality . . . 11
- 4.0.2 Excess Employment . . . 15
- 4.0.3 Excess Layoffs . . . 19
- 4.0.4 What about 2021? . . . 22

5 Discussion 23

6 Conclusion 25

References 26

Appendix 27

List of Figures

4.1 Binomial distribution of probability for type 1 errors, 28 observations 13
4.2 Excess mortality of the significant municipalities 13
4.3 Excess mortality of the 50 biggest municipalities 14
4.4 Binomial distribution of probability for type 1 errors, with 53 observations 18
4.5 Excess employment of the significant municipalities 18
4.6 Excess employment of the 50 biggest municipalities 19
4.7 Binomial distribution of probability for type 1 errors, with 11 observations 20
4.8 Excess Layoffs per 10000 in 2020 For Norwegian Counties 21
4.9 Excess Layoffs per 10000, March and April, 2021 For Norwegian Counties 22

List of Tables

4.1 Excess mortality (only statistical significant municipalities) 12
4.2 Excess employment, (only statistical significant municipalities) 16
4.3 Excess employment part 2, (only statistical significant municipalities) 17
4.4 Excess Layoffs 20

1. *Introduction*

The pandemic has affected every person in Norway. Policy makers are trying to reduce infections and keep the mortality rate at a minimum, while workers wants to keep their job and normal salary. Since Norway has never witnessed a situation quite like this, the government did not have any planed policy for facing the pandemic beforehand.

In March 2020, Norway chose a lockdown restriction which caused a huge amounts of layoffs. This thesis investigates the preliminary effect the pandemic did in 2020 for both mortality and employment. The reason for looking at these two effects are that, did the restrictions work as intended, are more people dying? And to try and measure the economic damage caused by the pandemic through the amount of employment. My motivation for writing this thesis is that there are reports of national effects presented by for example FHI, but these results can hide geographical variations that is of independent interest. Norway consists of many different regions, and they have different structural differences in health care, labour market and resources. Therefor I want to try and depict differences that can be caused by these differences.

The method used is simple, but this does not make it invalid. It makes it easy to use and understand, and it makes it easier to reuse for later pandemics or other events where these effects are of interest. Thus, in other words, it is easy to reproduce and update with present values.

The thesis presents preliminary data for Norway and it's municipalities and counties, which will be of interest to many different fields of study. For example, economical, psychological, and medical studies. It also presents evidence that are building blocks for further research within the same issue, just with recent numbers, and for a deeper look into the effects of the pandemic, for example. The thesis presents results that are important to witness. Meaning that, this is a first case scenario which will be highly valuable to learn from. And these results are backing up some of the positive outcomes of how the pandemic has been handled, but it also shed light to some of the more negative side-effects that occurred because of policies. And this is something that can be used by policy makers when they evaluate situations in the future. Since the calculations are simple, there is a low threshold for reproducing the results with success. The method used is one of the possible ways to calculate them, but you can cho ose different sizing options to fit what you try to depict for other cases. But In this case, there is a need for getting the results in the same sizing format for every region, per 10000 inhabitants. The way that the results are produced are also reusable for different countries which makes it usable in comparison to other countries.

The methods used, concludes that there has been no evidence of effect on excess all-cause mortality in Norwegian municipalities, but an increased excess decline in employment with geographical differences on county level . This are the same tendencies as for (Polyakova, Kocks, Udalova, & Finkelstein, 2020) paper, on how the initial economic damage of covid-19 has been higher than that of the excess all-cause mortality in the US with also differences on state level.

2. *Theory*

With a new virus that can cause respiratory and lethal consequences, you would assume that the number of people who dies, will increase if measures are not being taken. The Norwegian government have and still try to keep the number of infected to a bare minimum. This with measures like for example, a societal lockdown. The restrictions are useful in battling infections, but they can cause negative externalities, such as layoffs, and bankruptcy.
When the government forces a large part of the working force to stay home via layoffs, you create an enormous expense. This expense is being paid by everyone involved, from the government itself, to the employers and the employees. The person who is laid off does not go to work, and the government will have to pay money to this person by law, at least for a period of time. And the employer has to pay the price of the laid off persons salary the first days, plus not being able to run their business.
This theory section will present the existing methods for calculating excess mortality and excess decline in employment. It will also show the statistical measurements used. The first section will build the foundation for understanding numbers behind excess mortality and excess decline in employment.

2.0.1 Mortality and employment rate

The mortality rate tells you how many people are dying with respect to the population, (Porta, 2014). It uses the formula:

$$M_t = M/P * 10^n$$

Where M, is number of deaths in a specified period, and P, is number of people at risk of dying in the same period. The n, is a variable you choose to fit your data best, in my case, per 10000.

$$n = 4$$

And we can use the same formula for employment by just changing the formula slightly:

$$E_t = E/P * 10^n$$

Where E is used for number of employed people. As Porta 2014 presents, if the death rate is low, it is also a good measurement for the cumulative or crude death rate. This means that the population size matters a lot when looking at the bigger picture. If the sample you are trying to depict the rate from, have a small population size, a change of one unit will have a bigger effect on the rate than for a big sample. This is an important aspect to have in mind when looking at data for mortality and employment. In my case, you have some municipalities that have less than five hundred inhabitants, and the calculation shows that for example, when one person dies, the rate increase on a level that is not very representative to the actual outcome. Since the data is based on crude death, you can have one death in one year, and 2 the next year. This will show as a 100 percent increased mortality, when in fact it is just a 1 unit change. If this is the case in 2020, it will show as a huge impact and can be misinterpreted, when in fact it is not very significant due to the small sample size.

2.0.2 Excess mortality and excess decline in employment

The mortality rate tells you how many people are dying, while the excess mortality tells you how many more, or less are dying compared to the predicted deaths. These predicted deaths can be explained as the mean value of previous years. And in this case it is the years from 2016-2019. Excess decline in employment tells you the same thing, just that you look at the increased or reduced amount of employed people.
Excess mortality formula, (Max Roser & Hasell, 2020):

$$ExMort_t = M_t - PredictedM_t$$

Where M, is the number of dead, and PredictedM, is the average number of dead in previous years which the predicted deaths are based upon. The t, is time. As mentioned, the mortality values are fitted after per 10000 to be more comparable with other regions, and other countries. For excess employment, you use the same formula, but change M into E for employment.

$$ExEmp_t = E_t - PredictedE_t$$

2.0.3 Why look at all-cause deaths rather than official Covid deaths?

The reasons for not looking at the official covid-19 deaths, are because, when you look at the crude death or all-cause deaths, you include all the effects on mortality that the pandemic can have affected. When choosing to look at all-cause deaths, you can eliminate the possibility that your data is manipulated. In other words, there might be errors in the reporting of covid-19 deaths, that can skew the results one way or another. If one place is reporting deaths with Covid-19 as causation with a low threshold, it will increase the number of Covid deaths compared to other places with higher threshold. These two reasons are of importance, but the third reason might be the main reason for doing so, it will be more applicable for comparison across countries when doing so. Just like

Polyakova (2020) delivers the same study in USA, with all-cause deaths, you can use this thesis in comparison with other countries. This makes the investigation more attractive for re-use and it makes it more relevant for use for policy makers. By this I mean that it will make it easier to use as leverage one way or another if you can compare it to other people's work.

2.0.4 Why look at a municipality and or county level?

If you only look at national numbers, you might miss effects on a geographical level. For Norway, you have a wide area of different municipalities and counties, and it would be fair to say that for example, Oslo is highly different from Vardø. Oslo is mainly urban area and consists of approximately 670000 inhabitants, and Vardø is in the far north with only approximately 2100 inhabitants. It is not only the inhabitant number that matters here, but the structure of the labour market, available healthcare and resources available that can impact how a municipality face a pandemic. Some regions can have a higher number of workers in the public sector. These people are not struck with a quite as harsh reality as some in the private sector, due to how layoffs work in the public sector. This might have an effect on the outcome of excess employment in different regions. Small districts may have few employers, for example a factory, and if this industry is struck with shutdowns, it can cause the numbers of layoffs to skyrocket. On the other side, when looking at municipalities with bigger cities, you usually have more restaurants, bars and cafe's, these are more inclined to close because of stricter rules during the pandemic. Therefor when limiting the investigation to a national level, you might mask geographical differences that can occur.

2.0.5 Why employment, and not unemployment?

Unemployment is someone who doesn't work. But, the unemployment data can be difficult to use in the way that it may be inaccurate, (Barrow et al., 2004). There may be differences in the way that the publishers of data measure unemployment. For instance, in Barrow (2004), they talk about the government buying in on the unemployment roll and put them in the not in labour force. This will effectively reduce the number of unemployed because they are now not listed as unemployed, they are listed as someone who is not a part of the labour force. Thus they are so to say not included in either statistics for unemployment nor employment. The difference though is that this will not affect the employment rate, but it will indeed affect unemployment. Such instances are the reason why employment is more favorable to look at in this case. However, employment data does not come without issues. SSB reports that they do not include layoffs with a period of less than three months in their employment data, (Tonje Køber, 2021). This is a something that in this instance had to be addressed. And this is were the layoff data from NAV comes in as a solution to the problem. The layoffs here acts as a supplementary source for the employment data, and it will shed light to how many people that are employed, are laid off. One issue with the layoff data, is that it is registered as notice of layoffs from the employers. This means that they are not registered as actual number of layoffs that occur. But since the data have the same baseline for every year, the effect will effectively measure a change nonetheless.

2.0.6 Hypothesis

As of now early 2021, there has been done studies for Norway on a national level, (Folkehelse-instituttet, 2021). The results were clear, Covid-19 shows no sign of evidence that it affected the excess mortality negatively. My job is to look at a geographical level of municipalities and counties. I suspect that there can be differences in how much the pandemic has had an effect on the different regions. I suspect that population density will be a large factor on mortality. There might also be different levels of restriction-obedience and or whether people take the corona restrictions seriously. Some regions have had stricter policies that restricted travelers from entering, so there might be differences in these areas compared to those who did not have them. Some regions have a larger amount of elderly and visa versa, this can have an effect on whether the vulnerable die from the virus and not. A lower threshold for testing can reduce infected people, so in other words there might be differences in the way testing facilities are available in different regions, this can be a driving force behind lower death numbers.
When it comes to employment, I suspect that the effect will be more clear, many have already experienced layoffs during the start of 2020, and some have lost their job completely. Therefor I suspect that the excess decline in employment will be at a bigger significance than excess mortality, meaning that the economic damage will be higher than that of increased mortality. Also here, I suspect that there will be differences geographically since regions are different from each other. This hypothesis were based upon results from Polyakova's (2020) paper, for United states excess all-cause mortality and excess decline in employment.

3. *Method*

3.0.1 Excess mortality, excess decline in employment

The thesis estimates the excess mortality from mortality data and the excess decline in employment from employment data. When calculating the excess, it is important to look at what assumptions are made during the creation of variables. I found only total numbers for population for municipalities, optimally you would want age brackets and gender included in your data to weight different categories. By this is mean that a death of a person that is 20 years old would mean more lost years compared to a person that is 80 years. So, the 20 year old would have a higher weighting than that of the 80 year old. But, seeing that the data is the same for every municipality you can get an indicator for the results without these categories. Another point is to have the years you are comparing to in mind. In other words, the years you establish a predicted value from compare with the excess year. The trend of the previous years can explain the results or counterfeit the results if not included in your conclusion. Norway has had a downwards trend in mortality, this means that people are dying less at a higher age in general. For employment, the employment rate have generally been high, with a low unemployment rate, (O'Neill, 2021).

A supplementary method that can make the evidence more generalised and easy to compare across countries, is the called a p-score. I have made the calculations in R, but have not included it in the results. This due to the fact that it shows the same outcome as the excess mortality/decline in employment, only a generalised outcome in percentage form and not in excess form. The P-score measures the difference of the year t, compared to the predicted value of a given time-period in percentage, (Max Roser & Hasell, 2020). In my case, you look at mortality/employment in 2020 and compare it to the predicted value (mean), of the years 2016-2019. Starting with how to get the predicted values:

$$PredictedM_t = \frac{meanM_t}{P_t}$$

Were M, is the number of dead, in region X, and P is the population. And in my case, I use a continuation of per capita numbers, presented in the theory section. For per 10000, you adjust the per capita numbers:

$$PredictedM_t(per10000) = PredictedM_t * 10^n$$

Were p10000 is per 10000, and you can clearly see from the formula, that you can adjust the sizing after what fit's best for your data by choosing the n variable. P-score formula:

$$Pscore_t = \frac{M_t - PredictedM_t}{PredictedM_t} * 100$$

Excess mortality:

$$ExMort_t = M_t - PredictedM_t$$

Excess employment:

$$ExEmp_t = E_t - PredictedE_t$$

Were E, is number of employed people. For layoffs it's the same method, just with layoff data, you change the E, to L, layoffs. In my calculations I have made every value in the context of per capita, and from there, I made the data into per 10000. This resizes the values into the same aspect ratio for every municipality and county. This way you can represent the smaller municipalities without them being underrepresented when looking at a larger scale.

3.0.2 Statistical calculations

I have calculated the mean, variance and standard deviation from the data and they use the formulas in respective order:

$$\bar{x} = x/n$$

$$Var = \sqrt{\frac{1}{N}\sum' s_{i=1}^{N}(x_i - \bar{x})^2}$$

$$\sigma = \sqrt{\mu_2}$$

With the use of the calculated values above, I was able to find the confidence intervals with 4 degrees of freedom, at 95 percent significance level. The 2.776 value stems from the 4 degrees of freedom, and are the critical value in a t test with a 95 percent significance level, (Nist-Sematech, 2021).

$$CI_{Lower} = ExMort_t - 2.776 * sd(PredictedM_t)$$

$$CI_{Upper} = ExMort_t + 2.776 * sd(PredictedM_t)$$

And for excess employment they look like this:

$$CI_{Lower} = ExEmp_t - 2.776 * sd(PredictedE_t)$$

$$CI_{Upper} = ExEmp_t + 2.776 * sd(PredictedE_t)$$

Here sd, is the standard deviation to the predicted value. And the confidence interval will be sentered arround the excess values. I have used the binomial distribution density function to calculate the chance of a type 1 error to occur, (Statisticshowto, 2021):

$$P(x) = \frac{n!}{(n-x)!x!} p^x q^{n-x}$$

Were n is the number of observations, x is the number of successful events, p is the probability, (in this case 0.05, the alpha, from 95 percent significance level), and q is the probability of failure.

3.0.3 Data

The collection of data were from Statistics Norway (SSB), which is a official Norwegian statistical website. You have the option to make your own tables at SSB, were you choose your own variables (that they can provide), in the data you want to collect. In my case for looking at deaths before and during the pandemic, I found fitting data with statistics for number of deaths in nearly all of the Norwegian municipalities. To create a fitting R-code to this data, I used a JSON-query that SSB provides when you make your tables at their website. This allowed me to directly translate the table into data frames in r-studio. For employment and population I used the same method for collecting data, but they were on quarterly basis, in other words, not complete for a monthly comparison as we have mortality data on a monthly basis. These quarterly tables had to be manipulated, and I made the general assumption that quarterly data were a mean of the three months they contained. Therefor I replicated the number on quarterly level to be the same for all three months in that quarter. For layoffs, I collected the data from the Norwegian Labour and Welfare Administration (NAV). The data are on monthly basis with data for counties in Norway. The data was only available to download as excel files, which I had to treat in excel to fit a data frame format in r-studio. This means, remove unnecessary columns and row names to make them readable in r-studio. This data are listed in the references and are available to download directly from NAV's webpage. The treatment I did, were joining mass resignations and layoffs, but not include reduction of working hours, since there are no information about it in the years before 2020 in the data from NAV.

3.0.4 Descriptive data analysis

The data contains information about the number of people who have died, employed and the layoffs in Norwegian municipalities and counties. Starting with the data for deaths. The data are on a monthly level for every year between 2016 to 2020. There was missing data for 5 different municipalities in the years before 2020, these were: Hitra, Hamarøy, Narvik, Orkland and Heim. These were not included in the results of excess mortality and employment. The employment data from SSB are in the same time period. They do not include layoffs with a length shorter than three months. This might skew the employment results quite significantly. This is the reason why I had to add an extra set of data containing layoffs. These were also on a monthly level in the same period,

the data however did not contain municipalities. Thus layoffs are at a county level.
For deaths, the option were there to include gender and age, but seeing that it was no available population data including these two factors on a municipality level, they were removed from the deaths data.

4. *Results*

The results are measured at a yearly basis, but monthly results can be viewed in the appendix as plots. To look at the geographical differences, I found it sufficient enough to look at a yearly basis.

4.0.1 Excess Mortality

With a trend of declining mortality, you would also expect reduced mortality in 2020. And this is the case nation-wise, with 77 deaths less compared to 2019, (Sønstebø, 2021). This is the lowest number recorded ever, which further validates the results in this thesis. The results were clear, there was little to no evidence of effect regarding excess mortality on a municipality level. There were only 7,9 percent significant municipalities in the excess mortality results. And these were not at a higher level than 1,36 percent per 10000 at highest. And a problem regarding the ones with effect, they have few inhabitants. In these cases, it was the familiar result of extremes, when sample size is small. The municipalities that have a big increased excess mortality, are generally small municipalities with few inhabitants, and few deaths. This causes a high standard deviation and the results can not be looked at as significant. The ones with decreased excess mortality, are also at a level of no significance. The values are small in terms of percentage, and the ones at the lowest rate do have the same issues as the ones in the other end of the spectrum, they have big standard deviations. I have included two plots that illustrate the results, one with only statistical significant confidence intervals, and one for the fifty biggest municipalities. The reason for looking at the fifty biggest is because this is were most people in Norway live. The results in the fifty biggest show that they do for the most part include the null-hypothesis in the confidence interval, thus they are not statistical significant. This generally tells me that it shows no evidence of geographical differences for excess mortality. I would like to add a comment about this result, a null find here is a good find, it indicates that the restriction and precautions may have had the result of no increased mortality. And this has been one of the key points during the pandemic for the Norwegian government.

For the 28 significant municipalities, there are a 99.38 percent chance that the sample contains at least one type 1 error, measured with a binomial distribution for density. Meaning that there are almost certainly at least one type 1 error in the sample of 28 municipalities. There is also approximately 10 percent chance that 17 of these observations are type 1 errors. Meaning that it can explain the extremes and the barely significant results. This fit's well with the number of observations that have higher standard deviation, which gives me the confidence to say that the

results are a false positive for these observations.
The following tables for excess mortality represent the significant municipalities and plots in the significant and fifty biggest municipalities based upon inhabitants, and the binomial distribution:

Table 4.1: Excess mortality (only statistical significant municipalities)

	Region	Sd	Per 10000	Lower	Upper
1	Namsskogan	25.30	136.11	71.07	201.14
2	Vega	24.78	74.49	10.78	138.21
3	Fyresdal	19.28	64.81	15.24	114.37
4	Hjelmeland	20.79	53.87	0.42	107.32
5	Nesna	14.39	47.59	10.59	84.59
6	Dyrøy	16.09	43.49	2.13	84.84
7	Porsanger - Porsángu - Porsanki	6.26	40.32	24.23	56.41
8	Våler (Hedmark)	7.29	37.67	18.92	56.41
9	Samnanger	4.70	35.11	23.04	47.18
10	Tynset	2.14	27.10	21.60	32.61
11	Tingvoll	7.15	18.58	0.18	36.98
12	Eigersund	3.66	12.27	2.86	21.68
13	Tysvær	1.92	7.72	2.78	12.66
14	Trondheim	2.47	-6.67	-13.03	-0.32
15	Lillehammer	1.51	-7.22	-11.10	-3.34
16	Hammerfest	2.58	-12.39	-19.02	-5.75
17	Rauma	4.52	-13.23	-24.84	-1.61
18	Trysil	3.73	-15.15	-24.74	-5.57
19	Sør-Varanger	6.04	-16.90	-32.42	-1.37
20	Lillesand	4.30	-19.58	-30.64	-8.52
21	Flesberg	8.18	-21.54	-42.58	-0.50
22	Hareid	5.76	-29.88	-44.69	-15.08
23	Averøy	4.35	-42.88	-54.07	-31.69
24	Selbu	16.48	-50.15	-92.52	-7.77
25	Åmli	18.51	-50.45	-98.04	-2.85
26	Gulen	5.57	-52.17	-66.49	-37.84
27	Modalen	12.50	-59.78	-91.93	-27.64
28	Engerdal	22.35	-72.79	-130.26	-15.32

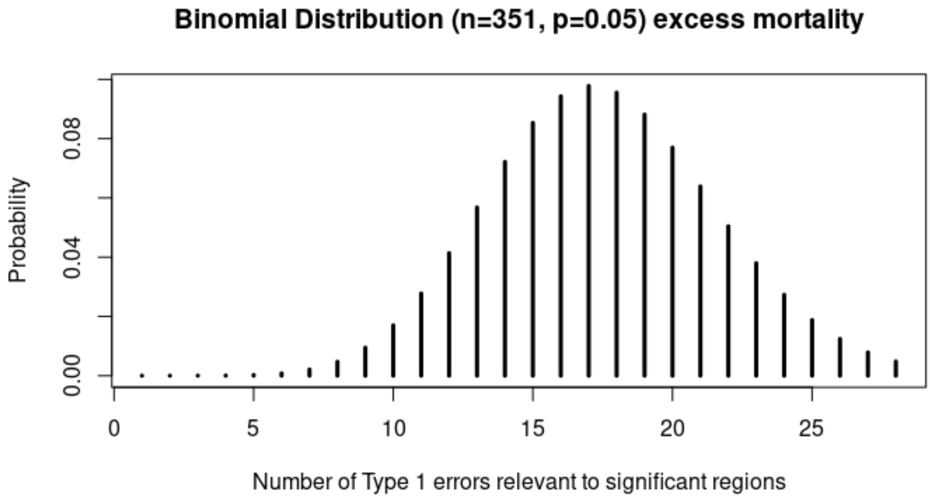

Figure 4.1: Binomial distribution of probability for type 1 errors, 28 observations

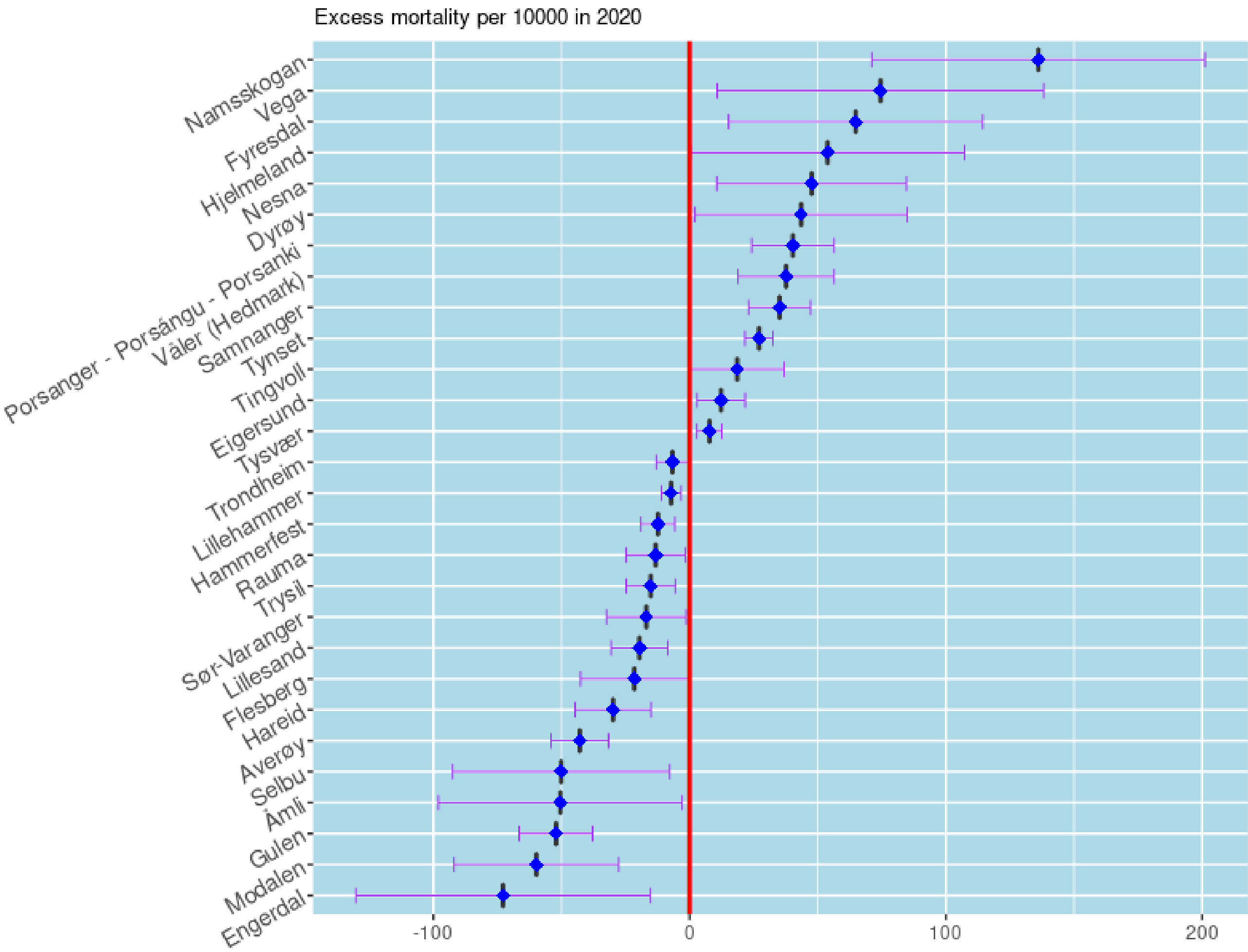

Figure 4.2: Excess mortality of the significant municipalities

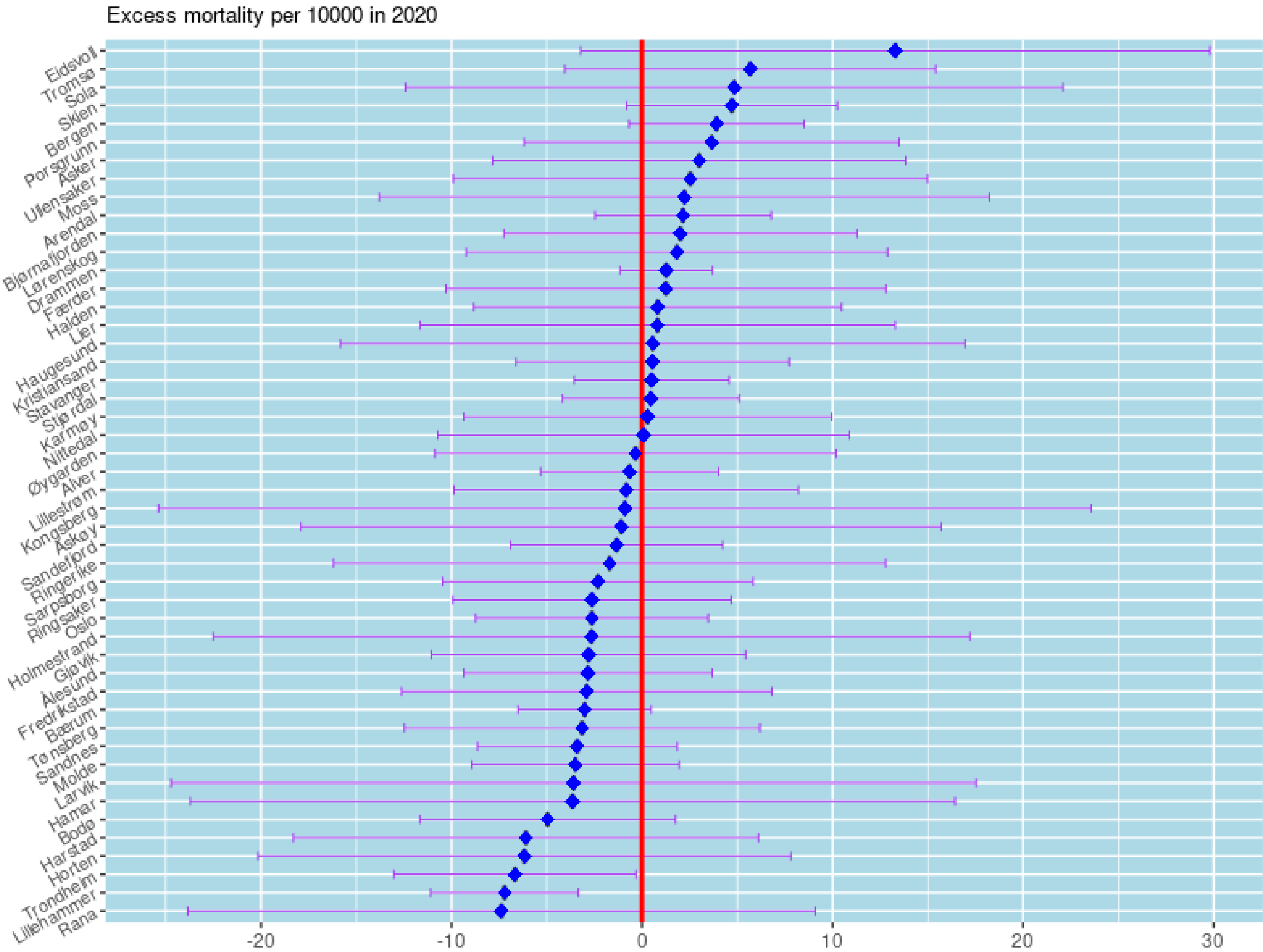

Figure 4.3: Excess mortality of the 50 biggest municipalities

The restrictions may have worked as intended, keeping infections down and the deaths low, but they have not come without a cost. I have included excess employment and excess layoffs to look at the economic damage in 2020 for municipalities and counties respectively. Starting with excess employment that include employment and population data from SSB on a municipality level.

4.0.2 Excess Employment

The evidence for excess employment follow the same pattern as excess mortality. The level of change is for the most part, meager and therefor not significant. Only roughly fifteen percent are significant. There is some municipalities that you clearly see an effect in, but these are exceptions from the general results. You can also see that the standard deviation is of a large size in many of them, this on either sides of the spectrum. The large confidence intervals can be explained by a small inhabitant size, and incidences that may have reduced the number of employment in earlier years. For the fifty biggest municipalities, you can see that most of them does include the null-hypotheses. This shows that you cannot say on a statistical level that the results are explained by the hypotheses. The results are under five percent for all except Ullensaker, and this with the insignificant confidence intervals tells me that the results show no evidence of geographical differences in decline in employment. For the 53 significant municipalities there are a 100 percent chance that the sample contains at least one type 1 error, measured with a binomial distribution density function. As you can see in figure 4.4, there are approximately a 10 percent chance that the sample size contains type 1 errors at 17 observations. This gives me the indicator that many of the significant regions may be false positives and should be rejected. This can explain the municipalities that have wide confidence intervals and those that are at the very limit of being significant. This can also explain the municipalities that have a small sample size, with extreme values. These false positives should be looked at as a negative, meaning that they are not significant and should be rejected. That the already small number of significant municipalities should be even smaller, further validates that the results are a null find. All the significant observations that have a narrow confidence interval are not on the extremes, but they are significant nonetheless and should be interpreted as evidence of effect. The reason why I say that it is a null find, is because the number of municipalities that are significant, are slim. With less than 15 percent significant results, out of all municipalities it is hard to draw a conclusion of evidence of effect, therefor a null find. The following tables and plots show the effect measured with employment data from SSB, and the binomial distribution:

Table 4.2: Excess employment, (only statistical significant municipalities)

	Region	Sd	Per 10000	Lower	Upper
1	Flatanger	127.96	566.60	237.62	895.59
2	Kvit'søy	154.32	561.24	164.49	958.00
3	Træna	168.97	460.19	25.76	894.62
4	Bokn	92.35	274.22	36.80	511.65
5	Sandnes	54.38	169.11	29.30	308.93
6	Rødøy	55.28	163.29	21.16	305.43
7	Osterøy	54.14	144.63	5.43	283.83
8	Eigersund	44.41	119.74	5.55	233.93
9	Dønna	33.72	116.35	29.67	203.04
10	Nesodden	20.31	62.09	9.87	114.31
11	Fredrikstad	10.82	-54.14	-81.97	-26.32
12	Nes	11.16	-70.76	-99.46	-42.07
13	Lørenskog	16.66	-71.50	-114.34	-28.66
14	Larvik	13.73	-77.36	-112.65	-42.08
15	Sunnfjord	29.04	-98.39	-173.05	-23.72
16	Kvam	24.77	-103.44	-167.14	-39.75
17	Ringsaker	12.02	-107.68	-138.57	-76.78
18	Harstad	34.90	-112.56	-202.29	-22.82
19	Averøy	43.73	-112.94	-225.38	-0.51
20	Arendal	36.89	-114.57	-209.41	-19.73
21	Notodden	11.90	-115.25	-145.85	-84.65
22	Gloppen	42.98	-115.66	-226.16	-5.15
23	Fauske - Fuosko	26.52	-121.23	-189.41	-53.04
24	Kongsvinger	44.22	-131.10	-244.79	-17.40
25	Trondheim	32.40	-148.67	-231.96	-65.38
26	Skjåk	49.28	-156.27	-282.96	-29.58
27	Elverum	38.46	-159.92	-258.79	-61.04
28	Saltdal	26.51	-166.47	-234.62	-98.33

Table 4.3: Excess employment part 2, (only statistical significant municipalities)

	Region	Sd	Per 10000	Lower	Upper
29	Verdal	41.40	-167.72	-274.17	-61.27
30	Stjørdal	49.93	-176.00	-304.37	-47.62
31	Gamvik	53.42	-177.21	-314.57	-39.86
32	Malvik	46.04	-186.53	-304.89	-68.18
33	Vegårshei	65.04	-186.58	-353.80	-19.36
34	Volda	24.63	-189.27	-252.60	-125.95
35	Østre Toten	49.05	-193.92	-320.02	-67.81
36	Øygarden	24.29	-205.37	-267.81	-142.93
37	Nissedal	39.70	-229.79	-331.86	-127.72
38	Tønsberg	88.98	-230.59	-459.36	-1.82
39	Raarvihke - Røyrvik	63.09	-243.66	-405.85	-81.46
40	Nordre Follo	10.71	-273.88	-301.40	-246.35
41	Åseral	90.24	-280.48	-512.48	-48.48
42	Sel	76.15	-299.62	-495.42	-103.83
43	Meråker	85.60	-312.52	-532.61	-92.43
44	Seljord	91.54	-336.55	-571.89	-101.21
45	Lillehammer	9.07	-351.31	-374.62	-327.99
46	Osen	104.88	-351.79	-621.44	-82.13
47	Vang	22.26	-360.06	-417.30	-302.82
48	Snåase - Snåsa	105.86	-374.81	-646.97	-102.66
49	Loabák - Lavangen	55.51	-436.52	-579.24	-293.81
50	Ulvik	63.29	-461.42	-624.14	-298.69
51	Etnedal	220.46	-578.74	-1,145.54	-11.94
52	Aukra	189.54	-625.35	-1,112.66	-138.04
53	Ullensaker	135.56	-1,312.08	-1,660.60	-963.57

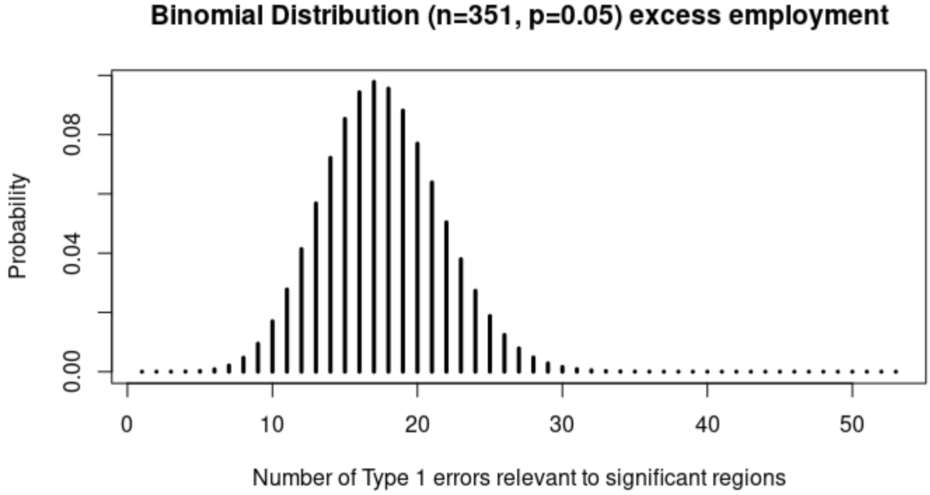

Figure 4.4: Binomial distribution of probability for type 1 errors, with 53 observations

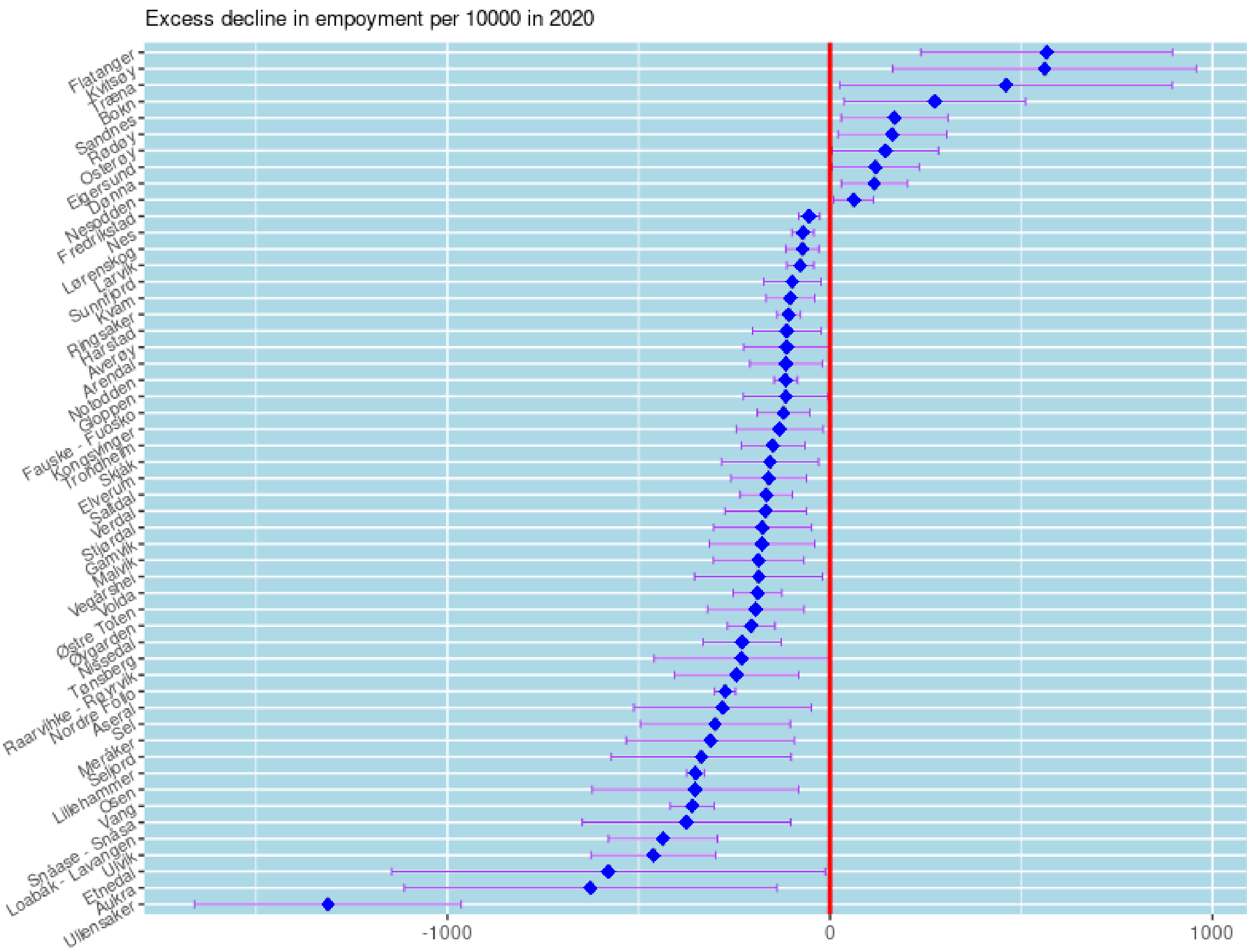

Figure 4.5: Excess employment of the significant municipalities

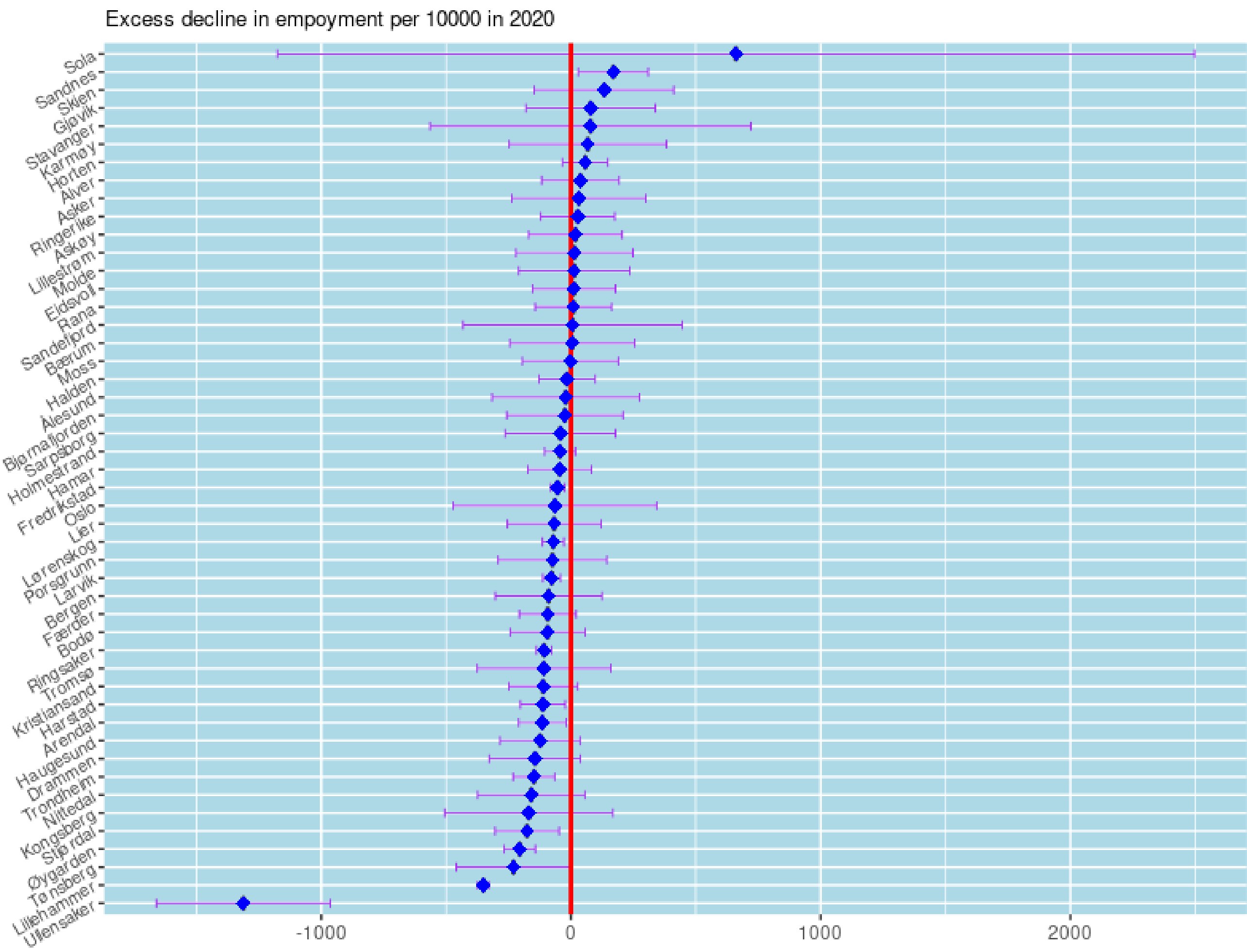

Figure 4.6: Excess employment of the 50 biggest municipalities

Finally, to try and unravel the economic damage caused by the pandemic, I looked at excess layoffs for Norwegian counties in 2020 with layoff data from NAV and population data from SSB.

4.0.3 Excess Layoffs

As mentioned, the data for employment from SSB had it's flaws, therefor I included layoff data from NAV to supply a deeper look into the economic damage that may have been caused by the pandemic. And yes, the results show evidence of geographical differences in Norwegian counties. There has been reported an increased number of layoffs throughout the whole 2020 in all counties. All with significant confidence intervals with one exception, Rogaland. This can be explained by the increased amount of layoffs in the period starting from 2016, were many employed in the oil industry were forced to look for new work. And of quite certainty, if there would not have been the change in the oil industry, Rogaland would most likely have had higher excess layoffs in 2020. What is interesting is that the biggest county in Norway with most inhabitants had the biggest amount of layoffs per 10000. The take away from this is that the amount of people that got laid off in 2020 were at a very high level compared to previous years. Measuring at 3,21 percent layoffs per

10000 in Oslo, shows that the layoffs had a rather large effect on employment. This decreased employment is something that harms both business and government spending. With laws that force the employer to pay 18 days, and the government has to pay the rest of the layoff, you clearly have a money drain that is very costly for the society. This money will have to be gained back through other measures that can be interesting, to say the least, for the future.
For the 10 significant counties, there are a 43.11 percent chance that the sample contains at least one type 1 error, measured with a binomial distribution density function. But as shown in figure 4.7, there is a 0 percent chance that all 10 counties are a type 1 error. This indicates that there might be at least one type 1 error in the sample, and those can be identified by a larger larger confidence interval. The following table and plots illustrate the effect of excess layoffs in 2020 for all Norwegian counties, and the binomial distribution:

Table 4.4: Excess Layoffs

	County	Sd	Per 10000	Lower	Upper
1	Oslo	21.68	321.88	261.69	382.07
2	Vestland	34.43	167.38	71.79	262.96
3	Viken	10.79	159.50	129.54	189.46
4	Møre og Romsdal	36.22	117.38	16.84	217.92
5	Trøndelag	11.04	114.93	84.29	145.56
6	Agder	36.31	109.88	9.07	210.69
7	Troms og Finnmark	29.06	108.08	27.40	188.76
8	Innlandet	5.24	105.79	91.25	120.33
9	Vestfold og Telemark	16.90	77.49	30.58	124.40
10	Nordland	18.29	60.56	9.78	111.33
11	Rogaland	110.06	52.32	-253.22	357.86

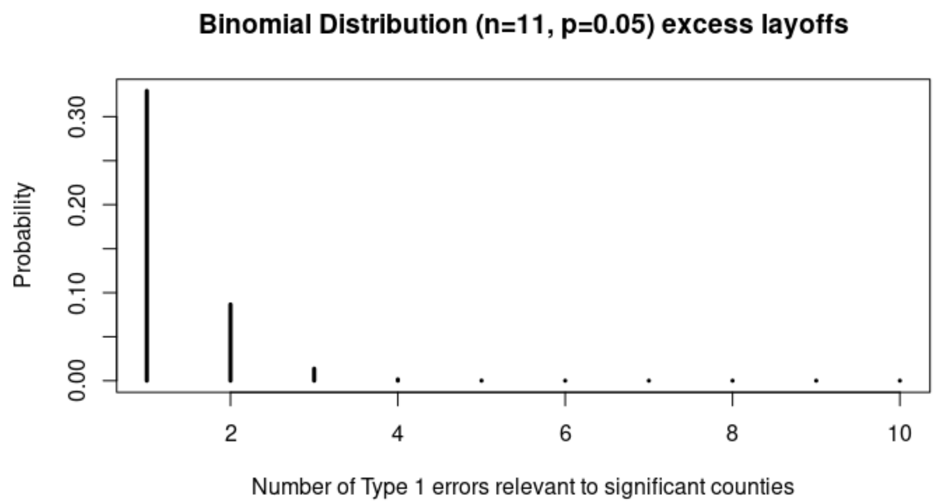

Figure 4.7: Binomial distribution of probability for type 1 errors, with 11 observations

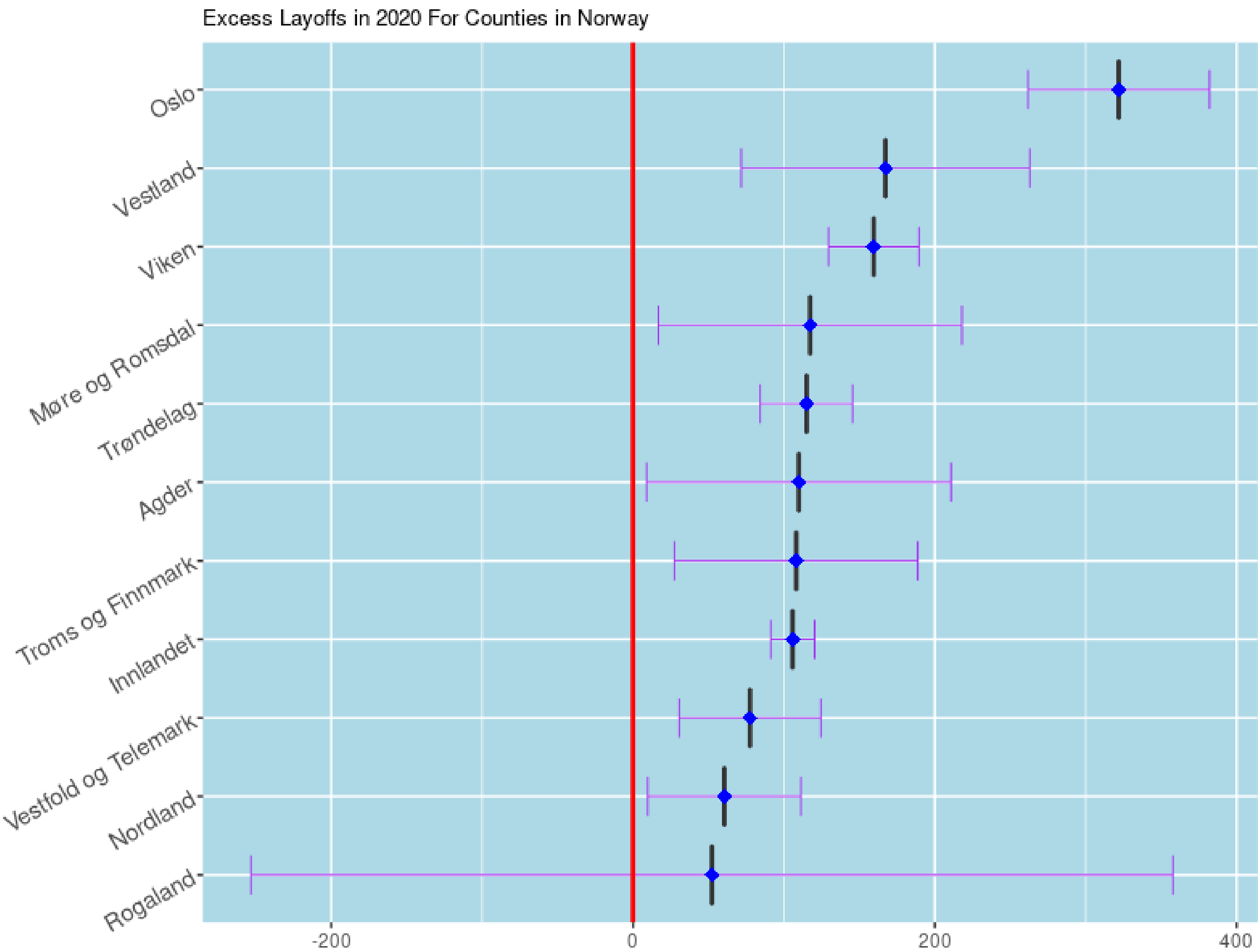

Figure 4.8: Excess Layoffs per 10000 in 2020 For Norwegian Counties

If you take away all the children, elderly and those that are not capable of working, the effects are rather high for the population. Over three percent extra layoffs in the highest populated county in Norway, is a big red flag. As mentioned, it is costly, and it also effects the general purchasing power of the inhabitants. When people are laid off, they only get sixty percent of their normal salary, this can be detrimental to those who does not have an economic buffer and it is a money drain on the public funds.

4.0.4 What about 2021?

The evidence from 2020 shows increased excess layoffs, but what about 2021? When looking at the excess layoffs for 2021 compared to the same time interval as earlier, the results show an decreased excess layoff, and lower evidence generally compared to that of 2020. Since the data from 2020 start from march, it is the same for 2021, months included are at this point March and April in 2021. And illustrated in figure 4.9, you can see that the results are not that significant. Significant counties are a minority and some might be type 1 errors, and the effect is less than 50 per 10000, which indicates that the effect has sunk quite drastically from 2020 numbers. This can give an indicator that the layoffs are at a declining rate for 2021. This can be explained by the reopening of the society. There is still people laid off, but not nearly as many as in 2020. The following plot shows the outcome of March and April 2021, and the same binomial distribution as for 2020 follows for this calculation:

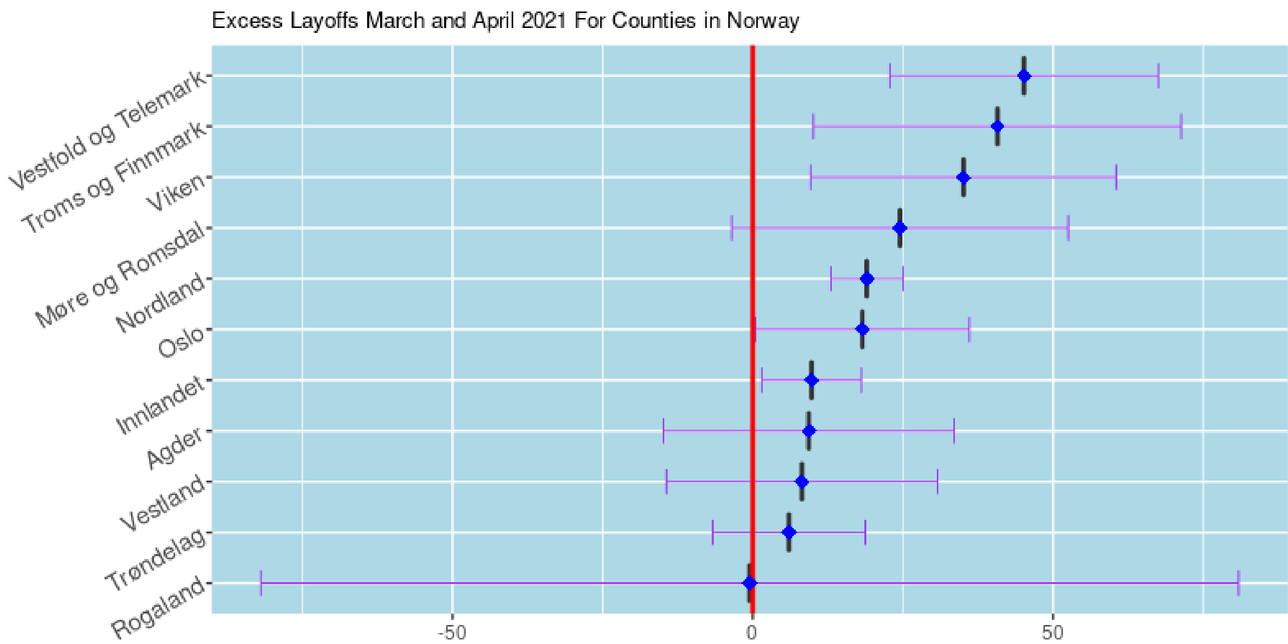

Figure 4.9: Excess Layoffs per 10000, March and April, 2021 For Norwegian Counties

5. *Discussion*

This thesis investigated the effect of the pandemic on excess mortality and excess decline in employment. The hypothesis were based upon earlier results from USA, in Polyakova's (2020) paper. And it was that both excess mortality and excess decline in employment would be affected negatively by the pandemic. Judging by this thesis results, only decline in employment showed sign of effect by the pandemic. But, given that the results were only significant when a separate data set were implemented, there is some discussion to be had around the data from SSB. When it comes to issues surrounding the data, the employment data from SSB showed to be rather poor for this case. There were multiple issues that are mentioned that can have skewed the results, and for future research, I would have stayed away from this data completely. They do not include what would be expected from employment data, and would need supplementary data to fulfill a complete data. Layoffs turned out to be the biggest factor in excess decline in employment, and when they are not included in the employment data, I would call it rather useless. It doesn't give the information that you would want from an employment data. If over 3 percent per capita are laid off, I find it rather weird to not include them as decreased employed in this data. They have chosen to put the laid off as employed as long as they are of a period under three months. And those who are laid off longer, will be put in the unemployment data at a later point. That is the reason why I chose to implement data from NAV, because they report all layoffs no matter reason or length. SSB also implemented a new way of getting the employment data after 2015, this means that the data from before 2016 were not comparable with later data. That is why the predicted value in the calculations consist only of data from 2016-2019. Layoffs had no available data on a municipality level, that's the reason why they are on a county level. But Nonetheless, the county data showed a geographical difference which was what the thesis wanted to measure.

Now, over to the results regarding layoffs. As presented, Oslo was the most affected county when it came to excess layoffs. And there might be a correlation between what this thesis tried to measure, and the outcome. Are there geographical differences in the way the pandemic hit? Yes, there clearly is. Oslo is mainly an urban city, and in the cities, there are more cafes, restaurants and obviously, more people. This can be some of the reasons for why Oslo has taken the biggest hit in the employment department. Another point is that infections have been rampant in Oslo and the regions surrounding Oslo, like Viken. Thus policy makers have made different rules for these areas. For example, low infected areas were allowed to reopen, but Oslo had to keep closed. More businesses have had to keep their doors closed, and for a longer period of time. To conclude this string of thought, the counties with the biggest cities show evidence of being more inclined to have more layoffs because of population density and labour structure, this becomes clear from the table and plot from the excess layoffs section.

6. *Conclusion*

The thesis looked at excess mortality and excess decline in employment on a municipality and county level respectively. This to unravel if there were differences at a geographical level in Norway in the year 2020. It showed no sign of evidence on excess mortality, which were in line with the trend for mortality in the present years. It did however show effect on excess decline in employment, were the counties with the highest density of people generally had the highest excess decline.
When doing future research, you should carefully look at what the data actually contains. You should be wary of the definitions when gathering data, for example, what employment or unemployment contains.
When looking at mortality, age brackets and genders should be included. This to depict if there is any effect on different age groups and between genders. It could also be useful to include a deeper look into how the mortality trend are regarding previous years.
Future research can build upon the work done here, and include other expenses to look at the total economic damage of the pandemic.
You could also look at the monthly results to see if there are correlations with respect to for example, number of infections and or date of restriction implementations. These monthly results can be gathered from the hyperlink in the appendix, were you get plots for excess mortality and excess decline in employment. The calculations for this are also included in the script from the same hyperlink.

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Appendix

`https://www.dropbox.com/sh/6dr4mkut4rfj5jp/AABV0NazxY-HlVQtSEhBdEYra?dl=0`

This link will give you access to the R-script used for gathering data, and all calculations done in the thesis. It also contains a pdf with the plots for monthly excess mortality, and excess decline in employment for municipalities. The layoff data that were collected from NAV, has been treated to fit a data frame format in R, this can also be found using the link. You will have to download these Excel files to run the respective R-script for layoffs. You need to set working directory in R, to the same as were you save these Excel files.

No login is needed, you simply click the link and files should be available to look at, or download after your choosing.