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The effect of labour market shocks on workers and the role of contract permanence

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Abstract

Mass layoffs cause scars to affected workers' potential earnings path and job security. Past research on mass layoffs has mainly focused on the recovery of displaced workers. However, the rate of recovery depends on labour market frictions, which most likely do not affect industries similarly. Employment in high-permanence (HP) industries may be subject to different labour market frictions than in low-permanence (LP) industries, depending on factors such as workforce adjustment costs or skill transferability. To assess labour market frictions by permanence, I use annual data on a panel of employer-employee relationships for 1995-2014, provided by Statistics Norway. My results show that estimated expected earnings three years after the mass layoff event are higher than in the preceding year. The earnings growth is slower in LP industries. I also find a reduction in the expected number of days employed, and the reduction is larger in HP industries. I conclude that workers in HP industries have more a more robust expected earnings path, but that once displaced, they struggle more to return to the initial level of employment.

All data wrangling and production of results have been done using R version 4.1.2 (2021-11-01). The code is available upon request.

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Chapter 1

Introduction

Mass layoffs in organisations can be economically and emotionally devastating for employees, but economic recovery may be quicker than expected. Intuitively, one might expect a slow return to the original potential earnings path, but this depends on a complex set of factors. Labour market frictions slow down the process of re-employment. Some individual characteristics may also determine whether the worker struggles more or less in the years following the mass layoff event. Several studies have attempted to capture how a mass layoff affects workers' earnings, family structure, and other life-cycle factors. However, few to none have attempted to find whether the role of contract permanence is of any importance.

In August 2011, up to 300 employees at the bank Nordea risked layoffs in the aftermath of the Global Financial crisis (Berge, 2011). Up to 60 teachers at Hjeltnes high school faced the same threat in 2018 due to few student applications to the school (Rydland and Moe, 2018). As I will outline in this paper, the finance and banking industry is characterised by few short-term employment contracts, and vice versa for the education industry. Bankers and teachers play vital societal roles, but it is unclear whether they are affected similarly by a mass layoff. Who would be worse off if both organisations carried out the mass layoffs? The bankers or the teachers? In other words: *How do adverse economic shocks impact mass layoffs in workers across sectors characterised by a high share of permanent versus non-permanent employed workers?* This question is of interest if there is a difference in how employees in different industries are affected by a mass layoff. E.g., if permanent workers such as bankers face more severe labour market frictions than teachers, should layoff regulations differ between permanent and non-permanent workers?

My thesis aims to contribute to the existing literature by exploring which industries are worse off in the case of a mass layoff, and whether labour market fricitons affect high-permanence (HP) or low-permanence (LP) industries[1] differently. Most studies on mass layoffs attempt to find how the displaced workers are affected. My thesis instead aims to find which industries are the most affected by labour market frictions in the years following the mass layoff. Additionally, it provides further insight into the mechanisms behind how adverse economic shocks affect the Norwegian labour market.

I have used a difference-in-differences model and a two-way fixed effects regression to estimate the effects of a mass layoff on income and possibilities for re-employment. The sample selection consists of employees in organisations that experience a mass layoff event. The event year is normalised to time zero (t = 0), and all estimates are then measured in change from one year before the mass layoff (t = -1). Later, the sample selection is split by industries, then by HP and LP industries. The same regression is run on the split samples.

My results show that workers in LP industries are worse off after a mass layoff in terms of estimated expected. However, both workers in HP and LP industries quickly recover. At t = 3, the workers' income in HP and LP industries is 13.5 per cent and 7.47 per cent higher than in the year before the mass layoff event occurred, respectively. In the same period, total employment has decreased by 0.1 per cent. The return to the initial number of days worked is slower than the return to initial earnings. At t = 3, the estimated number of days worked in HP and LP industries has decreased by about 11 and 7 days compared to t = -1, respectively. This is interesting because it implies that the expected earnings path in HP industries is more robust to adverse economic shocks. However, displaced workers in HP industries seem to struggle more to find new employment, perhaps because of their set of skills.

In my thesis, I will first outline the general state of the Norwegian labour market in the years of scope, 1995 to 2014. I will then recount existing literature on the consequences of mass layoffs and how contract permanence may affect employment conditions. Next, I will introduce labour market friction mechanisms and the potential consequences of mass layoffs. Based on the theory, I form four hypotheses on the potential outcomes of mass layoffs in the Norwegian labour market. To study these consequences, I have

[1]HP: Characterised by a low share of short-term employed workers; LP: Characterised by a high share of short-term employed workers.

prepared a microdata data set to extract a sample for analysis. I outline this preparation procedure before presenting my empirical method. In this section, I will also review model assumptions and whether they are likely to hold. Lastly, I report the results and discuss any weaknesses in my method.

Chapter 2

Background

2.1 The Norwegian labour market between 1995 and 2014

Figure 2.1 illustrates the unemployment rate of Norwegian workers between 1987 and 2022. My data range from 1995 to 2014, and I have extended the period by ± 8 years to illustrate the relative state of the economy in this period. I will mainly comment on the years within the scope of my thesis. The unemployment rate from 1995 to 2014 ranged between 4.9 per cent in 1995, to 2.5 per cent in 2007. The highest unemployment rate between 1987 and 2022 was 6.0 per cent in 1993.

The figure shows a sharp increase in unemployment between 1887 and 1993. Gross unemployment fell quite drastically from 1993 to 1998 before increasing to a peak in 2005. Upon entering the 1990s, the Norwegian economy was in a deep recession which lasted until the end of 1992. Then an increase in government spending, a lower key interest rate and booms in international markets led to an upturn in the Norwegian economy, which lasted until about 1998. Between 1993 and 1998, gross employment increased by almost 230'000 individuals. International issues such as the Asian financial crisis and a reduced oil price were the leading causes of the subsequent economic slowdown. A stock market bubble caused by high expectations of returns in the tech industry persisted until the first few years of the 2000s. Its burst then led to a minor recession starting at the end of 2002 (Benedictow, 2005).

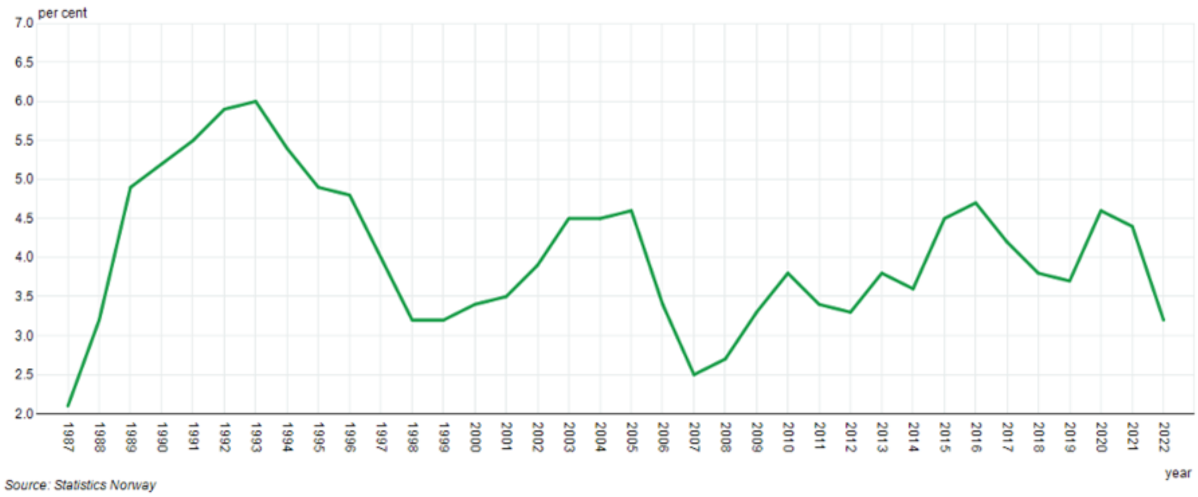

Figure 2.1: Labour force survey done by Statistics Norway, table no 08517: Unemployed persons (percentage of population), by year. Includes individuals aged 15-74 years (Statistics Norway, 2023c).

The unemployment then rate fell between 2005 and 2007. The enlargement of the EU in 2004 increased labour mobility across borders and slowed down the rising unemployment rates. The 2007-2008 financial crisis also caused significant turbulence in international markets, which also affected the Norwegian economy and contributed to the increase in unemployment between 2007 and 2010. Norway responded to the crisis with a successful policy restructuring, leading to a more positive economic development than expected throughout 2009 (Benedictow et al., 2010, pp. 3-4).

NAV[1] has published a monthly report on the status of the Norwegian labour market since 2006. In December 2007, they commented that the Norwegian labour market was defined by numerous vacant job positions and that there had been a trend of increasing labour demand since the end of 2004. They also reported a trend of a decreasing number of individuals registered as unemployed during the same period. This trend was consistent across all industries. 38'900 individuals were registered as unemployed in December 2007. The industries facing the lowest unemployment rates were education, engineering, and information and communication. The human health and social work activity industry also experienced a low rate of unemployment. The highest unemployment rates were found among those who worked in tourism and transport, as well as in service professions. The largest decrease in the unemployment rate between 2006 and 2007 happened among

[1] The Norwegian Labour and Welfare Administration.

engineers, in academic professions, and in the information and communication industry (Årethun, 2007). Sørbø and Årethun, 2007 also conducted a business survey for NAV in which 44 per cent of the participating organisations stated that they lacked candidates to fill vacant positions. Among these, half the organisations had fewer employees than desired due to recruitment problems.

At last, there was a peak in unemployment in 2016 after a relatively sharp spike in 2015. The US oil production increased unexpectedly in 2014. OPEC wished to keep their share of the oil market, and therefore responded to the increased supply by pumping oil at the same rate as before. This led to the price of oil falling drastically between the autumn of 2014 and the winter of 2016 (Aarøy, 2016). The price drop greatly affected the Norwegian economy and was the leading cause of the increase in unemployment during this period (Halvorsen et al., 2015, p. 3).

In their labour market analysis from December 2014, NAV reported that gross unemployment had increased to 84'300 persons. The largest increase in gross unemployment between 2013 and 2014 happened among engineers and those employed in information and communication. The largest decrease happened in construction. The tourism, transport, and construction industries faced the highest unemployment rate. On the other hand, the education industry and academic professions experienced the lowest unemployment rates. Access to job seekers was stable (Sørbø, 2014).

2.1.1 Unemployment duration

Figure 2.2 is also delivered by Statistics Norway and illustrates how long individuals tended to stay unemployed in the period 1996 to 2014. Data is shown in thousands of persons and is split by the duration of job search. It might be a good indicator of labour market frictions since frictions increases the duration of the employment period. Overall, Figure 2.2 shows the same trend as Figure 2.1. The unemployment rate and job search duration were high until 2005, and then there was a new rise after 2007. Most unemployed individuals stay unemployed for less than 13 weeks in all years.

The job search duration seems to peak around 1996, 2004 and 2010. The early 1990s recession could explain the 1996 peak, and the 2002 recession could explain the peak around 2004. Note that the unemployment rate was higher before 2005, yet a high share of individuals found new employment within four weeks. The low point around 2007 corresponds to the increase in labour demand and recruitment problems experienced by firms, as recounted above. Lastly, the peak around 2010 could be explained by high rates of labour immigration. In December 2010, NAV reported that the number of vacant positions fell sharply between January 2008 and January 2009. During the same period, the labour supply increased, and there was a growth in the unemployment rate of EU immigrants (Handal, 2010).

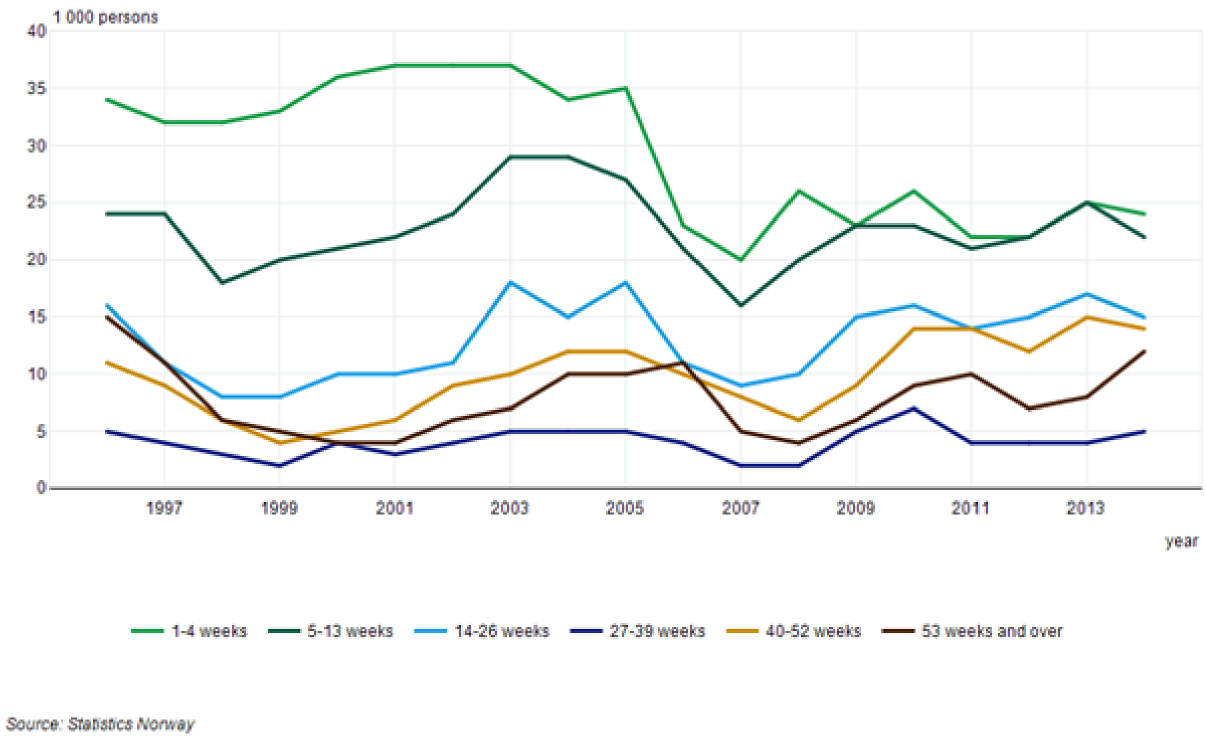

Figure 2.2: Labour force survey, table no 04553: Unemployed persons (in thousands), by duration of job search and year. Includes individuals aged 15-74 years. Note that the age limit was lowered from 16 to 15 years in January 2006 (Statistics Norway, 2023a).

2.2 Literature review

2.2.1 Effects of displacement on earnings and job mobility

The consequences of job displacement on earnings have been widely explored, particularly in the US. Most studies have focused on the difference between displaced and non-displaced workers. Ruhm (1991) was among the first to investigate the extent of the costs displaced workers experience. His data was gathered by the Michigan Panel Study of Income Dynamics, which collects panel data on US families. A displaced worker was defined as a worker whose job was terminated and who did not return to the original employed after two years. His findings show that displaced workers earned 10 to 13 per cent less four years after the job loss than non-displaced workers. This is supported by Kletzer and Fairlie (2003), who found that young adults who lost their jobs experienced a significant loss in earnings for the first three years after the job loss. For young workers who were less established in the labour market, the earning potential approached the pre-displacement potential after five years. Their sample consisted of data on US workers collected from the National Longitudinal Survey of Youth, in which job losses were reported.

Some US papers have also split the results by characteristics such as skill. von Wachter et al. (2009) studied workers employed in California. They found that workers with more than four years of college education had a lower earnings loss following a displacement than less educated workers. Similar results were found by Couch (1998). He studied mature US workers (50 and above) and found that displaced workers from the lowest educated group had the lowest re-employment rate after two years.

Results from Europe show a similar but weaker trend of reduced income following a job loss. Hijzen et al. (2010) studied the effects on UK workers and found that a job displacement caused by a mass layoff reduced income by 14 to 25 per cent per year after five years. However, the effect on wages was relatively small, indicating that most of the income reduction was driven by the period of unemployment.

These results were supported by Ehlert (2013). He compared displaced US and German workers and found that both faced an income reduction following a job loss. However, the reduction in income was more severe for US workers as he found them to have more firm-specific[2]. German high-income workers seemed to have more transferable skills and were therefore re-employed quite quickly in similarly paying jobs. Low-income workers faced higher displacement costs, but this was mostly caused by longer periods of unemployment. This group was characterised by fewer years of education, which in turn lowered the probability of re-employment. A similar study was done by Gangl (2004), who compared workers from the US and West Germany. He found that welfare benefits such as

[2]Firm-specific skills can be defined as skills that are not transferable between firms. Once a worker with firm-specific skills is displaced, their human capital will depreciate (Ehlert, 2013, p. 4). Similarly, industry-specific skills can be defined as transferable within an industry, but not between industries.

unemployment insurance helped workers find higher-quality jobs after the displacement and thus reduced earning losses.

A few studies on the topic have been conducted on Scandinavian workers as well. Seim (2019) found that displaced workers in Sweden experienced a 16.4 per cent loss in labour earnings seven years after displacement, compared to before the job loss. He also used military enlistment records to connect cognitive abilities to the probability of displacement. He found that high-skilled workers were less likely to be laid off but that there were no significant differences in recovery across skill levels. However, younger workers recovered faster than mature workers.

Huttunen et al. (2011) studied Norwegian residents and found a more moderate loss in labour earnings. After two years, the earnings loss for displaced workers relative to non-displaced workers was 4.8 per cent. This loss was entirely driven by those not re-employed within the same firm. The earnings of displaced workers started to decline somewhat already four years before the displacement. Interestingly, they found that skill was partly industry-specific and partly firm-specific.

2.2.2 The role of contract permanence

A change in the laws surrounding non-permanent employment in Norway came into force 1st of July 2015 in Norway's Working Environment Act. The goal was to make non-permanent hires more accessible for organisations. This was argued to give employers more room to correct wrongful hiring of unsuitable candidates, which might open the labour market for individuals of reduced ability to work. In turn, labour market frictions would be reduced, and unemployment would decrease (Ministry of Labour, 2015). On that occasion, a few reports were written on non-permanence in the Norwegian workforce and how more accessible short-term employment affected employment conditions.

Nergaard (2017) reported in a memorandum for Fafo how this law affected the trends in non-permanent contracts. As a part of the labour force survey done by Statistics Norway, about 500 short-term employed workers were asked why they were not instead permanently employed. In 2014, 24 per cent saw no reason to be short-term instead of long-term employed. Thirty per cent were substitutes, 19 per cent were on call, 15 per cent were undergoing training, and 14 per cent were employed for a project. Note that her findings imply that most short-term workers hold part-time jobs. After the new law made short-term employment more accessible, the substitutes and "no reason" groups experienced the most noticeable change. Five per centage points more workers gave no reason to be short-term employed, while seven per centage points fewer reported to be substitutes. Any changes in other groups were insignificant. In total, the number of short-term employees in the Norwegian workforce increased by 0.4 per cent between 2013 and 2016.

There are some differences between workers who are permanently and non-permanently employed. Svalund and Nielsen (2017) outlined some characteristics of non-permanently employed workers in Norway. Their study was also based on data from the labour force survey conducted by Statistics Norway. They found that non-permanent workers, on average, were seven years younger than permanent workers and two years younger than unemployed. Between 2000 and 2009, 39.9 per cent of short-term employees had a college or university education. The same was true for 33.2 per cent of permanently employed workers. Also, short-term employees were more likely to have been registered as job seekers at some point than permanently employed workers. Nergaard (2017, p. 14) reported similar descriptions of non-permanent workers. Of all non-permanent workers between 2012 and 2014, 59 per cent were women, and 39 per cent were in the age group 15 to 24 years old. She also reported that 28 per cent of non-permanent workers had achieved education at the primary school level, while high school and college-educated workers made up 36 per cent each.

Statistics Norway found that in 2022, 50.8 per cent of non-permanently employed workers in Norway wanted a permanent position instead (Statistics Norway, 2023d). Ahmed et al. (2016) found that non-permanent workers tended to be very hardworking in the first period of their employment. They were also highly committed to their job. The authors theorised that a wish to be rewarded with a permanent position was a strong motivator. However, if this wish was not fulfilled, job-related neglect[3] was found to increase significantly, and intention to leave[4] the organisation increased[5]. On the flip side, Yu (2012) studied the Japanese labour market and found that non-permanent employees experienced stigmatisation in the labour market. In fact, unemployed workers had a

[3]Job-related neglect was measured using a scale of six items which assessed employees' avoidance of role-specific tasks, avoidance of extra assignments, and avoidance of supervision.

[4]Intention to leave was measured using a scale of five items which assessed employees' attempts to search for new jobs.

[5]Note that the study was done on Bangladeshi workers and may not apply to the Norwegian labour market.

higher probability of attaining a permanent job than short-time employees.

Chapter 3

Theory

3.1 Labour market frictions

Whether workers easily find new occupations following a mass layoff depends to some extent on the severity of friction in the economy's labour market. Pissarides (2000) defines frictional unemployment as unemployment caused by matching issues between job seekers and vacant positions. Likewise, Jones (2018, p. 185) defines it as unemployment caused by job searching even though the economy is otherwise well-functioning since workers in a dynamic economy regularly change vacancies. I will discuss why frictional unemployment may happen: imperfect information, geographical immobility, and depreciating human capital.

Imperfect information happens when two parties in a trade have access to different information (Blink and Dorton, 2012, p. 153). In a market with imperfect information, job searchers must spend time and energy researching potential jobs to find a suitable match in which they can be productive. If there is limited access to information on vacant positions, the job searcher may spend more time and energy researching. In turn, they may stay unemployed for longer stretches of time. The Internet is a significant contributor to reducing the friction caused by imperfect information. Kuhn and Mansour (2014) found that from 2008 to 2009, the unemployment duration of job searchers that used the Internet was 25 per cent shorter than those who did not. Kuhn and Skuterud (2004) did a similar study on the period 1998 to 2000 and found the opposite results – using the Internet to search for jobs increased the length of unemployment. This is relevant to my thesis because my data stretches from when internet access was limited to when it likely reduced labour market friction. Note that researching jobs can be seen as an investment in human capital. Research may increase the probability that individuals end up in a suitable job where they are productive labour force members. Despite this, there is a negative relationship between the reservation wage[1] and the length of the unemployment period (Borjas, 2012, pp. 511-513). This could indicate that for some, spending too much time doing research might instead be a result of pickiness or unattractiveness in the labour market.

Vacant job positions are not necessarily located in the same city as the job searcher. This is of no consequence if the job searcher is fully willing to move, which they often are not. In an appendix to NOU 2000: 21, Stambøl describes the relationship between geographical mobility and labour market trends in Norway (NOU 2000: 21, appx. 6). He found that unemployed individuals willing to move had a higher chance of finding employment between 1988 to 1989 and 1994 to 1995[2]. There was an overrepresentation of unemployed individuals unwilling to move among those still unemployed or no longer in the labour force in 1988 and 1995.

Lastly, Becker (1993) studied the relationship between unemployment duration and predicted wages. He shaped the Human Capital Theory, which states that as unemployed individual does not use their skills, these skills depreciate over time. The longer an individual stays unemployed, the more the skill depreciates, lowering their predicted wages. The Signalling Theory developed by Spence (1973) is similar. It predicts that long periods of unemployment signal to the employer that the worker is unattractive in the labour market. In turn, this also negatively affects predicted earnings as the duration of unemployment increases.

3.1.1 Workforce adjustment costs

Adjustment costs are defined as costs experienced by a firm when adjusting its workforce size. These include hiring and firing costs. Hiring costs include advertising the job position, interviewing candidates, choosing the correct candidate, and training them, as well as any legal or financial obligations related to new hires. Firing costs may include building a case against the employee, paying separation benefits, or any emotional and

[1]The lowest wage rate an individual is willing to accept to do a certain job.

[2]The purpose of splitting the analysis into two periods was to see whether the results held in both a recession (first period) and a boom (second period).

cultural damages to the workplace. Adjustment costs can vary with the number of workers hired or fired, or they can be fixed. Variable adjustment costs include, e.g., training the new employee. Fixed adjustment costs are not dependent on the number of workers hired or fired[3].. Generally, government policies protecting employees cause firing costs to be higher than hiring costs[4] (Borjas, 2012, p. 127). Note that firing a worker may create a vacant position, generating a cost to the organisation. First, in the form of an opportunity cost since organisations are assumed to make zero expected profit on a vacant position. Second, production processes in the organisation may be dependent on specific roles. If these roles are vacant, the organisation's overall production process may be disrupted. Third, the organisation may have to take on the hiring costs if they need the vacant position to be filled (Mortensen and Pissarides, 2011, p. 85).

Hiring and firing costs affect labour market frictions. If hiring costs are high, firms will be more reluctant to hire new employees, which decreases the market labour demand. If firing costs are high, firms may hold on to unfit employees, decreasing labour demand by reducing the number of vacant positions[5]. High firing costs may also reduce the number of layoffs if the costs of firing an employee exceed the costs of keeping them. Short-term employment requires the employer to recruit employees more often. If hiring costs are high, the threshold for short-term employment may thus also rise. However, the decision can be relatively independent of firing costs since the employee is expected to leave the firm eventually. There is a risk of employing the wrong worker, and the costs of doing so can be high[6]. Thus, high firing costs may instead decrease the attractiveness of long-term employment.

[3]For more information on variable vs. fixed adjustment costs, see e.g., Hamermesh (1989)

[4]In Norway, a set of conditions must be met for an employer to be allowed to hire a worker non-permanently. The specific requirements can be found in the Working Environment Act (2005) § 14-9, paragraph (2).

[5]Note that a high job creation rate will counteract this force.

[6]There is no agreed-upon method of estimating cost of a wrongful hire. Some claim the cost is around 1.5 times the employee's annual salary (Opus Finance, n.d.). Others claim that the cost is between 250'000 and 500'000 (Kaspersen, 2009).

3.2 The consequences of mass layoffs

3.2.1 Displaced workers

Displaced workers lose their jobs because of reasons unrelated to them as employees (Cahuc et al., 2014, p. 570). As outlined in Chapter 2.1, the consequences of displacement caused by a mass layoff are found to be primarily negative. Most displaced workers experience a loss in earnings potential and implicit costs, such as learning new skills once re-employed. However, most literature on the subject studies the US or Europe, and it is unclear whether Norwegian employees face the same costs and, if so, of the same magnitude. Furthermore, few papers have studied how staying in the event organisation in the years following the mass layoff affects earnings.

A displaced worker will either be unemployed, re-employed, or non-participating in the year(s) following the mass layoff event. The job-to-job mobility depends on the state of the economy and the overall number of job vacancies. Individual factors also play a role. E.g., the displaced worker may have organisation- or industry-specific skills that do not apply to most vacant job positions. They may also prefer other jobs than those available and decide to wait before they apply for jobs in the hopes that a more attractive option comes along. Again, this may depend on the duration of unemployment benefits, the sum of benefits received relative to previous income, lifestyle, spending habits, and other factors.

There are reasons to believe that displaced workers will have a lower earning potential than if they had not been displaced. First, some workers exit the labour force permanently because of the displacement. Salvanes et al. (2021, p. 26) found this especially true for workers in their late fifties and older. Johnsen et al. (2022) also found that older workers are more likely to apply for disability pensions as an exit strategy that lowers the costs of exiting the labour force. Knowing their costs can be lowered may make exiting more attractive and less costly than finding a new job.

Second, some individuals may have specialised industry- or organisation-specific skills. Higher education is found to lower a worker's probability of becoming unemployed, but they are also found to invest more in the specific skills required at the workplace (Borjas, 2012, p. 501). If a highly educated individual is displaced, there may be fewer vacant positions where their skills can be utilised. This may prolong their period of unemployment.

If the layoff is caused by an adverse economic shock affecting all similar organisations, finding a suitable job may be even more challenging.

On the other hand, displacement could prove to be beneficial. Many papers have studied the relationship between external job mobility[7] and salary. Brett and Stroh (1997) found that male (and not female) managers received positive cash compensation for an external labour market strategy[8]. The same results were found by Dreher and Jr. (2000), who saw that an external labour market strategy was primarily beneficial to white males[9]. Lam et al. (2012) studied this across ages and found that young workers received more extensive benefits than mature ones.

Implicit costs to job hopping may discourage workers from having an external labour market strategy even though it can benefit them. Brochs-Haukedal (2017, p. 278) outlines some reasons people may resist changes in the work environment. Some employees view their work accomplishments as a significant part of their dreams and life goals. Even though they might earn more by changing employers, they might lose the progression of goals they are working on at their current workplace. Furthermore, employees establish habits and social relationships at their workplaces, which they would have to foresee and rebuild. Lastly, there may be more tangible costs, such as a loss in progress for promotions or accrued rights. Not mentioned by Brochs-Haukedal are costs such as the time spent searching for jobs, writing applications, or showing up to interviews.

These costs provide fair reasons for not having an external labour market strategy. However, displacement would force an employee to invest in finding a new employer. In conclusion, whether this would be beneficial or not to the employee depends on labour market frictions. The higher the level of friction, the higher the cost of displacement. It is fair to assume that unemployment benefits provide less income than the lost salary. If few jobs are available, employees might have to accept worse employment contracts with lower salaries.

[7] External job mobility is here defined as a worker's ability to move between organisations. Contrarily, internal job mobility is the worker's ability to move within an organisation, such as moving to a new department within the same firm.

[8] Moving between organisations.

[9] Note that both studies are more than 20 years old and on US workers. There may be time-dependent or location-dependent factors that affect expected results for Norwegian workers in 2023, such as culture. However, the main point still comes across – job hopping benefits some individuals.

3.2.2 The role of contract permanence

Svalund and Nielsen (2017) found that long-term employed Norwegian workers' job attachment was more secure than short-term employed workers between 2004 and 2013. Among workers registered as non-permanently employed in year zero, 11.2 per cent had an insecure attachment to the labour market after four years. The same was true for 5.6 per cent of those registered as permanently employed in year zero. Among short-term employed workers, men were more likely to have a secure attachment to the labour market than women. Note that they did not study the effects of mass layoffs specifically, and there is not much research on the relationship between mass layoffs and employment permanence. However, their results may indicate that short-term employed workers are also more at risk in a mass layoff event.

3.3 Hypotheses

Based on the theory of labour market frictions and the consequences of a mass layoff, I have formulated the following hypotheses:

Hypothesis 1: There are no differences between LP and HP industries. Both are worse off. This scenario is likely if there is high labour market friction and few job vacancies in all industries. It also implies that short-term and long-term employees are equally attractive in the labour market. This hypothesis is somewhat unreasonable given the description of the Norwegian labour market between 1995 and 2014 in Chapter 2.1.

Hypothesis 2: There are no differences between LP and HP industries. Both are better off. This case would require few frictions in the labour market and a surplus of job vacancies across all industries. This hypothesis may be plausible, as Norway had many vacant job positions between 1995 and 2014. Also, Blink and Dorton (2012, p. 212) point out that individuals that part from a job may move on to positions where they can be more productive contributors to the economy. However, this would imply that short-term and long-term employees are equally attractive on the labour market following a mass layoff. As recounted in Chapter 2.1, short-term employees in Japan experience a strong stigma (Yu, 2012). Similar conditions could exist in Norway as well.

Hypothesis 3: There are differences between LP and HP industries. LP industries are worse off. This hypothesis is reasonable if there are negative factors surrounding only non-permanence workers. E.g., the characteristics of short-term employees make them more attractive on the labour market and expose them to more friction than long-term employees. Such characteristics could be higher levels of education, which literature finds that a large percentage of short-term employees have attained.

Hypothesis 4: There are differences between LP and HP industries. HP industries are worse off. If the characteristics of short-term employed workers are disadvantageous, they may experience stronger labour market frictions. They may also be more likely to be selected for displacement, which would be reflected in the results as LP industries being worse off.

Chapter 4

Data and descriptive statistics

4.1 Data

My raw data is delivered by Statistics Norway and is accessed through the Innoprod[1] database. Each dataset connects the state register of employees delivered by NAV with the payroll and debit statement register delivered by the Norwegian Tax Administration. The state register of employees consists of Norwegian individuals who are employed at an organisation, work more than 4 hours a week, and receive a salary from the employer. It also provides information on the first and last work date, the total number of days worked each year, and grouped expected working hours[2]. The payroll and debit statement register delivers information on income higher than NOK 400 earned per individual from an employer.

I use data sets that span from 1995 to 2014. In this thesis, "income" is the total sum an individual earns yearly from an employer. Note that an individual can earn income from more than one employer. They can also work under more than one grouped expected working hours contract for the same employer.

Each dataset is imported into R using a function that stores all data files in a list. The function output is the list of datasets, which is then bound into a complete data table of 80'625'195 observations. I sum incomes if an individual earns the same income in the same year from the same employer. This reduces the number of observations to 60'897'100. I then calculate weighted income, log income, and log weighted income. Weighted income is

[1]More information on the Innoprod research project can be found here.

[2]Grouped expected working hours is an ordinal variable that categorises hours worked per week into three categories (1: 4-19.9 hours; 2: 20-29.9 hours; 3: 30 hours or more).

defined by equation 1 and reflects an individual's income if they received the same hourly wage but worked full-time.

$$weighted\ income_{it} = \frac{income_{it}}{\frac{number\ of\ days\ worked_{it}}{365}} \tag{4.1}$$

The raw data only includes employed individuals. I wish to balance the data set used for analysis so that each individual is included for all years, regardless of whether they receive income. However, the original data set is very large, and it is impossible to balance it due to the file size. The largest amount of data I can keep while still being able to balance the data table is a 30 per cent selection. Therefore, I randomly select 30 per cent of organisations and remove any not included in this selection. This ensures that all individuals in the selected organisations are kept. The data file now contains 17'198'925 observations before balancing the data and 52'399'684 after.

NACE codes classify organisations into industries and have been used in data sets from 2009 and onwards. All data sets up to and including 2008 use different classification codes. A separate data set from Statistics Norway links the old code system to the NACE codes. I use this to replace all old codes with their corresponding NACE codes. I then prune all NACE codes down to a two-digit level describing industry division.

4.2 Sample construction

My goal is to capture the effect of displacement on individuals employed by organisations that experience a mass layoff due to adverse economic shocks. Other individuals are filtered out. To do so, I first aggregate the data to the number of employees per organisation and year. The number of observations in the aggregated dataset is 1'010'352, and 2'492'840 after balancing.

If an organisation is very small, a reduction of, e.g., one employee will be reflected in the data as a significant reduction of employees. I therefore need to remove small organisations based on a certain threshold. When flagging mass layoff events, Salvanes et al. (2021, p. 14) use a sample of organisations limited to those with 20 or more employees in one of the base years. I use all years when flagging mass layoff events and Equations 4.2 and 4.3 for filtering small organisations. This filter will not exclude organisations with fewer than 20 employees in the years following the mass layoff event. It removes 2'367'160 observations so that 125'680 remain.

$$threshold_{jt} = \begin{cases} 1 & \text{if } employees_{jt} < 20 \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

$$\text{remove observation if } \sum \text{threshold}_{jt} < 2014 - 1995 + 1 \tag{4.3}$$

Salvanes et al. (2021, p. 13) define a mass layoff as a 30 per cent decrease in the number of employees from year t-1 to year t, year t being the year a mass layoff event takes place. I use the same criterion to flag the filtered sample of organisations with a binary operator. Additionally, I only keep the first mass layoff event per firm so that the first event is flagged while the following are ignored. This prevents overlaps in time from event regressors. The year 1995 is never flagged.

The mass layoff event year is then defined as a base year for each organisation. I follow individuals for seven years – three years before and after every event for all organisations. If an individual work in the organisation during the years leading up to the mass layoff event but quits before it takes place, they are not included in the sample. The final dataset sample consists of individuals that are displaced during the event year, as well as those who remain employed.

4.2.1 Categorising industries

I use data from the labour force survey conducted by Statistics Norway to categorise industries based on the prevalence of short-term contracts[3]. The sample consists of 21'000 observations per quartile between 2008 and 2022[4], and data is collected through phone interviews (Statistics Norway, 2023e). For each NACE code on the two-digit level, the data provides information on the percentage of short-term employed workers for all years. I calculate the mean percentage across the years 2008 to 2020 and use the median of this mean to characterise the industries. A binary variable equals 1 if the mean is above the median, 0 otherwise. I consider the above median industries to be characterised by

[3]Data is gathered from Statbank table no 07204, Statistics Norway (2023b).

[4]Although data ranges from 2008 to 2022, there was a data restructure in 2021 which made data gathered in 2021 and 2022 incomparable to data gathered in previous years. I have therefore chosen to only use data between 2008 and 2020. For more information, see Statistics Norway (2023e): About the statistics; Production; Comparability over time and space.

short-term employment contracts and vice versa. Above and below median industries are henceforth referred to as LP and HP industries, respectively.

4.3 Sample construction for robustness tests

4.3.1 Excluding part-time employees

A large percentage of non-permanent employees also work part-time, as outlined by Nergaard (2017) and recounted in Chapter 2.2. The labour demand for part-time employees may differ from the demand for full-time employees. This may, in turn, reduce or increase the period of unemployment. Also, part-time employees may have different characteristics, such as gender, motivation, or health. Such differences may also affect re-employment and may bias my results. I have constructed a separate sample for robustness testing by keeping only employees who work 30 hours or more per week. A similar method has been used by Salvanes et al. (2021, p. 14), who excluded individuals who work fewer than 20 hours a week in their principal analysis.

4.3.2 Using alternative criterion when flagging mass layoffs

Larger organisations require more employees to be laid off for them to be marked as in distress. Given the 30 per cent mass layoff criterion described in Chapter 4.2, an organisation of, e.g., 1000 employees must lay off 300 to be registered as a mass layoff data point. Conversely, an organisation of 50 employees need only lay off 15. This gives rise to potential false negatives, and underestimating the number of mass layoff events may lead to the model not picking up all variation in an individual's income or employment status that is caused by displacements.

The Worker Adjustment and Retraining Notification Act is a part of the U.S. labour law created to protect employees during mass layoff events (U.S. Department of Labor, n.d.). Its mass layoff criterion is similar to the one I use in that a 33 per cent reduction in the number of employees is registered as a mass layoff. However, it also includes all events that affect 500 or more workers as mass layoffs (Worker Adjustment and Retraining Notification Act, 1988)[5]. Inspired by this, I have added a new binary variable to my data

[5] Its exact definition of a mass layoff can be found in the Worker Adjustment and Retraining Notification Act of 1988, Pub. L. 100–379, § 2, 102 Stat. 890 (1988).

set. It flags the same organisations as initially, and all reductions in the number of employees equal 500 or greater. The broader criterion may be more accurate in flagging organisations in distress. However, it may also overestimate the annual mass layoffs caused by adverse economic shocks. This is especially true if other reasons than adverse economic shocks cause the reduction in employees.

4.3.3 Excluding the private sector

In terms of share of GDP, the public sector in Norway was the largest among all OECD countries in 2015. In 2016, about 860'000 individuals were employed in the public sector (Riekeles, 2017). The public sector had a somewhat higher share of short-term employment than the private sector from 2013 to 2016 (Nergaard, 2017, p. 9). The state of the public sector affects a significant share of the economy. As later shown in Figure 4.3, the public sector seems particularly susceptible to experiencing mass layoffs. Hence, it is worth exploring whether labour market frictions are different here than in the private sector.

Therefore, I have constructed a sample consisting of only public-sector industries. Using Statistics Norway's Table 13164[6], I have extracted the number of workers employed in the private sector per industry. The data is quarterly and ranges from Q1 2016 to Q3 2022. I then found the mean percentage of workers in the private sector across all quarters. In total, 62.3 per cent of all employees across all years and industries work in the private sector. An industry is then characterised as containing primarily public organisations if the mean percentage of workers employed in the public sector is lower than 62.3 per cent[7].

4.4 Descriptive statistics

4.4.1 Key variables

Summary statistics of the constructed sample are reported in Table 4.1. The mean log income of all employees is 11.6, with a standard deviation of 1.47. This is lower than

[6]Discontinued in 2022.

[7]The following sectors were characterised by having few workers employed in the private sector: Mining etc., manufacture, power and water supply; Public adm., defence, soc. Security; Education; Human health and social work activities.

Table 4.1: Summary of raw data

Statistic	Mean	St. Dev.	Min	Median	Max
Log income	11.579	1.467	−1.204	12.014	16.766
Days worked	287.252	114.475	1	365	366
Grouped exp. working hours	2.365	0.854	1	3	3
Employment status	0.999	0.028	0	1	1
Flagged	0.029	0.168	0	0	1
Median of means	0.129	0.335	0	0	1
Number of employees	1,788.765	3,533.243	1	252	15,362

Notes: Descriptive statistics of the sample selection. Grouped expected working hours is an ordinal variable that categorises hours worked into three categories. 3 = full-time. Employment status is a binary variable which equals 1 if the individual receives income for a given year, 0 otherwise. Flagged is a binary variable which equals 1 if the individual who works at an organisation that experiences a mass layoff, 0 otherwise. The median of the mean is a binary variable that equals 1 if the individual works in an industry with a mean percentage of short-term employed workers above the median of mean percentages across all industries, 0 otherwise. The mean is taken across the years 2008 to 2020. The number of employees is calculated using aggregated data on employees per organisation per year.

the median log income, which is reasonable as some very rich individuals are included in the data. Summary statistics of log income only include income higher than zero. The median number of days employed is 365 days, which indicates that most individuals in the data are full-time employed. The standard deviation of 114.5 days shows a large spread in the number of days employed. The mean days employed is 287.3 days, which points towards the variation mainly being driven by part-time employees. Note that when days worked equals one, the individual often has no income while they are still connected to an organisation. These individuals are likely on unpaid leave or temporarily laid off. The statistics describing grouped expected working hours show the same tendencies as days employed.

The mean employment level across all individuals and years is 99.9 per cent. A standard deviation of 2.8 per cent is not very large and implies that most individuals included in the data set are employed for most years. Across all years, 2.9 per cent of organisations experience a mass layoff event. This varies much across years, with a standard deviation as high as 16.8 per cent. The mean number of employees is also noteworthy. Some organisations are very large, which increases the mean and standard deviation. However, most organisations are medium-sized or small, reflected in the median of 252 employees.

Table 4.2 reports summary statistics from the data set provided by Statistics Norway on the share of short-term employed workers by NACE categories. There are 91

Table 4.2: Summary of mean percentage short-term employed workers across years 2008 to 2020

Statistic	Mean	St. Dev.	Min	Max
Mean % short-time employees	6.950	3.907	2.180	26.567
Median of means	0.385	0.489	0	1

Notes: Binary variable (0 or 1) indicates if mean percentage is above or below the median of the means. Descriptive statistics of NACE categories based on the labour force survey done by Statistics Norway (table no 07204) (Statistics Norway, 2023b).

NACE categories spread across 14 industries. The mean percentage of short-term employed workers across all categories is 6.95 per cent. The lowest percentage is 2.18 per cent (financial and insurance activities), while the highest is 26.57 per cent (unspecified). Excluding the unspecified category, education has the highest percentage of short-term employed workers, at 13.32 per cent.

Whether an industry is categorised as being characterised by a high percentage of short-time employees is determined by the mean percentage from 2008 to 2020. I then found the median of all means and categorised industries with a binary indicator which equals 1 if its mean is above the median, 0 otherwise. The probability that a NACE category is above the means median is 38.5 per cent. This means that 35 categories fall above the median of the mean share of short-time employed workers.

4.4.2 Short-term contracts by industry

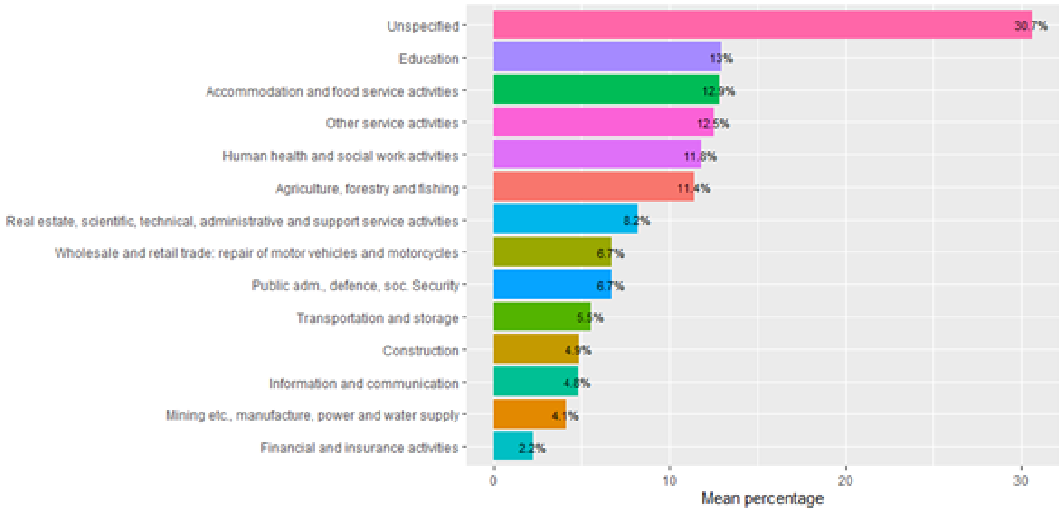

Figure 4.1: Mean percentage short-term employed workers, years 2008 to 2020. Based on the labour force survey done by Statistics Norway, table no 07204 (Statistics Norway, 2023b).

The same data described in Table 4.2 is used to create Figure 4.1. The mean percentage of non-permanent employees per industry has been found using the method described in Chapter 4.2. Excluding unspecified industries, education has the highest percentage of short-term employed workers, followed by accommodation and food service activities, and then other service activities. Other service activities include but are not limited to, hairdressing and other beauty treatments and physical well-being services such as massage studios. The industry with the lowest percentage of short-term employed workers is financial and insurance activities, followed by mining etc., manufacture, power and water supply, and information and communication.

4.4.3 Mass layoff trends

Figure 4.2 shows the number of mass layoff events by year in the 30 per cent sample. In Chapter 4.2, I outline how small mass layoff events are filtered for my analysis. For my analysis, I also remove mass layoff event observations if the same organisation experiences more than one event. The red line includes all mass layoff events after the filter has been applied. The blue line shows the number of mass layoff events observations I keep for my analysis. Figure y illustrates the share of organisations by industries that experience a mass layoff event. It is based on the same numbers as the red line, i.e., the number of mass layoff events in all organisations after the filter has been applied. Percentages are shown if an organisation's share of mass layoff events exceeds 20 per cent. I will briefly comment on the trends and compare them to the Norwegian labour market, as described in Chapter 2.1. Notable years are 2001, 2004 to 2005, 2007 and 2014.

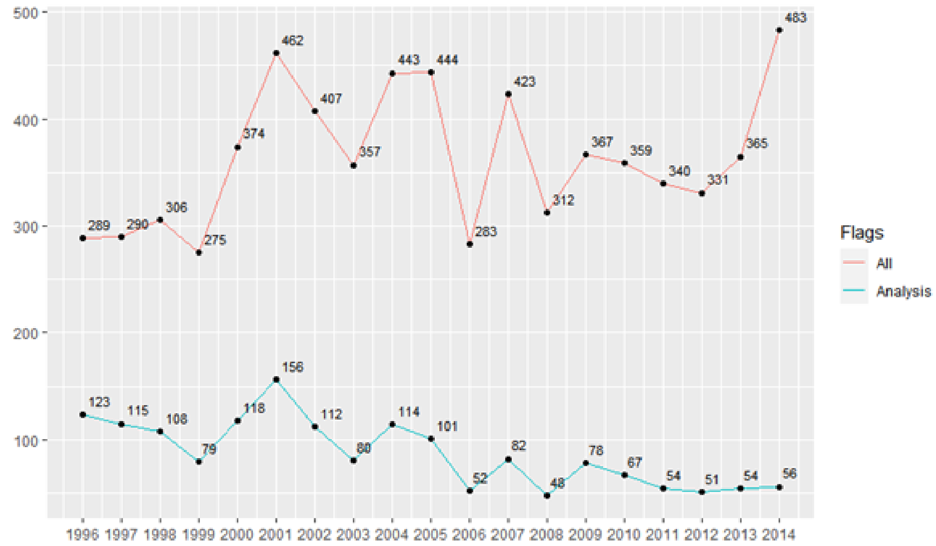

Figure 4.2: Number of organisations experiencing a mass layoff event per year in the 30 per cent sample.

There was a sharp increase in mass layoff events between 1999 and 2001. In 2001, 156 organisations experienced their first mass layoff event, while there were 462 events in total. Figure 2.1 shows a much more moderate increase in unemployment. This may indicate minimal labour market friction during this period and a high turnover rate in the labour market. The mass layoff events are spread evenly across industries. The slowdown in the Asian markets may explain the number of mass layoffs. The early 2000s also saw high expectations for the tech industry, and another possible explanation could be digitalisation.

In 2004 and 2005, the number of mass layoff events and unemployment were high. This may be explained by the minor recession that started at the end of 2002, caused by the tech industry bubble bursting. Still, figure y shows that most mass layoffs happened in the public adm., defence and soc. security industry, as well as the human health and social work activities sector.

The number of mass layoff events and the level of unemployment level were also conflicting in 2007. The level of unemployment was at a low point in 2007, yet there were as many as 423 mass layoff events in my sample. This may again point toward minimal labour market frictions during this period, which was confirmed in the report done by NAV. Almost half of the mass layoffs happened in the human health and social work activities industry. The share of mass layoffs happening in the wholesale etc. industry was also relatively large. At last, the number of mass layoff events spiked in 2014. This coincides with the unemployment rate, which increased in 2014 and onward due to the low oil price.

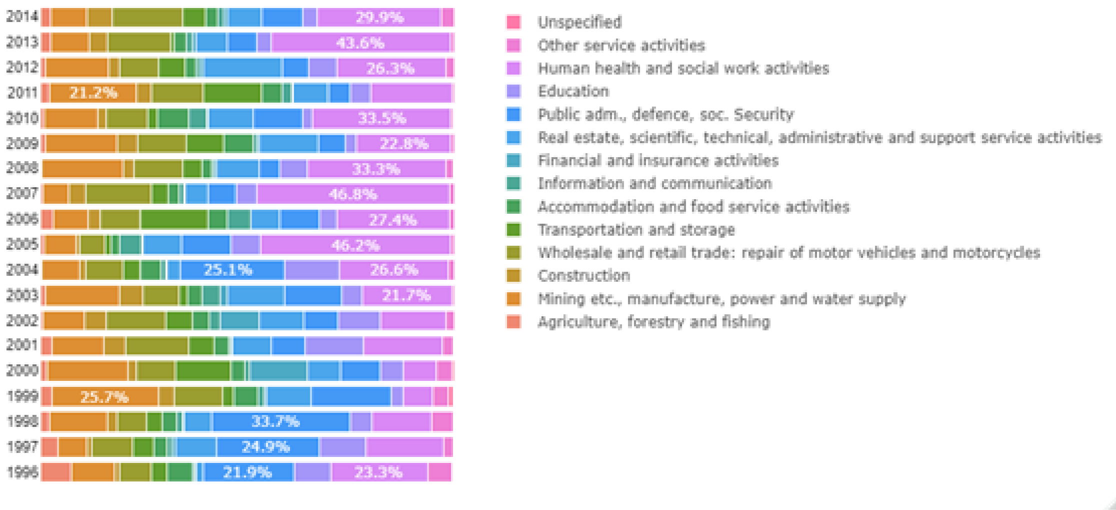

Figure 4.3: Share of mass layoff events per industry in the 30 per cent sample.

Overall, the number of mass layoff events does not overlap the unemployment rate, indicating varying degrees of labour market frictions across the years of scope. It is also worth noting that the public sector seems more susceptible to mass layoff events.

4.4.4 Organisational size

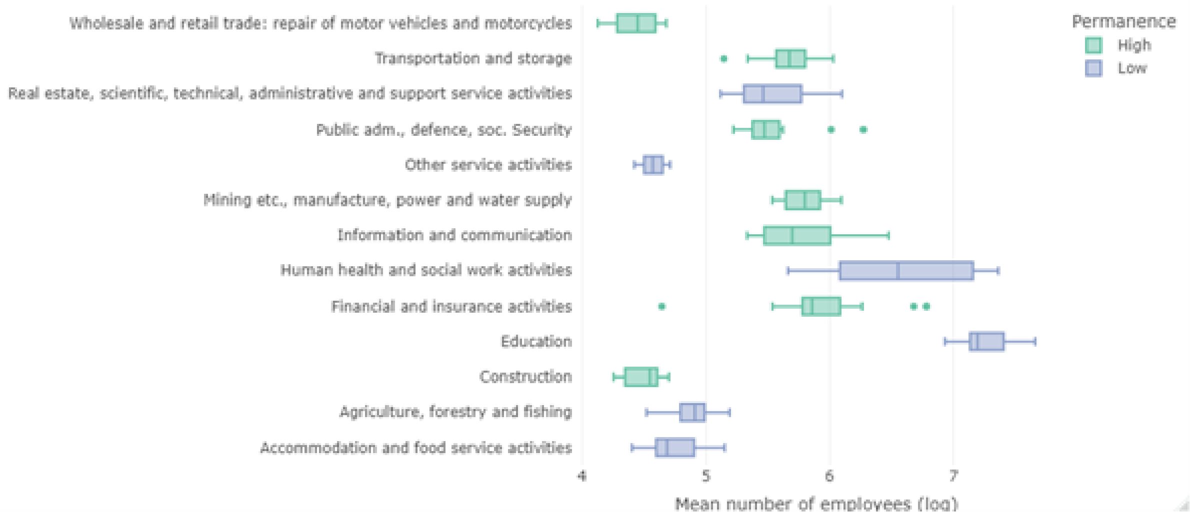

Figure 4.4: Mean log number of employed workers by industry.

The previous figures illustrated which industries experience the largest share of mass layoff events per year. The human health and social work activities, public administration etc., and mining etc. industries were the most prone to experience a mass layoff event. Figure 4.4 shows the log number of employees per industry, coloured by permanence. The figure is of interest because larger organisations require more employees to be laid off for it to count as a mass layoff. This will be further discussed in two of my robustness tests described in Chapters 4.3 and 6.4.

The boxes contain estimations between the first and third quartiles. The highlighted line shows the median value. Whiskers show minimum and maximum values, while the dots are suspected outliers. I have used the log number of employees because of the large spread in data. The largest organisations seem to be concentrated in the education and human health and social work activities industries. There does not seem to be a trend in organisational size between HP and LP industries.

4.4.5 Trends in income

Figure 4.5 is based on the main sample construction and shows employee income trends before and after the mass layoff event. The boxes contain estimations between the first and third quartiles. The highlighted line shows the median value. Whiskers show minimum and maximum values, while the dots are suspected outliers.

Looking at the income trends, we see a negative trend already before the mass layoff year. In the years following the mass layoff, the trend in income seems to be neutral, with a slight increase in the first year after the event. Weighted income is, as expected, generally higher than income. The difference between income and weighted income is larger from year 0 onward. This is likely due to employees being employed fewer days after the mass layoff event.

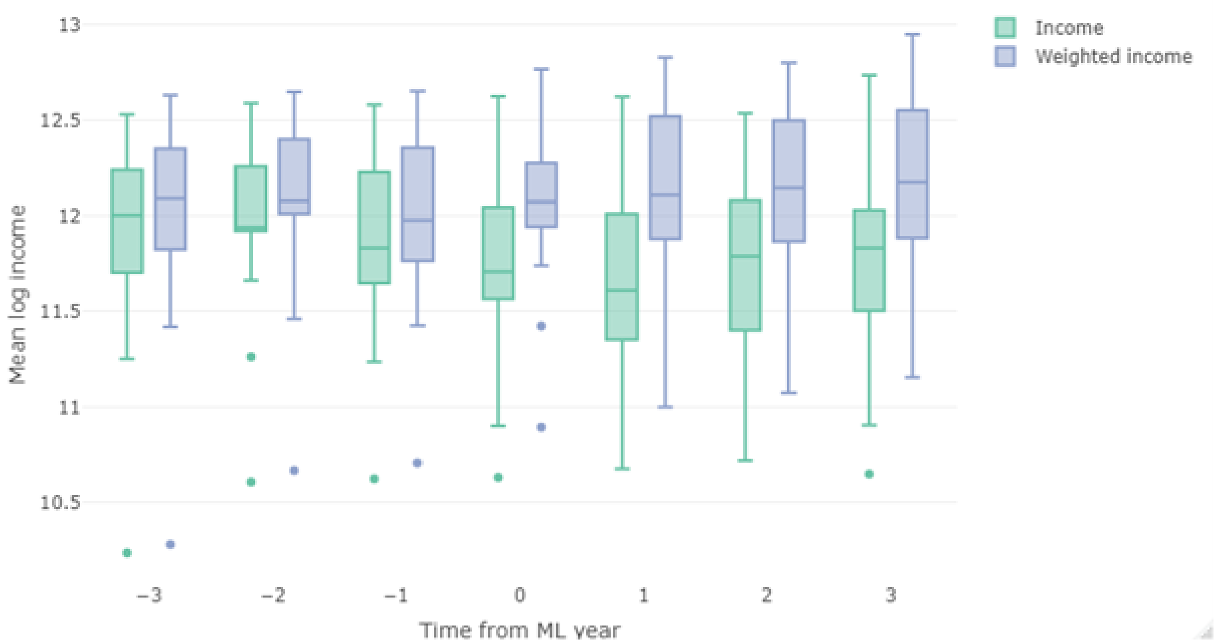

Figure 4.5: Mean log income in years before and after mass layoff event.

Chapter 5

Empirical method

My thesis aims to estimate the impact of a mass layoff in an organisation on its employees' income and re-employment opportunities. Specifically, I wish to examine whether working in an organisation that experiences a mass layoff impacts an individual's income versus if they work in an organisation that experiences no mass layoff events. I will use a dynamic two-way fixed effects regression with a staggered differences-in-differences model design to do so. A dynamic two-way fixed effects specification regresses outcome on individual and time-fixed effects and the relative time from treatment. A staggered difference-in-difference (DiD) design is used if treatment occurs in many groups across many periods. I use a within approach, which compares individuals with themselves at different points in time.

I study the effects of mass layoff events on log income, days employed during a calendar year, and employment status given by a binary indicator which equals 1 if employed, 0 otherwise. If an individual worked in an organisation that experienced a mass layoff event in the years preceding the event, they are defined as treated. This is true regardless of whether they are displaced. The period relative to treatment is given by b, and an individual i receives absorbing[1] treatment at time T_i. The time relative to treatment can then be specified as $T_i = t - b$. The treatment effect is captured by β_b[2]. Outcome y_{it} for individual i at time t is thus given by Equation 5.1:

$$y_{it} = \alpha_i + \gamma_t + \sum_b \beta_b \mathbf{1}\left\{t - T_i = b\right\} + \varepsilon_{it} \tag{5.1}$$

[1]Once an individual is treated, they remain affected by the treatment throughout the whole period.

[2]For b<0, the coefficients (leads) capture any common trends before treatment. For b>0, the coefficients (lags) capture dynamic treatment effects.

The individual effects are given by α_i which are constant over time, and the time effects by γ_t which are constant across individuals, as well as an error term capturing unobserved variables. The model is first used on the full sample selection as specified in 4.2. I then divide the sample by industries, and at last, into HP and LP industries.

5.1 Model assumptions

There are three main assumptions underlying the model. The first is the assumption of parallel trends. The second is the assumption of no anticipation. The average treatment effect of treated can be found if these two assumptions hold. The third assumption states that the treatment effect must be homogenous for lead beta coefficients. In the following paragraphs, I will present the assumptions and briefly discuss whether they hold for my model.

The parallel trends assumption for a staggered DiD states that if there had been no mass layoff in an organisation, the average change in log earnings of individuals working in this organisation would be fully explained by individual and time-fixed effects. In the case of no mass layoffs, individuals with similar characteristics, such as income level or innate abilities, would experience the same income growth trend. Similarly, time-dependent conditions affect treated and non-treated individuals equally:

$$E\left[y_{it}\middle|\ i,\ t\right] = \alpha_i + \gamma_t \tag{5.2}$$

Callaway and Sant'Anna (2021) suggest a slacker version of this assumption. Their alternative states that the parallel trends assumption only holds post-treatment, so there may be heterogenous development in earnings in the years leading up to the mass layoff event. In other words, the log earnings of individuals working in event organisations develop in parallel after the event – but not necessarily before – across all years the event may occur. The benefit of slackening the assumption is that the model may be more likely to capture the treatment effect. However, the beta coefficients may be less precise than in the stricter assumption.

The second assumption states that there is no anticipation. Roth et al. (2023) provide an intuitive definition of the no anticipation assumption: "Units do not act on the knowledge of their future treatment date before treatment starts." As done by Salvanes et al. (2021, p. 16), β_{-3}, β_{-2} and β_{-1} capture any relative trends in income between individuals before the mass layoff event. The results are biased if these relative trends are statistically different from zero, as this would indicate the existence of omitted variables that affect trends in income. I.e., if β_{-3} is negative and statistically significant, then the model would predict that an individual earns less in year t-3 than in year t-1. If both β_{-3} and β_{-2} are negative and statistically significant, then the model predicts a falling trend in income before the mass layoff event happens. If so, the predicted income after the event might be biased. It will be difficult to tell whether the trend is caused entirely by the mass layoff event or if the pre-existing trend continues into the years after the event.

The assumption is not likely to hold. As outlined in Chapter 2.1, most papers on the effects of displacement on earnings find a pre-trend in earnings before the mass layoff event. This is not a surprise. The same circumstances that lead to the adverse economic shock might force organisations to slow down growth in labour costs by reducing growth in salary before displacing the workers fully.

Lastly, the model assumes homogeneity in treatment for years $t < 0$. This assumption is outlined by Sun and Abraham (2021, p. 9 and p. 16), who argue that it is necessary because of the unobserved variables. E.g., two individuals may have different skill levels or be of different ages, which may affect how working in an event organisation impacts their earnings. As has already been laid out in Chapter 2.1, past papers prove that such variables indeed do affect the treatment outcome of an individual.

This assumption is easily violated. It is difficult to find a group of fully comparable individuals who experience the same trends in earnings once they both have been treated. Moreover, even if individuals have similar characteristics, such as skills or age, there may still be time-varying effects that affect their earnings. If one of the comparable individuals experiences a mass layoff in a labour market slump while the other does not, this may lead to different treatment effects even though they are otherwise the same.

5.2 Discussing the model specification and regression design

Several suggestions are presented in the literature on overcoming issues outlined here. As described, my thesis does have shortcomings, and some of these shortcomings are addressed by these modern methods. Given more time, applying them to my work would have been interesting.

Callaway and Sant'Anna (2021) present a method that uses not-yet-treated instead of never-treated individuals as control. Their method aims to overcome the potential issue that never-treated individuals never receive treatment due to individual-varying characteristics. Sun and Abraham (2021) propose an estimation method that will provide robust estimates, even if treatment effects are heterogeneous. The control group is never-treated individuals. The benefit of their method is that it only relies on the parallel trends assumption.

Recall from Chapter 4.2 that only the first mass layoff event observation is kept per organisation, and reoccurring events are removed. This model design reflects a reality in which individuals are only treated once. However, in my raw data, individuals may experience more than one treatment. Consider an "unlucky" individual who works in organisation a that experiences a mass layoff event in the year 1998. The individual is then displaced or quits and starts working in organisation b. Organisation b then experiences a mass layoff at a later point in time. This may create "forbidden" comparisons of individuals who have already been treated, and such comparisons may create negative weighting (Roth et al., 2023, pp. 14-15). Negative weighting would happen if the individual's earnings in organisation b are lower because of the mass layoff event in organisation a. Then it is unclear whether their estimated earnings three years after the mass layoff in organisation b are fully explained by treatment.

Another important shortcoming of this method that has not yet been addressed is absorption, another assumption in dynamic DiD models. An individual who works in an organisation that experiences a mass layoff may not remain in the same organisation forever. They may be displaced, or they may quit willingly in any year. Still, one could argue that the mass layoff event leaves a mark on the individual. An example is a mature individual who is displaced or quits and takes a new job in a different organisation or industry. The individual would then have to learn new skills specific to that organisation or industry. Since they are mature, they will never be fully trained before their pension age.

However, young workers also experience displacement. Recall the study by Kletzer and Fairlie (2003), which found that earning potential for young workers approached the pre-displacement potential after five years. Some individuals may be exceptionally skilled or otherwise attractive in the labour market and can easily find a new job and return to pre-event conditions. Another discussion point I will return to in Chapter 7 is whether displaced workers are randomly chosen. Intuitively, it is reasonable to believe that some workers are displaced while others are not because they are less productive. However, other factors, such as differences in contracts or other legal circumstances, may also have a say in who is displaced instead of skill or ability. Thus, it might not be fully reasonable to assume that all treated individuals are absorbed by treatment.

Chapter 6

Empirical results

6.1 OLS regression results

Results from the first-stage regression have been reported in Table 6.1. It shows the estimated change in the log income and the weighted log income from the year before the mass layoff event. All changes are statistically significant at the 10 per cent level. The F statistic is significant for both income and weighted income, rejecting the null hypothesis that coefficients differ from zero.

The coefficients on income and weighted income point in different directions after the mass layoff event. The weighted income multiplied by the percentage share an individual is employed during a calendar year equals their income. Similar to an hourly rate, it acts as a measure of earnings per time unit spent working. In other words, it measures the income an individual would earn if they had been employed all 365 days a year. The weighted income is relatively stable, which indicates that the compensation per time unit spent working does not change much. However, the OLS model predicts annual income to decrease, which means that the estimated number of days employed also must decrease. Equation 6.1 illustrates this mechanism. I will discuss the estimated change in the number of days employed later in Chapter 6.2.

$$\uparrow weighted\ income_{it} = \frac{\downarrow income_{it}}{\frac{\downarrow\downarrow number\ of\ days\ employed_{it}}{365}} \tag{6.1}$$

Also note that the R-squared is low for both models, indicating that the regression does not explain income variation fully. The R-squared is lower for weighted income than income, so the variation in the weighted log income is explained by variables that do not explain the variation in log income. The number of days employed likely affects both income and weighted income, but the computation of weighted income depends on the number of days employed. Therefore, I have chosen to study changes in income, not weighted income, in my following analyses.

In the year before the mass layoff event, the mean log income for all individuals in the sample is estimated to be 11.871. The model estimates the mean income to decrease by 0.242 log points (or 27.4 per cent) in the year following the mass layoff event, and it continues to decrease in all subsequent years. The standard error equals 0.007 for all years. It estimates the standard deviation of the coefficient on each year, and 95 per cent of observations should fall within a range of plus/minus 0.014 from the estimated coefficients for all years. The residual standard error measures the average error of the prediction and equals 1.381. No agreed-upon threshold determines whether this is a high or low error. However, the lower the residual standard error, the better.

The linear regression model does not consider differences between individuals and changes over time. In the real world, income grows over time due to salary settlements. This will affect the linear regression output because the income at time t+3 experiences (at least) two forces; the effect of the mass layoff, and the income growth over time. As such, the income in years after the mass layoff event is estimated to be higher than it would have been, had the model been corrected for the yearly growth in income. If assuming that the model is otherwise appropriate, then the estimates should be more negative after the mass layoff year, and more positive before. Also, the income varies vastly between individuals. Someone who earns NOK 100'000 might experience a different change in income than someone who earns NOK 1'000'000. For these reasons, I use a two-way fixed effects model as specified in Chapter 5 in my following analyses.

Table 6.1: OLS estimation of the changes in earnings following a mass layoff event, change from year t-1

	Income (log)	Weighted income (log)
	(1)	(2)
t-3	0.117***	0.089***
	(0.007)	(0.006)
t-2	0.089***	0.071***
	(0.007)	(0.006)
t	−0.127***	0.083***
	(0.007)	(0.006)
t+1	−0.242***	0.063***
	(0.007)	(0.006)
t+2	−0.251***	0.053***
	(0.007)	(0.006)
t+3	−0.284***	0.025***
	(0.007)	(0.006)
Constant	11.871***	11.995***
	(0.005)	(0.004)
Individual FE	*No*	*No*
Year FE	*No*	*No*
N	524,417	524,417
R^2	0.012	0.001
Adjusted R^2	0.012	0.001
Residual Std. Error (df = 524410)	1.381	1.216
F Statistic (df = 6; 524410)	1,077.717***	54.252***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

6.2 The consequences of mass layoffs in all industries

Table 6.2: Two-way fixed effect estimation of the changes in earnings following a mass layoff event, change from year t-1

	Income (log)		
	Default SE	Robust SE	Clustered SE
	(1)	(2)	(3)
t-3	−0.049***	−0.049***	−0.049***
	(0.005)	(0.004)	(0.005)
t-2	−0.021***	−0.021***	−0.021***
	(0.004)	(0.003)	(0.004)
t	0.024***	0.024***	0.024***
	(0.005)	(0.005)	(0.005)
t+1	−0.015***	−0.015***	−0.015***
	(0.005)	(0.005)	(0.005)
t+2	0.036***	0.036***	0.036***
	(0.005)	(0.005)	(0.005)
t+3	0.099***	0.099***	0.099***
	(0.005)	(0.005)	(0.005)
Individual FE	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*
N	524,417	524,417	524,417
R^2	0.002	0.002	0.002
Adjusted R^2	-0.432	-0.432	-0.432
F Statistic (df = 6; 365202)	148.332***	148.332***	148.332***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
The robust standard errors in column (2) are Huber-White standard errors (HC1).

Table 6.2 reports how a mass layoff in an organisation affects the log income of its employees, using different standard errors. The regression model design is a two-way fixed effects estimation with individual and time-fixed effects. All estimated coefficients are statistically significant. The F statistic is also significant and rejects the null hypothesis that all coefficients are equal to zero. The R squared is lower than in the linear regression model, indicating that the model explains 0.2 per cent of the variation in data. However, the R-squared criterion is mainly appropriate for OLS models and does not necessarily tell whether the two-way fixed effects model is better or worse than the OLS model used in Chapter 6.1 (Verbeek, 2017, p. 395).

The coefficients on time from the event estimate the expected mean change in log income for all workers who were employed in a mass layoff organisation at time t. The results can be interpreted as a measure of the labour market frictions in the economy following a mass layoff. At time t+3, the income has increased by 0.099 log points (or 10.4 per cent) from year t-1. The sign of this prediction is perhaps surprising. As outlined in Chapter 2.2, most literature finds that displaced workers experience a negative effect on earnings. However, my results include both displaced and non-displaced workers. It could be that the income growth of non-displaced workers is more positive than the income loss of displaced workers. Alternatively, the labour market frictions in Norway are not as severe as first assumed. This would be the case if displaced workers quickly find new occupations, which given the description of the state of the Norwegian labour market in Chapter 2.1 might be reasonable to believe. Also, recall from Chapter 2.2 that estimates in the US were more negative than in Europe, and estimated income in Europe was more negative than in Scandinavia.

The regression output also includes heteroskedasticity-robust and clustered standard errors. Standard errors are heteroskedastic if the variance of the error term is not constant across all observations. The default standard error ranges between 0.004 and 0.005 for all observations. Heteroskedasticity-robust standard errors range from 0.003 to 0.005 and differ from the normal standard errors at times t-3 and t-2. Since normal and heteroskedasticity-robust standard errors are not equal in all years, there may be a model misspecification. The clustered standard errors are equal to the normal standard errors and thus imply is minimal heteroskedasticity across clustered groups.

Table 6.3: Two-way fixed effect estimation of changes in employment status and days employed following a mass layoff event, change from year t-1

	Employment status	Number of days employed
	(1)	(2)
t-3	0.001***	−15.746***
	(0.0002)	(0.408)
t-2	0.0002	−10.126***
	(0.0002)	(0.370)
t	−0.001***	−13.618***
	(0.0002)	(0.392)
t+1	−0.002***	−21.832***
	(0.0002)	(0.401)
t+2	−0.002***	−19.091***
	(0.0002)	(0.411)
t+3	−0.001***	−9.627***
	(0.0002)	(0.428)
Individual FE	Yes	Yes
Year FE	Yes	Yes
N	524,423	524,423
R^2	0.001	0.011
Adjusted R^2	-0.435	-0.421
F Statistic (df = 6; 365208)	43.509***	657.384***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
Employment is indicated with a binary operator equal to 1 if employed, 0 otherwise.

The regression output of the effect of a mass layoff event on employment status and days employed in a year are reported in Table 6.3. Employment status is given by a dummy which equals 1 if the individual is employed, 0 otherwise. The employment status displays no significant pre-trend in the years leading up to the mass layoff event. However, there is a pre-trend in the number of days worked. In year t, 0.1 per cent fewer individuals are employed than in year t-1. The estimated mean number of days employed across all individuals is reduced by about 13.8 days or almost two weeks at time t. Workers continue to work fewer hours all subsequent years. The estimated reduction in employment may cause this, as unemployed individuals will have a negative weight. Alternatively, those employed work fewer days a year. Note that although the estimated expected income increases, the opposite is true for the number of days employed. Individuals may struggle to return to the same level of employment, but this does not seem to affect the compensation for each day employed.

6.3 The consequences of mass layoffs split by industries and level of permanence

Table 6.4 reports how income is affected by a mass layoff event in each industry. The industry names corresponding to the SN2007 NACE codes can be found in Appendix A. All F statistics are significant at the 10 per cent level. Most R-squares are quite low, indicating that variables other than the mass layoff event partly explain the variation in income over time. Such other variables could be present in all years, independent of whether there is a mass layoff. A high R-squared value could therefore imply a less volatile income in times with no adverse shocks to the economy. The highest R-squares can be found in columns (1), (7) and (8), which correspond to the agriculture, forestry and fishing, information and communication and financial and insurance activities industries.

Out of thirteen categories, seven industries exhibit a pre-trend that is significant at the ten per cent level. Out of these, only one industry – mining etc., manufacture, power and water supply – exhibits a pre-trend of a lower income level in year t-1 than in both preceding years. Six of the categories with a pre-trend are HP industries. The only LP industry with a pre-trend is real estate, scientific, technical, administrative and support service activities.

The mass layoff event has a significant effect on the income of eight industries after three years. All significant changes in income are positive from t-1, except in the accommodation and food service activities industry. HP industries experience a more positive change in income than in LP industries. This is in line with **Hypothesis 3**, which states that there are differences between LP and HP industries, and LP industries are worse off.

Results reported in Table 6.5 are split by HP and LP industries and show the same trends as Table 6.4. Both F statistics are significant at the 10 per cent level, and a null hypothesis stating that all coefficients are equal to zero can be rejected. At time t-3, both HP and LP industries experience a growth in earnings from year t-1. The growth is stronger in HP industries than in LP industries, at 0.127 log points (13.5 per cent) and 0.072 log points (7.47 per cent), respectively. Earnings in HP and LP industries are 0.024 log points (2.42 per cent) and 0.032 log points (3.25 per cent) higher in the mass layoff year than in the preceding year. Then the change in earnings from t-1 drop by 0.004 log points (0.40 per cent) in HP industries and 0.017 log points (1.71 per cent) in

LP industries in year t+1. This is the only year in which workers experience a decrease in earnings following a mass layoff event.

Figure 6.1 visualizes the effects. The dots indicate the estimated values while the bars show the standard errors. HP industries seem to follow a clear trend of increasing earnings both before and after the mass layoff event. The trend is thus most likely partly explained by other factors than the mass layoff event. The mass layoff does however cause a setback in year t+1, which may have affected the rate of earnings growth in the subsequent years. LP industries also experience an increasing trend in earnings in years before and after the mass layoff event, although not as steep.

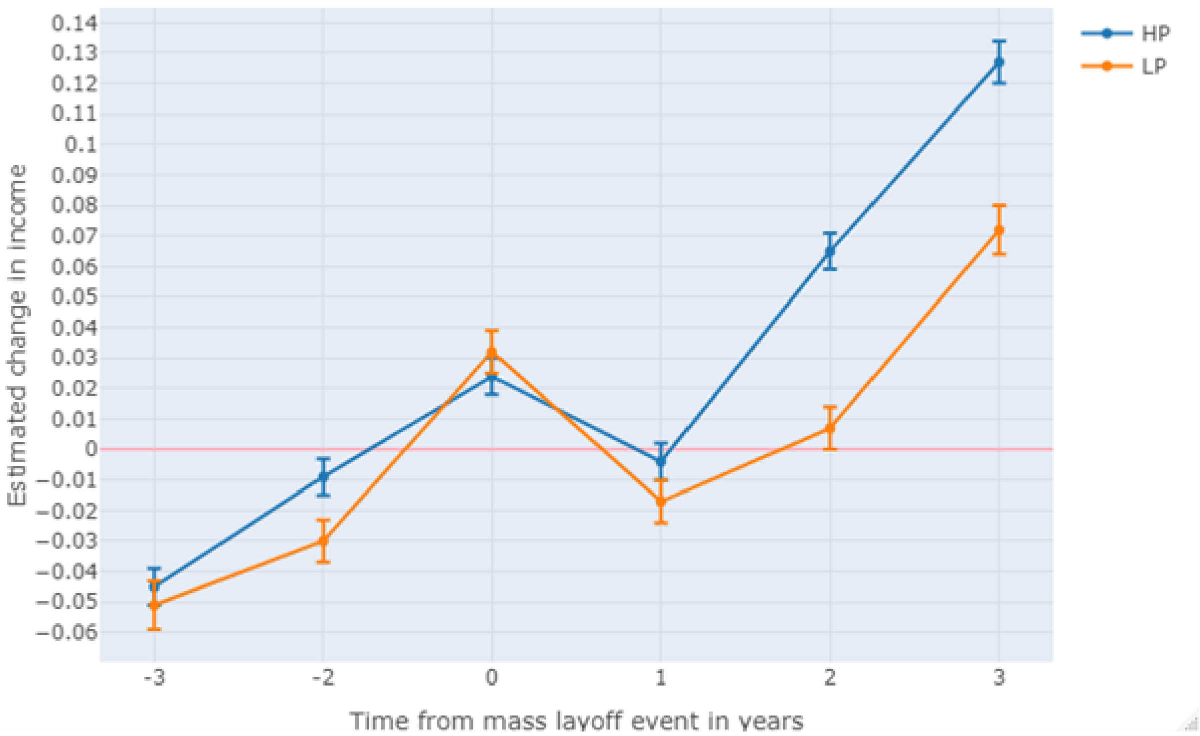

Figure 6.1: Change in income from year t-1, split by HP and LP industries.

Table 6.4: Two-way fixed effect estimation of the changes in earnings following a mass layoff event by industry (SN2007), change from year t-1

	Income (log)												
	01-03	05-39	41-43	45-47	49-53	55-56	58-63	64-66	68-82	84	85	86-88	90-99
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
t-3	0.049	0.098***	−0.078***	−0.094***	−0.086***	0.026	−0.135***	−0.126***	−0.067***	−0.170***	−0.031**	−0.053***	−0.088**
	(0.061)	(0.011)	(0.022)	(0.017)	(0.019)	(0.031)	(0.018)	(0.020)	(0.020)	(0.015)	(0.014)	(0.011)	(0.038)
t-2	−0.033	0.104***	−0.067***	−0.065***	−0.050***	−0.050*	−0.115***	0.013	−0.111***	−0.070***	0.012	−0.022**	−0.006
	(0.050)	(0.010)	(0.020)	(0.015)	(0.017)	(0.027)	(0.017)	(0.019)	(0.018)	(0.013)	(0.013)	(0.009)	(0.035)
t	−0.312***	0.088***	0.037	0.008	−0.213***	−0.115***	0.031*	0.101***	−0.007	0.066***	−0.020	0.112***	−0.176***
	(0.043)	(0.011)	(0.023)	(0.016)	(0.018)	(0.027)	(0.016)	(0.019)	(0.018)	(0.013)	(0.015)	(0.010)	(0.037)
t+1	−0.216***	0.093***	−0.072***	−0.072***	−0.114***	−0.100***	−0.008	0.121***	−0.076***	−0.053***	0.059***	−0.007	−0.113***
	(0.041)	(0.011)	(0.023)	(0.016)	(0.019)	(0.029)	(0.018)	(0.019)	(0.019)	(0.014)	(0.014)	(0.010)	(0.037)
t+2	−0.384***	0.170***	0.009	−0.038**	−0.032	−0.078**	0.012	0.135***	−0.054***	0.033**	0.120***	0.009	−0.031
	(0.042)	(0.011)	(0.023)	(0.017)	(0.020)	(0.031)	(0.019)	(0.021)	(0.020)	(0.014)	(0.015)	(0.010)	(0.039)
t+3	−0.487***	0.243***	−0.022	0.006	0.039*	−0.099***	0.168***	0.215***	0.063***	0.094***	0.228***	0.066***	0.055
	(0.045)	(0.012)	(0.024)	(0.018)	(0.021)	(0.033)	(0.020)	(0.022)	(0.022)	(0.015)	(0.015)	(0.011)	(0.040)
permanence	*Low*	*High*	*High*	*High*	*High*	*Low*	*High*	*High*	*Low*	*High*	*Low*	*Low*	*Low*
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	6,810	77,465	17,553	42,615	31,374	18,884	13,971	10,728	38,567	59,885	47,465	145,490	10,685
R^2	0.037	0.008	0.004	0.002	0.010	0.003	0.028	0.032	0.004	0.009	0.010	0.003	0.006
Adjusted R^2	-0.510	-0.376	-0.503	-0.487	-0.507	-0.676	-0.481	-0.308	-0.665	-0.545	-0.411	-0.438	-0.479
F Statistic	27.958*** (df = 6; 4342)	76.161*** (df = 6; 55839)	7.220*** (df = 6; 11636)	11.719*** (df = 6; 28593)	36.255*** (df = 6; 20597)	5.153*** (df = 6; 11237)	43.880*** (df = 6; 9170)	43.604*** (df = 6; 7941)	15.990*** (df = 6; 23069)	57.554*** (df = 6; 38414)	55.046*** (df = 6; 33314)	48.076*** (df = 6; 100901)	7.682*** (df = 6; 7178)

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6.5: Two-way fixed effect estimation of the changes in earnings following a mass layoff event split by HP and LP industries, change from year t-1

	Income (log)	
	High permanence	Low permanence
	(1)	(2)
t-3	-0.045^{***}	-0.051^{***}
	(0.006)	(0.008)
t-2	-0.009	-0.030^{***}
	(0.006)	(0.007)
t	0.024^{***}	0.032^{***}
	(0.006)	(0.007)
t+1	-0.004	-0.017^{**}
	(0.006)	(0.007)
t+2	0.065^{***}	0.007
	(0.006)	(0.007)
t+3	0.127^{***}	0.072^{***}
	(0.007)	(0.008)
Individual FE	*Yes*	*Yes*
Year FE	*Yes*	*Yes*
N	253,591	267,936
R^2	0.004	0.002
Adjusted R^2	-0.445	-0.475
F Statistic	115.109^{***} (df = 6; 174795)	48.592^{***} (df = 6; 181386)
Notes:		***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 6.6: Two-way fixed effect estimation of the changes in days employed following a mass layoff event split by HP and LP industries, change from year t-1

	Number of days employed	
	High permanence	Low permanence
	(1)	(2)
t-3	-15.409^{***}	-16.801^{***}
	(0.587)	(0.593)
t-2	-10.816^{***}	-9.131^{***}
	(0.530)	(0.527)
t	-16.597^{***}	-9.719^{***}
	(0.547)	(0.569)
t+1	-22.696^{***}	-19.030^{***}
	(0.566)	(0.575)
t+2	-19.884^{***}	-17.269^{***}
	(0.585)	(0.585)
t+3	-10.833^{***}	-6.923^{***}
	(0.616)	(0.606)
Individual FE	*Yes*	*Yes*
Year FE	*Yes*	*Yes*
N	253,594	267,939
R^2	0.012	0.009
Adjusted R^2	-0.433	-0.463
F Statistic	351.696^{***} (df = 6; 174798)	288.284^{***} (df = 6; 181389)
Notes:		***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table 6.6 reports the estimated change in days worked in HP and LP industries. Three years after the mass layoff event, those employed at time t in HP and LP industries worked 10.8 and 6.9 fewer days than in year t-1, respectively. This is interesting since estimated earnings have increased, which implies one of two things. Either expected weighted earnings increase significantly after a mass layoff event so that workers earn more for the same amount of work. Alternatively, some individuals struggle to find new employment and have a negative weight in the number of days employed. At the same time, the expected earnings of non-displaced employees increase enough to offset the lost earnings of displaced employees.

The overall level of employment is the highest in the year before the mass layoff event. In both HP and LP industries, there is a pre-trend in the years preceding t-1 of an increase in the expected number of days employed. The increase is steeper in LP industries than in HP industries. Then, the expected number of days employed falls in year t to about the same level as in year t-3 for HP industries. A reduction in the expected number of days employed reflects layoffs, displacements, or reduced hours worked per week. The fall in the expected number of days employed in year t is also less severe in LP than in HP industries. The years following year t provide a measure of labour market frictions after a mass layoff event. In both industries, the expected number of days employed continues to fall in year t+1, then slightly increases in year t+2 before experiencing an upturn in year t+3. The results correspond with **Hypothesis 4**, as HP industries are worse off regarding the number of days employed. Note that the opposite was true in terms of earnings. This might suggest that skills in HP industries are not as transferrable but that earnings of those who do not experience a displacement steadily increase despite the mass layoff event. On the other hand, there may be low hiring costs in the Norwegian labour market, which makes short-term employment more accessible than long-term employment.

6.4 Testing the robustness

Table 6.7: Robustness tests

	Income (log)			
	Main results	Full-time employees	Alt. flag criteria	Public sector industries
	(1)	(2)	(3)	(4)
t-3	−0.049***	−0.092***	−0.079***	−0.028***
	(0.005)	(0.005)	(0.004)	(0.006)
t-2	−0.021***	−0.057***	−0.030***	0.003
	(0.004)	(0.004)	(0.004)	(0.006)
t	0.024***	−0.047***	0.015***	0.072***
	(0.005)	(0.005)	(0.004)	(0.006)
t+1	−0.015***	−0.047***	−0.069***	0.014**
	(0.005)	(0.005)	(0.004)	(0.006)
t+2	0.036***	0.041***	0.023***	0.069***
	(0.005)	(0.005)	(0.004)	(0.006)
t+3	0.099***	0.127***	0.077***	0.135***
	(0.005)	(0.005)	(0.004)	(0.006)
Individual FE	*Yes*	*Yes*	*Yes*	*Yes*
Year FE	*Yes*	*Yes*	*Yes*	*Yes*
N	524,417	344,727	644,335	330,305
R^2	0.002	0.010	0.003	0.003
Adjusted R^2	-0.432	-0.457	-0.290	-0.411
F Statistic	148.332*** (df = 6; 365202)	375.188*** (df = 6; 234342)	287.415*** (df = 6; 497650)	126.453*** (df = 6; 233352)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 6.7 reports results from the robustness tests and compares them to the main results reported in Table 6.2. All F statistics are significant. About 65.7 per cent of individuals included are full-time employed. Full-time employees experience the same pre-trend of an already increasing income in years before t-1. However, the estimated income decreases instead of increases in the mass layoff event year. The estimated increase in the full sample is therefore likely to be driven by changes in the income of part-time employees. The estimated income continues to decrease in year t+1, before increasing in year t+2 and t+3. Once the trend turns, the increase in income is steeper for full-time employees than for all employees. A possible explanation is that labour market frictions are stronger for full-time employees than for part-time employees in the first couple of years following a mass layoff event.

The alternative criterion includes all mass layoff events that affect 500 or more workers in each firm. Thus, this regression includes almost 120'000 individuals more than the main regression. The larger sample size has lowered the standard erors somewhat. The coefficients on time from event are mostly similar to the main results, and all point in the same direction. In year t-1, the estimated income is lower than in the main results, and recovery in time t+2 and t+3 is also slower. Individuals included in this sample are therefore estimated to experience a larger reduction in income than in the main sample. The sample consists of the exact same individuals as the main sample, plus some employed in large organisations before the mass layoff event. One might therefore interpret the results as employees in larger organisations experiencing worse labour market frictions. This makes sense if large organisations are responsible for a large share of the labour demand within the industry. If such a large organisation experiences a mass layoff, displaced workers might find fewer alternative organisations when searching for new employment. The larger the share of labour demand within an industry, the larger the labour market friction a worker would experience once displaced. Individuals working in large firms may experience severe frictions regardless of whether their skills are industry-specific or firm-specific, since the firm is a large actor within the industry category.

Recall that the public sector sample selection is found by identifying industries characterised by a large share of employees employed in the public sector, as described in Chapter 4.3.2. This might explain why such a large share of individuals is included in the public sector sample selection. The public sector shown in column (4) does not seem to exhibit the same pre-trend as the joint regression results of the public and private sector shown in column (1). The estimated difference in income in year t-3 is much smaller than in the other columns. In year t-2, the estimated coefficient is not significant. This implies that the pre-trend is mainly experienced in the private sector. The public sector is also the only sample selection which does not experience a negative impact on income after the mass layoff event.

Figure 6.2 visualises the comparison between the main and robustness test results. Again, dots indicate estimated values, and bars show the standard errors. The figure illustrates the same pre-trend in the robust samples as in my main results. Again, the pre-trend is likely partly caused by omitted variables. However, the pre-trend for full-time employees is noticeably flatter than for the other sample sections, which indicates that using this sample selection may produce less biased results.

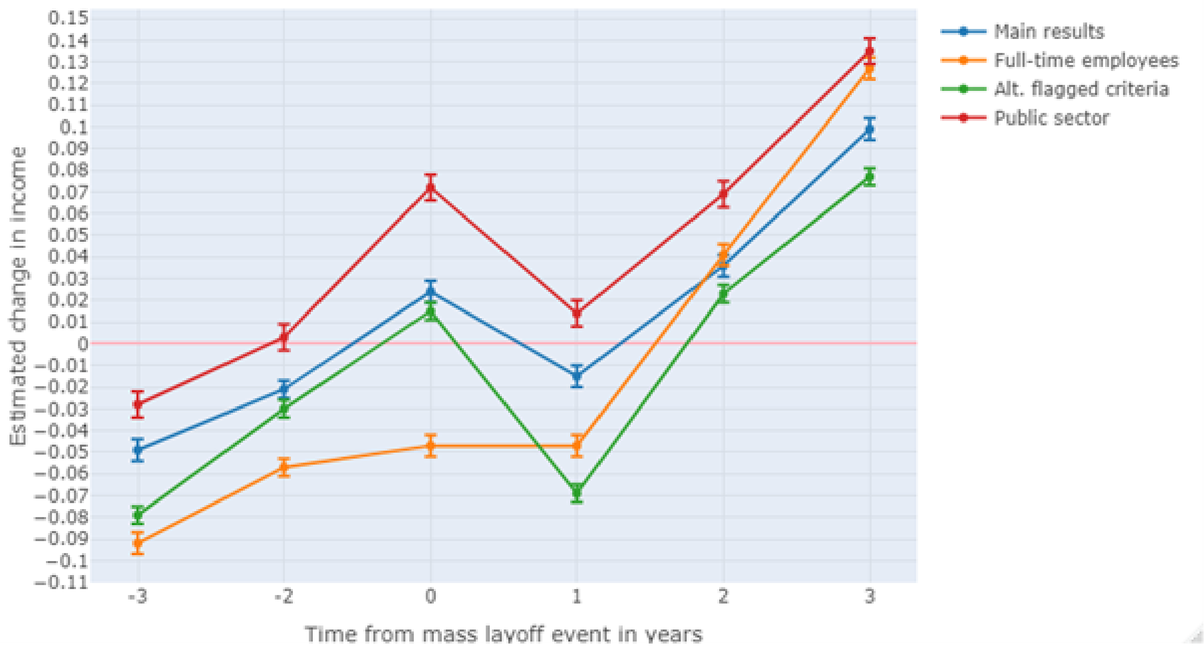

Figure 6.2: Change in income from year t-1, main vs. robust results

Chapter 7

Discussion

Although I have discussed most issues with my method in the previous chapters, a few worth noting remain. Some of these problems are more severe than others. However, given the time and resource constraints of a master's thesis, I will only discuss their consequences rather than attempt to make any adjustments.

As outlined, there is more than one way to define a mass layoff event. And, once defined, it might be difficult to know whether the reduction in the number of employees is caused by displacements. Cahuc et al. (2014, p. 570) outline four reasons employees might stop working in an organisation. These are voluntary resignments, retirements, being fired because of performance or other employee-specific factors, and displacements caused by adverse shocks to the organisation. Given my raw data, it is impossible to distinguish why a job loss happens, and there will likely be instances where employees lose their jobs for reasons other than displacement. The smallest number of employees laid off from an organisation for it to be flagged is six employees. It is reasonable to assume that cases where six or more workers lose their jobs for reasons other than displacement are few and far between. A consequence of overestimating the number of flagged organisations is that employees who leave for other reasons may have different expected earnings potential and potential for re-employment. If an organisation lays off five workers while a sixth decides to quit, then this sixth employee may have different characteristics than the other five, such as more or less education. This problem could bias the estimates if large enough.

Another issue with flagging mass layoffs is that organisations in LP industries may have a higher threshold for laying off workers than in HP industries. Different laws and regulations may exist regarding displacing workers in HP and LP industries. Also, organisations in LP industries may choose to partially or fully temporarily lay off their employees instead. This is especially true if economic circumstances force organisations to lay off some employees, even though their skills are valuable. If LP industries have stricter criteria for laying off workers, this could be reflected in the estimates on earnings potential. My estimates show that LP industry workers indeed are worse off, but this could be due to biased selection in which organisations are flagged. However, one could also interpret the results as the consequences of a mass layoff once it has occurred.

A third source of selection bias is the selection of which workers that are permanently employed or not. As outlined in Chapter 2.2, there are indeed differences between the workers employed under short-term and long-term contracts. A relatively large percentage of short-term workers are women and highly educated individuals. Such characteristics may affect their ability to return to their original potential earnings path, as well as their attractiveness on the labour market. Lastly, individual characteristics may also affect which workers are chosen for displacement. This may also depend on the reason for the displacement. If the organisation needs to cut the budget, they may choose to lay off the costliest employees. Other organisations may instead find a measure on the productivity of all their employees and lay off those that are the least productive. Sometimes, the employees could simply be picked based on their relationship with the manager doing the bidding.

Chapter 8

Conclusion

In this thesis, I have explored the relationship between mass layoff events and labour market frictions. Changes in income earned and days employed a year have been used to measure labour market friction in the years surrounding the event. My sample selection was produced from a panel of employer-employee relationships between 1995 and 2014. I used a two-way fixed effects model to estimate how a mass layoff impacts earnings and employment, controlling for individual- and time-fixed effects.

My results show that a mass layoff reduces earnings in the first year after the event. In the following years, the estimated expected change in earnings stabilises and turns positive. The expected number of days employed falls in the years after the mass layoff event, along with the level of employment.

I have then split the sample by high-permanence (HP) and low-permanence (LP) industries. I find that LP industries are worse off after a mass layoff event in terms of income. However, the income in both LP and HP industries is only expected to decrease in the first year after the mass layoff event. In terms of the expected number of days employed, HP industries are worse off. A possible explanation is that displaced employees in HP industries do not find new employment as easily as in LP industries, possibly because of specialised skills. However, non-displaced workers in HP industries may have a more stable earnings path. If the results are split by industry, we see that the pre-trends in HP industries are stronger than in LP industries. This might support the conclusion that the expected earning path in HP industries is more robust and that the impact of the mass layoff is less severe.

A suggestion for future research on how contract performance affects the consequences of a mass layoff is to bring in the level and nature of skills that Norwegian workers possess. Also, I suggest a more sophisticated mapping of short-term contracts. The method of the median of means is simple, and a more refined technique could perhaps further distil the role of contract permanence.

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Appendix

A SN2007

The following table shows which NACE codes correspond to which industries, as well as the category index I have given them.

Category	SN2007	Industry name
	00-99	All industries
1	01-03	Agriculture, forestry and fishing
2	05-39	Mining etc., manufacture, power and water supply
3	41-43	Construction
4	45-47	Wholesale and retail trade: repair of motor vehicles and motorcycles
5	49-53	Transportation and storage
6	55-56	Accommodation and food service activities
7	58-63	Information and communication
8	64-66	Financial and insurance activities
9	68-82	Real estate, scientific, technical, administrative and support service activities
10	84	Public adm., defence, soc. security
11	85	Education
12	86-88	Human health and social work activities
13	90-99	Other service activities
14	00	Unspecified