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The effect of local labour demand on disability insurance uptake

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Abstract

This thesis explores the relationship between local labour demand and the uptake of disability insurance (DI) in Norway. We employ a Bartik shift-share instrumental variable approach to perform an empirical analysis into the causal relationship between local labour demand and DI uptake. The empirical strategy exploits variation in industry composition between different localities in Norway and calculates local industry shares. The industry shares are interacted with the national employment growth in the different industries to construct an instrument for local labour demand and identify a causal relationship. Our main contributions to existing research consist of an exploration into the heterogeneous impact for different demographic groups. We also conduct an extensive descriptive analysis of the welfare careers of those who later become DI recipients, based on microdata.

The descriptive analysis shows that individuals who later take up DI often have a history of previous benefit uptake, and to a much larger extent than the general population take up both health-related benefits and labour market related benefits. Even ten years prior to the start of a disability insurance spell, individuals were more likely to take up both unemployment insurance and sickness benefits.

The empirical analysis finds that for the general population, a 1% decrease in local labour demand leads to a 0.852% increase in DI uptake. The effect is stronger for women than for men, possibly explained by the fact that women in general are more elastic than men when it comes to labour supply. However, the estimated elasticities by gender are not statistically significantly different from one another. For the different age groups, we uncover a U-shaped pattern with a stronger effect for those in the 30-40 and 40-50 age groups than for the under 30- and over 50 age groups. The different age group results are inconclusive as several are not statistically significant, nor are the results statistically significantly different from one another. All our empirical analysis results are consistent and robust using several robustness checks.

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1. Introduction

The increasing uptake of disability insurance (DI) in Norway has become a prominent topic in public debates, raising concerns about the fairness, efficiency, and sustainability of welfare programs. Understanding what drives the increase in uptake, and how different factors affect the probability of taking up DI can inform policy and reduce the costs of the program.

Over the last years, Norway, as other OECD countries, has had an aging population. The ratio of those who pay taxes to those who receive benefits has continued to decline and policymakers have emphasised the importance of having a high participation in the labour market (Ministry of Finance, 2021). Simultaneously, over 10% of the working age population is receiving some level of DI, and the Norwegian disability insurance scheme has grown to a cost of 118 billion kroner, almost 7% of the 2023 government spending (Ministry of Finance, 2022).

Previous research has shown that while some individuals on DI have pre-existing conditions or objectively observable symptoms, there is a group of marginal DI recipients whose entry into the program might be influenced by factors beyond health alone (Rege et al., 2009). Individuals who become DI recipients have lower socioeconomic status than the general population, and previous research has pointed to the connection between labour market difficulties and the uptake of DI (Autor & Duggan, 2003; Andersen et al., 2019; Bratsberg et al., 2013; Rege et al., 2009). Understanding how the system interacts with these individuals through different benefit programs before the beginning of the DI spell, and whether their labour market participation could be increased, can inform policy for a reduced cost of the program.

The theoretical framework that explains why there would be a connection between employment and DI uptake describes the connection as consisting of a health effect, an effect related to expected future earnings, and the interaction between them (Autor & Duggan, 2003). Both American and Norwegian studies building on this theoretical framework find that there is a negative relationship between employment and DI uptake (Andersen et al., 2019; Autor & Duggan, 2003, Charles et al., 2018). The results differ in size between countries and estimation methods, but the signage is consistently negative.

To the best of our knowledge this topic has not been widely researched using a labour demand perspective in Norway, but mostly through job displacement analysis. We expand on the previous research by using microdata to perform a descriptive analysis of the welfare careers of those who later become DI recipients, contributing to the understanding of the context of different benefit programs in Norway. Furthermore, by employing a labour demand perspective to the empirical analysis, we also expand on the understanding of the interaction between employment and DI uptake in Norway. Our empirical analysis contributes to the existing literature by being based on updated and modern data and examining heterogenous effects between different demographic groups.

Our research question is:

How does local labour demand affect the uptake of disability insurance?

We investigate this effect for different demographic groups, to examine whether there is a differential effect dependent on age and gender.

We employ a Bartik shift-share instrumental variable approach. This empirical strategy exploits variation in industry composition across locations and isolate demand by interacting these with national growth rates. Our data is aggregated to the commuting zone level, and is primarily retrieved from microdata.no, a public database owned and developed by Sikt and Statistics Norway (SSB).

Based on previous research, we expect to find a significant negative impact of decreased labour demand on the uptake of DI. Research from Norway has found stronger results for men than for women, and stronger results for the youngest and oldest age groups (Bratsberg et al., 2013). We would also expect strong results for the youngest age groups as they are less connected to the labour market and have less work experience. The individuals in the oldest age groups are likely of more marginal health, and the impact of local labour demand on DI uptake would therefore be higher.

We find consistent and robust results for both the general population and the gender sample splits. For the general population we find that a 1% decrease in local labour market demand leads to a 0.852% increase in disability insurance uptake. These results are driven by the female population with an elasticity of -1.343, while the male elasticity is -0.687. However, the coefficients are not statistically significantly different from one another. The results for the different age groups are more inconclusive. The different age groups include 18-30, 30-40, 40-50 and 50-67. The results reveal a U-shaped pattern; however, they are not statistically significantly different from one another. Furthermore, the youngest age group has results not statistically significantly different from zero and we cannot conclude that there is a negative causal relationship between labour demand and DI uptake for this group. The 30-40 age group is significant at the 10% level and the over 50 age group is significant at the 5% level, with elasticities of respectively -1.165 and -0.837. This is contradictory to the results we expected.

This thesis is organised in the following way. In chapter 2 we present relevant literature, firstly looking at a theoretical model for the connection between unemployment and DI, before presenting previous empirical results from Norway and the US. The next chapter presents the institutional background, to familiarise the reader with Norwegian social insurance programs and their different components. In chapter 4 we present the data used in both the descriptive- and empirical analysis.

In chapter 5 we present the results of a descriptive analysis, focusing on the development of uptake of DI over the last 20 years, in general and for different demographic groups. We also present the welfare careers of individuals who later become DI recipients, providing useful context for later analysis. Chapter 6 explains the Bartik shift-share instrumental variable strategy and its identifying assumptions.

Finally, in chapter 7, we present the results of the analysis and the estimates of the elasticity of DI in response to changes in local labour demand. Furthermore, we discuss the results, their robustness and policy implications before concluding in chapter 8.

2. Literature Review

The interconnectedness between disability insurance uptake and employment has been a prominent focus of research within labour economics for the last decades. In this section we present a summary of relevant literature which has examined disability insurance and the labour market, and the heterogenous impact of employment and labour markets on DI uptake within different groups.

Firstly, we present a theoretical framework that can be employed to understand why there is a connection between DI uptake and employment. Additionally, we point to previous studies that have identified different channels and situations in which decreased labour demand and unemployment could increase the uptake of DI. Thereafter we discuss Norwegian studies that have examined DI and employment. Finally, we present results from American studies, which provide an interesting point of comparison as they have applied the same empirical strategy as us.

2.1 Theoretical framework

Autor and Duggan develop a theoretical framework for the individual's decision to take up DI in their 2003 paper *The Rise in Disability Rolls and the Decline in Unemployment*. The authors assume there are three different types of individuals: those that quit their job to apply for DI, those that apply conditional on a job loss, and those that never apply, regardless of job loss. The model explains how an individual will maximise his discounted expected income from either work or DI, given the individual's health, the probability of job loss, the DI benefit level, and the probability of reemployment in the case of job loss. They outline that the expected future income from work is reduced in the case of job loss as an additional job search cost ensues. This decreased value of work income will reduce the opportunity cost of seeking DI instead. The authors emphasise that the conditional applicant group will be elastic to both the benefit supply, labour demand, and the interaction of the two.

This theoretical framework is further developed by Rege, Votruba and Kjelle (2009) who examine the impact of plant-downsizing on the uptake of DI among Norwegian workers. The theoretical framework is modified to only examine the impact of downsizing, meaning the demand side, and not the supply side of DI. According to the framework, there are two primary reasons why downsizing drives the demand for DI; a reduction in expected future earnings, and a health effect from downsizing. Newly unemployed individuals will have to endure a search cost associated with acquiring a new job. If the individual has poor chances in the labour market, the job search costs will increase and the relative cost of leaving the labour market will consequently decrease. In the situation where the individual is of marginal health, it is possible that the costs of a DI application are less than that of a job search.

The direct health effect from being let go is disputed, with a causal link being difficult to identify. A 2009 Swedish study exploits administrative register data in combination with information about plant closures. It identifies a causal connection between job loss and mortality, but find only significant results for men, and for alcohol-related deaths and suicides (Eliason & Storrie, 2009). Other research has found that unemployment accelerates physical health deterioration, but that the worse mental health of the unemployed is likely due to selection bias and not unemployment (Stauder, 2018). On the other hand, meta-analysis done on 237 cross-sectional and 87 longitudinal studies conclude that unemployment causes increased mental distress (Paul & Moser, 2009). Hence, the causal effect is disputed, but stating that both unemployment and job loss are correlated with worse mental and physical health is uncontroversial.

An additional consideration for the health effect is the impact of losing a source of work that takes an individual's health issues into consideration. A marginal worker, with previous health problems not completely debilitating for work, may struggle to get a new source of employment and rather choose to apply for DI. The job search cost for an individual of marginal health is therefore higher due to the increased difficulty of finding appropriate labour market opportunities.

The health effect and the change in expected future earnings explain the behaviour of the conditional applicants, however the system design and the interaction with social workers will also impact the potential uptake of an individual. Social workers tasked with evaluating applicants have knowledge about the local labour market opportunities and the applicant's possibilities within these markets. In cases with poor labour market conditions, social workers may feel badly and grant disability insurance more easily (Charles et al., 2018). In Norway, social workers also report feeling a responsibility to secure stable income for young individuals who have not been able to participate in the labour market, and more often approve them for DI (Ekelund, 2022). Thus, the interaction with social workers, and their knowledge of local labour market conditions, may be another reason why local labour conditions impact the uptake of DI.

2.2 Norwegian studies

Descriptive evidence from a 2006 report by the Frisch centre estimate that approximately 5% of the new DI uptake in the period 1993 to 2003 can be explained directly by downsizing in Norwegian business between 1992 and 2002 (Fevang & Røed, 2006). This estimate is found by examining the newly disabled, and whether they have experienced significant downsizing prior to the start of their DI spell. The authors note that their estimate is likely conservative compared to the actual results, as several individuals may have switched jobs prior to the downsizing. Furthermore, they find that 20% of the people who went on DI in 2002 were either unemployed or on some type of social insurance ten years prior (Fevang & Røed, 2006).

A more formal analysis of the impact of downsizing on DI uptake was done by Rege, Telle and Votruba in their 2009 paper *The Effect of Plant Downsizing on Disability Pension Utilization*. The paper utilises microdata for all Norwegian individuals between 1992 and 2003 and information on plant events, such as downsizing, to estimate the probability that a full-time employed individual in 1995 would be on DI in 2001. The paper finds that workers originally employed in plants that downsized more than 60% between 1995 and 2000 were 24% more likely to utilise DI than their counterparts in non-downsizing plants. The authors conclude that it is likely that the increased uptake comes from both the reduced expected earnings- and the health effect. Furthermore, they find that the effect of job displacement on DI uptake is largest for those of marginal health and old age.

Bratsberg et al. (2013) uses firm bankruptcy data to quantify the amount of Norwegian DI claims that can be directly related to employment shocks and opportunities. They employ historical data from 1992 to 2007 to the job search theory explained in Autor and Duggan (2003) and Rege et al. (2009). Furthermore, they draw on the findings in Huttunen et al. (2011), that document that job loss indeed leads to reduced expected future income in Norway. They find that displacement raises the permanent disability program propensity for men with 2.6 percentage points and by 1.6 percentage points for women six years after being displaced (Bratsberg et al., 2013).

Although previously shown in other studies, the Bratsberg et al. (2013) paper further emphasises how DI may be a result of unemployment; not due to changes in health, but rather due to a substitution effect. The authors note that the reported health in the population has increased over the last years with the DI uptake rates increasing simultaneously. This supports the notion that not all increases in disability insurance uptake result from health shocks; some are instead attributed to the decline in the individual's employment opportunities. Importantly, their analysis is limited to private-sector employees which leads to an overrepresentation of men, potentially biasing their results. To conclude, Bratsberg et al. (2013) state that the close causal link between employment opportunities and DI shows that these in some cases are substitutes.

All papers focusing on downsizing are impacted by the risk of selection bias as those who are displaced from businesses may not be similar to those who are not displaced. Selection bias can both over- and underestimate the results. As mentioned in Claussen et al. (2013), it is common in Norwegian businesses that the last to be employed are the first to be let go. This could lead to an underestimation of the results, if we assume that the “last in” are younger, healthier, and more able to adapt to the labour market changes. The results could also be overestimated in the cases where businesses take advantage of the downsizing to let inefficient or less healthy individuals go (Claussen et al., 2013).

Andersen et al. (2019) is to our knowledge the first study to employ the Bartik-type shift-share instrument method to investigate the relationship between local labour demand and DI uptake in Norway. Their motivation is to examine the grey area between DI and unemployment insurance, and they hypothesise that “as social insurance spells become longer, the ultimate causes behind the claims become more ambiguous” (Andersen et al., 2019, para. 1). For the general population they find that a one percentage point decrease in local labour demand leads to a 0.231 percentage point increase in DI uptake. For those unemployed, they find an even larger effect, with a one percentage point decrease in local labour demand leading to a 0.858 percentage point increase in DI uptake. They also investigate the effects within different subsamples based on age and level of education. They find that although there is a larger effect in groups with individuals of young age and low levels of education, the most important determinant of the size of the effect is the initial employment state. Naturally, the initial employment state is highly correlated with age and education level.

2.3 US studies

Autor and Duggan (2003) use their theoretical framework to examine whether program changes to DI and the decline in demand for less skilled labour could explain the increase in DI uptake between 1978 and 1998 in the US. The program changes represent changes in supply of benefits, whereas demand for benefits is isolated with a Bartik style instrument. Their theoretical model implies that the effects of labour demand have a larger effect on DI uptake post DI liberalisation, which coincides with their findings that the combination of the supply- and demand forces indeed has large effects on the conditional applicants (Autor & Duggan, 2003).

Charles et al. (2018) investigate the effect of changes in local labour demand on the change in uptake of DI in the US from 1970 to 2011. They exploit changes in the oil price and interact this with each locality's employment share from the oil industry. The employment shares are used to estimate changes in local labour demand as a result of the national fluctuations in oil prices, thereby isolating the part of employment fluctuations that result from changes in labour demand. Their analysis reveals an elasticity of –0.699, similar to estimates found in Black et al. (2002)

2.4 Implications for our study

Based on previous research, we expect to find a negative relationship between local labour demand and local DI levels. Our contribution to the existing literature is an analysis based on updated and modern data. Furthermore, we extend on Andersen et al. (2019) and Bratsberg et al. (2013) by investigating whether gender differences in DI uptake's responsiveness to local labour demand persist for a more balanced sample. We supply extensive descriptive evidence of the development of DI uptake in Norway over the last 20 years, exploiting microdata to see how individuals of different genders and age groups use other welfare programs before starting their DI spell, thus both extending and showing updated data for the results found by the Frisch centre report.

We are unable to separate the impact of the substitution- and health effect on increased DI levels. A thorough knowledge of the previous research regarding why there should be a connection between local labour market conditions and the uptake of disability insurance is however necessary to interpret the results of the analysis and provide a well-grounded discussion of what the drivers for the results are.

3. Institutional Background

This section will explain the institutional background of the Norwegian national insurance system, with a particular focus on the regulations and payouts related to unemployment insurance, sickness benefits, work assessment allowance, and DI. All information in this section is retrieved from the websites of the Norwegian Labour and Welfare Administration (NAV) unless otherwise specified.

3.1 Norwegian social insurance schemes

3.1.1 Disability insurance (DI)

The purpose of disability insurance is stated in Folketrygdloven § 12-1:

"*The purpose of disability insurance is to secure income for people who has had their earning capacity permanently reduced due to illness, injury or blemish*"[1] (Folketrygdloven, 2000).

Generally, to qualify for DI an individual must be a part of the Norwegian national social security scheme and have been a member of the scheme for the last five years, have at least 50% reduced work- and earnings capacity, and be between 18 and 67 years. An individual can be granted DI if their earnings capacity is reduced by 40% and they are on work assessment allowance when they apply for DI, or by 30% if the disability is a result of a work-related injury or illness (NAV, 2023).

The full-time DI replacement rate is 66% of an individual's average income over the best three years of the last five years, up to a maximum of 6G[2], currently 711 720kr. This will grant an annual payout of 469 735kr. For reference, the mean income in Norway in 2022 was 637 800kr (SSB, 2023). However, if the individual has had a low income, they will receive the minimum

[1] «Formålet med uføretrygd er å sikre inntekt for personer som har fått sin inntektsevne varig nedsatt på grunn av sykdom skade eller lyte» (Folketrygdloven, 2000)

[2] G is a measure used by the state as a basis from which different welfare benefits are calculated (Loen, 2023). The calculation of G is a flexible threshold that follows the general wage growth in Norway (Loen, 2023).

level of DI, which is between 270 454kr – 345 184kr, depending on whether they are married or living with a partner, or became disabled at a young age (NAV, 2023).

DI is a permanent benefit, meaning that once it is granted it is assumed that the individual will receive the benefit for the rest of their working age career, and will only move out of DI at the age of 68, when they will move into a pension (NAV, 2023). The fact that DI is a permanent benefit is one of the reasons why increased DI uptake, especially in the younger population worries policy makers.

To reduce the number of individuals who permanently left the work force, time limited disability insurance (tlDI) was introduced in 2004. tlDI was granted if it was believed that the person may not have lost earning capacity for the rest of their lives, and the goal of tlDI was to prevent that people who may in the future recover or improve from their disability be pushed into permanent disability insurance (Mæland, 2021). The target group for tlDI was younger people with previous attachment to the work force (Mæland, 2021). tlDI was given for one to three years with the same income replacement rate as permanent DI. In 2010, tlDI and several other social insurances were combined in work assessment allowance. Notably, most people who were on tlDI eventually ended up on permanent DI (Bratsberg et al., 2013)

3.1.2 Work assessment allowance (AAP)

AAP is a temporary social insurance aimed at individuals who have had their work capacity reduced and is either in the process of receiving treatment, re-education and/or being evaluated for DI, with an income replacement rate of 66% (NAV, 2023). To qualify for AAP, the work capacity must be reduced by at least 50%, but it must be possible for the work capacity to improve through treatment, re-education or employment schemes (NAV, 2023).

Most individuals who are approved for DI are either on AAP or have previously received it. NAV requires that all possible treatments or re-education schemes be tried before being approved for DI, and this is usually done while on AAP (NAV, 2023).

In 2018 the maximum length of AAP was reduced from four years to three years in an attempt to speed up the assessment process and prevent AAP-recipients from becoming passive insurance recipients (Myhre & Kann, 2022). Additionally, the requirements for receiving a two-year extension became stricter. Evaluation of this reform finds that the labour market participation rate is higher for the individuals who received AAP for only three years, but that younger individuals to a larger extent were declared for disability insurance (Myhre & Kann, 2022).

3.1.3 Sickness benefits

Sickness benefits are a temporary social insurance that replaces income when an individual cannot work because of injury or illness. Only employed individuals qualify for sickness benefits, with a maximum duration of 52 weeks. Employees are legally protected from contract termination during their sickness spell for up to 12 months. The first 16 days of sickness benefits are paid by the employer, after which the social insurance system will cover the cost. An individual qualifies for sickness benefits if they are a member of the social insurance system, have had work for at least four weeks prior to the sickness and is below 70 years old (NAV, 2023).

The income replacement rate of sickness benefits is 100% up to an income of 6G, meaning that sickness benefits are much more beneficial than DI or AAP. Most DI claimants will start their path with one or several periods of sickness benefits, before transferring to AAP.

3.1.4 Unemployment insurance

A necessary requirement to qualify for unemployment insurance is to have previously been employed, with a minimum salary of 1,5G over the last year, or 3G over the last 36 months (NAV, 2023). Unemployment insurance is a temporary social insurance with a maximum recipient time of 104 weeks. The income replacement rate is 62,4% of previous income, with previous income being capped at 6G (NAV, 2023).

3.2 Implications of system design

The different programs in the Norwegian social insurance system and the connections between them influence the uptake of DI, shaping the broader landscape of labour market participation.

For unemployed individuals who have not previously participated in the labour market, AAP and DI are the only ways to secure stable income. This is because they do not qualify for any of the other social insurances, which are directly related to previous labour market participation.

A thorough understanding of the system design of the Norwegian social insurance scheme is vital for interpreting descriptive nuances and explaining the analytical choices in our study. Understanding the welfare careers of individuals may provide further insight into how different groups are impacted by changes in employment opportunities.

4. Data

The investigation into DI uptake in Norway is twofold and the datasets differ between the descriptive- and the empirical analysis. The descriptive analysis uses individual level data, whereas the empirical analysis uses data aggregated to the commuting zone level. This section will first briefly present the data for the descriptive analysis and then present a more extensive explanation of the data for the empirical analysis.

The data for the empirical analysis is retrieved from SSB and microdata.no, and the data for the descriptive analysis is exclusively retrieved from microdata.no. Microdata.no is a tool that gives access to Norwegian register data and is developed and owned by SSB and Sikt, the Norwegian Agency for Shared Services in Education and Research. We have used microdata.no primarily as a tool for data collection, and not for analysis.

A complete overview of SSB tables and microdata.no variables used can be found in appendix A1.

4.1 Data sources

4.1.1 Data sources descriptive analysis

The descriptive analysis consists of a presentation of the general development of DI over time and an investigation into the welfare careers of those who will later become DI recipients. The analysis is based on averages calculated in microdata.no. The welfare careers are constructed by defining new DI recipients as those that receive DI benefits one year, but not the year prior. We investigate the uptake of various benefits up to ten years before and five years after the start of their DI spell at time t. This is repeated for all years between 2010 and 2019, such that the earliest year for analysing benefit uptake is 2000 and the latest is 2021, capped due to data constraints.

The benefits we have investigated include uptake of DI, uptake of AAP, uptake of sickness benefits and uptake of unemployment benefits. We also investigate the mean of earnings as a measure of how much the group worked.

4.1.2 Data sources empirical strategy

To empirically investigate the impact of local labour market conditions on DI uptake, we have constructed a panel data set on commuting zone level. The panel data set combines data on the number of individuals employed, hereby referred to as employment, and the number of individuals on DI, with a separately constructed instrumented employment change. The panel data set includes observations from year 2008 to 2014, paired with outcome year values five years later. In the construction of this data set, data has been retrieved from SSB and microdata.no.

As a large and sparsely populated country, the 19 Norwegian counties in 2008 are not accurate representations of local labour markets. Furthermore, the 430 municipalities are also inadequate in representing local labour markets as individuals tend to commute to other municipalities, perhaps in a different county, for work. The commuting zones in the analysis are based on Bhuller (2009), where Norway is divided into 46 distinct local labour markets. The definition of the labour markets is based on commuting patterns, making the commuting zones relatively stable over time and an accurate representation of local labour markets (Bhuller, 2009). All municipalities are converted to the 2009 classification to simplify the commuting zone construction. For the municipalities that were merged into a bigger municipality, their values were replaced with zeros as they were already accounted for in the new municipality.

Our analysis requires the construction of an instrument for employment, consisting of industry shares and national employment growth. The instrument is created in a separate panel data set based on information from SSB about the employment within different industries for each municipality in Norway. This data is collected for each year between 2008 and 2014 and aggregated up to commuting zone level, to become the basis for the industry shares. The national employment growth is calculated as the log difference between the total number of individuals employed in each industry in the outcome year and the base year.

Industries are defined based on the Statistical Classification of Economic Activities in the European Community (NACE), developed by the European Union to classify economic activities (Eurostat, 2008). The classification yields 21 different industries.

We obtain the full sample data on number of individuals employed, and on DI, at a municipality level from SSB. Group-specific data for sample splits is retrieved from microdata.no. We extract information about employment and DI uptake on municipality level for men, women, different age groups and for those employed with an income above 1G. This renders us with a panel data set containing 322 observations, or a balanced panel data set with 46 commuting zones over seven years.

Our outcome variable is the log change in number of individuals on DI. As we are interested in understanding the heterogenous impact on different groups, we additionally use six other outcome variables: change in number of individuals on DI for women, men, 18-30, 30-40, 40-50 and 50-67. This can be presented formally in the following way:

$$\Delta DI_{lt} = log(DI_{lt}) - log(DI_{lt-5})$$

Where the subscript l indicates commuting zone and the subscript t indicates the base year. Log transformation is used due to the large differences in size of the commuting zones, which impacts the number of DI recipients in the base and outcome year. Normalising the variable through a log transformation makes it easier to estimate an effect that will be consistent across commuting zones of different sizes. The log change in DI is approximately equal to the percentage change in DI uptake between the base year and the outcome year, for the given commuting zone.

The explanatory variable that is instrumented for is the log change in employment within a municipality, or formally:

$$\Delta emp_{lt} = log(emp_{lt}) - log(emp_{lt-5})$$

As for the outcome variable, we are interested in understanding both the general impact and the heterogenous impacts on different groups. We therefore create six additional explanatory variables, change in employment for women, men, 18-30, 30-40, 40-50 and 50-67. The log transformation of both the outcome- and the explanatory variable yields an elasticity interpretation of the estimated coefficient.

5. Descriptive analysis

Identifying which groups are driving the increase in DI uptake and examining through which channels DI recipients enter the program provides a more accurate context in which the results from the empirical analysis can be discussed. In this section, we examine the development of DI uptake over the last 20 years descriptively, and investigate which groups appear to drive the trend, focusing on gender and age. Furthermore, we investigate the connections between DI uptake and other welfare programs, and analyse the welfare careers of those that later go on DI.

5.1 Development of DI in Norway

The uptake of DI has increased steadily over the last years and in 2019 there were 352 197 DI recipients in Norway (NAV, 2023). Figure 5.1 shows the development in the proportion of the population receiving DI from 2000 to 2019. The proportion has been close to 10% all years, with the lowest uptake in 2013 at 9.1%, and the highest in 2019 with 10.07%. Since 2013, the proportion of the population on DI has increased, and NAV expects the proportion to continue to increase and be at 11% in 2024 (NAV, 2023).

The observed decrease between 2004 and 2010 can be explained by the introduction of tlDI. Some individuals who would otherwise have been accepted for DI were rather accepted for tlDI, creating the perception of a decrease in the number of individuals on DI. Out of the people that were granted tlDI in 2004, only 2% had returned to work by 2007, 65% were still on tlDI, and 29% had been granted permanent disability (Bratsberg et al., 2013). If we include the individuals on tlDI in the visual plot, the decrease in DI uptake between 2004 – 2010 disappears, as shown in figure 5.2.

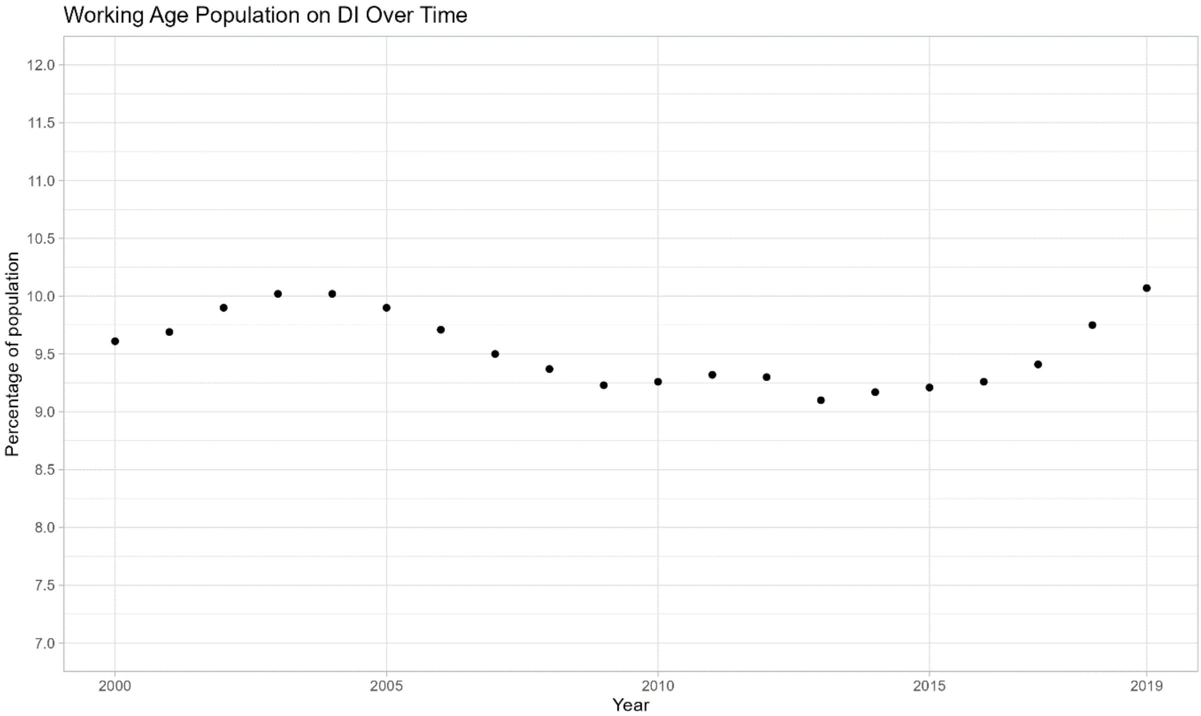

Figure 5.1: Percentage of working age population on DI.

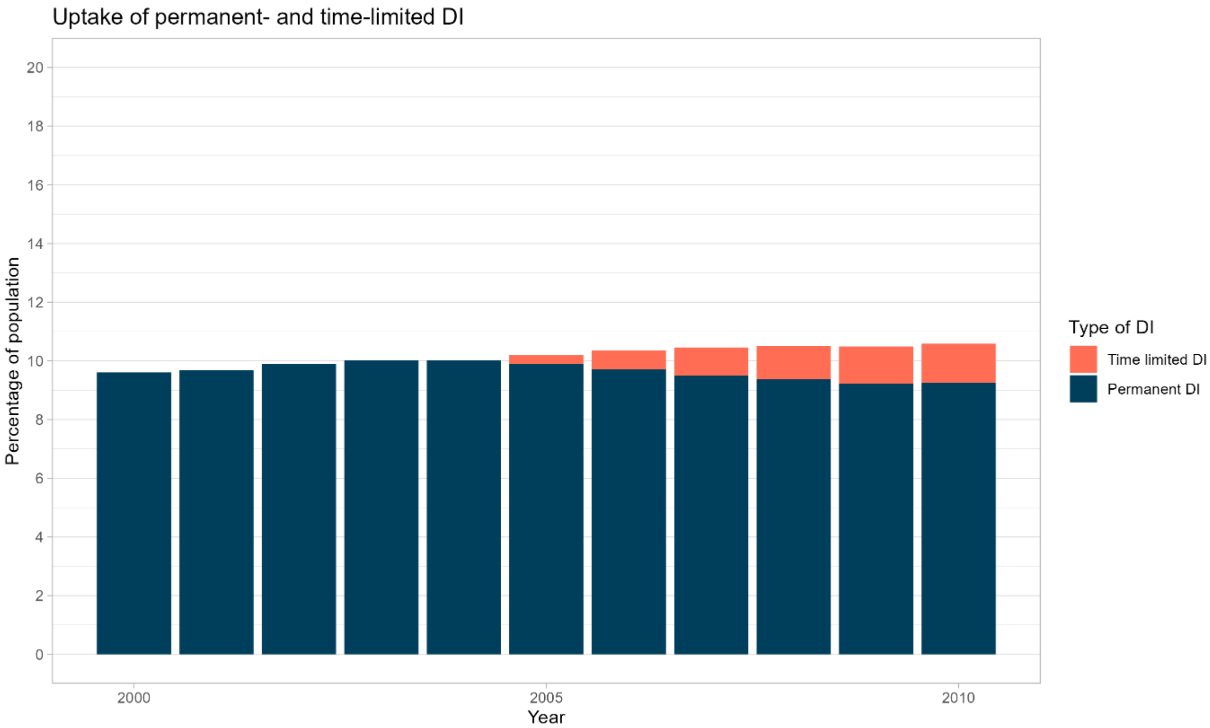

Figure 5.2: Percentage of working age population on DI or tlDI.

5.1.1 Gender and age

Women are more likely than men to be on DI, and the proportion of women on DI has increased quicker than for men, as visible in figure 5.3 and appendix table A2.1. In 2000, the percentage of women on DI was 3.3 percentage points higher than for men, and the gender difference has increased to 4.17 percentage points in 2019. Although the proportion of men on DI has increased as well, the 4.9% DI increase for the general population is largely driven by the female population.

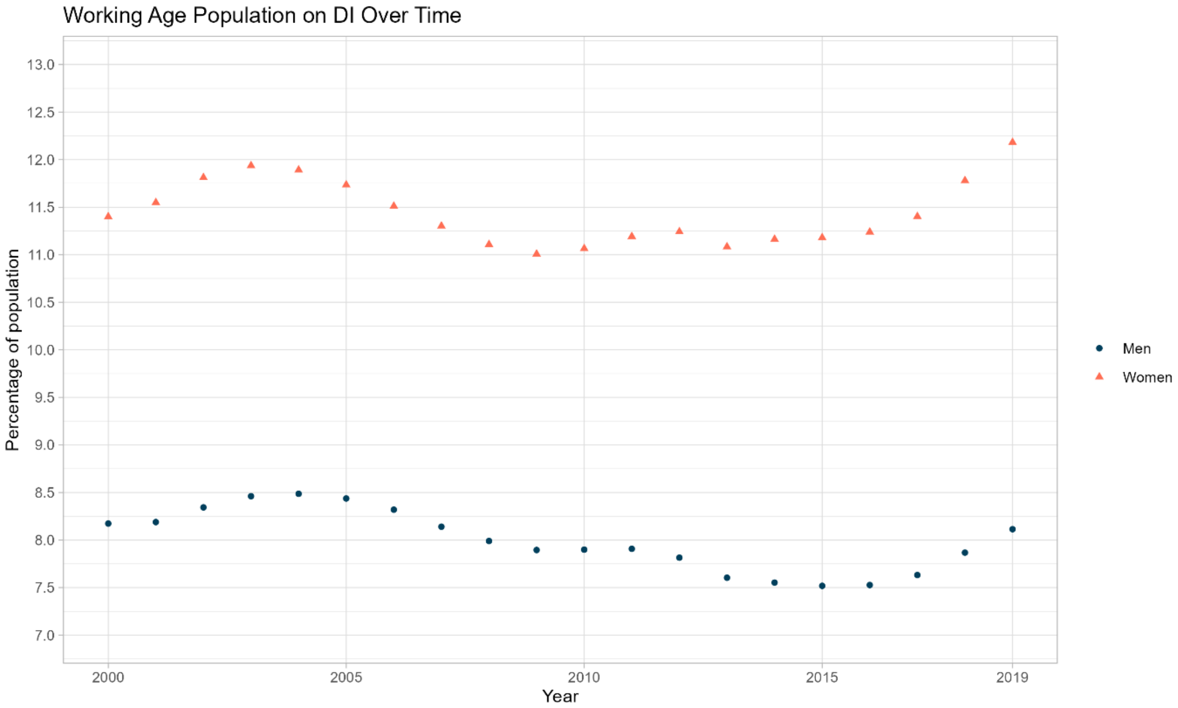

Figure 5.3: Gender split percentage of population on DI.

NAV has expressed concern for the increasing number of young people taking up DI (Bragstad, 2018, second edition). The 18-30 age group exhibits a persistent increase since 2000, as visible from figure 5.4 and 5.5. This group also has the highest percentage increase in DI uptake from 2000 to 2019, with an increase of over 106%, as shown in appendix table A1.2. Although the group's initial DI level is comparatively low, an increase in this population is particularly concerning due to the permanent nature of DI. Increased uptake of DI within the youngest part of the population has a higher long-term cost, both in actual payouts and due to long-term reduced labour-market participation. The 18-30 age group is the only age group in which women are less likely to be on DI than men. As the population ages, women start driving the increase from the age of 30.

The uptake of DI increases with age. Many illnesses are correlated with age, and as the population ages and stays longer in the work force a natural result would be an increased DI level. The Norwegian data shows a slightly contradictory result to this. Although the DI level is the highest among the oldest age groups, this is not true for the *changes* in DI uptake. The percentage of recipients of DI who are over 60 is decreasing. Additionally, the uptake of DI in the 60-67 age group is falling as a percentage of the population (NAV, 2023). Although the oldest age group has the highest level of DI recipients, it cannot explain an overall increase in DI recipients, even when taking growth of the age group into account.

Although the DI level in this group exhibits a falling trend, this does not necessarily indicate that a larger part of the population is staying in the workforce. Ordinary pension in Norway can be taken out between ages 62 and 75, with the most common age being 67 (Pedersen, 2021). The first panel in figure 5.5 shows how DI and pensions have been taken up by age group 60-67, with both DI- and pension levels falling. The level-shift in uptake around 2011 is likely due to the pension reform in 2011. The reform incentivised people to remain longer in the workforce and made it easier to combine work with pension (Pedersen, 2021; Fedoryshyn, 2018). Examining the trends in DI levels before and after the pension reform, we see that the downwards trend appears steeper after the reform. It is possible that as more individuals can combine work and pensions, their need for DI decreases since they have an alternative extra income to compensate for potential reduced work capacity. This cannot explain the entire decrease in DI uptake, as the downwards trend started before the pension reform, but perhaps the steeper trend after 2011. We cannot conclude confidently on this without more evidence. It is therefore difficult to say whether the increased uptake of pensions can explain the decreased uptake of DI among the oldest age group.

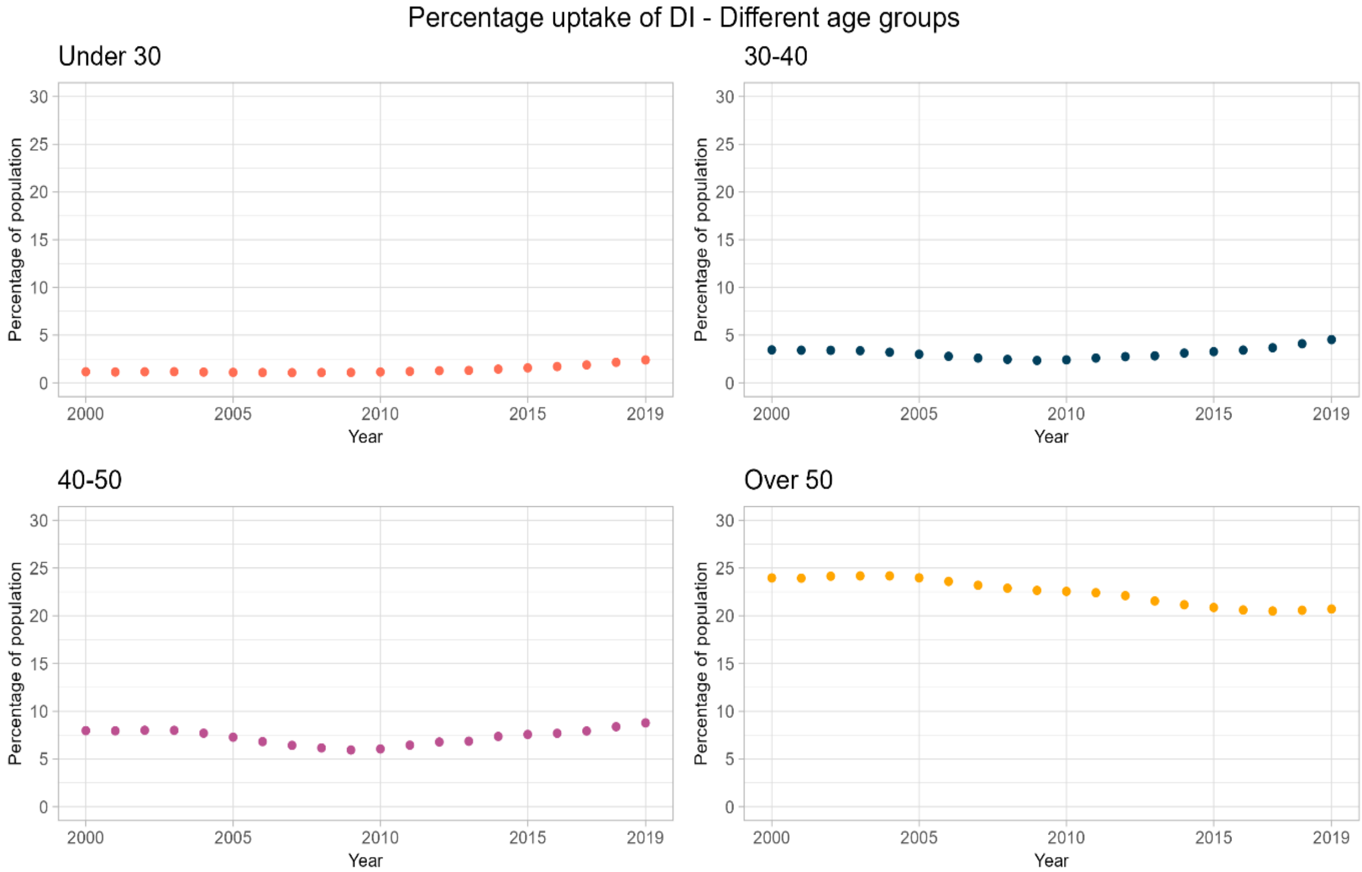

Figure 5.4: Uptake of disability insurance across groups.
Note: The DI rate is calculated for the defined age group each year.

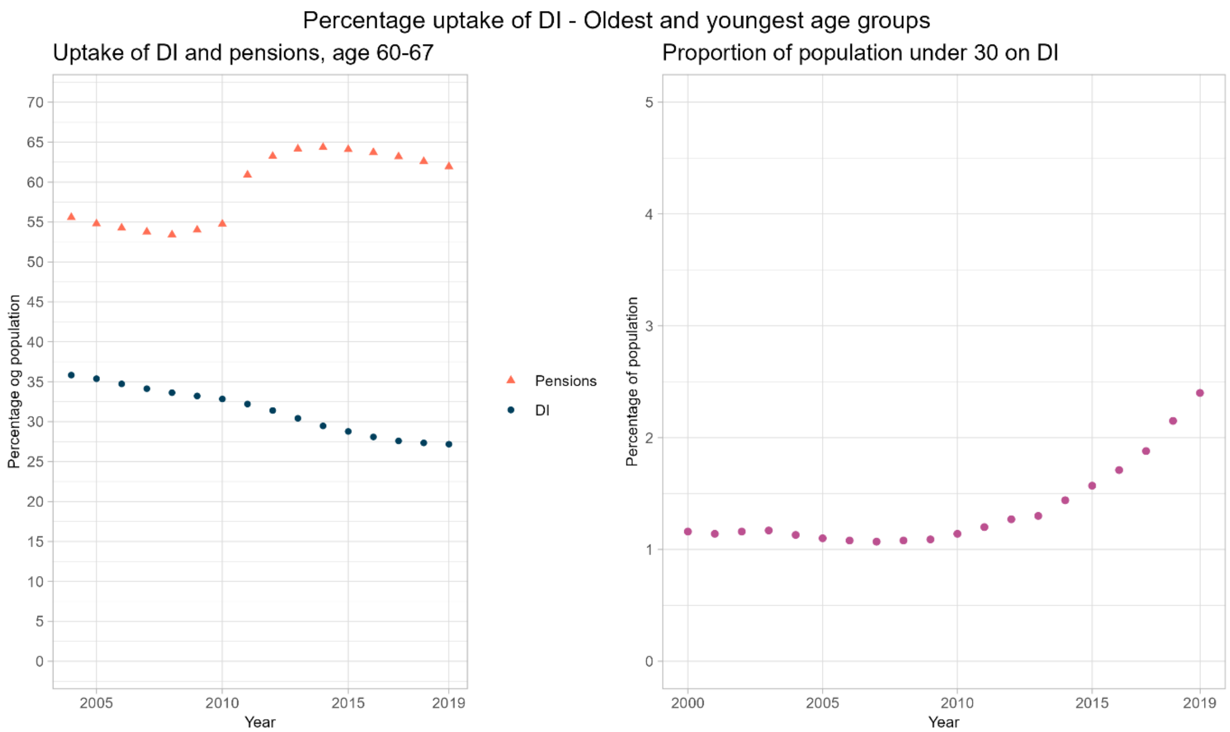

Figure 5.5: Percentage uptake of DI in the oldest and youngest age groups.
Note: The DI rate is calculated for the defined age group each year.

5.2 Welfare careers

This section examines the welfare careers of those who eventually take up DI. Using microdata to follow individuals over several years enables us to further understand the interaction between future uptake of DI and other social insurances, separated by gender and age. This expands on the presentation of the general development over the last 20 years by examining how benefit uptake for later DI recipients differ over the years, and whether it differs from the general population. Additionally, different groups contribute differently to the trend, and understanding more of their earlier benefit uptake can bring insight into why and how the group is contributing to the trend. If there is a connection between local labour market opportunities and uptake of DI, we also expect the uptake of unemployment benefits to be higher for those that later go on DI, than for the rest of the population. This investigation is done by examining the use of unemployment benefits and how work income changes in the years leading up to DI. Simultaneously, we examine the use of sickness benefits and AAP to further the understanding of the importance of the different channels and the timing of different benefits.

The uptake of sickness benefits for individuals who start their DI spell at time t is much higher in all pre-periods than the general population average of 18.77%[3]. The difference between the uptake of the general population and the future DI-recipients is interesting as it may point to fundamental differences in either the health of the groups, or the requirements of their sections of the labour markets. It might be that individuals who later go on DI occupy jobs that are less flexible and to a lesser extent can be changed to accommodate the individual's health situation. Even ten years prior, an individual who later in life will receive DI is almost twice as likely as the general population to receive sickness benefits, indicating that DI spells often are the results of long-term health problems. We can hypothesise that individuals who are of marginal health may be able to stay in the labour market for a while, before eventually taking up DI.

The uptake of sickness benefits increases until five years before the DI spell, before decreasing until DI approval, as depicted in figure 5.6. This is most likely due to an increasing number of individuals leaving the workforce and no longer qualifying for sickness benefits. If the individual is still unable to work after 12 months on sickness benefits, they will have to reapply

[3] Own calculation based on data from microdata.no.

for another benefit scheme. The majority of new DI recipients come from AAP, with an average of more than 70% since the introduction of AAP in 2011 (Ellingsen, 2023). Individuals are substituted into AAP, and it is rather this transfer of individuals that drive the downward slope at t-5. This is the intention of the system design. The first panel in figure 5.7 supports this, showing the proportion of DI recipients that have been on AAP before going on DI. The steepest increase in uptake is between t-6 and t-4, supporting the argument that around t-5 other benefits are increasingly substituted for AAP.

The uptake of unemployment benefits is at its highest ten years before the beginning the DI spell, with an uptake of 8.13%. Although the level decreases every year until t, the value of unemployment uptake in this group remains higher than the national average of 4.99%[4] every year before t-4. The higher uptake of unemployment benefits supports the idea that there is a connection between labour market opportunities and uptake of DI. However, whether this is a causal relationship or whether it is due to supply or demand cannot be said without further investigation. People who go on DI may have characteristics that limit their labour supply, such as lower education. Furthermore, these individuals may also have characteristics associated with both adverse health situations and the probability of being unemployed, such as low income and socioeconomic status.

The second panel in figure 5.7 further supports the findings in figure 5.6. It shows the reduction in earnings from work of those that go on DI. This measure of earnings includes sickness benefits, is adjusted for inflation and is not converted to full-time equivalents. The decrease in earnings starts eight years prior to uptake of DI. Whether this reduction of work is on the intensive or extensive margin is difficult to say, but like the descriptive analysis of uptake of unemployment benefits, this too motivates the investigation into the connection between local labour demand and the uptake of DI.

[4] Own calculation based on data from microdata.no and SSB, see comment in appendix A1.

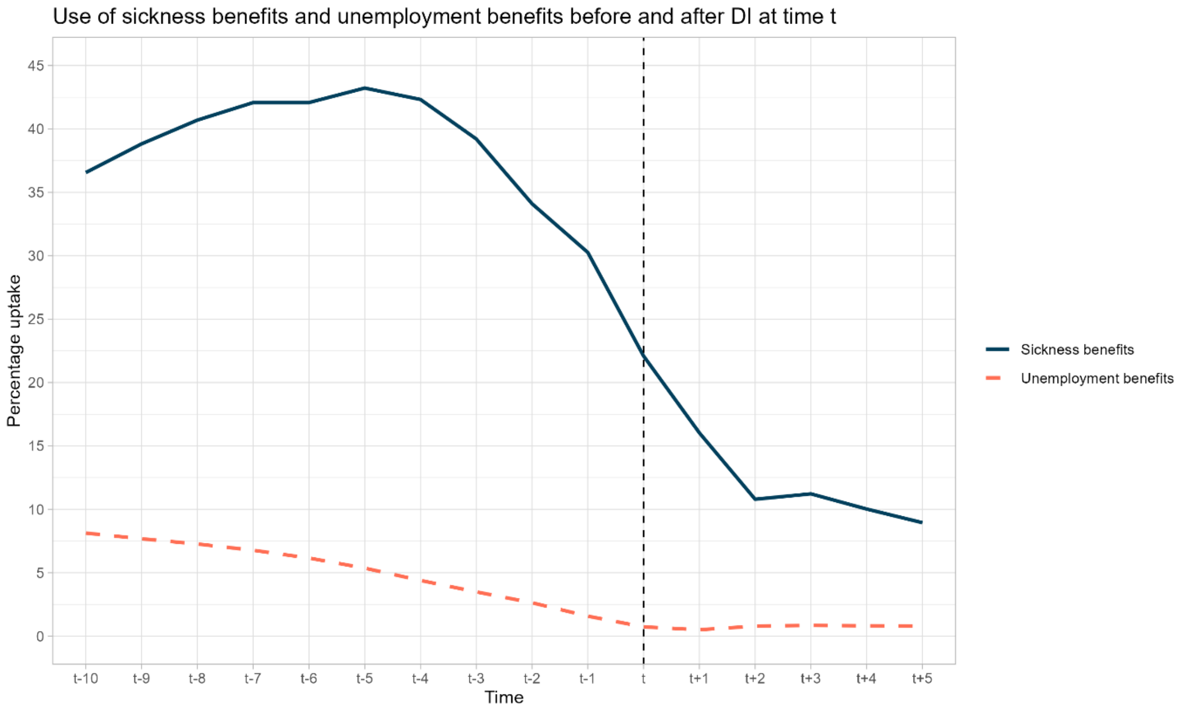

Figure 5.6: DI recipients' uptake of sickness and unemployment benefits.

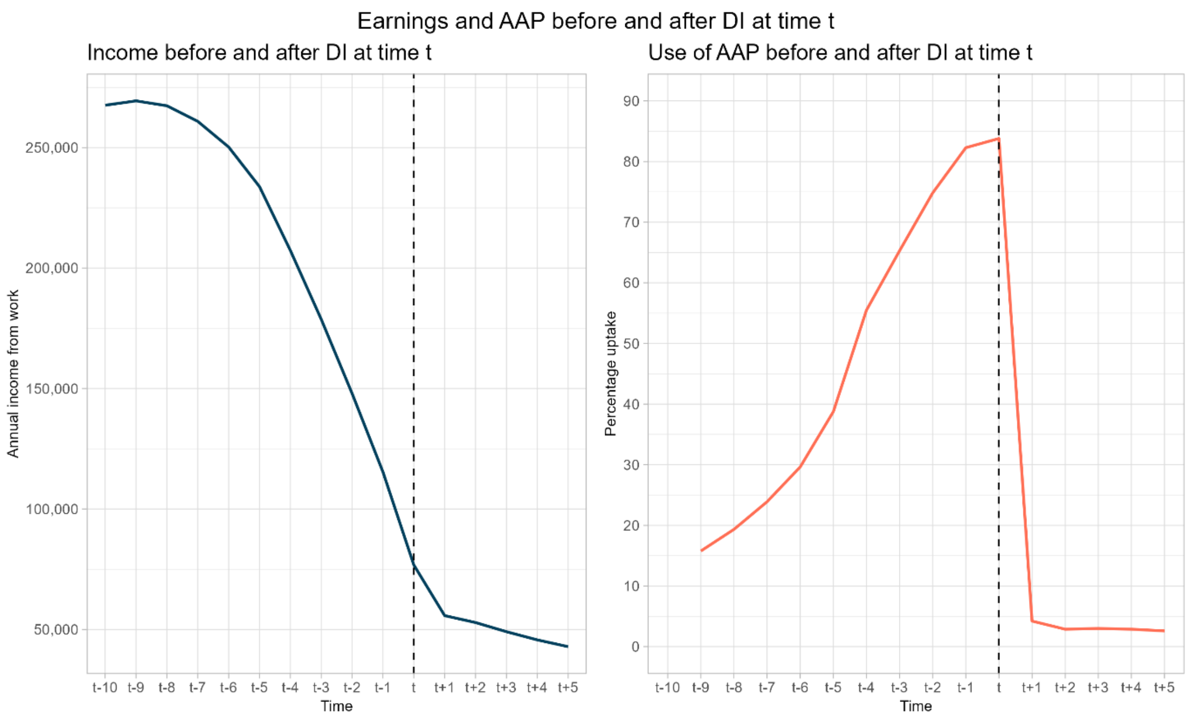

Figure 5.7: DI recipients’ income and uptake of AAP.

5.2.1 Heterogeneity in welfare careers

Figure 5.8 shows the development in earnings for different groups. Age groups are within the specified age at time t. All groups have decreasing earnings prior to their DI-spell, except those under 30. This is the group in which we will find those born with a disability or illness who start their DI spell young. Several individuals in this group will never have worked before starting DI, driving the earnings estimate downwards. Another factor that contributes to the low average levels, is that at t-10, the group is aged between 8 and 20. Throughout the period between t-10 and t as they get older, more of them will eventually be within the working age, but we still expect the average earnings for the group to be relatively low.

Except for the under 30 age group, all groups appear to have similar trends of falling earnings before going on DI. For women, it appears the downwards trend begins from t-8, for men from t-9 and for those over 50 from t-8. Those over 50 have the highest earnings before the downwards trend, and women have the lowest. However, women in general have lower earnings than men. This illustrates that gender differences in earnings are the same for the group that later goes on DI and the level overall. Although women have the lowest level of earnings before starting DI, they have the highest earnings after starting DI, indicating that women to a larger extent than the other groups combine their DI with work.

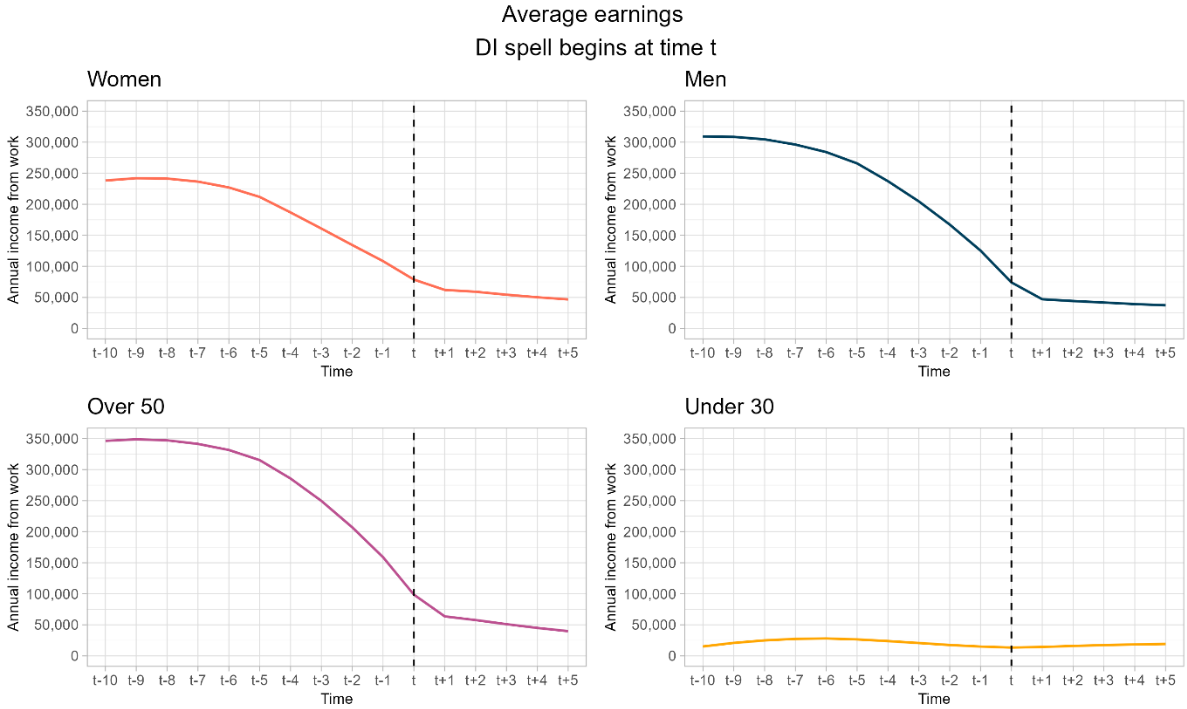

Figure 5.8: DI recipients' earnings split by gender and age.

Figure 5.9 shows the uptake of sickness insurance in the different groups. The group of individuals aged under 30 again demonstrate the lowest levels, but the developments are in accordance with the other groups. All groups have the highest uptake of sickness insurance five years before starting DI. Those over 50 have the highest uptake all years. This can be explained by the fact that older age is associated with more health issues. Interestingly, women have almost the same level of uptake as those over 50, whereas men's maximum uptake is 8.34 percentage points lower than women's.

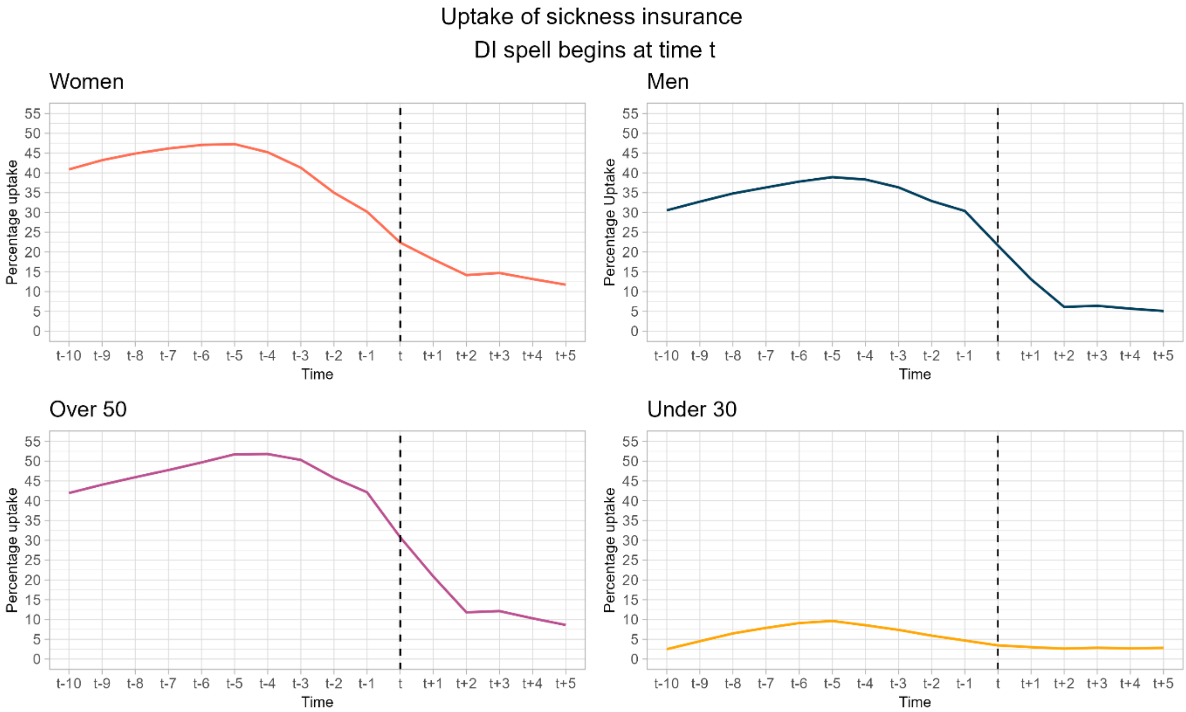

Figure 5.9: DI recipients' uptake of sickness insurance split by age and gender.

Figure 5.10 shows the uptake of unemployment insurance among those that later go on DI. For those under 30, we expect a very low uptake since relatively few in the group are in the workforce. We do see, however, that there appears to be a slightly higher uptake of unemployment benefits seven years prior to the DI spell. For the other groups, the time at which the probability of receiving unemployment benefits is the highest is ten years before. Men have the highest uptake at 9.36%. This could be an illustration of the findings in Bratsberg et al. (2013), that the connection between job displacement and uptake of DI is stronger for men than for women.

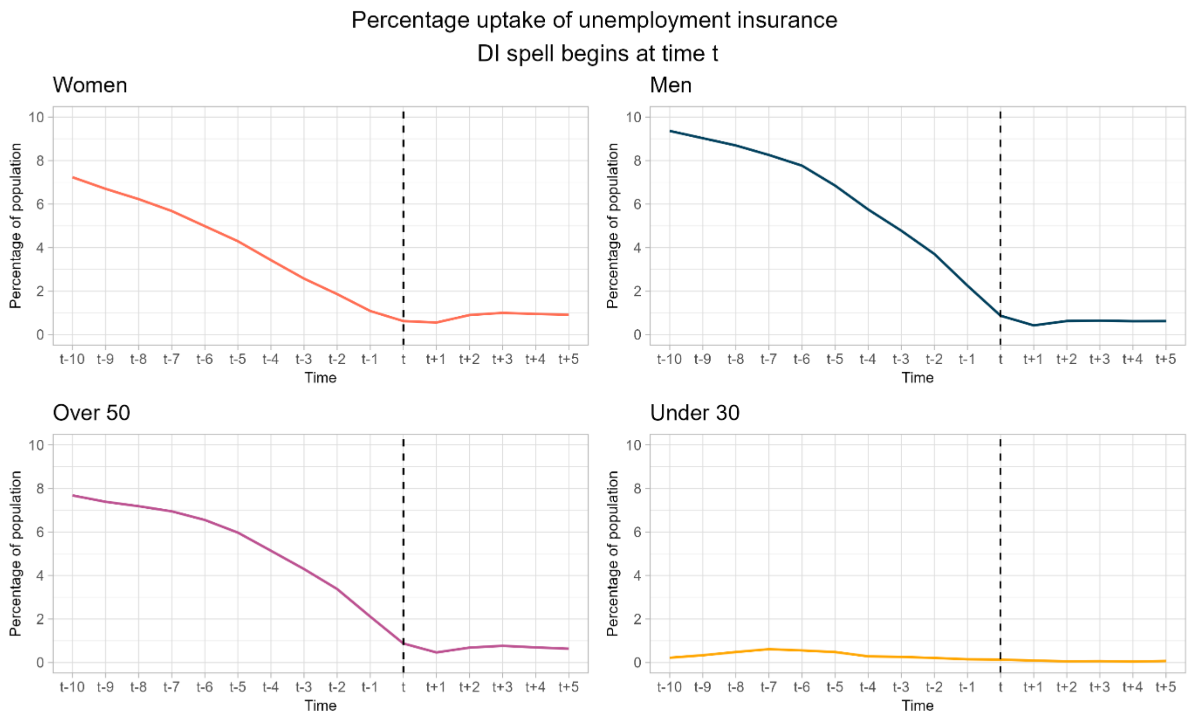

Figure 5.10: DI recipients' uptake of unemployment insurance split by age and gender.

5.3 Conclusion

The descriptive evidence in this section points to interesting connections between uptake of DI and other benefits. It is no surprise that individuals who will later receive DI has higher uptake of sickness benefits and AAP, both benefits that are directly health related. This is also the intention of the system design. However, we also find that DI recipients are more likely to have previously received labour market benefits. The investigation does not identify whether the same individuals are represented in both types of benefits or whether it is mostly different individuals making use of the two benefit types.

We also see that the benefit uptake begins many years prior to DI being granted. This indicates that individuals who later go on DI have struggled in the labour market for a long period of time. The descriptive evidence cannot say whether unemployment adversely affects health and therefore uptake of DI, or whether an adverse health situation is the reason the individual struggles with labour market participation. Another possible reason for the connection between unemployment benefits and DI is the one outlined in Andersen et al. (2019), that long social insurance spells may have uncertain underlying causes and that it is challenging to define a problem as strictly a health problem or strictly a labour market problem.

The descriptive evidence shows that it is particularly women who are driving the increase in DI uptake. The under 30 age group have also experienced a large percentage growth, however as the initial levels of this group are low, the increase does not largely impact the overall rate. However, it is still of interest as the increase in this group is particularly costly due to the permanency of DI.

Although the descriptive evidence does not conclude clearly that there is a connection between unemployment and the uptake of DI, it does indicate that individuals who end up on DI are likely to be less active participants in the labour market several years prior to the start of their DI spell. The patterns of their previous benefit utilisation vary across age and gender. Given that certain groups appear to be driving overall DI growth, this motivates a deeper investigation into the influence of local labour market conditions on DI uptake, both in the general population and within different demographic groups.

6. Empirical Strategy

In this thesis we want to explore whether there is a causal connection between local labour demand and the uptake of disability insurance. We use changes in numbers of employed individuals as a measure for local labour demand and utilise an instrumental variable (IV) method with a Bartik shift-share instrument to identify exogeneity.

In this section we provide insight into the theoretical framework and the identifying conditions that our empirical model builds on. Firstly, we present the structural from of our model. Thereafter we explain the Bartik shift-share instrument, its claim to exogeneity and the identifying assumptions necessary for causal inference.

6.1 Model specification

Our research design exploits the impact of several five-year labour demand changes, and how these impact the change in uptake of disability insurance in the given time periods.

The structural form of the equation is:

$$\Delta DI_{lt} = \beta_0 + \delta(\Delta emp_{lt}) + \epsilon_{lt}$$

Where ΔDI_{lt} is the change in the logarithm of number of individuals on DI in commuting zone l between year t and $t-5$. δ is the coefficient of interest with Δemp_{lt} indicating the change in labour market demand between the two periods. In a situation where there were no endogeneity concerns, δ would show the causal impact of labour market demand on uptake of disability insurance.

However, the structural equation suffers from endogeneity, biasing the coefficient of interest. Concerns are related to simultaneity, omitted variable bias and reverse causality, mathematically, $cov(emp_{lt}, \epsilon_{lt}) \neq 0$. For instance, if the population experiences a health shock this will both decrease employment and increase DI uptake. The increased DI uptake will not be causally related to the decreased employment, but rather the health shock which impacts both. Another example of the endogeneity issue is that labour market conditions are a result of the interaction between the demand and supply of labour. Only examining the change in employment would not solely capture the demand effect, but also reflect this interaction.

Instrumental variable (IV) estimation can mediate these concerns. The change in employment can be instrumented for with a variable that is related to employment, but completely unrelated to the error term. The instrument must fulfil the conditions of relevance, exclusion and exogeneity.

6.1.1 Bartik shift-share instrument

Bartik instruments isolate exogenous variations by interacting local industry shares and national employment changes to estimate a predicted local change. In our case, the technique exploits differences in industry composition across commuting zones and the impact of shifts in the national labour demand within industry. There is a large body of literature which has previously used Bartik instruments and IV-estimation in this fashion to solve endogeneity concerns (e.g., Black et al., 2002; Autor & Duggan, 2003; Charles et al., 2018; Andersen et al., 2019).

Employing only the national fluctuations separates out the employment change that is due to national level occurrences such as for instance changes in legislations, consumer interest and demand, trade relations or financial crises. These national shifts are likely exogenous for the local labour markets and identify solely the demand side changes of employment as national fluctuations to a much lesser extent are impacted by local supply-side variations. By this approach, the constructed instrument is purged of the variation that is due to specific local labour market shifts (Breuer, forthcoming).

Our Bartik shift-share instrument is calculated by interacting local industry shares with national industry employment, and then taking the sum of this within one commuting zone.

$$B_{lt} = \sum_k z_{klt-5} * g_{kt}$$

z_{klt-5} indicates the industry shares of industry k in location l in the base year, five years prior to the outcome. The industry shares are calculated as $\frac{emp_{klt-5}}{emp_{lt-5}}$, and are the industries' shares of localities, meaning that $\sum_k z_{kl}$ for one time period t would be equal to 1. This is the share component of the shift-share instrument.

This is multiplied with g_{kt}, the log change in industry k's employment between *t-5* and *t*, at the national level. g_{kt} is the shift component of the shift-share instrument, which is delocalized by using the national changes rather than commuting zone level of changes.

The Bartik instrument thus estimates the employment change in a commuting zone, given that all industries within the commuting zone had grown at national rates.

The Bartik instrument is utilised within the two-stage-least-squares (2SLS) framework in the first stage, where B_{lt} is the Bartik instrument.

$$\Delta emp_{lt} = \alpha_0 + \alpha_1 B_{lt} + u_{lt}$$

The fitted values from the first stage are then used in the second stage of the regression, to estimate the causal impact of the change in employment on the uptake of DI. The second stage is on the following form.

$$\Delta DI_{lt} = \gamma_0 + \gamma_1 \left(\Delta \widehat{emp}_{lt}\right) + \rho_{lt}$$

Although the Bartik instrument reduces simultaneity concerns, and concerns related to the implication of the supply side of the labour market demand, it does not in itself correct for time-variant or time-invariant unobservables. By estimating changes, and employing a first-difference style design, we correct for time-invariant unobservables. However, time-variant unobservables remain a concern and a possible confounding factor within the analysis.

6.1.2 Weighting

Commuting zones differ greatly by size. Weighting our observations by population size is a way to emphasise the results of those commuting zones with larger populations more than those with smaller populations. One could argue in favour of this as smaller commuting zones may be subject to more random variation in DI uptake and employment, and weighting may give more consistent results. However, as our empirical design is completely reliant on the variation between commuting zones, weighting may remove necessary variation. Additionally, if we hypothesise that large commuting zones may have some similarities in industry shares and thus be similarly exposed to shifts, we further run the risk of removing necessary variation and not getting correct estimates.

We choose to not weigh our estimates due to this risk of reduced variation, and thus reduced precision, but will present results from weighted regressions. Examining the difference between weighted and unweighted results can also garner a more thorough understanding of whether our results are consistent, and our model correctly specified (Solon et al., 2015).

6.1.3 Fixed effects

Our model exploits several pairs of base and outcome years for each commuting zone. Although our model is first-differenced, removing the risk of time-invariant omitted variables influencing our results, including fixed effects may be necessary to allow for causal interpretation. Including fixed effects in a selection of our models corrects for potential consistent differential response to common shifts. Different commuting zones may have consistent differences in reaction to shifts, and to avoid this biasing our estimates we include commuting zone fixed effects. Year fixed effects are included to correct for a potential time trend and time-variant effect of the shifts.

As with weights, we estimate several models with and without fixed effects to quantify the impact of the inclusion of fixed effects, and to further evaluate the robustness of our results.

6.2 Identifying assumptions

In recent years there has been an increasing amount of literature focusing on the identifying conditions of shift-share instruments, necessary conditions for causal inference, and correct estimation of standard errors for shift-share instruments. Most notably, several new papers have focused on the shift-share instruments' claim to exogeneity and whether a research design demands exogeneity of the shifts or the shares. Goldsmith-Pinkham et al. (2020) present an examination of shift-share instrumental variable estimation (SSIV) which finds that using a Bartik instrument is "equivalent to using local industry shares as instruments, and so the exogeneity condition should be interpreted in terms of the shares" (Goldsmith-Pinkham et al., 2020, p. 2587). Thus, with this research design the shares are the defining factor of the instrument's claim to exogeneity, and the identification builds on the locations, in our case commuting zones', exogenous exposure to shifts because of differing industry shares. On the other hand, Borusyak et al. (2022) present a shift-share research design in which the identification builds on the exogeneity of the shifts only and the shares are allowed to be endogenous. This insight is further built on by Adão et al. (2019) who present new estimations of standard errors, which takes into consideration the potential cross-regional correlation in regression residuals.

Both Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020) emphasise the importance of deciding whether the research design is pursuing exogeneity from shifts or shares prior to analysis. Goldsmith-Pinkham et al. (2020) argue that the research design is likely based on the shares assumption if "they (i) describe their research design as reflecting differential exogenous exposure to common shocks, (ii) emphasize a two-industry example, and/or (iii) emphasize shocks to specific industries as central to their research design" (Goldsmith-Pinkham et al., 2020, p. 2588).

In Norway, there has been a consistent decrease in employment within the manufacturing sector over the last 20 years, while employment share in the service sector has steadily increased (Andersen et al., 2019). The importance of the manufacturing sector varies over commuting zones due to inherent qualities within the commuting zone and historic factors. As an example, in 2014 the industry share of "C – Manufacturing" is 0.278 in Kongsberg while only 0.064 in Oslo. The importance of the manufacturing sector in Kongsberg can be traced back over 300 years and is a good example of how historic factors influence current industry shares (Thorsnæs & Lauritzen, 2023). This subsequently creates the variation in exposure to shifts exploited in our analysis. Increases in employment over the last 20 years have been the most prominent for health sectors and the construction industry, but the variation of industry shares across commuting zones differ to a lesser extent for these sectors (Andersen et al., 2019).

We believe that our research design is consistent with the Goldsmith-Pinkham et al. (2020) specification. Our research design exploits the differential exogenous exposure to common shifts due to the differing industry shares. The shifts are represented by the steadfast reduction of the manufacturing sector, and the increase in the service sector as shifts necessary for our identification. These national shifts in the different industries are the same for all localities. The exposure to the shifts for the different commuting zones thereby differs with the industries' importance within the commuting zone. We therefore focus on identifying assumptions from the share-perspective.

The defining exclusion restriction is then that the shares must be exogeneous to changes in the error term and changes in the outcome variable. Simply put, the industry shares cannot predict changes in the outcome through other channels than the national fluctuations in employment. The exclusion restriction must hold for every industry share for the IV estimator to be consistent (Apfel, 2022). In our situation, every industry share within a commuting zone as defined by the base year employment, must be unrelated to the change in DI between the base year and the outcome year. It is important to note that the industry shares must not be unrelated to the levels of DI uptake, but rather the change (Goldsmith-Pinkham et al., 2020). A level interpretation would have made it much harder to defend the exclusion restriction, as we in that case would have had to defend that the specific industry shares had no impact on the level of DI uptake. As an example of where this could be broken, lower education level is associated with a higher propensity of DI uptake, and in this situation industry shares could impact level of DI uptake through education. However, as the exclusion restriction is limited to the industry shares' impact on changes in DI uptake, it may be more defendable. In that case we must examine whether there are plausible connections between certain industries and an increased or decreased pace in DI growth. This could for example be if certain industries have experienced changes in the working environment that impacted workers' health, either increasing or decreasing their chances of taking up DI.

The Bartik estimator can be decomposed to a weighted sum of individual instrumental variable estimators for each industry share. The instruments are weighted by Rotemberg weights, which report the instrument's sensitivity to misspecification. If the instruments with the largest weights can be justified as exogenous, we can conclude that the exclusion restriction likely holds and that the empirical strategy is valid (Goldsmith-Pinkham et al., 2020).

7. Empirical analysis

In this section we present the results of our main model specification, discuss these results and the limitations of our model, perform robustness tests, and discuss the implications of our results.

Overall, we find consistent negative impacts of decreased local labour demand on the uptake of DI, over almost all samples. This supports our hypothesis that a decreased local labour demand is related to the increased uptake of DI.

7.1 Full sample – general population results

Table 7.2 show the results from 2SLS models described in the previous section and a simple OLS-regression as a comparison, with four different specifications. Table 7.1 shows the first stage estimates for the 2SLS specifications.

The first specifications show the model with no fixed effects and no weights, (1) and (2). The second specification shows the regressions with fixed effects for commuting zone and year, (3) and (4). The third specification shows the regressions with weights, (5) and (6), and the fourth with both weights and fixed effects, (7) and (8).

For the OLS-regressions, only (2) shows a statistically significant result at the 5% level. The OLS estimates, using actual change in employment as an explanatory variable, give consistently lower estimates for the impact of a change in employment on the uptake of DI compared to the 2SLS estimates. This could be because of the endogeneity issues in the OLS estimator. As explained in the empirical strategy chapter, the Bartik shift-share approach exploits only that part of local variation in employment which is exogenous. Contrastingly, the OLS estimates will exploit the entire variation. This will make the OLS estimates biased and unable to isolate whether it is supply or demand that drives employment growth.

The instrumental variable regressions in column (1), (3), (5) and (7) have differing point estimates, but do not differ qualitatively. Only regression (3) and (5) are statistically significant, with significance at the 5% level. For estimate (1) and (7) we see no significance, but we note that both estimates are significantly different from zero. All the variations of the 2SLS model (1), (3), (5) and (7) fulfil the relevance condition, with a Kleibergen-Paap F-statistic for excluded instrument higher than the rule of thumb cutoff of ten. We therefore know that the predicted employment change, as predicted by the Bartik instrument, is not a weak instrument for the actual employment change.

The models with significant results at the 5% level are (3) and (5). As mentioned in the previous chapter, a concern with adding weights is related to the removal or reduced emphasis on necessary variation in smaller commuting zones. The fact that our results show a larger effect for a regression excluding weights, may indicate that some of the effect is driven by these smaller commuting zones. The inclusion of fixed effects is to allow for correction of a time-trend and a consistent differential impact of shifts on certain commuting zones.

The coefficient is interpreted as an elasticity. Our confidence is rooted in regression (3), and if we believe that a causal interpretation is valid, a 1% decrease in local employment leads to a 0.852% increase in local DI uptake. As this is an elasticity, the percentage point changes will depend on the initial levels of DI in the local population. In 2022, 10.7% of the national population was on DI. If a commuting zone exhibited the same DI level, a 1% reduction in employment would lead to a 0.0912 percentage point increase in DI, ceteris paribus.

Main specification: first stage results

	Change in DI uptake			
	2SLS	With FE	With weights	With FE and weights
	(1)	(2)	(3)	(4)
Bartik	1.092***	1.589***	1.494***	2.045***
	(0.145)	(0.233)	(0.086)	(0.166)
Constant	-0.023***		-0.011	
	(0.004)		(0.008)	
First-stage F statistic	56.5	46.3	300.6	152.3
Observations	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors are clustered at commuting zone level.			

Table 7.1: First stage results for the different 2SLS model specifications.

Second stage and OLS results: Full sample

	Change in DI uptake							
	2SLS and OLS		With fixed effects		With weights		With fixed effects and weights	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrumented change in employment	-0.358		-0.852**		-0.402**		-0.309	
	(0.311)		(0.337)		(0.163)		(0.292)	
Actual change in employment		0.536**		-0.172		0.031		0.069
		(0.224)		(0.247)		(0.182)		(0.393)
Constant	0.044***	0.040***			0.082***	0.069***		
	(0.009)	(0.008)			(0.010)	(0.011)		
First-stage F statistic	56.5		46.3		300.6		152.3	
Observations	322	322	322	322	322	322	322	322
Adjusted R^2	-0.092	0.047	0.657	0.678	-0.069	-0.003	0.647	0.659
Residual Std. Error	0.071 (df = 320)	0.066 (df = 320)	0.040 (df = 269)	0.038 (df = 269)	0.009 (df = 320)	0.008 (df = 320)	0.005 (df = 269)	0.005 (df = 269)
Note:	*p<0.1; **p<0.05; ***p<0.01							
	Standard errors are clustered at commuting zone level.							

Table 7.2: Second stage and OLS estimates for different model specifications.

7.2 Sample split – Gender

Table 7.3 shows the sample splits by gender. The first stage results are shown in column (1) and (3), while the second stage results are shown in column (2) and (4). The sample splits are estimated through changing the dependent variable in both the first and second stage, from full sample changes to changes by gender. This means that the outcome in the first stage for the female regression would be the estimated log change in employed women within the commuting zone, and similarly the log change in DI uptake among women in the commuting zone for the second stage. The industry shares for each commuting zone are not changed based on gender. This is because even if women and men systematically work in different industries, this does not restrict them from working in certain industries and does therefore not reflect the actual local labour demand. This could have posed an issue if the predicted employment rate using national fluctuations and the full sample industry shares could not predict the gender split employment changes.

The results from the first stage F-statistics for gender show that the instrument is still relevant, with an F-statistic of 46.6 for the male sample split and 23.3 for women. It must nonetheless be noted that the F-statistic is lower for both sample splits, and especially for the sample split with women. National shifts in employment within industries and local industry shares are to a lesser extent able to predict the local employment changes of women, than of men. This may impact our analysis as less of the variation in local female employment is captured by the instrument.

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The results are significant at the 5% level for both men and women, with the effect of changes in employment being larger for women than for men. For women, the estimated effects are that a 1% decrease in local labour demand leads to a 1.343% increase in local DI-uptake. For men, the coefficient states that a 1% decrease in the predicted employment rate leads to a 0.687% increase in local DI-uptake. Although the effect for women appears larger than for men, the estimates are not statistically significantly different from one another.

Results from 2SLS: Gender

	Change in DI uptake			
	Men		Women	
	(1)	(2)	(3)	(4)
Bartik	1.899***		1.099***	
	(0.278)		(0.227)	
Instrumented change in employment		-0.687**		-1.343**
		(0.325)		(0.577)
First-stage F statistic	46.6		23.3	
Observations	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors are clustered at commuting zone level			

Table 7.3: First and second stage results for 2SLS estimation split by gender

7.3 Sample split – Age

Table 7.4 shows sample splits by age. Column (1), (3), (5) and (7) show the first stage results, while the remaining columns show the second stage. The age is measured in the base year and paired with outcome year observations five years later. The outcome variable is then the change in DI uptake for the base year age group over the last five years. As an example, the 18-30 group will be 23-35 in the outcome year.

All sample splits show significant first-stages, meaning that the Bartik instrument for the whole sample is correlated with a sufficient part of the employment change for the age subsets. However, as with the gender splits, the F-statistic is lower for the age splits. The 18-30 group has an F-statistic of 27.2, the 30-40 age group has 55.2, the 40-50 age group has 25.2 and lastly over 50 has an F-statistic of 29.6. From this we infer that the Bartik instrument predicts more of the change in employment for the 30-40 base year age group, than the other age groups.

Although the first stage results are relevant, the second stage results for several age splits are insignificant or only weakly significant. The 18-30 age split is insignificant and not significantly different from zero. The standard error is larger than the coefficient of the estimate, and we cannot say anything with confidence about the impact of local labour demand on the uptake of disability insurance from our results.

The results for the 30-40 age group show significance at the 10% level. The coefficient indicates that a 1% decrease in local labour demand leads to a 1.165% increase in uptake of DI within the age group in the commuting zone. Although the coefficient is only significant at the 10% level, and that we in this case cannot be fully confident of the point estimate, we can conclude that the signage is as expected, unlike what we are able to do with our results for the 18-30 age group.

The 40-50 age split shows the largest coefficient of all the estimates. However, it is not statistically significant. It does differ from zero, meaning that as in the case of the 30-40 age group, we can have some confidence in the signage. The hypothesis that decreased local labour demand leads to increased uptake of DI is therefore weakly supported for this age group as well.

The most significant results are found for the sample split over 50. This group would be between 50 and 62 in the base year, rendering them between 55 and 67 in the outcome year. 67 is the oldest age in which a person can receive DI and the cutoff is therefore made here. The estimate is significant at the 5% level and a 1% decrease in labour demand leads to a 0.837% increase in DI uptake for the over 50 group.

Results from 2SLS: Age

	Change in DI uptake							
	Under 30		30-40		40-50		Over 50	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik	2.436^{***}		1.514^{***}		0.827^{***}		1.178^{***}	
	(0.467)		(0.204)		(0.165)		(0.216)	
Instrumented change in employment		-0.201		-1.165^{*}		-1.543		-0.837^{**}
		(0.878)		(0.690)		(1.065)		(0.413)
First-stage F statistic	27.2		55.2		25.2		29.6	
Observations	322	322	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01							
	Standard errors are clustered at commuting zone level							

Table 7.4: First and second stage results for 2SLS estimation split by age.

7.4 Discussion of Results

Comparing our results to previous work reveals that for certain samples we get results consistent with previous work, whereas for other samples, our results differ from these earlier estimates. Some of this divergence may be due to the choice of empirical strategy whereas others may be a result of data selection. These considerations are discussed in the following section.

7.4.1 Discussion of full sample

Our full sample results show an elasticity of –0.852, showing a larger effect than results previously found from for instance Charles et al. (2018), who estimate elasticities in the US employing an oil-type Bartik shift-share instrument. They find an elasticity of -0.699, which is not statistically significantly different from our results. Although we would not expect or assume the same results as studies done in the US, it is interesting to note that both estimates identify similar reactions to changes in the local labour market. Given that our model and that of Charles et al. (2018) provide estimates that are unbiased for the full populations of the respective countries, a higher elasticity in the Norwegian estimate suggests that the Norwegian workforce's uptake of DI reacts more to changes in local labour market demand than the American workforce's.

Although the results show that there is a significant relationship between local labour market changes and the uptake of DI, it does not answer the question as to why this is the case. The purpose of DI in Norway is to provide income to those who are too sick, ill or disabled to work. Hence, if the program worked exactly as it should, worsening local labour market conditions should only increase the uptake of DI given that people were becoming ill or sick either from being unemployed or from becoming unemployed. However, it seems unlikely that the sole channel through which DI uptake changes is due to the health-worsening effects of being without work. Rather, the relationship is likely more complex, influenced by an individual's labour market decision, the flexibility of employers, interaction with social workers, and the design of the social insurance system. A limitation of our analysis is that we cannot isolate these different effects and the interactions between them.

7.4.2 Discussion of gender differences

We find a larger effect for women than for men, however the results are not statistically significantly different from one another. This differs from the results reported in Bratsberg et al. (2013), which find that DI uptake as a response to an adverse labour situation is more common for men than for women. We expected to find similar results but hypothesise that our results reflect a different adverse labour situation. While they investigate the effects of job displacement, we investigate the effect of local labour demand. The difference is that local labour demand allows for the inclusion of the entire working age population. This difference may seem small, but several papers emphasise the importance of the conditional applicant, that is those individuals that will not apply for DI as long as they have a job but will choose a DI application over a job search in the case of displacement (Rege et al., 2009; Autor & Duggan, 2003). Bratsberg et al. (2013) estimate the effect only of these conditional applicants whereas our analysis pertains to all individuals. Furthermore, we emphasise the differences in our samples. Bratsberg et al. (2013) investigates the effect of job displacement due to bankruptcy in mainly private sector male-dominated industries, which perhaps makes the women in their sample unrepresentative of the average Norwegian woman. Women make up only 25% of their total sample whereas in our case, the number is approximately 40%. As our sample includes the entire working population, it might be considered a more representative sample.

Our result is to some extent also supported by our descriptive findings as women in general are overrepresented among DI-recipients, both in levels and in changes over recent years. While our descriptive analysis did show a higher uptake of unemployment insurance for men than for women, women were still the drivers of the increased uptake of DI. The descriptive analysis, as a function of its form, can give little information about why women have a higher DI uptake rate than men. Our empirical results showing a higher elasticity for women, indicate that one reason could be a stronger reaction to local labour demand.

Finding estimates indicating that women are more sensitive to labour market changes than men is consistent with labour market literature in which women in general have a more elastic labour supply than men (e.g., Borjas, 2019; Cools & Strøm, 2015). Thoresen and Vattø (2015) reaffirm this in a Norwegian context in their study on the labour supply elasticities of Norwegian men and women. Men will to a larger extent supply the same amount of work regardless of other factors whereas women will seek other opportunities in a situation of reduced income (Thoresen & Vattø, 2015). Consistent with these estimates, we find that women to a larger extent substitute income for DI in an adverse local labour market situation, which can be interpreted as a situation of reduced expected future earnings (Huttunen et al., 2011).

A potential source of error in our analysis of gender differences, is that men to a larger extent than women work in business cycle-sensitive industries. As the production sector is male dominated and the service sector is female dominated, we get more variation in our male sample than our female sample. This could potentially be a source of error in our estimates.

7.4.3 Discussion of age differences

The age split results have differing coefficients and reveal a U-shaped pattern. The effect appears strongest for the age groups between 30-40 and 40-50. However, the age group results are not statistically significantly different from one another, and we cannot confidently conclude on the differential impact by age groups. We will discuss potential reasons why the coefficient estimates differ.

The uncertain results for the youngest age group are somewhat surprising, as we expected to find results with at least similar signage to Andersen et al. (2019). Andersen et al. (2019) find that when looking at age group sample splits, the largest effect is found for the youngest age group, between 18-30. However, our estimates build on the reaction to a five-year employment shift, while the estimates of Andersen et al. (2019) build on reactions to three-year employment shifts. Additionally, their estimates for DI include AAP, while our results are solely for permanent disability insurance. For the youngest group, using a five-year window may be too large. One of the ways in which our exclusion restriction can be broken is by many individuals moving across commuting zone boundaries. A large number of movers could reduce the significance and bias our results, as the change in uptake of DI would be impacted by the change in the population. This is especially important to consider when evaluating the youngest age groups. This group is more likely to move for employment opportunities than older age groups as they often have fewer commitments preventing them from moving, such as home ownership or families.

It is also common for young people to work part-time in periods when they are in university or college, and our employment measure does not take this fully into consideration. Any individual who is receiving labour income from an employer is considered employed, regardless of the amount. This could potentially impact the relevance of our results, especially for the younger individuals, as small part-time jobs are common within this group.

The 30-40 age group and 40-50 age group have higher estimated coefficients than the general sample. Although the differences are not statistically significant or only significant at the 10% level, the effects on these age groups will contribute to increase the effect for the total sample. These are the two groups in which most of the workforce is located. Therefore, the regression results for the age splits are indicative for the largest number of people. This is important to consider because it means that how these groups respond to low local labour demand could potentially be very costly to society. As only the 30-40 age group has a statistically significant coefficient, and only at the 10% level, we cannot confidently conclude whether local labour market initiatives could significantly decrease cost of DI uptake in these groups.

The result for the oldest age group is slightly lower than for the general population, although not statistically significantly so. The smaller effect estimated for the oldest age group is not consistent with Rege et al. (2009). We would have expected to see a larger impact on individuals in this age group. The group has more individuals of marginal health, as demonstrated from the descriptive evidence of the older age having a higher uptake of sickness benefits. However, our descriptive results also show that DI uptake in general for this group has been decreasing, increasingly so after the pension reform in 2011. It is possible that our research, conducted on primarily data after 2011, is impacted by this and that the need for DI has decreased as the opportunity to take up pension has increased.

7.4.4 Summary of results

There is a negative relationship between local labour demand and uptake of DI in Norway with the current DI system. The elasticity for the full sample is estimated to be -0.852. Contrary to what was expected, our results showed a higher elasticity for women than for men. However, this might be explained by research design, and is in line with previous labour market research on the elasticities of labour supply. The age split results show a U-shape, but only the over 50 results are significant at a 5% level. The under 30 result is not statistically significantly different from zero, meaning that we cannot conclude with certainty that there is a negative relationship between local labour demand and DI uptake for this group.

7.5 Robustness checks

To address the potential concerns with our model and evaluate its robustness, we have developed several alternative models with variations of the variables. Additionally, we have calculated the Rotemberg weights to investigate where our model is most sensitive to misspecification and discuss whether this area threatens the validity of the analysis. This section presents the results of the robustness tests, and we find that our model is largely robust to these concerns.

7.5.1 Leave-out Bartik instrument

Our main specification uses a Bartik instrument where the commuting zone employment growth per industry is included in the national employment growth. Using own-observation information, meaning information that will also be a part of the explanatory variable, increases the risk of finite sample bias (Goldsmith-Pinkham et al., 2020). When including a commuting zone's own industry growth rates in the national growth rates there is a risk of an endogeneity problem, as the national growth rates are not completely exogenous. This concern is especially relevant in situations where certain commuting zones are significant drivers of the national employment change within an industry.

Estimating a model based on leave-out growth rates and examining whether this differs significantly from our main specification is therefore a good robustness check and can indicate whether our results are impacted by a finite sample bias. However, as noted in Andersen et al. (2019), it is possible that employment changes in commuting zones are causally related to each other. For instance, due to movement of production plants or the movement of government jobs. In this case, using a leave-out Bartik instrument would not garner the most accurate results for causal interpretation.

The leave-out estimates are shown graphically in figure 7.2 and full regression outputs can be found in the appendix table A3.1 and A3.2. The leave-out estimates show somewhat similar results to our main specification, and this is consistent for all sample splits. The leave-out results show larger impacts of the instrumented change in employment on the uptake of DI, but the results are comfortably within the confidence interval of our main specification.

The first stage estimates for all sub-samples show lower F-statistics than for our main specification. This could indicate that within own commuting zone employment changes were a necessary explanatory factor for the instrument, however the F-statistics are still higher than the rule of thumb of ten for all sample splits, except for the sample split for women. Here the F-statistic is only 9.9, which is close to the critical value of ten.

Examining the difference for estimated commuting zone industry growth with and without leave-out shows a largely linear relationship, as shown in the first panel of figure 7.1. However, there are some significant outliers, where the top 20 outliers are presented in the second panel. These outliers are primarily from the cities and from the smallest industries. Small industries are easily subjected to the finite sample bias from using own-level observations. Although both these factors are concerning, the robustness of our results indicate that this is not a large issue.

In conclusion, both the estimates from the leave-out construction and our main specification are similar, building on the robustness of our results. The higher impact of the predicted employment change within the leave-out instrument may indicate that our main specification still suffers from some endogeneity, however, we cannot be certain of this.

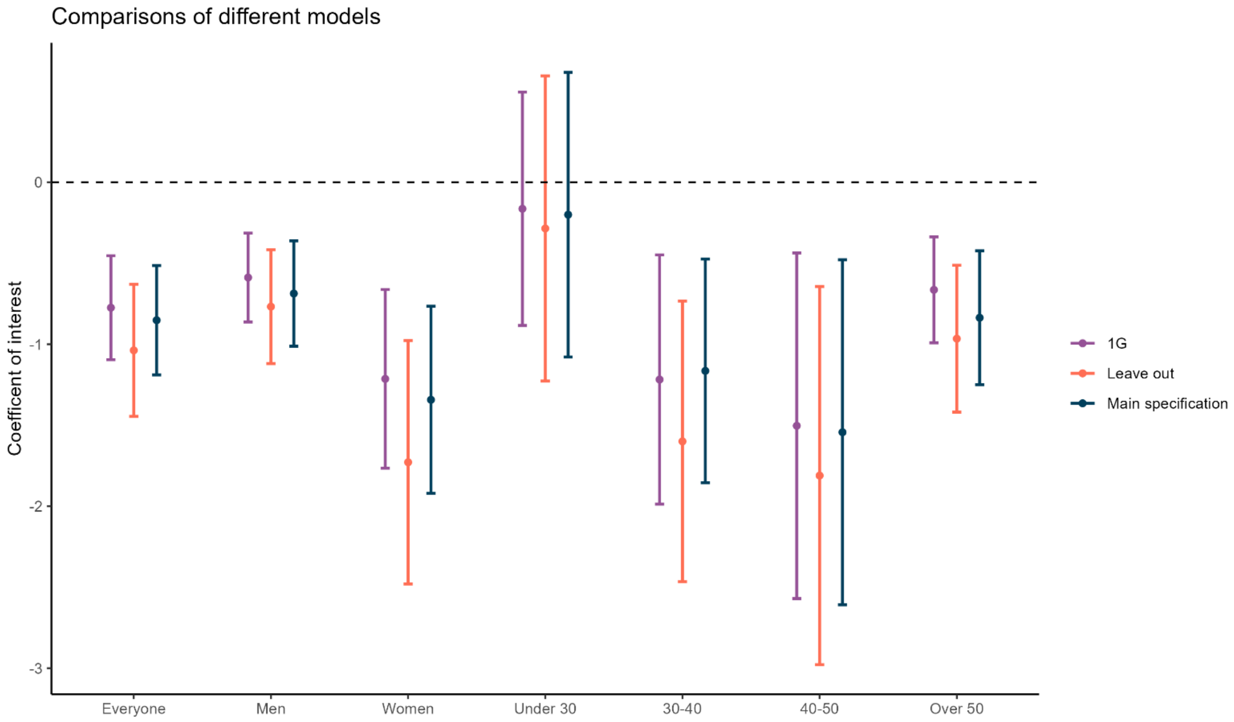

Figure 7.2: Graphical presentation of results from different model specifications.
Note: The standard errors are clustered at commuting zone level.

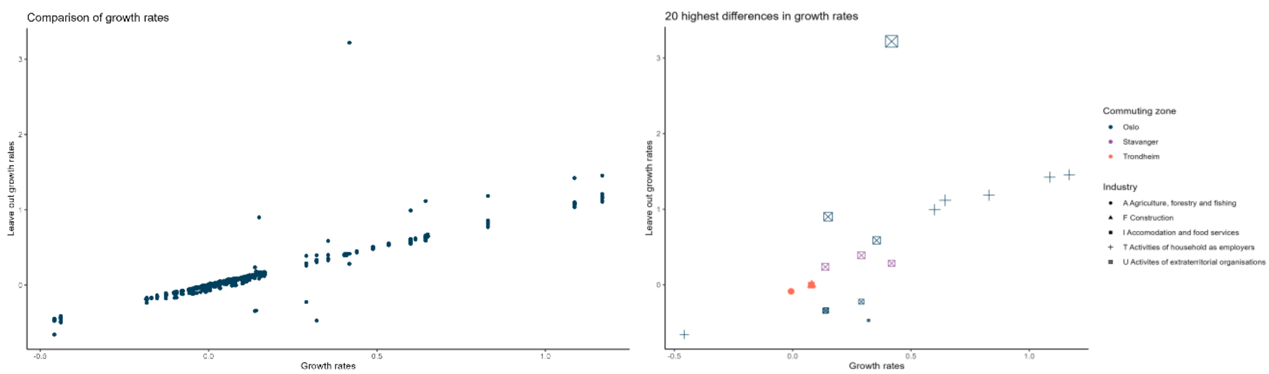

Figure 7.1: Comparison of growth rates and leave-out growth rates

7.5.2 Employment above 1G

One potential issue in our analysis is that the employment measure might be too inclusive. In our main specification, anyone earning work income is considered employed, even those engaged in minor part-time roles. It is plausible that individuals with part-time jobs are less influenced by local labour demand regarding their DI uptake. Some may be pursuing higher education as their primary economic activity, with part-time employment as a secondary economic activity. In such cases, their main economic activity remains unaffected by local labour demand. The inclusion of these individuals in our sample could therefore inflate our results and underestimate the actual effect. Furthermore, many DI recipients also engage in some form of work in the labour market, introducing a bias as their DI uptake will not be sensitive to fluctuations in the local labour market. To address these concerns, we narrow our sample, restricting the employment measure to those earning more than 1G.

The estimated effects from this specification reveal a coefficient of -0.775 for the full sample, well within the confidence interval of the main specification of [-1.189, -0.515]. Neither this, nor any of the results from the heterogeneous sample splits reveal results that are statistically significantly different from those in the main specification. The complete results from this specification are shown graphically in figure 7.2, with full results presented in the appendix A3.3 and A3.4.

As the estimates are lower than for our main specification, our concerns about underestimating of the coefficients due to low-level labour market participants seem to be rejected. If anything, it seems like low-level labour market participants could be impacted to a larger extent than individuals with income over 1G.

Revealing similar results as the main specification, this analysis reveals that our model is robust to concerns about a too inclusive employment measure.

7.5.3 Rates

Changes in population size between base and outcome years could bias our results. If a commuting zone experiences population contraction, both the difference in employment and the difference in uptake of DI is likely to be negative. This can bias the estimated effect downwards. To address this potential issue, we have developed a model that takes the population size of the commuting zone into account. Instead of investigating the logarithm of absolute changes in employment and DI, this specification investigates the percentage point change in employment- and DI rates. This specification will therefore also have an interpretation more comparable with Andersen et al. (2019).

The results from this specification are found in figure 7.3, with the full results presented in the appendix A3.5 and A3.6. The first stage F-statistic is sufficiently large for all subsamples.

The results of this specification reveal that a one percentage point decrease in the local employment rate leads to a 0.226 percentage point increase in uptake of DI. This is not statistically significantly different from the coefficient of Andersen et al. (2019) of -0.231. We would expect slightly lower results since Andersen et al. (2019) define DI as DI and AAP, and we do not include AAP. However, compared to Andersen et al. (2019) our time frame of five years is longer than theirs of three years which could lead to higher results, since it in many cases takes more than three years to be declared for DI. Hence, it seems reasonable to have results of similar size.

The heterogenous effects in this specification align with those in the main specification. Like the results in the main specification, this specification too predicts a larger effect for women than for men. The age effects are more difficult to interpret as several groups do not show significant results. This is, however, consistent with our main specification.

In conclusion, the specification with rates instead of absolute levels does not reveal significantly different results in comparison with the main specification. As such, we believe the main specification is robust to concerns about population changes.

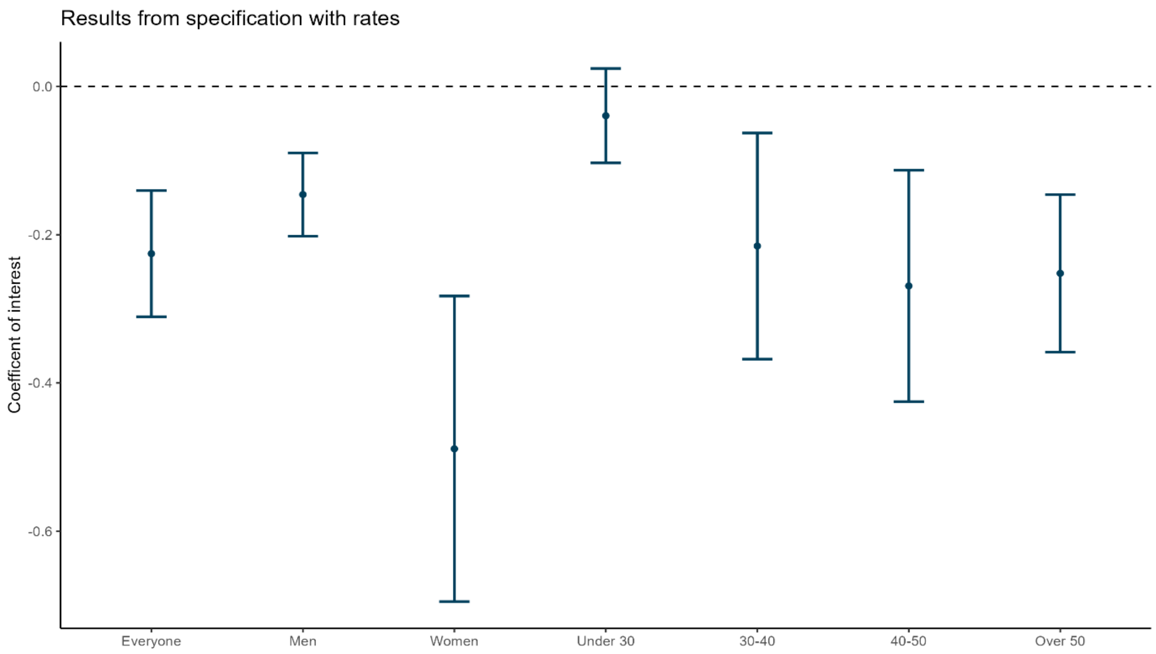

Figure 7.3: Graphical presentation of results from estimation using rates.
Note: The standard errors are clustered at commuting zone level.

7.5.4 Rotemberg weights

The Bartik instrument can be understood as a weighted sum of the individual IV estimators for each industry share based on the Rotemberg weights. These weights report how sensitive the model is to misspecification for each industry and reflect which variation in the data the estimator exploits (Goldsmith-Pinkham et al., 2020).

Figure 7.4 displays the Rotemberg weights for all industries, aggregated over all base years. Alpha shows the Rotemberg weights, while Beta shows the coefficient of interest for individual IV estimations. The single industry with the highest weight is “00 Unknown”, followed by “R – Arts, entertainment and recreation” and “U – Activities of extraterritorial organisations”. We expected more of the variation to come from the decline in “C – Manufacturing” and growth of “Q – Human health and social work activities”. This is, however, not an issue since the industry shares with the highest Rotemberg weights vary sufficiently between commuting zones.

For “00 – Unknown” it is naturally difficult to discuss whether it seems likely that the exclusion- and exogeneity conditions hold since we do not know who works in the industry, what they work with or how their working conditions are.

The untestable nature of exclusion and exogeneity restrictions poses a challenge in evaluating the validity of our research design and the causal interpretation of our estimates. Despite these challenges, we maintain confidence in our estimates, drawing support from an extensive body of previous literature that has not identified substantial issues related to these restrictions (e.g., Autor & Duggan, 2003; Charles et al., 2018; Andersen et al., 2019). This robust historical foundation enhances our confidence in the reliability of our estimates, providing a measure of reassurance. However, the identification of the Rotemberg weights informs us about in which industries a misspecification would be the most detrimental and provides information about what variation our method actually exploits. These are both pieces of knowledge that would otherwise be unavailable to us.

Aggregated Rotemberg weights

	Industry	Alpha	Beta
1	00 - Unknown	1.200	-2.231
2	R - Arts, entertainment and recreation	0.143	-2.228
3	U - Activities of extraterritorial organisations	0.139	-4.558
4	O - Public administration and defence; compulsory social security	0.125	-2.383
5	T - Activities of household as employers	0.032	81.518
6	L - Real estate activities	0.025	0.962
7	F - Construction	0.021	-4.234
8	H - Transportation and storage	0.019	-2.891
9	N - Administrative and support service activities	0.018	0.855
10	J - Information and communication	0.014	0.641
11	Q - Human health and social work activities	-0.001	-40.251
12	G - Wholesale and retail trade; repair of motor vehicles and motorcycles	-0.004	-7.227
13	S - Other service activities	-0.017	9.821
14	M - Professional, scientific and technical activities	-0.027	-12.262
15	A - Agriculture, forestry and fishing	-0.028	-10.666
16	K - Financial and insurance activities	-0.035	-0.310
17	E - Water supply; sewerage, waste management and remediation activities	-0.039	-0.224
18	D - Electricity, gas, steam and air conditioning supply	-0.045	-4.367
19	P - Education	-0.097	-2.720
20	I - Accommodation and food service activities	-0.112	-0.028
21	C - Manufacturing	-0.165	-2.564
22	B - Mining and quarrying	-0.166	-2.563

Alpha is the sum of the industry-year Rotemberg weights, summed over industry. Beta is the estimated coefficent per industry

Figure 7.4: Aggregated Rotemberg weights

7.5.5 Limitations

The limitations of our analysis include data constraints, the inability to estimate the cost effect of an increased uptake of DI and the large variation in industry size with several small industries. The analysis also has a limited external validity, although the estimated effects are similar in size to estimates from other studies.

Due to our data availability, individuals may be measured as both employed and on DI at the same time. This is because we are not able to distinguish what an individual’s main economic activity is. Additionally, we are not able to distinguish between the different levels of individual DI uptake or employment, but rather classify all individuals who receive some level of DI as DI recipients, and all individuals who receive working income as employed. This means that although our results are robust, they only give us information about how changes in local labour market demand impact the changes in uptake of any size of DI. There are obvious cost differences between an increased uptake in 20% graded DI and an increased uptake in 100% graded DI. Not being able to distinguish between these outcomes is a limitation of our study.

The industries differ greatly in size, and some small industries are only located in certain commuting zones. National employment changes in the small industries may be due to random variation within either one or a few commuting zones, potentially creating a source of bias in our estimates. Ideally, we would have been able to aggregate up the small industries to a higher appropriate level in order to mitigate this concern. This was not done as our chosen industry classification did not provide a higher level of aggregation than the one already applied in the analysis.

Lastly, the result from our analysis is likely not externally valid. The DI uptake decision is impacted by local factors, such as the institutional design of the social insurance systems and the interaction with social workers. Applying our results to another country, with both a different system design and culture would therefore be a questionable practice. Our results likely share most similarities to results found in other countries with similar systems and replacement rates of DI. We do note however, that our full sample results are of similar magnitude as those previously reported from American studies, even though the DI systems differ (Charles et al., 2018).

7.6 Policy implications

The negative relationship between local labour demand and DI uptake suggests that labour-oriented initiatives could lower long-term costs of DI. Local labour market demand can be improved by initiatives that make it easier or incentivise employers to employ those struggling on the labour market and less attached to it. Our empirical analysis finds inconclusive results regarding the youngest age group’s uptake of DI in response to labour demand. We can therefore not conclude that demand side initiatives will have a positive impact on this group. However, the descriptive evidence clearly shows that this group is increasing their uptake of DI. This group has a large cost saving potential and we therefore consider supply side initiatives as a supplement to demand side initiatives. Initiatives targeted at the supply side could be work training and education as demand for skilled labour will be increasing in the coming years (Cappelen et al., 2020).

The group most sensitive to local labour demand in their DI uptake is women, however the estimated elasticity is not statistically significantly different than for men. The over 50 age group also has a significant response, although the differential magnitude of the response is inconclusive between age groups. This suggest that general initiatives to increase local labour demand would be beneficial. This might be initiatives that encourage employers to take on more employees, especially those with a more marginal health. Currently, it is very costly to employ workers with high levels of sickness absence. As shown in the descriptive evidence, individuals who later go on DI have a higher uptake of sickness benefits than the general population. The state covers the sickness benefits once they exceed 16 days, but these first days must be paid in full by the employer, and if an employee starts a new period of sick leave, the first 16 days must be paid by the employer once more. Changing this system, making it less expensive for employers to hire workers with a more marginal health situation, would decrease the potential cost of hiring workers in this category. This could in the long run decrease the DI uptake in the population.

The older age groups have a more marginal health situation. Adapting their work situations to accommodate for this could include more flexible hours or information about how to combine work and partial retirement. For this group, specific programs that incentivise employers to hire older individuals could be beneficial as those over 50 are unemployed for longer than the younger age groups upon job displacement (Pettersen & Røv, 2022).

Additionally, the results illustrate the cost saving potential in short-term labour market initiatives to counteract unemployment in economic downturns. Although economic downturns are temporary, our results show that these situations can push conditional applicants into DI. This supports arguments in favour of government expenditure on short-term labour market initiatives, ensuring that labour demand is relatively high, even during economic downturns. Due to the permanency of DI, temporary expenditure on preventative measures is favourable. Naturally, policymakers must consider other concerns in addition to DI, and the choice of how to stimulate the economy in an economic downturn should balance all these concerns.

The younger age group has cost saving potential because their potential DI spell will be much longer than for the older age groups. Their sensitivity of DI uptake to local labour demand is not significantly different from zero. However, the descriptive evidence shows clearly that this is the group experiencing the largest percentage growth in uptake. Initiatives targeted towards this group should therefore be on the supply side, as our results are inconclusive on their reaction to changes in local labour demand. Supply-side initiatives could be ensuring that this group is sufficiently qualified and supporting introduction to the labour market.

8. Conclusion

The objective of our thesis has been to provide insight on what drives the increased uptake of DI, to enable policy makers to reduce the costs of the DI program while still ensuring dignified lives for those unable to work. Our focus has been on how changes in labour demand impact the uptake of DI, both for the general population and for several sample splits of interest. Both our gender split results and our full sample result show that there is a clear connection between worsened local labour market condition and an increased uptake of DI. For the general population we find that a 1% decrease in local labour market demand leads to a 0.852% increase in disability insurance uptake. These results are driven by the female population with an elasticity of -1.343, while the male elasticity is -0.687. However, we cannot from our results conclude confidently that these estimates are significantly different, as they are within one another's confidence interval.

Our thesis follows a line of international studies employing a Bartik shift-share IV in a similar fashion in order to estimate the increased uptake of DI. However, to our knowledge only Andersen et al. (2019) have attempted this technique in the Norwegian context. Our research adds to Andersen et al. (2019) and other papers focusing on job displacement and DI uptake by examining several sample splits and the gender differences.

Our full sample results are similar in magnitude to previously found estimates from the US and Norway. However, both our gendered sample splits and our insignificant results for the age splits are unexpected. Previous literature has found a higher impact of job loss on the DI uptake of men than of women, while we observe the opposite. This can be explained by the difference in research design, where our focus is on changes in the local labour demand, not job loss. Additionally, our dataset is more balanced for gender by including all industries, reducing the risk of selection bias.

The results for different sample splits by age are inconclusive. We consistently find insignificant results when examining the effect of local labour demand on uptake of DI. Several of the estimated coefficients are not statistically significant, nor are they statistically significantly different from one another. The 30-40 age group shows significance at the 10% level and the oldest age group at the 5% level. While the insignificance of our age split results was not as expected, they still provide interesting insight. Results from the 18-30 group is not statistically different from zero, while simultaneously showing the quickest percentage growth in the descriptive analysis. Hence, we cannot explain the increased DI uptake in the youngest group through labour demand but must rather look for reasons elsewhere.

A limitation of our study is that we are not able to identify the reason *why* there is a causal connection between local labour demand and the uptake of DI. Theoretical models for uptake, supported by previous research point to a combination of a health impact and a substitution effect, both influencing the uptake decision. Further research with a larger level of medical data availability is needed to identify which of these factors are the driving cause of the connection.

Our findings in combination with a thorough knowledge of the institutional setting provides relevant information for policy makers who wish to decrease the costs related to the DI program. Encouraging businesses and implementing programs on the demand side of the labour market will likely have an impact on DI uptake. The youngest age group's increased uptake should rather be tackled through a combination of supply-side and demand side policies, as the estimates for this group are inconclusive.

References

Adão, R., Kolesár, M., & Morales, E. (2019, November). Shift-Share Designs: Theory and Inference. *The Quarterly Journal of Economics, 134*(4), 1949-2010. Retrieved from https://doi.org/10.1093/qje/qjz025

Andersen, A. G., Markussen, S., & Røed, K. (2019, December). Local labor demand and participation in social insurance programs. *Labour Economics*. Retrieved from https://doi.org/10.1016/j.labeco.2019.101767

Apfel, N. (2022, July 5). *Relaxing the Exclusion Restriction in Shift-Share Instrumental Variable Estimation.* Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3408682

Arbeids- og inkluderingsdepartementet. (2022, October 6). *Økte kostnader på 40 milliarder*. Retrieved from Regjeringen.no: https://www.regjeringen.no/no/aktuelt/budsjett-pengene-i-folketrygden/id2930068/

Autor, D. H., & Duggan, M. G. (2003, February). The Rise in the Disability Rolls and the Decline in Unemployment. *The Quarterly Journal of Economics, 118*(1), 157-205. Retrieved from https://www.jstor.org/stable/25053901

Bhuller, M. S. (2009). *Inndeling av Norge i arbeidsmarkedsregioner*. SSB. Retrieved from https://www.ssb.no/a/publikasjoner/pdf/notat_200924/notat_200924.pdf

Black, D., Daniel, K., & Sanders, S. (2002, March). The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust. *American Economic Review, 92*(1), 27-50. Retrieved from https://www.aeaweb.org/articles?id=10.1257/000282802760015595

Borjas, G. (2019). Labor Supply. In *Labor Economics* (pp. 21-83). McGraw-Hill. Retrieved from https://scholar.harvard.edu/files/gborjas/files/lechapter2.pdf?fbclid=IwAR1Nu8zHo3cRigDpgRMJtsN_oeg_yPLeq7QCAHCDAaITIhCmyE__k0Tin2Q

Borusyak, K., Hull, P., & Jaravel, X. (2022, January). Quasi-Experimental Shift-Share Research Design. *The Review of Economic Studies, 89*(1), 181-213. Retrieved from https://doi.org/10.1093/restud/rdab030

Bragstad, T. (2018). Vekst i uføretrygding blant unge. *Arbeid og velferd*, 69-87. Retrieved from Arbeid og velferd: https://arbeidogvelferd.nav.no/journal/2018/2/m-2651/Vekst_i_uf%C3%B8retrygding_blant_unge

Bratsberg, B., Fevang, E., & Røed, K. (2013, October). Job loss and disability insurance. *Labour Economics, 24*, 137-150. Retrieved from https://doi.org/10.1016/j.labeco.2013.08.004

Breuer, M. (forthcoming). Bartik Instruments: An Applied Introduction. *Journal of Financial Reporting*. Retrieved from http://dx.doi.org/10.2139/ssrn.3786229

Cappelen, Å., Dapi, B., Gjefsen, H. M., & Stølen, N. M. (2020). *Framskrivingar av arbeidsstyrken og sysselsettingen etter utdanning mot 2040.* SSB. Retrieved from https://www.ssb.no/arbeid-og-lonn/artikler-og-publikasjoner/_attachment/436239?_ts=1758cde9da8

Charles, K. K., Li, Y., & Stephens Jr., M. (2018). Disability Benefit Take-Up and Local Labor Market Conditions. *The Review of Economics and Statistics, 100*(3), 416-432. Retrieved from https://doi.org/10.1162/rest_a_00692

Claussen, B., Næss, Ø., Reime, L. J., & Leyland, A. H. (2013). Proof firm downsizing and diagnosis-specific disability pensioning in Norway. *BMC Public Health*. Retrieved from https://doi.org/10.1186/1471-2458-13-27

Cools, S., & Strøm, M. (2015). *The effect of children on labor supply and wage elasticities in the household.* University of Oslo, Department of Economics. ESOP - Centre for the Study of Equality, Social Organization and Performance, Oslo. Retrieved from https://www.sv.uio.no/esop/english/publications/unpublished-works/working-papers/2011/M%3A%5Cpc%5CDokumenter%5CESOP%5CMedia%20eller%20papers%5CPapers%5Ccools%20strom%202011%20household%281%29.pdf?fbclid=IwAR1Ef3I8Sy3aNaSMefMPzS_VR6URkrfe-TjoKth7txTAhv9pLy

Ekelund, R. (2022). Kan "raskere avklaringer" bli for raske? *Arbeid og velferd*, pp. 69-80. Retrieved from https://www.nav.no/no/nav-og-samfunn/kunnskap/analyser-fra-nav/arbeid-og-velferd/arbeid-og-velferd/arbeid-og-velferd-nr.3-2022

Eliason, M., & Storrie, D. (2009). Does Job Loss Shorten Life? *The Journal of Human Resources, 44*(2), 277-302. Retrieved from https://www.jstor.org/stable/20648898

Ellingsen, J. (2023). *Utviklingen i uføretrygd per 31. desember 2022.* NAV. Retrieved from https://www.nav.no/_/attachment/download/0d37d0ae-ebd3-4fa3-b6e4-810eec3fbb97:803229ace4ea32dc4a88d033bdd09a3a3244f9e2/Statistikknotat_uf%C3%B8retrygd_desember2022.pdf

Eurostat. (2008). *NACE Rev. 2 Statistical classification of economic activities in the European Community.* Luxmebourg: Office for Official Publications of the European Communities. Retrieved from https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF?fbclid=IwAR24ruLzOOkK9WxSvsL_DLvNO21XtyZo0FFzHW8GPOt1WBYJJ7AEFW9oP4s

Fedoryshyn, N. (2018, March 1). *Lettere å kombinere arbeid og tidlig pensjon i privat sektor*. Retrieved from Statistisk Sentralbyrå: https://www.ssb.no/arbeid-og-lonn/artikler-og-publikasjoner/lettere-a-kombinere-arbeid-og-tidlig-pensjon-i-privat-sektor-2018-5

Fevang, E., & Røed, K. (2006). *Veien til uføretrygd i Norge.* Ragnar Frisch Centre for Economic Research. Oslo: Arbeids- og inkluderingsdepartementet. Retrieved from https://www.frisch.uio.no/publikasjoner/pdf/rapp06_10.pdf

Folketrygdloven. (2000). Retrieved from Folketrygdloven § 12-1: https://lovdata.no/nav/rundskriv/r12-00#KAPITTEL_2-1

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020, August). Bartik Instruments: What, When, Why, and How. *American Economic Review, 110*(8), 2586-2624. Retrieved from https://www.jstor.org/stable/26966340

Huttunen, K., Møen, J., & Salvanes, K. G. (2011, October). How Destructive is Creative Destruction? Effects of Job Loss on Job Mobility, Withdrawl and Income. *Journal of* *the European Economic Association, 9*(5), 840-870. Retrieved from https://www.jstor.org/stable/41305837

Loen, R. (2023, January 22). *SNL: grunnebløpet*. Retrieved from Store Norske Leksikon: https://snl.no/grunnbel%C3%B8pet

Ministry of Finance. (2021). *Meld. St. 14 (2020-2021) Perspektivmeldingen 2021*. Ministry of Finance. Oslo: The Norwegian Ministry of Finance. Retrieved from https://www.regjeringen.no/contentassets/91bdfca9231d45408e8107a703fee790/no/pdfs/stm202020210014000dddpdfs.pdf

Ministry of Finance. (2022, October 6). *Statsbudsjettet 2023: Statens inntekter og utgifter*. Retrieved from Regjeringen.no: https://www.regjeringen.no/no/statsbudsjett/2023/statsbudsjettet-2023-statens-inntekter-og-utgifter/id2931252/

Myhre, A., & Kann, I. C. (2022). Kortere makstid på AAP ga flere i arbeid og raskere uføretrygd. *Arbeid og velferd*, pp. 5-30. Retrieved from https://www.nav.no/no/nav-og-samfunn/kunnskap/analyser-fra-nav/arbeid-og-velferd/arbeid-og-velferd/arbeid-og-velferd-nr.2-2022/kortere-makstid-pa-aap-ga-flere-i-arbeid-og-raskere-uforetrygd

NAV. (2023, October 26). *Arbeidsavklaringspenger*. Retrieved from NAV: https://www.nav.no/aap

NAV. (2023, June 05). *Arkiv - Uføretrygd - Kvartalsstatistikk per 31. desember 2010-2019*. Retrieved from NAV: https://www.nav.no/no/nav-og-samfunn/statistikk/aap-nedsatt-arbeidsevne-og-uforetrygd-statistikk/relatert-informasjon/arkiv-uforetrygd-kvartalsstatistikk-per-desember-2010-2019

NAV. (2023, February 10). *Flere uføretrygdede i 2022*. Retrieved from NAV: https://www.nav.no/no/nav-og-samfunn/statistikk/aap-nedsatt-arbeidsevne-og-uforetrygd-statistikk/nyheter/flere-uforetrygdede-i-2022

NAV. (2023, November 23). *Sykepenger*. Retrieved from NAV: https://www.nav.no/sykepenger

NAV. (2023, December 04). *Uføretrygd.* Retrieved from NAV: https://www.nav.no/uforetrygd

Palmer, H. C. (2023, November 27). *Arbeidslinja er ikke et personlig ansvar!* Retrieved from Agenda magasin: https://agendamagasin.no/kommentarer/arbeidslinja-er-ikke-et-personlig-ansvar/

Paul, K. I., & Moser, K. (2009, June). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational Behavior, 74*(3), 264-282. Retrieved from https://doi.org/10.1016/j.jvb.2009.01.001

Pedersen, A. W. (2021, November 8). *Pensjon*. Retrieved from Store Norske Leksikon: https://snl.no/pensjon

Pettersen, M., & Røv, V. (2022, September 28). *Tyngre vei ut av arbeidsledighet for de i 50-årene*. Retrieved from SSB: https://www.ssb.no/arbeid-og-lonn/sysselsetting/artikler/tyngre-vei-ut-av-arbeidsledighet-for-de-i-50-arene?fbclid=IwAR2-pKTpflTfc80bdJLR4sBOHXuVIAU8FHNjlbNPwQpO4Oo5Bp8RFSWlBck

Rege, M., Vitruba, M., & Telle, K. (2009, June). The Effect of Plant Downsizing on Disability Pension Utilization. *Journal of the European Economic Association, 7*(4), 754-785. Retrieved from https://www.jstor.org/stable/40282788

Skårdalsmo, K., & Lee, I. K. (2023, October 9). *Slik skal hun gjenreise Ap: Advarer mot stakkarsliggjøring*. Retrieved from NRK: https://www.nrk.no/norge/slik-skal-hun-gjenreise-ap_-advarer-mot-stakkarsliggjoring-1.16581946

Solon, G., Haider, S. J., & Wooldridge, J. M. (2015). What Are We Weighting For? *The Journal of Human Resources, 50*(2), 301-316. Retrieved from https://www.jstor.org/stable/24735988

SSB. (2023, November 23). *Likestilling.* Retrieved from SSB: https://www.ssb.no/befolkning/faktaside/likestilling

Starheim, H. A. (2023, October 16). *Tonje Brenna ny arbeidsminister: - Vi må alle tenke litt annerledes fremover*. Retrieved from Altinget: https://www.altinget.no/artikkel/tonje-brenna-ny-arbeidsminister-vi-maa-alle-tenke-litt-annerledes-fremover

Stauder, J. (2019). Unemployment, unemployment duration, and health: selection or causation. *The European Journal of Health Economics, 20*(1), 59-73. Retrieved from https://doi.org/10.1007/s10198-018-0982-2

Thoresen, T. O., & Vattø, T. E. (2015, December). Validation of the discrete choice labor supply model by methods of the new tax responsiveness literature. *Labour Economics, 37*, 38-53. Retrieved from https://doi.org/10.1016/j.labeco.2015.09.001

Thorsnæs, G., & Lauritzen, P. R. (2023, June 1). *Store norske leksikon: Kongsberg*. Retrieved from Store norske leksikon: https://snl.no/Kongsberg

Appendix

A1 Data sources

All data from microdata.no is retrieved from the databank, no.ssb.fdb:24.

Comment on footnote 4 in chapter 5, section 2:

Footnote 4 refers to the national unemployment benefit uptake of 4.99%. The number of unemployment benefit recipients is retrieved from table 05645: Dagpenger ved arbeidsledighet from SSB and the number of individuals within the working age population is retrieved from microdata.no, through the use of variables for age and status.

A1.1 Data for descriptive analysis

Data	Source and variable name	Comment
Data for sample restriction	Microdata.no BEFOLKNING_FOEDSELS_AAR_MND BEFOLKNING_STATUSKODE BEFOLKNING_KJOENN	 Age restrictions. Restrict to living residents. Gender restrictions.
Uptake of DI	Microdata.no INNTEKT_KODE218	
Uptake of tlDI	Microdata.no TIDSUFOERPFDT_MOTTAK	
Uptake of pension	Microdata.no INNTEKT_FTRYG INNTEKT_AFP_SUM	
Uptake of sickness benefits	Microdata.no INNTEKT_SYKEPENGER	
Uptake of unemployment benefits	Microdata.no INNTEKT_ARBLED	
Earnings from work	Microdata.no INNTEKT_WYRKINNT	
Uptake of AAP	Microdata.no INNTEKT_SUM_ARBAVKL	

Table A1.1: Data sources and links for descriptive analysis

A1.2 Data for empirical analysis

Data	Source and variable name	Comment
Commuting zones	SSB Bhuller (2009)	Definition of commuting zones.
Number of DI recipients per municipality per year	Microdata.no INNTEKT_KODE218	
Number of employees per industry per municipality per year	SSB 08536: Kjønn og næringsfordeling	Calculation of industry shares. Calculation of industry growth.
Number of employed individuals per municipality per year	SSB 08536: Kjønn og næringsfordeling	

Table A1.2: Data sources and links for defined variables in empirical analysis

Data	Source and variable name	Comment
Status	Microdata.no BEFOLKNING_STATUSKODE	Restrict to living residents.
Age	Microdata.no BEFOLKNING_FOEDSELS_AAR_MND	Age restrictions.
Gender	Microdata.no BEFOLKNING_KJOENN	Gender restrictions.
Municipality	Microdata.no BOSATTEFDT_BOSTED	

Table A1.3: Data sources and links for additional variables in empirical analysis

Data	Source and variable name	Comment
Income	Microdata.no INNTEKT_WYRKINNT Skatteetaten (the Norwegian Tax Authority) Grunnbeløpet i folketrygden	Restrict employment measure to income above 1G

Table A1.4: Additional variables for 1G robustness checks

A2 Descriptive analysis

	2000	2019	% change
Proportion of working population on DI	9,96%	10,45%	+ 4,92%
Proportion of women in working-age on DI	11,63%	12,58%	+ 8,17%
Proportion of men in working-age on DI	8,33%	8,41%	+ 0,96%

Table A2.1: Population and gender split increases in DI uptake between 2000 and 2019

	2000	2019	% change
Mean age for DI recipients	53,95	52,87	-2,00%
Median age for DI recipients	56	56	No change
Proportion of population aged 18-29 on DI	1,16 %	2,40 %	+ 106,90%
Proportion of women aged 18-29 on DI	1,09%	2,26%	
Proportion of men aged 18-29 on DI	1,23%	2,54%	
Gender breach (women – men)	-0,14% - points	-0,28% - points	
Proportion of population aged 30-39 on DI	3,45 %	4,53 %	+ 31,30%
Proportion of women aged 30-39 on DI	3,82%	5,11%	
Proportion of men aged 30-39 on DI	3,09%	3,98%	
Gender breach (women – men)	0.73% - points	1,13% - points	
Proportion of population aged 40-49 on DI	7,97 %	8,78 %	+ 10,16%
Proportion of women aged 40-49 on DI	9,57%	10,91%	
Proportion of men aged 40-49 on DI	6,44%	6,75%	
Gender breach (women – men)	3,13% - points	4,16% - points	
Proportion of population aged 50-59 on DI	17,21 %	16,31 %	-5,23%
Proportion of women aged 50-59 on DI	21,21%	20,13%	
Proportion of men aged 50-59 on DI	13,35%	12,66%	
Gender breach (women – men)	7,86% - points	7,47% - points	
Proportion of population aged 60-67 on DI	37,07 %	27,18 %	-26,68%
Proportion of women aged 60-67 on DI	40,51%	32,61%	
Proportion of men aged 60-67 on DI	33,46%	21,8%	
Gender breach (women – men)	7,05% - points	10,81% - points	

Table A2.2: Age and gender split increase in DI uptake between 2000 and 2019

A3 Robustness checks

A3.1 Leave-out Bartik instrument

Results from leave-out estimation: Full sample and gender

	Change in DI uptake					
	All		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik	1.309^{***}		1.557^{***}		0.898^{***}	
	(0.355)		(0.412)		(0.285)	
Instrumented change in employment		-1.038^{**}		-0.768^{**}		-1.728^{**}
		(0.408)		(0.351)		(0.751)
First-stage F statistic	13.6		14.3		9.9	
Observations	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered at commuting zone level					

Table A3.1: First and second stage results from 2SLS estimation with a leave-out Bartik instrument, full sample and gender split

Results from leave-out estimation: Age

	Change in DI uptake							
	Under 30		30-40		40-50		Over 50	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik	2.111^{***}		1.235^{***}		0.711^{***}		0.997^{***}	
	(0.547)		(0.315)		(0.180)		(0.266)	
Instrumented change in employment		-0.286		-1.600^{*}		-1.811		-0.966^{**}
		(0.942)		(0.866)		(1.167)		(0.453)
First-stage F statistic	14.9		15.3		15.6		14.1	
Observations	322	322	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered at commuting zone level							

Table A3.2: First and second stage results from 2SLS estimation with a leave-out Bartik instrument, age split

A3.2 Employment above 1G

Results from 1G estimation: Full sample and gender

	Change in DI uptake					
	All		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik	1.747***		2.218***		1.216***	
	(0.280)		(0.322)		(0.277)	
Instrumented change in employment		-0.775**		-0.588**		-1.214**
		(0.321)		(0.274)		(0.551)
First-stage F statistic	38.9		47.5		19.3	
Observations	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered at commuting zone level					

Table A3.3: First and second stage results from 2SLS estimation with 1G restriction, full sample and gender split

Results from 1G estimation: Age

	Change in DI uptake							
	Under 30		30-40		40-50		Over 50	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik	2.979***		1.448***		0.849***		1.484***	
	(0.479)		(0.241)		(0.218)		(0.234)	
Instrumented change in employment		-0.164		-1.218		-1.503		-0.664**
		(0.721)		(0.769)		(1.067)		(0.327)
First-stage F statistic	38.7		35.9		15.2	40.4		
Observations	322	322	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are clustered at commuting zone level							

Table A3.4: First and second stage results from 2SLS estimation with 1G restriction, age split

A3.3 Rates

Results from rates estimation: Full sample and gender

	Change in DI uptake					
	All		Men		Women	
	(1)	(2)	(3)	(4)	(5)	(6)
Bartik	0.754***		0.894***		0.423***	
	(0.158)		(0.134)		(0.123)	
Instrumented change in employment		-0.226**		-0.146**		-0.489**
		(0.085)		(0.056)		(0.206)
First-stage F statistic	22.8		44.8		11.7	
Observations	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01					
	Standard errors are clustered at commuting zone level					

Table A3.5: First and second stage results from 2SLS estimation with rates, full sample and gender split

Results from rates estimation: Age

	Change in DI uptake							
	Under 30		30-40		40-50		Over 50	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bartik	0.670***		0.470***		0.495***		0.737***	
	(0.214)		(0.130)		(0.087)		(0.117)	
Instrumented change in employment		-0.039		-0.215		-0.269*		-0.252**
		(0.064)		(0.153)		(0.156)		(0.106)
First-stage F statistic	9.8		13.0		32.7		40.0	
Observations	322	322	322	322	322	322	322	322
Note:	*p<0.1; **p<0.05; ***p<0.01							
	Standard errors are clustered at commuting zone level							

Table A3.6: First and second stage results from 2SLS estimation with rates, age split