Health and unemployment during a negative labour demand shock[1]

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Abstract:
The association between unemployment and health is well documented, but causality remains unclear. This paper investigates how pre-existing health conditions amplify the effects of adverse labor market shocks. Using variation in local unemployment generated by a shock in the petroleum prices that hit the geographic center of the petroleum industry in Norway, but left other regions more or less unaffected, our study reveals that workers with compromised health face a higher likelihood of unemployment during downturns. Heterogeneity analysis reveals differences in susceptibility based on gender, age, education, and job type. Females exhibit greater sensitivity to health, and the youngest age group is most affected. Furthermore, higher education and white-collar jobs correlate with amplified health-related unemployment effects. Conversly, poor health in combination with high age, low education, and blue-collar jobs increases the uptake of social insurance during the economic downturn, pointing towards the substitutability between unemployment benefits and health-related benefits.

Keywords:
Health effects, Unemployment, Recession, Difference-in-difference
JEL Codes:
I12, J64, C21, C31

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1 Introduction

Numerous studies have consistently demonstrated that unemployment is associated with poor health.[2] However, the causal relationship between health and unemployment remains elusive. Obviously, there may be several mechanisms through which unemployment affects health adversely. Unemployment means loss of income; directly during the period of joblessness but also through detrimental impact on wage growth for individuals who eventually return to work, as well as increased likelihood of permanent exclusion from the labour market (Chan and Stevens, 2001; Couch & Placzek, 2010; Huttunen et al. 2011; Carrington & Fallick, 2017; Fackler et al. 2021). Thus, reduced health among the unemployed can result from a decrease in income that directly affects the ability to live a healthy life and receive proper medical care. Other adverse, health-threatening life events can follow from unemployment, too, e.g. increased probability of divorce (Rege et al, 2007) and destructive and harmful strategies to cope with stress and strain (Heggebø, 2022). Finally, the unemployment experience itself may affect mental health (Farré et al, 2018).

Still, impaired health among a cross-section of unemployed compared to the working population does not mean that unemployment has *caused* ill health. There may be individual unobservable effects (genetic and/or innate personal characteristics) that simultaneously affect health and the probability of becoming unemployed. It may be a selection of workers with poor health *into* unemployment (Riphahn, 1999; Lindholm et al., 2001) and/or a selection of healthy workers *out of* unemployment (Stewart, 2001; Mastekaasa, 1996), i.e. that workers with poor health tend to have longer unemployment durations. Furthermore, health shocks may simultaneously decrease health and lead to unemployment (Adams et al. 2003; Schmitz 2011).

Recent advances in individual longitudinal register data, particularly in the Nordic countries, have improved the ability to control for endogeneity in the form of selection and/or reversed causality. The use of panel data has enabled researchers to control for unobserved individual heterogeneity. Additionally, employer-employee register data have made it possible to use individual information about firm closures as an exogenous measure of

[2] See Barnay (2016) for a recent review.

unemployment.[3] Eliason and Storrie (2009) and Browning and Heinesen (2012) found that lay-offs in connection with restructuring may result in increased mortality for certain groups. Mortality is, however, a relatively crude measure of health, so other analyses have used alternative individual health information to provide further insights into the relationship between unemployment and poor health. For instance, Browning, Moller, and Heinesen (2006) found no effect of restructuring on stress-related hospitalizations. Similarly, Black, Devereux, and Salvanes (2015) conducted a wide-ranging health analysis but found few signs of health effects of restructuring (aside from poorer smoking habits).[4] Schmitz (2011) found, based on German panel data and using a fixed effect model with corporate closure as an exogenous measure of unemployment, no evidence that unemployment leads to impaired health. Additionally, Böckerman and Ilmakunnas (2009) found no effect of unemployment on self-rated health using Finnish panel data. In sum, the available empirical evidence on unemployment causing bad health appears to be weak. In a recent meta-analysis, Picchio and Ubaldi (2022) conclude that the average effect of unemployment on health is negative, but small in terms of partial correlation coefficient.[5] When endogeneity issues are accounted for, the unemployment effects on health are closer to be nil.

When a negative effect from unemployment on health is hard to detect and the correlation between unemployment and health still is negative, this increases the likelihood that causality goes the other way, namely that workers with poor health are selected into unemployment. To distinguish this from the alternative explanation, that unemployment causes poor health, it is essential to introduce some random variation in the risk of unemployment. Macroeconomic fluctuations have been used as exogenous sources to study individual implications of (poor) health on unemployment. In a recent paper, Bharadwaj, Bietenbeck, Lundborg and Rooth (2019), hereafter BBLR, used the recession and the accompanying sharp increase in unemployment in Sweden in the early 1990s to investigate how workers' predetermined health affected their probability of job loss. Using between-

[3] There is hardly any reason to believe that firms close down due to poor health of their employees. If poor health is observed among the dismissed workers, it is likely, therefore, that this is caused by the close-down.
[4]Rege, Telle and Votruba (2009) find a connection between restructuring and the admission of disability benefits, which is a health-related social security benefit. It is, nevertheless, well documented, see e.g. Andersen et al. (2019), that disability benefit is an inadequate measure of health, because labour market conditions, in addition to poor health, determine whether a person is granted social security.
[5] The analysis is based on 65 published papers in the period 1990 to 2021.

twins variation in birth weight as a proxy for pre-crisis health they found that workers' health status significantly influenced their likelihood of becoming unemployed during the economic downturn.[6]

While BBLR base their analysis on a nationwide recession hitting the entire labour force, the present paper examines the extent to which poor health affected the probability of becoming unemployed due to a *local* labour market shock in Norway, namely the consequences of a sudden and unexpected fall in oil prices in 2014. The price shock had extensive direct effect on employment in the Norwegian oil and gas industry, which primarily is located at the western part of Norway, particularly in the county of Rogaland. The fact that the downturn was restricted to certain geographical areas allows us to construct treatment group (region affected by the exogenous shock in world petroleum prices) and control group (region not affected) of comparable workers and compare labour market outcomes for the two groups before and after the shock.

The main focus in our paper, as well as in BBLR, is to examine whether and how an individual's pre-shock health status mediated their labour market status during the crisis. But while BBLR used birth weights as a proxy for adult health, we measure adult health directly, using pre-crisis data on visits to GPs. In the Norwegian health care system, all citizens are assigned to a GP. Users pay a fee which is topped up by the state to provide the full payment to the GP. Therefore, all GP-patient contacts are recorded, and remunerations to the GP are based on these records.

Arguably, there is no “perfect” measure of the many aspects of health. Researchers typically resort to self-reported health, physical measures such as Body Mass Index, negative health behaviours, or health care utilization. This paper falls in the latter category. In Picchio and Ubaldi’s (2022) meta-analysis, only 19 out of 327studies apply health care utilization data. In comparison, 117 studies apply self-assessed health. A potential pitfall of utilization data is

[6] In a series of related papers Ruhm (2000, 2003, 2005) studies how macroeconomic downturns affects health. He finds that it leads to *improved* health in the form of lower mortality rates in the average population. However, Ruhm also acknowledges that this finding does not negate the fact that the non-employed segment of the population generally has poorer health compared to employed individuals, and that this disparity applies also to those who become unemployed during recessions. (Ruhm 2003, p. 639.)

that they may depend on income, supply of health care services or only relate to limited aspects on health. Our measure is based on full population data on all GP contacts. More details are provided in the next section, but we argue that in the Norwegian context, with low co-payment, GP visits are a valid measure of general health. Visiting the GP has a time cost that is reduced when unemployed – we avoid that problem by using physician visits before the crisis. Admittedly, the inclination to see a physician may vary between individuals with similar health status. Even so, following a standard measurement error argument, if we measure "true" health with a random error, the estimate of a potential effect is biased downwards. Therefore, we are less worried of finding a false positive. By using administrative data, we also avoid disadvantages with self-reported data, such as reporting biases and justification bias (Barnay 2016).

Another potential pitfall could be that workers in poor health regard unemployment as an opportunity to exit the labour market with (some) economic compensation. If so, we could confuse unemployment with being out of the labour force. While leaving the labour force is a relevant topic, the present analysis aims to have a say on the causality direction in the health-unemployment correlation. We argue that the design of Norwegian social insurance, with extensive and generous sickness and disability benefits, goes against an interpretation of unemployment as a substitution for health-related exits from the labour force.[7]

By using the (twin) difference in birth weight as an exogenous measure, BBLR effectively correct for a number of unobserved confounders related to health disparity. While we do not have access to high quality twin data, our estimation strategy allows us to address a distinct type of unobserved selection bias: When individuals with poorer health are more likely to obtain less favourable and less stable job opportunities, there could be an overrepresentation of such cases in industries and sectors that are particularly susceptible to unemployment. To confront this potential selection bias, it is imperative to introduce exogenous variations in the likelihood of experiencing unemployment. Our difference-in-differences strategy allows us to account for this particular concern. If there are unobservable factors that influence selection to certain jobs and sectors, this presumably

[7] We do, however, open for the possibility that health-related benefits may be substitutes for unemployment benefits.

applies similarly to both the treatment group (Rogaland) and the control group (the rest of the country).

The unemployment rate in Norway is notably low, yet there is a correspondingly high percentage of the working-age population relying on health-related social insurance. This observation suggests a potential substitution effect between unemployment and the utilization of health-related social insurance programs. The upsurge in demand for health-related benefits during economic downturns, influenced by factors beyond health deterioration, has been consistently supported by various studies.[8] As unemployment rates increase, individuals seem more inclined to work assessment allowances and disability benefits rather than actively seeking new employment opportunities. Consequently, we extrapolate the implications of the oil price shock to include the uptake of health-related social insurance.

The paper proceeds with institutional background and data descriptions. In the results section, the main finding is that, indeed, poor health increases the unemployment risk: the least healthy group has a 57% higher probability of becoming unemployed. Heterogeneity analyses also reveal a pattern where workers with high productivity requirements are most at risk. This finding is complemented by a finding that some particularly vulnerable workers sort themselves into health-related social insurance.

2 Background

2.1 The Norwegian petroleum sector and the petroleum market shock

The petroleum sector is by far Norway's largest industry in terms of contribution to the GDP. In 2014, it accounted for approximately 21% of GDP and 61% of total exports. The International Energy Agency ranked Norway as the seventh largest exporter of crude oil and the third largest exporter of natural gas, highlighting the industry's significant impact on the country's economy (IEA, 2022).

[8] Notable contributions include the works of Autor and Duggan (2003), Rege et al. (2009), Bratsberg et al. (2013), Kann et al. (2016), Lima (2016), and Andersen et al. (2019).

The volatility of petroleum prices is a well-known phenomenon. This is depicted in Figure 1, which illustrates the fluctuation of crude oil prices during the first two decades of the 2000s. Although decreasing petroleum prices may potentially lower costs and stimulate economic growth in most countries, price declines tend to have adverse effects on petroleum-producing economies, including Norway's. Figure 1 presents two recent examples of extreme price declines. The first occurred during the financial crisis in 2008-2009, following years of increasing prices due to heightened demand, especially from China. The prices of crude oil rebounded relatively quickly before dropping substantially again, by over 70% between June 2014 and early 2016. This time, the primary factors driving the decline came from the supply side, notably increased shale oil production and lowered production costs. In addition came reduced growth in the global economy, resulting in reduced demand.

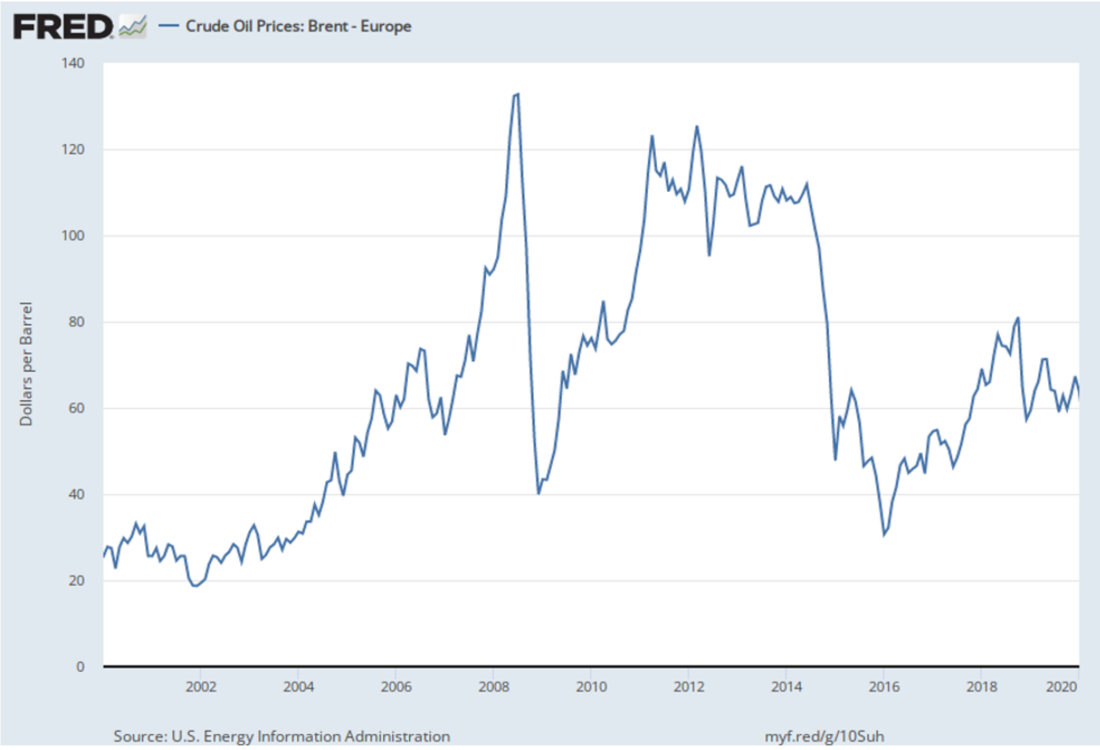

Figure 1 Crude Oil Prices: Brent – Europe, 2000-2020.
Source: U.S. Energy Information Administration

The petroleum income's fraction of government spending in Norway is regulated through a rule introduced by the Parliament in 2001, stating that the government should not spend more oil money in the annual budget than what corresponds to the expected annual return from the public petroleum fund. This means not exceeding 3% of the fund's capital to maintain budget balance.[9] Petroleum price fluctuations influence on the inflow to the fund, but not directly on yearly governmental spending. Price shocks do, however, have extensive effect on employment. In 2013, approximately 9% of the country's workforce was either directly or indirectly[10] employed in petroleum-related industries (Statistics Norway, 2017). The petroleum and petroleum-related industries employed around 232,000 individuals, but this number decreased to 206,000 in 2015 and 185,300 in 2016 (Statistics Norway, 2017).

Obviously, given the critical role of the petroleum sector in the Norwegian economy, various mechanisms are in place to mitigate the effects of declining oil and gas prices and reduced demand from the sector. The mechanisms include both monetary and fiscal policy measures. In 2014, the Bank of Norway responded to the poor economic prospects by reducing the base rate. The subsequent decline in oil and gas prices and lower base rate weakened the exchange rates, improving the competitiveness of the mainland economy. Additionally, fiscal policy became increasingly expansive. Overall, the authorities were able to largely alleviate the negative impacts of falling petroleum prices during the 2014-2016 period, with employment remaining relatively stable.[11]

The exception was in the most oil-dependent regions. A public commission which was appointed to discuss the consequences of the 2014 petroleum price shock, concluded (NOU 2016: 13, p.57):

> "The decline in oil prices since summer 2014 has contributed to lower growth and higher unemployment in the Norwegian economy, but the current downturn is less severe than during the crisis of the late 1980s and early 1990s and the international

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[9] Until 2017 the maximum was 4%. [10] *Direct employment* in the petroleum sector includes workers in the exploration, production, and refining of oil and gas. This includes engineers, technicians, and other skilled workers who work in the offshore oil and gas fields, as well as workers in onshore facilities such as refineries and processing plants. *Indirect employment* in the petroleum sector includes workers in other industries that support or are supported by the oil and gas industry. This includes industries such as shipping, construction, and engineering, which provide services or materials to the petroleum sector. Indirect employment also includes workers in industries that benefit from the economic activity generated by the petroleum sector, such as retail and hospitality.

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[11] Compared to previous price drops resulting from global recessions, the fact that prices this time were primarily driven by the supply side was positive for the Norwegian economy.

financial crisis. Unlike in the previous downturns, employment, activity levels in the mainland economy and prices have all continued to grow. *However, the geographical differences are large this time. It is particularly in oil-oriented regions that unemployment has risen* […].” (our italics)

Figure 2 displays the regions with the highest percentage of employees in petroleum-related activities in 2014 (Panel A) and those with the greatest increase in unemployment in 2015 (Panel B). Rogaland county (the darkest blue area) is the most striking example, with the unemployment rate rising by 108 percent in 2016 compared to the level in May 2014 (Lima, 2016). It is worth noting that the public sector was relatively unaffected by the shock in petroleum prices, also in Rogaland, with the decline primarily affecting the private sector.[12]

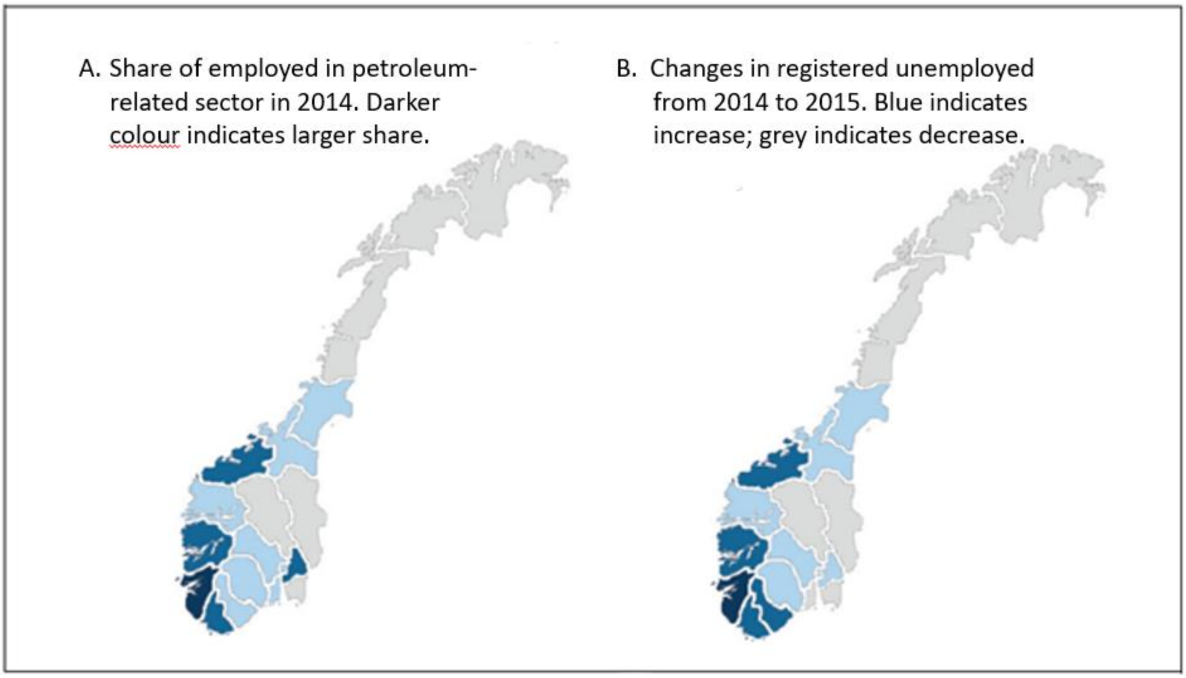


Figure 2 Regional (un-)employment; different counties.
Sources: NAV and International Research Institute of Stavanger.

The localized impact of the shock on specific geographical areas provides an opportunity to create a treatment group (regions affected by the exogenous shock in world petroleum

[12] Unemployment following the petroleum price shock also varied by occupation, with individuals with backgrounds in engineering and information and communications technology (ICT) being particularly affected.

prices) and a control group (regions not affected) of comparable workers. This enables us to compare labour market outcomes for the two groups before and after the shock.

2.2 *Unemployment, unemployment benefits and health related benefits in Norway*

All employees who earn above a minimum level[13] are entitled to universal unemployment insurance in the cases where they are fully or temporarily[14] laid off or have had their working hours reduced by at least 50%. The unemployment benefits provided to eligible workers amount to 62.4% of their previous year's or average of last three years' wage income, for a period of up to 104 weeks (52 weeks if their previous income was less than 2 G).

Despite offering relatively generous unemployment benefits, Norway has a consistently low unemployment rate compared to other European countries. Since the early 2000s, the rate has typically fluctuated between 2% and 3% (NOU 2021:2). However, the country's uptake of health-related benefits, which include sickness, rehabilitation and disability benefits, is exceptionally high.

While the Norwegian social insurance system is designed to maintain a clear distinction between unemployment and health-related benefits, in practice, the two are often intertwined. There are several reasons for this. As discussed above, job losses may, even though the effects appear to be quite small, lead to detrimental health effects for workers, which in turn can lead to a higher demand for health-related benefits during economic downturns.

However, job loss may increase the demand for health-related benefits even when health is unaffected by the economic downturn. Workers with poor health may opt for health-related benefits if the costs associated with search for a new job during a recession is relatively high compared to expected wages. Furthermore, general practitioners (GPs) and case workers at NIS – the gate keepers into health-related benefits – are instructed to take into account the availability of paid work when evaluating a worker's eligibility. This means that during times

[13] The requirements are at least 1.5 G the previous calendar year or at least 3 G in total during the last three calendar years. In this context, "G" refers to the National Insurance Scheme (NIS) basic amount, with 1 G being roughly equivalent to EUR 10,000 in 2023.

[14] Temporary layoffs occur when an employer instructs an employee not to report to work, and the employer is no longer obligated to pay the employee's salary. Despite the temporary cessation of work, the employment relationship continues, with the understanding that the layoff is not permanent.

of economic downturn, sickness and disability benefits may be easier to obtain as job opportunities become scarcer.

Finally, the eligibility requirements and compensation ratio for health-related benefits in Norway are favorable compared to unemployment benefits. Sick-leave benefits in Norway provide workers with 100% wage compensation from the first day of absence for up to one year and is available to all workers employed for more than four weeks. For sickness spells lasting less than nine days, most workers do not even need a medical certificate. For periods of nine days or longer, a medical certificate from a GP is usually required, but such certificates are seldom denied (Carlsen et al., 2020; Ferman et al., 2023). The sickness absence rate is high, with approximately 5-6% of contracted work hours lost due to certified sickness absence during our investigation period (Moberg, 2024). The majority of the cases involve long-term sickness periods. For instance, 86% of all medically certified sick leave days in 2018 lasted more than 16 days (NOU 2021: 2).

After one year the sick-leave benefits from NIS end and the employment relationship terminates. Subsequently, the worker will be referred to medical and vocational rehabilitation benefits known as the work assessment allowance, provided by the NIS. This benefit replaces 66% of the worker's previous earnings, which is slightly higher than unemployment benefits. As of December 2023, just over 5% of the working-age population were receiving the work assessment allowance (NAV 2024a).

If rehabilitation programs do not have det desired effect within one to three years, the next step is disability benefits. The replacement ratio for this benefit is also 66% of previous earnings. Once an individual is granted disability benefits, she is no longer required to participate in any rehabilitation activities. For the NIS, disability insurance is considered an absorbing state, and public statistics confirm that this is the case (NOU 2021: 2). The percentage of the working age population receiving disability benefits was 10.5% (NAV 2024b). The share of disability benefits receivers in Norway in recent years has typically been approximately twice as high as the OECD average (NOU 2021: 2).

Sick-leave benefits differ from work assessment allowance and disability benefits since the former requires being employed while the two latter require the opposite: that one no longer has a job. This means that work assessment allowance and disability benefits are mutually exclusive to employment, while sick-leave benefits are not. Sick-leave is therefore ignored as a separate state in the present paper; thus, health-related social insurance consists of work assessment allowance and disability benefits.

To sum up, the unemployment ratio is low in Norway, while the share of the working age population on health-related social insurance is correspondingly high. As mentioned in the introduction, this hints at the possibility of substitution between unemployment and health-related social insurance program utilization. The higher the unemployment, the stronger the incentives for applying for work assessment allowance and disability benefits rather than getting a new job. Increased demand for health-related caused by other factors than health deterioration is documented in several studies; see footnote 8. In this paper we ask whether it is plausible – despite good opportunities to receive health related benefits – that those with poor health still are more likely to become unemployed. Significant findings in that direction must be interpreted as lower bound estimates of the propensity of becoming unemployed.

3 Data and descriptive statistics

3.1 Data

We utilise individual register data administered by Statistics Norway covering the time period 2006-2018.[15] This comprehensive dataset includes detailed information on demographics, socioeconomic status, work histories (job tenure, firm, occupation, industry, sector, etc.), residency, education, and health records. We construct treatment (affected by the shock) and control groups (not affected) of workers and compare outcomes (uptake of unemployment and social insurance benefits) for the two groups before and after the shock. Our primary objective is to determine the influence of pre-existing health conditions on these outcomes.

Starting with the employers' register, we identify individuals who were employed when the price shock occurred. Specifically, we look for those who were registered as full-time

[15] Data access for this paper was permitted by the DEMOSOS project, see https://www.uib.no/en/rg/wsh/148538/demosos.

workers, meaning they worked 30 hours or more per week, as of August 1, 2014. To construct the treatment and control groups, we compare regions that were affected by the oil price shock to those that were not. The coastal area of Western Norway, particularly Rogaland county, was the hardest hit by the shock, while the rest of Norway was largely unaffected in terms of employment. We therefore select full-time workers from Rogaland as our treatment group and exclude workers from four other coastal counties.[16] The control group is composed of workers from the rest of Norway. We exclude workers below 30 or above 60 years of age and immigrants. Furthermore, since the economic downturn caused by the oil price shock impacted employment only in the private sector, we exclude public sector workers from the main analysis.[17]

We measure unemployment and social insurance using data from the income register, which provide information on individual income and transfers, including earnings, unemployment benefits, and health-related benefits. Our primary outcome variable is a yearly indicator of receiving unemployment benefits between 2006 and 2018. Moreover, we construct a yearly indicator for receiving health-related social insurance in the same period, comprising rehabilitation benefits and disability benefits.[18] The latter indicator may pick up if there is substitution between unemployment and long-term health related social insurance.

Census data on adult health is scarce in administrative register data. Information is usually conditioned on utilisation of different types of health services (visits to the GP, inpatient stays, and outpatient visits), during which also information related to diagnosis are collected. Census data on infant health is, however, available in many countries, which explains the frequent use of birth weight as proxy for adult health (BBLR; Behrman and Rosenzweig, 2004; Black et al., 2007; Bharadwaj et al., 2018). We too have access to data on infant health, including birth weight, but only from 1967 on. In 2014, data on birth weight incorporated the fraction of the population below 47 years of age only. Given this limitation, we choose *average number of visits to the GP in the period prior to the oil price shock* as our

[16] We excluded Vest-Agder, Aust-Agder, Hordaland, and Møre og Romsdal counties from our analysis. In sensitivity analyses, we will consider alternative definitions of the treatment and control groups.
[17] However, we use the public sector as an essential reference point in some parts of our analysis.
[18] As noted in Section 2.2, sick leave benefits (< 1 year) are not included. Employed as well as unemployed individuals may receive sick leave benefits, thus these do not define mutually exclusive states.

measure of adult health. Note that this provides us with a proxy for *predetermined* health.[19] We provide further support for GP visits as an appropriate health indicator in Table 3.

3.2 Descriptive statistics

Table 1 presents gender-specific descriptive statistics for the treatment and control groups in the year of the oil price shock (2014). Clearly, the treatment group is comprised of a substantial proportion of workers in the oil and gas industry (including supply), especially among males. The influence from the petroleum sector is associated with a tight labor market and high earnings in Rogaland prior to the downturn, with average earnings 17% higher for males in Rogaland compared to the rest of the country. The probability of males in the treatment group receiving unemployment benefits is only 2.5%, compared to 3.3% in the control group. Similarly, for females, earnings are 11% higher in the treatment group, while 2.8% receive unemployment benefits compared to 3.6% in the control counties. We also note that the treatment group is slightly younger and better educated.

Table 1. Descriptive statistics, measured in 2014 (year of the oil price shock)

	Treatment, males	Control, males	Treatment, females	Control, females
Oil/gas service and supply ind.	0.340	0.094	0.262	0.043
Unemployment benefit > 0	0.025	0.033	0.028	0.036
Social insurance benefit > 0	0.012	0.015	0.030	0.033
Earnings/10000 NOK[1]	75.89 (46.22)	64.91 (41.65)	56.73 (36.31)	50.95 (26.63)
Number of GP visits[2]	1.89 (2.79)	1.97 (2.80)	2.98 (3.38)	2.99 (3.39)
Age	44.31 (8.58)	44.69 (8.49)	43.78 (8.28)	44.05 (8.31)
Low education[1]	0.151	0.184	0.165	0.172
Medium education[1]	0.554	0.517	0.433	0.425
High education[1]	0.296	0.300	0.402	0.403
White collar worker	0.581	0.548	0.723	0.696
Married[1]	0.702	0.650	0.675	0.622
Number of children 0-17[1]	1.063 (1.146)	0.922 (1.056)	1.045 (1.062)	0.924 (0.998)
Immigrant	0.134	0.145	0.163	0.182
Number of individuals	54,993	355,321	21,886	153,747

Notes to the table: [1] Measured in 2013. [2] Average number of visits 2006-2013. Low education=primary school; Medium education=high school; High education=college or university. White collar=ISCO-08 occupation code 1 to 4; Blue collar=ISCO-08 occupation code 5 to 10.

[19] As noted in the introduction, visiting a GP takes time, so the time cost goes down if someone becomes unemployed. Using GP visits after the shock as a regressor could therefore be problematic, as we would be conditioning on an outcome. However, this is not an issue as long as we rely on predetermined information.

The well-known gender gap in the utilization of health-related benefits (Mastekaasa, 2014) is clearly evident, but the differences between treatment and control are modest for both genders. The number of visits to the GP shows a similar pattern, with differences between genders but no significant differences between treatment and control groups. As for the socioeconomic and demographic variables, the similarities are more notable than the differences between treatment and control groups, for both males and females.

Table 2 presents a comparison of health and labor market outcomes before (2006-2013) and after (2015-2018) the oil price shock. As expected, the sharp decline in petroleum prices led to an increase in unemployment in Rogaland, especially for male workers. Before the shock, only 3.3 (3.9) percent of male (female) workers in Rogaland received unemployment benefits, compared to 4.9 (5.1) percent in the control group. However, this changed dramatically in the three years following the crisis, with an average of 8.5 (9.3) percent of male (female) workers in Rogaland receiving unemployment benefits compared to 4.4 (5.0) percent in the control region. Note also the sharp increase in uptake of health-related benefits among men in Rogaland (from 1.7 percent before to 5.6 percent after the price shock).

Table 2. Descriptive statistics, measured pre and post oil price shock

	Treatment, males	Control, males	Treatment, females	Control, females
Pre shock (means 2006-2013)				
Unemployment benefit > 0	0.033	0.049	0.039	0.051
Social insurance benefit > 0	0.017	0.023	0.043	0.049
Earnings/10000 NOK	61.89 (45.97)	54.31 (40.01)	44.54 (30.00)	41.51 (24.26)
Number of observations	432,205	2,801,432	170,913	1,207,327
Post shock (means 2015-2018)				
Unemployment benefit > 0	0.085	0.044	0.093	0.050
Social insurance benefit > 0	0.056	0.055	0.073	0.074
Earnings/10000 NOK	76.63 (65.90)	71.35 (54.39)	59.11 (40.88)	56.51 (32.90)
Number of observations	217,951	1,410,753	86,933	611,080
Number of individuals	54,993	355,321	21,886	153,747

Our main health variable is the number of GP visits per year, categorized as 0-1, 2-3, and at least 4 visits. In Figure 3, we present the distribution of GP visits per year during the pre-crisis period. Bar 1 and 2, picturing the healthiest category with an average of 0-1 GP visits per year, constitutes less than 60 percent of the sample. The share is 23-24 percent in the intermediate group (bar 3 and 4/2-3 visits) and 16-17 percent in the group with the poorest health (remaining bars/4 visits or more). The shares across treatment and control are remarkably similar.[20]

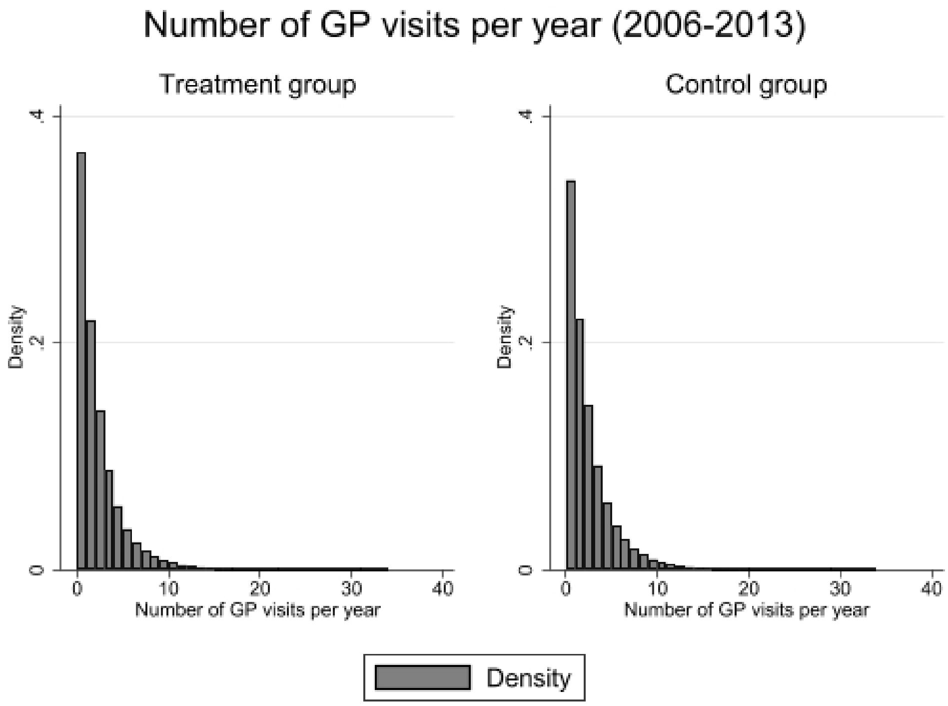


Figure 3 GP visits per year in treatment and control groups; fractions.

Table 3 describes the treatment and control groups conditional on health; i.e., on average number of GP visits per year prior to the shock. From Table 1 we know that the socioeconomic and demographic characteristics of the treatment and control groups were quite similar. To validate our measure of health, Table 3 also shows diagnosis, as recorded by the GP, and hospital visits (from the National Patient Register, NPR). Notice the similarities between treated and control. Looking across number of GP visits, we note that poor health as measured by GP visits is associated with less education and lower income. Furthermore, the least healthy group (>=4 GP visits) is to a larger extent associated with severe/chronic conditions, such as depressive disorders asthma, diabetes, or chronic back/neck disorders. Moreover, this group has more hospital visits, inpatient as well as outpatient. Visits to somatic and psychiatric hospitals were respectively 5 and 10 times as common for the least

[20] Further details in Table A3.

healthy category compared to the healthiest ones (column 1 and 2). All in all, this supports our choice of using GP visits as health indicator.[21]

Table 3. Descriptive statistics, by number of GP visits per year, treatment and control group. Average over 2006-2013 if not otherwise stated.

	Treatment 0-1 GP visits	Control, 0-1 GP visits	Treatment 2-3 GP visits	Control 2-3 GP visits	Treatment >= 4 GP visits	Control >= 4 GP visits
Male	0.804	0.787	0.659	0.650	0.525	0.525
Age[1]	42.98	43.21	43.43	43.82	43.13	43.68
	(8.29)	(8.29)	(8.63)	(8.49)	(8.89)	(8.76)
Labor incom/10000 NOK[1]	76.90	65.88	66.55	58.23	56.06	49.70
	(50.58)	(44.78)	(37.81)	(31.61)	(28.05)	(24.56)
Low education[1]	0.131	0.153	0.164	0.188	0.220	0.249
Medium education[1]	0.517	0.476	0.528	0.505	0.507	0.494
High education[1]	0.353	0.371	0.308	0.307	0.273	0.258
Married[1]	0.700	0.642	0.702	0.649	0.657	0.622
Number children 0-17	1.090	0.938	1.075	0.941	1.002	0.905
	(1.137)	(1.052)	(1.122)	(1.037)	(1.069)	(1.027)
White collar worker	0.644	0.621	0.611	0.582	0.564	0.527
Immigrant	0.133	0.147	0.147	0.155	0.166	0.187
Diagnosed with:[2]						
Depressive disorder	0.023	0.025	0.066	0.063	0.139	0.129
Asthma	0.022	0.025	0.045	0.054	0.077	0.082
COPD	0.002	0.002	0.007	0.006	0.014	0.012
Diabetes	0.005	0.005	0.021	0.020	0.042	0.040
Chron back/neck disord	0.091	0.099	0.180	0.194	0.248	0.263
Coronary heart disease	0.005	0.005	0.016	0.013	0.027	0.021
Cancer	0.007	0.005	0.017	0.013	0.020	0.016
Rheumatoid arthritis	0.005	0.005	0.013	0.011	0.020	0.016
Osteoarthritis	0.010	0.011	0.028	0.029	0.040	0.045
Anxiety disorder	0.010	0.010	0.028	0.027	0.062	0.055
Hospital visits[3]						
Inpatient stays, somatic	0.028	0.030	0.070	0.074	0.168	0.158
	(0.101)	(0.097)	(0.144)	(0.153)	(0.273)	(0.249)
Outpatient visits, somat	0.274	0.306	0.611	0.649	1.217	1.257
	(0.872)	(0.939)	(1.280)	(1.194)	(1.789)	(1.712)
Outpatient visits, psych	0.025	0.029	0.098	0.090	0.385	0.319
	(0.395)	(0.423)	(0.834)	(0.788)	(2.053)	(1.648)
Number of individuals	39,538	249,736	26,522	182,217	10,759	77,115

Notes to the table: [1] Measured in 2013. [2] Diagnosed by primary care physician (at least once) during 2006-2013. [3] Average number per year 2008-2013 (period of observation in NPR).

[21] In the sensitivity analysis, we will explore calculations and alternative groupings of the number of GP visits to assess the robustness of our findings.

Figure 4 displays trajectories of the outcome variables in private/public sector, by gender. Each graph shows rates for the treatment and control groups, and the difference. As noted above, sample inclusion is conditional on employment (>= 30 hrs/week) in August 2014. Public sector employees are included here for reference and will not be used in the main analysis.

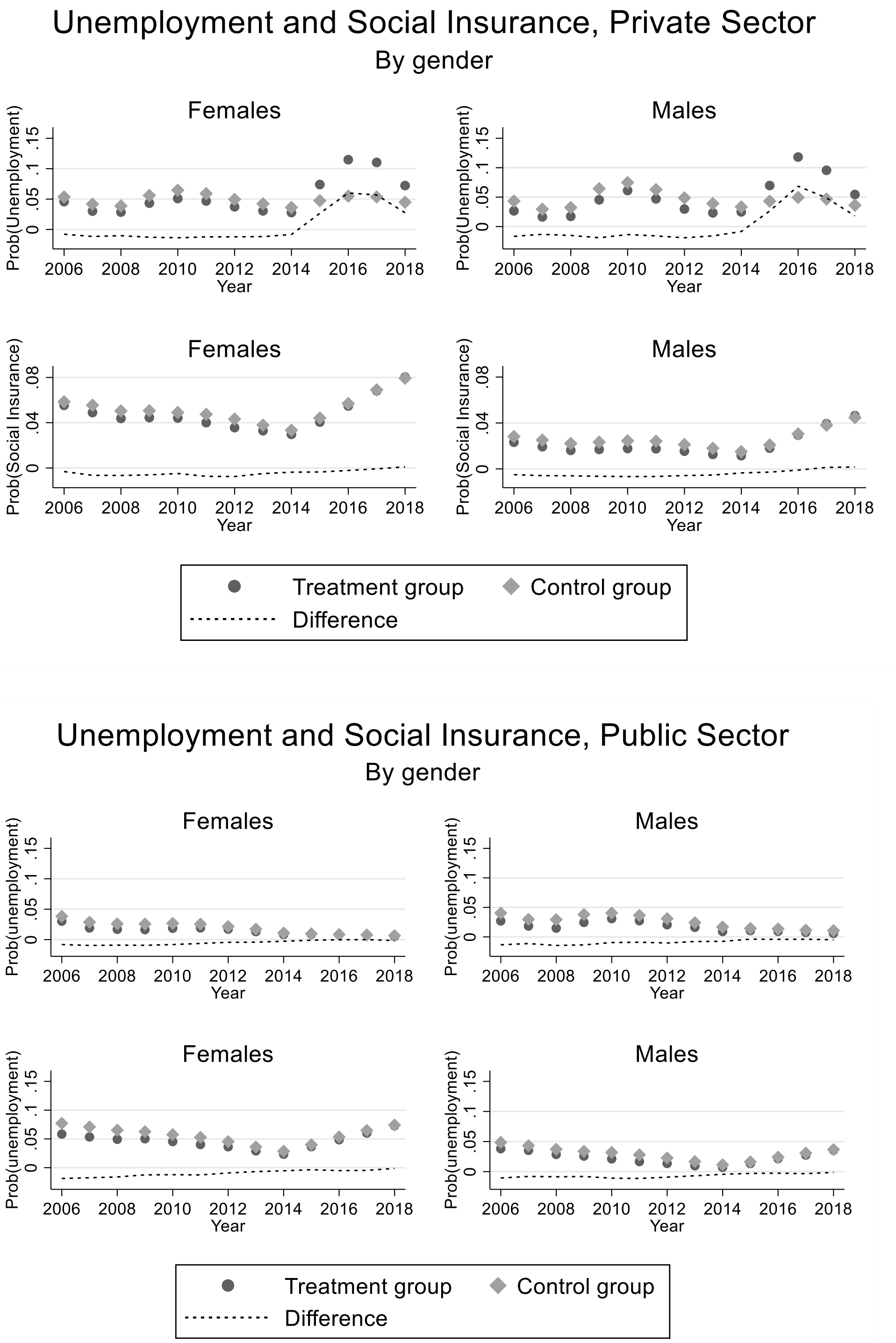


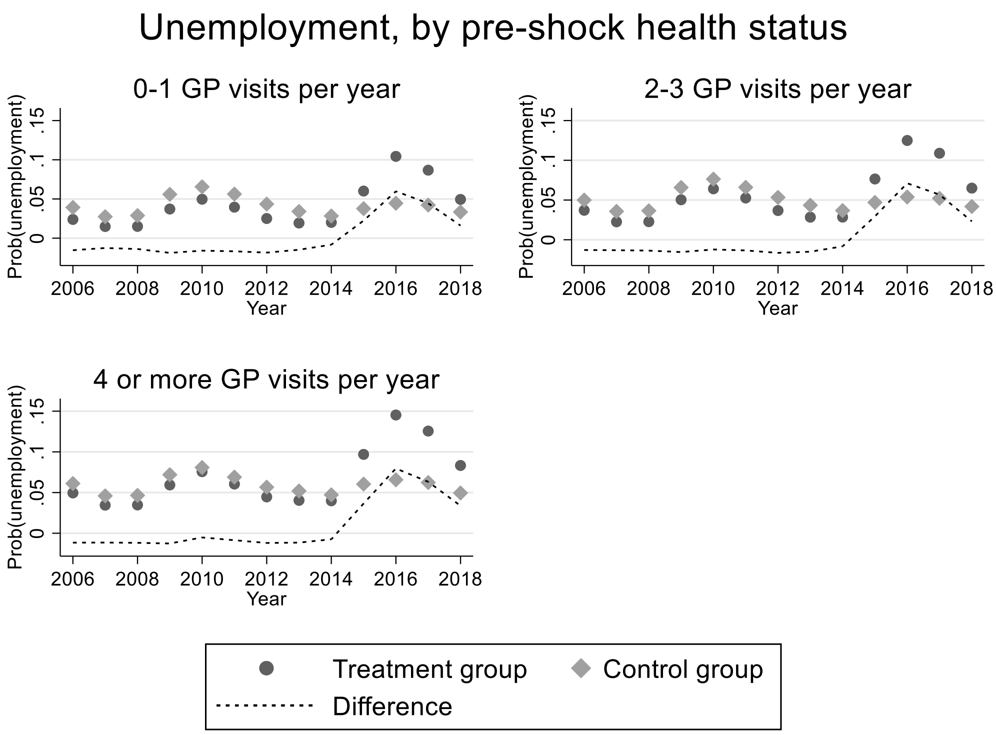
Figure 4. Unemployment in private vs public sector 2006-2018, by gender

The first two graphs in the top panel illustrate, firstly, that unemployment rates increased significantly more in Rogaland than in the control group after the petroleum price shock, and secondly, that there was a common trend in unemployment in treatment and control ahead of the shock.

The social insurance outcomes in the next two graphs also indicate similar trajectories in the treatment and control groups up to 2014. There is a small increase in the group difference after the oil price shock. The V-shape, apparent in particular for females, is due to the conditioning on employment in 2014. Some individuals on WAA benefits before 2014 were successfully rehabilitated and no longer on benefits at sample inclusion.

The lower panel of Figure 4 compares public sector unemployment in both treatment and control regions. Notably, there was little change in public sector unemployment in both groups following the crisis, indicating that the shock had a unique and exogenous effect on (our) the private sector treatment group.

Given that the gender differences are small and do not seem to affect the outcomes, we omit gender-specific descriptions for now. We return to gender differences in the heterogeneity analysis of Section 4. Figure 5 presents the impact of the economic downturn on unemployment and health-related social insurance, now common for both genders and for the private sector only, stratified by the predetermined number of GP visits as our measure of health. The upper panel of the figure shows the probability of receiving unemployment benefits each year. The pre trend appears to be common for all three outcomes. The number of GP visits appears to have the expected effect on the workers' vulnerability: The weaker the health, the stronger the tendency of becoming unemployed during a recession. The lower panel shows the probability of receiving health-related benefits in a given year. As in figure 4, there are only weak indications of difference in the differences after 2014, however, the indications seem to be slightly stronger in the least healthy group.



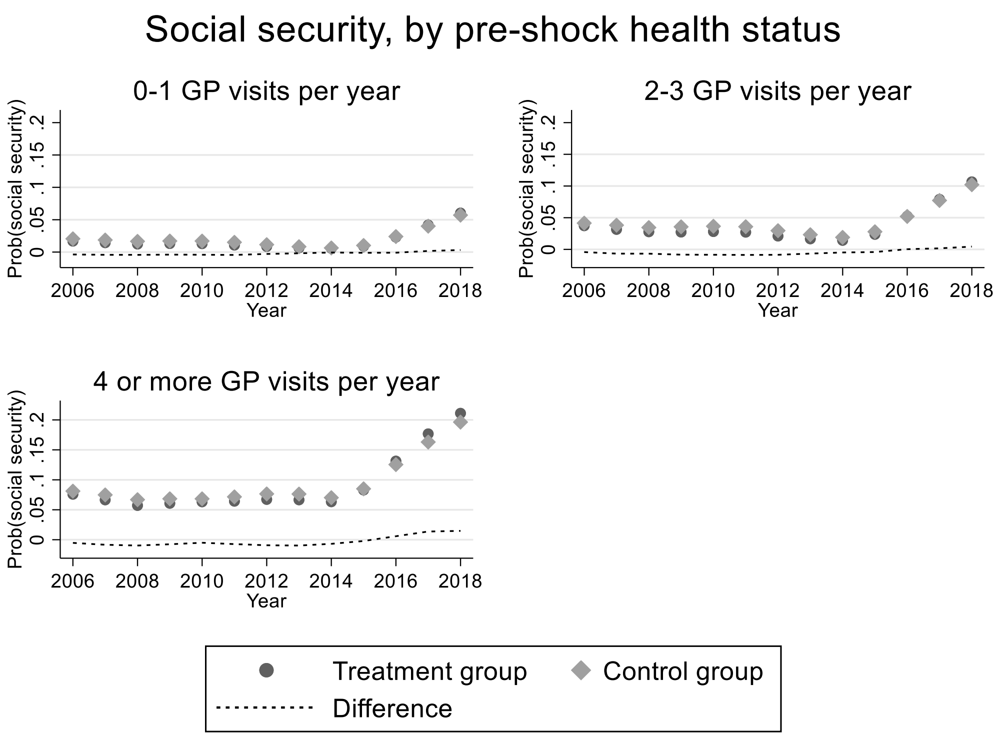


Figure 5. Unemployment and social security status by pre-shock health status, private sector.

4 Empirical setup and results

4.1 Empirical setup

We employ the oil price shock as a basis for a difference-in-differences model, comparing private sector workers in the municipalities of Rogaland County (treated) to private sector workers in municipalities that were not affected by the sudden price drop (control), before and after the shock in 2014. The purpose is to examine if poor (pre-determined) health makes workers vulnerable to negative labour market shocks. The variable $Health_i$ is the individual pre-shock health variable, measured as average number of visits to the GP in the period 2006-2013, categorized as [0-1, 2-3, 4 or more] with corresponding values $Health_i$ = (0, 1, 2). DD_{ijt} is an interaction between a Rogaland dummy and a post-shock dummy. DD_{ijt} = 1 indicates that worker *i* in municipality *j* is treated in periods *t* after the shock. To obtain the effect of predetermined health on unemployment (Y_{ijt}), we interact DD_{ijt} with the health variable. We estimate the following regression equation:

$$Y_{ijt} = \alpha DD_{ijt} + \beta_k 1(Health_i = k) + \delta_k DD_{ijt} \times 1(Health_i = k) + \theta X_{it} + \mu_j + \gamma_t + \varepsilon_{ijt},$$

where *k* = 1 or 2. μ_j and γ_t denote municipality and year fixed effects, and ε_{ijt} is a random error term with standard properties. The municipality fixed effects pick up local labour market conditions that may affect the unemployment risk in Rogaland, as well as in the control municipalities. X_{it} represents a vector of individual demographic and socio-economic controls. The dependent variable Y_{ijt} is a dummy indicating receipt of unemployment benefits in year *t*. In the supplementary analysis of health-related social insurance, Y_{ijt} denotes an indicator for receiving rehabilitation benefits or permanent disability benefits in year *t*.

In this regression, β_1 and β_2 show how frequent GP visits (2-3 or 4+) are associated with unemployment risk relative to the reference with 0-1 average visits per year. δ_1 and δ_2 give the causal effect of health/GP visits on unemployment: *the differential effect of predetermined health* for those individuals that worked in Rogaland (treated) and those that did not. The identifying assumption is that the average unemployment rate among the workers in the control municipalities captures the counterfactual development for the treated municipalities during the downturn period. Graphical evidence in the previous section (Figures 4 and 5) builds confidence in the common trend assumption.

4.2 Difference-in-difference results

Table 4 reports the key regression results. The first row shows the treatment effect of living in Rogaland after the oil price shock (α in the regression equation), while the next two co show the interaction terms with poor health (2-3 or 4+ GP visits). In the first column of coefficients, we observe that the treatment effect is 0.0409. In other words, the healthiest workers (0-1 GP visits per year) in the treated municipalities (Rogaland) experience an increase of more than 4 percentage points (pp) in the probability of becoming unemployed after the shock (2015 through 2018). However, our main finding is that this effect is amplified for workers with poorer health, with an increase of 0.73 pp for workers in the intermediate health category and 1.63 pp for those in the least healthy category. Note that our specification allows health to influence on unemployment for both the treatment and control groups during the entire observation period, as evidenced by the coefficients for the "2-3 GP visits" and "4 or more GP visits" categories. This means that the *differential* effect of poor health on the probability of becoming unemployed after the 2014 recession in Rogaland was almost 40 percent when comparing the healthiest category (4.1 pp) to the least healthy category (4.1 + 1.6 = 5.7 pp for 4 or more visits).

Table 4. Effect of the oil price shock om unemployment and uptake of social insurance, by pre-shock health status[1].

	Probability of unemployment	Probability of social insurance uptake
Base effect (Rogaland*Post)	0.0409*** (0.0057)	-0.0005 (0.0010)
Interaction, 2-3 GP visits	0.0073*** (0.0017)	0.0028 (0.0021)
Interaction, 4 or more GP visits	0.0163*** (0.0028)	0.0311*** (0.0061)
2-3 GP visits	0.0070*** (0.0004)	0.0153*** (0.0013)
4 or more GP visits	0.0114*** (0.0005)	0.0609*** (0.0336)
Mean *y (pre)*	0.0479	0.0302
Observations	7,524,481	7,524,481
Municipalities	332	332
Individuals	585,887	585,887

Notes to the table: [1] Municipality (where the firm is located) fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities. *, **, ***: statistically significant at 5, 1, 0.1 percent level.

The notable result reported in the second column is that there is a highly significant differential effect for the least healthy group after the 2014 recession. The probability of health-related social insurance uptake among the least healthy workers after 2014 is 6.1pp, and the additional effect of belonging to the treatment group is 3.1 pp, a 50% increase. However, there is no differential effect for the intermediate (2-3 visits) group. Thus, only the least healthy workers are sorted into long term social insurance due to the labour market shock.

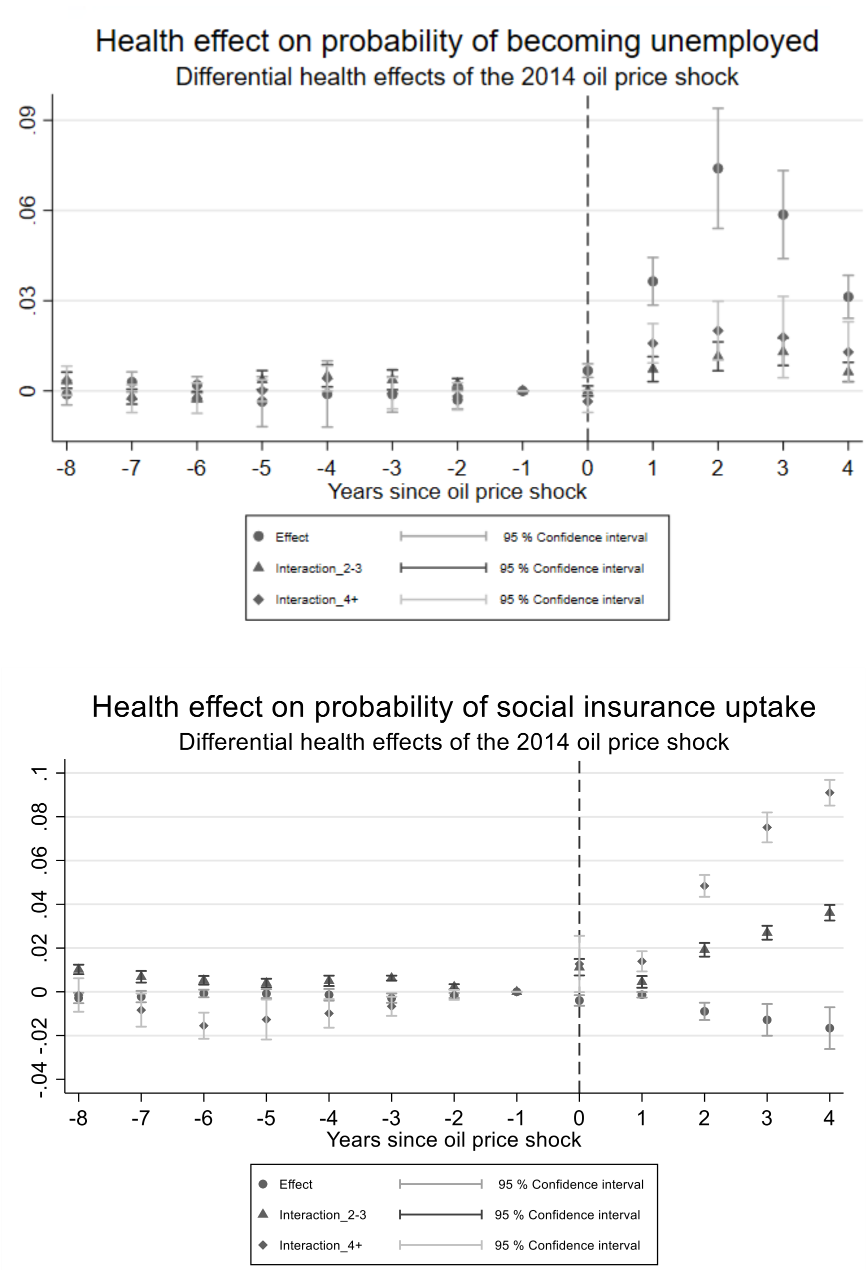


Figure 6 Year-by-year impact of health on receipt of unemployment benefits (upper panel) and health-related benefits. Coefficient and confidence intervals 2006-2018; 0 is 2014 (the year of the oil price shock).

While the coefficients measuring the health interactions in Table 4 are averages over the period 2014-2018, Figure 6 displays year-by-year impact of health on probability of becoming unemployed (upper panel) and receiving health-related benefits (lower panel) from 2006 to 2018. (Here, “effect” is the Rogaland dummy.)

Prior to the shock we see no measurable effect of health on unemployment. The post-2014 period is markedly different. Unemployment rises sharply for workers in the treated municipalities (Rogaland), peaking in 2016, and then gradually declines but remains significantly higher through 2018 compared to the pre-shock years. As for the interacted health effects, the variation across time is less apparent, but the coefficient plots and their associated confidence intervals reveal that there is an incremental deteriorating effect of poor health on unemployment throughout the period.

In the lower panel, we see that the general «Rogaland effect» on social insurance uptake is slightly negative after the shock, in accordance witt the results in Table 4. The interactions with poor health are positive, however, and increase over time. That makes sense, as work assessment allowance (WAA) and disability benefits in general are conditional on a one-year period of sickness benefits. It follows that in the first year after the shock relatively few workers are eligible for WAA or disability benefits (recall that the inclusion criterion is employment in 2014). As more workers become eligible for long term health related benefits, the differential effect of poor health in the treatment group increases. The oil price shock apparently increased the risk of permanently leaving the labour force for workers with poor health.

We offer an alternative exposition in the Appendix (Figure A1 and Table 1A). Health effects are estimated directly, without interactions, constructing different samples of health categories/number of GP visits. Table A1 (Appendix) reports regression coefficients averaged over the period 2014-2018, while Figure A1 plots the coefficients, year by year for the entire period (2006-2018)

4.3 Robustness Checks

Alternative Treatment and Control Groups

The recession in Rogaland was triggered by the oil price shock, and workers employed directly or indirectly in the petroleum sector soon experienced the impact. The impact extended to encompass private sector more broadly (within Rogaland). We have chosen to contrast the private sector in Rogaland with the private sector in the remaining regions of Norway (excluding four neighboring coastal counties to Rogaland). Workers employed in the petroleum industries located within the counties we have chosen as our control group constitute smaller portions of the total employment in these counties. Nonetheless, they were not immune to the effects of the oil price shock, as depicted in the diagram below.

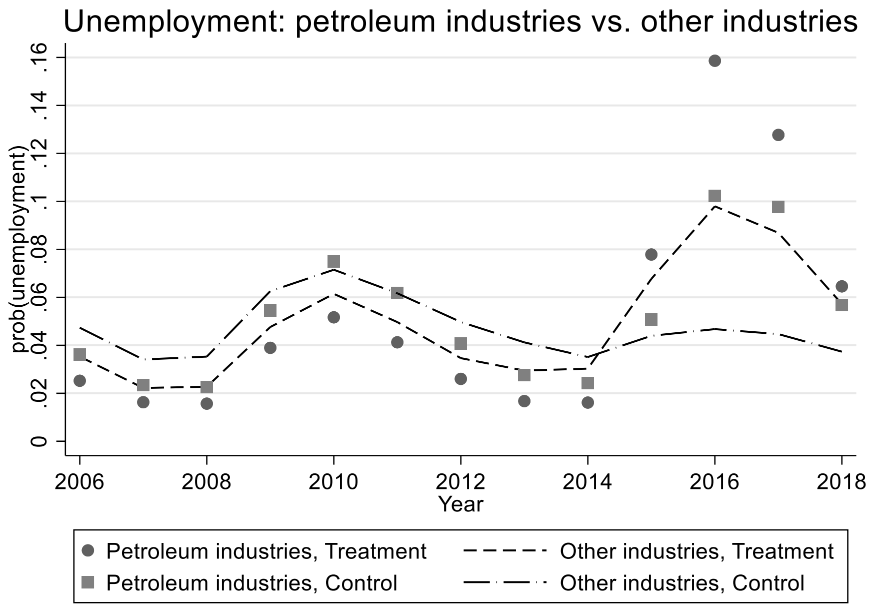


Figure 7. Unemployment in private sector, measured as year-by-year probability of receiving UI, petroleum vs other industries, treatment vs control.

A control group of without workers employed in the petroleum industries, represented as 'Other industries' in Figure 7, adds interesting results. The outcomes of this approach are detailed in Table A2, columns (1) and (2).Regarding the impact of health on unemployment, the effects are slightly strengthened compared to the findings from the complete sample presented in Table 4.

Columns (3) and (4) in Table A2 present results based on exclusion of petroleum workers from both the treatment and control groups. The coefficients see just minor changes, this time shifting in the reverse direction. From our observations, it can be deduced that the inclusion or exclusion of petroleum workers holds minimal influence over our results. Despite being significantly affected by the oil price shock in terms of employment, the pre-shock health status of this group does not appear to hold substantial significance as a predictor for unemployment.

Alternative grouping of GP visits

As previously highlighted, our access to individuals' health data before the price shock is limited. We rely on data on utilization of health services, namely yearly number of visits to the GP, as proxy for adult health. The frequency of these visits is reported in Figure 3 and in Table A3. The frequency is fairly similar for both treatment and control. Approximately 50% of the sample falls within the 0-1 yearly visits category, often encompassing routine check-ups. This category constitutes of workers in good health. Roughly 25% of individuals fall within the intermediate category, with 2-3 visits on average per year, while the remaining 25% make 4 or more visits, constituting the ill health category within our sample. Acknowledging that this categorization is somewhat arbitrary, an alternative approach could involve equal division into three portions. With our sample this results in the base category comprising 0-0.75 visits, the intermediate category encompassing 0.76-1.75 visits, and the ill health category including 1.76 or more visits. The regression findings are presented in Table A4. The influence of health on unemployment remains relatively unchanged regardless of the alternative stratification. The only noticeable exception is a significant reduced health effect for the intermediate category.

Alternative tabulations of GP visits

The reported count of GP visits is derived from tabulating yearly visits over the period from 2006 to 2013, averaged for each individual. Alternative measures could be considered, with the choice depending on our aim: emphasizing longer time spans with lower variance based on older health-status information or prioritizing more recent updates, albeit with potentially more noise. In Table A5, we present regression analyses using the number of GP visits calculated for different time frames: 2006-2013 (included as a reference), 2011-2013, and 2013 only. The results indicate that the health effect is largest and generally more precisely measured with our preferred time span. This indicates that our health measure functions sub-optimally if based solely on the most recent observation years.

Other checks

The oil price peaked during June 2014, followed by a steep decline for the remainder of that year. While we have designated 2014 as the initial year of the recession, there is a valid argument that 2014 could alternatively be considered part of the pre-shock period, and 2015 as the first year of recession. To explore this, we examine the implications in Table A6. Our findings remain robust regardless of how we redefine the pre- and post-shock periods: Whether we shift the year 2014 from the post-shock period to the pre-shock period or if we exclude it entirely. Lastly, Table A7 demonstrates why our Fixed Effects model with municipality fixed effects is favored. The FE model gives the more accurate and meaningful results, compared to the two alternative specifications (OLS, and FE without municipality fixed effects).

4.4 Heterogeneity

The influence of health on unemployment can differ across groups of workers. Additionally, as discussed in Section 1 and 2, we can anticipate the unemployment benefits and health related benefits serve as substitutes to a varying degree. Subsequently, we present the outcomes – the uptake of unemployment and social insurance benefits – derived from heterogeneity based on gender, age, educational levels, and blue/white-collar classification.

Gender

Examining Table A8, columns (1)-(4), we initially observe that the recession in Rogaland had a relatively small impact on the unemployment rate among healthy female workers (the reference category) compared to healthy males. While the average unemployment rate was fairly consistent between the two sets (4.9 % for females and 4.7% for males), the shock from the oil price increase nearly doubled male unemployment (up by 4.3 pp). Conversely, the employment diff-in-diff effect for females was 3.7 pp, reflecting an approximate 75% increase. However, the results differ when considering the health factor. The contrasting effect is evident in terms of female unemployment. In the group with the poorest health, there is a 1.9 pp difference, a more than 50% increase relative to the reference category. For males, the corresponding figure shows a 1.3 pp increase, equivalent to a 30% rise.

Turning to social insurance, the data reveals a noticeable disparity in the average percentage of individuals in our sample receiving benefits prior to the price shock (columns 2 and 4). Specifically, females had an approximate 50 % higher utilization rate than males (4.8 % versus 2.3 %). This trend aligns with the well-established gender gap in the utilization of health-related benefits, as recognized across most Western countries (Mastekaasa, 2014). Interestingly, the shock's impact was negligible on the baseline category (the healthiest individuals). However, an intriguing pattern emerges when we examine the least healthy category (4 or more GP visits): the uptake of social insurance benefits increased by 4.5 pp for males, compared to 2.5 pp for females. As hypothesized in Section 2.2, it is possible that workers with poor health, who most likely qualify for health-related benefits but may prioritize work over those benefits, might opt for the latter if they lose their job and face difficulties securing new employment during a recession. The significantly lower percentage of males receiving social insurance benefits *prior* to the shock compared to females is interesting. The difference could suggest that prior to the shock there were more males than females at the margin of becoming recipients of social insurance. Consequently, the shock may have disproportionately affected more males than females in this regard.

Age

Columns (5)-(10) display results categorized by age, with participants divided into three roughly equal-sized groups: 30-39, 40-49, and 50 or older. Before the price shock, the highest unemployment rate was observed in the youngest category (6.0 %, compared to 4.5 % and 3.9 % for the middle and oldest categories, respectively, when listed from youngest to oldest). For healthy workers, who form the base category, the impact of the price shock was nearly identical across all age groups, hovering around 4 %. However, when we consider the interaction with health, we observe a significantly stronger effect in the youngest group. Unemployment increased by 2.3 pp in the least healthy category, compared to 1.6 pp for the middle-aged group and only 0.7 pp for the oldest group.

Shifting our focus to the effect on the uptake of social insurance benefits (column 6, 8 and 10), we see even more pronounced effects across age groups. Before the shock, the lowest percentage of benefit recipients was found in the youngest category (3.1 %, compared to 3.3 % and 5.4 % when moving from the youngest to the oldest groups). The shock had virtually no impact on the youngest category, regardless of health status. In the intermediate age group, there were some measurable effects, though they remained relatively small. Conversely, in the oldest age category, poor health appeared to boost the uptake of health-related benefits, increasing by 6.0 pp from 5.4 % before the shock. We posit that this pattern might be explained by the functioning of health-related social insurance in Norway. It is well-documented that the eligibility criteria for receiving health-related benefits tend to be more lenient for older individuals. As discussed in Section 2.2, GPs and case workers at NIS are actually instructed to take into account the availability of paid work when evaluating worker's eligibility. Hence, health-related benefits are presumably a much closer substitute to unemployment benefits for the oldest age group in comparison to the younger cohorts. Additionally, seniority rules may offer some protection against unemployment for older workers.

Education and type of job (white vs blue collar)

Differences in education and job types exhibit several similarities both on employment and unemployment, as well as the influence of prior health conditions. This is demonstrated in Table A9.[22] We observe that during the pre-shock period, unemployment rates were relatively low for individuals with higher education and among white-collar workers. However, as noted in Section 2, these groups experienced the (relatively) most significant increases. Unemployment more than doubled – compared to the group average – for those with the highest education (rising by 3.6 pp from 3.2). In contrast, the increase for those with the lowest education was just under 60% (rising by 4.5 from 7.8). White-collar workers experienced a larger increase than blue-collar; in absolute terms (4.2 vs. 3.8 %) as well as relative terms (up 88 % from 4.7 compared to 55 % up from 6.8).

Not only did highly educated individuals and white-collar workers experience the most significant increase in unemployment; they are also the groups where prior poor health has the most impact on the probability of becoming unemployed. Highly educated individuals in the category with the poorest health face a 44 % higher chance of becoming unemployed (an increase of 2.3 pp from 3.6), while the increase is 31 % for the lowest educated (up 1.4 pp from 4.5 %). Similarly, for white-collar workers, there is a substantial 57 % increased

[22] This is in line with expectations, as white-collar work is highly correlated with higher education, while blue-collar work is associated with lower education levels.

probability for those with the worst health (a rise of 2.4 pp from 4.2), compared to a 26 % increase for blue-collar workers with poorest health (up 1 percentage point from 3.8).

The results w.r.t. social insurance go in the opposite direction: the differential effect of poor health (4+ GP visits) decreases with education level and white vs. blue collar work. Taking into account that disability benefits define an absorbing state (and WAA benefits often are followed by disability) we could interpret the results as follows: Highly educated workers with poor health were more at risk of losing their jobs than their less educated counterparts. We do not observe re-employment, but for most people, unemployment is temporary. If not, long-term social benefits is an exit route from the labour market. Taken together, highly educated workers are more at risk for losing their jobs in the short term, but are also more re-employable, even with poor health. Thus, the risk of permanent labour force exit (health related social insurance benefits) for someone with health problems is lower for highly educated workers than for those with less education. This is consistent with Rege et al. (2009) who find that downsizing affects disability probability stronger for workers with lower education level.

Why should health problems affect the unemployment risk more for the highly educated? A plausible explanation is that poor health affects productivity, and that the least productive workers are laid off first if the company must downsize. This process may be tougher in knowledge-intensive firms where we find more highly educated people. There are no legal requirements to follow seniority principles when downsizing, but collective agreements between unions and employers typically contain clauses about seniority (Nyström et al, 2020). We do not have data on unionization, but the general unionization rate has remained stable at about 50% from 2010 (Neergaard 2024). The degree of unionization is not less for the highly educated than for those with lower education. However, workers in smaller firms are unionized to a lesser degree than in larger firms (Neergaard 2024). Our data do not facilitate (?) investigatiation of whether white collar/highly educated employees actually work in smaller firm. On the other hand, our finding that the health effect on unemployment is strongest for young workers is consistent with the role of seniority, simply because younger workers on average will have shorter tenure.

5 Conclusion

Health is typically poorer in a cross section of unemployed compared to employed workers. Does this mean that unemployment is detrimental to one's health, or is it because individuals with poor health are more likely to be unemployed? Our paper aims to shed light on the latter. Armed with longitudinal data on adult health and utilization of health services, we investigate how pre-existing health can exacerbate the impact of adverse labor market shocks. The sudden and unexpected fall in oil prices in 2014 provides us with exogenous variation in the probability of becoming unemployed. Importantly, the price shock was local in the sense that it hit (the private sector of) one region strongly while the largest part of the country was practically unaffected. This provides us with treatment and control groups and forms the basis for difference-in-difference modelling.

We observed a substantial and significant increase in the probability of unemployment among workers with poorer health status prior to the shock. This suggests that individuals with compromised health are disproportionately affected by economic downturns. We also observed patterns of heterogeneity across different demographic and socio-economic groups. Female workers appear to be more vulnerable to health effects than their male colleagues. The youngest age group appears to be more sensitive to health-related vulnerabilities than older workers. Finally, education and job type exhibited consistent patterns, where individuals with higher education and those in white-collar jobs were not only more affected by the shock but also more susceptible to the influence of poor health on unemployment probabilities.

As expected, the oil price shock also led to an increase in the likelihood of receiving health-related benefits. Heterogeneity analyses reveal an interesting pattern regarding the significance of health in the interaction between unemployment benefits and other social insurances during an economic downturn: In many cases, the groups with the least increase in unemployment experience the greatest increase in health-related benefits, and vice versa. This sheds light on the seemingly counterintuitive finding that among those with the poorest health, the probability of becoming unemployed is highest for groups with the strongest labor market attachment. For example, highly educated individuals with the worst health experienced a 2.3 percentage point increase in the probability of becoming unemployed, but only a 0.9 percentage point increase in the probability of receiving health-related benefits.

For low-educated individuals, however, the corresponding figures were 1.4 and 4.6 percentage points. The same pattern is observed when stratifying by age: the oldest individuals with the worst health seemingly fare the best in terms of unemployment (0.7 percentage point increase), but the worst in terms of health-related benefits (5.5 percentage point increase). For the youngest, it is reversed: a 2.3 percentage point increase in unemployment and a 1.7 percentage point increase in health-related benefits. Both doctors and social security officials have a lower threshold for certifying health-related benefits for those with the weakest health and the bleakest prospects in the job market; to some extent, health-related benefits must therefore be considered as unemployment in disguise.

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APPENDIX

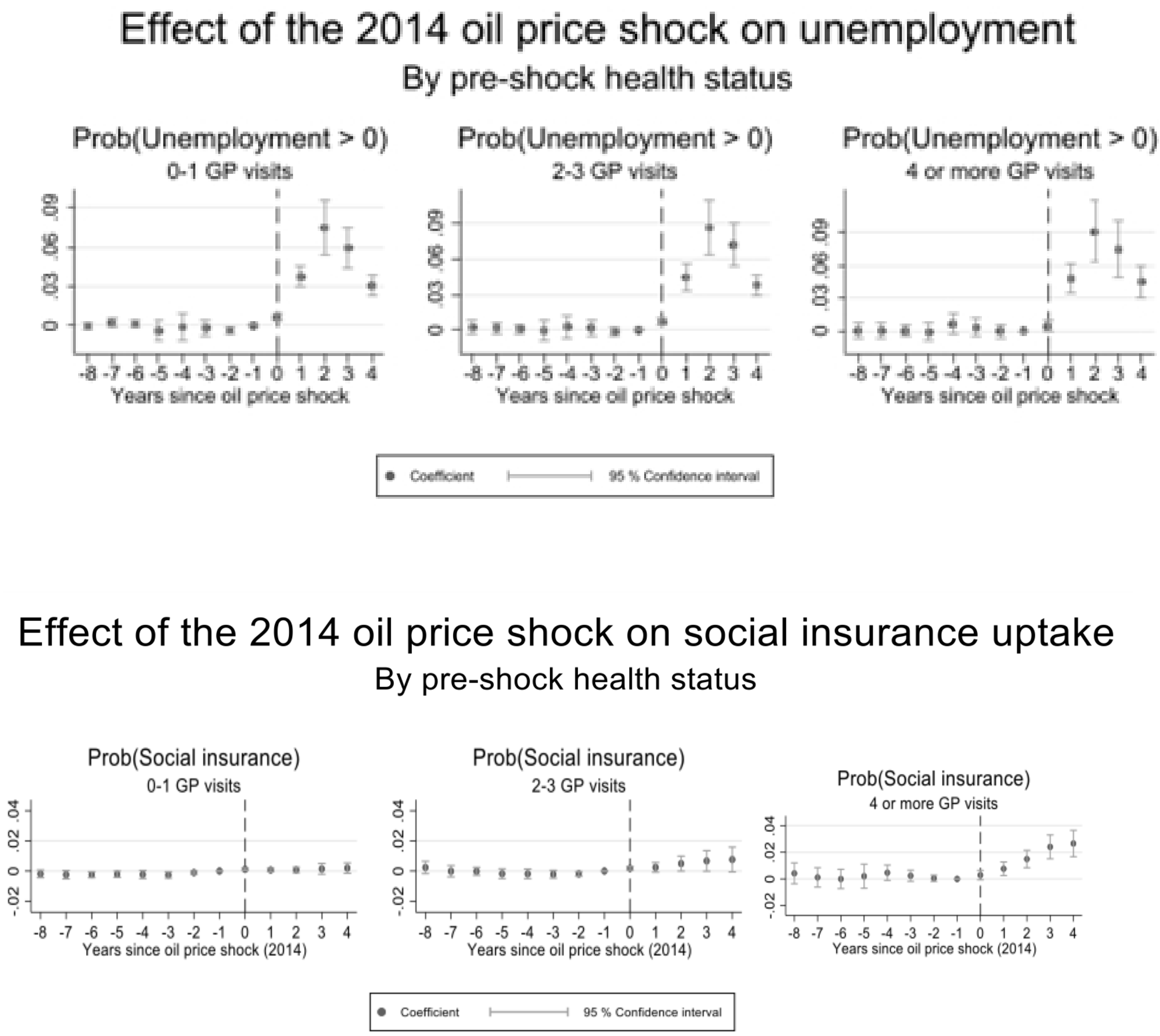

Figure A1. Year by year plots of coefficients estimated directly on subsamples of different pre-shock health status.

Table A1. Effects of the oil price shock on unemployment and social insurance uptake, estimated directly on subsamples of different pre-shock health status

	Probability of unemployment			Probability of social insurance uptake		
	0-1 GP visits	2-3 GP visits	>=4 GP visits	0-1 GP visits	2-3 GP visits	>=4 GP visits
Effect	0.0425***	0.0484***	0.0517***	0.0031***	0.0054***	0.0132***
	(0.0058)	(0.0069)	(0.0085)	(0.0006)	(0.0015)	(0.0041)
Mean y (pre)	0.0418	0.0517	0.0592	0.0151	0.0334	0.0720
Observations	3,706,459	2,687,565	1,130,457	3,706,459	2,687,565	1,130,457
Individuals	289,274	208,739	87,874	289,274	208,739	87,874

[1] Municipality fixed effects, standard errors are clustered at municipalities. Control variables: male, age, medium or high education (compared to low), married, children 0-17, white-collar worker, immigrant, year-dummies. *, **, ***: statistical significant at 5, 1, 0.1 percent level.

Table A2. Effect of the oil price shock om unemployment, conditional on pre-shock health status. Excluding workers from the o/g and supply industry.

	Excluding individuals employed in the oil/gas and supply industry from the control group		Excluding individuals employed in the o/g and supply industry from the treatm and control group	
	(1)	(2)	(3)	(4)
	Prob(Unemployment)	Prob(Social insurance)	Prob(Unemployment)	Prob(Social insurance)
Base effect (DD for 0-1 GP visits)	0.0434*** (0.0058)	-0.0001 (0.0010)	0.0346*** (0.0061)	-0.0004 (0.0011)
Interaction effect; DD x 2-3 GP visits	0.0075*** (0.0017)	0.0025 (0.0022)	0.0071*** (0.0021)	0.0039 (0.0023)
Interaction effect; DD x 4 or more GP visits	0.0164*** (0.0028)	0.0306*** (0.0063)	0.0115*** (0.0020)	0.0366*** (0.0069)
2-3 GP visits	0.0068*** (0.0004)	0.0156*** (0.0014)	0.0069*** (0.0004)	0.0158*** (0.0015)
4 or more GP visits	0.0114*** (0.0005)	0.0614*** (0.0040)	0.0114*** (0.0005)	0.0620*** (0.0043)
Mean *y (pre)*	0.0483	0.0310	0.0492	0.0317
Observations	7,010,022	7,010,022	6,697,133	6,697,133
Municipalities	332	332	332	332
Individuals	545,885	545,885	521,457	521,457

Notes: The table shows estimates of the effect from health measured as average visits to GP etc etc. Municipality (where the firm is located) fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities. *, **, ***: statistical significant at 5, 1, 0.1 percent level.

Table A3. Distribution of number of GP visits, in fraction of workers. Mean of yearly averages 2006-2013.

	Treatment group	Control group
0 GP visits	36.8%	34.4%
1 GP visits	22.1%	22.2%
2 GP visits	14.1%	14.6%
3 GP visits	8.9%	9.3%
4 GP visits	5.7%	6.0%
5 GP visits	3.7%	4.0%
6 GP visits	2.5%	2.7%
7 GP visits	1.7%	1.9%
8 + GP visits	3.4%	3.7%

Table A4. Effect of the oil price shock om unemployment, by pre-shock health status[1].
Alternative stratification of good, intermediate and ill health

	Prob(Unempl)	Unempl rel to income
Base effect (0-.75 GP visits)	0.0416*** (0.0059)	0.0114*** (0.0016)
Interaction, 0.76-1.75 GP visits	0.0020* (0.0010)	0.0013** (0.0005)
Interaction, 1.76 or more GP visits	0.0114*** (0.0016)	0.0069*** (0.0013)
0.76-1.75 GP visits	0.0048*** (0.0005)	0.0009*** (0.0002)
1.76 or more GP visits	0.0109*** (0.0005)	0.0024*** (0.0002)
Mean *y*	0.0478	0.0114
Observations	7,524,481	7,524,481
Municipalities	332	332
Individuals	585,887	585,887

[1] Municipality (where the firm is located) fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities.
*, **, ***: statistical significant at 5, 1, 0.1 percent level.

Table A5. Effect of the oil price shock om unemployment, conditional on pre-shock health status. Number of GP visits measured over different periods[1].

	Av. number of GP visits 2006-2013		Av. number of GP visits 2011-2013		Number of GP visits in 2013	
	Prob(Unempl)[2]	Prob(Social insurance) [2]	Prob(Unempl)	Prob(Social insurance)	Prob(Unempl)	Prob(Social insurance)
Base effect	0.0409***	-0.0004	0.0418***	-0.0004	0.0425***	-0.0001
	(0.0057)	(0.0010)	(0.0059)	(0.0012)	(0.0060)	(0.0008)
Interaction, 2-3 GP visits	0.0073***	0.0028	0.0010	-0.0001	0.0062***	0.0012
	(0.0017)	(0.0021)	(0.0009)	(0.0010)	(0.0013)	(0.0013)
Interaction, 4 or more GP visits	0.0163***	0.0308***	0.0098***	0.0141***	0.0087***	0.0236***
	(0.0028)	(0.0061)	(0.0017)	(0.0037)	(0.0022)	(0.0046)
2-3 GP visits	0.0070***	0.0153***	0.0037***	0.0060***	0.0040***	0.0107***
	(0.0004)	(0.0013)	(0.0004)	(0.0006)	(0.0003)	(0.0008)
4 or more GP visits	0.0114***	0.0603***	0.0105***	0.0351***	0.0082***	0.0409***
	(0.0005)	(0.0336)	(0.0004)	(0.0023)	(0.0004)	(0.0022)
Mean (pre)	0.0479	0.0302	0.0479	0.0302	0.0479	0.0302
Observations	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481
Municipalities	332	332	332	332	332	332
Individuals	585,887	585,887	585,887	585,887	585,887	585,887

[1] Municipality fixed effects, standard errors are clustered at municipalities. Control variables: male, age, medium or high education (compared to low), married, children 0-17, white-collar worker, immigrant, year-dummies. *, **, ***: statistical significant at 5, 1, 0.1 percent level. [2] Same regression model as reported in Table 4.

Table A6. Effect of the oil price shock om unemployment, conditional on pre-shock health status. Alternative post-shock periods.

	Post-shock period: 2015-2018		Exluding observations in 2014	
	Prob(Unemployment)	Prob(Social insurance)	Prob(Unemployment)	Prob(Social insurance)
Base effect (DD for 0-1 GP visits)	0.0490*** (0.0067)	-0.0030*** (0.0007)	0.0497*** (0.0069)	-0.0024** (0.0008)
Interaction effect; DD x 2-3 GP visits	0.0093*** (0.0019)	0.0064*** (0.0021)	0.0093*** (0.0019)	0.0058** (0.0022)
Interaction effect; DD x 4 or more GP visits	0.0199*** (0.0035)	0.0421*** (0.0062)	0.0200*** (0.0035)	0.0415*** (0.0062)
2-3 GP visits	0.0070*** (0.0004)	0.0152*** (0.0013)	0.0070*** (0.0004)	0.0157*** (0.0013)
4 or more GP visits	0.0115*** (0.0005)	0.0608*** (0.0037)	0.0112*** (0.0005)	0.0611*** (0.0037)
Mean *y (pre)*	0.0479	0.0302	0.0480	0.0302
Observations	7,524,481	7,524,481	6,938,594	6,938,594
Municipalities	332	332	332	332
Individuals	585,887	585,887	585,887	585,887

Notes: The table shows estimates of the effect from health measured as average visits to GP etc etc. Municipality (where the firm is located) fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities. *, **, ***: statistical significant at 5, 1, 0.1 percent level.

Table A7. Effect of the oil price shock om unemployment, conditional on pre-shock health status. Different model specifications.

	Probability of unemployment				Probability of social insurance uptake			
	OLS	OLS	FE[2]	FE	OLS	OLS	FE[2]	FE
Base effect	0.0268***	0.0286***	0.0410***	0.0420***	-0.0056*	-0.0040***	-0.0004	-0.0044***
	(0.0048)	(0.0050)	(0.0057)	(0.0057)	(0.0023)	(0.0011)	(0.0010)	(0.0007)
Interaction, 2-3 GP visits	0.0070***	0.0071***	0.0073***	0.0056***	0.0022	0.0024	0.0028	0.0073***
	(0.0017)	(0.0017)	(0.0017)	(0.0016)	(0.0018)	(0.0021)	(0.0021)	(0.0011)
Interaction, 4 or more GP visits	0.0157***	0.0163***	0.0162***	0.0121***	0.0303***	0.0303***	0.0308***	0.0479***
	(0.0028)	(0.0028)	(0.0028)	(0.0030)	(0.0055)	(0.0060)	(0.0061)	(0.0032)
2-3 GP visits	0.0096***	0.0071***	0.0070***	-	0.0202***	0.0156***	0.0153***	-
	(0.0004)	(0.0004)	(0.0004)		(0.0013)	(0.0012)	(0.0013)	
4 or more GP visits	0.0183***	0.0108***	0.0112***	-	0.0703***	0.0603***	0.0603***	-
	(0.0007)	(0.0006)	(0.0005)		(0.0038)	(0.0036)	(0.0336)	
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables[1]	No	Yes	Yes	No	No	Yes	Yes	No
Municipality fixed effects	No	No	Yes	No	No	No	Yes	No
Individual fixed effects	No	No	No	Yes	No	No	No	Yes
Observations	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481	7,524,481

[1] Control variables: male, age, medium or high education (compared to low), married, children 0-17, white-collar worker, immigrant. Standard errors are clustered at municipalities.

*, **, ***: statistical significant at 5, 1, 0.1 percent level. [2] Same regression model as reported in Table 4.

Table A8. Effect of the oil price shock om unemployment and social insurance uptake, by gender (column (1)-(4)), age (column (5)-(10)) and pre-shock health status

	Females		Males		Age < 40		Age 40 - 49		Age > 49	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance
Base effect	0.0366***	-0.0038	0.0430***	0.0004	0.0438***	0.0024	0.0412***	0.0037	0.0389***	-0.0075***
(0-1 GP visits)	(0.0057)	(0.0023)	(0.0057)	(0.0007)	(0.0063)	(0.0032)	(0.0056)	(0.0020)	(0.0061)	(0.0018)
Interaction,	0.0069**	0.0057*	0.0073***	0.0022	0.0077*	-0.0005	0.0077***	-0.0005	0.0053*	0.0095***
2-3 GP visits	(0.0024)	(0.0028)	(0.0022)	(0.0018)	(0.0037)	(0.0030)	(0.0022)	(0.0022)	(0.0023)	(0.0028)
Interaction,	0.0192***	0.0255***	0.0132***	0.0381***	0.0238***	0.0173*	0.0160***	0.0237***	0.0068***	0.0553***
4+ GP visits	(0.0044)	(0.0068)	(0.0038)	(0.0058)	(0.0039)	(0.0073)	(0.0030)	(0.0062)	(0.0023)	(0.0067)
2-3 GP visits	0.0059***	0.0193***	0.0073***	0.0145***	0.0124***	0.0142***	0.0075***	0.0164***	0.0033***	0.0148***
	(0.0007)	(0.0019)	(0.0004)	(0.0012)	(0.0006)	(0.0015)	(0.0005)	(0.0014)	(0.0006)	(0.0012)
4+ GP visits	0.0101***	0.0676***	0.0132***	0.0573***	0.0239***	0.0517***	0.0121***	0.0633***	0.041***	0.0634***
	(0.0008)	(0.0058)	(0.0006)	(0.0026)	(0.0009)	(0.0042)	(0.0009)	(0.0035)	(0.0008)	(0.0031)
Mean *y (pre)*	0.0493	0.0483	0.0473	0.0225	0.0597	0.0308	0.0451	0,0333	0.0391	0,0539
Observations	2,251,886	2,251,886	5,272,595	5,272,595	2,367,894	2,367,894	2,813221	2,813221	2,343,366	2,343,366
Individuals	175,633	175,633	410,254	410,254	186,416	186,416	218,208	218,208	181,264	181,264

[1] Municipality fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities. *, **, ***: statistical significant at 5, 1, 0.1 percent level.

Table A9. Effect of the oil price shock om unemployment, by education (column (1)-(6), blue/white collar jobs (column (7)-(10,)and pre-shock health status[1].

	Low education		Medium education		High education		Blue collar workers		White collar workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance	Prob. Unempl.	Prob. social insurance
Base effect	0.0447***	-0.0047**	0.0422***	-0.0006	0.0360***	0.0017	0.0378***	0.0012	0.0418***	-0.0012
(0-1 GP visits)	(0.0067)	(0.0016)	(0.0066)	(0.0011)	(0.0040)	(0.0021)	(0.0064)	(0.0012)	(0.0046)	(0.0016)
Interaction,	0.0069	0.0086**	0.0081***	0.0032	0.0069**	-0.0014	0.0060**	0.0036*	0.0088***	0.0024
2-3 GP visits	(0.0042)	(0.0034)	(0.0019)	(0.0019)	(0.0024)	(0.0019)	(0.0020)	(0.0017)	(0.0016)	(0.0021)
Interaction,	0.0136***	0.0455***	0.0150***	0.0371***	0.0228***	0.0091	0.0095***	0.0390***	0.0236***	0.0254***
4+ GP visits	(0.0033)	(0.0068)	(0.0024)	(0.0048)	(0.0040)	(0.0057)	(0.0030)	(0.0056)	(0.0035)	(0.0054)
2-3 GP visits	0.0081***	0.0248***	0.0070***	0.0167***	0.0063***	0.0102***	0.0077***	0.0212***	0.0065***	0.0117***
	(0.0014)	(0.0017)	(0.0004)	(0.0009)	(0.0004)	(0.0011)	(0.0006)	(0.0009)	(0.0004)	(0.0013)
4+ GP visits	0.0092***	0.0800***	0.0127***	0.0635***	0.0121***	0.0438***	0.0104***	0.0722***	0.0129***	0.0518***
	(0.0013)	(0.0037)	(0.0006)	(0.0024)	(0.0007)	(0.0041)	(0.0008)	(0.0021)	(0.0005)	(0.0040)
Mean *y (pre)*	0.0780	0.0627	0.0476	0,0410	0.0322	0,0231	0.0684	0.0396	0.0473	0.0239
Observations	1,305,706	1,305,706	3,740,926	3,740,926	2,447,849	2,447,849	3,033,763	3,033,763	4,490,718	4,490,718
Individuals	102,431	102,431	289,530	289,530	193,926	193,926	236,381	236,381	349,506	349,506

[1] Municipality fixed effects. Control variables: male, age, medium or high education (compared to low), married, white-collar worker, immigrant, year-dummies. Standard errors are clustered at municipalities. *, **, ***: statistical significant at 5, 1, 0.1 percent level