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RESEARCH ARTICLE

Health and Unemployment During a Negative Labor Demand Shock

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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. Conversely, poor health in combination with high age, low education, and blue-collar jobs increases the uptake of social insurance during the economic downturn, pointing toward the substitutability between unemployment benefits and health-related benefits.

JEL Classification: I12, J64, C21, C31

1 | Introduction

A large body of research documents a strong association between unemployment and poor health.[1] Yet the causal direction of this relationship remains ambiguous. While much of the existing literature has focused on the impact of unemployment on health, we take the opposite approach and ask: are individuals in poor health more likely to become unemployed, particularly during economic downturns?

Understanding whether poor health increases the risk of unemployment is important for several reasons. First, if health conditions systematically increase job loss risk, this may contribute to structural unemployment and labor market segmentation, with healthier individuals concentrated in stable employment and others pushed to the margins. Second, economic downturns may disproportionately affect workers with poorer health, exacerbating inequality and economic insecurity. Third, the welfare implications are substantial. In systems like Norway's, where health-related benefits are relatively generous, health-driven job losses may lead individuals to exit the labor market via disability pathways rather than return to work—raising concerns about long-term benefit dependency.

If health is a key determinant of unemployment, policy efforts such as preventive health interventions, workplace accommodations, and targeted retraining programs may help reduce job loss risk for vulnerable groups and should be prioritized accordingly.

Nonetheless, the dominant perspective in labor and health economics has been the reverse: unemployment has detrimental effects on health. Several mechanisms have been proposed.

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 labor market (Chan and Stevens 2001; Couch and Placzek 2010; Huttunen et al. 2011; Carrington and 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, for example 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).

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 unemployment.[2] 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. Other analyses have used other health information and reached other conclusions. For instance, Browning et al. (2006) found no effect of restructuring on stress-related hospitalizations. Similarly, S. E. Black et al. (2015) conducted a wide-ranging health analysis but found few signs of health effects of restructuring (aside from poorer smoking habits).[3] 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 (2024) conclude that the average effect of unemployment on health is negative, but small in terms of partial correlation coefficient.[4] When endogeneity issues are accounted for, the unemployment effects on health are closer to be nil.

Taken together, these findings suggest that the primary causal mechanism may not be unemployment affecting health, but rather health influencing unemployment, which forms the basis for our analysis.

Several studies support this alternative view. Riphahn (1999) and Lindholm et al. (2001) find that workers with pre-existing health conditions are more likely to be laid off, while Mastekaasa (1996) and Stewart (2001) report a selection of healthy workers out of unemployment. Furthermore, health shocks may simultaneously decrease health and lead to unemployment (Adams et al. 2003; Schmitz 2011).

Also macroeconomic fluctuations have been used as exogenous and random variation in the risk of unemployment. In a recent paper, Bharadwaj et al. (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 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.[5]

Building on this approach, we examine the extent to which poor health affected the probability of becoming unemployed due to a sudden economic downturn. But while BBLR base their analysis on a nationwide recession hitting the entire labor force, we exploit a *local* labor 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 labor 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 labor 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 general practitionsers (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.

Health is inherently difficult to measure, though. Researchers typically resort to self-reported health, physical markers (e.g., BMI), health behaviors, and health care utilization. Our approach falls in the latter category. In Picchio and Ubaldi's (2024) meta-analysis, only 19 out of 327 studies apply health care utilization data. In comparison, 117 studies apply self-assessed health. A potential pitfall of utilization data is 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. Furthermore, GP's economic incentives may affect the number of visits, as they are remunerated per visit. 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). There is a literature that considers the demand for GP visits as an indicator of health status, following R. Andersen and Newman (1973). For example, Gerdtham (1997), using Swedish survey data, finds that self-reported health explains physician visits when controlling for socio-economic characteristics. Nolan and Nolan (2008), using Irish data, find that self-assessed health status and the incidence of certain chronic conditions were important determinants, even though eligibility for free visits also was a factor.[6]

Another potential pitfall could be that workers in poor health regard unemployment as an opportunity to exit the labor market with (some) economic compensation. If so, we could confuse unemployment with being out of the labor force. While leaving the labor 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 labor force.[7]

By using the (twin) difference in birth weight as an exogenous measure, BBLR effectively correct for several 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 favorable 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 concern. If there are unobservable factors that influence selection to certain jobs and sectors, this presumably 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 almost 40% higher probability of becoming unemployed. Heterogeneity analyses also reveal a pattern where workers with high productivity requirements are most at risk. The use of health-related benefits during downturns sheds light on this finding: those with the weakest attachment to the labor market seem more likely to end up on these types of benefits instead of unemployment benefits. Thus, our paper estimates the extent to which the receipt of health-related benefits can be perceived as disguised unemployment.

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 (IEA) 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).

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 2 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

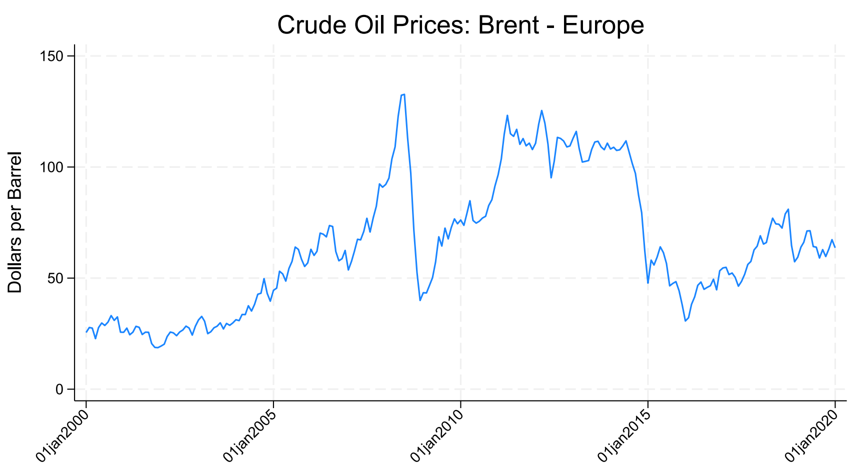

FIGURE 1 | Crude oil prices: Brent—Europe, 2000–2020. *Source:* U.S. energy information administration.

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, reduced growth in the global economy resulted in reduced demand.

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 (Norwegian Ministry of Finance 2016: 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 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 in both panels) is the most striking example, with the unemployment rate rising by 108% in 2016 compared to the level in May 2014 (Lima 2016). It confirms the localized impact of the shock on specific geographical areas, which provides an opportunity to create a treatment group (regions affected by the exogenous shock in world petroleum prices) and a control group (regions not affected) of comparable workers. This enables us to compare labor market outcomes for the two groups before and after the shock. In our preferred version, Rogaland is the treatment region and the gray and light blue regions in panel B are the control. Other categorizations are investigated in the robustness checks, notably a version whith the four neighboring coastal

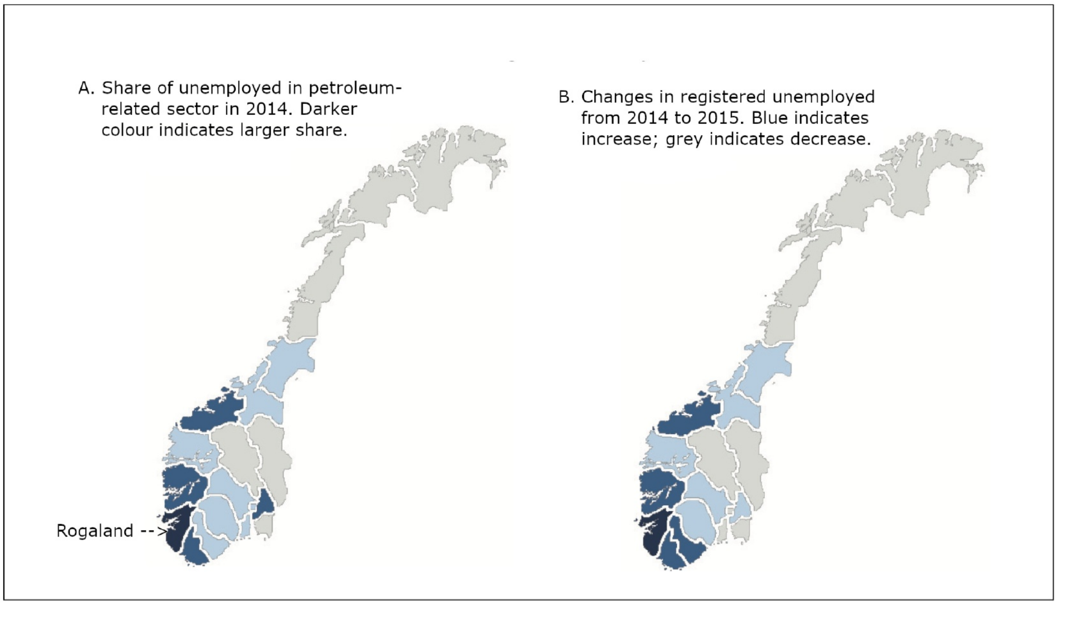

FIGURE 2 | Petrolum sector's influence on regional (un-)employment in Norway; different counties. Darkest blue: Rogaland; medium blue: neighboring coastal counties plus Oslo/Akershus (Panel A); light blue and gray: Counties less affected. *Source:* NAV and international research institute of stavanger.

counties (the medium blue areas in Panel B) in the treatment group.

As we will demonstrate later in the paper, the public sector was relatively shielded from the labor market impact of the shock in petroleum prices, also in Rogaland, with the decline primarily affecting the private sector.[12]

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 3 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% (Norwegian Ministry of Labour and Social Inclusion 2021). 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 consider the availability of paid work when evaluating a worker's eligibility. Thus, during times 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 1 year and is available to all workers employed for more than 4 weeks. For sickness spells lasting less than 9 days, most workers do not even need a medical certificate. For periods of 9 days or longer, a medical certificate from a GP is usually required, and 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). Most 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 (Norwegian Ministry of Labour and Social Inclusion 2021).

After 1 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 the desired effect within one to 3 years, the next step is disability benefits. The replacement ratio is 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 (Norwegian Ministry of Labour and Social Inclusion 2021). 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 (Norwegian Ministry of Labour and Social Inclusion 2021).

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 utilize individual register data administered by Statistics Norway covering the period 2006–2018.[15] This comprehensive dataset includes detailed information on demographics, socio-economic 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 workers, meaning they worked 30 h 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 uptake of unemployment benefits and social insurance benefits 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 utilization 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; S. 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 measure of adult health. Note that this provides us with a proxy for *predetermined* health.[19] We return with further support for using 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 service and supply industry), with a higher proportion of 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 13% higher for males in Rogaland compared to the rest of the country. The probability of

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	0.070	0.262	0.037
Unemployment benefit > 0	0.025	0.034	0.028	0.036
Social insurance benefit > 0	0.012	0.015	0.030	0.034
Earnings/10000 NOK[a]	75.89 (46.22)	67.24 (46.90)	56.73 (36.31)	53.74 (28.55)
Number of GP visits[b]	1.89 (2.79)	1.98 (2.81)	2.98 (3.38)	3.00 (3.39)
Age	44.31 (8.58)	44.68 (8.49)	43.78 (8.28)	44.03 (8.31)
Low education[a]	0.151	0.184	0.165	0.171
Medium education[a]	0.554	0.511	0.433	0.423
High education[a]	0.296	0.304	0.402	0.406
White collar worker	0.581	0.557	0.723	0.700
Married[a]	0.702	0.658	0.675	0.629
Number of children 0–17[a]	1.06 (1.15)	0.92 (1.06)	1.05 (1.06)	0.93 (0.99)
Immigrant	0.134	0.147	0.163	0.18
Number of individuals	54,993	345,164	21,886	152,283

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

males in the treatment group receiving unemployment benefits is only 2.5%, compared to 3.4% in the control group. Similarly, for females, earnings are 6% higher in the treatment group, while 2.8% receive unemployment benefits compared to 3.6% in the control counties.

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 5.0 (5.1) percent in the control group. However, this changed dramatically in the 3 years following the crisis, with an average of 8.5 (9.3) percent of male (female) workers in Rogaland receiving unemployment benefits compared to 4.3 (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% before to 5.6% after the price shock).

We use the average number of GP visits 2006–13 to construct our health indicator. Figure 3 shows the distribution of average visits per year in unit intervals. Note that as this average is a continuous variable, the first bar shows the interval 0–1 visits (only 3.2% have exactly 0 visits over this 8-year period). The histogram shows that it is common to have a couple of visits per year on average: 65.7% and 62.1% in the treatment and control groups, respectively, have 0–2 average GP visits per year (represented by the first 2 bars in the histogram). The share with 2–4 visits per year on average are 23.0% and 25.3%, while 11.3% and 13.6% have on average 4 or more visits. In the analysis, our health measure is a discrete variable based on the intervals $0 \leq$ average visits < 2, $2 \leq$ average visits < 4, and average visits ≥ 4.[20] We interpret this measure as according to “good”, “fair” or “poor” health. While our chosen intervals are somewhat arbitrary, we think it makes sense to allow for up to 2 average visits per year in the most healthy group, as the reasons for some visits may be trivial, such as annual routine check-ups, “health screenings,” and similar (the patient fee per visit is small). Moreover, using the visits variable directly without discretizing would imply a linear mapping from GP visits to health, something we find less reasonable than our ordinal measure: we do not think, for example, that a person with on average 2 GP vists per year is twice as healthy as a person with 4 visits. However, we also provide sensitivity analyses with other implementations of the health measure as part of our robustness checks, including alternative cut-offs and GP visits as a continuous variable.

Table 3 describes the treatment and control groups conditional on health, that is, the 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, compared to the base group, the least healthy group (≥ 4 GP visits) is to a larger extent associated with severe/chronic conditions, such as depressive disorders (4–5 times as frequent), asthma (3–4 times as frequent), diabetes (8 times as frequent), or chronic back/neck disorders (2–3 times as frequent). Moreover, this group has more hospital visits, inpatient as well as outpatient. Visits to somatic and psychiatric hospitals were respectively 5 and more than 10 times as common for the least 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]

Figure 4 displays trajectories of the outcome variables in private/public sector by gender. Each graph shows rates for the

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	0.050	0.039	0.051
Social insurance benefit > 0	0.017	0.024	0.043	0.049
Earnings/10000 NOK	61.89 (45.97)	53.53 (39.94)	44.54 (30.00)	41.29 (24.12)
Number of observations	432,205	2,720,466	170,913	1,195,666
Post shock (means 2015–2018)				
Unemployment benefit > 0	0.085	0.043	0.093	0.050
Social insurance benefit > 0	0.056	0.034	0.073	0.062
Earnings/10000 NOK	76.63 (65.90)	70.63 (54.61)	59.11 (40.88)	56.28 (32.82)
Number of observations	217,951	1,410,753	86,933	605,264
Number of individuals	54,993	345,164	21,886	152,283

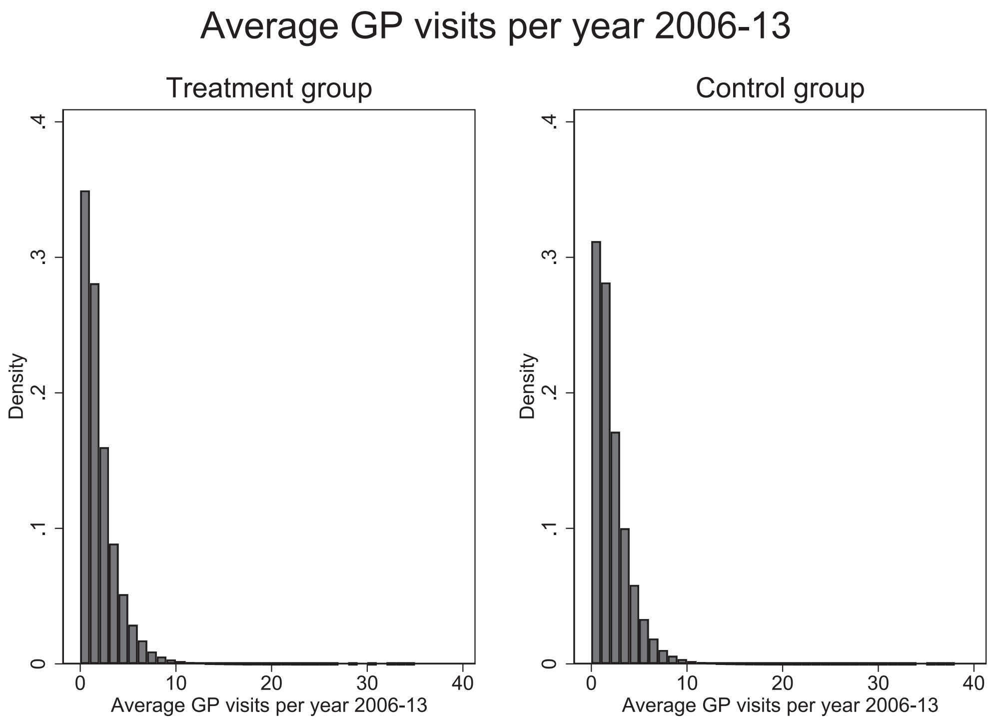

FIGURE 3 | Average GP visits per year for treatment and control; grouped in unit intervals.

TABLE 3 | Descriptive statistics, by average number of GP visits per year, treatment and control group.

	Treatment 0–2 visits	Control 0–2 visits	Treatment 2–4 visits	Control 2–4 visits	Treatment 4+ visits	Control 4+ visits
Male	0.804	0.783	0.659	0.645	0.525	0.522
Age[a]	42.98 (8.29)	43.20 (8.29)	43.43 (8.63)	43.80 (8.49)	43.13 (8.89)	43.65 (8.76)
Labor incom/10000 NOK[a]	76.90 (50.58)	64.92 (44.67)	66.55 (37.81)	57.46 (31.19)	56.06 (28.05)	49.22 (24.15)
Low education[a]	0.131	0.155	0.164	0.190	0.220	0.250
Medium education[a]	0.517	0.469	0.528	0.500	0.507	0.491
High education[a]	0.353	0.376	0.308	0.310	0.273	0.259
Married[a]	0.700	0.642	0.702	0.649	0.657	0.623
Number children 0–17	1.090 (1.137)	0.937 (1.050)	1.075 (1.122)	0.942 (1.036)	1.002 (1.069)	0.907 (1.017)
White collar worker	0.644	0.631	0.611	0.590	0.564	0.532
Immigrant	0.133	0.149	0.147	0.156	0.166	0.188
Diagnosed with:[b]						
Depressive disorder	0.023	0.025	0.066	0.063	0.139	0.129
Asthma	0.022	0.026	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	0.041
Chron back/neck disord	0.091	0.099	0.180	0.193	0.248	0.262
Coronary heart disease	0.005	0.005	0.016	0.013	0.027	0.021
Cancer	0.007	0.006	0.017	0.013	0.020	0.016
Rheumatoid arthritis	0.005	0.005	0.013	0.011	0.020	0.017
Osteoarthritis	0.010	0.011	0.028	0.029	0.040	0.044
Anxiety disorder	0.010	0.011	0.028	0.027	0.062	0.055

(Continues)

TABLE 3 | (Continued)

	Treatment 0–2 visits	Control 0–2 visits	Treatment 2–4 visits	Control 2–4 visits	Treatment 4+ visits	Control 4+ visits
Hospital visits[c]						
Inpatient stays, somatic	0.028 (0.101)	0.028 (0.094)	0.070 (0.144)	0.066 (0.146)	0.168 (0.273)	0.150 (0.237)
Outpatient visits, som.	0.274 (0.872)	0.300 (0.938)	0.611 (1.280)	0.625 (1.173)	1.217 (1.789)	1.156 (1.755)
Outpatient visits, psych	0.025 (0.395)	0.029 (0.488)	0.098 (0.834)	0.091 (0.792)	0.385 (2.053)	0.321 (1.653)
Number of individuals	39,538	243,031	26,522	178,332	10,759	76,084

Note: Average over 2006–2013 if not otherwise stated.
[a]Measured in 2013.
[b]Diagnosed by primary care physician (at least once) during 2006–2013.
[c]Average number per year 2008–2013 (period of observation in NPR).

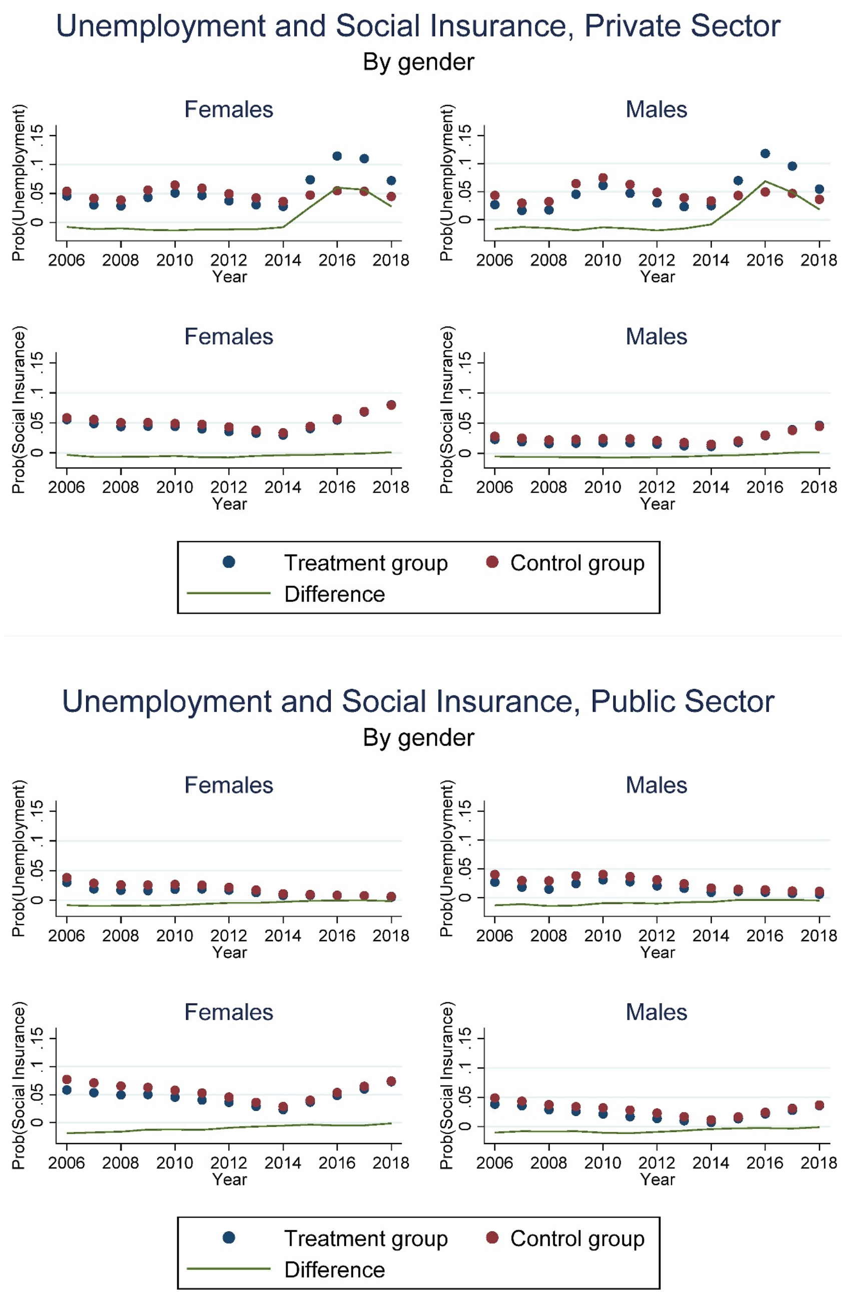

FIGURE 4 | Unemployment in private versus public sector 2006–2018, by gender.

treatment and control groups, and the difference. As noted above, sample inclusion is conditional on employment (≥ 30 h/week) in August 2014.

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, they suggest 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. As for the V-shape, apparent in particular for females, it is due to the conditioning on employment in 2014. Some individuals on WAA benefits before 2014 were successfully rehabilitated and are 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 the private sector treatment group.

To scrutinize the common trend assumption more explicitly, Figures A1 and A2 plots differences between the treatment and control groups relative to 2013, with confidence intervals, for the same groups as in Figure 4. These plots are "raw" difference-in-differences before adding control variables. For the common trend assumption to hold, the differences should be zero prior to treatment. For the private sector (top panels of Figures A1 and A2), the assumption holds—we also see a huge rise in the differences for unemployment but less so for social insurance uptake. For females in the public sector the assumption is debatable.

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 categories. 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.

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 regions[22] of Rogaland County (treated) to private sector workers in regions 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 labor market shocks. The variable $Health_i$ is the individual pre-shock health variable, measured as average number of visits to the GP per year in the period 2006–2013, categorized as 0–2, 2–4 or 4+ with corresponding values $Health_i = (0, 1, 2)$. DD_{ijt} is an interaction between the Rogaland dummy and a post-shock dummy. $DD_{ijt} = 1$ indicates that worker i in region j is treated in period 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 region and year fixed effects, and ε_{ijt} is a random error term with standard properties. The region fixed effects pick up local labor market conditions that may affect the unemployment risk in Rogaland, as well as in the control regions. 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. Standard errors are clustered at the region level.[23]

In this regression, β_1 and β_2 show how frequent GP visits, 2–4 or 4+, are associated with unemployment risk relative to the reference with 0–2 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 regions captures the counterfactual development for the treated regions during the downturn period. Graphical evidence in the previous section (Figures 4 and 5 plus Figures A1–A3) 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 working in Rogaland after the oil price shock (α in the regression equation), while the next two rows show the interaction terms with poor health, 2–4 or 4+ visits. In the first column of coefficients, we observe that the treatment effect is 0.0420. In other words, the healthiest workers, with less than 2 visits per year, in the treated municipalities (Rogaland) experience an increase of more than 4% points (pp) in the probability of becoming unemployed after the shock (2015 through 2018).

Our main finding, however, is that this base effect is amplified for workers with poorer health, with an increase of 0.74 pp for workers in the intermediate health category and 1.62 pp for those

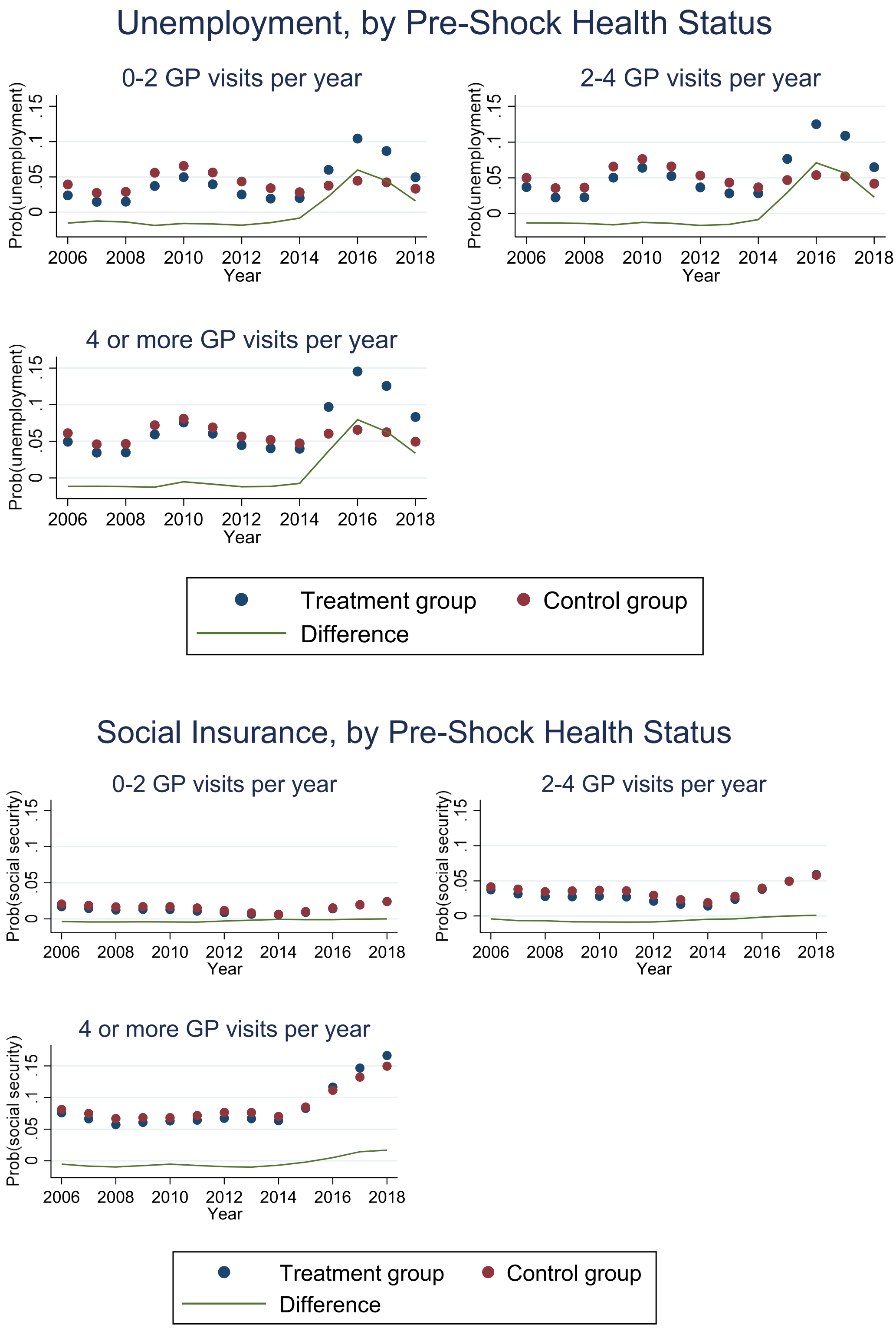

FIGURE 5 | Unemployment and social insurance by health status.

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 "2–4 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, "Rogaland*Post", was almost 40% when comparing the healthiest category (4.2 pp) to the least healthy category ($4.2 + 1.6 = 5.8$ pp for 4 or more visits).

The results reported in the second column suggest that the oil price shock had no additional effect on the probability of social insurance uptake for the treatment group in good or fair health. However, a striking finding is the highly significant differential

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

	Probability of unemployment	Probability of social insurance uptake
Base effect (Rogaland*Post)	0.0420*** (0.0087)	−0.0003 (0.0009)
Interaction, 2–4 GP visits	0.0074*** (0.0020)	0.0026 (0.0023)
Interaction, 4 or more GP visits	0.0162*** (0.0035)	0.0308*** (0.0078)
2–4 GP visits	0.0068*** (0.0005)	0.0154*** (0.0015)
4 or more GP visits	0.0113*** (0.0006)	0.0611*** (0.0041)
Mean *y (pre)*	0.0483	0.0302
Observations	7,374,039	7,374,039
Labor market regions	70	70
Individuals	574,266	574,266

[a]Region 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 regions.
*, **, ***: statistically significant at 5%, 1%, and 0.1% level.

effect observed for the least healthy group: following the 2014 recession, their probability of receiving health-related social insurance increases by 3.1 pp. This corresponds to a doubling of the uptake rate compared to the national average (3.0 pp). Hence, only the least healthy workers are sorted into long-term social insurance resulting from the labor market 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, with the timeline set to 0 in 2014. Here, the base effect is the Rogaland dummy, while the two interactions are the differential effects of fair and poor health, respectively.

The top left part of the graph shows a strong baseline effect on the unemployment probability in Rogaland, peaking in 2016. The interaction effects are smaller but largest for the least healthy group. However, the interaction effects also fluctuate before 2014, possibly because the financial crisis may have had a detrimental effect on workers in Rogaland—recall the volatile petroleum prices around 2010 that we saw in Figure 1.

In the lower panel, we see that the general « Rogaland effect » on social insurance uptake is slightly negative after the shock, in accordance with the results in Table 4. The interactions with poor health are positive, however, and increase over time—particularly the least healthy group. That makes sense, as work assessment allowance (WAA) and disability benefits in general are conditional on a 1-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 labor force for workers in poor health. As in the top panel, there are some fluctuations in the interaction coefficients before 2014, particularly for the least healthy group. Even so, the main impression from the lower part of Figure 6 is the strong interaction effect for the group with more than 4 GP visits.

We offer an alternative exposition in the Appendix (Table A1 and Figure A3). Health effects are estimated directly, without interactions, constructing different samples of health categories/number of GP visits. Table A1 reports regression coefficients averaged over the period 2014–2018, while Figure A3 plots coefficients year by year for the entire period (2006–2018). That is, Figure A3 shows cumulative health effects for each health group, whereas Figure 6 shows differential effects. For unemployment, the health effects in Table A1 are consistent with Table 4, but smaller. The difference between the "good" and "fair" health groups is now 0.57 pp (0.0494 −0.0437), compared to 0.74 in Table 4, and the difference by the least and most healthy is reduced to 0.86 pp. The effect on social insurance is positive but again smaller for the least healthy group. Figure A3 shows that unemployment increases in all groups, and most in the least healthy group. Regarding social insurance, the effect is clearly highest for the unhealthy group, while there is no significant increase in the healthiest group.

4.3 | Robustness Checks

4.3.1 | 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.

The outcomes for a control group without workers employed in the petroleum industries, represented as "Other industries, Control" in Figure 7, are detailed in Table A2, columns (1) and

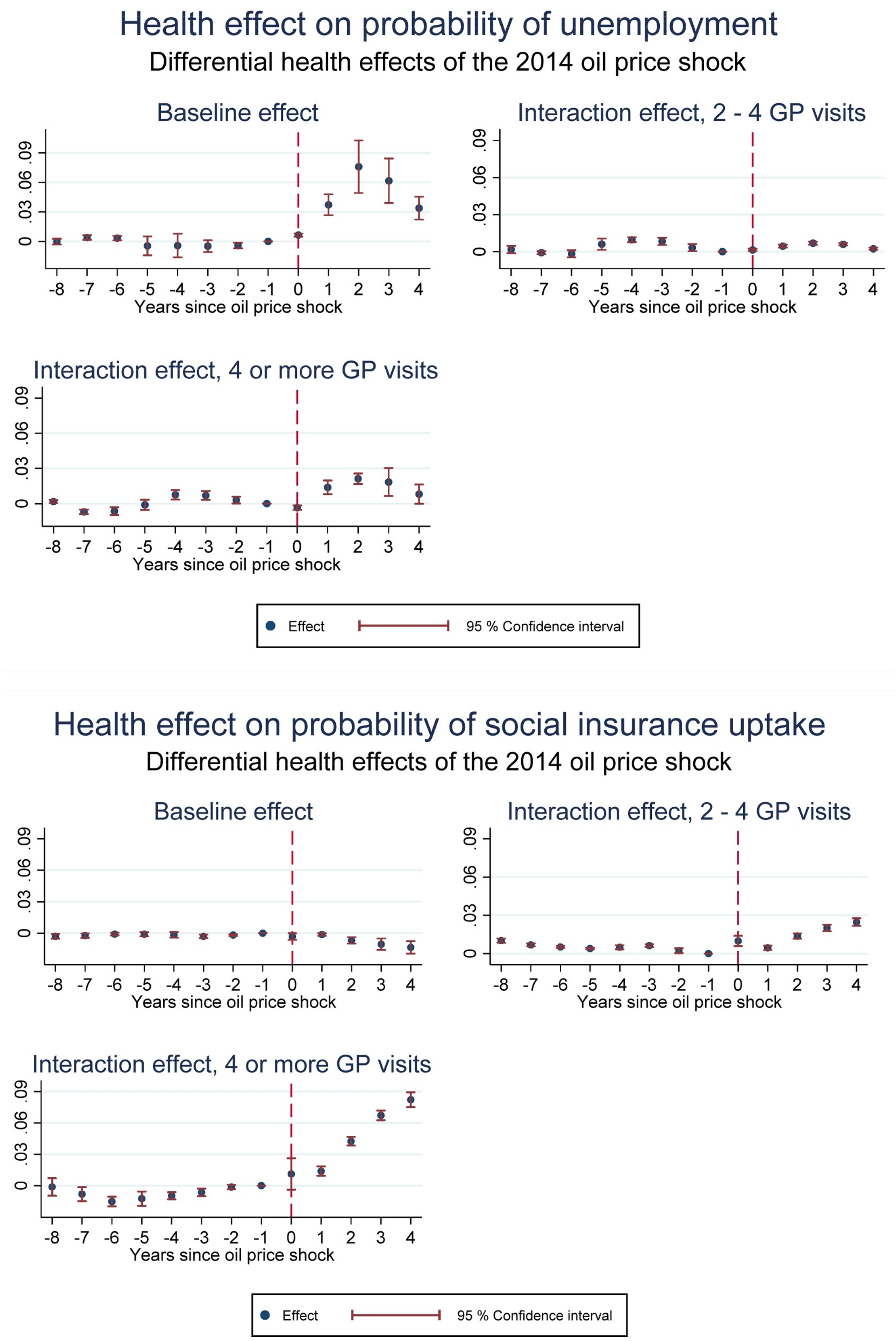

FIGURE 6 | Year-by-year impact of health on receipt of unemployment benefits (upper panel) and health-related benefits. Coefficient and confidence intervals 2006–2018; 2006–2013 is pre, 2014–2018 is post, 0 is 2014 (the year of the oil price shock).

(2). Regarding the impact of health on unemployment, the changes are negligible 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. Once again, the coefficients see just minor changes. Thus, 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.

A final exclusion check is reported in columns (5) and (6), where we examine the effect of migration between treatment and control groups by excluding individuals who moved to or from Rogaland after 2013. The number of individuals affected is relatively small: 1791 moved out of Rogaland, and 1029 moved in. Since some individuals appear in both categories, the total number excluded from the regressions is slightly lower—2545 in total. From the reported coefficients we can conclude that migration apparently had no measurable impact on our results.

We continue by checking the robustness of our initial choice of (i) including four neighboring coastal counties to Rogaland in the treatment group (the medium blue areas in Figure 2) and (ii) including public sector (in the treatment group if employed in Rogaland; in the control group if not). In Table A3 the effect of including the neighboring counties is reported in column (1) and (3); inclusion of public sector in column (2) and (4). Compared to the main results, the base effect of the shock on unemployment risk decreases by 38% (from 4.2 pp to 2.6 pp) when we include the additional counties. The base coefficients on "fair" and "poor" health (β_1 and β_2 in the model) are quite similar, however, indicating that the general association between health and unemployment probability is the same as in the main regression. On the other hand, the health interaction effects (i.e., the causal impact) are smaller and less precisely estimated. It seems plausible that this is because the extended treatment group also has a smaller direct effect on unemployment. For social insurance, we also see that the basic association between health and this outcome is quite similar. The base effect of the shock is much stronger than in Table 4, however, indicating that social insurance take-up decreased after the shock. The health interactions are positive as before and more precisely estimated. In summary, in particular the health effects on unemployment risk are reduced when we extend the treatment group. That could be because the overall risk of unemployment is reduced after the shock when we include the other four counties. Including public sector employees (the right-hand panel in Table A3) tells a similar story.[24] The estimated interaction effects in general are smaller and less precisely estimated. We interpret that as a consequence of including a large group of workers where the unemployment risk is smaller than in the private sector before the shock, and where the difference between treated and controls after the shock also is smaller.

4.3.2 | Alternative Implementations of the Health Measure

Our access to individual health data prior to the price shock is limited. We therefore use data on health service utilization—specifically, the annual number of GP visits—as a proxy for health. Inspection of the histograms in Figure 3 suggested that up to 2 visits per year on average is quite common, while more than 4 visits is less usual, and that led us to our choice of intervals—0–2, 2–4, 4 or more—to proxy "good", "fair", and "poor" health. Clearly, other specifications are conceivable, and we consider two: (i) a dummy indicating average yearly visits above the median, (ii) average yearly visits entered as a continuous variable. The results are shown in Table A4.

The left panel of Table A4 shows that visits above the median (1.5 average visits) increases the probability of unemployment by 1.37% points, somewhat less than for the "poor health" group in the main results (1.62 pp). While the results are consistent, just using the median misses the point that most of this effect is driven by those in the upper part of the distribution. Moreover, the interaction effect on social insurance is now insignificant. With a cut-off at the median, the "unhealthy" group apparently is too healthy to pick up any effect (in the main regression, only the interaction on 4 or more visits is significant).

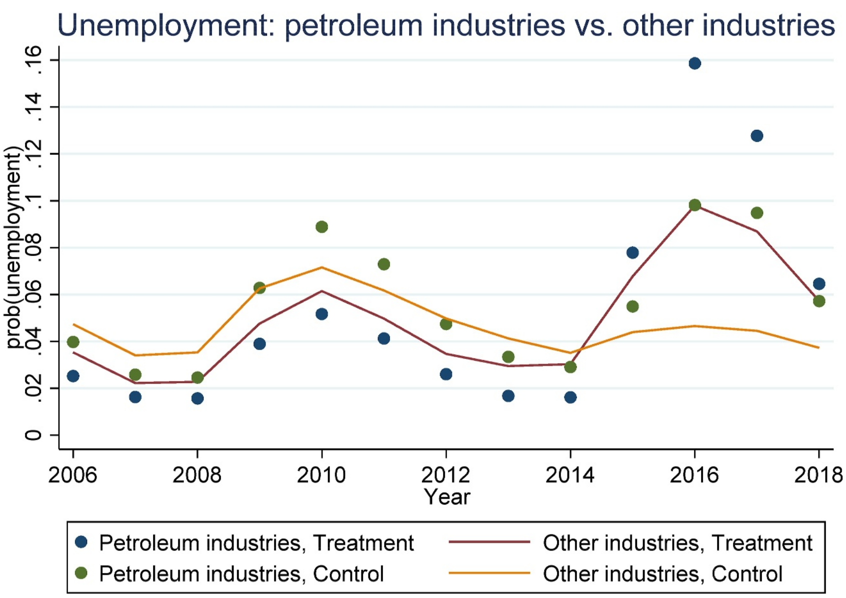

FIGURE 7 | Unemployment in private sector, measured as year-by-year probability of receiving UI, petroleum versus other industries, treatment versus control.

In the right panel we estimate the interaction effect to 0.0024 per visit—the unemployment risk increases by 0.24% point for each additional visit to the GP. That is, evaluated at 3 GP visits—the midpoint of the "fair" interval in the main results, we get 0.72 pp increased unemployment risk, which is the same as the estimated interaction for the "fair" group in the main results. At 6.75 visits (less than 3% of the sample) the linear specification yields the same effect on unemployment risk as the "unhealthy" group in the main specification. As in the previous specification, the effect on social insurance is imprecisely estimated.

Given that there is no precise mapping of GP visits to health, we prefer the specification in Table 4. Compared to the specification based on the median, we get estimates that allow the effects to increase with poorer health. The specification with GP visits as a continuous variable could be improved by relaxing the linear assumption. However, we prefer some sort of grouping because it accentuates the ordinal nature of our measure: doubling the number of GP visits is associated with poorer health, but not necessarily twice as poor. It is not the number of GP visits per se that affects unemployment risk, but the reduced health that is associated with more visits. Even so, it is a valid statement that the unemployment risk increases by 0.24% points per additional average visit. (As the average is over 8 years, the effect of a single visit is 0.03 pp.) Grouping is similar in spirit to studies that apply self-reported health, where respondents are asked to rank themselves on an ordinal scale. While we do not attempt to interpret the degree of reduced health quantitatively, we note that about 12% of the individuals in the sample have more than 4 average visits and belong to the least healthy. This fairly small group has 40% larger risk of unemployment (cf Section 4.2) due to the petroleum price shock than the about 65% in the group in "good" health. This group also is in significantly worse health by other measures: as we saw in Table 3, the least healthy group has 5 times more stays in somatic hospitals than the base group, and more than 10 times as many outpatient visits for psychiatric conditions. It is also 8 times more likely that individuals in this group has diabetes as in the group with up to 2 average GP visits, cf Table 3 and the surrounding discussion.

The reported count of GP visits is derived from averaging yearly GP visits for each individual over the period from 2006 to 2013. Alternative periods 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 in the main regression. This is consistent with more random noise due to temporary health shocks, and we maintain averaging over 2006–2013 as our preferred specification.

4.3.3 | 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 2014 entirely. Lastly, Table A7 compares our model with region fixed effects to OLS without fixed effects and a model with individual fixed effects. The estimated health effects are rather similar in the OLS specifications but smaller with individual FE. However, there is a large efficiency loss in the latter because of the big number of parameters to estimate or difference out.

4.4 | Heterogeneity

The relationship between health and the probability of becoming unemployed is likely to vary across worker groups. As discussed in Sections 1 and 2, we must also allow for heterogeneity in the degree of substitution between unemployment benefits and health-related benefits. These considerations would apply even if we had access to a perfect and objective measure of health. In practice, however, our health measure—the number of GP visits—serves only as a proxy for underlying health status, introducing additional sources of measurement error and interpretational ambiguity. For instance, it is well established that women tend to visit doctors more frequently than men, and that older individuals, on average, utilize health services more than younger individuals. As a result, a given number of doctor visits may signal very different underlying health conditions depending on age and gender. For example, a high number of visits by a young male may be a stronger indication of poor health than the same number of visits by an older female. The heterogeneity analyses that follow address the former issue. The latter—variation in the informational content of the proxy across subgroups—is a limitation inherent in our health measure. This must be kept in mind when interpreting the results.

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.

4.4.1 | 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 (coloumn 1 and 3) was fairly consistent between the two sets (5.0% for females and 4.8% for males), the shock from the oil price increase nearly doubled male unemployment (up by 4.4 pp), while the diff-in-diff effect for females was 3.7 pp, reflecting an approximate 75% increase. The results differ also when considering the health effect. For females 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 (columns 2 and 4), the data reveals a noticeable disparity in the average percentage of individuals in our sample receiving benefits prior to the price shock. Specifically, females had an approximate 50% higher utilization rate than males (4.8% vs. 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 3.8 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.

4.4.2 | 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: 6.3%, compared to 4.6% and 3.7% for the middle and oldest categories, respectively. For healthy workers—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, but this time the health effect hits hardest in the oldest group. Before the shock, the percentage of benefit recipients was fairly similar (3.2%, compared to 3.3% and 2.6% when moving from the youngest to the oldest groups). For the groups with good and fair health the shock had virtually no impact, no matter age group. Conversely, in the oldest age category, poor health appeared to boost the uptake of health-related benefits, increasing by 5.5 pp. 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 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.

4.4.3 | 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.[25] 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 2.9). In contrast, the increase for those with the lowest education was 55% (rising by 4.6 from 8.3). White-collar workers experienced a larger increase than blue-collar; in absolute terms (4.2 vs. 4.1%) as well as relative terms (up 122% from 3.4 compared to 5.8% up from 7.0).

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 28% for the lowest educated (up 1.3 pp from 4.6%). Similarly, for white-collar workers, there is a substantial 57% increased probability for those with the worst health (a rise of 2.4 pp from 4.2), compared to a 22% increase for blue-collar workers with poorest health (up 0.9 pp from 4.1).

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 (4.5, 3.6 and 0.1 pp for low, median and high education, repspectively) and blue versus white collar work (3.8 and 2.5 pp for blue and white collar, respectively). 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 labor 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 labor 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 (Nergaard 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 (Nergaard 2024). Our data do not facilitate investigation 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.

Finally, note that the heterogeneity analyses in this section are subject to the limitation that the proxy variable may not be equally calibrated across groups. This means that estimated differences in, for example, gender or age groups, may reflect both substantive heterogeneity in vulnerability and systematic variation in how the health proxy captures actual health status. Accordingly, the results should be interpreted with caution. They point to meaningful patterns of heterogeneity in how health conditions affect labor market outcomes, but also reflect the inherent limitations of using a single proxy variable across diverse subpopulations.

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 modeling.

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% point increase in the probability of becoming unemployed, but only a 0.9% point increase in the probability of receiving health-related benefits. For low-educated individuals, however, the corresponding figures were 1.4 and 4.6% 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% point increase), but the worst in terms of health-related benefits (5.5% point increase). For the youngest, it is reversed: a 2.3% point increase in unemployment and a 1.7% 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.

The study closest to ours, Bharadwaj et al. (2019), provides a foundational contribution by leveraging a macroeconomic shock —the early 1990s recession in Sweden—to study the causal impact of pre-existing health (proxied by birth weight) on job loss. The current paper closely follows this approach in spirit but introduces several innovations: We exploit a regional labor deman shock whereas BBLR use a nationwide recession, we use adult in stead of early-life health proxy and, finally, we include health-related social insurance as an outcome in addition to unemployment, expanding the understanding of how poor health affects broader labor market attachment and benefit reliance. Both studies attempt to address endogeneity. BBLR do so via within-twin variation in birth weight, while the current study relies on a difference-in-differences (DiD) framework that compares outcomes across regions with and without exposure to the exogenous oil shock. While the DiD strategy may be vulnerable to residual confounding from unobserved regional characteristics, pre-trend tests and robustness checks support the validity of the approach.

This study confirms BBLR's key finding that poor health increases vulnerability during economic downturns. It adds a novel dimension by documenting how the least healthy are also disproportionately sorted into long-term health-related social insurance programs—suggesting potential substitution between unemployment and disability routes.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

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

[2] There is hardly any reason to believe that firm closures are related 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.

[3] Rege et al. (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 for example A. G. Andersen et al. (2019), that disability benefit is an inadequate measure of health, because labor market conditions, in addition to poor health, determine whether a person is granted social security.

[4] The analysis is based on 65 published papers in the period 1990 to 2021.

[5] 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, 639).

[6] We are not aware of studies that validate GP visits in the Norwegian system as a health measure against other health indicators.

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

[8] Notable contributions include the works of Autor and Duggan (2003), Rege et al. (2009), Bratberg and Monstad (2015), Bratsberg et al. (2013), Kann et al. (2016), Lima (2016), and A. G. Andersen et al. (2019).

[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: 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: 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.

[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.

[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.

[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 11,000 in 2025.

[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.

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

[16] We excluded Vest-Agder, Aust-Agder, Hordaland, and Møre og Romsdal—corresponding to the medium blue counties in Panel B of Figure 2—from our analysis, but they will be included in alternative definitions of the treatment and control groups in the sensitivity analyses.

[17] The rationale for excluding the public sector will be examined later in the paper. In the section on sensitivity analyses, we will also present results where the sector is included.

[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.

[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 since we rely on predetermined information.

[20] For ease of exposition, we simplify the group labels to 0–2, 2–4, and 4 or more.

[21] In the sensitivity analysis, we will explore alternative implementations of the health measure to assess the robustness of our findings.

[22] «Region » refers to economic regions as defined by Statistics Norway standard NOS C 616. Economic regions are defined as a level between municipality and county, defined by criteria based on labor market and trade (Hustoft et al. 1999). For example, the county Rogaland has 4 regions, and the county Hordaland has 5 regions—a total of 90 regions across 19 counties.

[23] It is common practice to cluster at the treatment level. It might be argued that in our case treatment is at the county level, however 19 clusters are too few to obtain consistent error estimates, and we consider the region level as an acceptable alternative.

[24] With its high concentration of well-paid jobs in the petroleum sector, the share of public sector employment in Rogaland is somewhat lower than the national average. In our sample, approximately 32% work in the public sector, compared to about 42% in the control group.

[25] 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.

References

Adams, P., M. D. Hurd, D. McFadden, A. Merrill, and T. Ribeiro. 2003. "Healthy, Wealthy, and Wise? Tests for Direct Causal Paths Between Health and Socioeconomic Status." *Journal of Econometrics* 112, no. 1: 3–56. https://doi.org/10.1016/s0304-4076(02)00145-8.

Andersen, A. G., S. Markussen, and K. Røed. 2019. "Local Labor Demand and Participation in Social Insurance Programs." *Labour Economics* 61: 101767. https://doi.org/10.1016/j.labeco.2019.101767.

Andersen, R., and J. F. Newman. 1973. "Societal and Individual Determinants of Medical Care Utilization in the United States." *Milbank Memorial Fund Quarterly - Health & Society* 51, no. 1: 95–124. https://doi.org/10.2307/3349613.

Autor, D., and M. Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics* 118, no. 1: 157–206. https://doi.org/10.1162/00335530360535171.

Barnay, T. 2016. "Health, Work and Working Conditions: A Review of the European Economic Literature." *European Journal of Health Economics* 17, no. 6: 693–709. https://doi.org/10.1007/s10198-015-0715-8.

Behrman, J. R., and M. R. Rosenzweig. 2004. "Returns to Birthweight." *Review of Economics and Statistics* 86, no. 2: 586–601. https://doi.org/10.1162/003465304323031139.

Bharadwaj, P., J. Bietenbeck, P. Lundborg, and D.-O. Rooth. 2019. "Birth Weight and Vulnerability to a Macroeconomic Crisis." *Journal of Health Economics* 66: 136–144. https://doi.org/10.1016/j.jhealeco.2019.05.001.

Bharadwaj, P., P. Lundborg, and D.-O. Rooth. 2018. "Birth Weight in the Long Run." *Journal of Human Resources* 53, no. 1: 189–231. https://doi.org/10.3368/jhr.53.1.0715-7235r.

Black, S., P. Devereux, and K. G. Salvanes. 2007. "From the Cradle to the Labor Market? The Effect of Birth Weight on Adult Outcomes." *Quarterly Journal of Economics* 122, no. 1: 409–439. https://doi.org/10.1162/qjec.122.1.409.

Black, S. E., P. J. Devereux, and K. G. Salvanes. 2015. "Losing Heart? The Effect of Job Displacement on Health." *ILR Review* 68, no. 4: 833–861. https://doi.org/10.1177/0019793915586381.

Böckerman, P., and P. Ilmakunnas. 2009. "Unemployment and Self-Assessed Health: Evidence From Panel Data." *Health Economics* 18, no. 2: 161–179. https://doi.org/10.1002/hec.1361.

Bratberg, E., and K. Monstad. 2015. "Worried Sick? Worker Responses to a Financial Shock." *Labour Economics* 33: 111–120. https://doi.org/10.1016/j.labeco.2015.02.003.

Bratsberg, B., E. Fevang, and K. Røed. 2013. "Job Loss and Disability Insurance." *Labour Economics* 24: 137–150. https://doi.org/10.1016/j.labeco.2013.08.004.

Browning, M., A. M. Danø, and E. Heinesen. 2006. "Job Displacement and Stress-Related Health Outcomes." *Health Economics* 15, no. 10: 1061–1075. https://doi.org/10.1002/hec.1101.

Browning, M., and E. Heinesen. 2012. "Effect of Job Loss Due to Plant Closure on Mortality and Hospitalization." *Journal of Health Economics* 31, no. 4: 599–616. https://doi.org/10.1016/j.jhealeco.2012.03.001.

Carlsen, B., J. T. Lind, and K. Nyborg. 2020. "Why Physicians Are Lousy Gatekeepers: Sicklisting Decisions When Patients Have Private Information on Symptoms." *Health Economics* 29, no. 7: 778–789. https://doi.org/10.1002/hec.4019.

Carrington, W. J., and B. Fallick. 2017. "Why Do Earnings Fall With Job Displacement?" *Industrial Relations: A Journal of Economy and Society* 56, no. 4: 688–722. https://doi.org/10.1111/irel.12192.

Chan, S., and A. H. Stevens. 2001. "Job Loss and Employment Patterns of Older Workers." *Journal of Labor Economics* 19, no. 2: 484–521. https://doi.org/10.1086/319568.

Couch, K. A., and D. W. Placzek. 2010. "Earnings Losses of Displaced Workers Revisited." *American Economic Review* 100, no. 1: 572–589. https://doi.org/10.1257/aer.100.1.572.

Eliason, M., and D. Storrie. 2009. "Does Job Loss Shorten Life?" *Journal of Human Resources* 4, no. 2: 277–302. https://doi.org/10.3368/jhr.44.2.277.

Fackler, D., S. Mueller, and J. Stegmaier. 2021. "Explaining Wage Losses After Job Displacement: Employer Size and Lost Firm Wage Premiums." *Journal of the European Economic Association* 19, no. 5: 2695–2736. https://doi.org/10.1093/jeea/jvab022.

Farré, L., F. Fasani, and H. Mueller. 2018. "Feeling Useless: The Effect of Unemployment on Mental Health in the Great Recession." *IZA Journal of Labor Economics* 7, no. 1: 8. https://doi.org/10.1186/s40172-018-0068-5.

Ferman, B., G. Torsvik, and K. Vaage. 2023. "Skipping the Doctor: Evidence From a Case With Extended Self-Certification of Paid Sick Leave." *Journal of Population Economics* 36, no. 2: 935–971. https://doi.org/10.1007/s00148-021-00841-6.

Gerdtham, U. G. 1997. "Equity in Health Care Utilization: Further Tests Based on Hurdle Models and Swedish Micro Data." *Health Economics* 6, no. 3: 303–319. https://doi.org/10.1002/(sici)1099-1050(199705)6:3<303::aid-hec270>3.0.co;2-p.

Heggebø, K. 2022. "Gendered Health Consequences of Unemployment in Norway 2000–2017: A Register-based Study of Hospital Admissions, health-related Benefit Utilisation, and Mortality." *BMC Public Health* 22, no. 1: 2447. https://doi.org/10.1186/s12889-022-14899-8.

Hustoft, A. G., H. Hartvedt, E. Nymoen, M. Stålnacke, and H. Utne. 1999. *Standard for Økonomiske Regioner. Etablering Av Publiseringsnivå Mellom Fylke Og Kommune*. Report 99/6. Statistics Norway.

Huttunen, K., J. Møen, and K. G. Salvanes. 2011. "How Destructive is Creative Destruction? Effects of Job Loss on Job Mobility, Withdrawal and Income." *Journal of the European Economic Association* 9, no. 5: 840–870. https://doi.org/10.1111/j.1542-4774.2011.01027.x.

International Energy Agency (IEA). 2022. *Norway 2022*. International Energy Agency.

Kann, I. C., J. Yin, and P. Kristoffersen. 2016. "Arbeidsavklaringspenger – Utviklingen i hvem som kommer inn [Work Assessment Allowance – The Development in Recipients]." *Arbeid og velferd* 2: 63–76.

Lima, I. A. Å. 2016. "Hvordan har økt ledighet påvirket bruken av helseytelser og økonomisk sosialhjelp? [How Has Increased Unemployment Affected the Use of Health Benefits and Means-Tested Social Benefits?]." *Arbeid og velferd* 3: 131–150.

Lindholm, C., B. Burström, and F. Diderichsen. 2001. "Does Chronic Illness Cause Adverse Social and Economic Consequences Among Swedes?" *Scandinavian Journal of Public Health* 29, no. 1: 63–70. https://doi.org/10.1080/14034940151107064.

Mastekaasa, A. 1996. "Unemployment and Health: Selection Effects." *Journal of Community & Applied Social Psychology* 6, no. 3: 189–205. https://doi.org/10.1002/(sici)1099-1298(199608)6:3<189::aid-casp366>3.0.co;2-o.

Mastekaasa, A. 2014. "The Gender Gap in Sickness Absence: Long-Term Trends in Eight European Countries." *European Journal of Public Health* 24, no. 4: 656–662. https://doi.org/10.1093/eurpub/cku075.

Moberg, L. L. 2024. "Utviklingen i legemeldt sykefravær [The development in Doctor-Certified Sickness Absence]." In *Sykefraværsstatistikk – Årsstatistikk* 2023. NAV.

NAV. 2024a. "Mottakere Av Arbeidsavklaringspenger (AAP) [Receivers of Work Assessment Allowance (WAA)]."

NAV. 2024b. "Uføretrygd – Kvartalsstatistikk [Disability Benefits – Quarterly statistics]."

Nergaard, K. 2024. "Organisasjonsgrader, Tariffavtaledekning Og Arbeidskonflikter 2022 [Membership Rates, Collective Agreement Coverage and Labour Disputes 2022]." Fafo-notat 2024:05.

Nolan, A., and B. Nolan. 2008. "Eligibility for Free GP Care, "Need" and GP Visiting in Ireland." *European Journal of Health Economics* 9, no. 2: 157–163. https://doi.org/10.1007/s10198-007-0054-5.

Norwegian Ministry of Finance. 2016. *NOU 2016:15 The Wage Formation in Light of New Economic Development*. Norwegian Official Reports.

Norwegian Ministry of Labour and Social Inclusion. 2021. *NOU 2021:2 Skills, Activity, and Income Security—Measures for Increased Employment*. Norwegian Official Reports.

Nyström, B., B. J. Mulder, and M. Schlachter. 2020. "Seniority in a Comparative Perspective." *Arbeidsrett* 17, no. 2: 114–151. https://doi.org/10.18261/issn.1504-3088-2020-02-02.

Picchio, M., and M. Ubaldi. 2024. "Unemployment and Health: A Meta-Analysis." *Journal of Economic Surveys* 38, no. 4: 1437–1472. https://doi.org/10.1111/joes.12588.

Rege, M., K. Telle, and M. Votruba. 2007. *Plant Closure and Marital Dissolution*. Discussion paper no. 54. Statistics Norway.

Rege, M., K. Telle, and M. Votruba. 2009. "The Effect of Plant Downsizing on Disability Pension Utilization." *Journal of the European Economic Association* 7, no. 4: 754–785. https://doi.org/10.1162/jeea.2009.7.4.754.

Riphahn, R. T. 1999. "Income and Employment Effects of Health Shocks – A Test Case for the German Welfare State." *Journal of Population Economics* 12, no. 3: 363–389. https://doi.org/10.1007/s001480050104.

Ruhm, C. J. 2000. "Are Recessions Good for Your Health?" *Quarterly Journal of Economics* 115, no. 2: 617–650. https://doi.org/10.1162/003355300554872.

Ruhm, C. J. 2003. "Good Times Make You Sick." *Journal of Health Economics* 22, no. 4: 637–658. https://doi.org/10.1016/s0167-6296(03)00041-9.

Ruhm, C. J. 2005. "Healthy Living in Hard Times." *Journal of Health Economics* 24, no. 2: 341–363. https://doi.org/10.1016/j.jhealeco.2004.09.007.

Schmitz, H. 2011. "Why Are the Unemployed in Worse Health? The Causal Effect of Unemployment on Health." *Labour Economics* 18, no. 1: 71–78. https://doi.org/10.1016/j.labeco.2010.08.005.

Statistics Norway. 2017. *Economic Survey 1*. Statistics Norway.

Stewart, J. M. 2001. "The Impact of Health Status on the Duration of Unemployment Spells and the Implications for Studies of the Impact of Unemployment on Health Status." *Journal of Health Economics* 20, no. 5: 781–796. https://doi.org/10.1016/s0167-6296(01)00087-x.

Appendix A

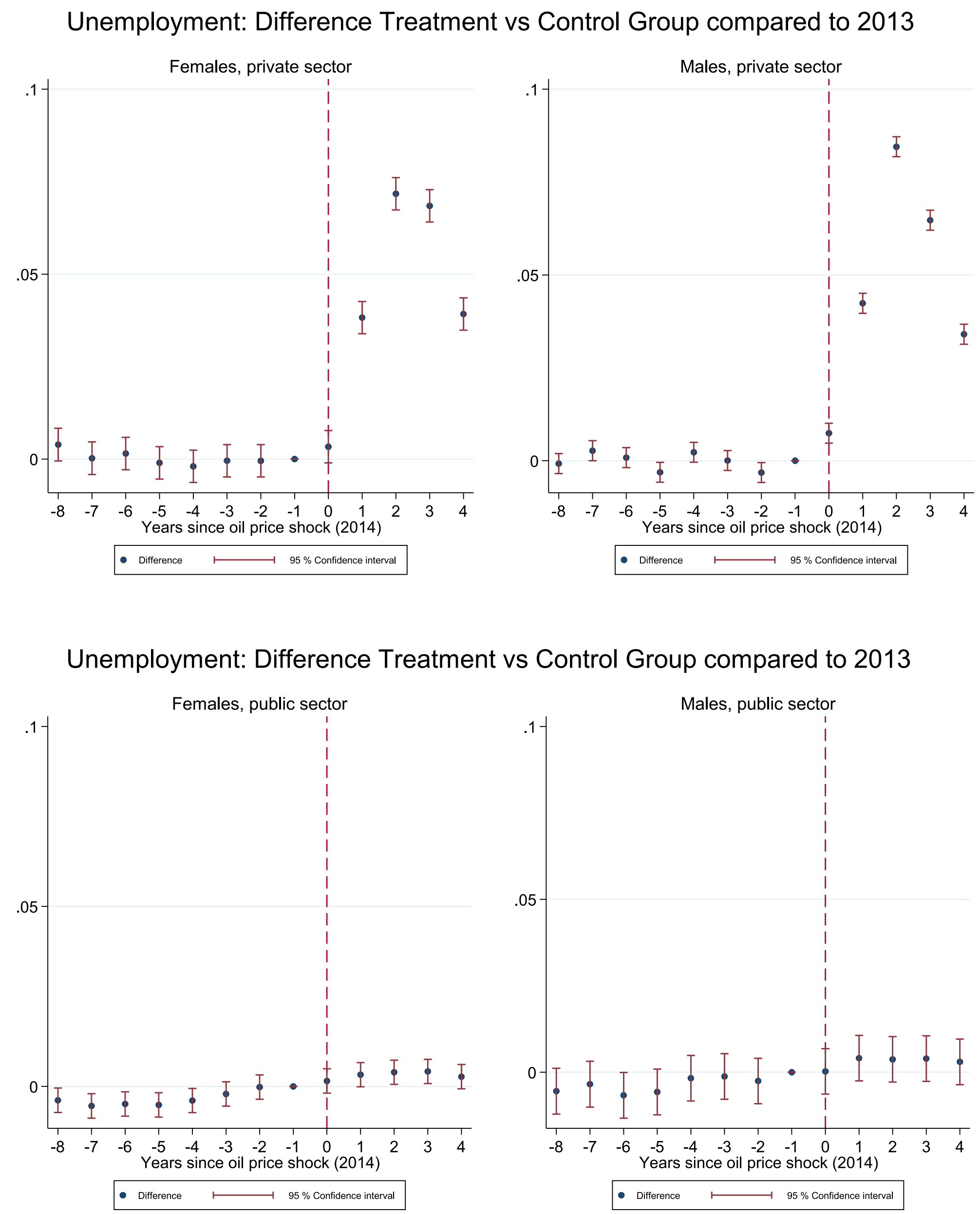

FIGURE A1 | Unemployment: Difference treatment versus control group compared to 2013, by gender and sector.

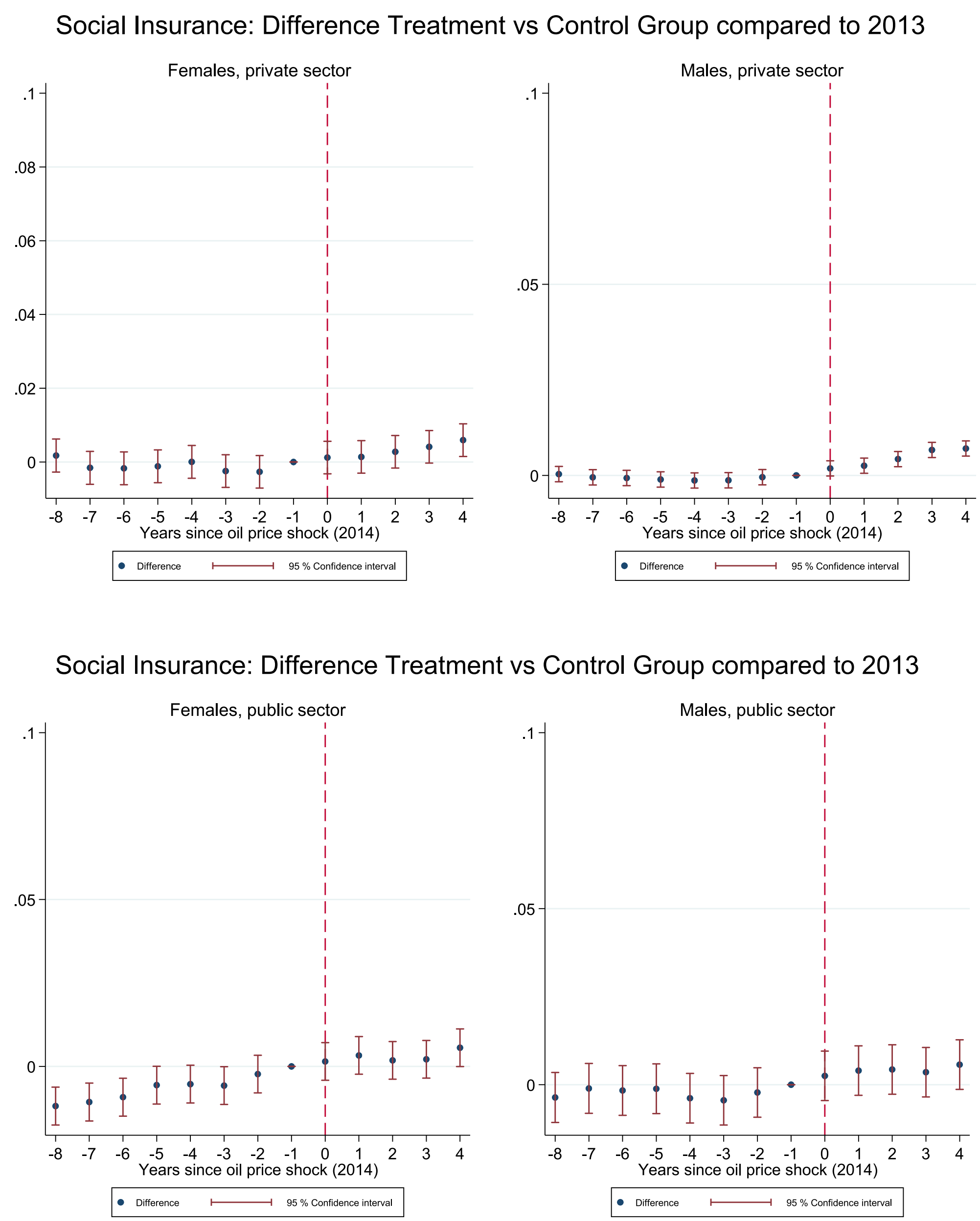

FIGURE A2 | Social insurance: Difference treatment versus control group compared to 2013, by gender and sector.

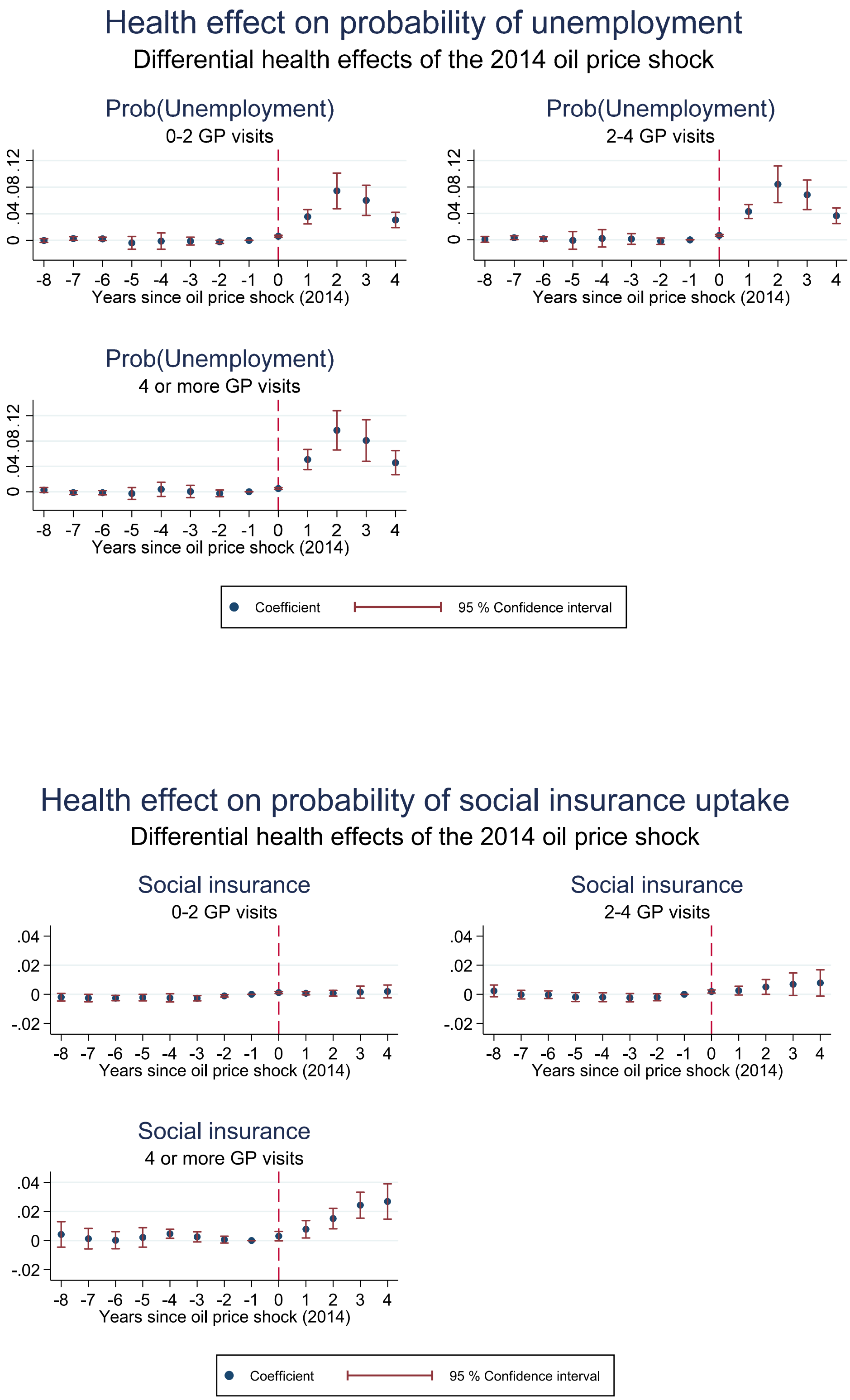

FIGURE A3 | Treatment effect on unemployment and social insurance, estimated by health groups.

TABLE A1 | Effects of the oil price shock on unemployment and social insurance uptake, estimated directly on subsamples of different pre-shock health status.[a]

	Probability of unemployment			Probability of social insurance uptake		
	0–2 GP visits	2–4 GP visits	4+ GP visits	0–2 GP visits	2–4 GP visits	4+ GP visits
Effect	0.0437*** (0.0086)	0.0494*** (0.0109)	0.0523*** (0.0122)	0.0032*** (0.0007)	0.0057*** (0.0016)	0.0134** (0.0050)
Mean y (pre)	0.0422	0.0521	0.0595	0.0153	0.0338	0.0724
Observations	3,619,695	2,637,220	1,117,124	3,619,695	2,637,220	1,117,124
Individuals	282,569	204,854	86,843	282,569	204,854	86,843

[a]Region fixed effects, standard errors are clustered at regions. 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%, and 0.1% level.

TABLE A2 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Sensitivity to excluding groups of workers.[a]

	Excluding individuals employed in the oil/gas and supply industry from the control group		Excluding individuals employed in the oil/gas and supply industry from the treatment and control group		Excluding individuals moving to/ from Rogaland after 2013	
	(1) Prob (unempl)	(2) Prob (soc insurance)	(3) Prob (unempl)	(4) Prob (soc insurance)	(5) Prob (unempl)	(6) Prob (soc insurance)
Base effect	0.0435*** (0.0086)	−0.0000 (0.0009)	0.0346*** (0.0083)	−0.0004 (0.0011)	0.0410*** (0.0086)	−0.0003 (0.0009)
Interaction, 2–4 visits	0.0067*** (0.0020)	0.0025 (0.0023)	0.0072*** (0.0018)	0.0039 (0.0026)	0.0074*** (0.0020)	0.0028 (0.0023)
Interaction, 4+ visits	0.0163*** (0.0035)	0.0305*** (0.0078)	0.0115*** (0.0026)	0.0366*** (0.0084)	0.0153*** (0.0034)	0.0309*** (0.0080)
2–4 GP visits	0.0067*** (0.0005)	0.0156*** (0.0015)	0.0067*** (0.0005)	0.0158*** (0.0016)	0.0068*** (0.0005)	0.0155*** (0.0015)
4 or more GP visits	0.0113*** (0.0006)	0.0613*** (0.0043)	0.0113*** (0.0007)	0.0619*** (0.0044)	0.0112*** (0.0006)	0.0612*** (0.0041)
Mean *y (pre)*	0.0483	0.0311	0.0492	0.0317	0.0483	0.0302
Observations	6,993,024	6,993,024	6,680,135	6,680,135	7,342,434	7,342,434
Labor market region	70	70	70	70	70	70
Individuals	545,885	545,885	520,142	520,142	571,721	571,721

[a]Region 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 regions.
*, **, ***: statistical significant at 5%, 1%, and 0.1% level.

TABLE A3 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Sensitivity to including more counties and public sector.[a]

	Including all counties[b]		Including public sector employees[c]	
	Prob (unemployment)	Prob (social insurance)	Prob (unemployment)	Prob (social insurance)
Base effect (Rogaland*Post)	0.0257*** (0.0047)	−0.0034*** (0.0012)	0.0329*** (0.0069)	0.0016 (0.0014)
Interaction, 2–4 GP visits	0.0033* (0.0015)	0.0060** (0.0020)	0.0031* (0.0015)	0.0016 (0.0023)
Interaction, 4 or more GP visits	0.0084** (0.0032)	0.0389*** (0.0055)	0.0064*** (0.0016)	0.0246*** (0.0062)
2–4 GP visits	0.0069*** (0.0005)	0.0152*** (0.0012)	0.0054*** (0.0005)	0.0152*** (0.0014)
4 or more GP visits	0.0112*** (0.0006)	0.0596*** (0.0033)	0.0079*** (0.0006)	0.0567*** (0.0034)
Mean *y (pre)*	0.0486	0.0311	0.0398	0.0341
Observations	9,267,873	9,267,873	12,488,818	12,488,818
Labor market regions	90	90	70	70
Individuals	721,378	721,378	970,942	970,942

[a]Region 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 regions.
[b]Private sector employees in the counties Hordaland, Møre og Romsdal and Vest/Sør Agder are included in the treatment group.
[c]Public sector employees included (In the treatment group if employed in Rogaland, in the control group if not).
*, **, ***: statistically significant at 5%, 1%, and 0.1% level.

TABLE A4 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Alternative specifications of GP visits.[a]

	Probability of unemployment	Probability of social insurance uptake	Probability of unemployment	Probability of social insurance uptake
Base effect (Rogaland*Post)	0.0433*** (0.0091)	0.0027* (0.0013)	0.0420*** (0.0089)	0.0014 (0.0025)
Interaction, GP visits above median	0.0137*** (0.0004)	0.0045 (0.0042)		
GP visits above median	0.0072*** (0.0019)	0.0363*** (0.0028)		
Interaction GP visits (continuous variable)			0.0024*** (0.0006)	0.0018 (0.0019)
GP visits (continuous variable)			0.0036*** (0.0001)	0.0162*** (0.0011)
Mean *y (pre)*	0.0483	0.0302	0.0483	0.0302
Observations	7,374,039	7,374,039	7,374,039	7,374,039
Labor market regions	70	70	70	70
Individuals	574,266	574,266	574,266	574,266

[a]Region 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 regions.
*, **, ***: statistically significant at 5%, 1%, and 0.1% level.

TABLE A5 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Number of GP visits measured over different periods.[a]

	Av. number of GP visits 2006–2013		Av. number of GP visits 2011–2013		Number of GP visits in 2013	
	Prob (unempl)[b]	Prob (social insurance)[b]	Prob (unempl)	Prob (social insurance)	Prob (unempl)	Prob (social insurance)
Base effect	0.0420*** (0.0087)	−0.0003 (0.0009)	0.0429*** (0.0089)	−0.0001 (0.0011)	0.0436*** (0.0090)	0.0001 (0.0006)
Interaction, 2–4 GP visits	0.0074*** (0.0020)	0.0026 (0.0023)	0.0010 (0.0010)	−0.0002 (0.0010)	0.0062** (0.0023)	0.0011 (0.0014)
Interaction, 4 or more GP visits	0.0162*** (0.0035)	0.0308*** (0.0078)	0.0098*** (0.0020)	0.0138*** (0.0045)	0.0088*** (0.0015)	0.0233*** (0.0056)
2–4 GP visits	0.0068*** (0.0005)	0.0154*** (0.0015)	0.0035*** (0.0005)	0.0061*** (0.0007)	0.0038*** (0.0004)	0.0107*** (0.0008)
4 or more GP visits	0.0113*** (0.0006)	0.0611*** (0.0041)	0.0104*** (0.0005)	0.0353*** (0.0026)	0.0081*** (0.0004)	0.0411*** (0.0026)
Mean (pre)	0.0483	0.0302	0.0483	0.0302	0.0483	0.0302
Observations	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039
Labor market regions	70	70	70	70	70	70
Individuals	574,266	574,266	574,266	574,266	574,266	574,266

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

TABLE A6 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Alternative post-shock periods.[a]

	Post-shock period: 2015–2018		Exluding observations in 2014	
	Prob (unemployment)	**Prob (social insurance)**	**Prob (unemployment)**	**Prob (social insurance)**
Base effect (Rogaland*Post)	0.0503*** (0.0101)	−0.0028*** (0.0006)	0.0510*** (0.0104)	−0.0022*** (0.0006)
Interaction, 2–4 GP visits	0.0095*** (0.0025)	0.0063** (0.0023)	0.0094*** (0.0025)	0.0056* (0.0024)
Interaction, 4 or more GP visits	0.0198*** (0.0043)	0.0417*** (0.0079)	0.0199*** (0.0043)	0.0411*** (0.0080)
2–4 GP visits	0.0068*** (0.0005)	0.0153*** (0.0014)	0.0068*** (0.0005)	0.0158*** (0.0015)
4 or more GP visits	0.0113*** (0.0006)	0.0610*** (0.0041)	0.0110*** (0.0006)	0.0613*** (0.0041)
Mean *y (pre)*	0.0483	0.0306	0.0483	0.0306
Observations	7,374,039	7,374,039	6,799,773	6,799,773
Labor market regions	70	70	70	70
Individuals	574,266	574,266	574,266	574,266

[a]Region 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 regions.
*, **, ***: statistical significant at 5%, 1%, and 0.1% level.

TABLE A7 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status. Different model specifications.[a]

	Probability of unemployment				Probability of social insurance uptake			
	OLS	**OLS**	**FE[b]**	**FE**	**OLS**	**OLS**	**FE[b]**	**FE**
Base effect	0.0273*** (0.0060)	0.0291*** (0.0069)	0.0420*** (0.0087)	0.0430*** (0.0085)	−0.0057* (0.0027)	−0.0042*** (0.0013)	−0.0003 (0.0009)	−0.0043*** (0.0008)
Interaction, 2–4 GP visits	0.0070*** (0.0022)	0.0071*** (0.0020)	0.0074*** (0.0020)	0.0056* (0.0024)	0.0022 (0.0019)	0.0022 (0.0022)	0.0026 (0.0023)	0.0073*** (0.0010)
Interaction, 4+ GP visits	0.0158*** (0.0035)	0.0164*** (0.0034)	0.0162*** (0.0035)	0.0121*** (0.0036)	0.0301*** (0.0071)	0.0302*** (0.0077)	0.0308*** (0.0078)	0.0479*** (0.0041)
2–4 GP visits	0.0096*** (0.0005)	0.0070*** (0.0005)	0.0068*** (0.0005)	—	0.0204*** (0.0015)	0.0157*** (0.0014)	0.0154*** (0.0015)	—
4 or more GP visits	0.0182*** (0.0008)	0.0107*** (0.0007)	0.0113*** (0.0006)	—	0.0705*** (0.0041)	0.0605*** (0.0039)	0.0611*** (0.0041)	—
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables[a]	No	Yes	Yes	No	No	Yes	Yes	No
LM region fixed effects	No	No	Yes	No	No	No	Yes	No
Individual fixed effects	No	No	No	Yes	No	No	No	Yes
Observations	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039	7,374,039

[a]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.
[b]Same regression model as reported in Table 4.
*, **, ***: statistical significant at 5%, 1%, and 0.1% level.

TABLE A8 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status, gender (column (1)–(4)), and age (column (5)–(10)).[a]

	Females		Males		Age < 40		Age 40–49		Age > 49	
	(1) Prob. unempl.	(2) Prob. social insurance	(3) Prob. unempl.	(4) Prob. social insurance	(5) Prob. unempl.	(6) Prob. social insurance	(7) Prob. unempl.	(8) Prob. social insurance	(9) Prob. unempl.	(10) Prob. social insurance
Base effect (Rogaland*Post)	0.0366*** (0.0079)	−0.0037* (0.0019)	0.0444*** (0.0088)	0.0007 (0.0005)	0.0451*** (0.0091)	0.0026 (0.0033)	0.0422*** (0.0086)	0.0040* (0.0015)	0.0396*** (0.0093)	−0.0073*** (0.0019)
Interaction, 2–4 GP visits	0.0073*** (0.0015)	0.0056* (0.0026)	0.0075* (0.0033)	0.0020 (0.0019)	0.0081* (0.0035)	−0.0008 (0.0029)	0.0076*** (0.0022)	−0.0007 (0.0019)	0.0055*** (0.0011)	0.0093*** (0.0025)
Interaction, 4+ GP visits	0.0194*** (0.0050)	0.0253*** (0.0077)	0.0132*** (0.0032)	0.0375*** (0.0075)	0.0236*** (0.0036)	0.0170* (0.0083)	0.0160*** (0.0029)	0.0234*** (0.0065)	0.0065 (0.0045)	0.0548*** (0.0083)
2–4 GP visits	0.0057*** (0.0008)	0.0194*** (0.0020)	0.0071*** (0.0004)	0.0146*** (0.0014)	0.0098*** (0.0007)	0.0144*** (0.0016)	0.0072*** (0.0006)	0.0165*** (0.0015)	0.0032*** (0.0006)	0.0148*** (0.0013)
4+ GP visits	0.0099*** (0.0009)	0.0676*** (0.0061)	0.0120*** (0.0007)	0.0577*** (0.0030)	0.0184*** (0.0008)	0.0520*** (0.0045)	0.0120*** (0.0010)	0.0635*** (0.0039)	0.0041*** (0.0009)	0.0637*** (0.0037)
Mean *y (pre)*	0.0495	0.0484	0.0477	0.0229	0.0628	0.0324	0.0457	0330	0.0372	0259
Observations	2,232,945	2,232,945	5,141,094	5,141,094	2,326,048	2,326,048	2,756,141	2,756,141	2,291,850	2,291,850
Individuals	174,169	174,169	400,097	400,097	183,180	183,180	213,800	213,800	177,286	177,286

[a]Region 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 region.
*, **, ***: statistical significant at 5%, 1%, and 0.1% level.

TABLE A9 | Effect of the oil price shock on unemployment and social insurance uptake, by pre-shock health status, education (column (1)–(6)), and blue/white collar jobs (column (7)–(10)).[a]

	Low education		Medium education		High education		Blue collar workers		White collar workers	
	(1) Prob. unempl.	(2) Prob. social insurance	(3) Prob. unempl.	(4) Prob. social insurance	(5) Prob. unempl.	(6) Prob. social insurance	(7) Prob. unempl.	(8) Prob. social insurance	(9) Prob. unempl.	(10) Prob. social insurance
Base effect (Rogal. *Post)	0.0456*** (0.0098)	−0.0043*** (0.0011)	0.0439*** (0.0102)	−0.0002 (0.0008)	0.0362*** (0.0052)	0.0017 (0.0021)	0.0406*** (0.0098)	0.0016 (0.0008)	0.0420*** (0.0064)	−0.0012 (0.0016)
Interaction, 2–4 GP visits	0.0067 (0.0038)	0.0083* (0.0040)	0.0081*** (0.0022)	0.0029 (0.0017)	0.0071*** (0.0011)	−0.0015 (0.0018)	0.0060*** (0.0018)	0.0030* (0.0012)	0.0090*** (0.0020)	0.0024 (0.0020)
Interaction, 4+ GP visits	0.0128** (0.0040)	0.0454*** (0.0106)	0.0150*** (0.0028)	0.0364*** (0.0046)	0.0230*** (0.0048)	0.0089 (0.0058)	0.0088*** (0.0026)	0.0380*** (0.0067)	0.0237*** (0.0034)	0.0253*** (0.0060)
2–4 GP visits	0.0080*** (0.0015)	0.0248*** (0.0019)	0.0068*** (0.0005)	0.0169*** (0.0010)	0.0061*** (0.0004)	0.0103*** (0.0012)	0.0072*** (0.0008)	0.0217*** (0.0009)	0.0064*** (0.0005)	0.0117*** (0.0014)
4+ GP visits	0.0090*** (0.0016)	0.0799*** (0.0040)	0.0125*** (0.0007)	0.0640*** (0.0029)	0.0120*** (0.0007)	0.0441*** (0.0043)	0.0100*** (0.0011)	0.0730*** (0.0023)	0.0128*** (0.0005)	0.0519*** (0.0043)
Mean *y (pre)*	0.0834	0.0514	0.0489	0.0307	0.0292	0195	0.0698	0.0406	0.0343	0.0240
Observations	1,292,063	1,292,063	3,629,713	3,629,713	2,452,263	2,452,263	2,919,522	2,919,522	4,454,517	4,454,517
Individuals	101,375	101,375	280,950	280,950	191,941	191,941	227,560	227,560	346,706	346,706

[a]Region 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 regions.
*, **, ***: statistical significant at 5%, 1%, and 0.1% level.