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Labor Market Impacts of the Green Transition: Evidence from a Contraction in the Oil Industry*

Cloé Garnache[†] Elisabeth T. Isaksen[‡] Maria Nareklshvili[§]

Abstract

The transition to a low-carbon economy requires a contraction of fossil fuel sectors, raising questions about the labor market costs of reallocation. We study the 2014 oil price shock as a natural experiment to examine the contraction of Norway's oil industry. Using matched employer–employee data, we estimate long-run effects on earnings and employment using two complementary approaches. A difference-in-differences design shows moderate losses for all oil workers, while an event study reveals substantially larger and more persistent losses among displaced workers—up to 10% in earnings and 5% in employment nine years after displacement, especially for those with lower educational attainment. Although few displaced workers transition into green jobs, they are equally likely to enter green and brown (non-oil) sectors when accounting for the size of each destination sector. Earnings losses are larger for those entering green jobs rather than brown (non-oil) jobs, but smaller than for those entering other sectors. Decomposition results indicate that differences in establishment wage premiums—rather than skill mismatch—explain most of the observed gaps.

Key words: green transition, oil industry, job displacement, distributional effects, establishment wage premium, skills mismatch

JEL codes: Q32, Q52, J24, J63

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1 Introduction

Meeting the mitigation targets set out in the Paris Agreement will require a major shift away from fossil fuels and toward cleaner sources of energy ([European Commission, 2023](#)). This transition is expected to reduce activity in fossil fuel extraction, processing, and distribution, while creating new opportunities in green sectors such as renewable energy, energy efficiency, and environmental services. However, such structural change raises important labor market challenges. In particular, it is unclear whether jobs lost in carbon-intensive industries—many of which employ lower-skilled workers—will be replaced by comparable positions in the green economy. Differences in skill requirements and job characteristics between sectors may hinder the smooth reallocation of workers, creating risks of displacement, wage losses, and long-term unemployment.

A central concern is how workers in fossil fuel industries will fare during this transition. What are the long-run employment and earnings consequences for workers affected by a sectoral contraction? And to what extent do displaced fossil fuel workers move into green jobs—and does such reallocation mitigate their losses? While a large literature has examined the labor market impacts of mass layoffs, technological change, and globalization (e.g., [Autor et al., 2014](#); [Hummels et al., 2014](#); [Graetz and Michaels, 2017](#); [Schmieder et al., 2023](#)), these disruptions differ from the decline of the fossil fuel sector. Workers in the fossil fuel sector often possess highly specialized skills, are geographically concentrated, and face limited mobility within a shrinking sector. At the same time, it remains uncertain whether emerging green sectors can absorb displaced fossil fuel workers at scale, and whether such transitions preserve pre-displacement earnings. While recent studies suggest some overlap in skill requirements between green and brown occupations and jobs (e.g., [Vona et al., 2018](#); [Marin and Vona, 2019](#); [Saussay et al., 2022](#); [Curtis and Marinescu, 2023](#)), evidence on realized transitions and their consequences remains limited.

To address these questions, we study the effect of the 2014 oil price shock, which triggered a 21% decline in employment in Norway’s oil industry between 2013 and 2017. The sharp and unexpected fall in oil prices—driven by global oversupply and slowing demand in major oil-importing economies—was plausibly exogenous to the Norwegian context and thus provides a natural experiment to examine the labor market effects of a sudden contraction in fossil fuel profitability ([Global Economic Prospects, 2018](#)). We implement two complementary empirical strategies. First, we estimate a difference-in-differences (DiD) model to assess the overall impact of the oil sector contraction, comparing workers in oil-exposed establishments to a matched control group in non-oil establishments. Second, we use an event-study design centered around the year of displacement to trace the dynamic impacts on earnings, employment, and wages for displaced oil workers relative to comparable controls. These analyses leverage rich Norwegian administrative register data covering the full working-age population from 2009 to 2023. The matched employer–employee

records track individuals’ wages, annual labor earnings, occupations, and employers over time, along with detailed demographic and firm-level characteristics.¹ This dataset enables us to examine both long-run labor market outcomes and the reallocation patterns of displaced oil workers across sectors and occupations.

The results show that the contraction of the oil sector had persistent and unequal effects. Workers employed in oil-related jobs in 2013 experienced a sustained decline in annual labor earnings (-5.6%) and employment (-3.2%) over the subsequent decade. These losses are largely driven by sectoral reallocation and early retirement and are concentrated among senior, highly educated, and male workers. Among those displaced from their 2013 oil job, earnings and employment losses are substantially larger and more persistent: nine years after displacement, annual earnings and employment remain 10.1% and 5.2% lower, respectively, compared to the control group. Notably, while older, more educated workers were most affected among the broader oil workforce, the largest earnings losses among displaced workers are concentrated among those with lower educational attainment.

Furthermore, we find that, once accounting for the relative size of destination sectors, displaced oil workers are equally likely to transition into green jobs as into brown (non-oil) jobs. However, transitions into green sectors are associated with larger earnings losses than transitions into brown sectors, though smaller than losses for workers entering other sectors. This pattern suggests that, from the perspective of minimizing earnings losses, the green sector serves as a second-best destination for displaced oil workers—less costly than exiting into the residual “other” sector, but not as favorable as reallocation into non-oil, high-emission industries.

To understand the sources of these earnings differences, we decompose post-displacement earnings gaps among workers transitioning into brown, green, and other sectors. The analysis reveals that lower establishment wage premiums account for most of the observed earnings gaps, while occupational skill distance plays a relatively minor role. Establishment wage premiums are highest in the oil and brown sectors, which also have the smallest skill distances—indicating that skills are more easily transferable between these sectors. In contrast, while skill distance between oil and green jobs is modest, wage premiums in the green sector are lower, contributing to greater earnings losses for those who make that transition. Nonetheless, both wage premiums and skill distance are more favorable in green sectors than in the residual “other” sector, which helps explain why displaced oil workers are more likely to reallocate into green jobs than into unrelated occupations, conditional on sector size.

¹Labor earnings include wages, business income, parental allowance, sick pay, and unemployment benefits. The data also include information on age, education, residence, wealth, and social transfers, as well as establishment- and firm-level characteristics such as 5-digit industry codes, trade activity, CO₂ emissions, participation in the EU Emissions Trading System, R&D expenditures, and patenting. These sources are linked to occupation-level measures of job tasks and skills, allowing us to classify all jobs into four mutually exclusive sectors: oil-related, brown (non-oil), green, and other.

These findings have important implications for climate and labor market policy. Reallocation alone may not be sufficient to preserve earnings after fossil sector displacement. While transitions into other high-emission sectors involve smaller losses, green jobs emerge as a second-best alternative. Expanding access to higher-paying green-sector jobs and improving skill alignment could help offset earnings losses and ease the costs of transition.

Our study complements a rich literature documenting worker displacements and worker-level transitional costs using linked employer-employee data, e.g., from globalization and trade shocks (e.g., [Autor et al., 2014](#); [Balsvik et al., 2015](#)), technology-induced layoffs ([Graetz and Michaels, 2017](#)), offshoring ([Hummels et al., 2014](#)), mass layoffs (e.g., [Huttunen et al., 2018](#); [Salvanes et al., 2021](#); [Bertheau et al., 2023](#)), and environmental regulation ([Walker, 2013](#)). Our analysis focuses on the fossil fuel sector, where displacement may differ in magnitude and persistence due to sector-specific rents and skill profiles. Our findings suggest that displaced oil workers experience somewhat higher labor earnings declines than workers in the broader economy or workers in other Northern European countries ([Bertheau et al., 2023](#)). The study closest to ours is [Ellingsen et al. \(2022\)](#) who examine in a concomitant paper the effect of mass layoffs in the Norwegian oil sector on the labor earnings of displaced oil workers. We contribute to this literature by investigating the destination sectors to which displaced oil workers transition into and examining the factors explaining the earnings gap, including the skills necessary for the green transition. As such, our study characterizes the distributional effects and potential skill biases related to the green transition.

Second, this study contributes to the literature on the effect of the fossil fuel sector decline on labor outcomes using linked employer-employee data.² Focusing on the closure of coal mines in the UK in the 80s and early 90s, [Rud et al. \(2024\)](#) find that coal miners incur significantly higher displacement costs than other manufacturing workers. Two recent OECD studies examine the effects of mass layoffs on displaced workers in high-emission industries in Germany and in a pool of 14 countries ([Barreto et al., 2023, 2024](#)). Unlike these studies, we exploit a plausibly exogenous shock to investigate the effect of the green transition and the fossil fuel sector contraction on worker transitional costs. We find that displaced oil workers face smaller earnings losses than those documented for displaced workers in other carbon-intensive sectors such as coal mining in the UK ([Rud et al., 2024](#)) or heavy industry in Germany ([Barreto et al., 2023](#)).³

²Related studies that do not exploit employer-employee data include [Haywood et al. \(2024\)](#) who, using a structural approach in the context of the phasing out of coal in Germany, find that older workers face the largest earnings losses due to high seniority and wages. Using county-level employment and wages, [Du and Karolyi \(2023\)](#) find that employment and wages decline in coal-producing counties compared to non-coal-producing counties. Our study also broadly relates to the literature on the employment effects of environmental policies (e.g., [Greenstone, 2002](#); [Lehr et al., 2012](#); [Curtis, 2018](#); [Yip, 2018](#); [Känzig, 2023](#)). These studies largely use data at the firm level, with little attention to worker-level transitional costs or skill composition.

³[Barreto et al. \(2024\)](#) find an average earnings loss of around 36% over the six years following displacement when averaged across countries, which is substantially higher than our findings. They also compare

Finally, this paper contributes to the emerging literature on green skills and green jobs, which often uses occupational definitions or job advertisement data to describe skill content and wage differentials (e.g., [Vona et al., 2018](#); [Saussay et al., 2022](#); [Curtis et al., 2024](#); [Bluedorn et al., 2023](#)).⁴ Unlike these studies, we observe realized transitions from fossil fuel to green jobs and estimate the associated earnings impacts at the worker level. Our results show that few displaced oil workers move into green sectors, but those who do experience smaller earnings losses than workers entering other, non-brown sectors. However, we also find that these differences are driven primarily by firm wage premiums rather than differences in skill requirements—highlighting a key challenge for policies relying solely on reskilling.

The remainder of the paper is organized as follows. Section 2 provides background on Norway’s oil sector and the 2014 oil price shock. Section 3 describes the data. Section 4 outlines the empirical strategy. Section 5 presents the results. Section 6 concludes.

2 Background on the Norwegian oil sector and the price shock

Norway discovered oil in 1969. Crude oil accounted for 31% of exports and 19% of GDP in 2013 ([Statistics Norway, 2025b,a](#)). We define the “oil sector” as the oil and gas extraction industries and the service and manufacturing industries that are closely linked to the extraction sector through deliveries (see Section 3.2). A little over 60,000 workers were employed in the extraction of crude oil and gas and closely related services, such as drilling, in 2013. Additionally, over 86,000 workers were employed in petroleum-oriented manufacturing such as the building of platforms and modules, reparation of machinery, and installation work on platforms and modules (Figure A.1). These service and manufacturing industries are highly dependent on the activity in the extraction sector.⁵ Figure B.1 depicts the 5-digit industry codes that are related to the oil sector in Norway. While oil sector-related jobs are concentrated on the West Coast of Norway, there are still 20 (out of 159) local labor markets where over 15% of the workforce is employed in the oil sector. Furthermore, the majority of local labor markets in Norway have at least 4% of their workforce employed in the oil sector (Figure B.2).

Between June 2014 and December 2014, the oil price dropped by 57% (Figure 1, panel

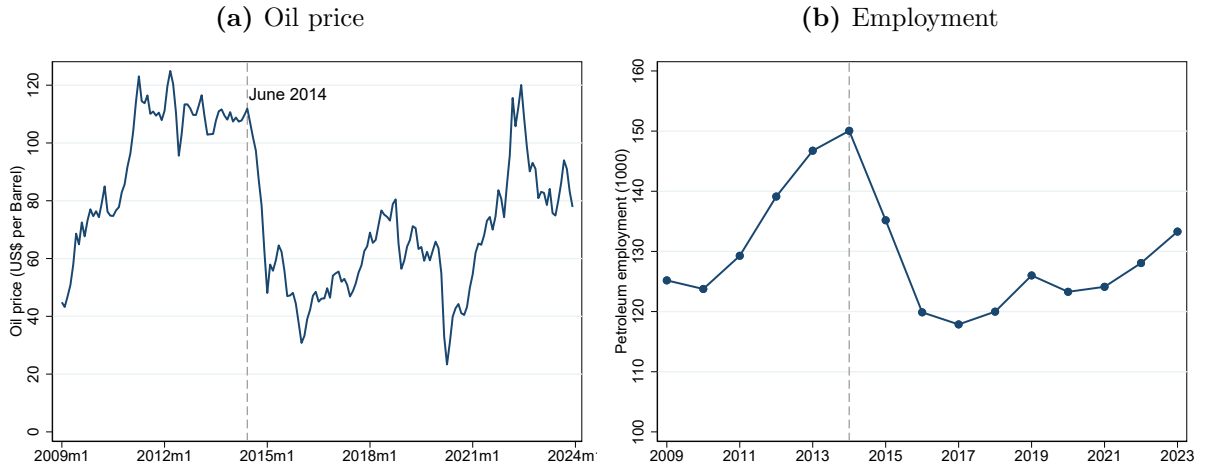
effects to similar job losses in low-carbon sectors and find that workers displaced from high-emission sectors face particularly large earnings losses in all countries.

⁴Closer to our study is [Bluedorn et al. \(2023\)](#), who use labor force survey data for a large cross-country sample to examine the potential consequences of the green economic transformation, albeit without an exogenous shock.

⁵Using a broader definition of the oil sector that includes all workers directly or indirectly related to the oil sector through supply and demand links, [IRIS \(2015\)](#) report that more than 200,000 people were employed in the oil sector in 2013.

(a)). The oil price continued to decline with a 70% drop in the oil price between June 2014 and January 2016. The collapse in the world oil price was largely due to forces external to the Norwegian economy. The widely-accepted drivers of the oil price drop were a lower than expected demand in China and the shale gas development in the US ([Global Economic Prospects, 2018](#)). The drop in oil prices led to a 21% reduction in oil sector employment in Norway between 2014 and 2017, with employment still 11% below its 2014 peak as of 2023 (Figure 1, panel (b)). Furthermore, the production from petroleum-oriented manufacturing declined sharply in Norway (Figure A.2). Production volumes in the extraction industry show a slight downward trend between 2009 and 2012, with no detectable changes around 2014. However, investment costs in the extraction industry rose sharply between 2010 and 2014, then fell steeply from 2014 to 2017 (Figure A.3). They remained well below their 2014 levels in 2023.

Figure 1: Oil price and employment in the Norwegian oil sector (2009-2023)



Notes: Panel (a) shows the monthly price of crude oil (Brent) in US Dollars per barrel ([IndexMundi, 2022](#)). Panel (b) shows aggregate employment (in thousands) in the fourth quarter each year from 2009 to 2023 in 5-digit industries defined as oil-related ([Statistics Norway, 2022](#)). See Figure B.1 for a list of oil-related industries and Figure A.1 for oil employment by two sub-sectors. Employment includes all workers aged 15–74 years in a given year.

3 Data and sample definitions

3.1 Data

We use rich population-wide administrative datasets on Norwegian residents between 2009 and 2023. The primary data source is the Norwegian State Register of Employers and Employees, which provides complete information on all workers and establishments. This register contains detailed job spell-level data, including earnings, occupation, contracted weekly hours, and start and end dates. We focus on job spells active in November of each year and identify an individual’s main employer as the job spell with the highest total

earnings in that year. Hourly wage, constructed from reported earnings and contracted hours, serve as our primary outcome measure.⁶

The analysis combines job spell data with tax records using unique individual identifiers, adding detailed information on income, government transfers, and wealth. The second outcome, annual labor earnings, is based on [Salvanes et al. \(2024\)](#) and includes pre-tax income from labor and self-employment, as well as taxable transfers such as parental leave, sick pay, and unemployment benefits. The third outcome measures employment status, distinguishing between employed, unemployed, and not in the labor force.⁷ Individuals without a registered employer and who receive unemployment benefits during the year are defined as unemployed. Individuals without an employer, and those who are not registered with unemployment benefits during the year, are defined as not in the labor force. In some of our analyses, we also use information on the (contracted) hours worked per week, gross and net income, and wealth. Throughout, we deflate monetary values to 2018 prices, and winsorize monetary values and hours worked at the 1st and 99th percentiles separately by year.

The core dataset on earnings and employment is enriched with individual-level demographic information from the Central Population Register and educational attainment from the National Education Register. Each individual is assigned to a county and local labor market based on their place of residence,⁸ rather than workplace location, to account for offshore oil establishments. Establishment-level data from the Central Register of Establishments and Enterprises provide information on industry codes (SN2007), sector affiliation (e.g., public, private), and firm identifiers. Additional firm-, industry-, and occupation-level data support the classification of non-oil jobs into green, brown, or other sectors, as described in Section 3.3.

3.2 Constructing a sample of oil workers and a control group

We start by restricting the population to workers registered with an employer in 2013 – the year prior to the oil price shock – who worked at least 30 hours per week, did not have ongoing education that year, and were employed in a private sector job.⁹ The sample includes individuals aged 24–61 in 2013 (20–57 in 2009) and follows them throughout the study period.¹⁰ To maintain a balanced panel, the sample is further restricted to individuals residing in Norway from 2009 to 2023 with non-missing tax records.

⁶Because the hourly wage is calculated based on the contracted number of hours per week rather than actual hours worked, this measure does not necessarily reflect the effective hourly wage.

⁷An individual is classified as employed in a given year if registered with an establishment identification number.

⁸Local labor markets follow the definition in [Gundersen et al. \(2019\)](#), which groups Norwegian municipalities into 159 housing and labor market regions based on commuting patterns.

⁹Private sector jobs made up around 99% of oil jobs in 2013.

¹⁰Since retirement decisions may serve as an important adjustment margin, workers older than the minimum pension age of 62 are retained in the sample.

The treatment group consists of workers employed in the oil sector in 2013, the year prior to the oil price shock. Classification of petroleum jobs relies on the 5-digit industry codes of establishments (see Figure B.1). We use a broad definition of the oil sector from Statistics Norway, which consists of both oil extraction and exploration industries, as well as industries that supply goods and services to the oil sector. Identifying an appropriate control group requires selecting workers in industries largely unaffected by the oil price shock. While input-output tables could, in principle, be used to identify industries with minimal links to the oil sector, these tables are highly aggregated, leaving few industries truly isolated from oil-related demand. Instead, we use detailed industry-level data from a published report (IRIS, 2015). The report provides detailed information on oil sector deliveries in 2014 using administrative data, interviews, and surveys. Based on this report, our control group includes workers employed in 5-digit industries where less than 1% of employment is linked to oil sector deliveries (see Figure B.3).

The two first columns in Table 1 show summary statistics for the years 2009-2013 for oil workers and the control group, respectively. As seen from the table, these two groups of workers differ substantially in both demographics, education, and earnings. For example, the workforce in the oil sector is more male and has a higher salary than in the rest of the economy. In the unmatched sample, only 18% of oil workers are female, compared to 36% in the control group. Oil workers also earn significantly more: average annual labor earnings are 786,000 NOK for oil workers versus 556,000 NOK for the control group. Figure 2, panel (a), shows that the earnings distribution for oil workers is shifted to the right compared to the control group. Some of these differences are not uncommon. For instance, Barreto et al. (2024) find that workers in high-emission industries are typically older, have low educational attainment, and are predominantly male compared with workers in low-emission industries, while for the particular case of Germany, Barreto et al. (2023) observe that employees within high-emission industries typically receive wages approximately 19% higher than their counterparts in low-emission sectors. These workers also tend to be older, with an average age difference of two years, and possess longer job tenure by about 1.5 years. Furthermore, there is a notable under-representation of university graduates in high-emission industries, where the workforce predominantly engages in routine manual tasks, as opposed to non-routine activities. In our sample, however, we see that a higher share of oil workers have long university education (more than three years) – 14% compared to 7% in the control group – while fewer have less than a high school education (17% vs. 28%).

While including worker fixed effects in our empirical strategy (Section 4) will control for any time-invariant differences across oil workers and non-oil workers, the two groups of workers are likely to have different expected earnings profiles over time – even in the absence of the oil price shock. As a consequence, a naive comparison of individuals working in the oil sector in 2013 to workers in non-oil industries in 2013 may lead to

Table 1: Summary statistics for all samples

	Unmatched sample		Matched sample			
	DiD		DiD		Event	
	Oil (1)	Control (2)	Oil (3)	Control (4)	Oil (5)	Control (6)
Female	0.18 (0.38)	0.36 (0.48)	0.19 (0.39)	0.19 (0.39)	0.18 (0.39)	0.18 (0.39)
Age	40.92 (10.09)	40.43 (10.31)	41.35 (10.08)	41.43 (10.04)	39.21 (8.24)	39.23 (8.36)
Less than high school	0.17 (0.37)	0.28 (0.45)	0.21 (0.41)	0.21 (0.41)	0.16 (0.37)	0.16 (0.37)
High school	0.47 (0.50)	0.44 (0.50)	0.44 (0.50)	0.44 (0.50)	0.50 (0.50)	0.50 (0.50)
University (1-3 years)	0.21 (0.41)	0.21 (0.41)	0.22 (0.41)	0.22 (0.41)	0.22 (0.41)	0.22 (0.42)
University (>3 years)	0.14 (0.35)	0.07 (0.25)	0.12 (0.33)	0.12 (0.33)	0.12 (0.32)	0.12 (0.32)
Employed	0.95 (0.22)	0.93 (0.26)	0.96 (0.18)	0.96 (0.18)	0.99 (0.10)	0.99 (0.10)
Labor earnings (1000 NOK)	786 (386)	556 (281)	706 (325)	697 (335)	746 (328)	729 (342)
Log labor earnings	6.53 (0.61)	6.19 (0.60)	6.45 (0.55)	6.43 (0.54)	6.52 (0.45)	6.49 (0.46)
Log of hourly wage	5.60 (0.49)	5.29 (0.44)	5.49 (0.45)	5.48 (0.44)	5.53 (0.44)	5.51 (0.43)
Log gross income	6.58 (0.54)	6.26 (0.51)	6.49 (0.49)	6.49 (0.51)	6.55 (0.44)	6.54 (0.48)
Log net income	6.23 (0.47)	5.97 (0.44)	6.16 (0.42)	6.15 (0.45)	6.22 (0.38)	6.21 (0.42)
Hours per week	36.46 (3.44)	36.23 (4.44)	36.77 (3.26)	36.75 (3.44)	36.83 (2.75)	36.80 (3.17)
N (individual-year)	543,435	2,894,100	351,945	351,945	113,831	113,831
N (individuals)	108,687	578,820	70,389	70,389	20,406	20,406

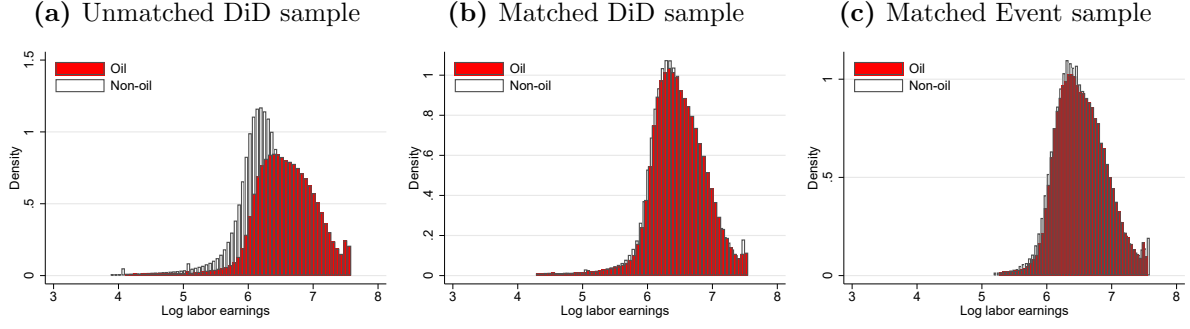
Notes: The table shows summary statistics for treated and control workers across three different samples. Summary statistics are based on the years 2009-2013 for the DiD samples (columns 1-4), and from t-2 to t-9 relative to layoff in the event study sample (columns 5-6). Standard deviations are shown in parentheses. All monetary values are expressed in 2018 prices. The displaced worker sample is restricted to oil workers who separated from their 2013 oil employer between 2014 and 2018. The sample is further restricted to long-tenured workers, defined as those with at least three years of tenure at their 2013 employer.

biased estimates of the oil price fall on workers' job market outcomes.

3.2.1 Matched treated and control workers

To improve the comparability of the control and treatment groups, we match the 2013 oil workers to a subset of more similar control workers following standard practice in the job displacement literature (e.g., [Bertheau et al., 2023](#); [Schmieder et al., 2023](#)). We begin

Figure 2: Histogram of log labor earnings



Notes: The figure shows histograms of log labor earnings across three different samples. Histograms are based on the years 2009-2013 for the DiD samples (panels a and b), and from t-2 to t-9 relative to layoff in the event study sample (panel c). All monetary values are expressed in 2018 prices. Labor earnings are winsorized at the 1st and 99th percentiles separately by year. Histograms display values in the 1-99 percentile for each of the two groups.

by exactly matching workers based on gender, county of residence, 1-digit education, and employment and unemployment status from 2009 to 2013. Within each cell, we estimate a propensity score model for the likelihood of being employed in the oil sector in 2013.¹¹ The model includes log labor earnings, log hourly wages, and age – all measured in 2013. We then apply a 1:1 nearest neighbor matching algorithm without replacement to assign one control worker to each treated worker.

Columns 3 and 4 in Table 1 show summary statistics for the trimmed sample of oil and non-oil workers, respectively. As we require an oil worker to be paired with a control worker that is an exact match on certain criteria (i.e., gender, county, education, employment status), some oil workers drop out of the sample as no suitable control workers exist. Compared to the unmatched sample, the number of oil workers in the matched sample is reduced from 108,687 to 70,389. The matched oil and non-oil workers are similar in terms of demographics, education, and earnings. Figure 2, panel (b), shows that the earnings distributions are comparable across oil workers and non-oil workers.

Columns 5 and 6 in Table 1 show summary statistics for a subset of displaced oil workers, measured from nine to two years prior to layoff, and their matched control group. These samples are described in more detail in Section 4.2.

3.3 Defining green and brown jobs

In this paper, we want to examine to what extent oil workers transition into green and brown (non-oil) jobs, and how the development in oil workers' labor earnings differs across these post-displacement sectors. To do so, we augment the administrative datasets with detailed data at the firm, industry, and occupational level to classify a job as green, brown,

¹¹We estimate the propensity score via probit using the Stata 18 command `psmatch2`, with a 0.01 caliper.

or other.¹²

Green jobs: We define a job as green based on four key data sources. First, we define an establishment as green if the establishment operates in a set of 5-digit industries related to renewable electricity generation and waste management (see Table B.1 for the complete list). Second, we combine export data at the firm-product level from administrative registers with a list of 6-digit commodities defined as environmental goods by the International Monetary Fund (IMF, 2021).¹³ We define a firm as green if the firm’s average export share of environmental goods in 2009-2023 is 50 percent or more (Figure B.4). Third, we combine data on firm-level patent applications from the Norwegian Industrial Property Office with information on the Y02 classification of each patent from the European Patent Office (EPO). The Y02 tag is used to classify patents that are relevant to climate change mitigation or adaptation (European Patent Office, 2024). We classify a firm as green if the share of Y02-patents in 2009–2021 is 50 percent or more (Figure B.5).¹⁴ Lastly, a different way of defining a job as green is via the skills required to perform specific tasks within an occupation. We use a taxonomy of green skills from the European Classification of Occupations, Skills and Competences (ESCO), which was published in 2022 (European Commission, 2022).¹⁵ The classification system identifies a set of skills and knowledge concepts that are considered to be particularly relevant for a greener labor market (570 out of 13,890). The green skill share of an occupation ranges from 0 to 60 percent, where two-thirds of occupations require at least some green skills (Figure B.6). We define a 4-digit occupation as green when the green skill share is in the 95th percentile, which implies a green skill share of around 24 percent or more (Figure B.7).¹⁶ We define a job as green when at least one of these four criteria is met, and when the job is not defined as an oil job.¹⁷ We refer to the group of green jobs as the “green sector.”

Brown (non-oil) jobs: A job falls into the brown (non-oil) category based on two criteria. First, we classify 5-digit industries as brown if at least one establishment reports

¹²See also Godøy and Isaksen (2025) for a similar classification of green and brown jobs, and for more detailed descriptions of the data sources.

¹³Environmental goods are defined to include both goods connected to environmental protection and goods that have been adapted to be more environmentally friendly or “cleaner.” For more details, see IMF (2021)

¹⁴Patent data are only available until 2021.

¹⁵We use version ESCO v1.1.1, which is available from esco.ec.europa.eu/en/use-esco/download.

¹⁶A similar type of classification of green occupations is available from the Occupational Information Network (O*NET), which is based on U.S. occupations. We use the ESCO version to avoid the use of multiple crosswalks.

¹⁷The cut-offs chosen to classify an employer (50%) or an occupation (95th percentile) as green is admittedly arbitrary. Godøy and Isaksen (2025) perform sensitivity checks to examine how the estimated green wage premium vary with firm-level thresholds ranging from 0% to 80%. Overall, thresholds between 40% and 80% yield quantitatively similar results. Lower cut-offs tend to yield a higher green wage premium.

emissions under the EU Emissions Trading System between 2009 and 2023 (Table B.2), excluding certain industries outside manufacturing, resulting in 32 brown industries; see table notes for details. Second, a firm qualifies as brown if it reports positive CO2 emissions to the Norwegian Environment Agency at any point during 2009–2023. We classify a job as brown (non-oil) if it meets either of these criteria and does not belong to the oil sector.¹⁸ We refer to the group of brown jobs as the “brown sector.”

Figure B.8 illustrates the distribution of oil, green, brown, and ‘other’ workers in the Norwegian economy in 2013. The green and oil sectors each represent a similar share of total employment – approximately 7.8% to 7.9% – while the brown sector makes up about 3.5%. Figure B.9 shows the shares of green workers (panel a) and brown workers (panel b) by local labor market as of 2013. While oil workers are more concentrated along the coast, workers in green and brown jobs are more dispersed across the country.

4 Empirical Strategy

4.1 Difference-in-difference analysis of the oil price shock

We first examine the direct effects of the oil price shock on oil workers using a difference-in-differences (DiD) framework (Wooldridge, 2007; Villa, 2016). Let Y_{it} denote labor market outcomes, in this setting, employment status, labor earnings, or hourly wages, for individual worker i in year t . Formally, the specification of the DiD model is given as follows:

$$Y_{it} = \beta_0 + \beta_1 \times Oil_i \times Post_t + \mathbf{X}_{it}\beta + \gamma_{tc} + \lambda_i + \varepsilon_{it}, \quad (1)$$

where a worker is defined as treated ($Oil_i = 1$) if the worker was employed in the petroleum sector in 2013, while the level of treatment is at the 5-digit industry. $Post_t$ is a binary variable taking the value of zero before the year 2013 and one after. γ_{tc} denotes year-fixed effects that are specific to each local labor market, capturing unobservable changes over time, while λ_i represents individual fixed effects and reflects unobservable changes for each employee. \mathbf{X}_{it} is a vector of age-specific year fixed effects.¹⁹ We cluster the standard errors at the level of treatment, i.e., the 5-digit industry code in 2013.

The parameters in equation (1) are denoted by β_m for $m = 0, \dots, 1$. β_0 is an intercept, the mean outcome of the control group at the baseline (before the year 2013). β_1 is the DiD estimand, the coefficient of interest in our paper.

¹⁸As a comparison, Vona et al. (2018) and Bluedorn et al. (2023) classify brown jobs based on the pollution intensity of four-digit North American Industry Classification System (NAICS) codes. Specifically, they define 66 industries as brown based on being in the 95th percentile of pollution intensity (emissions per worker) for at least three pollutants (CO₂, CO, VOC, NO_x, SO₂, PM₁₀, PM_{2.5}, and lead).

¹⁹Results are robust to alternative ways of controlling for age, such as including a cubic polynomial in age minus 40, omitting the linear term (following Card et al., 2018).

Our identifying assumption is that without the oil price shock, the average difference between the outcomes of treated and non-treated individuals in the post and pre-treatment periods would be the same. In the absence of the oil price drop, the difference between these potential outcomes of the treated group would be equal to the observed difference between the outcomes of the control group in the post and pre-treatment periods, correspondingly.

In addition to a classical DiD approach, we implement a dynamic DiD as shown in the following model:

$$Y_{it} = \beta_0 + \sum_{k=2009}^{2023} \beta_k \times \mathbb{1}\{t = k\} \times Oil_i + \mathbf{X}_{it}\beta + \gamma_{tc} + \lambda_i + \varepsilon_{it}, \quad (2)$$

where β_k denotes the vector of yearly DiD estimands for the years 2009-2023. We omit β_{2013} such that β_k captures how the outcome Y_{itc} develops relative to the year 2013. The dynamic DiD allows us to validate the parallel trends assumption prior to the treatment, as well as observe the year-to-year effects of the oil price drop on various labor market outcomes.

4.2 Event study of oil job displacement

In our first DiD analysis, we focus on the direct effect of the oil price shock on all oil workers – irrespective of whether they stay or leave their initial job. We also want to examine the transitional costs for oil workers who separate from their 2013 oil employer after the shock. Following the job displacement literature, we use an event study, or stacked DiD design, to examine the effects of the job separation event by re-centering the intervention date to the year of displacement. We restrict the treatment group to oil workers that at some point in 2014–2018 separate from their 2013-oil employer (i.e., we construct five stacked treatment and control cohorts). We label these workers as *displaced*. We focus on the immediate years following the oil price shock (2014-2018) when defining displaced oil workers, as displacements during this period are more likely to have been involuntarily and attributable to the shock.²⁰

We follow the existing literature (e.g., [Schmieder et al., 2023](#); [Athey et al., 2023](#)) and focus on workers with at least three years of tenure at their pre-displacement employer. We further restrict the sample to individuals aged 24-54 in 2013 (instead of 24-61) to limit the influence of early retirement. The existing job displacement literature often defines displaced workers as those that separate from plants where there have been a large (e.g., at least 30%) drop in employment. As we exploit a plausible exogenous negative shock

²⁰The spike in unemployment in 2016, followed by a return to much lower levels in 2019, suggests that the majority of involuntary job displacements linked to the oil price shock likely occurred between 2015 and 2018 (see Appendix Figure [C.2](#), panel d).

to employment (induced by the oil price drop), we do not further restrict the sample to plants with mass layoffs.

To ensure that displaced oil workers and control workers have the same employment status in the years prior to the displacement event, we (re-)match each displaced oil worker to a non-oil worker using the same criteria described in Section 3.2.1, but apply the matching to the period prior to displacement rather than prior to 2014. Specifically, we do the matching separately for each displacement cohort, where the control cohort is assigned a placebo displacement year equal to the matched treated unit. As existing studies often find that earnings start to decline in the year prior to displacement (e.g., [Jacobson et al., 1993](#)), we estimate the propensity score model using log earnings and log hourly wages measured in year $k = -2$ and $k = -3$ relative to displacement. Columns 5 and 6 in Table 1 show summary statistics for the matched sample of displaced oil workers and non-oil workers, while Figure 2, panel (c) shows the earnings distribution. Overall, the treatment and control groups are closely matched in demographics and education, and show similar patterns in labor market outcomes.

To provide empirical estimates of the effects of job separation for oil workers, we estimate the following regression model using the five stacked treatment and control cohorts that are displaced in the years 2014–2018:

$$Y_{itc} = \sum_{k=-9}^9 \delta_k \times \mathbb{1}\{t = c_i + k\} \times D_i + \sum_{k=-9}^9 \omega_k \times \mathbb{1}\{t = c_i + k\} + \pi_{tc} + \alpha_i + \mathbf{X}_{it}\beta + \varepsilon_{itc}. \quad (3)$$

Here, c_i denotes the calendar year when the displacement event occurs (cohort) and k denotes the number of years since displacement.²¹ Y_{itc} is a labor market outcome for worker i in displacement cohort c observed in year t . The sum of ω 's control for the year relative to the calendar year in which the individual has been displaced from the 2013 oil job. D_i is an indicator variable for whether worker i is a displaced oil worker or belongs to the control group. α_i are worker fixed effects, π_{tc} are year fixed effects specific to each local labor market, and \mathbf{X}_{it} are year fixed effects specific to each age. The coefficients of interest are the estimates of δ_k , which capture how the outcome Y_{itc} for the treatment group develops k periods after displacement relative to the control group.²² Note that for workers displaced in 2014, we observe outcomes up to $k = 9$, while for workers displaced in 2018, we only observe outcomes up to $k = 5$. This implies that we have a balanced panel only in the relative period $k \in [-5, 5]$. In addition to taking logs of continuous outcome variables (such as labor earnings), we also normalize these outcomes by dividing

²¹E.g., if displacement occurs in year 2014, $k = 0$ corresponds to year 2014 and $k = 9$ corresponds to year 2023.

²²We omit δ_{-4} and one of the year dummies to avoid collinearity. This means that δ_k can be interpreted as the difference in the change between the two groups relative to year $t = c_i - 4$.

them by the individual's value in $k = -2$. Using the normalized outcome variable, we can interpret δ_k as the percentage change relative to this pre-displacement value.

We also provide empirical estimates of the average treatment effects by estimating the following regression model:

$$Y_{itc} = \delta_k \times Post_{tc} \times D_i + \omega_k \times Post_{tc} + \pi_{tc} + \alpha_i + \mathbf{X}_{it}\beta + \varepsilon_{itc}, \quad (4)$$

where $Post_{tc}$ is an indicator variable equal to 1 for the post-displacement years for cohort c , and 0 otherwise. Similar to other studies in the job displacement literature, the identifying assumption is that, conditional on the control variables and fixed effects, the development of the displaced oil workers' outcomes would have followed a similar path as the control group in absence of the oil job displacement.

4.3 Mechanisms of labor earnings losses

In this paper, we want to examine how displaced oil workers' labor earnings develop when transitioning into green, brown (non-oil) or other jobs. To better understand the sources of potential earnings gaps between post-displacement sectors, we examine the role of (i) establishment wage premiums, and (ii) skill distance.

4.3.1 Establishment wage premiums

To understand the role of persistent differences in employer wages in explaining potential earnings gaps across sectors, we use the well-established model of [Abowd et al. \(1999\)](#) – hereafter referred to as AKM – to estimate establishment wage premiums. We use the universe of full-time employees in Norway aged 20–61 in 2009–2023. We use hourly earnings constructed from the linked employer-employee dataset as our outcome variable. Letting $\ln(w_{it})$ denote the natural logarithm of hourly wages, we estimate the following regression model:

$$\ln(w_{it}) = \alpha_i + \psi_{j(i,t)} + X'_{it}\beta + \theta_t + \varepsilon_{it}, \quad (5)$$

where $\psi_{j(i,t)}$ is a vector of establishment fixed effects, capturing the wage premium paid by establishment j , and α_i is a vector of worker fixed effects, capturing abilities and skills that are equally valued across jobs. X_{it} includes a cubic polynomial in age minus 40 (following [Card et al. \(2018\)](#)), and θ_t controls for calendar time. The residual ε_{it} is a composite error term capturing idiosyncratic match effects and transitory shocks to the worker or the establishment. The estimated establishment fixed effects $\psi_{j(i,t)}$ can be interpreted as the adjusted mean of wage differences relative to a single omitted establishment.²³

In equation (5), the worker and establishment effects are separately identified within

²³As we are interested in examining changes over time, the choice of which establishment to omit is unimportant.

the connected set of workers. For smaller establishments with few hires, these parameters are estimated based on very few observations. A well-known problem when there are few movers connecting establishments is that the variance of the estimated establishment effects will be biased upward (Andrews et al., 2008; Bonhomme et al., 2023). While this issue is a known problem for variance decompositions, it is less relevant for our purpose as we are focusing on mean differences in establishment fixed effects across groups of workers.

Another possible concern is that the oil price shock in 2013 and the following displacement of oil workers will contribute to the estimates of the establishment fixed effects. To address this concern, previous literature often drops the displaced workers in the years following displacement. In our case, this would involve dropping a very large share of the workers in the oil industries, leaving us with few observations in the post period to identify establishment wage premiums. We hence keep all workers in the estimation sample, but also show results when using alternative estimation samples in robustness checks.²⁴

We will use the establishment fixed effects for two purposes: (i) to examine whether displaced oil workers move to lower-paying establishments by using $\hat{\psi}_{j(i,t)}$ as an outcome variable, and ii) to examine how much of the earnings loss is explained by establishment wage premiums by including $\hat{\psi}_{j(i,t)}$ as a control in an earnings decomposition exercise (see Section 5.3.3).

4.3.2 Skill distance

Another potential source of earnings loss when transitioning away from oil is an increased skill distance to the initial job. Let $s = [1, S]$ denote skills and $j = [1, J]$ index jobs. Let l_{js} denote the level of skill s demanded by job j . A job can then be expressed as a vector of length S :

$$job_j = [l_{j1}, \dots, l_{jS}]. \quad (6)$$

We can then express the (Euclidean) skill distance between two jobs, j and j' , as:

$$d_{jj'} = \sqrt{\sum_{s=1}^S (l_{js} - l_{j's})^2}, \quad (7)$$

where the larger the skill space between two jobs, the more dissimilar the jobs are, and $d_{jj} = 0$ and $d_{jj'} = d_{j'j}$. The skill distance expressed by equation (7) allows us to compare the similarities between two jobs. Previous literature has shown that skill distance measures can help explain individual wage dynamics and occupational mobility (see e.g., Gathmann and Schönberg, 2010).

²⁴Specifically, we show results when (i) restricting the sample to years prior to the oil price shock (2009–2013), and (ii) when dropping the matched displaced oil workers from the sample in the years following displacement; see Appendix E.2.

As job-specific skill data is difficult to obtain, we follow the existing literature by focusing on the skill distance between occupations (see e.g., [Macaluso, 2025](#)). To measure occupational skills, we rely on data from the Occupational Information Network (O*NET).²⁵ The O*NET dataset provides detailed descriptions of over a 1,000 occupations in the United States in terms of the knowledge, skills, and abilities they require of workers. To operationalize our skill distance measure, we use the combination of skills required in an occupation. There are in total 35 different skills in the O*NET database. Examples of skills are: *Writing*, *Programming*, *Mathematics*, *Active Learning*, or *Coordination*; see Table B.3 for a complete list. For each occupation, each of the 35 skills is assigned a score between 1 and 5, reflecting to what extent the skill is needed in jobs within that occupation. These values are the basis of the skill distance measure.

To calculate the skill distance measure, we first need to convert the O*NET occupations to Norwegian occupations.²⁶ We go from 8-digit SOC occupations to 4-digit STYRK occupations using several crosswalks, including crosswalks developed by [Hoen \(2016\)](#). In each step, we average the skill scores. Our final dataset consists of 349 occupations. For each occupation pair, we calculate the Euclidean distance using equation (7).²⁷ Figure B.10 shows the distribution of skill distance, which ranges from 0 to 10.8, with an average skill distance of 4.2. As an example, the closest occupation to *Economists* is *Accountants* (with a skill distance of 1.87), and the most distant occupation is *Car and related cleaners* (with a skill distance of 8.6). Figure B.11 shows the average employment-weighted skill distance between oil jobs and brown, green, or other jobs, based on 2013 employer-employee data. Brown jobs are the closest to oil jobs in the skill space with an average skill distance of 1.1, while the average skill distance between oil and green is 2, which is smaller than for other jobs in the economy (3.8).

We will use the skill distance measure for two purposes: (i) to examine whether displaced oil workers move to occupations that are further away (in the skills space) from their initial oil job by using $d_{jj'}$ as an outcome variable, and ii) to examine how much of the potential earnings losses is explained by skill distance to the 2013 oil job by including $d_{jj'}$ as an explanatory variable in a decomposition exercise (see Section 5.3.3).

5 Results

5.1 Direct effects of the oil price shock

Table 2, columns (1)–(3), presents the estimated effects of the oil price shock on labor outcomes for oil workers compared to non-oil workers. The main specification incorporates

²⁵We use version 24.0 of O*NET, released in August 2019.

²⁶O*NET classifies occupations according to its own taxonomy, which is again based on the Standard Occupational Classification (SOC).

²⁷We calculate the Euclidean distance in STATA using the `matrix dissimilarity` command.

worker fixed effects, local labor market-by-year fixed effects, and age-year fixed effects.²⁸ The findings indicate that the oil price shock caused a 3.2% reduction in employment probability and a 5.6% decrease in labor earnings (including when labor earnings are normalized to their pre-treatment levels). Among those who remained employed, hourly wages fell by 1.6%, although this effect is not statistically significant.

Table 2: Effect of the oil price shock or oil job displacement on different outcomes

	DiD estimates of the oil price shock			Event estimates of oil job displacement		
	Coefficient (1)	Std.err. (2)	N (3)	Coefficient (4)	Std.err. (5)	N (6)
Panel A: Main outcomes						
Employed	-.032***	.0048	1961741	-.111***	.0076	609661
Labor earnings (log)	-.056***	.013	1894481	-.168***	.0169	596560
Labor earnings (norm.)	-.056***	.0106	1952102	-.118***	.017	606330
Hourly wages (log)	-.016	.0122	1766807	-.044***	.0144	565353
Panel B: Additional outcomes						
Unemployed	.016***	.003	1961741	.041***	.0048	609661
Not in the labor force	.016***	.004	1961741	.071***	.0043	609661
Retired	.013***	.0035	1961741	.018***	.0018	609661
Disability	.008***	.0025	1961741	.038***	.0037	609661
Gross income (log)	-.056***	.0114	1952102	-.13***	.0147	606330
Net income (log)	-.046***	.0095	1952102	-.111***	.0129	606330
Hours per week	-.18	.1508	1773994	-.558***	.1345	567394

Notes: Table shows regression results from the estimation of equation (1) (columns 1–3) and equation (4) (columns 4–6). The sample is trimmed using propensity score matching based on labor earnings, log hourly wages, age, gender, education code (1-digit), and county of residence. Labor earnings is defined as the sum of wages, business income, parental allowance, sick pay, and unemployment benefits. Inflation adjusted values in NOK 2018. Year 2014 is dropped from the DiD sample (columns 1–3). All regressions include worker fixed effects, age-by-year fixed effects, and local labor market-by-year fixed effects. Local labor market refers to the location of residence in 2013. Event regressions also include years relative to layoff dummies. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. * p<0.10, ** p<0.05, *** p<0.01.

Additional outcomes, reported in Table 2, panel B, show that the oil price shock led to a 5.6% reduction in gross income and a 4.6% drop in net income for oil workers. Among those no longer employed, roughly half transition into unemployment and half exit the labor force, each accounting for 1.6% of the sample. Of those exiting the labor force, the majority enter early retirement, which represents 1.3% of workers.

Figure 3 illustrates the temporal effects of the oil price shock on log labor earnings and labor earnings normalized, employment, and log hourly wages. Panel (a) shows a gradual deterioration of labor earnings that peaks at nearly 10% in 2017. Although labor

²⁸Alternative specifications, adding progressively more fixed effects, or substituting age-by-year fixed effects with a cubic polynomial in age minus 40 or local labor market fixed effects with county fixed effects, yield qualitatively similar results; see Appendix C.3.

Figure 3: Yearly DiD estimates of the effect of the oil price shock on employment, log labor earnings and log hourly wage



Notes: Figure shows the DiD estimates from equation (2) on employment, log labor earnings, and normalized labor earnings (relative to 2013). Numbers reported in the bottom left corner are average DiD treatment effects and standard errors (in parentheses) from the estimation of equation (1). The specifications include worker fixed effects, age-by-year fixed effects, and local labor market-by-year fixed effects. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Vertical bars depict 95%-confidence intervals. Appendix Figure C.1 shows yearly raw means of outcome variables, by oil workers and control workers.

earnings begin to recover thereafter, they remain 2.5% below those of control workers by 2023 – although this difference is not statistically significant at the 5% level. These effects are somewhat larger than those reported by Walker (2013), who finds earnings losses of under 4% four years after the implementation of the 1990 U.S. Clean Air Act Amendments. When restricting the sample to workers who remain employed in the post-treatment period, the earnings loss is smaller—averaging 3.2%—but follows a similar trajectory. Panel (b) shows a nearly identical pattern for normalized labor earnings. Panel (c) reveals a steep drop in employment beginning in 2015 and bottoming out at over 6% in 2016, before improving to around -2% by 2023. Panel (d) displays a modest and non-significant dip in hourly wages followed by a full recovery by 2022.

Yearly estimates for additional outcomes are provided in Figure C.2. Gross and net incomes exhibit trends similar to labor earnings, while unemployment, early retirement, and disability benefits all increase. These findings highlight how the labor market impacts

of the oil price shock on oil workers evolved over the decade that followed. Although labor earnings and hourly wages show signs of recovery by 2023, the probability of being employed has stabilized at a lower level.

5.1.1 Heterogeneous effects

The average labor market consequences may mask substantial heterogeneity. To identify potentially vulnerable groups, we re-estimate equation (1) across various sub-groups, utilizing workers' pre-treatment characteristics from 2013. Specifically, we analyze differences based on gender, age, educational attainment, labor earnings, and wealth.

Figure 4: Effect of the oil price shock on employment, labor earnings and hourly wage, by worker type



Notes: The figure shows regression results from the estimation of equation (1) for different worker groups. Each coefficient is estimated from a separate regression. All covariates are measured using 2013 values. The sample is trimmed using propensity score matching based on labor earnings, hourly wages and age, gender, education category, and county of residence. The specifications include worker fixed effects, age-by-year fixed effects, and local labor market-by-year fixed effects. Standard errors are clustered at the 5-digit NACE industry where the worker was employed in 2013. The year 2014 is excluded from the sample. Horizontal bars depict 95%-confidence intervals.

Figure 4 illustrates the average DiD effect of the oil price shock on employment (panel (a)), the log of labor earnings (panel (b)), and the log of hourly wages (panel (c)) across various sub-groups. Older oil workers (aged 55–61 in 2013) are the most affected, experiencing a 9% drop in employment probability—three times the decline observed in younger age groups (ranging from -1% to -3%). This larger effect is primarily attributed to early retirement, as shown in Figure C.5, panel (b). Workers without a high school degree are slightly less likely to remain employed compared to those with higher levels of education, although this difference is not statistically significant at the 5% level. Panel (b) suggests that male, older, relatively well-educated workers (with more than three years of university education), and high earners as of 2013 are the sub-groups that experience the

steepest declines in labor earnings. A similar pattern emerges for the log of hourly wages, except for the age gradient. Taken together, these results suggest that the negative earnings effects for older workers are driven more by employment status than by reductions in wages.

Additional dimensions: Figure C.6 shows substantial disparities in labor earnings across initial (2013) occupations. High-skilled occupations, such as *Professionals*, experience the largest earnings losses (-10%), while low-skilled occupations, such as *Service workers* (-0.01%) and *Elementary workers* (0.02%) – including cleaners and kitchen assistants – experience no statistically significant earning losses (p-value>0.05).

5.1.2 Stayers and leavers

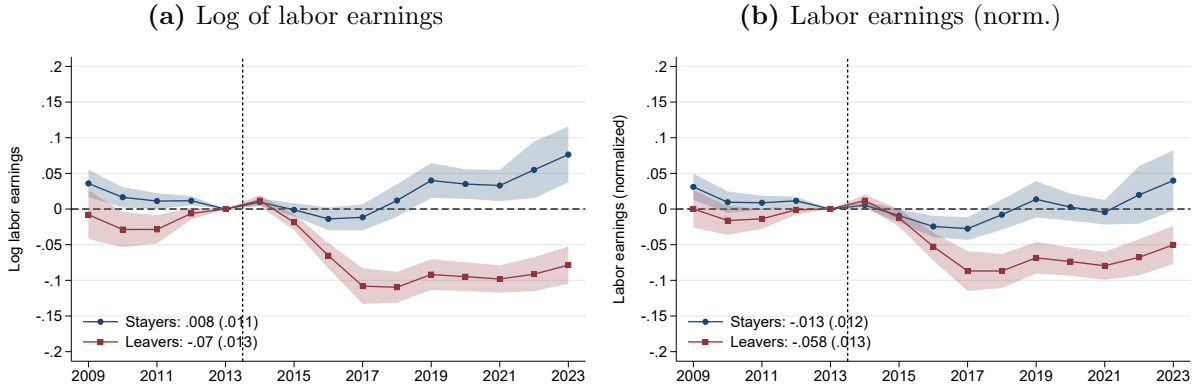
We decompose the effect of the oil price shock on log labor earnings by distinguishing between workers who remain in their initial employment and those who leave. Workers who stay with their initial employer are likely to have higher (prospective) wages, potentially reflecting above-average ability, compared to those who leave. Following Walker (2013), we re-estimate equations (1) and (2) separately for stayers and leavers. The estimated effects should be interpreted cautiously, as dividing the sample based on post-displacement outcomes may introduce endogeneity, potentially biasing the coefficients.

We stratify the treatment group into two sub-groups: stayers, defined as those who remain with their initial 2013 employer throughout the post-treatment period, and leavers, who exit their 2013 employer at some point during the post-treatment period.²⁹ This setup allows us to compare the impact of the oil price shock within each group before and after the shock, effectively controlling for any time-invariant unobservable characteristics of stayers and leavers.

Figure 5, panel (a), demonstrates that the decline in log labor earnings among employed oil workers is almost entirely driven by those who leave their initial employer during the post-treatment period, with a 7.0% average decline in earnings for leavers compared to a 0.8% increase for those who stay with their initial employer. The gap is slightly smaller when investigating normalized labor earnings, where leavers face a 5.8% decline in earnings compared to 1.3% decline for stayers (panel (b)). In Figure C.3, we examine alternative definitions of “initial employment,” using the (5 or 2-digit) industry code, or the (4 or 2-digit) occupation code. The results remain qualitatively consistent across these definitions; stayers experience no significant changes in labor earnings, while leavers experience substantial losses (ranging from -4.5% to 8.5%). Industry leavers are worse off than occupation leavers.

²⁹To ensure consistent employment composition across treatment and control groups, we restrict the sample to individuals employed in a given year between 2014 and 2023. This is particularly important as oil sector workers exhibit a higher likelihood of retiring compared to non-oil sector workers after the oil price shock.

Figure 5: Yearly DiD estimates of the effect of the oil price shock on labor earnings across workers that stay or leave their 2013 employer



Notes: Figure shows the yearly DiD estimates on log labor earnings (panel a) and normalized labor earnings (panel b) from the estimation of equation (2). Leavers are defined as oil workers that at some point in 2014–2023 leave their 2013 employer. Stayers are defined as oil workers that stay at their 2013 employer in 2014–2023. Sample is restricted to individuals that are employed in a given post treatment year. All regressions include worker fixed effects, age-by-year fixed effects, 2013 local labor market-by-year fixed effects. Definitions of stayers and leavers are based on the initial (2013) employment. The sample is trimmed using propensity score matching. Inflation adjusted values in NOK 2018. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Shaded areas depict the 95%-confidence intervals. Numbers reported in the bottom left corner are average DiD treatment effects and standard errors (in parentheses) from the estimation of equation (1).

5.2 Effect of the oil price shock on displaced workers

In this section, we focus on workers employed in the oil sector in 2013 who separate from their initial employer and evaluate outcomes for these ‘displaced’ workers relative to the time of displacement within an event study framework. Following the approach commonly used in the job displacement literature (e.g., Schmieder et al., 2023), we focus on workers with a minimum tenure of three years at their initial employer as of 2013.

Figure 6 illustrates the effects of the oil price shock on displaced oil workers’ labor earnings (log and normalized), employment, and log hourly wages over time, while Table 3 shows corresponding event study estimates in table format for post-displacement years ($k = 0, 1, 4, 9$).

Effect on labor earnings: Displaced oil workers experience an average decline of 16.8% in log labor earnings during the post-displacement period (Figure 6, panel (a)), with earnings reaching their lowest point one year after displacement—28.1% below pre-displacement levels (Table 3, column (1)). Earnings partially recover in the following years but remain 17.5% below pre-displacement levels after four years, and 10.1% lower after nine years. When restricting the sample to workers who remain employed post-displacement, the earnings decline is smaller—averaging 10.5%—particularly in the first year after displacement. Nevertheless, the decline remains statistically significant nine years later (p-value<0.05).

The average effect on normalized labor earnings (-11.8%; panel (b)) is slightly smaller

than the effect on log earnings (-16.8%). Estimates using normalized labor earnings reveal a milder pattern: a 16.6% drop one year after displacement, followed by a gradual recovery, with earnings 6.6% lower after nine years (column (2)). When conditioning on continued employment, the average decline in normalized earnings is 8.0% and is not statistically significant nine years after displacement (p-value>0.05).

Table 3: Event study estimates of the effects of job displacement for oil workers on labor earnings, employment, and hourly wage

	(1) Labor earnings (log)		(2) Labor earnings (norm.)		(3) Employment (0/1)		(4) Hourly wages (log)	
k=0	-0.115***	(0.0216)	-0.057**	(0.0275)	-0.304***	(0.0152)	-0.069***	(0.0136)
k=1	-0.281***	(0.0199)	-0.166***	(0.0191)	-0.139***	(0.0102)	-0.064***	(0.0172)
k=4	-0.175***	(0.0178)	-0.134***	(0.0178)	-0.074***	(0.0066)	-0.049***	(0.0161)
k=9	-0.101***	(0.0325)	-0.066**	(0.0312)	-0.052***	(0.0082)	-0.012	(0.0170)
N	596,560		606,330		609,661		565,353	

Notes: The table reports the coefficients δ_k from the event study model (equation 3). k denotes the years since displacement. Standard errors are reported in parentheses and are clustered at the 5-digit NACE industry where the worker is employed in 2013. N corresponds to the number of person-year observations. * p<0.10, ** p<0.05, *** p<0.01.

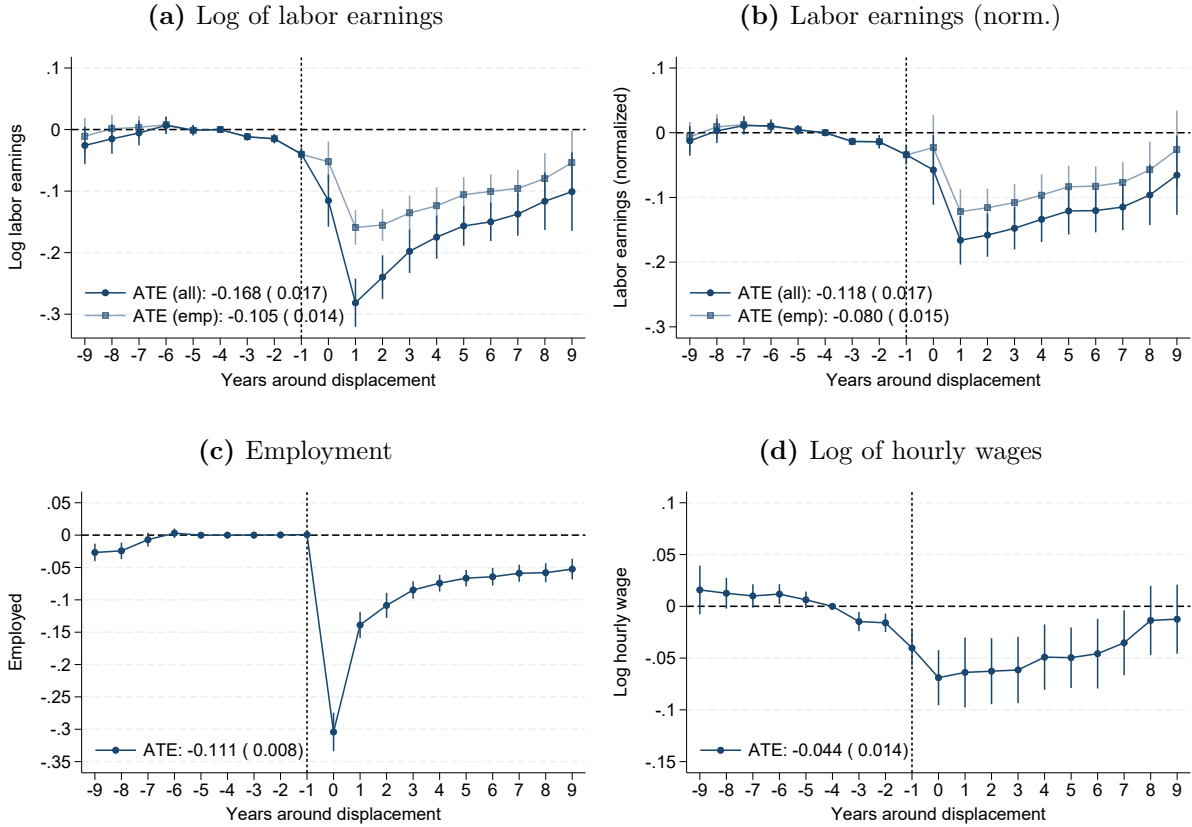
To benchmark our results, we compare them with findings from the broader literature on the effects of mass layoffs and job displacement. This includes studies covering the general economy (Bertheau et al., 2023), high-emission versus low-emission industries (Barreto et al., 2023, 2024), the coal mining sector in the U.K. during the 1980s and 1990s (Rud et al., 2024), and the Norwegian oil sector in response to the 2014 oil price shock (Ellingsen et al., 2022). Overall, our estimated labor earnings and employment effects are somewhat larger than those reported for Northern European countries more broadly, but substantially smaller than the impacts found for carbon-intensive jobs in Germany and for coal miners in the U.K.

For example, Bertheau et al. (2023) find that displaced workers in Denmark and Sweden experience an average earnings decline of 11.5% five years after displacement, using normalized earnings as the outcome.³⁰ In comparison, our estimated declines in labor earnings four years after displacement are larger in magnitude: 17.5% based on log earnings and 13.4% using normalized earnings.

Studies examining job loss in high-carbon sectors find even larger impacts. Barreto et al. (2023) report that workers displaced from high-emission industries in Germany earned 43% less than their pre-displacement trend in the first year, and 23% less after four years. In contrast, our estimated four-year effect on normalized labor earnings is 13.4%, roughly 10 percentage points lower.

³⁰Their study uses data from 1983–2017 for Denmark and 1994–2016 for Sweden. Note that in their framework, $k = 1$ refers to the year of displacement, meaning $k = 5$ corresponds to $k = 4$ in our analysis.

Figure 6: Event study estimates of the effects of job displacement for oil workers on labor earnings, employment, and hourly wages



Notes: The figure shows regression results from the estimation of equation (3). Numbers reported in the bottom left corner are average event study effects and standard errors (in parentheses) from the estimation of equation (4). All regressions include worker fixed effects, age-by-year fixed effects, 2013 local labor market-by-year fixed effects, and years relative to layoff dummies. Local labor market refers to the location of residence in 2013. Standard errors are clustered at the 5-digit NACE industry where the worker is employed in 2013. Vertical bars depict 95%-confidence intervals. Appendix Figure D.1 shows raw means of the outcome variables, by displaced oil workers and the control group.

A broader cross-country comparison by Barreto et al. (2024) shows wide variation in post-displacement earnings losses across 14 countries. During the six years after displacement, average losses range from -68% in Portugal to -17% in Norway. Our average estimated earnings effect (during the nine years after displacement) based on normalized labor earnings (-11.8%) is somewhat lower than the OECD estimate for Norway, while our log earnings estimate (-16.8%) is nearly identical. These cross-country differences underscore the importance of national context and industry composition in shaping displacement outcomes. For example, offshore oil workers in Norway may face different reemployment prospects than coal workers in Germany or the U.K.

Barreto et al. (2024) also find that job displacement in high-emission industries consistently leads to larger earnings losses than in low-emission sectors. For Norway, the estimated gap is about 5.8 percentage points, with cross-country differences ranging from 1.8 percentage points in Sweden to 15 percentage points in Spain. These findings sug-

gest the need to study displacement effects in high-carbon sectors separately to better understand the sector-specific challenges of the green transition.

Our estimated effects are also smaller than those found for coal miners in the U.K., where earnings fell by 40% one year after displacement and remained 20% below pre-displacement levels even 15 years later, conditional on employment (Rud et al., 2024).

Finally, our results align closely with those of Ellingsen et al. (2022), who estimate a 15% decline in earnings for displaced Norwegian oil workers four years after displacement, despite using a smaller sample of 1,553 displaced oil workers.

Effect on employment and hourly wages: On average, employment among displaced workers declines by 11.1% in the post-displacement period (Figure 6, panel (c)). The sharpest drop occurs in the year of displacement, with employment falling by 30.4%, followed by a gradual recovery to 5.2% below pre-displacement levels after nine years (Table 3, column (3)). These effects fall in the middle of the range reported by Bertheau et al. (2023). Specifically, our estimate for the first year lies between the larger employment losses found in Spain, Italy, and Portugal (-35% to -46%) and the smaller effects observed in Denmark and Sweden (-18% to -20%). By four years post-displacement, our estimate converges toward those of Denmark and Sweden after five years (-4%), whereas Southern European countries continue to show much larger effects (-16% to -18%).

Log hourly wages decrease by an average of 4.4% over the same period (panel (d)). Wages fall by 6.9% in the year of displacement and remain persistently lower for several years (column (4)). By year four, they recover slightly to a 4.9% decline, and the effect is no longer statistically significant after nine years ($p\text{-value} > 0.1$). These results are broadly in line with those for Denmark and approximately half the size of the effects reported for Sweden by Bertheau et al. (2023). However, they are substantially smaller than the effects for high-carbon industries in Germany, where displaced workers experience wage losses of around 23% four years after displacement.

Overall, these results highlight the significant and prolonged labor market impacts of job displacement on oil workers following the oil price shock. At the same time, the earnings losses in the oil industry in Norway are substantially smaller than those in carbon-intensive industries in Germany and coal industries in the U.K.

Additional outcomes: Table 2, right panel (columns (4)–(6)), shows the effects of job displacement on oil workers’ gross income, net income, and employment status. Displacement leads to a 13.0% decline in gross income and an 11.1% decline in net income. These losses are smaller than the estimated 16.8% drop in log labor earnings, suggesting that taxes and transfers partially cushion the impact. Employment falls by 11.1%, with around one-third of displaced workers entering unemployment (4.1%) and the remaining two-thirds exiting the labor force (7.1%). Of those leaving the labor force, about one-third go early retirement, accounting for 1.8% of all displaced workers.

5.2.1 Heterogeneous effects by worker type

In this section, we analyze whether displaced oil workers experience differential employment and labor earnings losses across various demographic and socioeconomic groups. Using workers' pre-treatment characteristics from 2013, we re-estimate equation (4) separately by gender, age decile, educational attainment, labor earnings, and wealth.

Figure 7: Event study estimates of the effects of job displacement on employment, log labor earnings, and log hourly wages, by worker type



Notes: Figure shows regression results from the estimation of equation (4) for different worker groups. Each coefficient is from a separate regression. All covariates are 2013-values. The sample is trimmed using propensity score matching based on labor earnings, log hourly wages, age, gender, education code (1-digit), and county of residence. Labor earnings is defined as the sum of wages, business income, parental allowance, sick pay, and unemployment benefits. Inflation adjusted values in NOK 2018. The specifications include worker, age-by-year fixed effects, and 2013 local labor market-by-year fixed effects. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Year 2014 is dropped from the sample. Horizontal bars depict 95%-confidence intervals.

Figure 7 shows the effects of displacement on employment (panel (a)), log labor earnings (panel (b)), and log hourly wages (panel (c)) across different worker groups. (The event studies by educational attainment, age group, and gender, are relegated to Appendix D.3.) The results reveal a clear skill gradient, proxied by educational attainment: workers with lower levels of education experience more severe negative impacts from oil sector displacement. This effect is more pronounced than when examining the effect on all oil workers (Figure 4), highlighting the importance to follow displaced fossil fuel workers to understand the effect of green transition. For example, compared to workers with more than three years of university education, those without a high school diploma face employment losses that are three times larger (-18% vs. -6%; panel (a)) and earnings losses that are nearly twice as large (-23% vs. -12%; panel (b)). Importantly, the steep earnings decline for workers without a high school education is driven largely by a higher employment decline, as hourly wage effects are similar across education levels (panel (c)).

The results also reveal differences by pre-displacement earnings. Workers earning below the median in 2013 experience nearly twice the decline in employment compared to higher earners (-15% vs. -8%; panel (a)), yet their hourly wages remain unaffected. In contrast, higher earners experience an 8% decline in hourly wages following displacement (panel (c)). Consistent with DiD results shown in Figure 4, a clear age gradient emerges: workers aged 45–54 experience declines in both employment and labor earnings that are approximately 1.5 times greater than those of younger workers. Finally, there are no statistically significant differences ($p\text{-value} > 0.1$) between men and women across any of the three outcomes.

Figure D.6 shows labor earnings disparities across initial (2013) occupations, where low-skilled occupations such as *Service workers* (-31.8%) and *Clerical workers* (-21.8%) experience the largest earnings losses and high-skilled occupations such as *Managers* (-8.9%) experience the smallest earning losses.

Comparing the heterogeneous effects of the oil price shock on all oil workers (Section 5.1) to those on displaced oil workers reveals both similarities and differences. Initially, the direct impact of the oil price shock on all oil workers indicates that less “vulnerable” groups, such as high earners, males, older individuals, and the highly educated such as *Professionals*, are more adversely affected. In contrast, among displaced workers, the negative effects are more concentrated in vulnerable groups, particularly those with lower educational attainment such as *Service workers* and *Clerical workers*. Overall, the skill gradient is more pronounced when focusing solely on displaced workers compared to all exposed oil workers. These findings suggest that examining only displaced workers may yield different conclusions about distributional effects and vulnerable groups than analyses considering the broader population of oil workers.

These observations align with existing literature documenting heterogeneous effects of job displacement across various demographics. For example, Barreto et al. (2024) find that displaced workers who are older, have longer tenure, lower educational attainment, and lower skills, face larger earnings declines.

5.2.2 Stayers and leavers

Figure 8 illustrates the impact of displacement on log labor earnings (panel (a)) and log hourly wages (panel (b)), distinguishing between workers who remain in or exit their initial industry or occupation. The sample is restricted to workers that are re-employed, as otherwise, the occupation and industry are not defined after displacement. Overall, the figure shows that workers who remain in their initial industry are better off in terms of labor earnings than those who leave, while occupational change matters less for earnings (panel (a)). Notably, workers who leave their initial 2- or 5-digit industry experience declines in labor earnings (-13.0% to -12.6%) that are more than twice that of workers who stay (-3.5% to -3.4%, respectively). Occupational change at the 2 or 4-digit level

matters less, with no statistical difference between stayers and leavers at the 5%-level. Overall, hourly wages do not differ between displaced oil workers who stay or leave their initial industry or occupation (panel (b)). Overall, these findings suggest that occupation-specific characteristics may play a smaller role than industry-specific characteristics in explaining earnings losses.

Figure 8: Event study estimates of the effect of displacement on log of labor earnings and log of hourly wages across stayers and leavers, by initial industry or occupation



Notes: Figure shows regression results from the estimation of equation (4) on log of labor earnings (panel a) and log of hourly wages (panel b) across stayers and leavers, by initial industry or occupation. Sample is restricted to individuals that are employed in any given year in the post period. Definitions of stayers and leavers based on the initial (2013) 5-digit NACE industry code, 2-digit NACE industry code, 4-digit occupation, and are indicated by the headings. The specifications include worker fixed effects, age-by-year fixed effects, 2013 local labor market-by-year fixed effects, and year dummies relative to displacement event. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Horizontal bars depict 95%-confidence intervals.

Our findings on industry switchers are consistent with Walker (2013) and Barreto et al. (2023), who both find that workers who stay in their initial sector face lower earnings losses after displacement. For occupational switchers, however, we show that leavers are only slightly worse off than stayers, while Barreto et al. (2023) finds that occupational leavers experience earnings losses that are 2.5 times that of stayers. These findings suggest that occupation-specific skills may play a smaller role in explaining earnings losses in the Norwegian oil industry compared to high-carbon sectors in Germany.

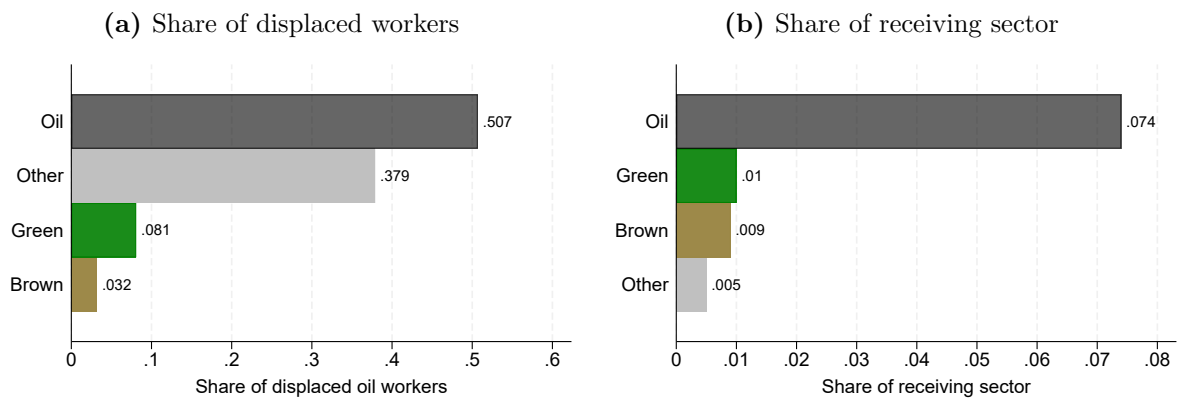
In the subsequent section, we explore the extent to which displaced oil workers transitioning out of their industry or occupation move into green, brown, or other jobs. We aim to disentangle the contributions of establishment wage premiums and skill transferability in explaining the earnings disparities observed between post-displacement sectors.

5.3 Transitioning from oil to green?

5.3.1 Transition into green jobs

Figure 9 illustrates the sectors into which displaced oil workers transition post-displacement, focusing on those employed in subsequent years. Panel (a) reveals that 50.7% of these workers remain within the oil sector. Among those who exit, 8.1% secure employment in the green sector, 3.2% transition to the brown (non-oil) sector, and the remaining 37.9% move to other industries. Although the proportions entering the green and brown sectors appear modest, this is partly due to the relatively small employment shares these sectors hold within the broader economy.

Figure 9: Displaced Oil Workers, by Post Displacement Sector



Notes: The figure shows the destination sectors where (matched) displaced oil workers ($N=20,406$) move. Panel (a) shows displaced oil workers in four post-displacement job categories, or sectors (oil, green, brown (non-oil), other) as a share of all displaced oil workers. Panel (b) shows displaced oil workers as a share of sectoral employment. The sample is restricted to full-time employed workers, and to post displacement years (i.e., 2014–2023).

Panel (b) contextualizes these transitions by depicting displaced oil workers as a percentage of total employment within the receiving sectors. When adjusting for sector size, it becomes evident that displaced oil workers disproportionately enter green and brown industries compared to other sectors. Notably, these workers are almost equally likely to move into the brown and green sectors when considering sector size, with displaced oil workers constituting approximately 1% of employment in both green and brown sectors.

Table E.1 provides a detailed breakdown of the industries, defined at the 4-digit level, absorbing the largest numbers of displaced oil workers. Panel A lists the top green industries, with *Distribution and production of electricity*, as well as *Engineering activities and related technical consultancy* leading the influx. Panel B highlights the top brown industries, where *Aluminum production* stands out as the primary destination. Panel C enumerates other industries receiving displaced oil workers, offering an overview of their post-displacement employment landscape.

5.3.2 Transitional costs and the role of skill distance and establishment wage premium

Figure 10, panel (a), presents the log labor earnings of displaced oil workers who remain in the oil industry or transition to green, brown, or other industries. It is important to interpret these estimates cautiously, as categorizing the treatment group based on post-displacement outcomes may introduce bias due to workers' endogenous selection of post-displacement sectors. The analysis indicates that displaced workers moving to brown industries experience a smaller labor earnings loss (approximately -3.2%) compared to those transitioning to green industries (around -10.1%). Furthermore, panel (b) indicates that workers entering green industries face a lesser hourly wage reduction than those moving into 'other' industries (approximately -4.5% vs. -6.4%). These findings suggest that the skills and competencies required, as well as wage premiums, may be more closely aligned between oil and brown jobs than between oil and green jobs.

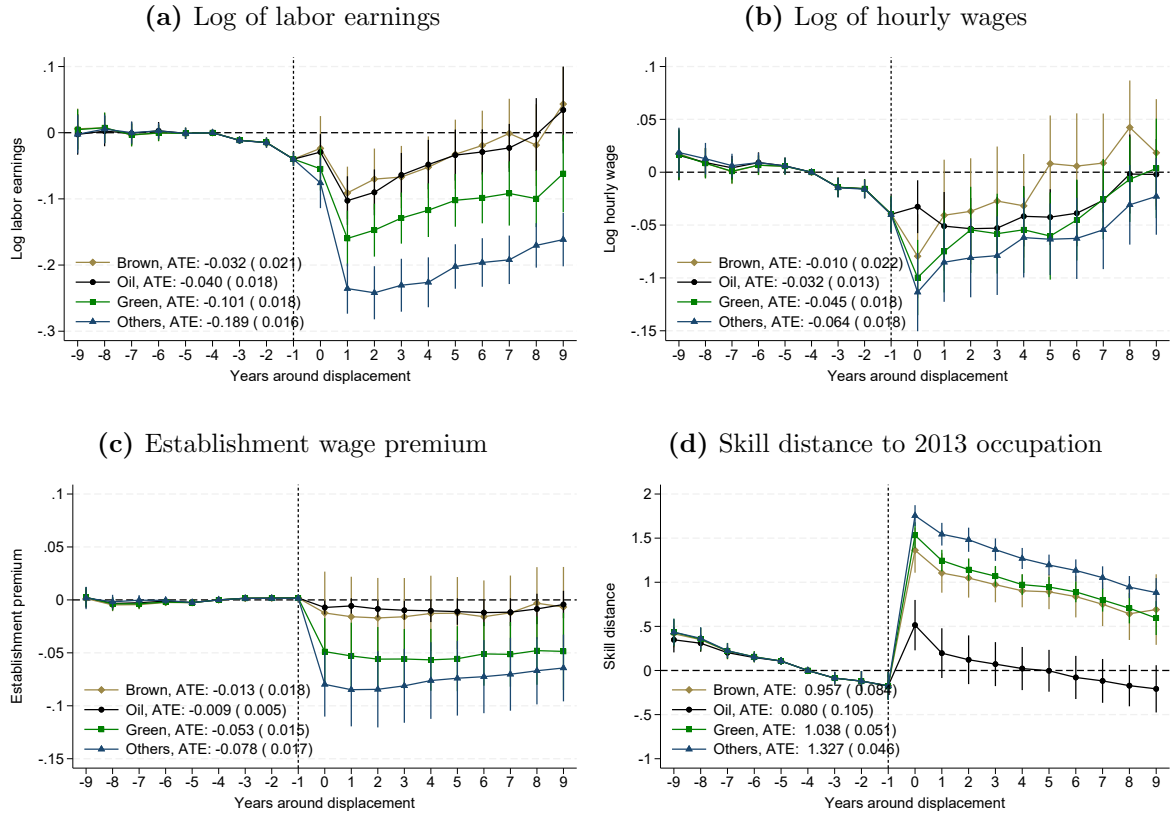
We proceed by investigating how variations in labor earnings across sectors can be attributed to occupation-specific skill distance and establishment wage premium. First, we estimate establishment wage premiums using equation (5). Figure 10, panel (c) plots the estimated effect of job displacement on the AKM establishment wage premium, by post displacement sector, and reflects the extent to which displaced oil workers move to higher or lower paying establishments.³¹ The figure shows that the brown establishments where displaced workers move to have a relatively similar wage premium compared to oil establishments, while green establishments offer a lower wage premium, and 'other' establishments an even lower wage premium. By comparing the coefficients in panel (c) to those in panel (a), we find that the change in establishment wage premium makes up about 6% (-0.006/-0.103) of the drop in labor earnings in the first year post displacement ($k = 1$) for workers who remain in the oil sector.³² Corresponding numbers for the first year post displacement for workers who move to the brown, green, or other sectors are 18%, 33%, and 36%, respectively.³³ This suggests that a large part of the earnings gaps across post-displacement sectors is due to establishment characteristics rather than worker characteristics. The establishment wage premium results are also consistent with the observation that displaced workers are more likely to move into the brown and green sectors than into other sectors as a share of total employment in the destination sectors, as shown in Figure 9, panel (b). These findings are consistent with the job displacement literature, which shows that the loss of establishment wage premiums explains a large portion of wage losses after displacement, as evidenced in Germany (Schmieder et al.,

³¹Appendix Table E.2 reports coefficients in table format.

³²See also panel B in Appendix Table E.2.

³³On average, the establishment premium makes up approximately 25% of the drop in labor earnings and 61% of the drop in hourly wages in $k = 1$ (Appendix Table E.2). Ellingsen et al. (2022) report a similar pattern based on mass layoffs in the petroleum industry, where employer premiums explain a larger fraction of earnings losses for displaced workers that leave the oil sector.

Figure 10: Event study estimates of the effects of job displacement on log of labor earnings, log of hourly wages, establishment wage premium, and skill distance, by post displacement sector.



Notes: Figure shows results from the estimation of equation (3) by post-displacement sector on four different outcomes: log of labor earnings (panel a), log of hourly wages (panel b), AKM establishment wage premiums (panel c), and skill distance (panel d). The establishment wage premium used as the outcome variable in panel (c) is based on the estimation of equation (5), where log hourly wage is used as the outcome variable (see section 4.3.1). The skill distance used as the outcome variable in panel (d) is calculated based on equation (7). Sample is restricted to individuals that are employed in the post period. The sample is trimmed using propensity score matching (see section 3.2.1 and section 4.2). Inflation adjusted values in NOK 2018. The specifications include individual fixed effects, age-year fixed effects, and local labor market-year fixed effects. Standard errors are clustered at the 5-digit NACE industry where the worker is employed in 2013. Numbers reported in the bottom left corner are average event study estimates and standard errors (in parentheses) from the estimation of equation (4).

2023) and other European countries (Bertheau et al., 2023; Barreto et al., 2024).

Second, we assess the skill distance between the occupations that displaced workers transition into and their original 2013 occupation, where skill distance is calculated based on equation (7). As shown in Figure B.10, the distribution of the skill distance ranges from around 0 to 10, with a mean of 4.2. Figure 10, panel (d) shows the estimated effect of job displacement on the skill distance between the post-displacement occupation of oil workers and their original occupation in 2013. Estimates suggest that the skill distance is minimal for workers who secure employment within the oil industry post-displacement. Conversely, those moving into the brown sector encounter a more substantial skill distance, which slightly increases for individuals entering the green sector. The greatest skill distance is

observed among workers transitioning into the ‘other’ sector.³⁴ These findings align with the earlier observation that displaced workers are more inclined to enter brown and green sectors than other industries, relative to the total employment in the destination sectors, as illustrated in Figure 9, panel (b). This pattern suggests that workers may prefer sectors where their existing occupation-specific skills are more transferable, thereby minimizing the skill distance and potentially mitigating earnings losses. These findings align with Barreto et al. (2023), who identify that skill distance is a key factor explaining earnings losses of displaced workers from carbon-intensive industries in Germany.

5.3.3 Decomposition of the earnings gap between post-displacement sectors

To investigate how much of the earnings gap between post-displacement sectors can be attributed to differences in observable worker characteristics, such as sorting effects, and how much reflects changes in observable job characteristics, we apply an Oaxaca-Blinder decomposition method (see e.g., Barreto et al., 2023, 2024). We begin by calculating the change in average outcomes for each displaced oil worker i as the difference-in-differences between the displaced oil worker (D) and their matched non-oil control (C) before and after displacement:

$$\Delta y_i = (\bar{y}_{i,\text{after}}^D - \bar{y}_{i,\text{before}}^D) - (\bar{y}_{i,\text{after}}^C - \bar{y}_{i,\text{before}}^C), \quad (8)$$

where $\bar{y}_{i,\text{after}}^D$ and $\bar{y}_{i,\text{before}}^D$ denote the average outcomes for displaced oil worker i after and before displacement, and $\bar{y}_{i,\text{after}}^C$, $\bar{y}_{i,\text{before}}^C$ refer to the corresponding outcomes for their matched control. We then examine how these individual treatment effects (Δy_i) vary depending on the post-displacement destination – whether the worker remains in the oil sector (Δy_i^{Oil}) or transitions into the brown, green, or other sectors. We denote the latter sectors as $S \in [B, G, O]$ and the associated earnings for each post-displacement sector as Δy_i^S . We then estimate the following linear models of various observable characteristics measured at the establishment, worker, or local labor market level (denoted by X_i^{Oil} and X_i^S , respectively):

$$\begin{aligned} \Delta y_i^{\text{Oil}} &= X_i^{\text{Oil}} \beta_{\text{Oil}} + \nu_i^{\text{Oil}} \\ \Delta y_i^S &= X_i^S \beta_S + \nu_i^S \end{aligned} \quad (9)$$

where ν_i^{Oil} and ν_i^S are error terms. The observable characteristics are measured in the year prior to the displacement event, with the exception of establishment premiums and

³⁴Note that the skill distances between oil jobs and green jobs – and between oil jobs and other jobs – are smaller when based on observed job transitions than when calculated using employment-weighted averages from 2013 B.11. This suggests that relying on average-based comparisons may overstate the true skill distances between groups of jobs.

skill distance, which are measured as the post-pre difference.³⁵

Using equations (8) and (9), the Oaxaca-Blinder decomposition differences the mean treatment effects for displaced oil workers that transition into a non-oil sector S , Δy_i^S , and workers that remain in the oil sector, Δy_i^{Oil} :

$$\Delta \bar{y}_i^S - \Delta \bar{y}_i^{\text{Oil}} = (X^S - X^{\text{Oil}})\hat{\beta}^S + X^{\text{Oil}}(\hat{\beta}^S - \hat{\beta}^{\text{Oil}}). \quad (10)$$

The first term on the right-hand side, referred to as the “explained” part, captures the part of the earnings gap across post-displacement sectors that can be accounted for by observable differences in worker and job characteristics (*composition effect*). This includes worker characteristics such as age and education, initial job characteristics such as occupation, and local labor market characteristics such as the unemployment share. Here, we are particularly interested in examining the role of employer wage premium in the *new* job relative to the 2013 oil job, as well as the skill distance between the new and old job. The decomposition exercise enables us to quantify the contribution of these specific characteristics to the observed differences in earnings outcomes across post-displacement sectors.

The second term, known as the “unexplained” part, captures the earnings gap between post-displacement sectors that cannot be attributed to observable differences in worker and firm characteristics (*structural effect*). Instead, it reflects structural differences in how these characteristics influence earnings outcomes, such as varying returns to experience or education between sectors. Additionally, it may encompass the effects of unobserved factors that are not included in the analysis, such as individual preferences or unmeasured skills.³⁶

Since workers may appear in multiple sectors after displacement, we include all workers who at any point during the post-displacement period are employed in the sector of interest. To ensure consistency, we restrict the sample to workers who are employed in the specified sector for at least 50% of the post-displacement period.³⁷

Figure 11 shows the decomposition of log labor earnings across three post-displacement sectors (brown, green, other).³⁸ Focusing on workers who move to the green sector (panel b), the included covariates explain about 87% of the earnings gap between workers who stay in oil and workers who move to the green sector. A lower employer wage premium in the post-displacement job is the single most important explanation for the earnings gap,

³⁵The latter two variables are measured as differences, as we are interested in examining to what extent establishment premiums and skill requirements in the *new* jobs explain potential earnings gaps.

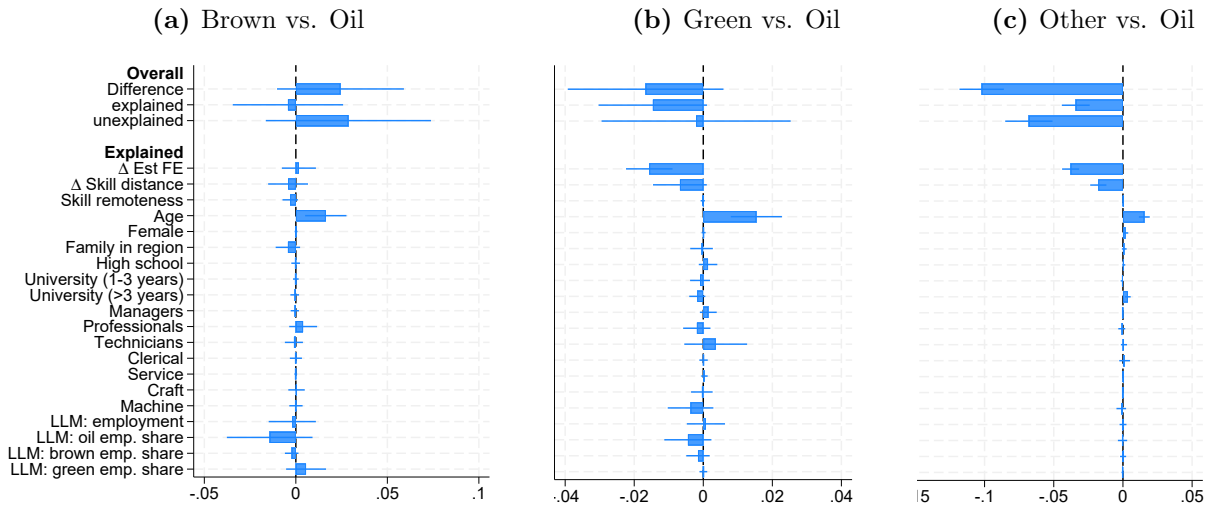
³⁶The Oaxaca-Blinder decomposition is known to be sensitive to the choice of the reference group. In our results, we use workers who remain in the oil sector as the reference group. We estimate the decomposition separately for workers who transition to brown jobs, green jobs, and other jobs.

³⁷Note that these restrictions differ from those used in the event study shown in Figure 10, where we restrict the sample to workers employed in any given post-displacement year. This means that the average treatment effects across sectors are not identical across these two settings.

³⁸Appendix Table F.1 shows the corresponding coefficients.

explaining around 92% of the gap. A larger skill distance to the pre-displacement occupation also plays a significant role, explaining around 41% of the earnings gap. Differences in workers' age reduce the explained earnings gap, as workers who move to green jobs are younger and being younger is associated with a lower earnings loss – conditional on the other explanatory variables. Gender, education, occupation, and local labor market conditions have relatively little explanatory power. Few relevant jobs in the local labor market prior to the oil price shock, measured by *skill remoteness* (Macaluso, 2025), could potentially lead to involuntary transitions to non-oil sectors, making it more likely to take an earnings hit. Conditional on the other explanatory variables, however, differences in skill remoteness do not explain the earnings gap across post-displacement sectors.

Figure 11: Oaxaca-Blinder Decomposition of Log Labor Earnings



Notes: The figure shows results of the Oaxaca-Blinder decomposition (eq. 10) of log labor earnings. All explanatory variables are measured in 2013, with the exception of establishment FE and skill distance, which are measured as the change over time relative to the control group (i.e., the DiD). LLM denotes local labor market. Skill remoteness is constructed following Macaluso (2025).

Examining displaced workers moving to the ‘other’ sector (panel c), the included covariates explain about 33% of the earnings gap between displaced workers remaining in oil and those moving to the ‘other’ sector. A lower employer wage premium in the post-displacement job is the single most important explanation for the earnings gap, explaining around 37% of the gap. A larger skill distance to the pre-displacement occupation plays a smaller role, explaining around 17% of the earnings gap. Other worker characteristics, with the exception of age, do not contribute much to explaining the earnings gap.

Appendix F provides a more detailed discussion of how observable characteristics influence the treatment effects for workers who remain in the oil sector and those who transition to non-oil sectors.

Overall, our findings are consistent with recent research emphasizing the role of establishment wage premiums in explaining a substantial portion of displaced workers’ earnings

declines across sectors and countries (e.g., [Bertheau et al., 2023](#)). For example, in Germany and across OECD countries, about two-thirds of the earnings gap between displaced workers from high-emission industries relative to those from low-emission industries could be explained by workers’ and establishments’ characteristics ([Barreto et al., 2023, 2024](#)).

6 Conclusion

This paper examines the labor market consequences of the green transition by analyzing the impact of the 2014 oil price shock on Norwegian oil workers. The oil price shock serves as a unique natural experiment for investigating the labor market effects of a transition away from fossil fuels. Unlike policy-induced transitions, which may unfold gradually and be shaped by political and economic trade-offs, the oil price shock led to an abrupt and exogenous contraction in the fossil fuel sector. This setting allows us to isolate the effects of a large-scale decline in oil employment, mirroring key aspects of the labor market disruptions that would likely occur under ambitious climate policies, such as carbon pricing, fossil fuel divestment, and regulatory restrictions. Moreover, because the shock was exogenous to the Norwegian economy – originating from a combination of global oversupply and weakening demand – it enables us to examine worker displacement and reallocation dynamics in a way that is less confounded by endogenous policy responses or firm-level adaptation strategies. Thus, the oil price shock serves as an informative proxy for studying the employment risks and transitional costs associated with a broader green transition.

Using rich administrative data and an event study approach, we document substantial labor earnings losses among displaced oil workers that persist even nine years post-displacement, with effects varying by education, age, and gender. Our findings suggest that the transferability of skills between occupations in the oil and green sectors may be limited, with establishment wage premiums playing a significant role in shaping labor market outcomes. At the same time, our results suggest that green jobs are closer in the occupation-specific skill and wage premium space to oil jobs compared to other (non-oil, non-brown) jobs.

Our results contribute to the broader literature on job displacement, which consistently finds that mass layoffs result in significant and often persistent earnings losses. However, the magnitude of these losses varies across contexts. The earnings losses for displaced oil workers who exit carbon-intensive sectors are larger than for those who remain. These findings are consistent with the argument that earnings losses are particularly severe in contexts where rent-sharing plays an important role, as proposed by [Jacobson et al. \(1993\)](#). Our study further supports the hypothesis that the loss of firm-specific rents is a critical factor behind wage losses following displacement. The transition of displaced workers from higher-paying to lower-paying employers appears to be a key driver of post-

displacement wage declines. This mechanism is particularly relevant in the oil sector, where high establishment wage premiums may not be easily replicated in alternative employment.

These results underscore the importance of considering worker-level transitional costs in the shift to a low-carbon economy. Policies aimed at mitigating these costs should consider both occupational skill mismatches and wage differentials between sectors. Future research should further explore the mechanisms behind labor market frictions in the green transition, including the role of firm dynamics, regional labor demand, and long-term career trajectories of displaced workers. Understanding these dynamics is crucial for designing policies that balance economic efficiency and impact to the most vulnerable workers in the transition toward a green economy.

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Online Supporting Material

For “Labor Market Impacts of the Green Transition: Evidence from a Contraction in the Oil Industry”

by Cloé Garnache, Elisabeth T. Isaksen, and Maria Nareklishvili

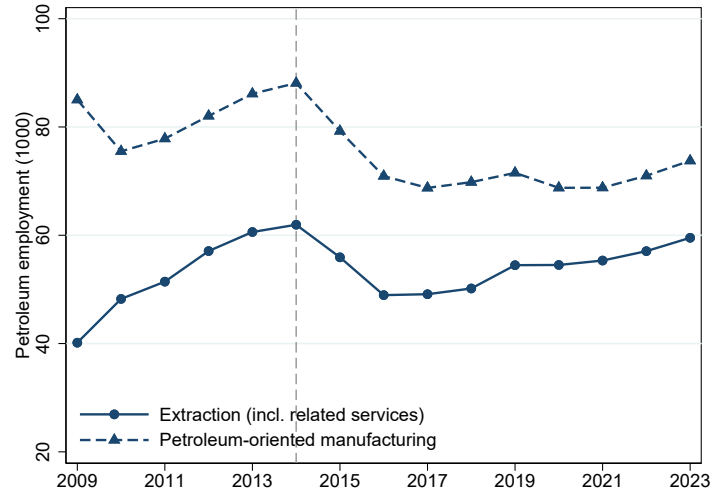
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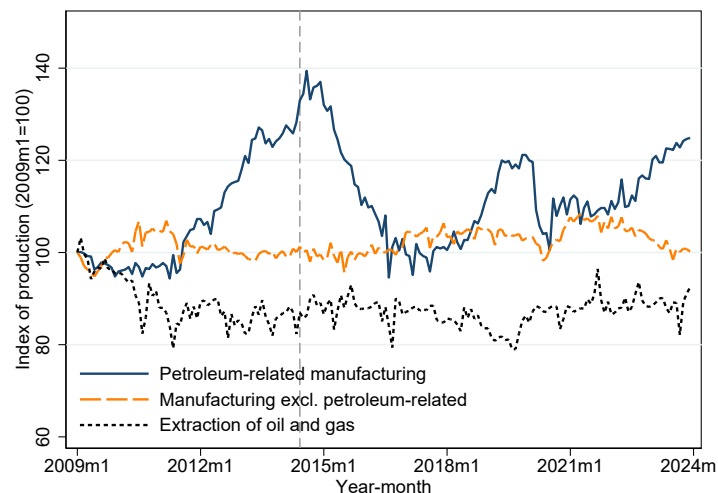
Appendix A Background on the oil price shock

Figure A.1: Employment in the Norwegian oil sector, by two sub-sectors (2009–2023)



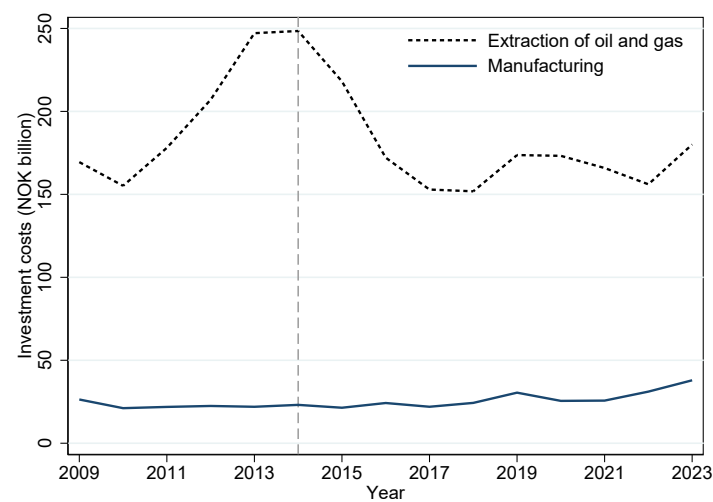
Notes: Figure shows aggregate employment (in 1000) from 2009 to 2023 for two aggregate groups of oil industries: (i) the extraction of crude oil and gas and related services (SN 2007: 06, 09.101, 09.109, 49.450), and (ii) petroleum-oriented manufacturing industries (the remaining industries listed in Figure B.1). The former group corresponds to the formal definition used by Statistics Norway when reporting annual statistics on oil and gas activity. The latter group corresponds to industries that Statistics Norway have defined as petroleum-oriented manufacturing. The industrial classification follows the Norwegian standard industrial classification (SN 2007), which builds on EU's industrial classification NACE Rev. 2 and UN's industrial classification ISIC Rev. 4. Employment reflects employed persons per 4th quarter each year. Source: [Statistics Norway \(2025\)](#).

Figure A.2: Production volumes in Norwegian manufacturing and extraction (2009–2023)



Notes: Figure shows an index of production (January 2009 = 100) for three aggregated industries. Vertical line indicates June, 2014. Source: Statistics Norway, Table 07095: <https://data.ssb.no/api/v0/en/table/07095/>.

Figure A.3: Investment costs in Norwegian manufacturing and extraction in NOK billions (2009–2023)

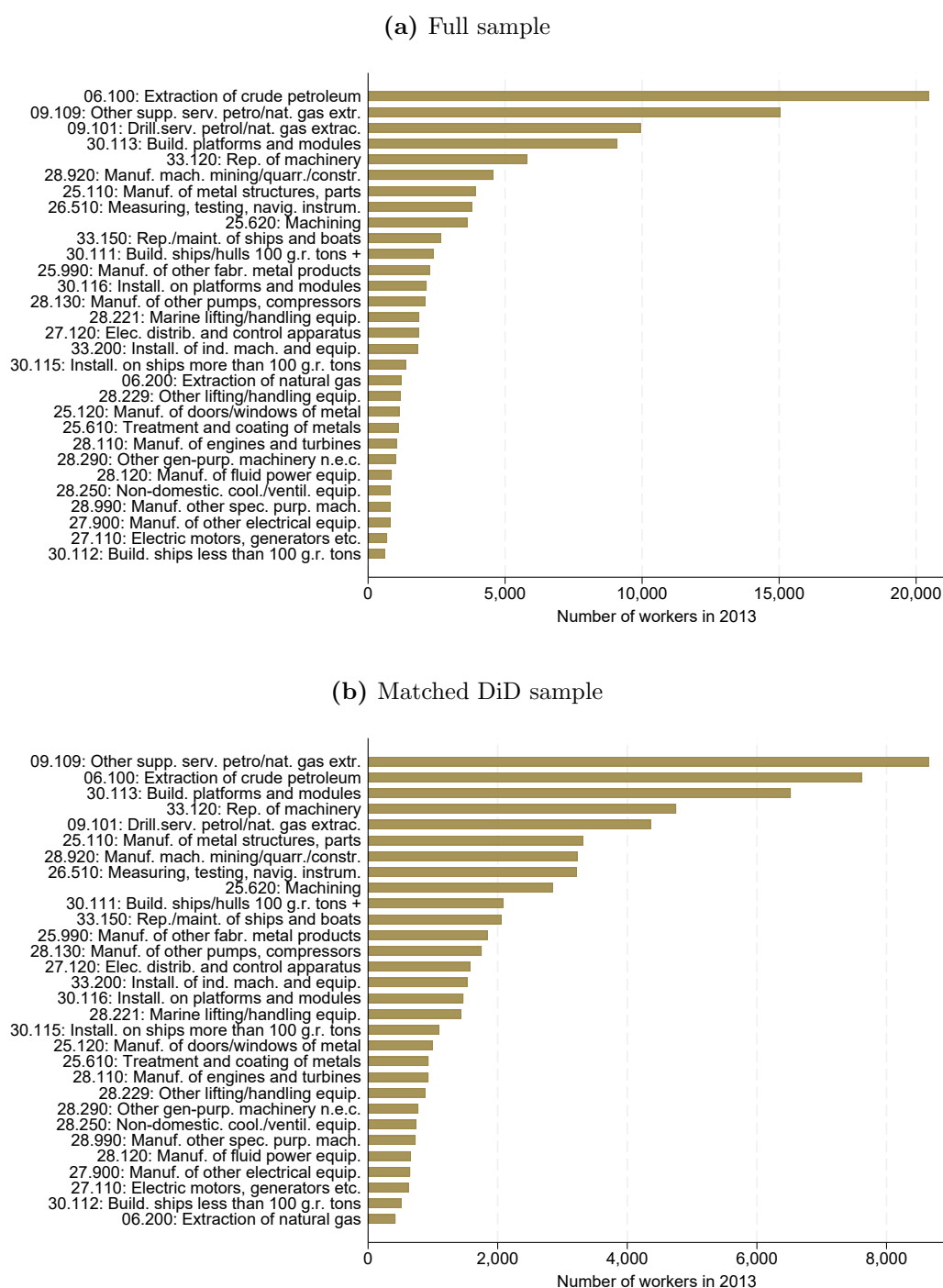


Notes: The figure shows investment costs in NOK billions (in 2018 prices) for two aggregated industries. Source: Statistics Norway, Table 07155: <https://data.ssb.no/api/v0/en/table/07155/>.

Appendix B Data and descriptives

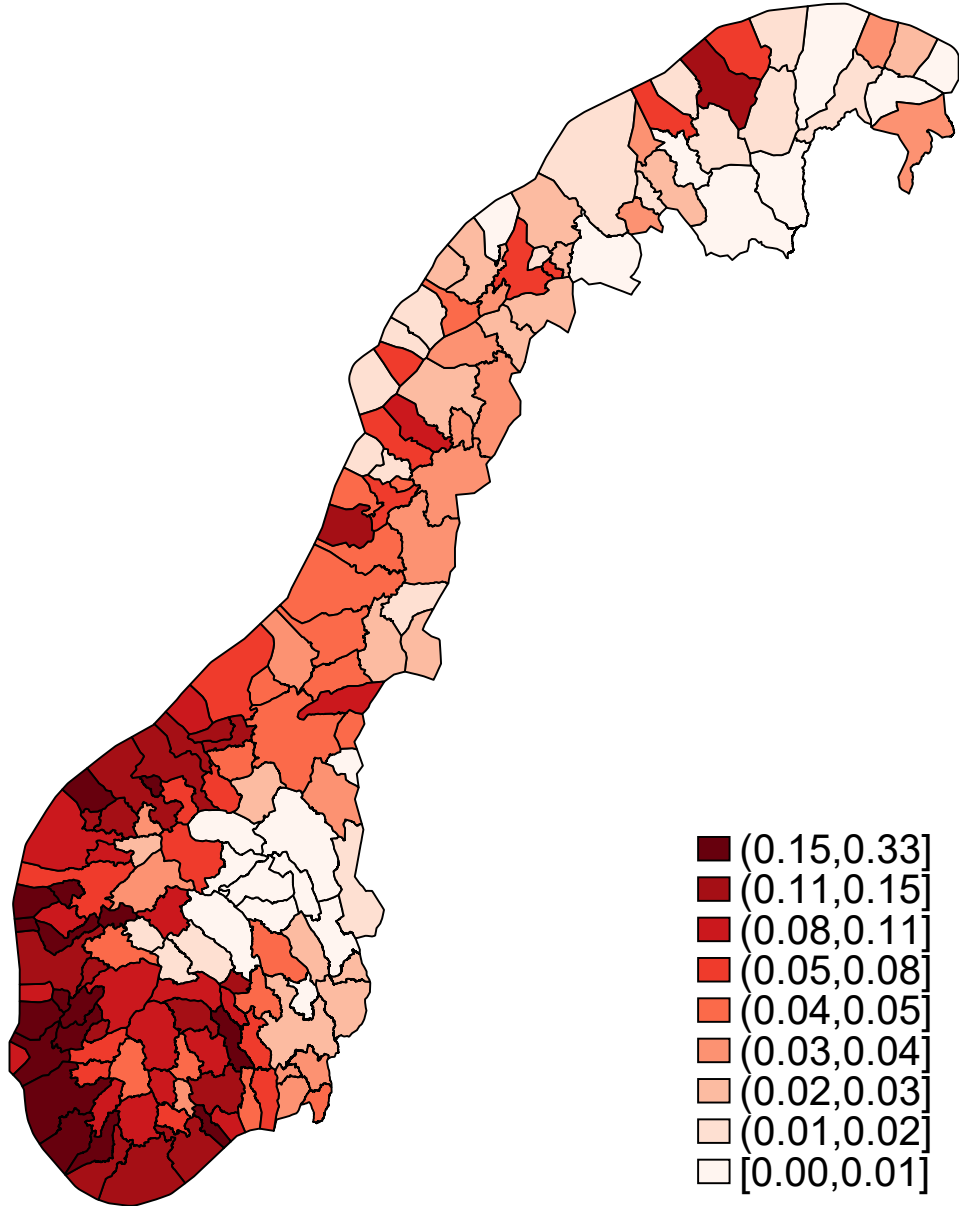
B.1 Treatment and control group

Figure B.1: Number of workers in oil, by industry



Notes: Definition of petroleum related industries from Statistics Norway. Calculations are based on restricted administrative data. Panel (a) show results from the full sample of workers. Panel (b) show results from the matched DiD sample.

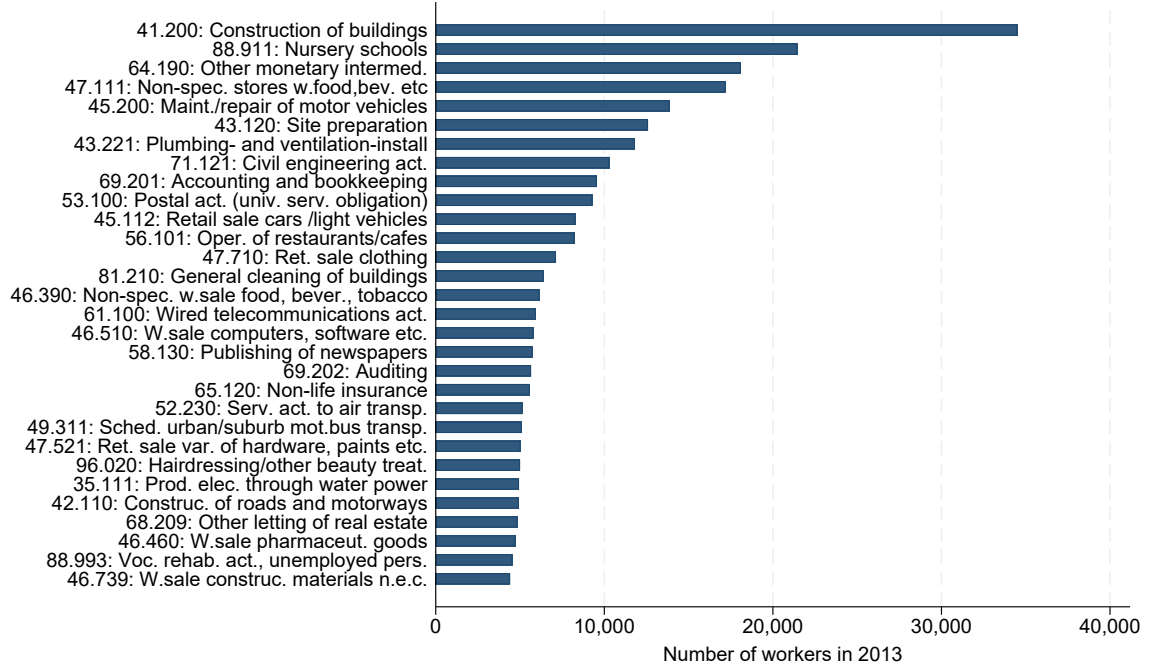
Figure B.2: Oil workers as share of local labor market workforce



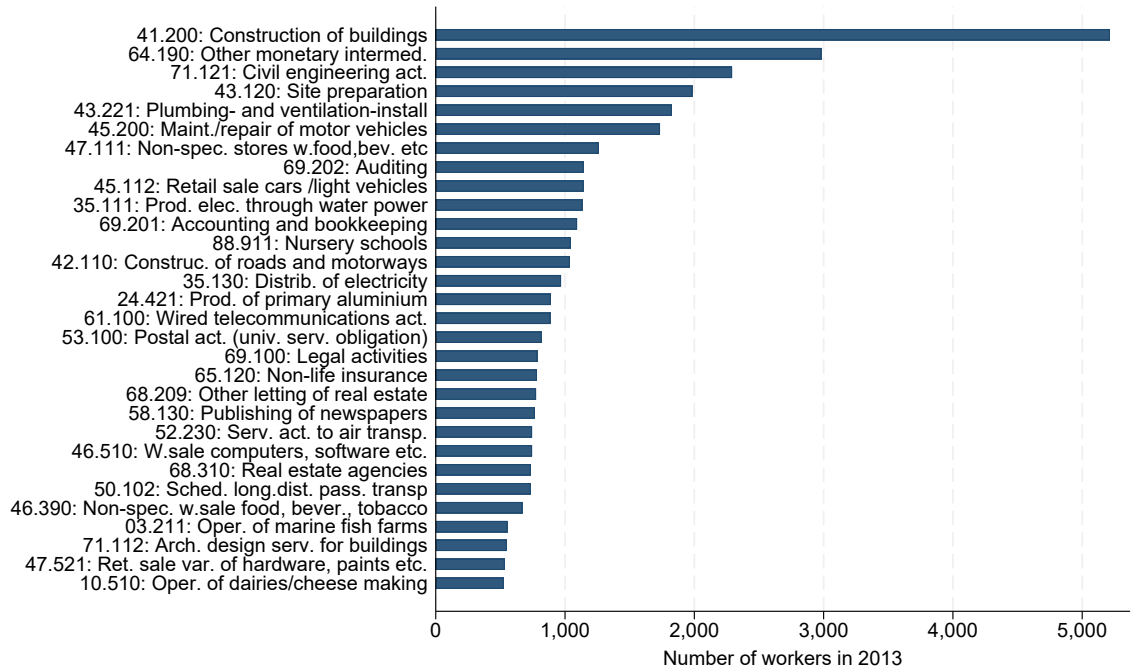
Notes: The figure shows oil workers as a share of the local labor market workforce in 2013. Population is restricted to full-time workers. The definition of local labor markets is based on [Gundersen et al. \(2019\)](#). There are in total 159 local labor markets in Norway.

Figure B.3: Number of workers in non-oil, by industry

(a) Full sample



(b) Matched DiD sample



Notes: Definition of non-petroleum related industries from [IRIS \(2015\)](#). Calculations are based on restricted administrative data. Panel (a) show results from the full sample of workers. Panel (b) show results from the matched DiD sample.

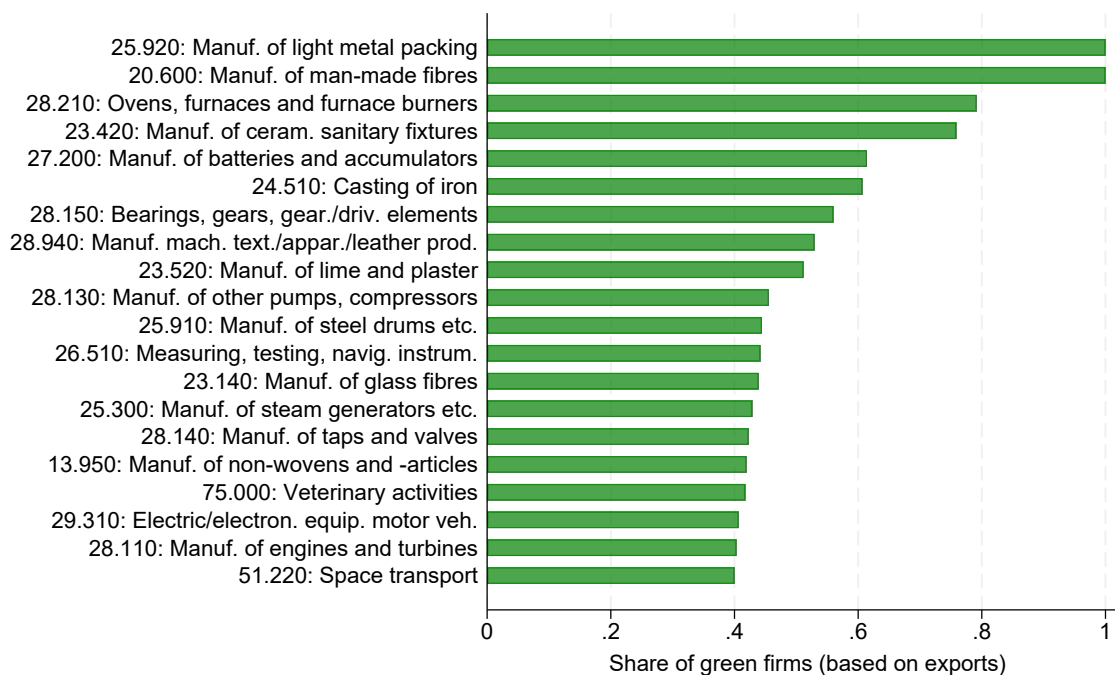
B.2 Classification of green jobs

Table B.1: Green industries based on industry code

Code	Title
35.111	Production of electricity through water power
35.112	Production of electricity through wind power
35.113	Production of electricity through biofuel
35.120	Transmission of electricity
35.130	Distribution of electricity
35.140	Trade of electricity
35.300	Steam and air conditioning supply
36.000	Water collection, treatment and supply
37.000	Sewerage
38.110	Collection of non-hazardous waste
38.120	Collection of hazardous waste
38.210	Treatment and disposal of non-hazardous waste
38.220	Treatment and disposal of hazardous waste
38.310	Dismantling of wrecks
38.320	Recovering of sorted materials
39.000	Remediation activities and other waste management services
42.210	Construction of utility projects for fluids
42.220	Construction of utility projects for electricity and telecommunications

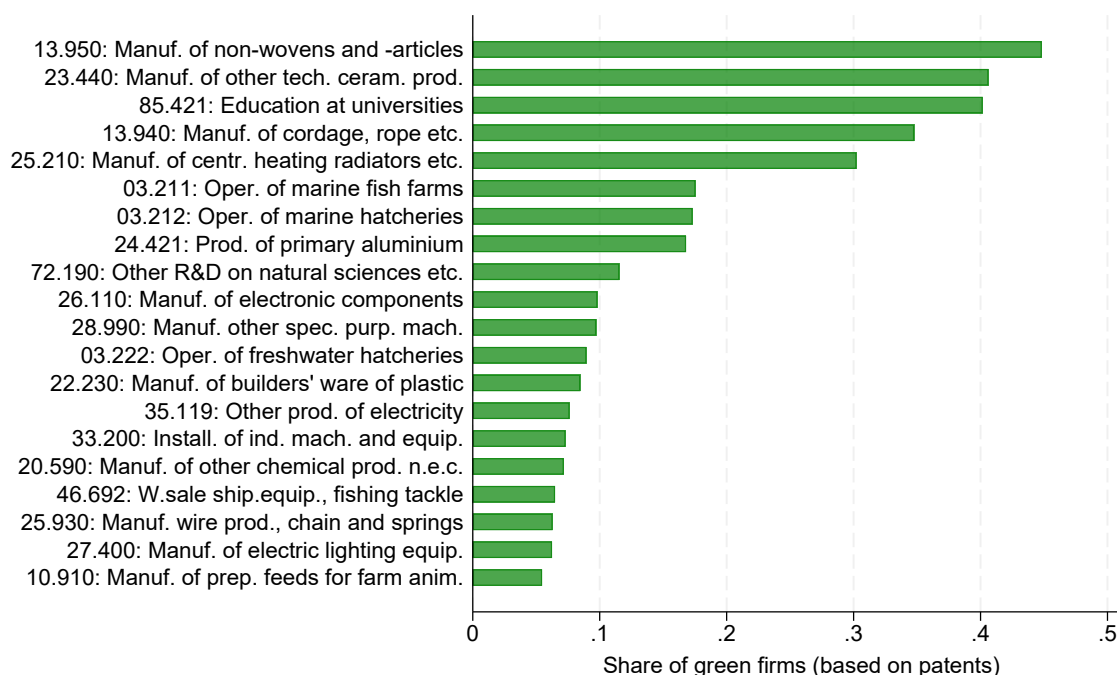
Note: The table lists the 5-digit industries defined as green. The industry codes correspond to the Sn2007 classification.

Figure B.4: Green export share



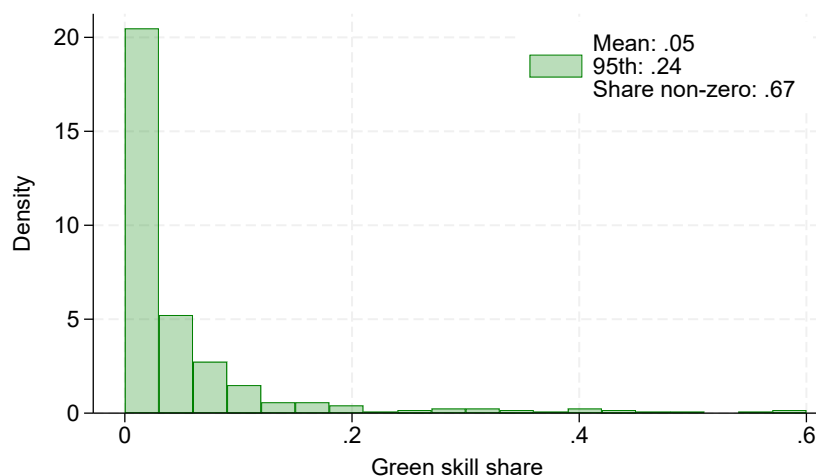
Notes: The figure shows the average share of green firms in a 5 digit industry based on export data. A firm is defined as green if its average green export share between 2009 and 2023 is above 50 percent. The list is restricted to the 20 industries with the highest share of green firms.

Figure B.5: Green patent share



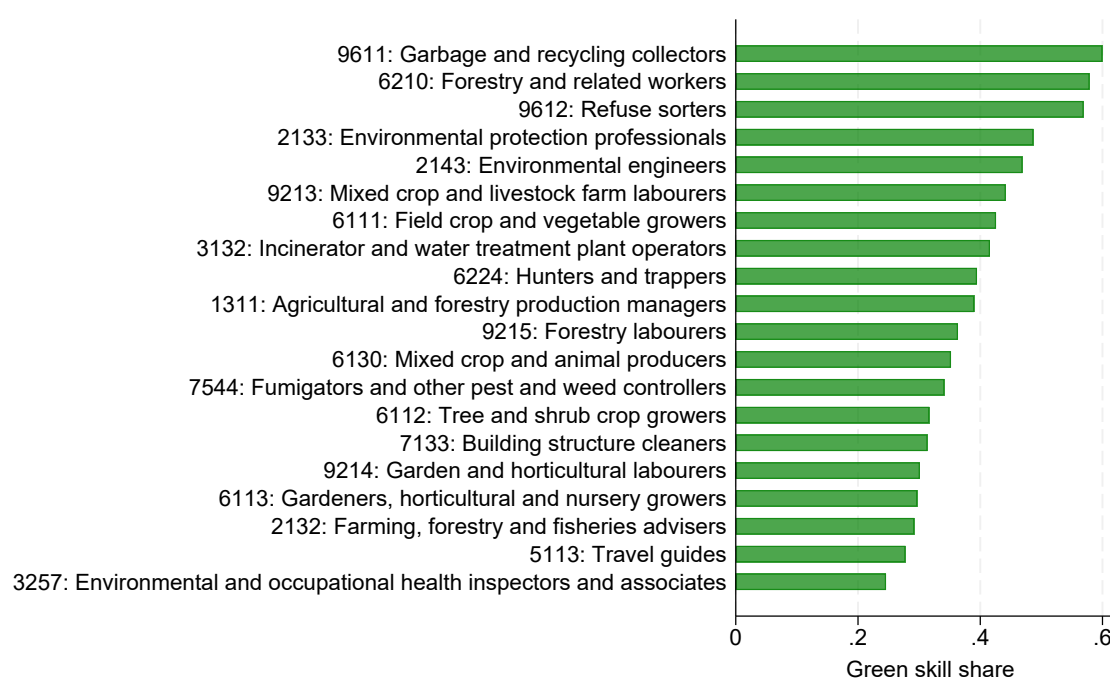
Notes: The figure shows the average share of green firms in a 5 digit industry based on patent data. A firm is defined as green if its average green patent share between 2009 and 2021 is above 50 percent. A patent is tagged as green if it has the Y02 tag. The list is restricted to the 20 industries with the highest share of green firms.

Figure B.6: Histogram of the green skill share of occupations



Notes: Figure shows the distribution of the green skill share of 4 digit STYRK occupations. Green skills are based on the definition from ESCO.

Figure B.7: Green occupations



Notes: The figure displays 4-digit occupations with a green skill share in the 95th percentile, i.e, 24% or above. Occupations are based on the STYRK-08 classification, which builds on ISCO-08. The share of green skills are calculated based on ESCO v1.1.1.

B.3 Classification of brown, non-oil jobs

Table B.2: Brown industries based on EU ETS reporting

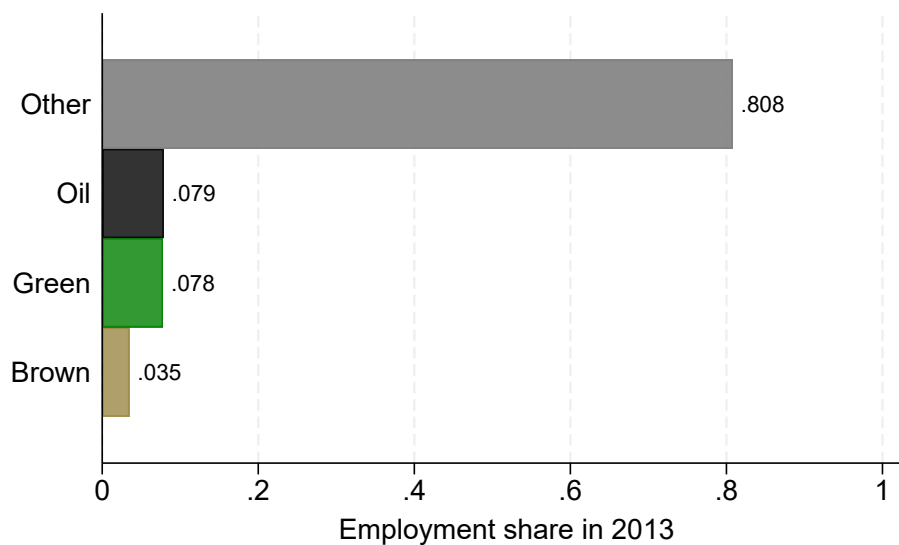
Code	Title
08.990	Other mining and quarrying n.e.c.
10.209	Other proc./preserv. of fish etc.
10.411	Manuf. of crude fish oils and fats
10.510	Oper. of dairies/cheese making
10.910	Manuf. of prep. feeds for farm anim.
16.210	Veneer sheets, wood-based materials
17.110	Manufacture of pulp
17.120	Manuf. of paper and paperboard
17.210	Manuf. of corrugat. paper and -board
17.220	Manuf. of household and sanitary goods
17.290	Manuf. of other art. of paper/-board
19.200	Manuf. of refined petroleum prod.
20.120	Manuf. of dyes and pigments
20.130	Manuf. of other inorg. basic chem.
20.140	Manuf. of other organic basic chem.
20.150	Fertilisers and nitrogen compounds
20.160	Manuf. of plastics in primary forms
21.100	Manuf. of basic pharm. products
22.210	Manuf. of plastic plates, sheets etc.
23.140	Manuf. of glass fibres
23.320	Construction prod. in baked clay
23.510	Manuf. of cement
23.520	Manuf. of lime and plaster
23.620	Plaster prod. for construc. purposes
23.990	Manuf. of other non-met. min. prod.
24.101	Manuf. of basic iron and steel
24.102	Manuf. of ferro-alloys
24.421	Prod. of primary aluminium
24.430	Lead, zink and tin production
35.114	Prod. elec. through natural gas
35.210	Manuf. of gas
35.220	Distrib. gaseous fuels through mains

Note: This table lists the 5-digit industries defined as brown based on reporting to the EU ETS. The industry codes correspond to the Sn2007 classification. The following industries are excluded from the brown definition despite reporting activity: 70.220 (Business and other management), 52.230 (Service activities incidental to air transportation), 46.710 (Wholesale of solid, liquid, and gaseous fuels), 41.109 (Other development and sale of real estate), 38.210 (Treatment and disposal of non-hazardous waste), 35.300 (Steam and air conditioning supply), 35.111 (Production of electricity through water power), and 35.120 (Transmission of electricity). Oil industries are also excluded from the definition of brown.

B.4 Sector composition in full and matched samples

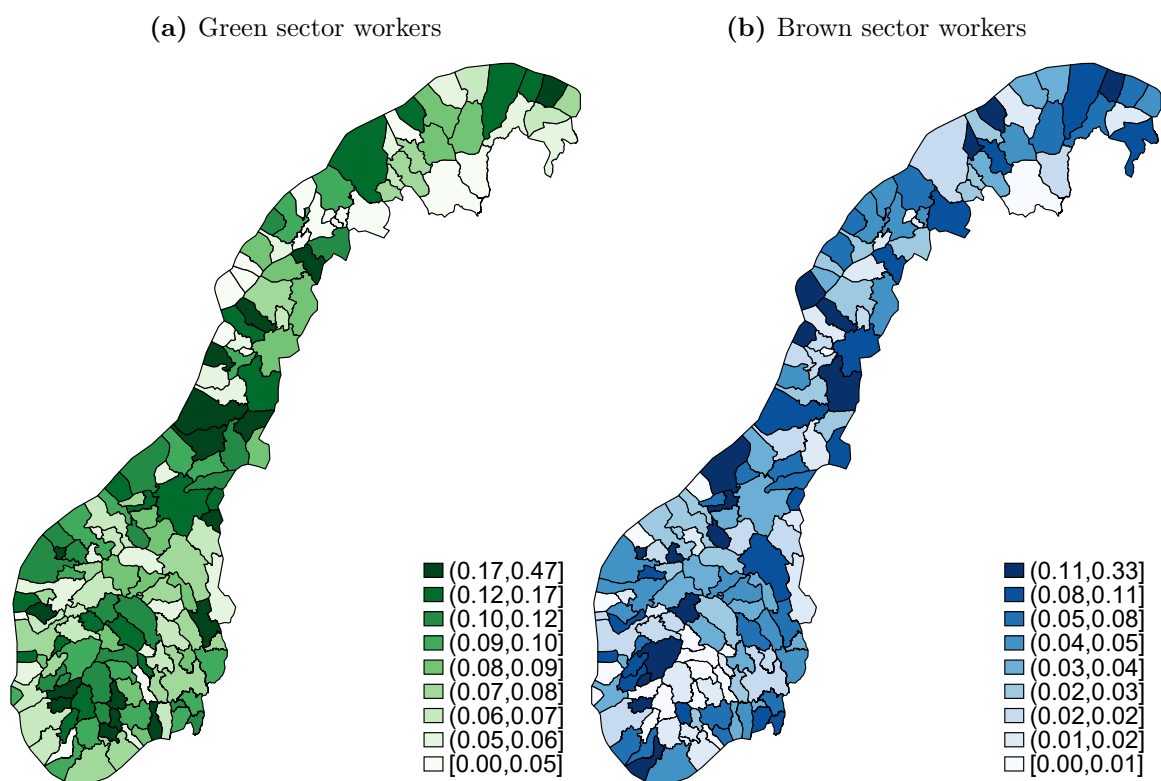
Figure B.8 depicts the size of the oil and green sectors relative to the rest of the economy in Norway. In the full sample, the green and oil industries are small and of comparable sizes. In the trimmed sample, the oil industry is by construction of the same size as the green sector and the rest of the economy together. The implication is that now the green sector is much smaller than the oil sector.

Figure B.8: Share of workers in green, brown, oil, and other, 2013.



Notes: Figure shows employment shares by four sectors (oil, green, brown, and other) in 2013. The numbers are based on the universe of full-time workers in 2013.

Figure B.9: Green and brown sector workers as share of local labor market workforce (2013)



Notes: The figure shows green-sector workers (panel a) and brown-sector workers (panel b) as a share of local labor markets in 2013. The population is restricted to full-time workers.

B.5 Occupation skills in O*NET

Table B.3: Complete list of O*NET skills

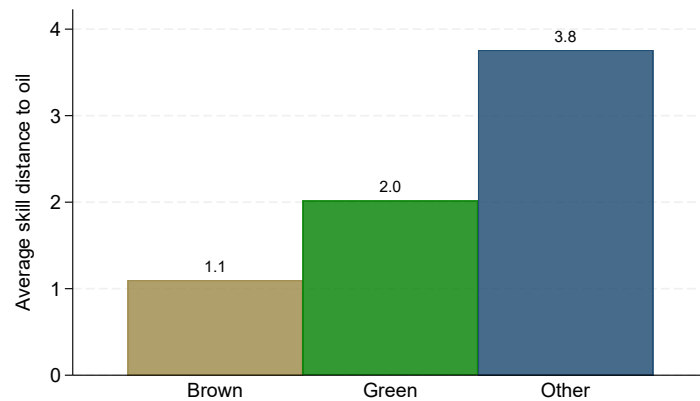
Active Learning
Active Listening
Complex Problem Solving
Coordination
Critical Thinking
Equipment Maintenance
Equipment Selection
Installation
Instructing
Judgment and Decision Making
Learning Strategies
Management of Financial Resources
Management of Material Resources
Management of Personnel Resources
Mathematics
Monitoring
Negotiation
Operation Monitoring
Operation and Control
Operations Analysis
Persuasion
Programming
Quality Control Analysis
Reading Comprehension
Repairing
Science
Service Orientation
Social Perceptiveness
Speaking
Systems Analysis
Systems Evaluation
Technology Design
Time Management
Troubleshooting
Writing

Figure B.10: Histogram of skill distance



Notes: Figure shows the distribution of the skill distance between 349 occupations. Skills are based on the 35 skills defined by O*NET. Occupations are based on the STYRK-08 classification, which again is based in the ISCO-08 classification. Skill distance is calculated as the Euclidean distance.

Figure B.11: Skill distance between oil jobs and brown, green, and other jobs

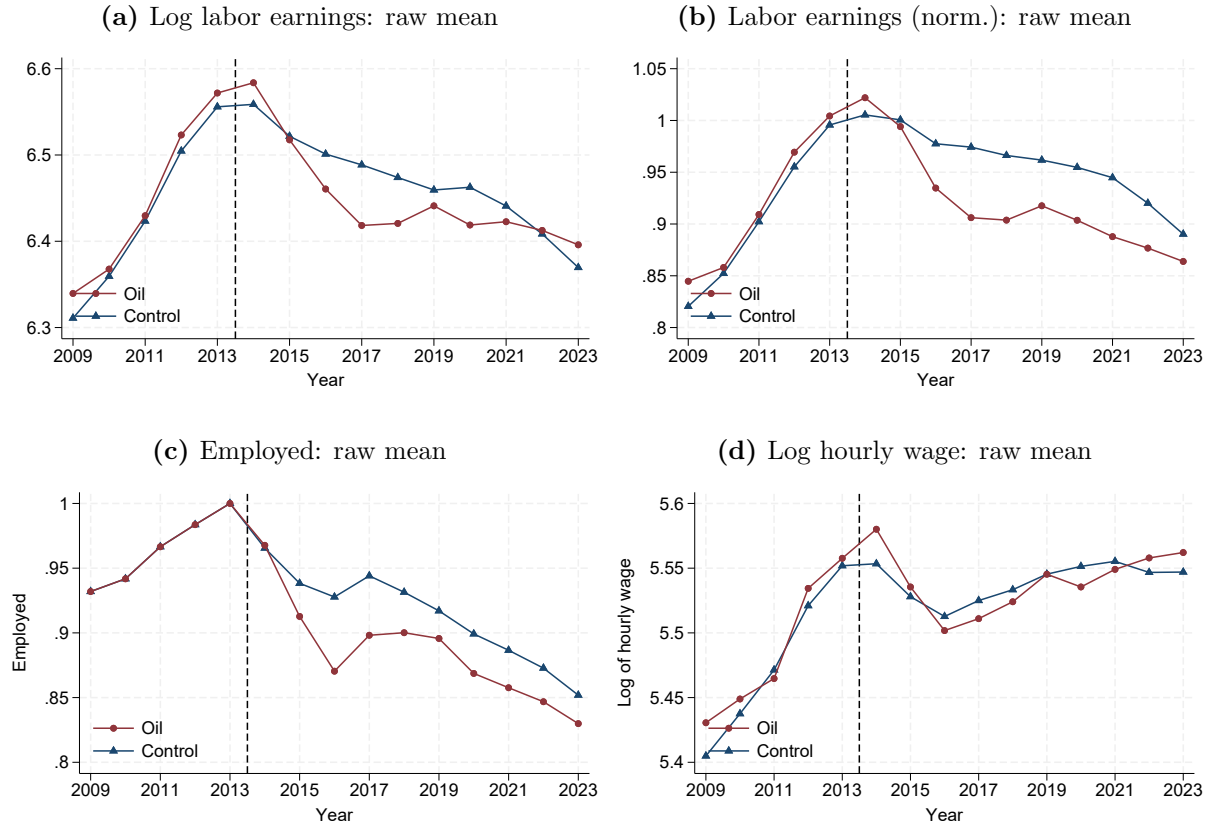


Notes: Figure shows the average, employment-weighted skill distance between workers in oil jobs and workers in brown, green, and other jobs using employer-employee data from 2013. Skills are based on the 35 skills defined by O*NET. Occupations are based on the STYRK-08 classification, which again is based in the ISCO-08 classification. Skill distance is calculated as the Euclidean distance.

Appendix C Direct effects of the oil price shock - supporting results

C.1 Raw means

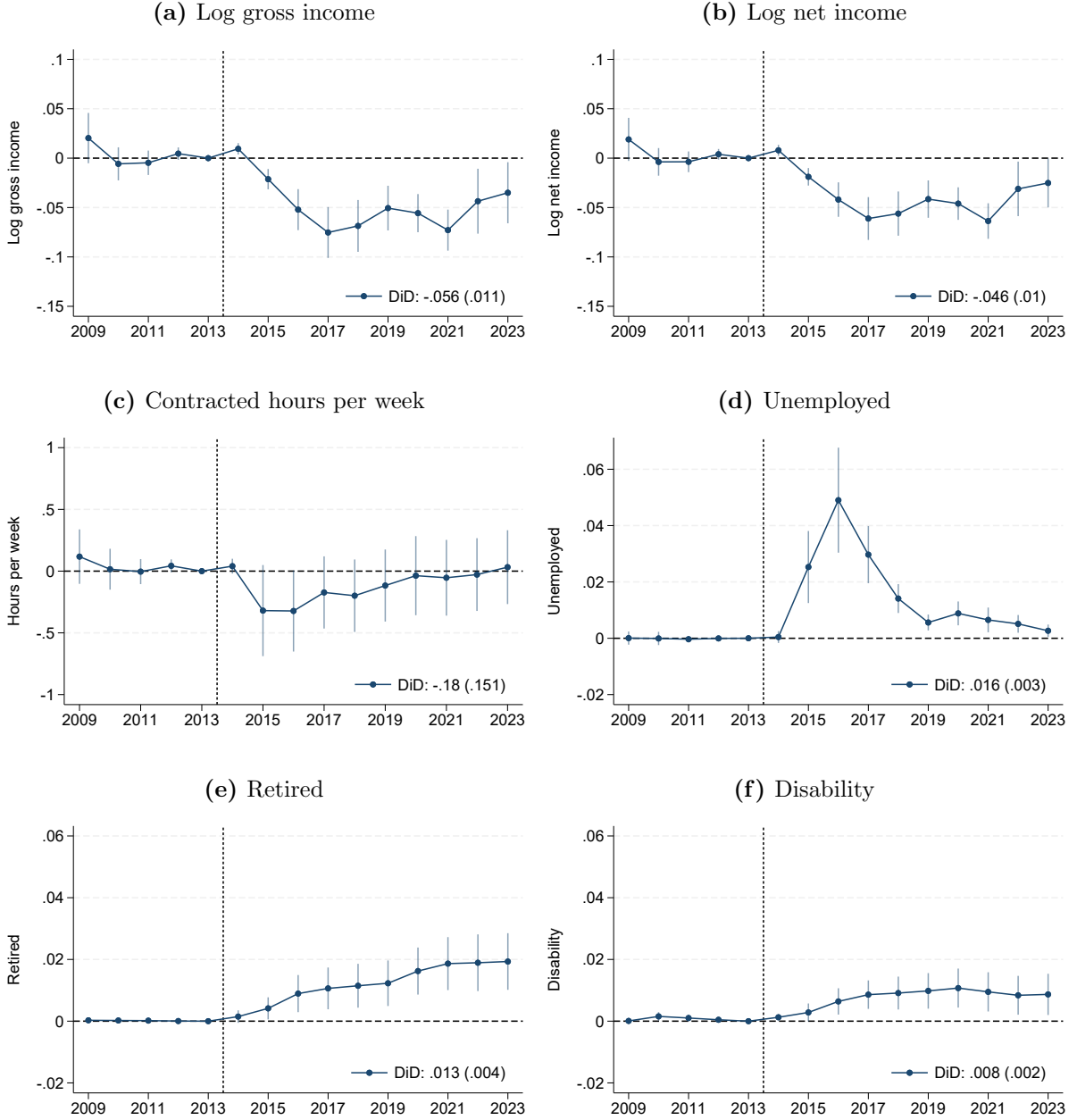
Figure C.1: Yearly raw means of employment, labor earnings and hourly wage



Notes: Figure shows the yearly raw means of on employment, log labor earnings, normalized labor earnings (relative to 2013), and hourly wages.

C.2 Yearly DiD estimates for additional outcomes

Figure C.2: Yearly DiD estimates of the effect of the oil price shock on normalized labor earnings, log gross income, log net income, hours worked, unemployed, retired, or receiving disability benefits



Notes: Figure shows the yearly DiD estimates from equation (2) on log wages, log net income, number of individuals employed, unemployed, retired, or receiving disability benefits. Numbers reported in the bottom left corner are average DiD treatment effects and standard errors (in parentheses) from the estimation of equation (1). The sample is trimmed using propensity score matching based on labor earnings, log hourly wages, age, gender, education code (1-digit), and county of residence. Labor earnings is defined as the sum of wages, business income, parental allowance, sick pay, and unemployment benefits. Inflation adjusted values in NOK 2018. All regressions include worker fixed effects, age-by-year fixed effects, and local labor market-by-year fixed effects. Local labor market refers to the location of residence in 2013. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013.

C.3 Robustness of DiD estimate to different specifications

Table C.1: DiD estimates of the effects of the oil price shock on employment, log labor earnings, and log hourly wage.

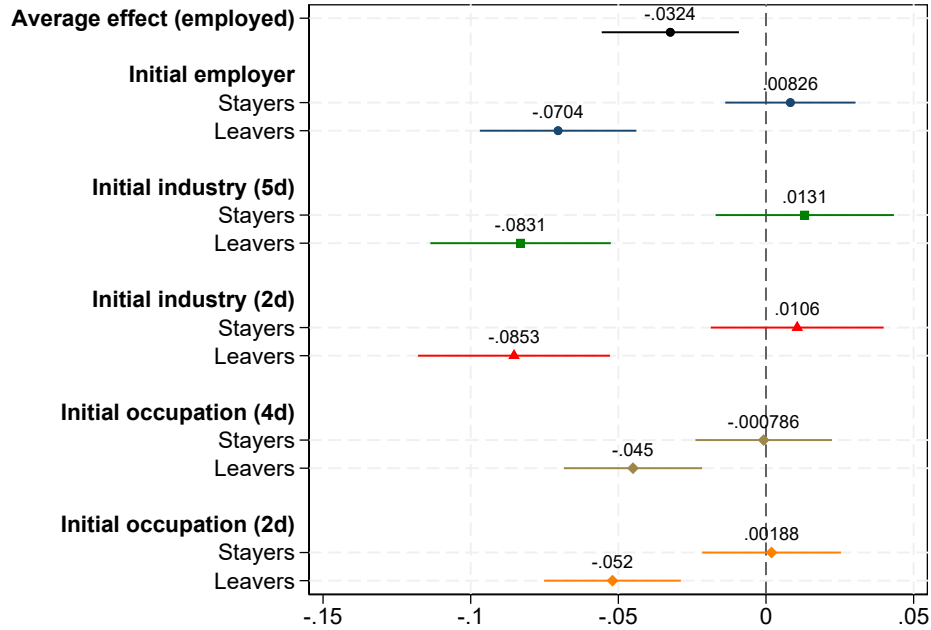
	(1)	(2)	(3)	(4)	(5)
Panel A: Employed					
Oil \times post	-0.0323*** (0.00521)	-0.0328*** (0.00513)	-0.0328*** (0.00495)	-0.0326*** (0.00482)	-0.0323*** (0.00475)
N (individual-year)	1,961,741	1,961,741	1,961,741	1,961,741	1,961,741
Panel B: Log labor earnings					
Oil \times post	-0.0460*** (0.01700)	-0.0542*** (0.01526)	-0.0542*** (0.01270)	-0.0571*** (0.01287)	-0.0559*** (0.01300)
N (individual-year)	1,894,481	1,894,481	1,894,481	1,894,481	1,894,481
Panel C: Normalized labor earnings					
Oil \times post	-0.0564*** (0.01059)	-0.0574*** (0.01221)	-0.0573*** (0.01045)	-0.0573*** (0.01039)	-0.0561*** (0.01063)
N (individual-year)	1,952,102	1,952,102	1,952,102	1,952,102	1,952,102
Panel D: Log hourly wage					
Oil \times post	-0.0137 (0.01216)	-0.0166 (0.01205)	-0.0167 (0.01165)	-0.0168 (0.01166)	-0.0158 (0.01223)
N (individual-year)	1,766,807	1,766,807	1,766,807	1,766,807	1,766,807
Year FE	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓
Age poly		✓	✓		
Age-year FE				✓	✓
County-year FE			✓	✓	
LLM-year FE					✓

Notes: Table shows regression results from the estimation of equation (1). The sample is trimmed using propensity score matching. Labor earnings is defined as the sum of wages, business income, parental allowance, sick pay, and unemployment benefits. ‘Age poly’ denotes a cubic polynomial in age minus 40. ‘LLM’ denotes local labor market and refers to the location of residence in 2013. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Year 2014 is dropped from the sample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Stayers and leavers

Figure C.3 shows that the labor earnings of leavers decline more than those of stayers for all definitions considered, with the exception of occupation.

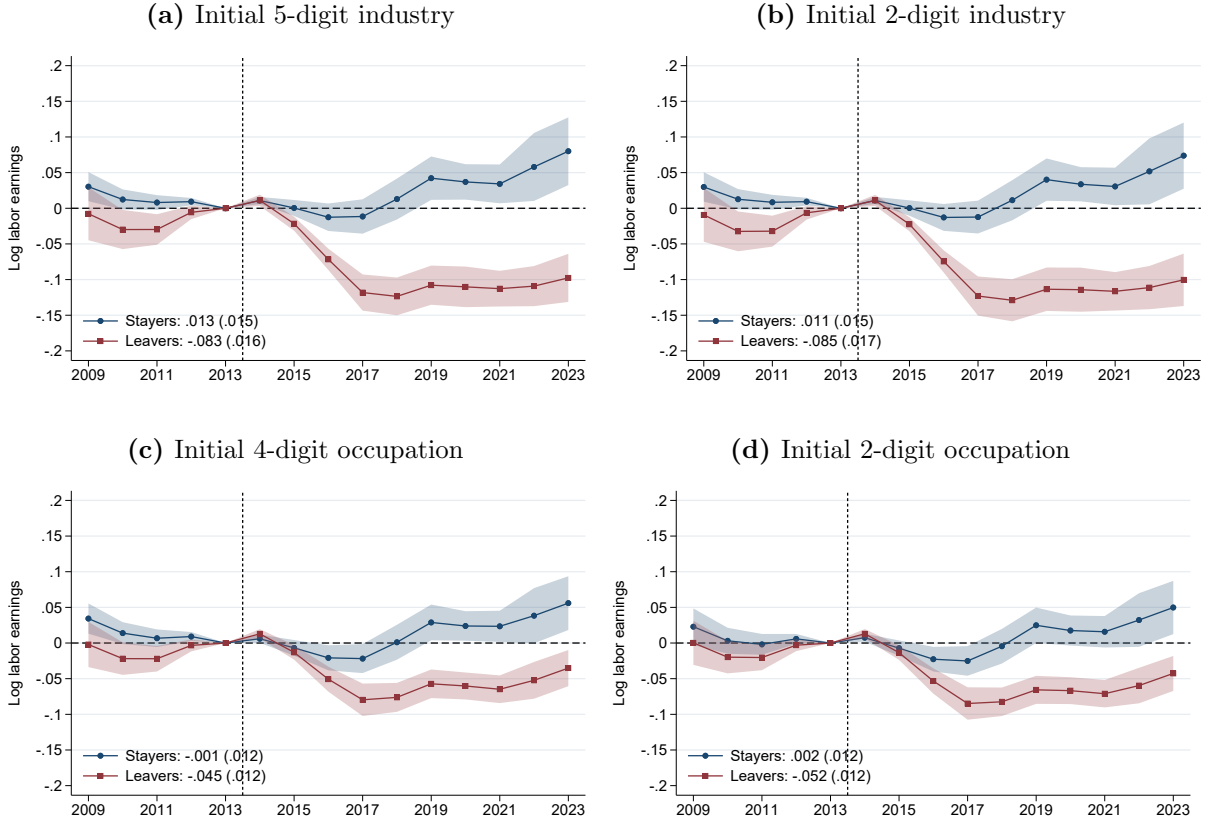
Figure C.3: DiD estimates of the effect of the oil price shock on log of labor earnings across stayers and leavers, by initial employer, industry, or occupation



Notes: Figure shows the average DiD estimate on log labor earnings. Sample is restricted to individuals that are employed in the period 2014–2023. Definitions of stayers and leavers based on the initial (2013) employer, 5-digit NACE industry code, 2-digit NACE industry code, 4-digit occupation, 2-digit occupation, and are indicated by the headings. The sample is trimmed using propensity score matching. Inflation adjusted values in NOK 2018. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013.

Figure C.4 shows that the labor earnings of leavers decline sharply ($p\text{-value} < 0.01$), while those of stayers are, on average, not significantly affected by the oil price shock ($p\text{-value} > 0.1$). The findings are robust to definitions of stayers and leavers at the initial employer, 5-digit NACE industry code, 2-digit NACE industry code. The labor earnings gap becomes smaller when defining stayers and leavers using initial occupation at the 4-digit or 2-digit level. Together these findings suggest an industry-specific wage premium, while occupation or occupation-specific skills may play a smaller role for labor earnings.

Figure C.4: Yearly DiD estimates of the effect of the oil price shock on log of labor earnings across stayers and leavers, by initial employer, industry, or occupation



Notes: Figure shows the yearly DiD estimates on log labor earnings. Sample is restricted to individuals that are employed in a given year in 2014–2023. All regressions include worker fixed effects, age-by-year fixed effects, and 2013 local labor market-by-year fixed effects. Definitions of stayers and leavers are based on the initial employer (Panel (a)), initial 5-digit NACE industry code (Panel (b)), initial 2-digit NACE industry code (Panel (c)), initial 4-digit occupation (Panel (d)). The sample is trimmed using propensity score matching. Inflation adjusted values in NOK 2018. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Shaded areas depict the 95%-confidence intervals. Numbers reported in the bottom left corner are average DiD treatment effects and standard errors (in parentheses) from the estimation of equation (1).

C.5 Heterogeneity by worker group

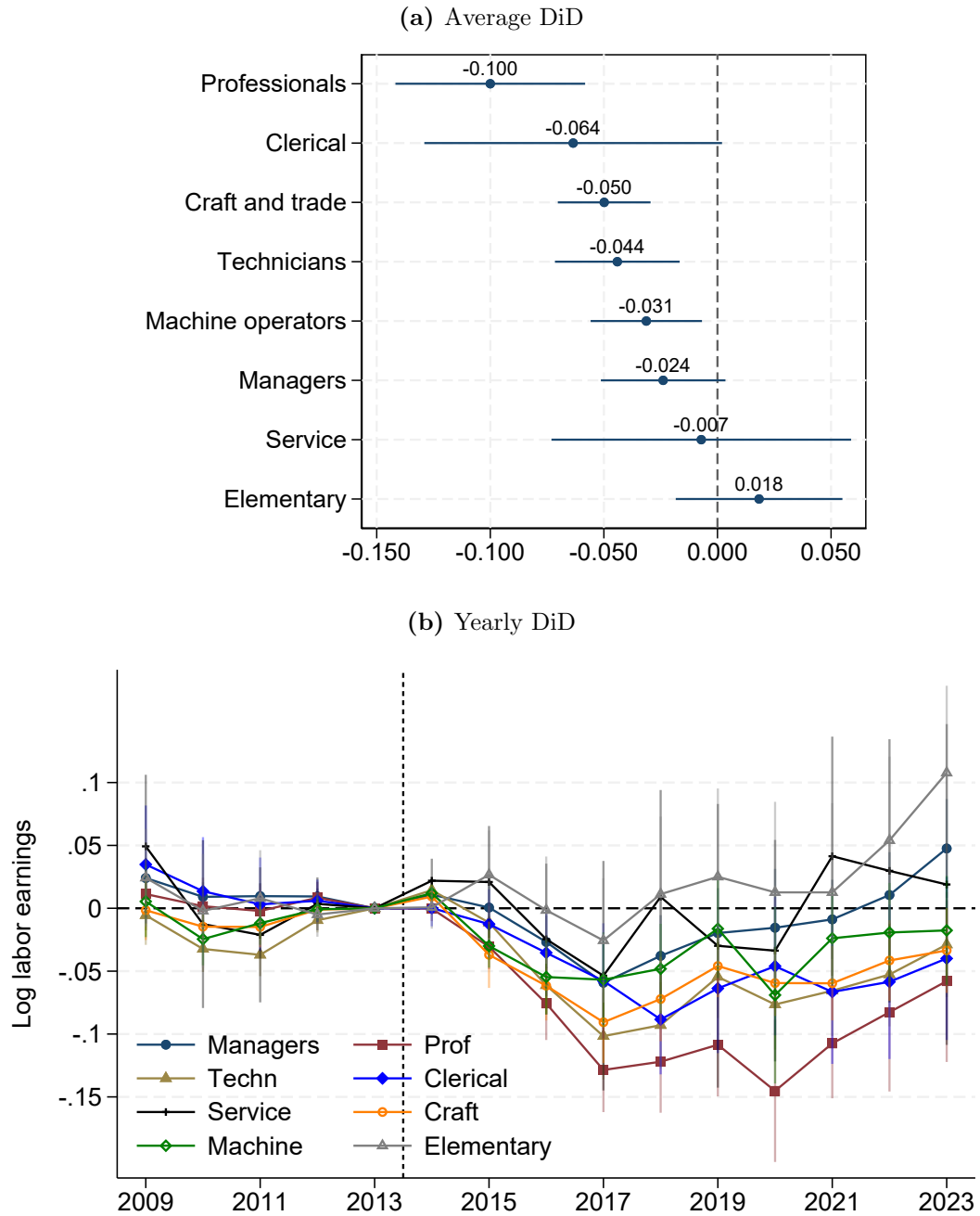
Figure C.5: Effect on log labor earnings and retirement, by socioeconomic characteristics (in 2013)



Notes: Figure shows the yearly DiD estimates on log labor earnings. The sample is trimmed using CEM based on labor earnings and age deciles, gender, education category, and county of residence. Inflation adjusted values in NOK 2018. All panels include age-by-year fixed effects. Numbers reported in the bottom left corner are average DiD treatment effects and standard errors (in parentheses) from the estimation of equation (1). Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Vertical bars denote 95%-confidence intervals.

C.6 Heterogeneity by initial occupation

Figure C.6: DiD effects on log labor earnings by initial occupation in 2013



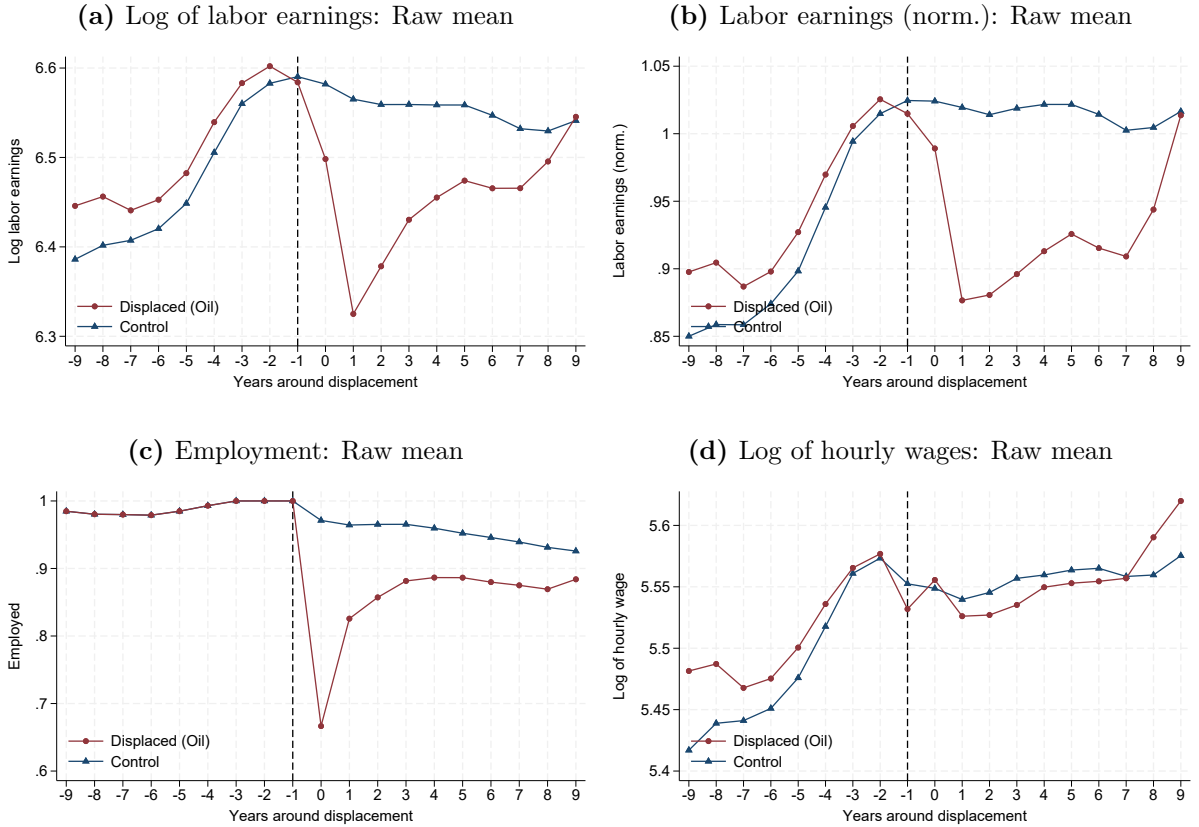
Notes: Figure shows the yearly DiD estimates on log labor earnings. The sample is trimmed using PSM based on labor earnings and age deciles, gender, education category, and county of residence. Inflation adjusted values in NOK 2018. Regressions include age-by-year fixed effects. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Vertical bars denote 95%-confidence intervals. *Professionals* (university/academic): occupations that require a university degree. *Clerical* support workers: e.g., accounting, insurance, logistics. *Craft and trade*: e.g., carpenters, painters, mechanics. *Technicians* (college): occupations that require college degree. *Elementary*: e.g., cleaners, kitchen assistant.

Appendix D Effects on displaced workers (event study)

- supporting results

D.1 Trends in raw data

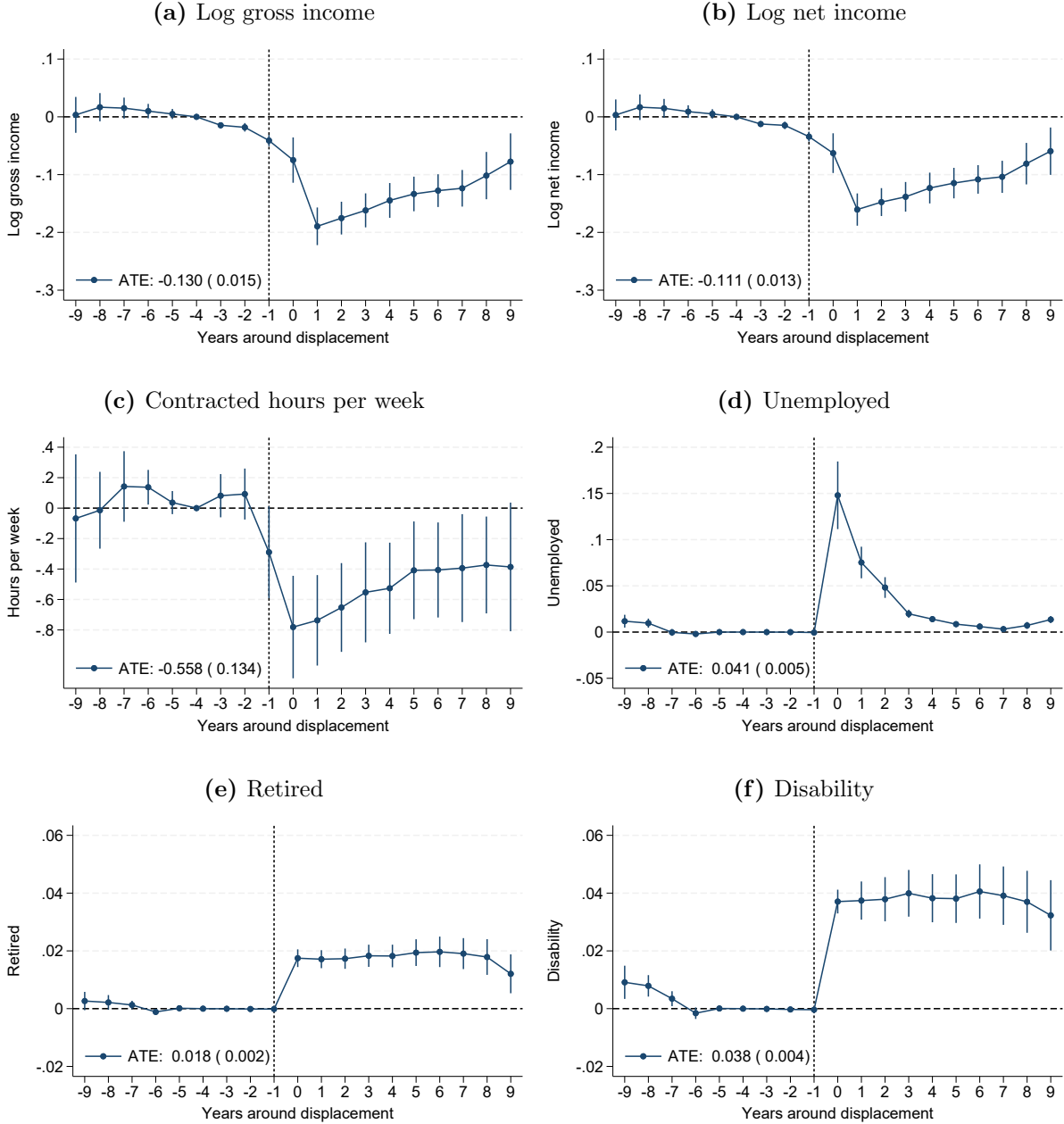
Figure D.1: Event study estimates of the effects of job displacement for oil workers on labor earnings, employment, and hourly wage



Notes: Panels show raw means of the outcome variable indicated by the sub-figure heading, by displaced oil workers and the control group.

D.2 Additional earnings and employment outcomes

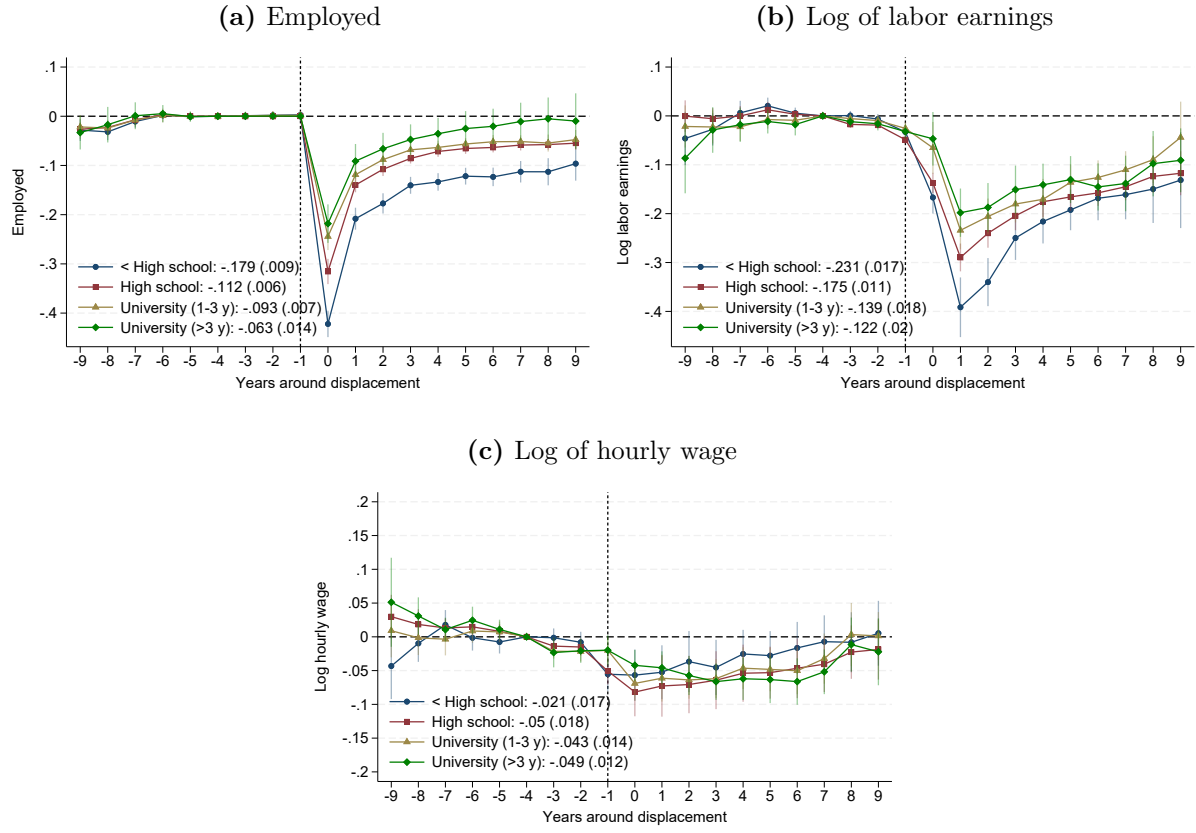
Figure D.2: Yearly Event estimates of the effect of displacement on log wages, log net income, employed, unemployed, retired, or receiving disability benefits



Notes: Figure shows the yearly event study estimates from equation (3) on the outcomes indicated by the sub-figure headings. Numbers reported in the bottom left corner are average event study estimates and standard errors (in parentheses) from the estimation of equation (4). The sample is trimmed using propensity score matching based on labor earnings, log hourly wages, age, gender, education code (1-digit), and county of residence. Labor earnings is defined as the sum of wages, business income, parental allowance, sick pay, and unemployment benefits. Inflation adjusted values in NOK 2018. All regressions include worker fixed effects, age-by-year fixed effects, local labor market-by-year fixed effects, and years relative to layoff dummies. Local labor market refers to 2013. Standard errors clustered at the 5-digit NACE industry where the worker is employed in 2013. Vertical bars denote 95%-confidence intervals.

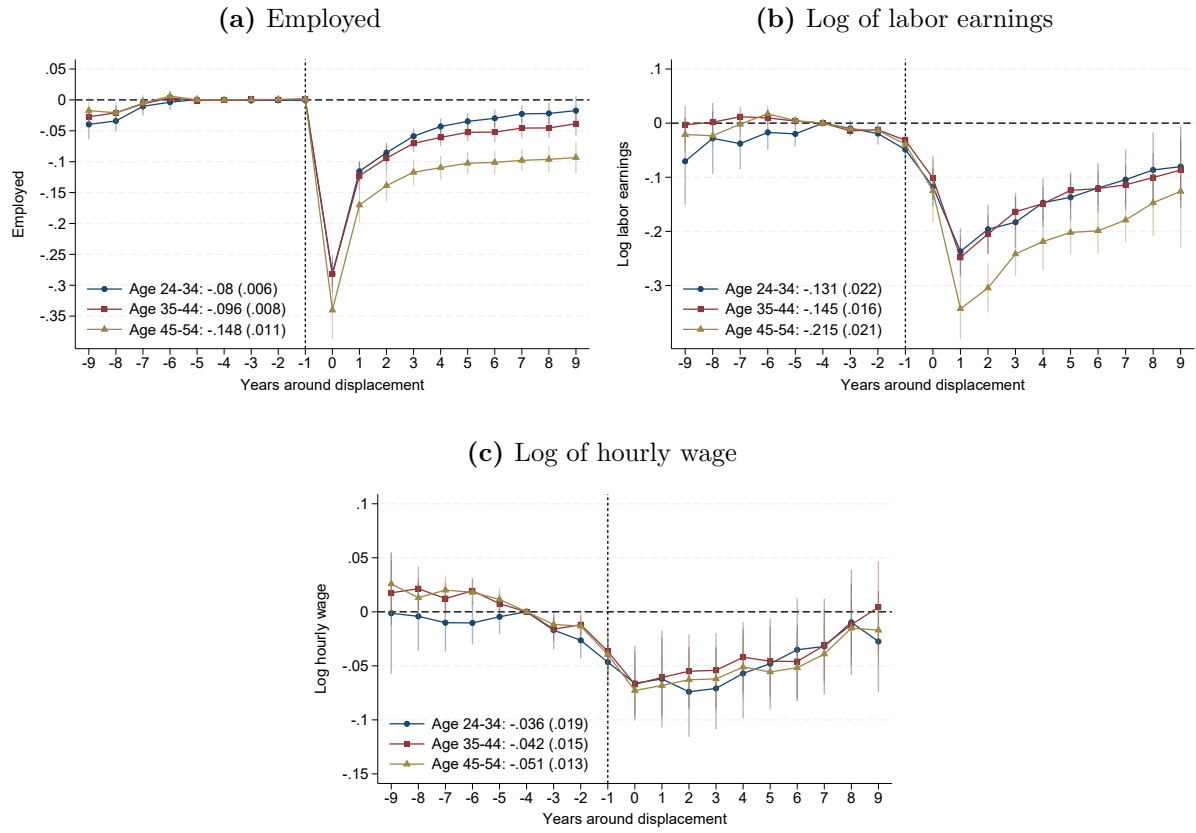
D.3 Heterogeneity by worker group

Figure D.3: Event study estimates by skill group



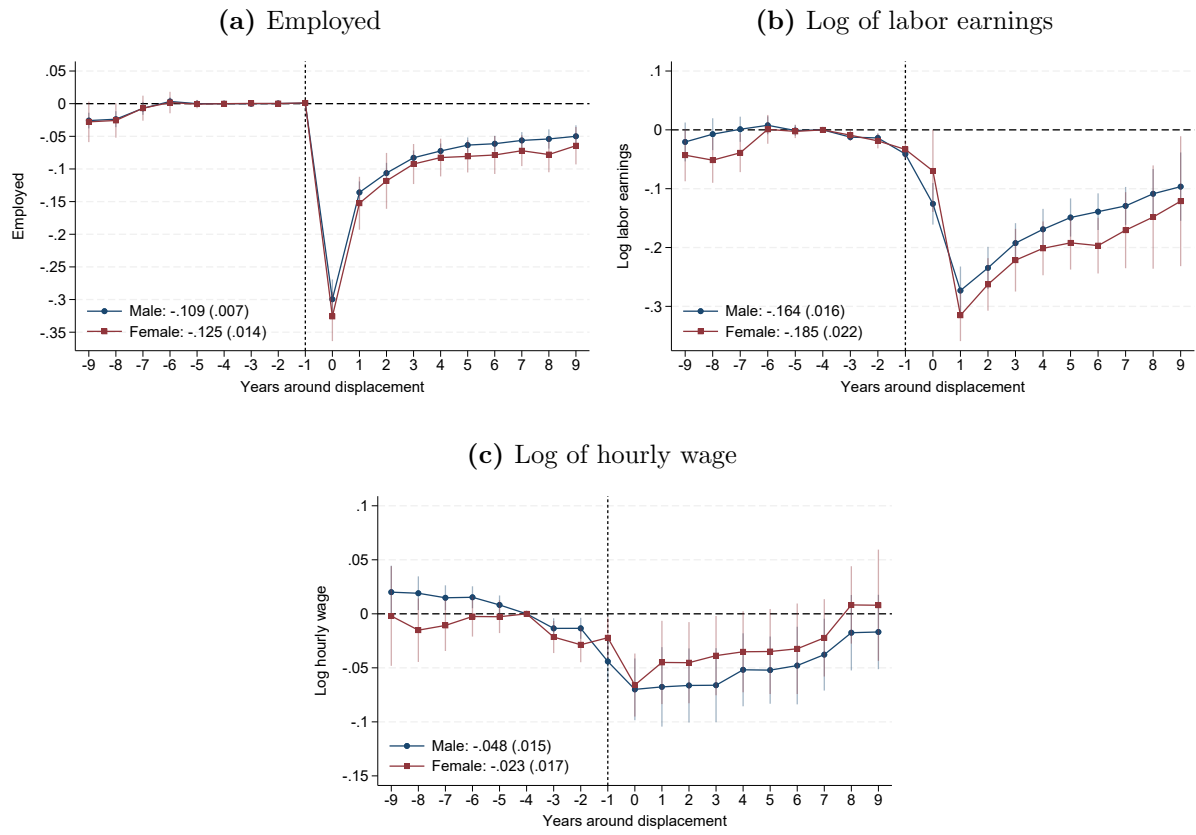
Notes: Figure shows regression results from the estimation of equation (3), where regressions are run separately for each skill group.

Figure D.4: Event study estimates by age group



Notes: Figure shows regression results from the estimation of equation (3), where regressions are run separately for each age group.

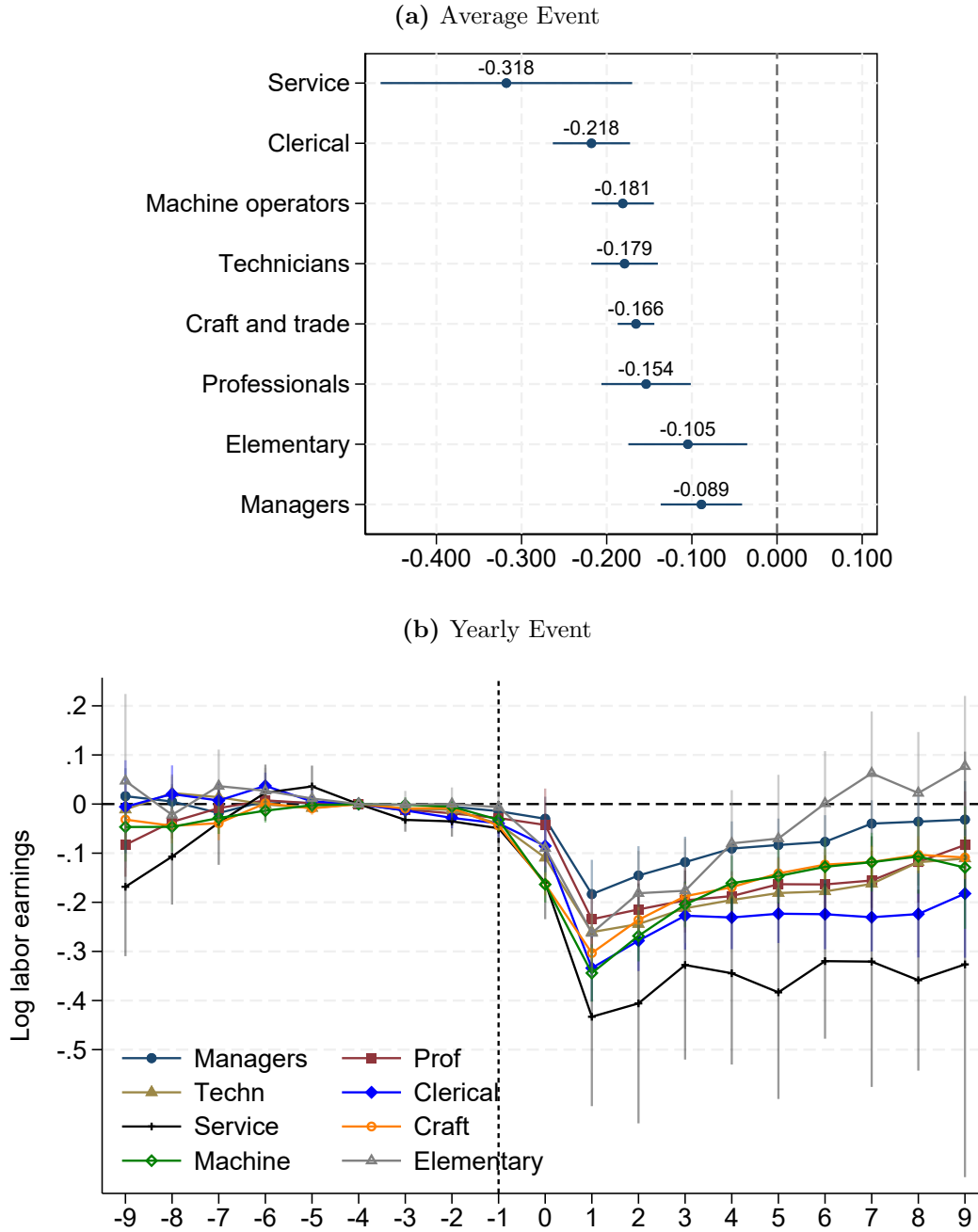
Figure D.5: Event study estimates by gender



Notes: Figure shows regression results from the estimation of equation (3), where regressions are run separately for each gender.

D.4 Heterogeneity by initial occupation

Figure D.6: Event effects on log labor earnings by initial occupation in 2013



Notes: The figure shows regression results from the estimation of equation (3) on log labor earnings, where regressions are run separately for each occupation. The sample is trimmed using PSM based on labor earnings, age, gender, education category, and county of residence. Inflation adjusted values in NOK 2018. Standard errors are clustered at the 5-digit NACE industry where the worker is employed in 2013. *Professionals* (university/academic): occupations that require a university degree. *Clerical* support workers: e.g., accounting, insurance, logistics. *Craft and trade*: e.g., carpenters, painters, mechanics. *Technicians* (college): occupations that require college degree. *Elementary*: e.g., cleaners, kitchen assistant.

Appendix E Transitioning from oil to green

E.1 Post-displacement industries

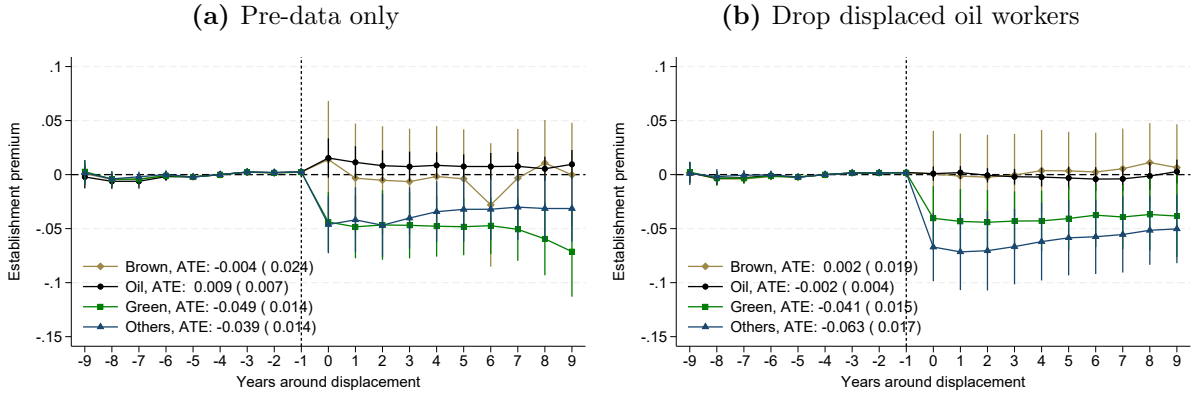
Table E.1: Top 10 green, brown (non-oil), and other post-displacement industries

Industry	Displaced oil workers	
	N	Share
Panel A: Top green industries		
35.13: Distrib. of electricity	279.4	0.059
71.12: Engineer. act./rel. tech. consult	276.4	0.011
35.11: Prod of electricity	269	0.060
43.22: Plumbing etc.	114.7	0.009
42.22: Constr. utility proj. el./telecomm.	77	0.034
45.11: Sale of cars/light mot veh.	74.2	0.009
03.21: Marine aquaculture	69.5	0.019
38.11: Coll. of non-hazardous waste	69.2	0.020
46.69: W.sale other mach. and equip.	61	0.006
35.14: Trade of electricity	58.1	0.042
Panel B: Top brown industries		
24.42: Aluminium production	341.8	0.080
10.91: Manuf. of prep. feeds for farm anim.	120.1	0.076
10.51: Oper. of dairies /cheese making	110.8	0.030
10.11: Processing and preserving of meat	108.1	0.030
10.20: Process. and preserv. of fish etc.	107.9	0.019
24.10: Manuf. basic iron and steel etc.	104.4	0.084
20.13: Manuf. of other inorg. basic chem.	97.8	0.061
52.23: Serv. act. to air transp.	82.5	0.019
20.15: Fertilisers and nitrogen compounds	59.5	0.062
23.99: Manuf. of other non-met. min. prod.	57	0.040
Panel C: Top other industries		
41.20: Construction of buildings	1283.8	0.038
71.12: Engineer. act./rel. tech. consult	896.2	0.034
64.19: Other monetary intermed.	585.1	0.034
43.12: Site preparation	521.7	0.041
43.22: Plumbing etc.	443.4	0.035
45.20: Maint./repair of motor vehicles	426.7	0.033
69.20: Account./bookkeep./tax consult.	425	0.031
78.20: Temporary employment agency act.	399.6	0.031
42.11: Construc. of roads and motorways	272.7	0.034
88.91: Child day-care activities	257.4	0.005

Note: This table lists the 4-digit industries with the highest number of displaced oil workers that move to green jobs (panel A), brown jobs (panel B) or other jobs (panel C). A job is defined as green if (i) the firm's average patent, export, or R&D share in 2009-2023 exceeds 50%, (ii) if the firm operates in a 5-digit industry classified as green, or (iii) if the 4-digit occupation has a green skill share above 20%. A job is defined as brown if (i) the firm operates in an EU ETS industry, or (ii) if the firm has positive CO₂ emissions in 2009–2023. *N* refers to the average number of displaced oil workers per year in 2014–2023. The industry codes correspond to the Sn2007 classification. *Share* refers to the employment share within the respective 4-digit industries.

E.2 Establishment wage premium based on alternative samples

Figure E.1: Displacement effects on establishment wage premium, by post displacement sector.



Notes: Figure shows regression results from the estimation of equation (3) on establishment premiums by post-displacement sector. Establishment premiums are estimated based on equation (5). In Panel (a), establishment premiums are based on data prior to the oil price shock (2009–2013). In Panel (b), establishment premiums are based on both the pre and post period (2009–2023), but we drop the matched displaced oil workers from the estimation sample in the years following displacement. Standard errors are clustered at the 5-digit NACE industry where the worker is employed in 2013. Numbers reported in the bottom left corner are average event study estimates and standard errors (in parentheses) from the estimation of equation (4).

E.3 Event study estimates by post displacement sector

Table E.2: Event study estimates of the effects of job displacement for oil workers. Average effects and effects by post displacement sector.

	(1)		(2)		(3)	
	Log labor earnings		Log hourly wages		Establishment premium	
Panel A: All displaced oil workers cont. on employment						
k=0	-0.052***	(0.0166)	-0.069***	(0.0136)	-0.039***	(0.0081)
k=1	-0.159***	(0.0143)	-0.064***	(0.0172)	-0.039***	(0.0083)
k=4	-0.124***	(0.0151)	-0.049***	(0.0161)	-0.039***	(0.0093)
k=9	-0.054**	(0.0265)	-0.012	(0.0170)	-0.033***	(0.0091)
N	574,770		565,353		571,759	
Panel B: Oil post displacement						
k=0	-0.029**	(0.0138)	-0.033**	(0.0127)	-0.007**	(0.0033)
k=1	-0.103***	(0.0187)	-0.051***	(0.0164)	-0.006	(0.0037)
k=4	-0.048**	(0.0190)	-0.042***	(0.0145)	-0.010*	(0.0054)
k=9	0.034	(0.0334)	-0.002	(0.0171)	-0.004	(0.0066)
N	503,987		497,591		501,581	
Panel C: Brown post displacement						
k=0	-0.024	(0.0248)	-0.079***	(0.0202)	-0.012	(0.0199)
k=1	-0.091***	(0.0202)	-0.041	(0.0268)	-0.016	(0.0192)
k=4	-0.052**	(0.0237)	-0.032	(0.0249)	-0.013	(0.0181)
k=9	0.043	(0.0286)	0.018	(0.0258)	-0.007	(0.0193)
N	436,008		430,709		433,557	
Panel D: Green post displacement						
k=0	-0.055***	(0.0167)	-0.100***	(0.0181)	-0.049***	(0.0161)
k=1	-0.160***	(0.0214)	-0.075***	(0.0197)	-0.053***	(0.0160)
k=4	-0.117***	(0.0207)	-0.054***	(0.0208)	-0.057***	(0.0149)
k=9	-0.062**	(0.0298)	0.004	(0.0240)	-0.049***	(0.0186)
N	443,086		437,555		440,604	
Panel E: Other post displacement						
k=0	-0.076***	(0.0194)	-0.113***	(0.0188)	-0.080***	(0.0155)
k=1	-0.236***	(0.0193)	-0.085***	(0.0190)	-0.085***	(0.0176)
k=4	-0.226***	(0.0192)	-0.062***	(0.0192)	-0.076***	(0.0184)
k=9	-0.162***	(0.0206)	-0.023	(0.0185)	-0.064***	(0.0160)
N	487,632		479,705		484,607	

Notes: The table reports the coefficients δ_k from the event study model (equation 3). Panel A shows average effects for all displaced workers that are employed in a given year, while Panels B to E show effects by post displacement sector. k denotes the years since displacement. Standard errors are reported in parentheses and are clustered at the 5-digit NACE industry where the worker is employed in 2013. N corresponds to the number of person-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix F Oaxaca-Blinder Decomposition by Group

In this appendix, we provide a more detailed descriptions of the decomposition results presented in the main text.

F.1 Decomposition results: summary

Table F.1: Oaxaca-Blinder Decomposition of Log Labor Earnings

	(1)		(2)		(3)	
	Brown vs. Oil		Green vs. Oil		Other vs. Oil	
Panel A: Overall						
Group 1 (S = B,G,O)	-0.006	(0.718)	-0.048	(0.000)	-0.105	(0.000)
Group 2 (Oil)	-0.031	(0.000)	-0.031	(0.000)	-0.003	(0.565)
Difference	0.024	(0.168)	-0.017	(0.146)	-0.102	(0.000)
Explained	-0.004	(0.778)	-0.015	(0.068)	-0.034	(0.000)
Unexplained	0.029	(0.212)	-0.002	(0.882)	-0.068	(0.000)
Panel B: Explained						
Δ Est FE	0.002	(0.722)	-0.016	(0.000)	-0.038	(0.000)
Δ Skill distance	-0.004	(0.445)	-0.007	(0.088)	-0.018	(0.000)
Skill remoteness	-0.003	(0.154)	-0.000	(0.621)	0.000	(0.327)
Age	0.016	(0.004)	0.015	(0.000)	0.015	(0.000)
Female	0.000	(0.766)	0.000	(0.740)	0.002	(0.048)
Family in region	-0.004	(0.201)	-0.000	(0.765)	0.001	(0.279)
High school	-0.000	(0.931)	0.001	(0.313)	0.001	(0.294)
University (1-3 years)	-0.000	(0.993)	-0.001	(0.521)	-0.001	(0.137)
University (>3 years)	-0.001	(0.609)	-0.002	(0.144)	0.004	(0.001)
Managers	-0.001	(0.623)	0.001	(0.244)	-0.000	(0.739)
Professionals	0.004	(0.303)	-0.002	(0.354)	-0.001	(0.503)
Technicians	-0.001	(0.674)	0.004	(0.439)	0.001	(0.511)
Clerical	0.000	(0.985)	0.000	(0.901)	0.001	(0.536)
Service	-0.000	(0.899)	0.000	(0.473)	0.000	(0.443)
Craft	0.000	(0.869)	-0.000	(0.793)	-0.000	(0.980)
Machine	0.000	(0.974)	-0.004	(0.275)	-0.001	(0.501)
LLM: employment	-0.002	(0.768)	0.001	(0.785)	0.000	(0.970)
LLM: oil emp. share	-0.014	(0.232)	-0.004	(0.200)	-0.000	(0.861)
LLM: brown emp. share	-0.002	(0.233)	-0.002	(0.373)	0.000	(0.932)
LLM: green emp. share	0.006	(0.315)	0.000	(0.975)	-0.000	(0.530)

Notes: The table shows results of the Oaxaca-Blinder decomposition (eq. 10) of log labor earnings. P-values are reported in parentheses. All explanatory variables are measured in 2013, with the exception of establishment FE and skill distance, which are measured as the change over time relative to the control group (i.e., the DiD). LLM denotes local labor market. Skill remoteness is constructed following Macaluso (2025).

F.2 Green vs. oil

Table F.2 reports the individual group regressions estimated using equation 9. These coefficients inform us about important differences in how observable characteristics in-

fluence treatment effects for workers who transition to the green sector and those who remain in the oil sector, respectively. For workers moving to the green sector (column (1)), establishment fixed effects contributes significantly with a positive coefficient (0.571, $p < 0.001$), indicating that transitioning to establishments with higher wage premiums relative to their pre-displacement oil jobs significantly improves treatment effects for the switchers. This effect is notably smaller than that observed for the oil sector stayers (Group 2), who show a stronger positive association (0.711, $p < 0.001$) between establishment fixed effects and treatment effects. The difference is likely due to higher firm-specific human capital and bargaining power of stayers, while switchers encounter transition costs and reduced initial productivity in new establishments.

Age has a non-linear relationship for both groups, with green switchers showing marginally significant age effects while stayers have highly significant age coefficients, suggesting that accumulated experience and adaptability play a significant role particularly for workers who remain in the oil sector. The negative first-order age coefficient likely reflects that older workers face higher displacement costs due to longer tenure. We observe similar findings for switchers to other sectors than brown and green (Table F.4).

Skill distance in Table F.2, measured as the Euclidean distance between post- and pre-displacement periods, negatively affects treatment effects for both groups. Education levels show divergent patterns: green switchers with higher education (4+ years) experience significantly worse treatment effects (-0.098, $p = 0.027$), while oil stayers show negative coefficients across all education levels ($p < 0.01$), suggesting that higher education may not protect against earnings losses in either scenario. These findings suggest that workers with higher baseline earnings potential, particularly older, more educated workers who have accumulated greater firm-specific skills, experience more severe treatment effects from displacement, as they have more to lose from earnings disruptions relative to their pre-displacement wage levels.

Table F.1, column (2) shows that displaced oil workers who transition to the green sector experience significantly worse treatment effects than those who remain in the oil sector ($\Delta \bar{y}_i^{\text{Oil}} - \Delta \bar{y}_i^{\text{Green}} = -0.017$), but this difference is statistically insignificant. First, establishment fixed effects contribute negatively (-0.016, p-value<0.001), indicating that green switchers work at establishments with lower wage premiums relative to their pre-displacement oil jobs, or may possess lower firm-specific human capital. Second, skill distance contributes negatively (-0.007, p-value<0.1), suggesting that greater occupational mismatch between pre- and post-displacement jobs widens the earnings gap for sectoral transitions. Third, the lower age of green switchers contributes positively (0.015, p-value<0.001), acting as a factor that reduces the earnings gap. The unexplained component is small and statistically insignificant (-0.002, p-value>0.1), indicating that returns to characteristics are similar across sectors and that unobserved factors play a minor role.

Table F.2: Oaxaca-Blinder: individual group regressions for green and oil

	(1)		(2)	
	Group 1:		Group 2:	
	Move to green		Remain in oil	
Δ Est FE	0.571	(0.000)	0.711	(0.000)
Δ Skill distance	-0.009	(0.032)	-0.009	(0.000)
Skill remoteness	-0.023	(0.335)	0.013	(0.255)
Age	-0.167	(0.073)	-0.154	(0.000)
Age ²	0.004	(0.084)	0.004	(0.000)
Age ³	-0.000	(0.082)	-0.000	(0.000)
Female	0.032	(0.274)	0.007	(0.583)
Parents in LLM	0.001	(0.962)	0.010	(0.475)
Siblings in LLM	0.025	(0.295)	-0.001	(0.937)
High school	-0.046	(0.179)	-0.073	(0.000)
University (1-3 years)	-0.030	(0.450)	-0.056	(0.002)
University (>3 years)	-0.098	(0.027)	-0.067	(0.001)
Managers	0.082	(0.360)	-0.011	(0.796)
Professionals	0.060	(0.495)	0.012	(0.772)
Technicians	0.047	(0.583)	-0.026	(0.523)
Clerical	0.010	(0.919)	-0.001	(0.990)
Service	-0.323	(0.137)	-0.019	(0.826)
Craft	0.015	(0.859)	-0.055	(0.167)
Machine	0.086	(0.347)	-0.014	(0.735)
LLM: employment	-0.135	(0.765)	0.351	(0.106)
LLM: oil emp. share	0.261	(0.265)	0.151	(0.129)
LLM: brown emp. share	0.421	(0.353)	-0.096	(0.626)
LLM: green emp. share	0.031	(0.971)	0.696	(0.056)
Constant	2.366	(0.047)	1.760	(0.001)

Notes: The table reports results from the Oaxaca-Blinder decomposition model, equation 9: $\Delta y_i^{\text{Oil}} = X_i^{\text{Oil}} \beta_{\text{Oil}} + \nu_i^{\text{Oil}}$ (column 2) and $\Delta y_i^{\text{G}} = X_i^{\text{G}} \beta_{\text{G}} + \nu_i^{\text{G}}$ (column 1). y_i denote log of annual labor earnings. P-values are reported in parenthesis.

F.3 Brown vs. oil

While green sector switchers show significant negative effects of age and education, consistent with the hypothesis that workers with more to lose experience worse outcomes, brown sector switchers have no statistically significant age or education effects (see column (1) of Table F.3). This divergence could indicate fundamental differences between brown and green sectors: brown sectors may offer more stable employment opportunities that are less sensitive to worker characteristics, or they may attract a different selection of workers who are less affected by age and education differentials. Alternatively, brown sectors might provide better opportunities for older, more educated workers due to their established nature and potentially higher skill requirements, offsetting the typical displacement penalties associated with age and education. The lack of statistical significance could also stem from the smaller sample size of brown switchers, reducing the power to detect significant effects, or from greater heterogeneity in brown sector opportunities that masks systematic age and education effects.

Column (1) in Table ?? additionally suggests that displaced oil workers who transition to the brown sector do not experience statistically significant losses than those who remain in the oil sector. The explained component is small and statistically insignificant (-0.004 , $p\text{-value}>0.1$), indicating that observable characteristics play a minimal role in accounting for the gap. However, age emerges as the only significant contributor to the explained portion (0.016 , $p\text{-value}<0.001$), suggesting that the the lower average age of workers switching to the brown sector contributes to their relatively better outcomes. The unexplained component (0.029 , $p\text{-value}>0.1$) captures the majority of the (non-significant) gap, indicating that differences in returns to characteristics or unobserved factors drive the small disparity between groups.

Table F.3: Oaxaca-Blinder: individual group regressions for brown and oil

	(1)		(2)	
	Group 1:		Group 2:	
	Move to brown		Remain in oil	
Δ Est FE	0.754	(0.000)	0.680	(0.000)
Δ Skill distance	-0.007	(0.369)	-0.008	(0.000)
Skill remoteness	-0.093	(0.020)	0.006	(0.589)
Age	0.093	(0.556)	-0.143	(0.000)
Age ²	-0.003	(0.450)	0.004	(0.001)
Age ³	0.000	(0.399)	-0.000	(0.000)
Female	0.025	(0.602)	0.012	(0.360)
Parents in LLM	-0.048	(0.301)	0.009	(0.492)
Siblings in LLM	-0.014	(0.716)	0.002	(0.851)
High school	-0.065	(0.251)	-0.077	(0.000)
University (1-3 years)	-0.001	(0.994)	-0.060	(0.001)
University (>3 years)	-0.083	(0.271)	-0.083	(0.000)
Managers	-0.082	(0.512)	0.004	(0.925)
Professionals	-0.101	(0.407)	0.024	(0.551)
Technicians	-0.144	(0.213)	-0.021	(0.606)
Clerical	-0.215	(0.114)	0.008	(0.857)
Service	-0.144	(0.616)	-0.050	(0.560)
Craft	-0.138	(0.211)	-0.045	(0.255)
Machine	0.003	(0.977)	-0.009	(0.824)
LLM: employment	0.238	(0.722)	0.238	(0.262)
LLM: oil emp. share	0.475	(0.217)	0.142	(0.146)
LLM: brown emp. share	-0.664	(0.176)	-0.048	(0.807)
LLM: green emp. share	1.927	(0.112)	0.624	(0.080)
Constant	-0.381	(0.850)	1.733	(0.001)

Notes: The table reports results from the Oaxaca-Blinder decomposition model, equation 9. y_i denote log of annual labor earnings. P-values are reported in parenthesis.

F.4 Other vs. oil

Column (3) of Table F.1 verifies that displaced oil workers who transition to other sectors experience significantly worse treatment effects than those who remain in the oil

sector (-0.102 , $p\text{-value} < 0.001$). Other sector switchers face a substantially more negative average treatment effect (-0.105) compared to oil sector stayers (-0.003), with this difference being highly statistically significant. The explained component accounts for approximately 33% of the total gap (-0.034 , $p\text{-value} < 0.001$), indicating that observable characteristics play a substantial role in accounting for the disparity. Within the explained portion, establishment fixed effects emerge as the largest negative contributor (-0.038 , $p\text{-value} < 0.001$), suggesting that switchers work at establishments with reduced wage premiums relative to their pre-displacement oil jobs, or experience significant losses in firm-specific human capital. Skill distance also contributes significantly to the negative gap (-0.018 , $p\text{-value} < 0.001$), indicating that greater occupational mismatch between pre- and post-displacement jobs magnifies earnings losses for sectoral transitions. However, age serves as an important mitigating factor (0.015 , $p\text{-value} < 0.001$). The unexplained component explains the majority of the gap (-0.068 , $p\text{-value} < 0.001$), indicating that differences in returns to characteristics or unobserved factors drive a substantial portion of the disparity. These findings suggest that other sector transitions involve significant structural challenges, with particular attention needed for preserving firm-specific human capital and reducing occupational skill gaps, while recognizing that lower age and education can serve as protective factors against earnings losses.

Table F.4: Oaxaca-Blinder: individual group regressions for other and oil

	(1)		(2)	
	Group 1:		Group 2:	
	Move to other		Remain in oil	
Δ Est FE	0.738	(0.000)	0.650	(0.000)
Δ Skill distance	-0.016	(0.000)	-0.003	(0.132)
Skill remoteness	0.017	(0.200)	0.016	(0.256)
Age	-0.103	(0.039)	-0.183	(0.000)
Age ²	0.003	(0.050)	0.005	(0.000)
Age ³	-0.000	(0.043)	-0.000	(0.000)
Female	0.029	(0.046)	0.015	(0.368)
Parents in LLM	0.015	(0.327)	0.002	(0.881)
Siblings in LLM	0.005	(0.701)	-0.006	(0.632)
High school	-0.060	(0.000)	-0.066	(0.000)
University (1-3 years)	-0.045	(0.027)	-0.069	(0.001)
University (>3 years)	-0.101	(0.000)	-0.063	(0.009)
Managers	0.018	(0.681)	0.087	(0.085)
Professionals	0.034	(0.424)	0.097	(0.049)
Technicians	0.034	(0.422)	0.029	(0.550)
Clerical	0.033	(0.466)	0.096	(0.087)
Service	0.073	(0.376)	-0.070	(0.475)
Craft	0.001	(0.975)	-0.001	(0.983)
Machine	0.036	(0.413)	0.025	(0.616)
LLM: employment	-0.010	(0.968)	0.248	(0.342)
LLM: oil emp. share	0.021	(0.861)	0.102	(0.385)
LLM: brown emp. share	-0.022	(0.928)	0.086	(0.717)
LLM: green emp. share	-0.287	(0.495)	0.814	(0.062)
Constant	1.390	(0.032)	2.139	(0.001)

Notes: The table reports results from the Oaxaca-Blinder decomposition model, equation 9. y_i denote log of annual labor earnings. P-values are reported in parenthesis.