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Lost in transition?
Earnings losses of displaced petroleum workers

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Abstract

We estimate the earnings losses of displaced petroleum workers using a matched employer-employee longitudinal data set from Norway, coupled with an event-study framework of the oil price drop in 2014. Displacement leads to sizable and persistent earnings losses, and the magnitudes are particularly large for petroleum workers moving to other industries. More importantly, we document that almost 70 percent of the earnings losses can be attributed to lost industry-specific earnings premiums caused by workers moving from an industry characterized by large resource rents. In contrast, worker-industry match effects are negligible.

JEL-codes: E32, F41, J22, J31, J63, P28, Q33

Keywords: Dutch disease, Resource movements, Difference-in-differences, Labor mobility, Displaced

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1 Introduction

Over the following decades, petroleum producers face a major structural transformation due to the green transition. The tightening of environmental policy regulations combined with technological innovations in renewable energy production will induce a reallocation of workers away from the petroleum industry. The macroeconomic effects of structural changes in an open economy due to a booming resource sector are well-established, leading to large increases in real income and aggregate demand, shifts in relative prices, and resource movements between industries.[1] However, the micro-level mechanisms of this literature are vague, and little is known about the adjustments happening at the micro level when resource movements between industries occur. In particular, as the green transition reverses the booming sector and reduces labor demand, petroleum workers will face costs when moving to other industries. These costs will partly depend on their earnings premiums in the petroleum industry and how industry-specific their human capital is. The petroleum industry is characterized by large resource rents, and there is a common belief that petroleum workers receive substantial earnings premiums due to rent-sharing. Accordingly, the earnings losses of displaced petroleum workers moving to other industries may be particularly large.

In this paper, we estimate the earnings losses of displaced petroleum workers and, importantly, the underlying drivers. We do this by utilizing rich administrative data from a major petroleum producer, Norway, coupled with an event study framework. Particularly, we exploit the large, unexpected, and exogenous to Norway drop in oil prices in 2014 as a natural experiment. Since the market expected prices to stay at a lower level for a long time[2], the price drop induced a substantial reallocation of labor away from the petroleum industry in 2015 and 2016 due to reduced profitability and a weaker outlook. Using a matched employer-employee longitudinal data set containing earnings, hours, and a broad set of characteristics for all workers participating in the Norwegian labor market, we track the labor market outcomes of workers in the petroleum industry displaced within 2015 and 2016. To estimate the dynamic effects of displacement on earnings, we use the interaction-weighted estimator proposed by Sun and Abraham (2021), where the control group is stably employed petroleum workers.

Our results indicate that displacement leads to persistent earnings losses for all petroleum workers and are in line with the existing literature studying displacement costs.[3] However, this estimate includes both displaced workers that remain in the petroleum industry and those who move to other industries, hereafter denoted as industry movers. While those who remain in the

[1]The classic economic model describing the Dutch disease was first introduced by Corden and Neary (1982) to explain the decline of the manufacturing sector in the Netherlands after the discovery of a large natural gas field. Following the seminal paper of Corden and Neary (1982), an extensive literature has examined the Dutch disease further in various settings and with several extensions, e.g., Bjørnland and Thorsrud (2016) and Bjørnland et al. (2019).

[2]Forward markets were suggesting no or only modest increases in oil prices from mid-2014 to 2017, see Figure 2b in Section 3.

[3]See Table 1 in Couch and Placzek (2010) and Table 3 in Lachowska et al. (2020) for an overview of the literature.

petroleum industry will not lose their industry-specific earnings premium, the industry movers will. Accordingly, industry movers may experience higher displacement costs. Our empirical findings provide support for this hypothesis. When considering a sub-sample of the displaced petroleum workers, namely the industry movers, we find that these workers indeed suffer notably higher earnings losses. Specifically, four years after displacement, displaced petroleum workers in general experience earnings losses of about 15 percent compared to a stably employed comparison group, while the industry movers suffer earnings losses of about 27 percent.

There are several possible explanations behind the loss in earnings for displaced workers. Our focus is on the industry affiliation of workers. Therefore, we study the drivers at the industry level instead of the firm level, in contrast to, e.g., Lachowska et al. (2020), Pytka and Gulyas (2021) and Schmieder et al. (2022). We follow Lachowska et al. (2020) in decomposing the earnings losses into lost earnings premiums and lost match effects, respectively. The approach combines the AKM model of Abowd et al. (1999) and an extension suggested by Woodcock (2015). We modify the design to be able to do the decomposition at the industry level and not the firm level. Specifically, we decompose the loss in earnings into industry-specific effects and worker-industry match effects. Following Card et al. (2022), we define the industry-specific earnings premium as a weighted average of the earnings premiums for the firms in that particular industry. Similarly, inspired by Woodcock (2008), we define the worker-industry match effects as a duration-weighted sum of the worker-firm match effects in a specific industry.

Intuitively, the industry-specific effects capture the effect of moving from a higher-paying industry to a lower-paying industry. In our setting, these effects capture rent-sharing in the petroleum industry. The worker-industry match effects encompass all time-invariant factors specific to the relationship between a worker and her industry affiliation that increase the value of the match. After accounting for these two effects, the remaining loss in earnings consists of effects at the firm level and more direct displacement effects, such as so-called scarring effects that arise because of negative signaling or asymmetric information and result in a post-displacement wage penalty. If firms can choose who to lay off, Gibbons and Katz (1991) argue that the market will infer that laid-off workers are of low ability and therefore offer them low wages in their next jobs. Loss of seniority and job tenure may also lead to wage losses that are independent of the change in industry-specific wage premiums or the quality of the worker-industry match.

When decomposing the earnings losses into industry-specific effects and worker-industry match effects, we find that the petroleum-industry-specific earnings premium is the primary driver of earnings losses of displaced petroleum workers. For displaced workers in general, it accounts for 40 percent of the earnings loss after four years. However, a substantial share of these workers remain in the petroleum industry after displacement and do not lose the industry-specific earnings premium. When only considering the displaced workers that move to other industries, we find that the industry-specific earnings premium accounts for as much as 68 percent of the earnings loss after four years. Match effects, on the other hand, play a minor role, both for displaced workers in general and the industry movers.

This paper integrates the macro literature on Dutch disease with the micro literatures on job displacements, industry reallocation, and inter-industry wage differentials. We relate and contribute to the literature in the following ways. First, we add to the vast literature on job displacement, which has consistently documented that displaced workers experience large and long-lasting consequences in general and in earnings losses more specifically.[4] While there is a consensus in the literature on job loss that displacements lead to large and persistent earnings losses, the magnitude has been found to depend on which industries are studied, demographics, and business cycle conditions, among others. The evidence presented in this paper for displaced workers, in general, is in the lower tier of the results in the literature and similar in magnitude to the results of Couch and Placzek (2010). However, the estimates for the industry movers are in the higher tier and more similar to the results of the seminal paper of Jacobson et al. (1993). These results are in line with the notion of Jacobson et al. (1993) that earnings losses are larger in settings where rent-sharing is likely to be prevalent.

Second, we contribute to the literature that has documented larger earnings losses for displaced workers reallocating to other industries than those who stay in the same industry.[5] As noted by Kletzer (1998), the reason for this could be both due to loss of industry-specific human capital and loss of industry premiums. Our results indicate that the loss of industry premiums due to rent-sharing is the main driver of earnings losses of displaced petroleum workers switching industries, while match effects play a minor role.

Third, our paper is related to the literature on inter-industry wage differentials. A major empirical regularity in the literature is the existence of large and persistent wage differentials among industries after controlling for a wide range of worker and job characteristics (Carruth et al., 2004). In their influential paper, Krueger and Summers (1988) argue that workers in high-wage industries receive non-competitive rents and that inter-industry wage differentials reflect causal pay premiums rather than unmeasured worker ability. Non-competitive theories of wage determination, such as models of efficiency wages, rent-sharing, or union threat, seek to explain why firms may find it profitable to pay a higher wage than the market-clearing rate. However, other studies argue that wage differentials reflect unobserved worker skills and abilities and claim that workers with higher unobserved skills will select into higher-paying industries. In our paper, when estimating the industry fixed effects using the AKM model, we control for characteristics of workers that are constant over time and transferable across firms. The estimated industry fixed effects should, therefore, essentially capture non-competitive rents, such as the resource rent in the petroleum industry. We find that the petroleum industry exhibits the largest earnings premiums of all industries in Norway and that the earnings premium in the petroleum industry is 23 percent on average compared to other industries. The loss of the non-competitive rent in

[4]See e.g. Topel (1990); Jacobson et al. (1993); Farber et al. (1993); Neal (1995) Farber et al. (1997); Fallick (1996); Fairlie and Kletzer (1998); Kletzer (1998); Farber (2015); Farber (2017); Stevens (1997); Von Wachter et al. (2009); Couch and Placzek (2010); Davis and Von Wachter (2011); Walker (2013); Carrington and Fallick (2017); Krolikowski (2017); Jung and Kuhn (2019); Seim (2019); Lachowska et al. (2020); Blien et al. (2021); Jarosch (2021); Fackler et al. (2021); Raposo et al. (2021); Schmieder et al. (2022).

[5]See e.g. Podgursky and Swaim (1987); Krueger and Summers (1988); Gibbons and Katz (1991); Carrington (1993); Jacobson et al. (1993); Neal (1995); Parent (2000); Stevens (1997); Couch and Placzek (2010).

the petroleum industry is then a necessity when moving to another industry, simply because workers are moving from a higher-paying to a lower-paying industry.

Fourth, related to this paper, Lorentzen (2022) use the oil price drop in 2014 and Norwegian data to study the reallocation effects of petroleum workers moving to other industries. However, while the focus of Lorentzen (2022) is on the equilibrium effects on the earnings distribution in the destination industries of the moving petroleum workers, we study the earnings losses of the petroleum workers in particular. Accordingly, these two studies complement each other in explaining the effects of worker reallocation away from the petroleum industry in response to a downsizing.

Fifth, our paper is related to the literature on the effects of trade and globalization. For instance, Dauth et al. (2021) show that earnings losses are larger for workers in industries declining due to import competition from low-wage countries. While the source of their industry shock is different from ours, there are similarities in the mechanisms. Both shocks are industry-specific and lead to lower demand for labor in the industry.

Lastly, the job displacement literature has documented that earnings losses of displaced workers depend on the aggregate state of the economy and the labor market conditions in particular. For example, Davis and Von Wachter (2011) and Schmieder et al. (2022) find that earnings losses are substantially larger during recessions. The oil price drop had a marked adverse impact on the Norwegian economy, and some regions where the petroleum industry is key, like the Stavanger region, were particularly negatively affected. However, a sharp exchange rate depreciation accompanied by expansive monetary and fiscal policy dampened the negative impulses, and the aggregate Norwegian economy did not enter a recession. Moreover, the exchange rate depreciation improved the export industry's competitiveness. Accordingly, a large recession in the Norwegian economy following the oil price fall should not drive our estimate.

The paper is organized as follows. Section 2 gives an overview of the data and the descriptive statistics, while Section 3 describes the research design and the empirical strategy. Section 4 presents the results, and Section 5 discusses the results' implications and concludes. The Appendices provide additional information about the data and several robustness checks.

2 Data

We use a monthly employer-employee longitudinal dataset from Statistics Norway containing earnings, hours, and a broad set of characteristics for all workers participating in the Norwegian labor market and their respective employers for 2009-2020. The data set contains worker-specific information, such as age, gender, citizenship, education, etc., and firm-specific information, such as industry classification and the number of employees. When we refer to a firm as an employer, we focus on the establishment level, i.e., the lowest level of a firm. We also have information about the employment relationship, such as occupation in the specific firm. This allows us to track the labor market outcomes of individual workers, such as re-employment, non-employment, and earnings, over time and to investigate heterogeneity in responses.

For earnings, we use a broad measure that contains all cash benefits from the employer, including agreed monthly salary, fixed and irregular allowances, bonus, overtime pay, severance pay, and other cash benefits not specified here, before tax. The data on earnings are reported monthly by employers to the Norwegian Labour and Welfare Administration (NAV), Statistics Norway, and the Norwegian Tax Administration.[6] We aggregate the data on earnings to annual frequency due to significant seasonal effects (the date of bonuses especially). In addition, the monthly entries are often contaminated due to revisions because employers are allowed to make corrections in one month due to errors in previous months. However, the sum of earnings over a calendar year has to be correct due to the reporting to the Norwegian Tax Administration.

2.1 The Petroleum Industry

We identify 76 858 unique workers distributed over 474 firms[7] in the Norwegian petroleum industry in 2014, using the same definition of the petroleum industry as Statistics Norway (Ekeland, 2017). This definition is based on the Standard Industrial Classification 2007 (SIC 2007), and includes both enterprises that are directly involved in petroleum extraction and enterprises that are indirectly involved through producing input factors specific to the petroleum industries, see Table 1.

In addition to these indirectly involved enterprises, several other enterprises supply goods and services to the petroleum industries. However, because this is not their principal activity, they are classified as other industries than the ones specified in Table 1.[8] For instance, this may be enterprises producing office supplies, cleaning services, cafeteria, catering services, etc. Studies using input-output tables based on figures from the Norwegian national accounts, such as Prestmo et al. (2015), have estimated that the total amount of employment linked to the petroleum industry in 2014 was about 240 000. For our analysis, it is convenient with a stricter definition to ensure that the petroleum workers we consider indeed are petroleum workers displaced from the petroleum industry.

[6] After 2015, this is done through a coordinated service called A-ordningen in Norwegian.

[7] In addition, there were 1977 firms registered in the petroleum industry without any employees.

[8] To be counted as an enterprise in an industry in SIC, the main part of the enterprise's production must be aimed at goods and services in the relevant industry. For enterprises engaged in more than one activity, SIC 2007 requires that it is determined by which activity is the principal one, primarily based on the one that makes the greatest contribution to the value added. If the value added is unavailable, measures such as the gross output of goods and services or the number of persons employed will be used.

Table 1: Classification of the petroleum industry.

SIC code	Description
06.100	Extraction of crude petroleum
06.200	Extraction of natural gas
09.101	Drilling services for petroleum and natural gas extraction
09.109	Other support activities for petroleum and natural gas extraction
49.500	Transport via pipeline
30.113	Building of oil-platforms and modules
30.116	Installation and completion work on platforms and modules
52.223	Offshore supply terminal

Notes: The classification is based on Ekeland (2017) and uses the Standard Industrial Classification 2007 (SIC 2007).

2.2 The Displaced Worker Analysis Sample

Following Lachowska et al. (2020), Couch and Placzek (2010) and Jacobson et al. (1993), we restrict our analysis to long-tenured workers with at least six years of job tenure with the same primary employer during 2009-2014 and positive annual earnings. We focus on long-tenured workers because they are most likely to have accumulated substantial amounts of industry-specific human or "match" capital before displacement (Jacobson et al., 1993).[9] Moreover, we define *primary employer* as the employer that in each month accounts for the highest number of agreed working hours.[10] Furthermore, we require that workers were between 20 and 50 years in 2014 to exclude early retirements. We also require all workers to have at least one month per calendar year with positive earnings from the date of displacement and throughout 2020. This means displaced workers are only allowed to experience periods of unemployment or be outside the labor force for less than one year. The estimates should therefore be interpreted as the effects of displacement on workers who remain attached to the Norwegian labor force. While this is a common restriction used in the literature, it has potential drawbacks. In particular, as emphasized by Jacobson et al. (1993), the excluded workers, i.e., those not attached to the labor force during some calendar year after displacement, may suffer both systematically larger or smaller long-term earnings losses.

Since displacement is unobservable in our dataset, we follow the literature on job displacement and define a worker as *displaced* if the worker ends a contract with her primary employer and that primary employer experiences a mass layoff within 12 months before or after the contract was terminated. The mass layoff term is often applied when there is no information available in administrative data on displacements to assure that workers did not voluntarily separate from a firm (Couch and Placzek, 2010).

[9] However, we show in Appendix B.3 that our results are robust to a shorter tenure requirement.

[10] This is in accordance with other studies conducted by Statistics Norway, and due to the contaminated monthly entries on earnings, as explained above. However, this differs from other papers in the literature that often defines the primary employer as the employer from whom the worker had the largest share of earnings.

Following the mass layoff definition of Davis and Von Wachter (2011) and Lachowska et al. (2020), an employer is counted as having a mass layoff in a month during 2015 or 2016 due to the oil price shock in 2014 if (i) employment dropped by 30 percent or more in a given month in 2015 or 2016 compared with the peak of 2014, and (ii) peak employment in 2014 was less than 130 percent of peak employment in 2013. The first condition ensures that employment drops sufficiently for the firm to be characterized as having a mass layoff, while the second condition ensures that firms that are experiencing a contraction solely due to an artificially high expansion period are not identified as having a mass layoff. We also require that minimum employment in a firm was more than 30 persons[11] in the period 2009-2014, since mass layoffs are defined by percentage changes in employment. Without this restriction, small employers may be falsely identified as mass layoff firms when experiencing relatively small absolute changes in employment. In total, we identify 63 firms as mass layoff firms, which includes approximately 13 percent of firms with a positive number of employees.

Workers who end a contract with an employer that does not experience a mass layoff are left out of the displaced worker group because the decision to leave is more likely to be voluntary and a result of the worker's choice or by employer selection. Applying this definition, we identify 12,031 petroleum workers displaced in 2015 and 2016 due to a mass layoff. Together with the sample restrictions described above, we are left with 1,553 long-tenured stably-employed displaced petroleum workers who remain attached to the Norwegian labor force.

After displacement, workers experience different types of labor market outcomes. Workers may get temporarily unemployed or leave the labor force, find a new job in the petroleum industry or move to other industries. Because we focus on industry reallocation, we are especially interested in the displaced workers moving to other industries. We define a displaced worker as an *industry mover* if the worker does not have any contract with an employer in the petroleum industry after displacement and until the end of 2020. Our definition of industry movement is then the most strict. Workers with a contract with an employer in the petroleum industry at some point after displacement and up until the end of 2020 are defined as *petroleum industry affiliates*. This does not mean that they may not move to other industries. Our restriction allows them to do so temporarily. However, they stay attached to the petroleum industry after displacement in a way that the industry movers do not. Applying these definitions, we find that out of 1,553 displaced petroleum workers, 278 are industry movers, while 1,275 are industry affiliates.

Finally, we define *stayers* as workers that were not displaced and that stay employed with the same primary employer as in 2014 throughout 2020. We also require that the primary employer is a firm with (minimum) employment of more than 30 persons in 2009-2014 to ensure

[11] This is less than the requirement of minimum 50 persons in Lachowska et al. (2020), but in line with Huitfeldt et al. (2022), and due to Norway being a relatively small country than other investigated. Requiring a minimum of 30 persons reduces the number of firms with employees from 474 to 146 and mechanically increases the average firm size from 157 to 445 employees. Applying the other mass layoff restrictions, in addition, reduces the number of firms further to 63 and decreases the average firm size to 390 employees.

comparability with the mass layoff firms. We identify 7,629 stayers.

2.3 Descriptive statistics

Table 2 gives an overview of the descriptive statistics. The first column represents the stayers, while the other three represent the displaced workers. In the second column, we report the descriptive statistics for all displaced workers, while in the third column, we report the statistics for industry movers. The fourth column represents the petroleum industry affiliates.

Average earnings are higher for stayers than displaced workers and lowest for the industry movers. Hours, age, and the share of workers with Norwegian citizenship are similar across groups. The share of men is higher for displaced workers than stayers but somewhat lower for industry movers.

Furthermore, we define high-skilled occupations as occupations associated with at least one year of higher education or being a manager. Slightly more than 50 percent of stayers have a high-skilled occupation, and the share is similar for the industry movers. Among the petroleum industry affiliates, however, the share of workers with a high-skilled occupation is notably lower. More than 70 percent are employed in low-skilled occupations. This means that there is a preponderance of workers in low-skilled occupations among those who stayed attached to the petroleum industry after displacement. If we look at the education level, the picture is the same. The level of education is lower among petroleum industry affiliates than among stayers and industry movers. This could indicate that options outside the petroleum industry are lower for workers with low-skilled occupations and/or low education. Finally, Table 2 shows that stayers were, on average, employed in larger enterprises than displaced workers.

Figure 1 displays the labor market outcomes for displaced petroleum workers from the first month following displacement up to 4 years after. The results show that approximately 65 percent of the workers are not in an employment relationship in the month following the displacement, where approximately 60 percent of them are registered as unemployed. Approximately 20 percent are employed in another industry, while 15 percent find a new job in the petroleum industry. However, after one year, approximately 60 percent of workers are employed in the petroleum industry, 30 percent are employed in other industries, and 8 percent are registered as unemployed. After four years, these numbers are adjusted to 67, 30, and less than 1 percent, respectively. Hence, most displaced workers eventually end up working in the petroleum industry. However, a substantial part of the displaced workers moves to other industries.

Table 2: Descriptive statistics.

	Stayer	Displaced		
		All	Industry movers	Petroleum industry affiliates
Average annual earnings and weekly hours, 2009-2012				
Earnings (2014 NOK)	816,059	725,639	686,532	734,166
	(372,278)	(246,298)	(256,008)	(243,399)
Hours	36	36	36	36
	(3)	(3)	(3)	(3)
Worker characteristics, 2014M12				
Male (share)	0.78	0.87	0.68	0.91
Norwegian (share)	0.96	0.97	0.99	0.96
High-skilled occupation (share)	0.56	0.33	0.54	0.29
Higher education (share)	0.39	0.23	0.34	0.21
Age	42	40	41	40
	(6)	(7)	(6)	(7)
Occupation (share)				
Engineer	0.33	0.16	0.24	0.15
Other high-skilled	0.24	0.17	0.30	0.14
Machine operators, crafts and trades	0.32	0.43	0.24	0.47
Other low-skilled	0.12	0.24	0.23	0.24
Employer characteristics, 2014M12				
Employer size (Number of workers)	1,525	643	626	646
	(1,421)	(808)	(819)	(806)
Number of employers (firms)	114	68	46	64
Number of workers	7,629	1,553	278	1,275

Notes: Occupation codes follow the Classification of Occupations 08, where we define high-skilled occupations from the first digit in the occupation code. Specifically, a worker is classified as high-skilled if the first digit in the occupation code is either 1 (managers), 2 (professionals) or 3 (technicians and associate professionals). Higher education is defined as having a bachelor or masters degree. All numbers in parenthesis represent standard deviations.

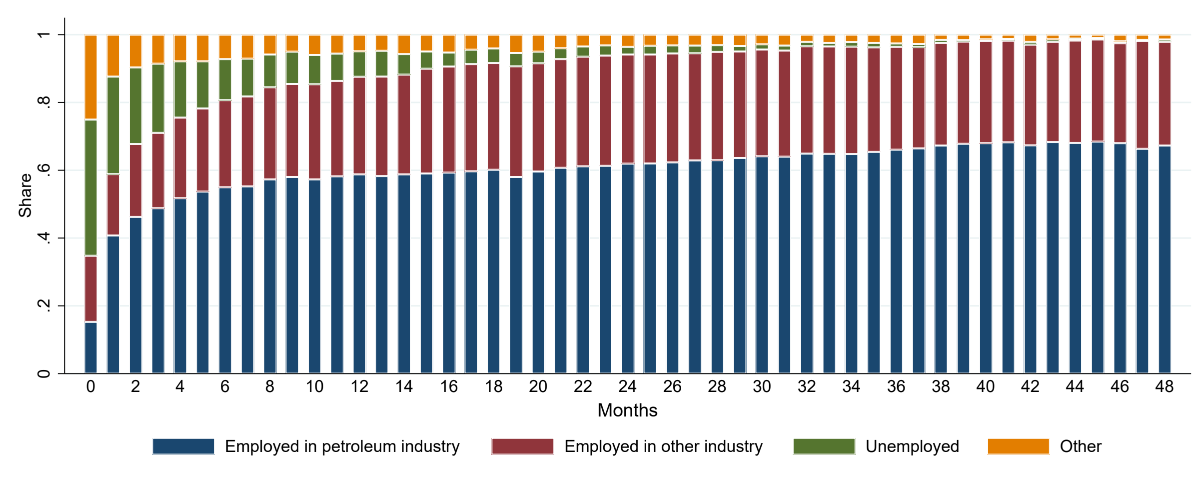


Figure 1: Event-study: Labor market status for displaced petroleum workers

Notes: The figure displays the labor market status of the displaced workers after displacement, where 0 is the month of displacement (i.e. the first month without their previous primary employer). The y-axis represents the share.

Table 3 gives an overview of which industries the industry movers moved to after being displaced from the petroleum industry. Industry movers may move in and out of industries; accordingly, the shares do not sum to 100 percent. The largest destination industries are Administrative and support service activities, Manufacturing, Professional, scientific and technical activities, and Construction, constituting 30, 26, 21, and 18 percent of the moves, respectively.

Table 3: Destination industries.

Industry	Share of workers
Administrative, support service	30.21
Manufacturing	25.67
Profess., scientific, tech. art.	21.12
Construction	17.91
Domestric trade, car repair shop	12.83
Public adm., defence, soc. security	9.36
Human health, social work	9.36
Transportation and storage	8.56
Information and communication	8.29
Education	6.42
Accomodation, food service	3.74
Real estate activities	3.48
Water supply, sewerage, waste	2.94
Other service activities	2.67
Electricity and gas supply	2.14
Financial and insurance activities	1.87
Arts, entertainment and recreation	1.07

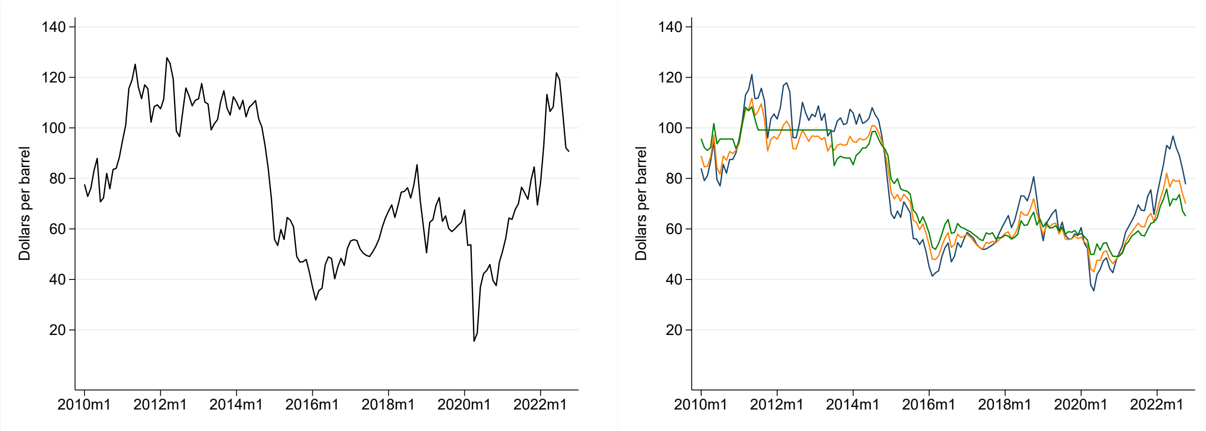
Notes: The table shows the number of industry movers , where the industries are the highest level of aggregation industries from the Standard Industrial Classification 2007 (SIC 2007). Note that workers can be in multiple industries after displacement from the petroleum industry. Accordingly, the shares do not sum to 100 percent.

3 Research design

3.1 The Oil Price Shock as a Natural Experiment

The price of Brent crude oil collapsed from around \$110 in the mid of 2014 to below \$50 per barrel at the beginning of 2016, see Figure 2a, due to changes in both supply and demand. Slower demand in emerging market economies contributed to the decline, also reflected in decreases in industrial metal prices. However, the much more significant drop in oil prices than metal prices suggests that oil supply factors also played a role. The Organization of the Petroleum Exporting Countries (OPEC) maintained its production levels at the same time as the shale revolution in the United States had led to steady increases in production from non-OPEC countries. The oil prices stayed low throughout 2015, hit record low levels at the beginning of 2016, and were expected to stay low for a longer period, as indicated by forward prices in Figure 2b.

This substantial and unexpected drop in oil prices was arguably an exogenous event to Norway, a non-OPEC country producing around 2 percent of global oil demand. Being perceived as a rather persistent shock, it led to substantial reallocations of labor away from the petroleum industry in 2015 and 2016, see Figure 3. In this paper, we exploit the oil price shock as a natural experiment to study the earnings losses of workers displaced from the petroleum industry due to lower profitability. We follow workers displaced from the petroleum industry in 2015 and 2016 using an event-study design described below.



(a) Oil price (b) Oil futures price

Figure 2: Oil price: brent blend

Notes: The left figure shows the spot price of brent blend oil, while the right figure shows futures prices 1 year (blue line), 3 years (orange line) and 6 years (green line) ahead, respectively.
Source: Refinitiv Datastream

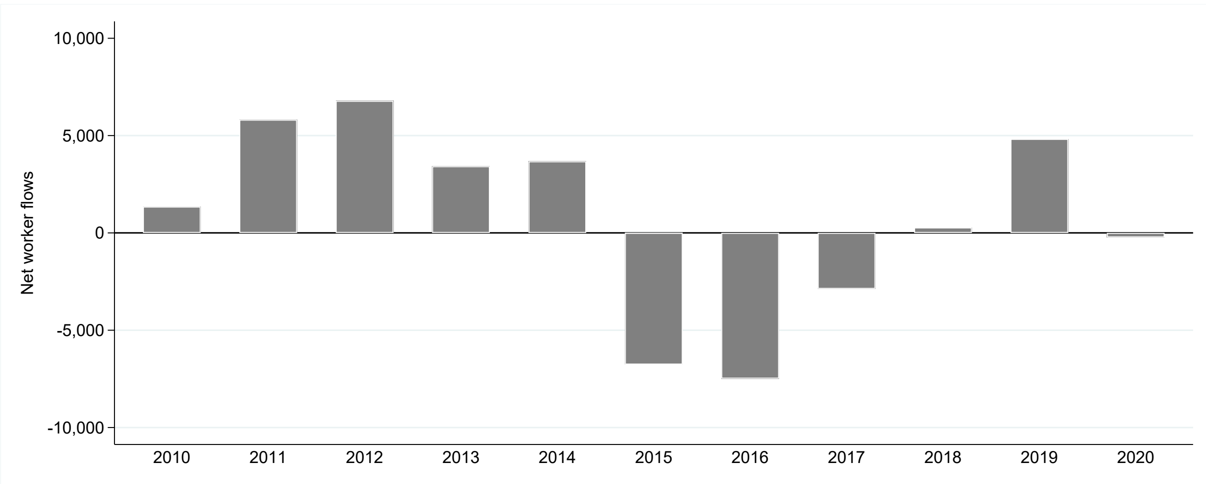


Figure 3: Net worker flows in the petroleum industry

Notes: The bars represent the year-over-year change in the number of workers in the petroleum industry. Employment is measured in December each year.

The oil price shock negatively impacted the Norwegian economy, especially in the Stavanger region, where the petroleum industry is key. However, the depreciation of the Norwegian krone, together with accommodating monetary and fiscal policy measures, dampened the adverse effects of the shock on the overall economy. In addition, the oil price shock turned out to be of a more temporary kind than first expected, with oil prices increasing about 20 percent in the second half of 2017 and averaging at 67 dollars per barrel in 2018-2019 (before the COVID-19 pandemic hit at the beginning of 2020). As the economic conditions in the petroleum industry improved, it is not surprising that many of the petroleum workers displaced during the oil price shock returned to the petroleum industry, as observed in Figure 1.

3.2 Event-Study with Staggered Treatment

We estimate the earnings losses of displaced petroleum workers using an event-study design with staggered treatment. In our setting, treatment refers to a worker being displaced. The treatment is staggered because workers can be displaced in 2015 or 2016. To follow the literature, we refer to workers displaced in 2015 and 2016 as different cohorts. Our comparison group consists of stayers, as described in Section 2.2. The treatment is absorbing because once a unit receives treatment, it will remain treated. Accordingly, we use a difference-in-difference design to estimate the earnings losses. Moreover, we are not only interested in the immediate effect of the treatment but also in estimating the dynamic treatment effects.

Two-Way Fixed Effects (TWFE) regressions, including leads and lags of the treatment, were the preferred estimation method for a long time in such difference-in-difference settings. However, the recent literature has shown that the coefficients measuring the dynamic treatment effects may be contaminated in settings with multiple time periods, staggered treatment, and where we cannot assume that the treatment effect is constant between groups and over time (Athey and Imbens, 2022; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; De Chaisemartin and D'Haultfoeuille, 2022; Goodman-Bacon, 2021; Sun and Abraham, 2021). Therefore, we use the interaction-weighted estimator proposed by Sun and Abraham (2021) due to its simple and familiar regression specification, robustness to heterogeneity in treatment effects, and the possibility of estimating the dynamic path of treatment effects.

To introduce some notation, let E_i denote the year of displacement for worker i, and e denote the cohorts, i.e., $e = \{2015, 2016\}$. The building block of the interaction-weighted estimator of Sun and Abraham (2021) is the so-called cohort-specific average treatment effect on the treated ($CATT$) ℓ periods from the initial treatment:

$$CATT_{e,\ell} = E[Y_{i,e+\ell} - Y^{\infty}_{i,e+\ell} | E_i = e] \tag{1}$$

where Y denotes the outcome variable, earnings or hours, and $Y^{\infty}_{i,e+\ell}$ denotes the potential outcome of worker i in the counterfactual scenario where worker i was not displaced.

The estimation scheme in Sun and Abraham (2021) is a three-step procedure. First, the $CATT_{e,\ell}$ is estimated using a linear TWFE model where relative period indicators interact with cohort indicators:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{e \in \{2015,2016\}} \sum_{l=-7, l \neq -2}^{5} \delta_{e,l} \mathbb{1}\{E_i = e\} D^l_{i,t} + \epsilon_{i,t} \tag{2}$$

where α_i is a worker-specific fixed effect and λ_t is a time-specific fixed effect. We include seven periods before displacement and five periods after,[12] and use two years before displacement as the reference year. Note that $\hat{\delta}_{e,l}$ is a DID estimator for $CATT_{e,\ell}$. Second, the weights for each $CATT_{e,\ell}$, denoted by $Pr\{E_i = e|E_i \in [-\ell, T-\ell]\}$, are estimated using sample shares of each cohort in the relevant periods, ℓ. Finally, the IW estimator is formed by taking a weighted average of the estimates of $CATT_{e,\ell}$ from step 1, using the weights from step 2. Formally, the IW estimator is:

$$\nu_\ell = \sum_e CATT_{e,\ell} Pr\{E_i = e|E_i \in [-\ell, T-\ell]\} \tag{3}$$

Assuming parallel trends and no anticipation effects, the IW estimator in (3) is consistent for a weighted average of the $CATT_{e,\ell}$.

Figure 4 displays annual earnings and agreed weekly hours for stayers and the two cohorts of displaced workers, displaced in 2015 and 2016, respectively. Panel 4a shows the results for earnings, while Panel 4b shows the results for hours. Panel 4a indicates that stayers had a higher level of earnings both before the oil price shock and after the displacements took place. However, also they experienced a contraction in earnings after the shock, reflecting reduced productivity in the petroleum industry. For the displaced workers, the drop in earnings around displacement is substantial. As indicated by the descriptive statistics in Table 2, industry movers had lower earnings prior to the shock than the petroleum industry affiliates. However, note that the earnings trends before the shock seem similar across groups. The difference-in-difference design does not require random or as good as random assignment to treatment and control groups. However, parallel trends before the shock are required to argue that the control group is a valid counterfactual for the treatment group. Figure 4a is reassuring and does not indicate a violation of the parallel trends assumption.

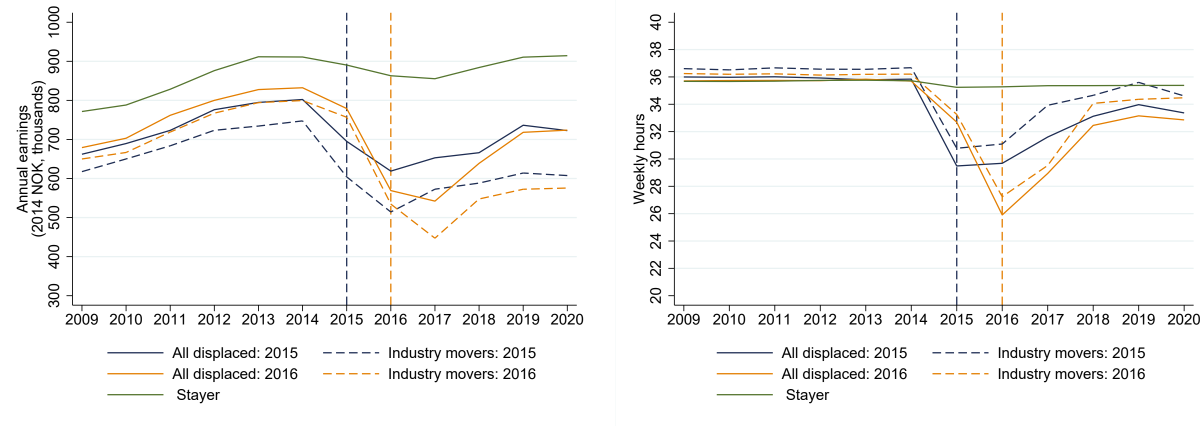
Figure 4b also indicates that trends in hours before the shock were similar across both the control and treatment groups, and the high number of weekly hours suggests that the workers in our sample were full-time employees in general[13]. For both cohorts of displaced workers, the drop in weekly hours around displacement is substantial and seems somewhat larger for the industry movers in the 2016 cohort. However, hours seem to catch up to a larger extent than earnings.

3.3 The decomposition of earnings losses

As our focus is on industry reallocation, we study the drivers behind the earnings losses of displaced petroleum workers at the industry level. We follow Lachowska et al. (2020) when decomposing the earnings losses into firm-specific effects, worker-firm match effects, and other displacement effects. Then, following Card et al. (2022), we define the industry-specific effects

[12] Accordingly, our model is fully saturated.

[13] Note that this is not a mechanical result. The sample restrictions require workers to have been stably employed in 2009-2014 but do not restrict agreed weekly hours. Workers may therefore be stably-employed part-time employees.



(a) Earnings

(b) Hours

Figure 4: Event-study

Notes: The left figure shows annual earnings in constant 2014 NOK, while the right figure shows agreed weekly working hours. The solid blue and orange lines represent displaced workers, while the dashed blue and orange line represents industry movers. The green line represents workers staying in the same firm. The dashed vertical lines represent the year of displacement, where blue is 2015 and orange is 2016.

as a weighted average of the firm-specific effects in that particular industry. Similarly, inspired by Woodcock (2008), we define the worker-industry match effects as a duration-weighted sum of the worker-firm match effects in a specific industry. The residual represents other displacement effects, which will capture more direct displacement effects, as discussed in Section 1.

3.3.1 Petroleum-specific earnings premiums

To investigate the role of industry characteristics in determining earnings losses of displaced petroleum workers, we build on the literature emphasizing that premiums paid by employers are important determinants of earnings (Abowd et al., 1999). However, instead of focusing on employer premiums, we focus our attention on industry premiums (Krueger and Summers, 1988; Card et al., 2022). As discussed in Section 1, and following the literature on Dutch disease, the petroleum industry is characterized by resource rents stemming from extracting natural resources. To the extent that workers in the petroleum industry receive a share of this rent as earnings premiums, we expect the reallocation to other industries paying a lower premium to explain parts of the earnings losses for the displaced workers.

The so-called AKM model developed by Abowd et al. (1999) is the classical framework used to estimate firm-specific earnings premiums. When the emphasis is on the industry level instead of the firm level, as in our context, one alternative is to estimate the standard AKM model at the industry level. However, as emphasized by Card et al. (2022), the so-called "industry hierarchy effect" introduces an attenuation bias in the industry fixed effect.[14] To account for this bias,

[14] Workers that move to another industry, so-called industry movers, may move up or down the industry ladder. Industry movers that move up the ladder tend to move from higher-paying firms in their origin industry to lower-paying firms in their destination industry. Conversely, industry movers who move down the ladder will often move

Card et al. (2022) define the industry-specific earnings premium as a weighted average of the earnings premiums for the firms in that particular industry. Following their so-called bottom-up approach, we estimate the industry-specific earnings premium in the following way. First, we residualize earnings by regressing log earnings on year indicators, age, gender, and education. Denoting the residualized earnings for worker i at year t by y^r_{it}, we then estimate the following to-way fixed effects model, referred to as the AKM model[15]:

$$y^r_{it} = \alpha_i + \phi_{f(i,t)} + \varepsilon_{it} \tag{4}$$

where α_i denotes characteristics of worker i that are transferable across firms and constant over time and $\phi_{f(i,t)}$ denotes characteristics of firm f that result in above- or below-average earnings for all employees in firm f that are constant over time. ϕ_f is identified by workers switching employers. Estimating (4) provides one ϕ_f for each firm. One interpretation of ϕ_f is that it represents earnings policies constant over time at firm f relative to the omitted baseline. Moreover, it can be interpreted as the advantage/disadvantage of being employed in firm f relative to the omitted baseline. The literature highlights limited mobility bias as a potential threat to the identification of ϕ_f. In our data set, the average number of moves per firm is about 28. Andrews et al. (2012) argues that limited mobility bias is not likely to pose a threat as long as the average moves per firm are more than 6. Accordingly, we are confident that this issue does not drive our estimates.

Next, following Card et al. (2022), we obtain the earnings premium for industry j by computing the weighted average of the firm premiums from equation (4) for all firms in industry j, where the weights are the relative (to the other firms in industry j) number of person-year observations in a given firm. Formally, let $j(f)$ denote the industry of firm f and N_f denote the number of worker-month observations for firm f. Then, the industry earnings premium is defined as:

$$\psi_j = \frac{\sum_{j(f)=j} N_f \phi_f}{\sum_{j(f)=j} N_f} \tag{5}$$

The sample used to estimate the AKM model is described in Appendix A. We use the highest level of aggregation industries from the Standard Industrial Classification 2007 (SIC 2007) and treat the petroleum industry, as defined in Table 1, as the omitted baseline. Finally, we use the estimated industry premiums, $\hat{\psi}_j$, as the dependent variable in a regression like equation (2) and (3) to obtain the effect on log earnings of reallocating to an industry with different earnings premiums. The estimates now represent the difference in industry premiums

from lower-paying firms in one industry to higher-paying firms in another. Consequently, the move in the industry hierarchy is negatively correlated with the move in the firm hierarchy, causing the industry hierarchy effect that needs to be accounted for. Card et al. (2022) show that cross-sectional estimates of the wage differences between industries dramatically *overstate* the true differentials, while estimates based on industry movers significantly *understates* them.

[15] Lachowska et al. (2020) omit both the sample of displaced workers and the comparison group when estimating the AKM model to avoid a mechanical relationship between the fixed effect and displaced workers losses, potentially overstating the role of fixed effects. As robustness, we remove the displaced workers and the stayers used in the main analysis when estimating equation (4). This does not affect our results.

for displaced workers relative to stayers from before to after displacement. Accordingly, negative values represent lost industry premiums (e.g., lost resource rent) due to reallocating to an industry with lower premiums. The results are presented in Section 4.2.

3.3.2 Worker-Industry Match Effects

In this section, we investigate the role of so-called worker-industry match effects in explaining earnings losses for displaced petroleum workers. A worker's productivity may differ among industries due to industry-specific skills, or contractual agreements that increase the worker's productivity in a given industry. Again, we follow Lachowska et al. (2020) and estimate worker-firm match effects that are constant over time for earnings using the fixed effects estimator of Woodcock (2015). Then, inspired by Woodcock (2008), we define the worker-industry match effects as a duration-weighted sum of the worker-firm match effects in a specific industry. We use the same sample to estimate the match effects as we use to estimate the industry fixed effects.

The estimate of worker-industry match effects is constructed in two steps. First, we identify all worker-firm pairs, i.e., all observations for person i working in firm f, and compute the average (log) earnings ($\overline{\log Y}_{if}$) for each of the matches. We use the same controls as in the AKM model. Second, we estimate the following two-way fixed effects model:

$$\overline{\log Y}_{if} = w_i + \beta_{f(i)} + \mu_{if} \tag{6}$$

where w_i is a worker fixed effect and $\beta_{f(i)}$ is a firm fixed effect. Accordingly, the estimated residuals from equation (6), $\hat{\mu}_{if}$ represent the variation in $\overline{\log Y}_{if}$ left after controlling for worker and firm effects.

Next, we obtain the worker-industry match effect by computing the duration-weighted average of the worker-firm match effects in a given industry, denoted by Λ_{ij}. The duration here refers to the number of years a worker is employed in a firm in a given industry relative to the number of years a worker is employed in any firm in the industry. Finally, we use the estimated worker-industry match effects as the dependent variable in a regression like equation (2) and (3) to obtain the effect on log earnings of moving to an industry with a different worker-industry match effect. The estimates now represent the difference in the worker-industry match for displaced workers relative to stayers from before to after displacement. Accordingly, negative values represent lost worker-industry match effects due to moving to an industry with a lower worker-industry match. The results are presented in Section 4.3.

3.4 Selection bias

Our empirical strategy is associated with worker selection challenges, which may bias our estimates. First, it is not necessarily random which workers are laid off. This is a common challenge in the literature on job displacements. In particular, the least experienced and productive workers who have attained less human capital and industry-specific skills might be more likely to face displacement. Accordingly, the displaced workers might be of lower quality than the non-displaced, which could bias the results toward higher earnings losses. On the other hand, as we require all workers to have at least one month per calendar year with positive earnings, we exclude all workers that are either long-term unemployed or outside the labor force after displacement. A mechanical result is that the estimated earnings losses are lower than for the full sample of workers.[16] Moreover, the requirement of at least six years of tenure reduces the concern that the displaced workers are the least experienced. Accordingly, the sign of the bias for displaced workers, in general, is ambiguous.

Second, selection effects might determine which workers are reallocating to other industries. However, also here, the direction of the bias is ambiguous. On the one hand, a worker might be forced to reallocate to a non-petroleum industry because she is not productive enough for the petroleum industry. This will bias the results towards higher earnings losses for the industry movers. On the other hand, industry movers might reallocate voluntarily. This choice might be driven by amenities such as more favorable working hours, lower risk (both physical risk and job-loss risk), or the workers' view of the industries' prospects. Moreover, industry movers could be workers with relatively favorable prospects in other industries. This will bias the results towards lower earnings losses for the industry movers. In sum, the sign of the selection bias related to the industry movers is ambiguous. All these concerns are partly addressed by investigating the parallel pre-trends in earnings. However, to the extent that selection is related to non-observables and not reflected in pre-displacement earnings, our results may suffer from selection bias.

4 Results

4.1 Estimates of Earnings Losses of Displaced Petroleum Workers

The difference-in-difference analysis described in Section 3 enables us to estimate the earnings loss for displaced petroleum workers using stayers as a comparison group. The results are summarized in Figure 5 and reported in log points[17]. Panel 5a reports the results for all displaced petroleum workers, while Panel 5b reports the results for industry movers specifically.[18] Table 5 summarizes the results.

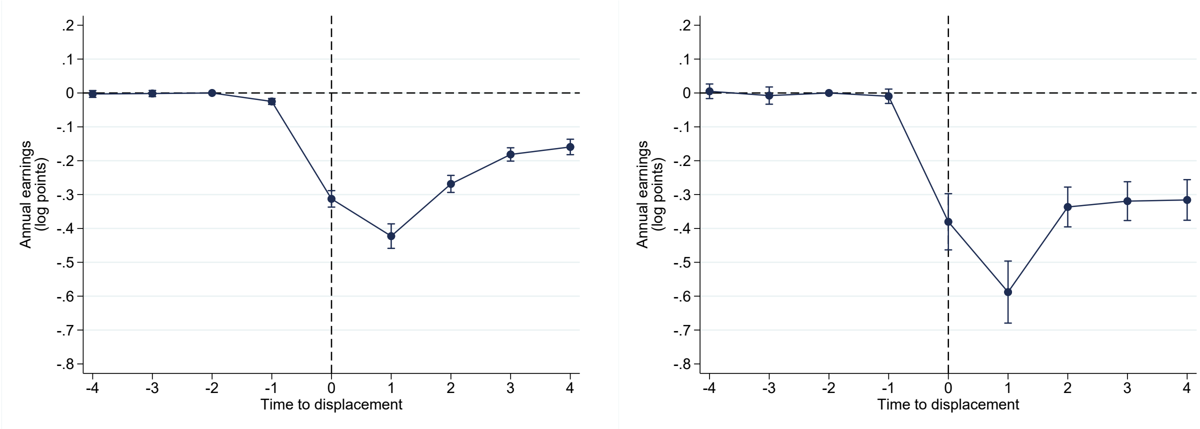
First, it is important to note that the results in Figure 5 do not indicate a violation of the parallel trends assumption. Secondly, displacement leads to a sharp immediate drop in earnings, and the earnings loss is substantially larger for industry movers than for displaced petroleum workers in general. Finally, the earnings losses are persistent.

Specifically, after one year, the earnings loss for all displaced petroleum workers is approximately 35 percent, while the industry movers suffer earnings losses as large as approximately 45

[16] This is true for the periods in which they are not employed. However, for the workers that eventually return to the labor market, the earnings loss in their new job might be lower and higher than for the workers in the restricted sample.

[17] The point estimates given in log points, x, can be translated into percentage change by using the following formula: $100(e^x - 1)$.

[18] Adding controls such as age, age^2, gender, and education does not change the results.



(a) Displaced

(b) Industry movers

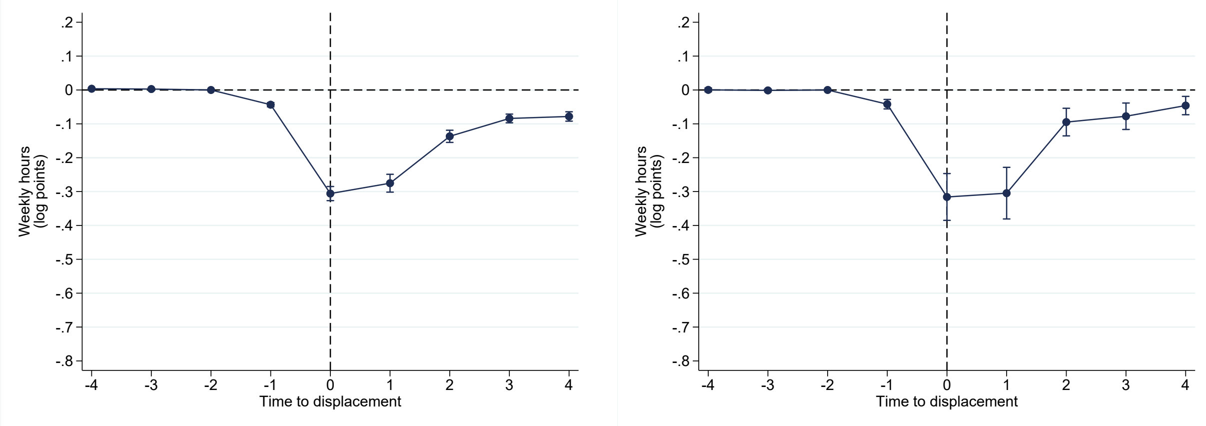
Figure 5: Estimated earnings losses for displaced workers

Notes: The figures show the estimates of the cohort-weighted average treatment effect, ν_ℓ, from equation (3) with log earnings (measured in 2014 NOK) as the dependent variable. The x-axis denotes the year relative to displacement, and the dashed vertical line at 0 denotes the year of displacement. The circles represent point estimates measured in log points, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

percent. As more workers move out of unemployment and return to the labor force, find better jobs, and/or acquire more experience, earnings recover to some extent. We observe a steady recovery among displaced workers in general. After four years, the earnings loss for displaced workers reduces to approximately 15 percent. Industry movers experience a recovery in earnings between the first and second year after displacement, but after that, the earnings loss stays relatively stable at approximately 27 percent.

We follow the literature on job displacement when using stayers as a comparison group. However, as described in Section 2.2, stayers are required to stay stably employed with the same primary employer as in 2014 throughout 2020, while displaced workers are allowed to move between employees after displacement. Stayers are then subject to stricter restrictions than displaced workers. Therefore, we also use non-displaced workers without any restriction on stable employment after 2015 as a robustness check; see Appendix B.1. This has little effect on the results and does not change the result pattern.

The loss in earnings is partly due to a reduction in agreed weekly hours. Figure 6 displays the results from the difference-in-difference analysis for hours and indicates that displaced workers in general (Panel 6a) and the industry movers (Panel 6b) experienced similar reductions in hours. After one year, the reduction was 26 and 27 percent, respectively. However, as more workers moved out of unemployment and returned to the labor force, hours came much closer to recovering to pre-displacement levels than earnings. Specifically, the hours were reduced to about 7 and 8 percent after four years, respectively. Also, here, adding controls, does not affect the results.



(a) Displaced

(b) Industry movers

Figure 6: Estimated working hour losses for displaced workers

Notes: The figures show the estimates of the cohort-weighted average treatment effect, ν_ℓ, from equation (3) with log weekly hours as the dependent variable. The x-axis denote the year relative to displacement, and the dashed vertical line at 0 denotes the year of displacement. The circles represent point estimates measured in log points, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

4.2 Industry fixed effects

The estimated industry premiums, ψ_j, from equation (4) for each industry, are displayed in Table 4 in a descending order, where the petroleum industry is used as the baseline. The evidence suggests that the petroleum industry exhibits the largest premiums of all industries in Norway, with 23 percent higher earnings on average compared to other industries. These results confirm the hypothesis that the petroleum industry is characterized by large premiums.

This estimate is based on the whole sample period. Some may argue that the relative profitability of the petroleum industry decreased after the oil price shock. We explore how subsampling in the AKM-model affects the estimates in Appendix B.2, and find that dividing the sample into a pre- and post-shock period has a limited effect on the estimates of the industry fixed effects and that it yields the opposite result than one might have expected when considering the average petroleum industry-specific earnings premium. Before the shock, the petroleum industry-specific earnings premium was 20,6 percent on average compared to other industries, while after the shock increased to 21,3 percent.

Using the estimated industry effects from the AKM model, we estimate the impact on earnings of moving to an industry with a different industry fixed effect; see Figure 7. The estimates represent the difference in industry effects for displaced workers relative to stayers and the baseline year. Negative values represent lost industry earnings premiums due to reallocating to an industry with lower earnings premiums. Figure 7b suggests that a large amount of the earnings loss experienced by industry movers, is due to loss of petroleum industry-specific earnings premiums, accounting for approximately 68 percent after four years, see Table 5.

Table 4: Industry fixed effects.

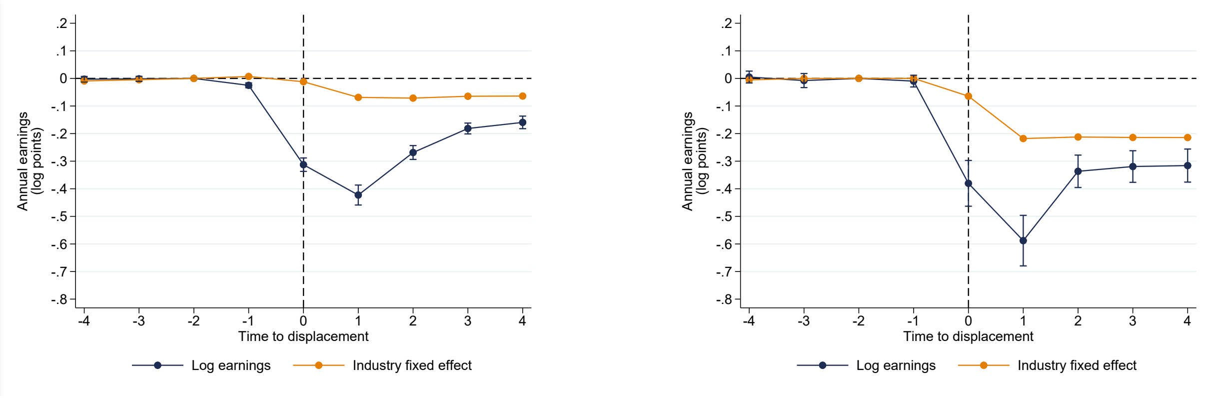
Industry	Fixed effect
Petroleum industry	0.0000
Average non-petroleum industries	-0.2297 (-0.2126)
Mining and quarrying	-0.0923
Financial and insurance activities	-0.0931
Public adm., defence, soc. security	-0.1250
Information and communication	-0.1291
Manufacturing	-0.1674
Profess., scientific, tech. art.	-0.1775
Electricity and gas supply	-0.1775
Human health, social work	-0.1917
Real estate activities	-0.1930
Domestic trade, car repair shop	-0.2065
Construction	-0.2095
Water supply, sewerage, waste	-0.2345
Transportation and storage	-0.2598
Other service activities	-0.2721
Agriculture, forestry and fishing	-0.2857
Extraterr. organisations and bodies	-0.3089
Education	-0.3223
Administrative, support service	-0.3542
Arts, entertainment and recreation	-0.3593
Accomodation, food service	-0.4337

Notes: The table shows the estimates of the industry-specific fixed effect for each industry j, ψ_j, from equation (4) with log earnings as the dependent variable. The industries are the highest level of aggregation industries from the Standard Industrial Classification 2007 (SIC 2007). Industries are sorted in descending order based on the estimated fixed effects, and the petroleum industry is used as the baseline, represented by a fixed effect equal to zero. The average fixed effect for non-petroleum industries displays the unweighted average, and the weighted average is shown in parenthesis, where the weights are employee shares in the respective industries.

The estimate for displaced workers, in general, includes both industry movers and the petroleum industry affiliates. The affiliates may also experience earnings losses due to the loss in petroleum industry-specific earnings premiums. They do not permanently move to other industries, such as the industry movers, but they can temporarily move to other industries. For these workers, the petroleum industry-specific earnings premium obviously constitutes a smaller share of the earnings loss than for the industry movers. Figure 7a and Table 5 show that the contribution of the industry fixed effect is still sizable, with the petroleum industry-specific earnings premium accounting for approximately 40 percent of the earnings loss that all displaced workers experience four years after displacement. Also, here, the results are robust when adding controls.

4.3 Worker-industry match effects

The worker-industry match effects encompass all time-invariant factors specific to the relationship between a worker and her industry that increases the value of the match. A worker's



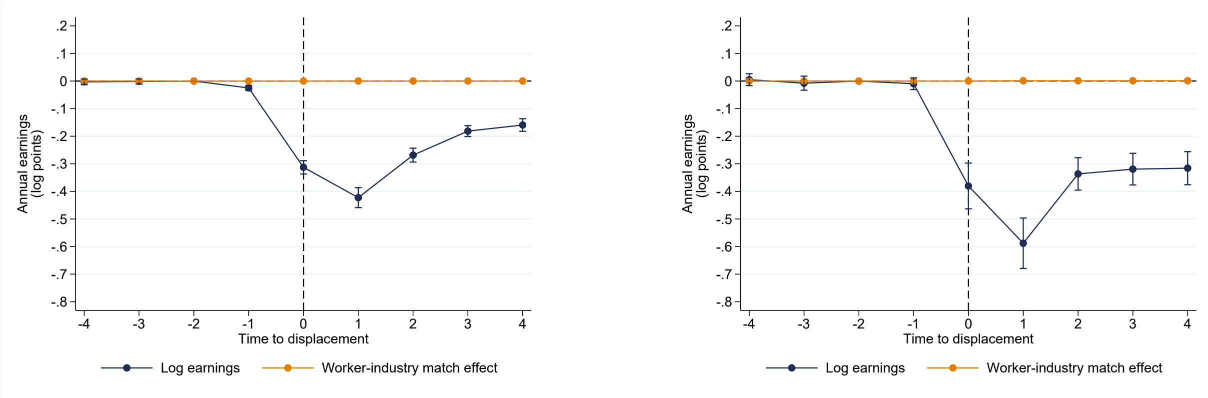
(a) Displaced

(b) Industry movers

Figure 7: Estimated earnings losses for due to lost industry fixed effects

Notes: The figures show the estimates of earnings losses due to lost industry premiums, ψ_j, (represented by the orange line), and the full estimated earnings losses due to displacement as in Figure 5 (represented by the blue line). The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

productivity may differ among industries due to industry-specific skills, or contractual agreements that increase the worker's productivity in a given industry. However, Figure 8 suggests that worker-industry match effects play a minor role in explaining the earnings losses of displaced petroleum workers. The estimates are essentially 0 in all years after displacement for displaced workers in general and industry movers.



(a) Displaced

(b) Industry movers

Figure 8: Estimated earnings losses for due to lost worker-industry match effects

Notes: The figures show the estimates of earnings losses due to lost worker-industry matches, Λ_{ij}, (represented by the orange line), and the full estimated earnings losses due to displacement as in Figure 5 (represented by the blue line). The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

Table 5: Decomposition of earnings losses.

Year	Log change (% change)	Percent of losses
	All displaced	
1		
Earnings	-0.423 (-34.5)	
Industry fixed effects	-0.069 (-6.6)	16.3
Worker-industry match effects	0.000 (0.0)	-0.0
Other effects	-0.354 (-29.8)	83.8
2		
Earnings	-0.269 (-23.6)	
Industry fixed effects	-0.071 (-6.9)	26.5
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.197 (-17.9)	73.5
3		
Earnings	-0.181 (-16.6)	
Industry fixed effects	-0.065 (-6.3)	35.6
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.117 (-11.0)	64.5
4		
Earnings	-0.159 (-14.7)	
Industry fixed effects	-0.064 (-6.2)	40.1
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.096 (-9.1)	60.0
	Industry movers	
1		
Earnings	-0.588 (-44.5)	
Industry fixed effects	-0.218 (-19.6)	37.1
Worker-industry match effects	0.001 (0.1)	-0.2
Other effects	-0.371 (-31.0)	63.1
2		
Earnings	-0.337 (-28.6)	
Industry fixed effects	-0.212 (-19.1)	63.1
Worker-industry match effects	0.001 (0.1)	-0.3
Other effects	-0.125 (-11.8)	37.2
3		
Earnings	-0.319 (-27.3)	
Industry fixed effects	-0.214 (-19.3)	67.0
Worker-industry match effects	0.001 (0.1)	-0.3
Other effects	-0.106 (-10.1)	33.3
4		
Earnings	-0.316 (-27.1)	
Industry fixed effects	-0.214 (-19.3)	67.8
Worker-industry match effects	0.001 (0.1)	-0.3
Other effects	-0.103 (-9.8)	32.5

Notes: The table shows earnings losses following displacement and the decomposition into lost industry fixed effects, lost worker-industry match effects, and the residual.

5 Conclusion

This paper provides empirical estimates of the private costs of job loss and reallocation among petroleum workers in response to a downsizing of the petroleum industry. We provide three key insights. First, we document large earnings premiums in the petroleum industry relative to non-petroleum industries. This suggests that there is substantial rent-sharing between capital owners and workers in the petroleum industry, in line with theories of non-competitive rents.

Second, in line with the literature on earnings losses of displaced workers, we document that displaced petroleum workers suffer large and persistent earnings losses. Importantly, we show that the earnings losses are not evenly distributed among all the displaced petroleum workers. In particular, there is a significant idiosyncratic risk between petroleum workers in the face of a decline in the petroleum industry. The earnings losses are largely concentrated on workers moving to other industries, creating substantial heterogeneity in earnings outcomes. The industry movers experience significantly higher and more persistent earnings losses than workers remaining in or turning back to the petroleum industry.

Third, the major driver of long-term earnings losses, i.e., earnings losses four years after displacement, is loss of industry premiums, while worker-industry match effects are negligible. Accordingly, the main driver of the heterogeneous responses in earnings is that workers staying or moving back to the petroleum industry keep participating in the favorable rent-sharing, while workers reallocating to other industries do not. As worker-industry match effects are negligible, the loss of industry-specific human capital seems to play a limited role in future labor market outcomes.

In terms of external validity, we believe our empirical estimates provide valuable information about the reallocation costs of a decline in the petroleum industry beyond the exact case study of the oil price drop in 2014. The ongoing green transition, leading to a structural transformation of economies producing fossil fuels, entails reallocation costs, which partly depend on the labor market outcomes of displaced workers in the fossil fuel industry. Regarding policy implications, both the magnitudes and sources of earnings loss following displacements matter. In the context of a green transition inducing a reduced profitability of the petroleum sector, losses in industry-specific premiums for industry movers, i.e., petroleum workers reallocating to other industries, are, to some extent, unavoidable.

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Appendices

Appendix A AKM model sample

To estimate the AKM model in equation (4), we use administrative matched employer-employee data from Norway from 2008-2020. When we refer to a firm as an employer, we focus on the establishment level, i.e., the lowest level of a firm. The data set is on a monthly frequency, but we aggregate it to an annual frequency in the following way, following Lachowska et al. (2020). First, each month, we identify the primary employer of each worker, defined as the employment relationship where the worker had the largest contracted weekly work hours.[19] Next, we define an employment spell of a given worker as a period of at least five consecutive months with the same primary employer. Further, we drop the first and last to months for each of these employment spells to improve inference. While the first disregards partial months of employment, the latter disregards earnings in the month before and the month of ending an employment relationship. Next, using only the identified months of employment spells, we identify the primary employer in a given year as the employment relationship where the worker had the highest total earnings. Lastly, we annualize earnings conditional on the calendar year, including at least two consecutive months of earnings from the same primary employer, by multiplying the average monthly earnings in these months by 12. Moreover, inspired by Huitfeldt et al. (2022), we apply some further sample restrictions on firms and workers. First, we disregard firms that had fewer than 30 employees during the sample period. Second, we restrict workers' ages to between 20 and 61 years. Third, we restrict weekly hours to at least 30. The firm premiums are only identified within the so-called "connected set" of firms linked to each other through workers moving between these firms. The descriptive statistics of the largest connected set are displayed in Table 6.

Table 6: Descriptive statistics: largest connected set

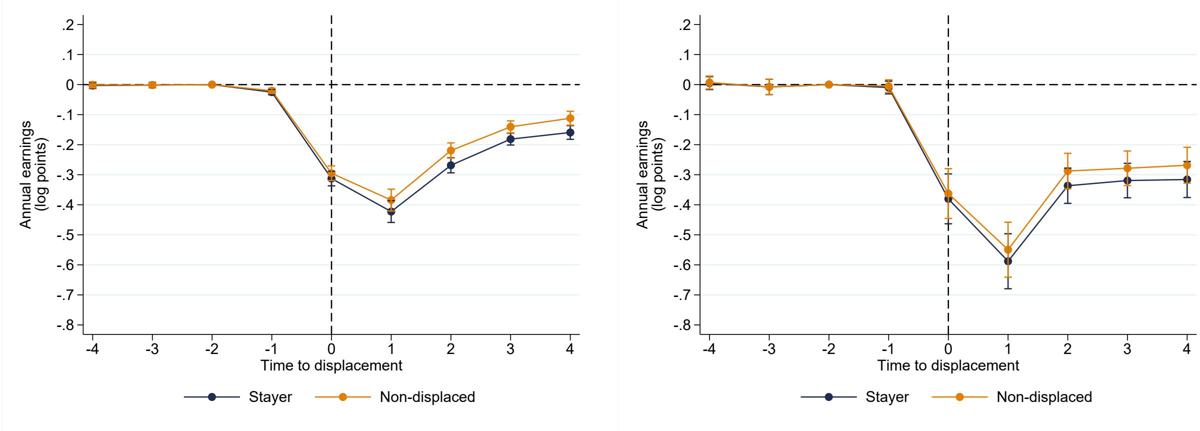
	Largest connected set
Number of worker/year observations	10,773,336
Number of unique workers	1,305,469
Number of unique firms	36,781
Number of unique movers	625,738
Number of mover/year observations	1,036,811

Notes: The table displays descriptive statistics for the largest connected set used to estimate the AKM model.

[19] Lachowska et al. (2020) use quarterly earnings instead of hours to identify the primary employer. However, in our data set, the monthly earnings data may be relatively imprecise due to employer corrections over the year. However, contracted hours are a much more precise measure.

Appendix B Additional results

B.1 Non-displaced as control group

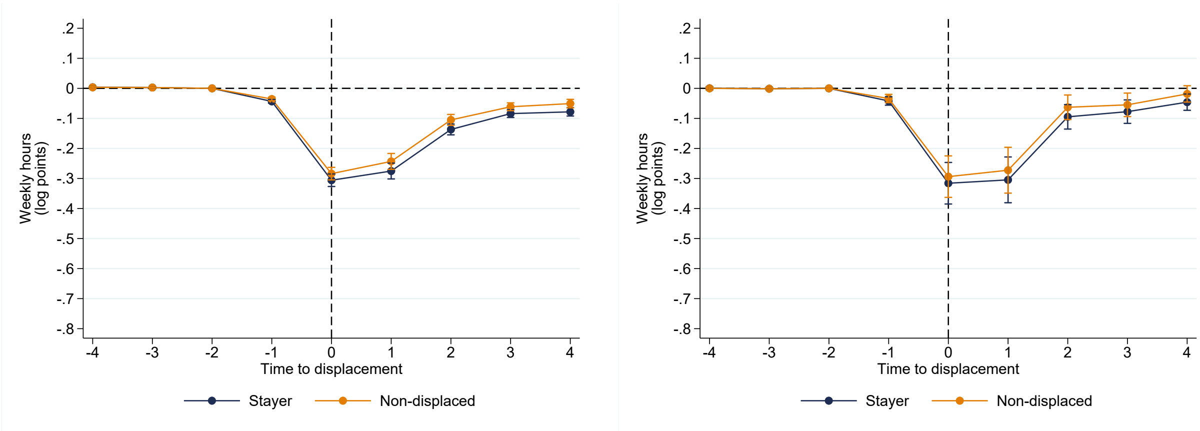


(a) Displaced

(b) Industry movers

Figure 9: Estimated earnings losses for displaced workers

Notes: The figures show the estimates of the cohort-weighted average treatment effect, ν_ℓ, from equation (3) with log earnings (measured in 2014 NOK) as the dependent variable. The x-axis denotes the year relative to displacement, and the dashed vertical line at 0 denotes the year of displacement. The circles represent point estimates measured in log points, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

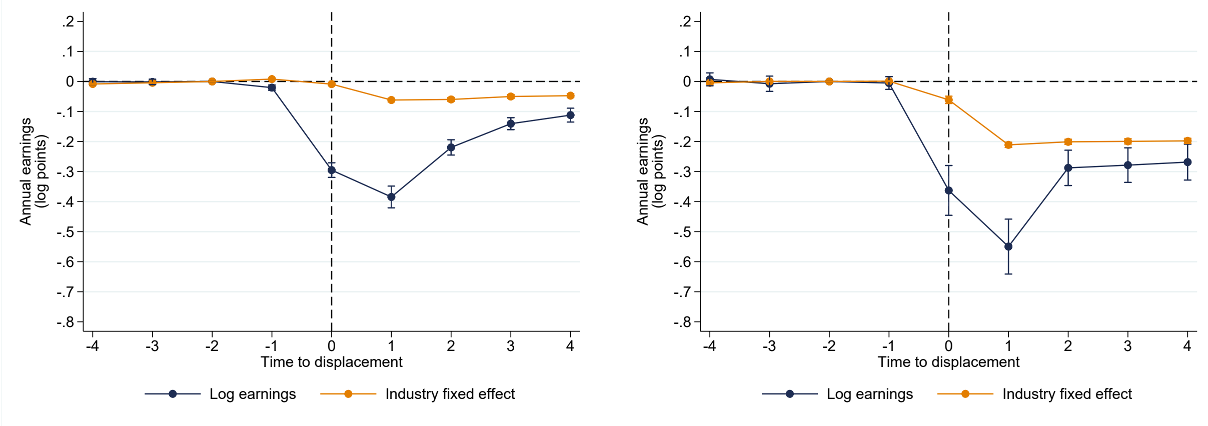


(a) Displaced

(b) Industry movers

Figure 10: Estimated working hour losses for displaced workers

Notes: The figures show the estimates of the cohort-weighted average treatment effect, ν_ℓ, from equation (3) with log weekly hours as the dependent variable. The x-axis denotes the year relative to displacement, and the dashed vertical line at 0 denotes the year of displacement. The circles represent point estimates measured in log points, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

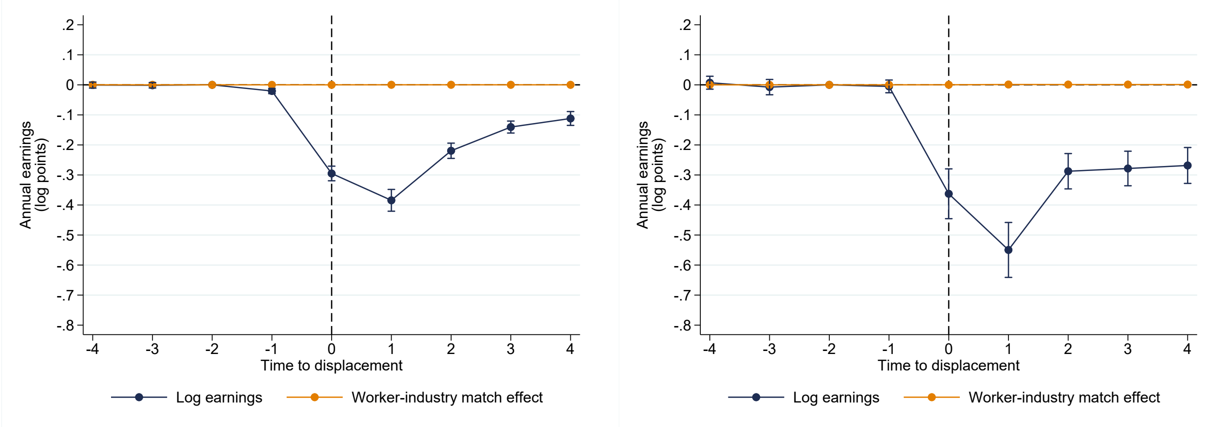


(a) Displaced

(b) Industry movers

Figure 11: Estimated earnings losses for due to lost industry fixed effects

Notes: The figures show the estimates of earnings losses due to lost industry premiums, ψ_j, (represented by the orange line), and the full estimated earnings losses due to displacement as in Figure 9 (represented by the blue line). The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.



(a) Displaced

(b) Industry movers

Figure 12: Estimated earnings losses for due to lost worker-industry match effects

Notes: The figures show the estimates of earnings losses due to lost worker-industry matches, Λ_{ij}, (represented by the orange line), and the full estimated earnings losses due to displacement as in Figure 9 (represented by the blue line). The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

Table 7: Decomposition of earnings losses.

Year	Log change (% change)	Percent of losses
	All displaced	
1		
Earnings	-0.384 (-31.9)	
Industry fixed effects	-0.062 (-6.0)	16.1
Worker-industry match effects	0.000 (0.0)	-0.0
Other effects	-0.323 (-27.6)	84.0
2		
Earnings	-0.219 (-19.7)	
Industry fixed effects	-0.060 (-5.8)	27.2
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.160 (-14.8)	72.8
3		
Earnings	-0.141 (-13.1)	
Industry fixed effects	-0.050 (-4.9)	35.6
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.091 (-8.7)	64.5
4		
Earnings	-0.112 (-10.6)	
Industry fixed effects	-0.047 (-4.6)	42.3
Worker-industry match effects	0.000 (0.0)	-0.1
Other effects	-0.065 (-6.3)	57.8
	Industry movers	
1		
Earnings	-0.550 (-42.3)	
Industry fixed effects	-0.211 (-19.0)	38.4
Worker-industry match effects	0.001 (0.1)	-0.2
Other effects	-0.340 (-28.8)	61.8
2		
Earnings	-0.288 (-25.0)	
Industry fixed effects	-0.201 (-18.2)	69.8
Worker-industry match effects	0.001 (0.1)	-0.3
Other effects	-0.088 (-8.4)	30.5
3		
Earnings	-0.278 (-24.3)	
Industry fixed effects	-0.199 (-18.1)	71.6
Worker-industry match effects	0.001 (0.1)	-0.3
Other effects	-0.080 (-7.7)	28.7
4		
Earnings	-0.268 (-23.5)	
Industry fixed effects	-0.198 (-17.9)	73.6
Worker-industry match effects	0.001 (0.1)	-0.4
Other effects	-0.072 (-6.9)	26.7

Notes: The table shows earnings losses following displacement and the decomposition into lost industry fixed effects, lost worker-industry match effects, and the residual.

B.2 AKM model sub-sampling

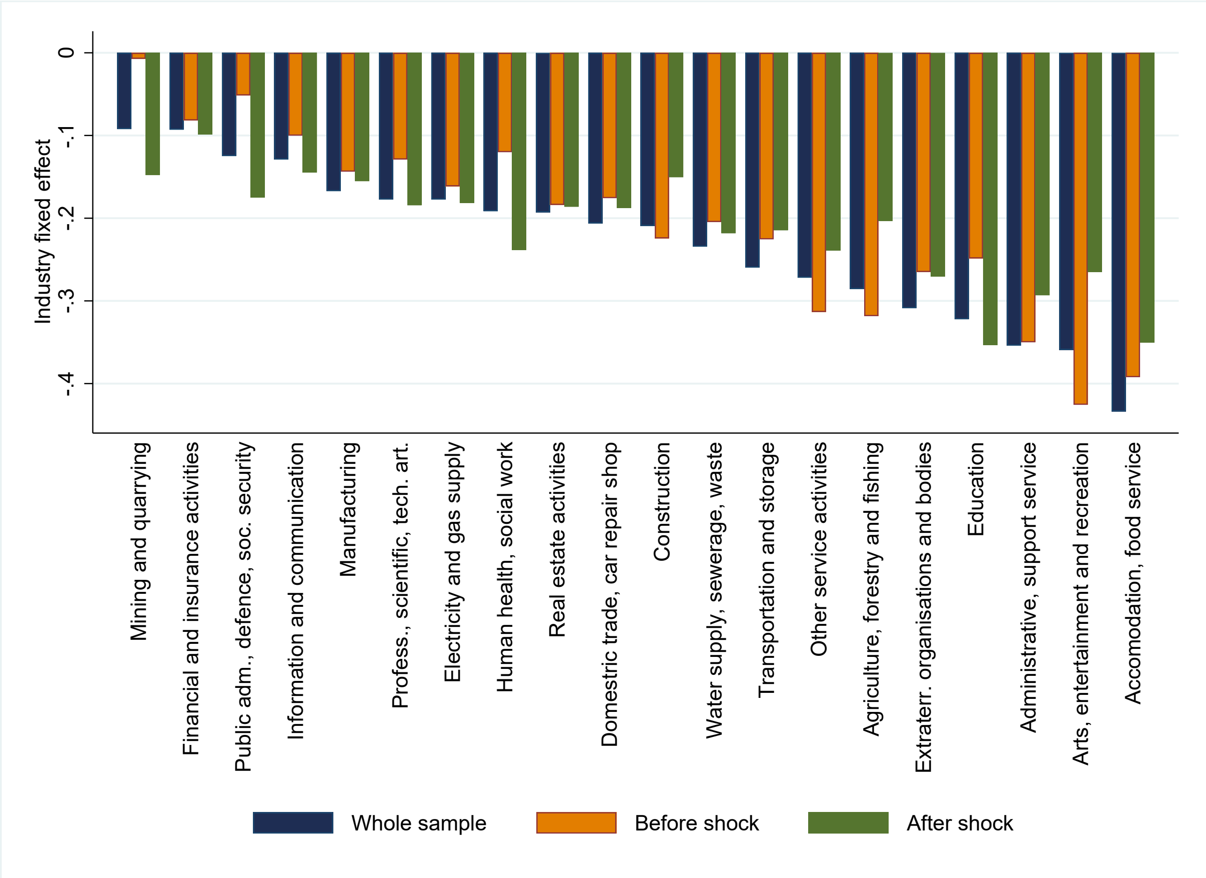


Figure 13: Industry fixed effects for different sub-samples

Notes: The figure compares the estimates of the industry fixed effects, ψ_j, for all the industries using different sub-samples. The sub-samples are 2009-2014 (before shock) and 2015-2020 (after shock), respectively.

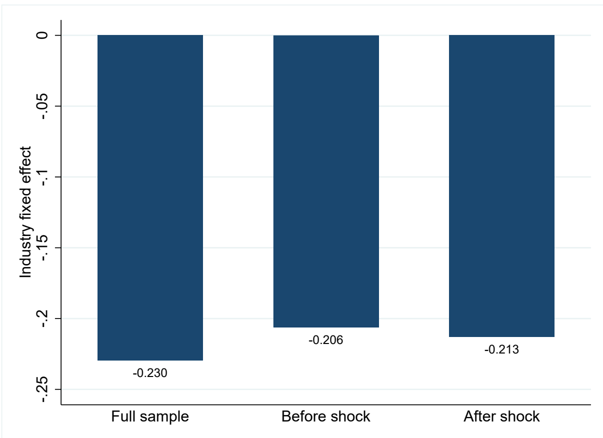
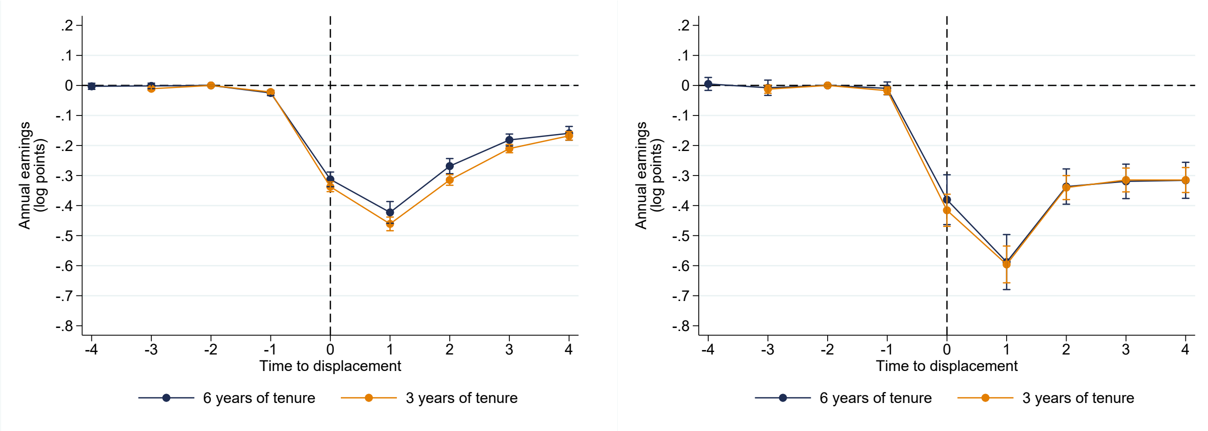


Figure 14: Average petroleum industry earnings premium for different sub-samples

Notes: The figure compares the average petroleum industry earnings premium, where the fixed effect of the petroleum industry is compared to the average fixed effect for all other industries, using different sub-samples. The sub-samples are 2009-2014 (before shock) and 2015-2020 (after shock), respectively.

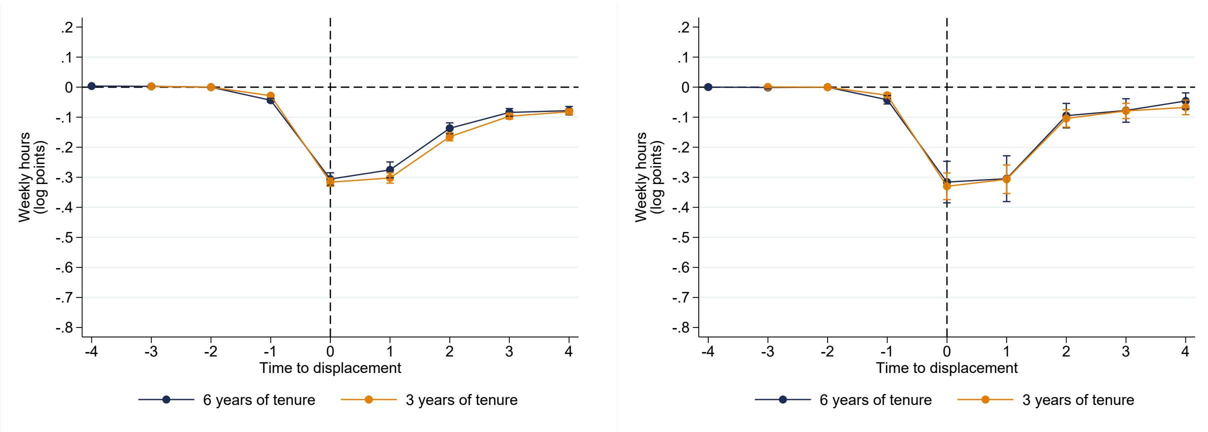
B.3 Alternative tenure requirements



(a) Displaced (b) Displaced and reallocated

Figure 15: Estimated earnings losses for displaced workers using alternative tenure requirements

Notes: The figures show the estimates of earnings losses for different tenure requirements. The blue line represents the estimates conditional on at least six years of tenure (see Figure 5), while the orange line represents the estimates conditional on at least three years of tenure. The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.



(a) Displaced (b) Displaced and reallocated

Figure 16: Estimated weekly hours losses for displaced workers using alternative tenure requirements

Notes: The figures show the estimates of weekly hours losses for different tenure requirements. The blue line represents the estimates conditional on at least six years of tenure (see Figure 6), while the orange line represents the estimates conditional on at least three years of tenure. The circles represent point estimates, while the whiskers represent 95 percent confidence intervals. Standard errors are clustered at the worker level.

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