Domino Effects: Understanding Sectoral Reallocation and its Wage Implications*

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Abstract

This paper studies the impact of the collapse in the price of Brent Crude Oil in 2014 on worker reallocation and earnings in Norway. Using Norwegian panel data, I document that workers in the destination sectors of moving oil workers experienced declines in earnings growth and increased worker mobility. To capture the complex worker transmission pathways following the shock, I estimate a multisector Roy model with sectoral skill correlations. Counterfactual simulations show substantial but varying wage declines across non-tradable sectors and highlight that reallocation between non-oil sectors accounted for up to 42% of the total worker reallocation following the shock.

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KEYWORDS: Sectoral shocks, Realloction, Local labor markets, Wages, Inequality

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1 Introduction

How do sector-specific shocks make workers move between sectors, and what are the associated equilibrium effects on the distribution of earnings? Several studies have documented how sector-specific shocks driven by international trade, climate change, automation, or a pandemic induce worker reallocation across sectors.[1] While we know that workers in sectors that are directly exposed to sector-specific shocks have falling earnings and sectorally reallocate (Walker, 2013; Autor, Dorn, Hanson, & Song, 2014; Kovak & Morrow, 2022; Costinot, Sarvimäki, & Vogel, 2024), less is known about the impact on workers in the destination sectors of the moving workers. These destination sectors may face wage declines, leading to further reallocation of workers even between sectors not directly impacted by the initial shock. Thus, sector-specific shocks can have far-reaching effects, influencing workers across all sectors through a chain reaction of worker reallocation.

This paper provides novel empirical evidence on how sector-specific shocks affect equilibrium wages in the destination sectors of the moving workers and lead to additional reallocation between sectors not directly exposed to the initial shock. These new findings indicate that shocks have widespread equilibrium effects throughout the economy. While the domino effects of worker reallocation are significant, capturing the complex transmission pathways in empirical data is challenging. Therefore, I develop a model which identifies the network of sectoral reallocation driven by a sector-specific shock and quantifies the associated equilibrium effects. This new model helps in understanding the worker transmission mechanism and the magnitude of the equilibrium effects across the economy.

I study worker reallocation in Norway driven by the unexpected and substantial fall in the price of Brent Crude Oil in 2014 (see Figure 1).[2] As a small, open economy that extracts about 2% of the world's total oil and gas supply (BP, 2022), Norway experienced this price shock as an exogenous event. However, with oil and gas accounting for about half of Norway's total goods exports (Norwegian Petroleum, 2022), the price collapse had a considerable impact on the Norwegian labor market by making workers move out of the oil sector. Using Norwegian panel data on earnings and employment, I examine the worker reallocation driven by this shock and its effects on the distribution of earnings. The data reveal asymmetric worker reallocation, with varying intensities of oil worker inflows across different destination sectors[3]. Specifically, workers leaving the oil sector disproportionately moved into certain sectors (see Figure 2), leading to expectedly larger equilibrium effects in these sectors. Interestingly,

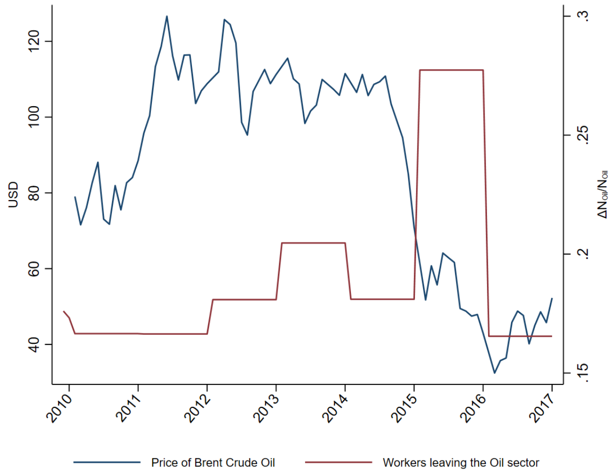
[1] Among others, Autor, Dorn, and Hanson (2013) study import competition, Costinot, Donaldson, and Smith (2016); Cruz (2021); Lyn, Ortiz-Bobea, Rudik, and Tan (2022) climate change, Dauth, Findeisen, Suedekum, and Woessner (2021); Galle and Lorentzen (2022) automation, and Barrero, Bloom, Davis, and Meyer (2021) the COVID-19 pandemic.

[2] Other papers studying the micro-level effects of oil price fluctuations in Norway are Juelsrud and Wold (2019), Ellingsen and Espegren (2022), and Fagereng, Gulbrandsen, Harmenberg, and Natvik (2022). Furthermore, Kehrig and Ziebarth (2017) analyze the labor market response to oil supply shock in the US when oil is an energy used as input in production, and Kline (2008) examines the response of employment and wages in the US oil and gas field services industry to changes in the price of crude petroleum.

[3] This is in line with the findings in Müller, Stegmaier, and Yi (2017). They show that there is variation in which degree workers can reallocate to other jobs across industries in Germany.

while many workers left the oil sector, I show that a considerable portion of the reallocation driven by the shock occurred between non-oil sectors. This paper provides a framework for examining these cross-sectoral worker movements and the associated implications on earnings.

Figure 1: An unexpected fall in the price of Brent Crude Oil in 2014



Notes: The figure shows the price evolution of Brent Crude Oil and share of workers leaving the Oil sector from 2010 to 2017. Data on the price of Brent Crude Oil is collected from U.S. Energy Information Administration (2024). The share of workers leaving the oil sector is calculated as the number of workers who are not working in the oil sector in a given year but were working in the oil sector in the previous year, relative to the number of workers working in the oil sector in 2013. The sample includes prime-age, full-time working individuals who are either employed or self-employed.

I provide three pieces of novel empirical evidence on the impact on the destination sectors of the moving oil workers. By exploiting variation in into which sectors oil workers had been moving pre-shock, I build a novel exposure term to worker reallocation across local labor markets and destination sectors. Firstly, I show that workers in non-tradable sectors with higher exposure to inflows of oil workers experienced a relative reduction in earnings growth. Secondly, these workers had also an increased probability of leaving their sectors in the years following the shock. Thirdly, by comparing the average post-period earnings of the moving oil workers to the earnings of the average worker in the destination sectors, the data reveals variation in how moving oil workers shifted the average worker composition in these sectors. In many destination sectors, the oil workers earned higher earnings compared to the average worker, indicating that they had an absolute advantage in the sectors they moved into. Both the shift in sectoral equilibrium wages and the shift in the composition of workers affected average sectoral earnings but in different directions. Separating them is important for understanding the distributional effects of the sector-specific shock.

Next, I develop and estimate a multisector Roy model that identifies the sectoral reallocation network driven by the shock and quantifies the associated equilibrium effects. In the Roy model, workers have sector-specific skills and sort into sectors by maximizing labor income given sectoral wages. A shock to wages makes it optimal for some workers to move between sectors. Following the seminal work on Roy-type selection (Heckman & Sedlacek, 1985; Heckman & Honoré, 1990), I assume skills to be distributed log-normally, but in a multisector setting. Moreover, I allow skills to be correlated across sectors so that workers moving out of a specific origin sector tend to move toward certain destination sectors. A key contribution of this paper is to estimate the parameters of the skill distribution, including skill correlations, by using the model-implied relationship between sectoral wage changes and worker reallocation flows, both of which will be observed in the panel data. The estimated model fits the data well and, compared to state-of-the-art models, is able to explain both the directions and magnitudes of the sectoral reallocation driven by a sector-specific shock.[4]

Following Train (2009), I introduce the mixed Roy model as an approximation to the pure discrete choice problem. The approximated model offers several advantages: it speeds the estimation process while maintaining precision, allows for reallocation flows that deviate from sectoral wage changes (as observed in the data), and includes a parameter that measures how closely the approximated model aligns with the pure discrete choice Roy model. I derive an estimation equation for this parameter and show how this parameter helps assess the importance of the Roy model in explaining sectoral reallocation. My findings indicate an elasticity in line with the Roy model is indeed predicting observed sectoral reallocation well and is explaining a large share of the variation in the data.

Finally, I use the estimated model to illustrate the importance of the network of sectoral reallocation in understanding the impact of a sector-specific shock. In a counterfactual oil price collapse, the model simulates how workers move from the oil sector to different destination sectors. This reallocation results in a fall in non-tradable sector real wages, particularly for local sectors with a large inflow of moving oil workers. The quantitative results show that while some non-tradable sector workers do not experience any real wage decline following the shock, the maximum real wage decline is 56% of the oil sector's real wage decline. On average, across local non-tradable sectors, the impact is 7%. Furthermore, as a result of falling earnings, non-tradable sector workers move toward other sectors, including alternative tradable sectors, mitigating the fall in non-tradable sector wages. Reallocation across non-oil sectors accounts for up to 42% of the total reallocation in a CZ. Reduced-form exercises on the simulated data indicate that movements towards the non-oil tradable sectors have a smaller, but a considerable impact on non-tradable sector wages compared to movements out of the oil sector in response to the counterfactual shock.

The contribution of this paper is threefold. I first provide novel empirical evidence on the equilibrium domino effects in the destination sectors of the moving workers in response to a sector-specific shock.

[4] In recent literature on reallocation and Roy models, skills are often assumed to be distributed i.i.d. Fréchet (Burstein, Morales, & Vogel, 2019; Hsieh, Hurst, Jones, & Klenow, 2019; Burstein, Hanson, Tian, & Vogel, 2020; Galle, Rodríguez-Clare, & Yi, 2022; Galle & Lorentzen, 2022). This assumption ensures analytical tractability and explicit estimation equations, but also implies linear relationships between aggregate earnings changes and sectoral shares. While this paper explains variation in data on sectoral reallocation, it comes at the cost of reduced analytical tractability. Similar trade-offs between analytical tractability and data fit for different functional forms have been discussed in other settings Novy (2013); Head, Mayer, and Thoenig (2014); Lind and Ramondo (2022). These studies provide model predictions that explain a larger share of observed data compared to predictions from models with standard assumptions.

Second, I estimate a Roy model to study the sectoral reallocation driven by the shock. Specifically, I build a new structural framework for estimating a multi-sector log normal Roy model where skills can be correlated across sectors by the simulated method of moments. This model is richer and better matches microdata on sectoral reallocation compared to state-of-the-art models. Third, I use the estimated model for counterfactual simulations to show how the network of sectoral reallocation is crucial for understanding how a sector-specific shock propagates through the economy.

Related literature This paper contributes and relates to several strands of the economic literature.

First, this paper contributes to the extensive body of reduced-form studies that investigate the labor market effects of trade shocks, including Topalova (2010); Autor et al. (2013); Kovak (2013); Dix-Carneiro and Kovak (2017); Bloom, Handley, Kurmann, and Luck (2019); Kovak and Morrow (2022); Costinot et al. (2024) by providing new empirical evidence. I construct a novel exposure term for worker reallocation following a trade shock that exploits variation in indirect exposure through worker reallocation. Unlike similar exposures used in the literature, it not only exploits variation in the initial size of the directly exposed sector across local labor markets, but also exploits variation in which destination sectors workers from the directly exposed sector had been moving to pre-shock. The two-dimensionality allows for absorbing trends in outcomes across multiple dimensions. As in Autor et al. (2014) and Costinot et al. (2024), I study outcomes of a trade shock at the worker level. Autor et al. (2014) focus on the outcomes of the directly exposed workers, while Costinot et al. (2024) show that in markets with many workers working in directly exposed firms, also non-directly exposed workers will be relatively more affected by a trade shock. My results align with their findings, but I go further by specifically showing that non-directly exposed workers who experience inflows of directly exposed workers are more affected by the trade shock. Autor et al. (2013) also separate the directly exposed and indirectly exposed outcomes at the sectoral level. In contrast to them, I disentangle changes in equilibrium wages and changes in the composition of workers across sectors by separating the incumbent workers from the moving workers.

Second, this paper aligns with structural approaches that quantify the effects of trade shocks on labor market outcomes, focusing on sectoral mobility, as in Artuç, Chaudhuri, and McLaren (2010); Dix-Carneiro (2014); Caliendo, Dvorkin, and Parro (2019); Dix-Carneiro, Pessoa, Reyes-Heroles, and Traiberman (2022), and Galle et al. (2022).[5] In particular, I build on papers employing Roy frameworks, which is a benchmark framework for studying sectoral reallocation driven by international trade (Dix-Carneiro, 2014; Adão, 2016; Kim & Vogel, 2021; Galle et al., 2022), but also immigration (Burstein et al., 2020; Bratsberg, Moxnes, Raaum, & Ulltveit-Moe, 2022), technical change (Burstein et al., 2019;

[5]Studies focusing on measuring the labor market adjustment costs of sectoral mobility in data are Walker (2013), Autor et al. (2014), and Müller et al. (2017). This paper complements these studies by building a model incorporating workers' variation in the reallocation possibilities across sectors due to variation in sectoral skill correlation.

Galle & Lorentzen, 2022), and sectoral productivity differences (Lagakos & Waugh, 2013). Unlike recent studies, I assume skills to be distributed log-normally in a multisector setting, which allows the model to explain a large share of micro-level data on sectoral reallocation and to capture the complexity of worker reallocations following a shock. I develop a structural estimation procedure for the multisector log-normal skill distribution, by targeting data on sectoral worker reallocation flows. Burzynski (2020) also set up a multisector Roy model with log-normally distributed skills. However, while I estimate the covariance matrix by targeting observed sectoral reallocation, Burzynski (2020) compute the covariance matrix by correlating task data. Seo and Oh (2023) use the matrix of sectoral worker reallocation to estimate a model of sectoral reallocation. While they structurally estimate sectoral utilities and switching costs, this paper estimates the parameters of the skill distribution, including skill correlations across sectors.

Third, already prior to using variations across local labor markets, several studies explored the margins of labor market adjustment to trade shocks, including Artuç, Chaudhuri, and McLaren (2008); Artuç et al. (2010); Dix-Carneiro (2014); Artuç and McLaren (2015); Hakobyan and McLaren (2016). These papers show that when worker reallocation is slow, the gains from trade are reduced. In contrast, this paper adopts a before-and-after analysis without dynamics. While adding dynamics opens up a wide range of interesting questions regarding the role of sectoral reallocation for the gains of trade, in this paper, the focus is to quantify the equilibrium effects of a trade shock across all workers.

Fourth, this paper relates to the literature on the impact of migration on local workers, including Card (2001); Angrist and Kugler (2003); Ottaviano and Peri (2012); Bratsberg and Raaum (2012); Borjas (2013); Burstein et al. (2020), and further surveyed by Peri (2016) and Edo (2019). There are parallels in how migration affects native workers and the way reallocated workers impact incumbent workers in this study, but there are also differences that exist. In migration scenarios, local labor markets expand, increasing the demand for non-tradable goods, with immigrants originating from outside the economy. Moreover, the non-immigrating workers do not affect aggregate earnings of the economy.

This paper is organized as follows. Section 2 presents the model, Section 3 explains the data and discusses the background, Section 4 presents the empirical evidence, Section 5 presents the model estimation, and Section 6 quantifies of the equilibrium effects of a counterfactual collapse in oil price. Last, Section 7 concludes.

2 Model

I set up a two-period model where N number of workers are located across R number of local labor markets, each consisting of S number of sectors. Each local labor market is a small open economy consisting of a set of tradable- and non-tradable sectors.[6] The tradable sectors are operating at the world market for tradable goods and output prices are determined exogenously. For the non-tradable sectors, however, output prices are determined in the local market for non-tradable goods. In the model, there are no connections between the local labor markets.[7]

2.1 Equilibrium

Preferences Workers are assumed to have identical Cobb-Douglas preferences over the S number of consumption goods. A worker i in a market r obtains utility

$$U_{i,r} = \prod_{s=1}^{S} c_{i,r,s}^{\beta_s}$$

where $c_{i,r,s}$ is consumption of good s and $\sum_{s=1}^{S} \beta_s = 1$. Workers maximize utility given their labor income $y_{i,r}$ and the market-specific good prices $p_{r,s}$. It follows that a worker i's consumption expenditure on good s is

$$p_{s,r} c_{i,s} = \beta_s y_{i,r}$$

and total consumption expenditure on goods produced by sector s in a market r will be

$$p_{s,r} C_{r,s} = \beta_s Y_r, \tag{1}$$

where Y_r is the total labor income in the market. Furthermore, I define the local price index for consumption goods as

$$P_r \equiv \prod_{s=1}^{S} p_{r,s}^{\beta_s}. \tag{2}$$

Labor Supply Workers are endowed with one unit of time which they supply to the labor market as in Roy (1951). Workers have a vector of sectoral skills $\boldsymbol{z}_i$ such that

$$\log z_{i,s} \equiv \widetilde{\mu}_s + v_{i,s}$$

and $v_{i,s}$ are drawn from a multivariate normal distribution with mean zero and covariance matrix $\boldsymbol{\Sigma}$, where $\boldsymbol{\Sigma}$ is a positive semidefinite. A worker located in market r would in sector s obtain a potential income

$$y_{i,r,s} = w_{r,s} z_{i,r,s}. \tag{3}$$

[6] While many papers, including Artuç and McLaren (2015), Traiberman (2019), and Kleinman, Liu, and Redding (2022), are studying reallocation in a dynamic framework, in this paper, I preform a before-after analysis without dynamics.

[7] Appendix Table A.1 shows that only 2.9% of all full-time, employed or self-employed, prime-age workers in Norway moved across CZs in the period 2013 to 2017. Correspondingly, 9.9% moved across sectors, while 0.8% moved both across sectors and CZs. Among the workers that were working in the oil sector in 2013, but in a non-oil sector in 2017, 10.4% also moved across CZs. Even though the data shows that workers did move across CZs, compared to sectoral reallocation, the across CZs reallocation margin is moderate in magnitude.

where $w_{r,s}$ is the local sector-specific wage per effective unit of labor. For later use, sector-specific *levels* within each market are defined as

$$\mu_{r,s} \equiv \log w_{r,s} + \widetilde{\mu}_s. \tag{4}$$

As in Lagakos and Waugh (2013) and Galle et al. (2022), workers sort into sectors by maximizing income given sectoral wages per effective labor unit. A worker located in labor market r, will supply her time to sector s if and only if $\boldsymbol{z_{i,r}} \in \Omega_{r,s}(\boldsymbol{w}_r)$, when

$$\Omega_{r,s}(\boldsymbol{w}_r) \equiv \{\boldsymbol{z_r} \mid y_{i,r,s} \geq y_{i,r,k} \text{ for all } k\}. \tag{5}$$

It follows that the share of workers selecting into a sector s in a market r is the probability of drawing a skill vector that maximizes income in sector s

$$\pi_{s,r} \equiv \Pr\left(\boldsymbol{z_r} \in \Omega_{s,r}\right). \tag{6}$$

The supply of labor units to a local sector is the total number of sector s specific skill units of the workers selecting into sector s in market r

$$Z_{r,s} \equiv \int_{i:z_{i,r} \,\in\, \Omega_{r,s}} z_{i,r,s} di. \tag{7}$$

Production Each sector s in each market r produces output with labor as only input in production. For a sector s in market r, production is

$$F_{r,s} = Z_{r,s}. \tag{8}$$

Perfect competition implies that for each sector in each market, the wage per effective labor unit will be given by the output price

$$w_{r,s} = p_{r,s}. \tag{9}$$

Equilibrium For the tradable sectors, $p_{r,s}$ are exogenous world prices. For the non-tradable sectors, however, output prices are determined in local equilibrium. Local supply is given as the value of local sectoral production, which is the local sector-specific output price times the production given by (8). Local demand for goods is given as local household expenditures, as in (1). Hence, in equilibrium

$$\beta_s Y_r = p_{r,s} F_{r,s}. \tag{10}$$

2.2 A shock to the world prices

A shock in the world price of a tradable sector affects the vector of wages per effective labor unit across markets and induces sectoral reallocation. I use exact hat algebra and define $\widehat{x} \equiv \frac{x'}{x}$ when x and x' are the values in the first and second period respectively. For all sectors within all markets, the changes in the wage equalize the changes in the output price

$$\widehat{w}_{r,s} = \widehat{p}_{r,s}. \tag{11}$$

For the tradable sectors, wage changes will be exogenously given in the world market.

Worker reallocation Workers observe equilibrium wage changes in their market and, depending on their individual vector of sectoral skills, decide to stay incumbent or move to a different sector within their market.[8] Workers take the equilibrium wage changes as given and move if it is income maximizing. While workers are indifferent to the driver of sectoral wage changes in their market, workers will have a higher propensity to move toward sectors with relatively increasing wags. The share of workers in market r, that is moving from sector s to sector s' is

$$\lambda_{r,s,s'} \equiv Pr\left(\boldsymbol{z_r} \in \Omega'_{r,s,s'} \mid \boldsymbol{z_r} \in \Omega_{r,s}\right) \tag{12}$$

which is the probability of drawing a skill vector that makes sector s' income maximazing in the second period, conditional on sector s being income maximizing in the first period. The change in effective labor units supplied to a sector s in a market r is

$$\widehat{Z}_{r,s} = \frac{Z_{r,s} + \sum_k^S \left[\int_{i:z_{i,r} \in \Omega'_{r,k,s}} z_{i,r,s} di - \int_{i:z_{i,r} \in \Omega'_{r,s,k}} z_{i,r,s} di\right]}{Z_{r,s}}. \tag{13}$$

Equilibrium real wage changes For non-tradable sectors, wage changes are determined in local equilibrium, and the log change in the real wage for a non-tradable sector s is

$$\log \frac{\widehat{w}_{r,s}}{\widehat{P}_r} = \log \frac{\widehat{Y}_r}{\widehat{P}_r} - \log \widehat{Z}_{r,s}. \tag{14}$$

First, a fall in total real income in a market r lowers the demand for non-tradable goods, resulting in falling sectoral real wages for all non-tradable sectors. While the fall is constant across sectors within markets, it is more dominant in markets that are more exposed to the shock by having a larger initial

[8]The model does not include frictional unemployed, as in Kim and Vogel (2021) or Galle and Lorentzen (2022). First, the main focus of this paper is the equilibrium effects on wages for workers working in sectors not directly exposed to a sector-specific shock. Second, for the shock I will be studying in particular, after the oil price collapse in 2014, a lion's share of the moving oil workers in Norway was again employed at the end of 2016 (Næsheim, 2018).

share of workers in the directly exposed sector. Second, when the shock induces sectoral reallocation, there will be a change in the supply of labor units to non-tradable sectors. If the reallocation is such that there is variation in the change in labor supply units across non-tradable sectors, there will be variation in the real wage changes across sectors within markets. Hence, for this case, the realized real wage changes will differ across non-tradable sectors within markets. In contrast, if there is no reallocation or if reallocation is such that the change in labor units is equal across non-tradable sectors, real wage changes will be the same for all non-tradable sectors within markets. Depending on the shape of the covariance matrix Σ, workers moving from a specific sector will be more likely to move toward certain destination sectors compared than others. Accordingly, there can be variation in $\widehat{Z}_{r,s}$ both across and within local labor markets.

3 Data and background

3.1 Data

I use the Norwegian register data on individual employment and earnings for the period 2000 - 2017. The data is an extensive panel where I follow individual workers over time and observe detailed employment information, labor market earnings, and a comprehensive set of individual characteristics at each point in time. Compared to a cross-section data, the data allows for observing worker reallocation and labor market outcomes with much more precision and detail.

Until 2014 I use earnings data from the yearly wage survey conducted by Statistics Norway. The survey is conducted in September/October every year and covers about 70% of the private sector and the entire public sector. I use monthly total labor income as labor earnings, which is the sum of base salary, bonus, unexpected additional salary, and average overtime salary at the annual frequency. In 2015, there was a break in the Norwegian wage data, and I from then on use wage data from “A-ordningen”, which is a coordinated collection of data on employment and earnings. For all years, the wage data contains information on the sector of employment, gender, and age. By matching the wage data with the register-based employment data, I also obtain employment status and living municipality data for all years. I restrict my sample to full-time working individuals of prime working age, that is, between 25 and 58 years old, that are either employed or self-employed.[9] Furthermore, I match the earnings and employment data with individual education data containing completed education levels. As to be used as control variables, I construct age- and education groups. Specifically, I group workers into 9 age groups with a five-year span. Moreover, I construct five education groups based on their highest education level. I group individuals into the following education groups: No registered education from

[9] From 2015, I disregard a small share of individuals who are reported with duplicates, and I drop a few observations with no reported sectors.

high school level or higher; High school; College or Bachelor degree; Higher degree education at the university level, including Master's degree; Ph.D.

I follow Bhuller (2009) and construct 44 Norwegian Commuting Zones (CZs) by using living municipality codes.[10] Moreover, I follow Statistics Norway (2015) and define sectors with at least 50% of its value of production that can be related to the petroleum sector to be part of the oil sector. With this definition, the oil sector includes the extraction and petroleum supply industries. Furthermore, I define non-tradable (NT) sectors as sectors with less than 25% of value-added from exports.[11] For the empirical evidence, I construct fifteen non-tradable sectors based on the first level in the hierarchy of the sector definitions of SIC2007. For the structural exercises, I aggregate up to seven secotrs; five non-tradable sectors and two tradable sectors.[12]

I use the sectoral intermediate input-output table from Statistics Norway for 2013 to construct consumption shares β_s for the model simulations and a control variable to be used in the empirical evidence. I construct β_s as the value of final consumption expenditures by households for sector s as the share of the total value of final consumption expenditures by households. Moreover, to be used as a control, for each sector I construct the value of sales to the oil sector relative to the value of total use.

3.2 Setting

Figure 1 shows the collapse in the price of Brent Crude Oil in 2014. Between June 2014 and December 2014, the monthly average price of Brent crude oil fell by 44% of its original value. Norway is a small and open economy that at the end of 2013, extracted about 2% of the global demand for oil (BP, 2022), and it is reasonable to assume that the shock was exogenous to the Norwegian economy. Close to all extraction of oil and gas in Norway is exported, and oil and gas cover about half of the total value of Norwegian exports of goods (Norwegian Petroleum, 2022). Moreover, Figure A.1 shows the oil sector to be a large sector of employment in Norway, though with variation in the share of workers working in the oil sector across Norwegian CZs. The CZs with a large initial share of workers working in the oil sector are mostly located in the south of Norway, particularly on the west coast. For some CZs in particular, the share of workers in the oil sector was higher than 25% in 2013. By comparing the average oil worker to the average worker in the economy the year before the shock, Table A.1 reports the average oil worker was more likely male, less likely to have a college degree, and obtained higher earnings compared to the average worker, even after abstracting variation due to age, gender, and education.

The oil price collapse in 2014 had a considerable impact on the Norwegian labor market by making oil workers move out of the oil sector. Table A.1 reports that among the workers working in the oil

[10] Due to changes in the composition of Norwegian municipalities, I have made some minor adjustments.

[11] Sectors classified as tradable are "Agriculture, forestry and fishing", "Mining and quarrying", "Manufacturing", "Water supply", "Wholesale and retail trade" and "Transportation and storage".

[12] An overview of the sector aggregation is presented in Table A.7.

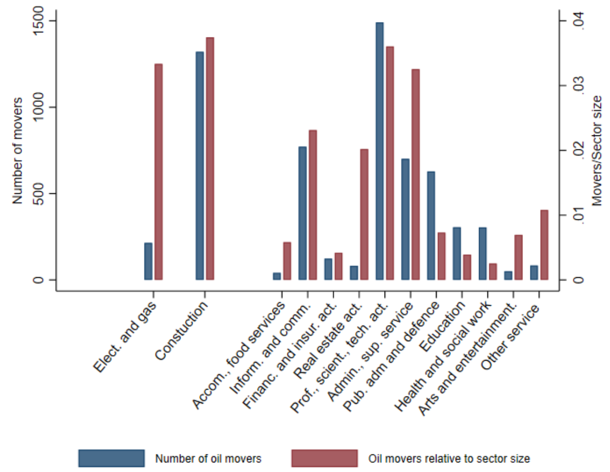
sector the year before the shock (2013), 12,7% worked in a non-oil sector three years after the shock (2017).[13] By comparing the average moving oil workers to the average oil worker, I find the moving oil workers to be younger, more likely female, and more likely to have a college degree. In fact, 60% of the workers leaving the oil sector had a college education, which is in contrast to 44 % for the initial oil sector and 51% for all workers. On the other hand, the data shows that, on average, the moving oil workers had lower earnings compared to the average oil worker in the pre-period 2013, Hence, on average, the moving oil workers were on the lower side of the oil sector income distribution. This paper focuses on the sectoral reallocation driven by the oil price collapse. Most of the moving oil workers stayed within their CZ, and the data shows that only 10,5% of the workers that worked in the oil sector in 2013 but in a non-oil sector in 2017, moved to another CZs. For all workers, I find that only 2.9% moved to another CZ over the same period. Figure 2 shows there to be variation in the number and intensity of incoming oil workers across NT destination sectors. Relative to the initial size of the sector, the oil workers more intensively moved toward "Electricity and gas supply", "Construction", "Professional, scientific and technical activities", and "Administrative and support service activities".[14] By comparing the worker characteristic of the average moving oil worker to the average workers across the destination sectors, Table A.2 reports moving oil workers to be younger in age for all NT sectors, for most NT sectors, less likely to be female and for many NT sectors more likely to have a college education.[15]

[13] Margins not incorporated in this paper include unemployment, retirement, and exit from the labor market or country. Table A.1 reports that 73.8% of oil workers remained full-time employed or self-employed from 2013 to 2017. According to Næsheim (2018), displaced oil workers did became unemployed post-shock, but most were employed by the end of 2016. Retirement is less relevant due to the focus on prime-age workers, however some workers are excluded due to aging out of the prime age range.

[14] "Electricity and gas supply" covers Electric power generation, transmission and distribution, manufacture of gas, and steam and air conditioning supply. "Professional, scientific and technical activities" covering Legal and accounting activities, Activities of head offices, Architectural engineering activities scientific research and development, advertising and market research.

[15] Exceptions are "Electricity and gas supply" and "Construction", where there are very few female workers. In "Financial and insurance activities", "Professional, scientific and technical activities", "Education", and "Human health, social work" there is a larger share of workers with college education compared to for the moving oil workers.

Figure 2: Oil worker inflows across non-tradable sectors



Notes: The figure shows the inflows of oil worker to NT sectors between 2013 and 2017. The blue bars are measured at the left axis as the number of workers that were working in the oil sector in 2016 and were working in NT sectors in 2017. The red bars are measured at the right axis as the number of workers that were working in the oil sector 2013 are working in NT sectors in 2017 relative to the number of workers working in the corresponding NT sector in 2017. The numbers reported in the figure are calculated over the sample that includes fulltime, employed or self-employed workers, between 25 and 58 years old.

4 Empirical evidence

As explained by Equation (14), the model predicts that the worker reallocation driven by the oil price collapse will affect equilibrium real wages in the NT destination sectors of the moving workers. This, in turn, may induce further reallocation between sectors not directly exposed to the shock. According to the model, sectors with a larger increase in labor supply will experience a larger relative decline in real wages for incumbent workers and an increased the likelihood of further worker movements. This section aims to provide empirical evidence in line with these model predictions. Although the shock was exogenous to the Norwegian economy, the reallocation flows driven by the shock were endogenous. As explained by the Roy model, into which sectors workers move is a function of sectoral real wage changes, and workers will have a higher propensity to move toward sectors with relatively increasing wages. To provide empirical evidence on worker reallocation affecting equilibrium real wages and inducing further reallocation between sectors not directly exposed to the shock, I, therefore, build a novel exposure term as a proxy for the oil worker reallocation flows into NT destination sectors in the years after the shock. I next provide reduced form evidence on the total effects of exposure to reallocation in line with model predictions.[16] [17]

[16]By alternatively regressing the outcomes of interest on the observed oil worker inflows into NT sectors in an OLS regression, the model predicts the obtained estimated coefficients to be biased toward zero. This follows from workers having a lower propensity to move toward sectors with relatively falling wages. In Appendix Table A.5, I compare the reduced form results presented in Section 4.2 to the corresponding OLS results. Specifically, as in Regression Equation 16, outcome variable of these regressions are log change in earnings for incumbent workers in NT sectors ($\log \widehat{y}_{i,r,s,t,t+1}$). Indeed, the results presented in Appendix Table A.5 show a clear bias toward zero for the OLS, in line with what is expected from the model.

[17]When reallocation induces further reallocation, the exclusion restriction fails, and the exposure term cannot be used as an instrument in an IV-regression.

4.1 Exposure measure to the inflows of moving oil workers

I construct a novel exposure measure for NT sector workers to the inflow of moving oil workers. For a worker that is located in CZ r and working in NT sector s, the exposure is defined as

$$\mathbb{Z}_{r,s} \equiv \frac{N_{oil,r}}{N_r} \cdot \frac{N_s^{oil}}{N_s}. \tag{15}$$

In the expression, $N_{oil,r}$ is the number of workers working in the oil sector in CZ r, N_r the number of workers located in CZ r, N_s^{oil} the number of workers working in sector s with a previous employment spell in the oil sector[18], and N_s is the number of workers working in sector s, all constructed for the pre-shock year 2013. The exposure term exploits variation in inflows of oil workers both across CZ and NT sectors. First, workers' exposure to incoming oil workers increases with the initial size of the oil sector in their CZ. Thereby, the exposure aligns with commonly used shift-share exposures for examining local labor market outcomes of trade shocks (Topalova, 2010; Autor et al., 2013; Kovak, 2013). Second, consistent with the model, workers' exposure to incoming oil workers varies across destination sectors due to skills are differently related across sectors. To capture variation in sector characteristics that determine how likely oil workers are to move into different destination sectors, I exploit pre-shock data on oil workers' sectoral movements. Workers are more exposed to inflows of oil workers if they work in sectors with a larger share of workers with a previous employment spell in the oil sector at the national level. To my knowledge, this is data variation not previously exploited in other studies. By measuring the two factors, I find that $N_{oil,r}/N_r$ has a mean of 0.081 across CZs with a standard deviation of 0.088, and N_s^{oil}/N_s has a mean of 0.018 across sectors with a standard deviation 0.015. Histograms of these two factors are presented in Figure A.2, showing variation across CZs and sectors.

Relevance Workers in CZs with a larger share of oil workers, and those in sectors with a higher proportion of workers who previously worked in the oil sector, are more exposed to inflows of oil workers into their local sector. By correlating the exposure term with observed data on oil worker inflows, I find that the exposure term significantly predicts these inflows across NT destination sectors and explains a large share of the data variation. Examining the exposure term in parts, Figure A.3a shows a clear positive relationship between $N_{oil,r}/N_r$ and the total number of oil workers moving into NT sectors between 2013 and 2017 across CZs, with a correlation of 91%. Similarly, Figure A.3b shows a positive relationship between N_s^{oil}/N_s and the total number of incoming oil workers across NT destination sectors in the same period, with a correlation of 55%. Next, Table A.3 further examines the correlation between the exposure term and observed worker movements from the oil sector to local NT sectors post-shock. The table shows that the exposure term is highly significantly correlated with these

[18] I construct the measure for employment spells between the years 2000 and 2012.

movement flows, explaining a large share of the variation in the data. Specifically, it alone accounts for 34% of the variation in oil worker inflows into local NT sectors. This is in line with the exposure term does well in predicting the actual inflows of oil workers to NT sectors and is highly relevant.

Validity The validity of the exposure term, conditional on controls, rests on its exogeneity to sectoral wage changes and further reallocations between non-oil sectors.[19] Although the exposure term is constructed using pre-determined data and is likely exogenous to the outcomes of interest, spurious correlation due to confounding factors remains a potential concern.[20]

Given that the exposure term exploits variations across CZs and destination sectors, I will control for both CZ and sector fixed effects at the yearly level to mitigate concerns. First, the model predicts wage declines for all NT sectors in CZs experiencing a drop in demand for goods, as explained by Equation (14). CZs with a larger share of workers in the oil sector, and therefore more exposed to the oil price collapse, are expected to experience a relative decline in total real earnings, followed by a subsequent decrease in demand for NT goods. The CZ fixed effects absorb this confounding factor. Second, there may be sectoral trends not predicted by the model. NT sectors can be linked to the oil sector through input-output sales linkages or might directly use oil as an input in production, exposing NT sectors to the shock beyond worker reallocations. The sector fixed effects absorb these potential confounding factors at the national level. Additionally, there could be systematic differences in outcome variables across workers correlated with the exposure term. No pre-trends support the hypothesis of no systematic differences correlated with the exposure term. Lastly, in Section 4.5, I discuss and adress possible of spurious correlation due to confounding factors at the CZ-sector level. Moreover, I discuss potential concerns of a multiplicative interaction term as exposure.

4.2 The effect on equilibrium wages

Figure 3 presents the relationship between exposure to inflows of oil workers and earnings growth for incumbent workers in NT sectors, by estimating the following reduced-form estimation

$$\log \widehat{y}_{i,r,s,t-1,t} = \gamma_{r,t-1} + \gamma_{s,t-1} + \sum_k \beta^k \cdot \mathbb{Z}_{r,s}\, \mathbb{I}(t-1=k) + \boldsymbol{X'_{i,t-1}}\beta_2 + \epsilon_{i,r,s,t-1} \tag{16}$$

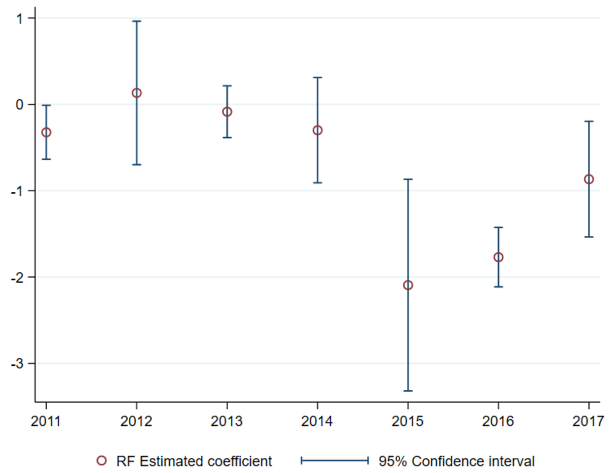
where $\log \widehat{y}_{i,r,s,t-1,t}$ is the log change in earnings from year $t-1$ to year t for incumbent workers located in CZ r and working in NT sector s, $\gamma_{r,t-1}$ and $\gamma_{s,t-1}$ are commuting zone-year and sector-year fixed

[19] My exposure term is in the spirit of the Bartik or shift-share instruments (Bartik, 1991). However, related to the discussion in Goldsmith-Pinkham, Sorkin, and Swift (2020), my exposure term does not include a shifter, and the variation comes from the two pre-shock determined shares only. Hence, the validity of the exposure term is, conditional on controls, resting on the exogeneity of the product of the two sub terms.

[20] The validity of estimates when using interaction terms are discussed in Nizalova and Murtazashvili (2016). In line with their setup, the two subterms of the exposure can be considered as treatment and a source of heterogeneity respectively, or the other way around. Thereby, for the exercises to be consistent, each of the subterms and omitted variable(s) needs to be jointly independent of the other subterm.

effects respectively, $\boldsymbol{X'_{i,t-1}}$ contains controls at the individual level including age group, gender and education level, and $\epsilon_{i,r,s,t-1}$ is the error term. I estimate the form over the period 2011 to 2017, clustering standard errors at the CZ level.[21]

Figure 3: Wage growth for incumbent workers in non-tradable sectors and exposure to inflows of moving oil workers



Notes: The figure reports β with 95% confidence intervals for the years 2011 to 2017 by estimating Equation (16). The sample includes incumbent workers in NT sectors, that is, workers staying in the same sector and commuting zone over the years t and $t+1$. Included controls are commuting zone-year and sector-year fixed effects, age group, gender, and education level. The standard errors are clustered at the commuting zone level.

Figure 3 reports the estimated coefficients β^k from estimation Equation (16). The figure shows a sharp and significant decline in relative earnings growth for incumbent workers in NT sectors that are more exposed to oil worker inflows in the years following the shock. This is consistent with a relative decline in equilibrium wage growth for NT sectors in response to worker reallocation inflows driven by the oil price collapse, as explained by Equation (14). The effect diminishes over time, which is expected as worker flows out of the oil sector decrease as time passes after the shock (see Figure 1).

Moreover, Figure 3 shows no pre-trends, indicating that there were no systematic differences in earnings growth for incumbent workers in NT sectors correlated with the exposure term in the years before the shock. The average incumbent worker in NT sectors had an exposure of 0.001 and experienced an earnings growth approximately 0.6 percentage points lower over the period 2015-2017 compared to workers with zero exposure. Over the same period, a worker at the 90th percentile had an earnings growth 1.3 percentage points lower than workers with zero exposure.[22] [23]

[21]The oil price collapse in 2014 is used as a natural experiment, and there is not a staggered treatment. Moreover, I use multiple cross-section data where each observation is a worker that is staying incumbent and is working in a sector s, in a region r at a given year $t-1$.

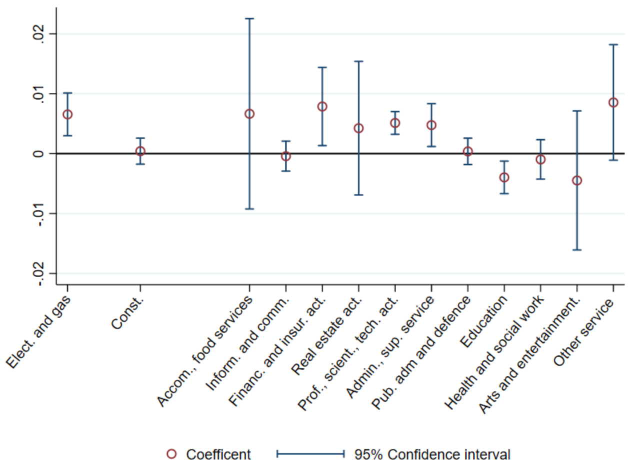
[22]These numbers are calculated as the sum of the baseline estimated coefficients for the years 2015-2017, reported in Figure 3 and in the first column of Table A.4, multiplied by the average and 90th percentile of the exposure term across incumbent workers in NT sectors, respectively.

[23]Table A.4 reports the estimated coefficients with standard errors, both with and without additional controls for exposure to worker outflows towards tradable sectors and sales to the local oil sectors.

4.3 The change in the average worker composition

Worker reallocation changes average sectoral earnings for potentially two reasons: changes in the equilibrium wage per effective labor unit and changes in the composition of workers. While Figure 3 presents results consistent with worker reallocation out of the oil sector to have a significantly negative effect on the equilibrium wage changes, I now turn to examine how the moving oil workers shifted the average worker composition in the sectors they moved into. By comparing the average earnings of the moving oil workers to the average earnings in their destination sector in the post-period of 2017, I examine the change in the composition of workers across sectors.

Figure 4: Moving oil workers and the shift in the residualized log earnings distribution across non-tradable sectors



Notes: The figure reports β_s/α_s with 95% confidence intervals from estimating Equation (17) for each NT sector s separately, for the year 2017. In Equation (17), $\log y_{i,s}$ is defined as residualized log earnings, that is log earnings after taking out variation steaming from gender, education, and age group. The estimated coefficients times 100 can be interpreted as the average percentage deviation in 2017 residualized log earnings for workers that were employed in the oil sector in 2013, relative to the 2017 average residualized log earnings in their destination sector.

Figure 4 compares the average residualized log earnings of the moving oil workers to the average residualized log earnings in their destination sectors in the post-year of 2017. The observed log income distribution is residualized across all workers by extracting variation from age group, gender, education, and CZ.[24] Next, for each NT sector, I regress the following form

$$\log y_{i,s} = \alpha_s + \beta_s \cdot \mathbb{I}(Oil\ Mover) + \epsilon_{i,s} \tag{17}$$

where $\log y_{i,s}$ is residualized individual log earnings for the year 2017, $\mathbb{I}(Oil\ Mover)$ is a variable indicating whether a worker was working in the oil sector in 2013, and $\epsilon_{i,s}$ is the error term.

Figure 4 reports β_s relative to the log earnings mean α_s for each NT sector s. Formally, the esti-

[24] Table A.2 shows that on average, the moving oil workers are, compared to workers in many of their NT destination sectors, younger in age, less likely to be female, and more likely to have a college degree.

mated coefficients times 100 can be interpreted as the average percentage deviation in 2017 residualized log earnings for workers that were employed in the oil sector in 2013, relative to the 2017 average residualized log earnings in their destination sector. An estimated zero coefficient would indicate that the moving oil workers are, on average, similar to the average worker in their destination sector in terms of residualized log earnings levels. However, the figure shows variation in how oil workers affected the earnings distribution across NT destination sectors. In a subset of NT sectors, workers who were employed in the oil sector in 2013 achieved significantly higher residualized log earnings compared to the average worker in their destination sector. This suggests that the moving oil workers had an absolute advantage in some of the sectors they moved into. Conversely, the figure also reports that in a few sectors, the moving oil workers obtained lower residualized log earnings compared to the average worker. Since the log earnings are residualized, these results are not driven by differences in gender, education level, or age group.[25]

4.4 The effect on the probability of leaving sector

Figure 5 presents the relationship between exposure to inflows of oil workers and the probability of leaving their sector for NT sector workers, by estimating the following reduced-form estimation

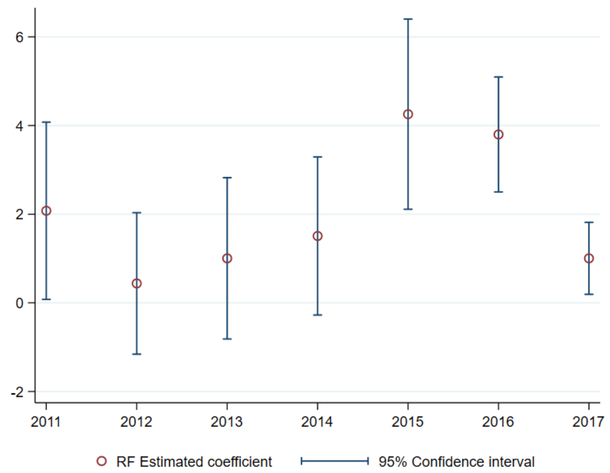
$$\mathbb{I}_{i,r,s,t-1,t}(leave) = \gamma_{r,t-1} + \gamma_{s,t-1} + \sum_{k} \beta^k \cdot \mathbb{Z}_{r,s}\, \mathbb{I}(t-1=k) + \boldsymbol{X'_{i,t-1}}\beta_2 + \epsilon_{i,r,s,t-1} \tag{18}$$

where $\mathbb{I}_{i,t}(leave)$ is indicating whether a worker i located in CZ r and working in sector s is leaving her sector between year $t-1$ and year t which I define as the worker in period t not being observed in her period $t-1$ sector and also not being observed to be working in the oil sector in year t. $\gamma_{r,t-1}$ and $\gamma_{s,t-1}$ are commuting zone-year and sector-year fixed effects respectively, $\boldsymbol{X'_{i,t-1}}$ contains controls at the individual level including age group, gender and education level, and $\epsilon_{i,r,s,t-1}$ is the error term. I estimate the model form from 2011 to 2017, and standard errors are clustered at the CZ level.

Figure 5 reports the estimated coefficients β^k from estimating estimation Equation (18) for workers in NT sectors. Figure 5 reports a significant increase in the probability of leaving their sector in the years after the shock for workers in local NT sectors that are relatively more exposed to inflows of oil workers. Moreover, Figure 3 reports no significant pre-trends for all except the first pre-shock years. These results are consistent with sectoral reallocation driven by the sector-specific shock induced further reallocation between sectors that were not directly exposed to the shock, suggesting that the shock had equilibrium effects throughout the economy. For interpretation, I calculate the magnitude of the estimated reduced

[25] The findings are puzzling when compared to standard model assumptions. Specifically, as discussed by Adão (2016), Roy's model of sectoral reallocation, with the commonly used assumption of independently and identically distributed (iid) Fréchet skills, would not be able to reproduce the outcome where moving workers shift the earnings distribution upward in their destination sectors.

Figure 5: Probability of leaving sector and exposure to inflows of moving oil workers



Notes: The figure reports β with 95% confidence intervals for the years t starting in 2011 ending at 2017, by estimating Equation (18). The sample includes workers in NT sectors, and movement is defined as not observed in the same sector in year $t-1$ and year t and not observed to be working in the oil sector in year t. Included controls are CZ-year and sector-year fixed effects, age group, gender, and education level. The standard errors are clustered at the CZ level.

form effects. The average worker in NT sectors, with an exposure equal to 0.001, experienced a 0.01 probability units higher chance of leaving her sector over the period 2015-2017 compared to workers with zero exposure. Similarly, a worker at the 90th percentile had a 0.03 probability units higher chance of leaving her sector over the same period compared to workers with zero exposure.[26] [27]

4.5 Discussion

Although the exposure term allows for controlling for trends in outcome variables across CZs and sectors at the yearly level, there may be trends at the CZ-sector level that fixed effects cannot absorb, potentially biasing the results. Potential concerns include alternative mechanisms driven by the same shock or coinciding shocks with correlated loadings on worker groups with the exposure term at the CZ-sector level.

First, due to the fall in price of Brent Crude Oil, the Norwegian Krone depreciated. The depreciation shock affected all tradable sectors and may have induced worker reallocation from NT sectors to non-oil tradable sectors. If exposure to worker outflows toward tradable sectors correlates with exposure to inflows of moving oil workers, this could bias the results. To address this, I constructed a similar exposure term for non-oil tradable sectors. Second, the same sectors that oil workers are likely to move into could be connected to the oil sector through sales linkages. Sector-fixed effects will absorb sales linkages affecting sectors equally across CZs. However, sectors in CZs with a large oil sector might be

[26] The numbers are calculated as the sum of the baseline estimated coefficients for the years 2015 - 2017 that are reported in Figure 5 and in the first column of Table A.6, times the average and 90th percentile of the exposure term across NT sector workers respectively.

[27] I report results for the estimated coefficients both with and without controls for exposure to worker outflows toward tradable sectors and sales to the local oil sectors in Table A.6.

more connected to the oil sector through sales linkages. If exposure to sales linkages correlates with sectors' exposure to inflows of oil workers, this could bias the results. I address this by constructing a control variable, combining the sectoral share of total sales to the oil sector with the relative size of the oil sector in the CZ. Table A.3 shows that neither of the two constructed control variables is correlated with the inflows of oil workers into NT sectors when regressing worker inflows into NT sectors from the oil sector on the exposure term, in addition to the two controls. This consistency indicates alternative mechanisms are not a significant concern. Nevertheless, results with the additional controls for both Section 4.2 and Section 4.4 are reported in Table A.4 and Table A.6, respectively. By including the additional controls, outcomes in all post-periods (except the last post-period for one outcome) remain highly significant, and the wage effect magnitudes even increase.

Third, the fall in demand in more exposed CZs may have particularly affected certain sectors. If these are the same sectors with high exposure to oil worker inflows, this could bias the results. As previously explained, the CZs fixed effect will absorb average trends in outcomes across sectors within CZ, but not variations across sectors within CZs. The construction sector, which is typically sensitive to the business cycle, poses a particular threat to the validity of the results. Coinciding with many oil workers moving into this sector (see Figure 2), the demand for construction goods might have fallen in CZs that were more exposed to the shock due to having a large initial share of workers in the oil sector. If the construction sector primarily drives the results, disentangling the effect of oil worker inflows from the potential fall in demand for sectoral output becomes challenging. As a robustness check, Table A.4 and Table A.6 report additional results excluding the construction sector. The results presented in Sections 4.2 and 4.4 are robust to leaving construction workers out of the sample, indicating that the construction sector is not the main driver.

Finally, as highlighted by Hainmueller, Mummolo, and Xu (2019), there are two potential concerns when using multiplicative interaction terms, such as those presented in Equation (15). First, the effect of one subterm may not change at a constant rate relative to the other subterm. Second, the results can potentially be misleading due to a lack of support for either subterm. To address these concerns, I follow the suggested guidelines in Hainmueller et al. (2019) and present results on conditional marginal effects using the Binning estimator in Figure A.4. The analysis shows that both subterms have support and that the estimates from the Binning estimator cannot reject marginal linear effects at the one-percent significance level in either dimension.

5 Estimation

The empirical findings indicate that the oil price collapse had widespread equilibrium effects across the Norwegian economy. While these findings suggest that the domino effects of the shock are significant, capturing the complex network of worker reallocation driven by the shock in empirical data is challenging. To explain the network of worker reallocation following the shock and to quantify the magnitude of the associated equilibrium effects, I return to the model. This section estimate the parameters of the multivariate log-normal skill distribution by using the simulated method of moments (SMM). In the Roy model, the skill distribution parameters govern the reallocation response to the shock: workers observe sectoral wage changes and move between sectors according to their skills. I estimate the skill distribution parameters by using the model implied relationship between sectoral wage changes and worker movements across sectors. To this end, I employ micro data on sectoral reallocation to infer the structural parameters, given identified sectoral wage changes. The results show that skills are correlated across sectors, with some sectors having highly positive correlations and others having highly negative correlations. These properties will be important for understanding the reallocation pattern following a shock.

5.1 Simulated method of moments

I estimate the parameters of the multivariate log-normal skill distribution, including the skill covariance matrix $\mathbf{\Sigma}$ and the levels $\boldsymbol{\mu_r}$, using SMM. I identify one common set of skill covariance matrix parameters across CZs, such that there are $(S \times S) - S)/2) + S$ number of parameters to be estimated. For the levels, I identify one set of levels for each CZ. The levels will be standardized to one sector within every CZ, such that there are $(S-1) \times R$ number of levels to be estimated. To obtain the SMM estimates, I solve:

$$\{\mathbf{\Sigma}, \boldsymbol{\mu_r}\} = \operatorname{argmin} \sum_{r,s,k} \left(\frac{\pi^{sim}_{r,s} - \pi^{obs}_{r,s}}{\overline{\pi^{obs}_{r,s}}} \right)^2 + \left(\frac{\left(\frac{\lambda^{sim}_{r,s,k}}{\pi^{sim}_{r,k}}\right) - \left(\frac{\lambda^{obs}_{r,s,k}}{\pi^{obs}_{r,k}}\right)}{\overline{\left(\frac{\lambda^{obs}_{r,s,k}}{\pi^{obs}_{r,k}}\right)}} \right)^2 + \left(\frac{\overline{\log y^{sim}_{r,s}} - \overline{\log y^{obs}_{r,s}}}{\overline{\overline{\log y^{obs}_{r,s}}}} \right)^2 \tag{19}$$

conditional on the skill covariance matrix $\mathbf{\Sigma}$ being a positive semidefinite. I solve the problem given the set of observed CZ-sector specific wage changes, denoted as $\widehat{w}_{r,s}$. These changes are identified using a fixed-effects approach with the set of incumbent workers, as explained in Section 5.4. The standard errors from the structural estimation are bootstrapped (see Appendix B.3 for further details). In the expression, $\pi_{r,s}$ is sectoral employment shares, $\lambda_{r,s,k}$ is net-movement flows such that $\lambda_{r,s,k} \equiv \lambda^{gross}_{r,s,k} - \lambda^{gross}_{r,k,s}$, and $\overline{\log y_{r,s}}$ is average sectoral earnings.[28] The observed moments are measured in the data as explained in Section 5.5, and the corresponding simulated moments are measured as explained in Section 5.3 and in Appendix B.1. Because there are magnitude differences between the different moment types, for every moment, the distance between simulated data and observed data is normalized to the mean

[28] Secifically, I feed sectoral wage changes ($\widehat{w}_{r,s}$) into the exercise, while average sectoal earnings ($\overline{\log y_{r,s}}$) is a targeted moment. Specifically, $\widehat{w}_{r,s}$ is earnings changes in a CZ-sector and is the change in earnings for incumbent workers in the local sector. $\overline{\log y_{r,s}}$ is average earnings for all workers in CZ-sectors at the initial equilibrium.

observed moment type. There are $(S-1)\times R$ independent sectoral shares and $((((S\times S)-S)/2)-1)\times R$ independent movement flows to be targeted.[29] I normalize the average log sectoral earnings within each CZ, such that there are $(S-1)\times R$ number of independent average sectoral earnings.[30]

The estimation exercise contrasts with the procedure used in the literature for estimating the Roy model in the context of sectoral reallocation. The dispersion of the skill distribution is estimated by relying on predictions consistent with the Roy model on changes in sectoral selection shares and aggregate average earnings (Galle et al., 2022). This approach requires only repeated cross-sectional data and identifies the model without needing data on worker movements. However, whenever a panel is available such that the researcher knows the worker movement matrix, I show how to employ other predictions of the Roy model to estimate skill distribution parameters. The key to the estimation procedure proposed in this paper is utilizing the actual movement flows observed in the data to estimate the model parameters. The main strength of this model is that it will explain a large share of the actual reallocation pattern observed in data. Although I estimate the Roy model in the setting of sectoral reallocation, the estimation procedure can be applied to many different models where there are movements in a discrete choice setting.

The rest of this section presents an approximated model used for computing simulated moments, examples of simulated comparative statics exercises, identification of the wage changes and observed moments in the data, the results on SMM estimated parameters, and model fit exercises on both targeted and non-targeted moments. Monte Carlo simulations of the SSM estimation are presented in Appendix B.2. Appendix B.4 reports estimation results for heterogenous groups defined by education level.

5.2 Model approximation

In the Roy model, workers face a discrete choice problem whereby they select the sector that maximizes their individual labor income. To estimate the parameters of the skill distribution, I simulate a large number of individual skill draws and calculate moments based on these draws. As the number of sectors is increasing, however, the number of draws needed to ensure precision is rapidly increasing to a very high number (see Figure A.7). Thereby, the exercise is becoming computationally heavy and potentially imprecise. To mitigate this computational burden, I introduce an approximation of the discrete choice problem. Drawing from developments in the discrete choice literature (McFadden, 1989; Train, 2009), I introduce an individual sector-specific non-pecuniary utility draw $A_{i,s}$ which acts as smoother to the

[29] The share of stayers ($\lambda_{r,s,s}/\pi_{r,s}\,\forall s$) is in fact redundant as it follows dependently from the number of movers between all sector pairs and sectoral shares. It is therefore left out as a targeted moment.

[30] It follows that the model with only one CZ ($R=1$) will be underidentified by one moment. However, since I use observed data from multiple CZs, the estimation is highly overidentified. Moreover the degrees of freedom is restricted even more since the minimization problem is constraint. The SMM estimation will be over the 5 CZs Oslo, Stavanger, Bergen, Kristiansand, and Tromsø.

individual discrete choice problem[31]. Workers choose in which sector to work by solving the following maximization problem

$$\max_s\{\frac{1}{\kappa} \cdot \log y_{i,s,r} + A_{i,s}\} \tag{20}$$

where $y_{i,s,r}$ is the worker's potential earnings, as described in Equation (3), and $A_{i,s}$ is an independently and identically distributed (i.i.d.) extreme value draw, consistent with Train (2009)[32]. A worker with a vector of potential income $\boldsymbol{y}_{i,r}$, selects into sector s with probability

$$\pi_{i,r,s,t} \equiv \frac{e^{\log y_{i,s}/\kappa}}{\sum_s e^{\log y_{i,s}/\kappa}}, \tag{21}$$

such that for a local labor market r

$$\pi_{r,s,t} \equiv \frac{1}{N}\sum_{i=1}^{N} \pi_{i,r,s}. \tag{22}$$

This approximation has several benefits, which are further discussed in Appendix B.1.

Increasing κ smooths the discrete choice problem by increasing the importance of the non-pecuniary utility draw relative to earnings in the sectoral choice. Simulations in Figure A.7 show that the approximation model's predictions are close to the pure discrete choice model's predictions when κ is low. Notably, higher κ values reduce the number of draws needed for smoothness in the simulated predictions in the skill distribution parameters. To determine the optimal level of smoothing, in Appendix B.1 I derive an estimation equation for κ. I show that the parameter can be interpreted as the inverse of the elasticity informing us on how important the Roy component is in explaining sectoral reallocation. Interestingly, as κ increases, workers are more likely to make choices inconsitently with the sectoral wage changes. Intuitively, if the Roy model is a good model in explaining reallocation, workers should indeed move in the directions of sectors with increasing wages, relative to in the opposite directions. This implies a high elasticity (and a low κ). On the other hand, the lower is the elasticity, the less does the Roy model explain the data on sectoral reallocation, justifying a higher degree of smoothing. I show the estimation equation to be independent of the skill distribution parameters, such that κ can be micro founded in the data independently of the skill distribution parameters. The estimated elasticity is presented in Table A.11, and I set the parameter to the value 0.1. The results are in line with the Roy model does indeed explain a large and significant share of the data on reallocation, but still allow for enough smoothing to reduce the computational burden of the skill distribution parameter estimation.

Both in the SMM estimation and in the counterfactual simulations, I will use the approximated model. Because in the approximated model there are gross movement flows, throughout the rest of this

[31] Recently, Johnson and Moxnes (2023) use a similar approximation for numerically solving a Ricardian model of trade with a finite number of goods.

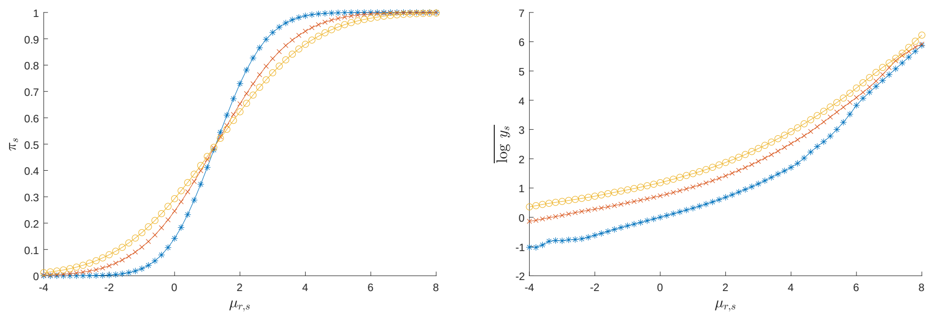
[32] $A_{i,s}$ can be interpreted of as a sector-specific amenity, allowing for non-pecuniary preferences. The approximation introduces selection behavior inconsistent with the strict Roy model, which aligns with empirical data. This is consistent with literature on labor market outcomes and amenities including and further reveiwed by Hall and Mueller (2018); Sorkin (2018); Lamadon, Mogstad, and Setzler (2022).

paper (except in Appendix B.1), I define $\lambda_{r,s,k} \equiv \lambda^{gross}_{r,s,k} - \lambda^{gross}_{r,k,s}$

5.3 Simulated moments

To provide insight into how moments of the model depend on the parameters of the log-normal skill distribution, I show model simulated comparative static exercises for the moments used as targets in the structural estimation. Although the parameters jointly determine the simulated moments, the exercises demonstrate how the moments depend on key parameters, given the remaining set of parameters.[33]

Figure 6: Sector shares and average earnings
$\sigma_s^2 < \sigma_s^2 < \sigma_s^2$



(a) Sector share (b) Average earnings

Notes: The figure shows examples of model simulated comparative statics exercises. In both panels, the horizontal axis measures the sector-specific level, $\mu_{r,s}$. The vertical axis of panel (a) measures the share of worker working in sector s, and the vertical axis of panel (b) measures the average log earnings of workers working in sector s. The colors/shapes represent different values of skill variation σ_s^2, in increasing order: blue/stars, red/crosses, and yellow/circles.

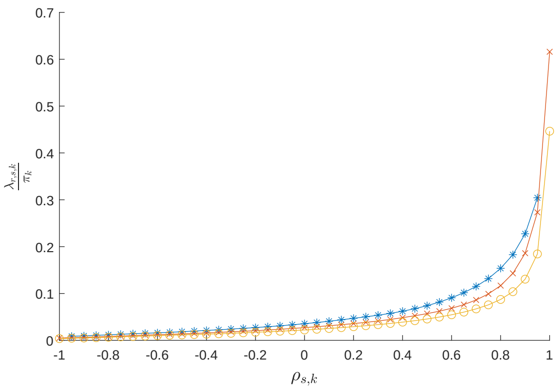
Equilibrium Figure 6 presents examples of model simulated comparative statics exercises showing how the sectoral worker shares and average sectoral earnings in a sector s depend on the level $\mu_{r,s}$ and the variance parameter σ_s^2. Panel (a) shows the share of workers selecting into the sector to be increasing in the level $\mu_{r,s}$. The higher is $\mu_{r,s}$, the more workers sort into that sector. By shifting σ_s^2, the blue/star (yellow/circle) plot shows that for a lower (higher) variation in sectoral skills, the share of workers selecting into the sector will be relatively lower (higher) for low values of the level, and relatively higher (lower) for high values of the level. Intuitively, when the tails of the marginal skill distribution are smaller, the number of workers selecting to the sector is more sensitive to level differences across sectors.

Panel (b) shows the average sectoral earnings to be increasing in the level $\mu_{r,s}$. For all cases in the figure, there is a positive selection bias; the average earnings of the workers selected into the sector is higher compared to the level. The degree of selection bias depends on the variation in the sectoral

[33] In the simulated comparative statics exercises presented in this section, other parameters than those presented in the figures are fixed as follows: σ_s^2 values are equal to one, $\rho_{s,k}$ values are equal to zero, and $\mu_{r,s}$ values are equal to zero. Moreover, I use the set of wage changes $\widehat{w}_{r,s}$ identified in Section 5.4 for the CZ Stavanger. Sector s is Oil, and Sector k is Electricity, Gas Supply, and Construction.

skills, σ_s^2. When there is more variation in skills, there is more selection bias resulting in higher average earnings in the sector. Moreover, while a higher variation in skills, σ_s^2 shifts the average earnings upwards, the selection bias is shrinking in $\mu_{r,s}$. As $\mu_{r,s}$ is increasing and more workers select into the sector, more of the marginal skill distribution is observed such that the average earnings for the sector moves toward the level.

Figure 7: Worker movements: From origin sector s to destination sector k
$\sigma_k^2 < \sigma_k^2 < \sigma_k^2$



Notes: The figure shows an example of a typical model simulated comparative statics exercise. The horizontal axis measures values of $\rho_{s,k}$, which is the Pearson's correlation coefficient, defined as $\sigma_{s,k}/\sigma_s\sigma_k$, when $\sigma_{s,k}$ is the covariance between sector s and sector k skills, and σ_s and σ_k are the standard deviation of sector s and sector k skills respectively. The vertical axis measures $\lambda_{r,s,k}/\pi_{r,k}$, which is the share of workers in CZ r moving from origin sector s to destination sector k, relative to the initial share of workers in r working in destination sector k. The different colors/shapes represents different values of the destination sector k skill variation, σ_s^2, in increasing order: blue/stars, red/crosses, and yellow/circles. The set of wage changes $\widehat{w}_{r,s}$ identified in Section 5.4 for the CZ Stavanger. Sector s is Oil, and sector k is Electricity, Gas Supply, and Construction.

Worker reallocation Figure 7 presents examples of model-simulated comparative exercises for worker reallocation when there is a negative wage shock in a sector s. Given the remaining set of parameters, the number of workers moving from the origin sector s to the destination sector k, relative to the size of the destination sector k, is increasing the correlation coefficient for sector s and sector k skills $\rho_{s,k}$. For the simulated data presented in the figure, when the two sectors are more correlated in skills, workers are more sensitive to a relative wage change between the two sectors. Moreover, as the figure shows, the relationship depends on the degree of variation in skills for the destination sector, determined by σ_k^2. When there is less variation in the destination sector skills, more workers in the origin sector are sensitive to the negative wage shock.

5.4 Identifying sectoral wage changes

I identify the sectoral wage changes to be used as input in the parameter estimation exercise. I follow Kim and Vogel (2020) and identify the equilibrium wage changes for each sector for each CZ by a fixed effect approach where I use the set of incumbent workers. In the model, incumbent workers have income changes equal to $\log \widehat{y}_{i,t} = \log \widehat{w}_{r,s,t}$. Since earnings growth in the data may be correlated with demographic characteristics, I include Mincer controls in a fixed-effects regression. Specifically, I estimate the vector of $\log \widehat{w}_{r,s,t,t+1}$ by the form

$$\log \widehat{y}_{i,r,t,t+1} = \mathrm{FE}_{r,s,t,t+1} + \mathbf{X}'_{i,t}\beta + \varepsilon_{i,t}, \tag{23}$$

where $\mathbf{X}'_{i,t}$ includes age group, gender, and education level, such that

$$\log \widehat{w}_{r,s,t,t+1} \equiv \mathrm{FE}_{r,s,t,t+1}. \tag{24}$$

To maximize the set of observations, I repeat the identification exercise for each year t between 2013 and 2016 separately. Afterward, I aggregate the identified wage changes over the sample period, and I define the local sector-specific log wage changes over the period 2013 to 2017 as

$$\log \widehat{w}_{r,s} \equiv \sum_{t}^{T-1} \log \widehat{w}_{r,s,t,t+1}. \tag{25}$$

Conditional on the individual demographic characteristics, the identifying assumption is that log changes in wages are independent of whether workers are staying incumbent or moving.

5.5 Identifying moments in data

I identify the moments that I use as targets in the SMM estimation in actual data. At the CZ level, I calculate employment shares, worker movement flows, and average sectoral earnings.

Sector shares and worker flows $\pi_{r,s}$ is the share of workers selecting into sector s in CZ r, and $\lambda_{r,s,k}$ is the share of workers moving from sector s to sector k in CZ r. I use $\pi_{r,s}$ and $\lambda_{r,s,k}/\pi_{r,k}$ as targets in the estimation exercise, and identify the moments in the data by $\pi_{r,s} = \frac{N_{r,s}}{N_r}$, and $\frac{\lambda_{r,s,k}}{\pi_{r,k}} = \frac{\Delta N_{r,s,k}}{N_{r,k}}$ where $N_{r,s}$ is the number of workers working in sector s in CZ r, N_r is the total number of workers in CZ r, and $\Delta N_{r,s,k}$ is the number of net-movers moving from sector s in CZ r into sector k. $N_{r,s}$ and N_r are calculated for year 2013, and $\Delta N_{r,s,k}$ is calculated for the time period 2013 to 2017.

Sectoral earnings For each CZ, I identify average sectoral earnings to be used as targets in the estimation exercise. I exclude variation in the income distribution that is due to age, gender, and education in a Mincer type of regression of the following form

$$\log \widetilde{y}_i = \alpha_0 + \alpha_{r,s} + \boldsymbol{X_i'}\beta + \epsilon_{i,r,s} \tag{26}$$

where $\widetilde{y}_i$ is observed log labor income in the year 2013, α_0 is the constant across workers, $\alpha_{r,s}$ is the CZ-sector constant, $\boldsymbol{X'_{i,t}}$ is the set of included controls, and ϵ_i is the residual. I define the log income distribution used to construct the targeted moments as

$$\log y_i \equiv \alpha_0 + \alpha_{r,s} + \epsilon_{i,r,s}. \tag{27}$$

For each sector within each CZ, I compute average log earnings over the log income distribution $\log y_i$.

5.6 Estimation results

The SMM estimated sectoral skill correlation matrix is presented in Table 1. The correlation coefficients presented in the table supports sectoral skills not to be independently distributed. Some sector pairs are highly positively correlated in skills, while other sector pairs are highly negatively correlated in skills. In particular, I find Oil sector skills to be positively correlated with Electricity, Gas Supply, and Construction skills and with Tradable sector skills. Oil sector skills are weakly positively correlated with skills in Services and the Public sector, and negatively correlated with skills for Financial Services, and Scientific and Technical activities. Some other stark patterns are as follows. First, the Tradable sector is highly positively correlated with Scientific and Technological activities skills, but negatively correlated in skills with all other (except Oil) sectors. Second, while Electricity, Gas Supply and Construction skills are highly positively correlated with Oil sector skills, the correlations with all other sectors are negative. Third, Public sector skills are highly positively correlated with skills in Scientific and Technical activities, Services, and Financial Services.

Table A.9 presents the SMM estimated sector specific standard diviations. The estimation results shows some sectors to have larger variation in skills relative to others. In particular, the Oil sector has large variation in skills, while the Public sector and the Service sector the variation in skills across workers is estimated to be relatively small.

The tables A.15, A.16, A.17, and A.18 present estimation results by education group. The results show that workers of different level of education are estimated have skills drawn from different distributions. Specifically, I find low educated workers to have higher variation in skills for all sectors. Moreover, the skill correlation structure differ for worker of different education level.

5.7 Model fit

Targeted moments Table 2 presents the result of the model fit exercise where the targeted moments are regressed on moments simulated by the SMM estimated model. The simulated moments significantly predict many of the targeted moments. For movement flows and average earnings, the linear

Table 1: Estimated $\rho_{s,k}$ values

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
Elect & Const	1.000	-0.414	-0.100	-0.326	-0.284	0.503	-0.248
	(-)	(0.14)	(0.12)	(0.20)	(0.11)	(0.07)	(0.15)
Services	-0.414	1.000	0.014	-0.360	0.414	0.106	-0.002
	(0.14)	(-)	(0.19)	(0.15)	(0.10)	(0.14)	(0.20)
Financial	-0.100	0.014	1.000	0.008	0.233	-0.085	-0.206
	(0.12)	(0.19)	(-)	(0.13)	(0.13)	(0.14)	(0.13)
Scient & Tech	-0.326	-0.360	0.008	1.000	0.452	-0.127	0.578
	(0.20)	(0.15)	(0.13)	(-)	(0.17)	(0.16)	(0.08)
Public	-0.284	0.414	0.233	0.452	1.000	0.048	-0.011
	(0.11)	(0.10)	(0.13)	(0.17)	(-)	(0.12)	(0.26)
Oil	0.503	0.106	-0.085	-0.127	0.048	1.000	0.274
	(0.07)	(0.14)	(0.14)	(0.16)	(0.12)	(-)	(0.11)
Trade	-0.248	-0.002	-0.206	0.578	-0.011	0.274	1.000
	(0.15)	(0.20)	(0.13)	(0.08)	(0.26)	(0.11)	(-)

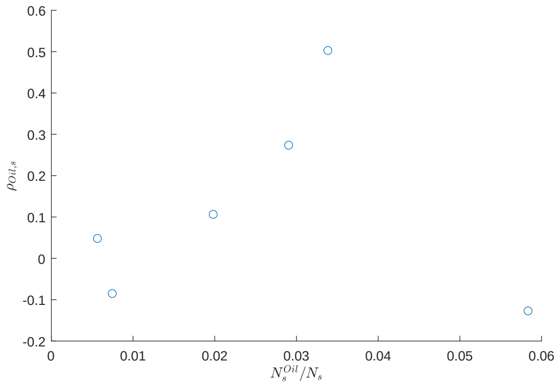
Notes: The table presents the estimatd skill correlation coefficients $\rho_{s,k}$ for all sector pairs. Specifically, the correlation coefficients are the Pearson's correlation coefficient, defined as $\sigma_{i,j}/\sigma_i\sigma_j$, when $\sigma_{i,j}$ is the covariance between sector i and sector j skills, and σ_i and σ_j are the standard deviation of sector i and sector j skills respectively. Bootstrapped standard errors are reported in parentheses.

Table 2: Model fit to targeted moments

	Actual $\pi_{r,k}$	Actual $\frac{\lambda_{r,s,k}}{\pi_{r,k}}$	Actual $\overline{\log y_{r,s}}$
$\pi_{r,k}$	-0.056		
	(0.234)		
$\frac{\lambda_{r,s,k}}{\pi_{r,k}}$		0.932	
		(0.055)	
$\overline{\log y_{r,s}}$			0.668
			(0.081)
Constant	0.151	0.003	0.031
	(0.040)	(0.001)	(0.012)
R^2	0.002	0.579	0.672
Observations	35	210	35

Notes: The table reports the estimated model fit coefficients from regressing the targeted data moments on the corresponding moments simulated by the SMM estimated model. Formally, I run the regression $x^{actual} = \beta_0 + \beta_1 x^{sim} + \epsilon$, where x^{actual} represents the moments observed in the actual data, x^{sim} represents the moments simulated by the SMM estimated model, and ϵ is the error term. The specifications, from left to right, evaluate model fit for sectoral shares, movement flows, and average sectoral earnings. Standard errors are reported in parentheses.

Figure 8: Model fit to non-targeted moments



Notes: The figure measures the share of workers working in sector s with a previous employment spell in the Oil sector on the horizontal axis (N_s^{Oil}/N_s), against the SMM estimatad correlation coefficents between the oil sector and sector s ($\rho_{Oil,s}$) on the vertical axis. Each observation represents a different sector.

fit is significantly positive, and the simulated data explains a high share of the variation in the data. Particularly for the movement flows, the fit is very good. A linear fit equal to unity cannot be rejected, and the model simulated data explains as much as 56% of the data variation. Hence, the model is close to replicating all the data on worker movement flows across sectors. For average sectoral earnings, the fit it also very good and the model explains 67% of the variation in the data. In other words, the model does a good job in replicating the fact that there is differences in worker earnings across sectors, within CZs. The model does not fit the sectoral shares well. However, when estimating the model by education group, as demonstrated in Appendix B.4, the fit improves considerably and the estimated model then fits all targeted moments very well. For both highly educated and low-educated workers, the model explain observed sectoral shares, movement flows, and average sectoral earnings (see Table A.19 and Table A.20).

Non-targeted moments In addition to evaluating how well the estimated model fits the targeted moments, I also assess the fit of simulated moments to non-targeted moments. Figure 8 demonstrates that the estimated correlation coefficients are in line with the exposure term discussed in Section 4. Specifically, the correlation coefficients for oil sector skills and other sectors are for all except one sector, strongly in line with the share of workers in corresponding sectors who have previously worked in the oil sector.[34] [35]

[34]For the sector Professional, scientific and technical activities, the two measures are not aligned. Though the exposure measure takes a high value, the estimated correlation coefficient with oil skills is relatively low. One potential explanation is heterogeneity across worker groups in how related the two sectors are in skills. Table A.15 and Table A.16 show that high and low educated workers are estimated to have very different skill correlation coefficents between the two sectors.

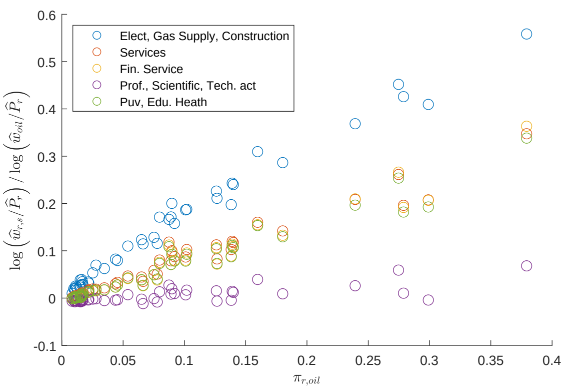
[35]I also test how well the model is in predicting moments for the pre-period 2009 - 2013. Table A.10 shows that compared to the results presented in Table 2, the pre-period model fit coefficient is unequal unity for all moment types, and the model simulated data explains a small share of the variation in the observed pre-period data. Table A.8 shows the estimated κ to be higher for the pre-period, and less precisely estimated. This is in line with the Roy model in less degree can explain sectoral reallocation in the pre-period. The lower estimated elasticity with higher standard errors may

6 Counterfactual simulations

I use the SMM estimated model to simulate worker reallocation following a counterfactual oil price collapse and to quantify the associated impact on workers' earnings. Beetween 2013 and 2017, the price of Brent Crude Oil fell by approximately 50% (see Figure 1), and as a counterfactual exercise, I shock the model with $\widehat{p}_{oil} = 0.5$. The shock changes the vector of sectoral wages and induces worker reallocation from the oil sector to non-oil sectors. Due to both shifting labor supply and a fall in aggregate demand for NT goods, equilibrium NT real wages change, leading to sectoral worker reallocations originating from non-oil sectors. Section 4 provided reduced form evidence on the domino effects of the shock in the destination sectors of the moving oil workers. In this section, however, the model explains the overall impact of the shock across all workers. To understand the overall impact of the shock, this section presents the equilibrium wage changes, explains the sectoral reallocation response, and conducts reduced-form exercises on the simulated data.

Equilibrium wage changes Figure 9 illustrates the quantified magnitude of the equilibrium real wage changes for NT sectors relative to the changes in the real wage for the oil sector in the corresponding CZ. While some local NT sectors did not experience any reduction in real wages, at the maximum, the shock is associated with a real wage change of 55.8% of the oil sector real wage change. On average, across local NT sectors, the number is 6.9%. For CZs more exposed to the shock, NT sectors, on

Figure 9: Impact of the oil price collapse on non-tradable sector real wage changes



Notes: The figure shows the impact on NT sector real wage changes relative to the impact on the oil sector real wages, across Norwegian CZs. Specifically, the horizontal axis measures the initial share of workers working in the oil sector for CZs r ($\pi_{r,oil}$), and the vertical axis measures the impact on log real wages for NT sectors s in CZ r, relative to the impact on real wages for the oil sector in the same CZ r $((\log(\widehat{w}_{r,s}/\widehat{P}_r))/(\log(\widehat{w}_{oil}/\widehat{P}_r)))$.

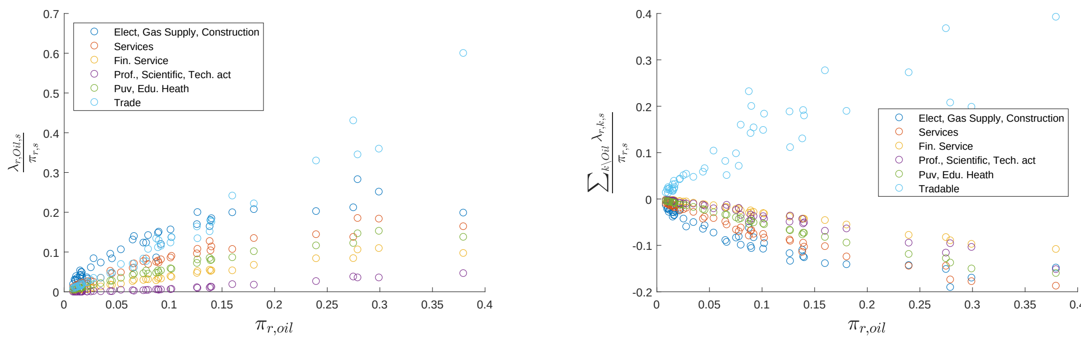
average, experience a larger relative decline in real wages, but with variation across sectors within CZs. As Equation (14) explains, this arises from multiple channels affecting NT wages. First, the shock

be due to more measurement error during a period without a clear shock leading to worker reallocation. The estimation may suffer from attenuation bias, leading to an estimated elasticity biased toward zero with high standard errors.

induces worker reallocation out of the oil sector, leading to increased labor supply for the destination sectors of the moving oil workers, resulting in falling NT sector wages. In CZs with a larger share of workers in the oil sector, more oil workers move, leading to greater downward pressure on the wages. This is particulary the case for the NT sectors the oil workers are intensely moving into. Second, due to a fall in aggregate earnings, the shock leads to a fall in demand for NT goods. The fall in demand is more pronounced in CZs specialized in oil, resulting in wage decline in NT sectors in these CZs.[36] Third, in response to declining wages, workers in NT sectors move toward the tradable sector, mitigating the equilibrium NT wage decline. These three channels create variations in the relative magnitude of equilibrium effects across NT sectors both across and within CZs, as illustrated by Figure 9.

Understanding the sectoral reallocation In response to the decline in oil sector wages, oil workers move to non-oil sectors. Figure 10a illustrates the model-simulated shift in employment across destination sectors due to incoming oil workers. In CZs with a larger oil sector, the employment shift is greater. However, there is variation across sectors, consistent with the estimated skill correlation structure. In particular, Oil skills are highly positively correlated with the skills of the Tradable sector and Electricity, Gas Supply and Construction, and these two sectors are in particular experiencing a large increase in employment due to oil worker movement flows. Interestingly, the increase in oil worker inflows to NT sectors is slowed down as the CZ is getting more exposed to the shock by having larger employment share in the oil sector. In these CZs, non-tradable equilibrium wages fall more, making NT sectors less attractive destinations for oil workers.

Figure 10



(a) (b)

Notes: Panel (a) shows the shift in employment due to inflows of moving workers ($\lambda_{r,Oil,s}/\pi_{r,s}$) on the vertical axis, against the initial size of the oil sector in the CZ ($\pi_{r,oil}$) on the horizontal axis. Panel (b) shows the shift in employment due to net-inflows of moving workers from all other sectors except Oil ($\sum_{k\setminus Oil}\lambda_{r,k,s}/\pi_{r,s}$) on the vertical axis, against the initial size of the oil sector in the CZ ($\pi_{r,oil}$) on the horizontal axis. In both panels, each observation represents a different local sector.

[36]Given the assumption that workers have identical Cobb-Douglas preferences over the S consumption goods, consumption expenditures remain a constant share of total income. Consequently, within this framework, the reduction in demand for NT goods is the same across all NT sectors within each CZ. The only source of variation in real wage changes across NT sectors within CZs in this model, is asymmetric worker reallocation.

As a response to NT sector wages decline, workers move out of NT sectors. Figure A.6 shows these domino responses in sectoral reallocation to be sizable. At the maximum, the number of workers moving out of non-oil sectors equals 42% of total reallocation. And as I will soon show, the additional reallocation between non-oil sectors substantially impacts equilibrium wage changes. Figure 10b presents the net growth for each local sector, excluding inflows of oil workers. The figure highlights that most sectors experience worker net-outflows, while the Tradable sector sees additional worker net-inflows from all other non-oil sectors. All NT sectors experience worker outflows, although smaller in magnitude compared to the inflows of oil workers. The tradable sector, however, receives a substantial number of workers from NT sectors, for many CZs equal to or greater than those from the oil sector.

Reduced form analysis on simulated data Table 3 presents the results from reduced-form regression exercises on the simulated real wage changes for NT sectors in response to the counterfactual oil shock. The goal is to examine the importance of the three main channels influencing non-tradable wage

Table 3

	$\log \frac{\widehat{w}_{r,s}}{\widehat{P}_r}$	$\log \frac{\widehat{w}_{r,s}}{\widehat{P}_r}$	$\log \frac{\widehat{w}_{r,s}}{\widehat{P}_r}$
$\left(1+\rho_{Oil,s}\right) \cdot \pi_{r,Oil}$	-0.443	-1.045	-0.696
	(0.016)	(0.044)	(0.036)
$\pi_{r,Oil}$		0.708	-0.138
		(0.049)	(0.060)
$\left(1+\rho_{Trade,s}\right) \cdot \pi_{r,Oil}$			0.456
			(0.027)
R^2	0.761	0.875	0.945
Observations	230	230	230

Notes: The table reports the estimated reduced form coefficients from regressing three different model-constructed explanatory variables on real wage changes for NT sectors, as simulated by the SMM estimated model. The explanatory variables, listed by row, are: (1) the skill correlation with the oil sector and the local size of the oil sector; (2) the size of the local oil sector; and (3) the skill correlation with the tradable sector and the local oil sector size. Standard errors are reported in parentheses.

changes: inflows of oil workers, a fall in demand for non-tradable goods, and the worker reallocation towards the tradable sector. I develop three explanatory variables: (1) exposure to inflows of oil workers, measured by skill correlation with the oil sector and the local size of the oil sector; (2) exposure to a fall in demand for non-tradable goods, measured by the size of the local oil sector; and (3) exposure to movements toward the tradable sector, measured by skill correlation with the tradable sector and the local oil sector size.

According to the third column of Table 3, all three explanatory variables significantly explain the changes in non-tradable wage changes. In CZs with a larger oil sector, non-tradable real wages fall more when the NT sector is closely aligned in skills with the oil sector. Conversely, non-tradable real wages fall less when the NT sector is closely aligned in skills with the tradable sector. While the magnitude shows the the relation to the oil sector has a larger impact, both these opposing channels are of relative considerable size. Additionally, the second row shows that real wages fall more in all NT sectors in

CZs with a larger oil sector. This is due to a more considerable fall in aggregate earnings in these CZs, leading to reduced demand for non-tradable goods and downward pressure on non-tradable sector wages. While this channel is important, its impact is less pronounced compared to the two former channels. Ultimately, the three explanatory variables collectively explain nearly all the variation in the simulated real wage data.

7 Conclusion

This paper provides new insights into the equilibrium effects of sector-specific shocks on labor markets, using the 2014 oil price collapse in Norway as a natural experiment. By examining how workers reallocate across sectors and the subsequent impact on earnings in destination sectors, this study highlights the complex patterns of worker movements and wage adjustments. The empirical evidence shows that inflows of oil workers into non-tradable sectors lead to wage growth declines and further worker reallocation, documenting the widespread impacts of such shocks. By building and estimating a multisector Roy model, this paper improves our understanding of worker reallocation. The model demonstrates how this mechanism is critical for quantifying the the aggregate and distributional effects of sector specific shocks more accurately than existing models. Through counterfactual simulations, the model reveals how sectoral interconnectedness in the labor market propagates shocks through the economy. This emphasizes the importance of considering the entire network of labor reallocation in economic policy and research when studying labor market adjustments to economic shocks.

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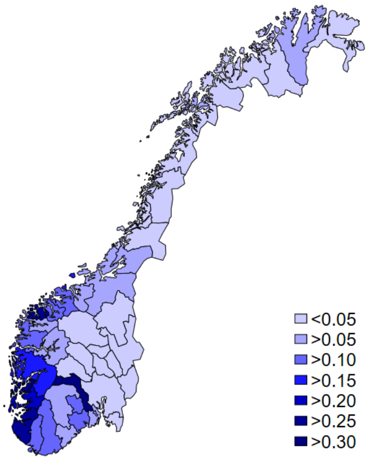
Appendices

A Supplementary Tables

Figure A.1: Oil sector employment share across commuting zones



Notes: The map shows the share of workers working in the oil sector across commuting zones in Norway for the year 2013. The worker shares are conducted for the sample of employed or self-employed full-time workers between 25 and 58 years. Darker colors represent larger shares of workers working in the oil sector in the commuting zone.

Table A.1: Descriptive characteristics for workers by group

	All workers	Non-tradable workers	Oil workers	Movers from oil
Age	42.004	41.989	41.358	37.281
Female	0.426	0.509	0.205	0.273
College education	0.510	0.625	0.441	0.597
log $y_{i,r,s}$	1	0.998	1.018	1.012
log $y_{i,r,s}$, residualised	1	0.999	1.022	1.016
Moving across sectors	0.099	0.099	0.127	1.000
Moving across CZs	0.029	0.032	0.031	0.105
Moving across sectors and CZs	0.008	0.008	0.013	0.105
Remaining fulltime employed	0.743	0.754	0.738	1.000

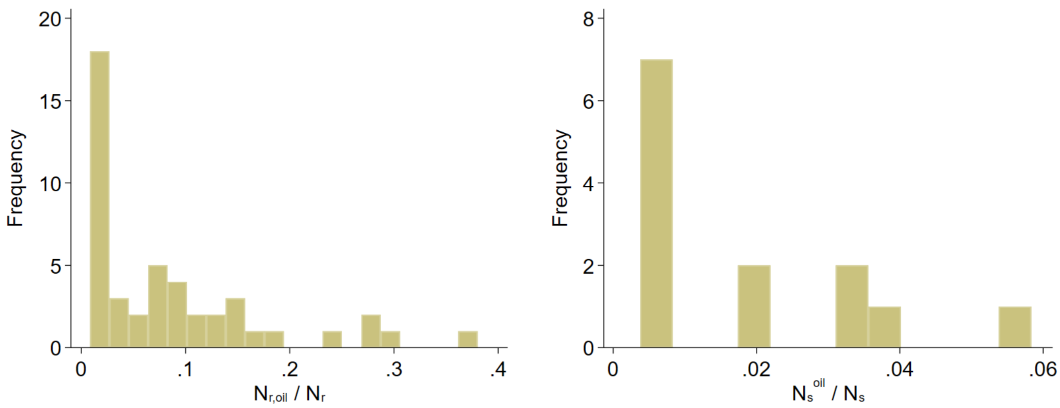
Notes: The table presents descriptive statistics for different groups of workers. The columns represent various worker groups, from left to right: all workers in the sample in 2013; workers in non-tradable sectors in 2013; workers in the oil sector in 2013; and workers who remained in the sample from 2013 to 2017, having worked in the oil sector in 2013 and in non-oil sectors in 2017. The rows provide specific descriptive statistics. From the top, the rows show the average age in 2013; the share of female workers in 2013; the share of workers with a college degree in 2013; average log earnings normalized to the average for all workers in 2013; average log residualized earnings normalized to the average for all workers in 2013, where earnings are residualized to remove variation due to age, gender, and education. The rows also include the share of workers in both 2013 and 2017 who did not remain in the same sector over that period; the share of workers in both 2013 and 2017 who did not remain in the same CZ over that period; the share of workers in both 2013 and 2017 who changed both sector and CZ over that period; and the share of workers present in the sample both in 2013 and 2017. The sample includes full-time employed or self-employed workers aged between 25 and 58 years.

Table A.2: Descriptive Table: Oil Movers and Non-tradable workers

	Age	Female	College education
Movers from oil	37.281	0.273	0.597
Elect. and gas supply	44.661	0.205	0.428
Construction	41.177	0.080	0.156
Accommodation, food service	38.361	0.488	0.244
Information and communication	40.588	0.302	0.673
Financial and insurance act.	42.808	0.466	0.610
Real estate activities	41.483	0.369	0.512
Prof., scientific, tech. act.	40.226	0.399	0.748
Admin., support service	40.772	0.387	0.264
Public adm., defence, soc. security	43.202	0.468	0.659
Education	42.798	0.617	0.893
Human health, social work	42.137	0.770	0.668
Arts, entertainment and recreation	42.534	0.483	0.575
Other service act.	42.953	0.538	0.515

Notes: The table presents descriptive statistics for workers who were in the sample both in 2013 and 2017, transitioned from the oil sector in 2013 to non-tradable sectors in 2017, by sector. The columns show the average age in 2013, the share of female workers, and the share of workers with a college degree. The sample includes full-time employed or self-employed workers aged between 25 and 58 years.

Figure A.2: The distribution of exposure across CZs and sectors



(a) Across CZs (b) Across sectors

Notes: Panel (a) reports the frequency of $N_{oil,r}/N_r$ across CZs. Panel (b) reports the frequency N_s^{oil}/N_s across sectors. $N_{oil,r}$ is the number of workers working in the oil sector in commuting zone r, N_r the number of workers located in commuting zone r, N_s^{oil} is the number of workers working in sector s with a previous employment spell in the oil sector, and N_s is the number of workers working in sector s, all constructed for the pre-shock year 2013. Previous employment spells are measured for the pre-shock years from 2000 to 2012.

Table A.3: Correlation: Exposure and movements

	(1) $\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$	(2) $\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$	(3) $\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$	(4) $\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$
$\mathbb{Z}_{r,s}$	8.794***	4.799***	4.793***	4.884***
	(0.509)	(0.851)	(0.852)	(1.084)
$\mathbb{Z}_{r,s}^{Trade}$			-0.0412	-0.0813
			(0.130)	(0.173)
Sales to local oil sector				3.661***
				(0.675)
R-squared	0.335	0.480	0.480	0.513
Fixed effects	No	Yes	Yes	Yes
Observations	595	595	595	411

Notes: $\Delta N_{r,oil,s}$ is the number of workers moving from the oil sector to sector s in commuting zone r. $\mathbb{Z}_{r,s}^{Alt.Trade} = \frac{N_{Alt.Trade,r}}{N_r} \cdot \frac{N_s^{Alt.Trade}}{N_s}$, and *Alt. Trade* is defined to include all tradable sectors except the oil sector. *Sales to local oil sector* is an exposure term defined as a sector's initial share of sales to the oil sector, measured in the input-output table, interacted with the relative size of the oil sector in the local market. The last three coloumns include sector and CZ fixed effects.
*** Significantly different from zero at 99 percent confidence level.
** Significantly different from zero at 95 percent confidence level.
* Significantly different from zero at 90 percent confidence level.

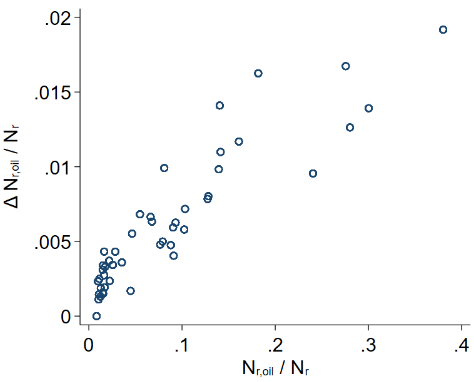
Table A.4: Wage growth for incumbent workers and exposure to inflows of moving oil workers

	(1) $\log \hat{y}_{i,r,s,t,t+1}$	(2) $\log \hat{y}_{i,r,s,t,t+1}$	(3) $\log \hat{y}_{i,r,s,t,t+1}$
2011 × $\mathbb{Z}_{r,s}$	-0.323**	-0.448**	-0.346**
	(0.160)	(0.217)	(0.166)
2012 × $\mathbb{Z}_{r,s}$	0.133	-0.111	0.260
	(0.424)	(0.610)	(0.478)
2013 × $\mathbb{Z}_{r,s}$	-0.0845	-0.398*	0.111
	(0.153)	(0.199)	(0.190)
2014 × $\mathbb{Z}_{r,s}$	-0.299	-0.554	-0.210
	(0.311)	(0.580)	(0.293)
2015 × $\mathbb{Z}_{r,s}$	-2.094***	-2.387***	-1.105
	(0.625)	(0.605)	(1.014)
2016 × $\mathbb{Z}_{r,s}$	-1.770***	-2.023***	-1.140***
	(0.176)	(0.395)	(0.202)
2017 × $\mathbb{Z}_{r,s}$	-0.866**	0.00387	-1.244***
	(0.342)	(0.531)	(0.137)
Additional controls		Yes	
Sample restriction			Without Construction
Observations	3614068	3614068	3290221

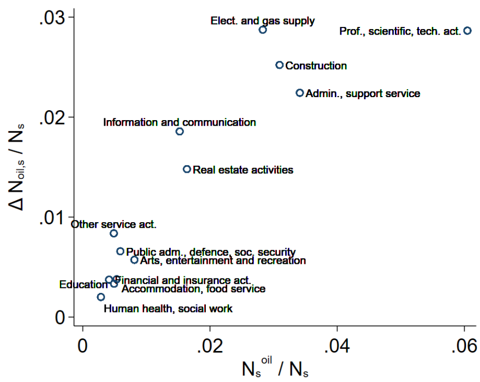
Notes: The table reports β_1 for the years 2010 to 2016, estimated using Equation (16). The sample includes incumbent workers in non-tradable sectors, specifically those who remained in the same sector and commuting zone over two years. For all columns, the included controls are commuting zone-year and sector-year fixed effects, age group, gender, and education level. In the second column, additional controls include exposure to outflows of moving workers to tradable sectors and exposure to sales to the local oil sector.The exposure to outflows of moving workers to tradable sectors, $\mathbb{Z}_{r,s}^{T}$, is defined as $\frac{N_s^{Alt.Trade}}{N_s} \cdot \frac{N_{Alt.Trade,r}}{N_r}$. The exposure to sales to the local oil sector is defined as a sector's initial share of sales to the oil sector (measured in the input-output table) interacting with the relative size of the oil sector in the commuting zone. The last column excludes workers in the construction sector. Standard errors are clustered at the CZ level.
*** Significantly different from zero at 99 percent confidence level.
** Significantly different from zero at 95 percent confidence level.
* Significantly different from zero at 90 percent confidence level.

Figure A.3: Variation in the exposure term and movements

(a) Variation across CZs



(b) Variation across sectors



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Notes: In panel A.3a the horizontal axis measures the share of workers working in the oil sector in the pre-period 2013. $N_{oil,r}$ is the number of workers working in the oil sector in CZ r, and N_r is the number of workers located in CZ r. The vertical axis measures the share of workers moving out of the oil sector and into non-tradable sectors between 2013 and 2017. $\Delta N_{r,oil}$ is the number of workers that are working in the oil sector in 2013, in a non-tradable sector in 2017, and are located in CZ r in 2017. In panel A.3b the horizontal axis measures the share of workers with a previous employment spell in the oil sector in the pre-period of 2013. N_s^{oil} is the number of workers working in sector s with a employment spell between the pre-period years of 2008 and 2013 in the oil sector, and N_s is the number of workers working in sector s in the pre-period of 2013. The vertical axis measures the number of oil workers moving into non-tradable sectors between 2013 and 2017. $\Delta N_{oil,s}$ is the number of workers that are working in the oil sector in 2013 and working in a non-tradable sector s in 2017.

Table A.5: Wage growth for incumbent workers: Comparing OLS and Reduced Form

	(1)	(2)
	$\log \widehat{y}_{i,r,s,t,t+1}$	$\log \widehat{y}_{i,r,s,t,t+1}$
2011 × $\log \widehat{L}_{r,s}^{Oil}$	-0.0332	
	(0.0263)	
2012 × $\log \widehat{L}_{r,s}^{Oil}$	-0.0218	
	(0.0378)	
2013 × $\log \widehat{L}_{r,s}^{Oil}$	0.0210	
	(0.0261)	
2014 × $\log \widehat{L}_{r,s}^{Oil}$	-0.0145	
	(0.0198)	
2015 × $\log \widehat{L}_{r,s}^{Oil}$	-0.252***	
	(0.0587)	
2016 × $\log \widehat{L}_{r,s}^{Oil}$	0.0230	
	(0.0404)	
2017 × $\log \widehat{L}_{r,s}^{Oil}$	0.00479	
	(0.0401)	
2011 × $\mathbb{Z}_{r,s}$		-0.323**
		(0.160)
2012 × $\mathbb{Z}_{r,s}$		0.133
		(0.424)
2013 × $\mathbb{Z}_{r,s}$		-0.0845
		(0.153)
2014 × $\mathbb{Z}_{r,s}$		-0.299
		(0.311)
2015 × $\mathbb{Z}_{r,s}$		-2.094***
		(0.625)
2016 × $\mathbb{Z}_{r,s}$		-1.770***
		(0.176)
2017 × $\mathbb{Z}_{r,s}$		-0.866**
		(0.342)
Observations	3613887	3614068

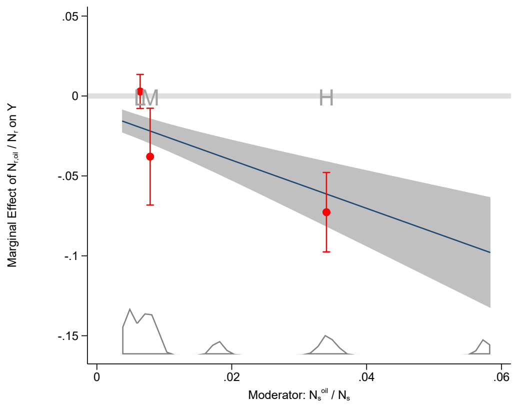
Notes: Notes: In the table, the first column reports the estimated coefficient for the years 2010 to 2016 by regressing the outcome variable in Equation (16) on the observed inflows of oil workers across local non-tradable sectors by OLS where $\log \widehat{L}_{r,s}^{Oil} \equiv \log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$ and $N_{r,s}$ is the number of workers working in non-tradable sector s in CZ r in 2013 and $\Delta N_{r,oil,s}$ is the number of oil workers moving into sector s in CZ r between 2013 and 2017; in the second column reports β_1 for the years 2010 to 2016 by estimating Equation (16) where $\mathbb{Z}_{r,s}$ is the exposure term defined in Equation (15). The sample includes incumbent workers in non-tradable sectors, that is workers that are staying in the same sector and commuting zone between year t and $t+1$. Included controls are commuting zone-year and sector-year fixed effects, age group, gender, and education level. The standard errors are clustered at the commuting zone level.
*** Significantly different from zero at 99 percent confidence level.
** Significantly different from zero at 95 percent confidence level.
* Significantly different from zero at 90 percent confidence level.

Table A.6: Leaving sector and exposure to inflows of moving oil workers

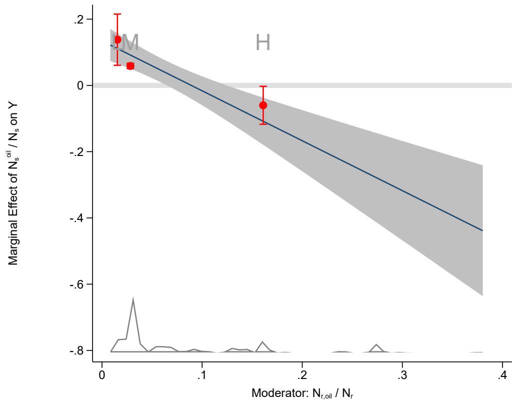
	(1)	(2)	(3)
	$\mathbb{I}_{i,r,s,t-1,t}(move)$	$\mathbb{I}_{i,r,s,t-1,t}(move)$	$\mathbb{I}_{i,r,s,t-1,t}(move)$
2011 × $\mathbb{Z}_{r,s}$	2.078**	0.386	3.685***
	(1.020)	(1.298)	(1.143)
2012 × $\mathbb{Z}_{r,s}$	0.439	1.348	1.425
	(0.814)	(1.167)	(1.004)
2013 × $\mathbb{Z}_{r,s}$	1.004	2.333**	0.449
	(0.928)	(1.051)	(0.966)
2014 × $\mathbb{Z}_{r,s}$	1.509	3.390***	1.594*
	(0.910)	(1.120)	(0.941)
2015 × $\mathbb{Z}_{r,s}$	4.257***	3.765***	3.902***
	(1.094)	(1.136)	(0.669)
2016 × $\mathbb{Z}_{r,s}$	3.799***	3.671***	3.652***
	(0.661)	(0.734)	(0.570)
2017 × $\mathbb{Z}_{r,s}$	1.005**	0.723	1.180***
	(0.414)	(0.449)	(0.408)
Additional controls		Yes	
Sample restriction			Without Construction
Observations	4520266	4520266	4071553

Notes: The table reports β_1 for the years 2010 to 2016 by estimating Equation (18). The sample includes workers in non-tradable sectors, and movement is defined as not observed in the same sector in year $t-1$ and year t and not observed to be working in the oil sector in year t. For all columns, the included controls are commuting zone-year and sector-year fixed effects, age group, gender, and education level. In the second column, additional controls include exposure to outflows of moving workers to tradable sectors and exposure to sales to the local oil sector.The exposure to outflows of moving workers to tradable sectors, $\mathbb{Z}^T_{r,s}$, is defined as $\frac{N_s^{Alt.Trade}}{N_s} \cdot \frac{N_{Alt.Trade,r}}{N_r}$. The exposure to sales to the local oil sector is defined as a sector's initial share of sales to the oil sector (measured in the input-output table) interacting with the relative size of the oil sector in the commuting zone. The last column excludes workers in the construction sector. Standard errors are clustered at the CZ level.
*** Significantly different from zero at 99 percent confidence level.
** Significantly different from zero at 95 percent confidence level.
* Significantly different from zero at 90 percent confidence level.

Figure A.4



(a) Marginal effect of $\frac{N_{r,oil}}{N_r}$, over $\frac{N_s^{oil}}{N_s}$



(b) Marginal effect of $\frac{N_s^{oil}}{N_s}$, over $\frac{N_{r,oil}}{N_r}$

Notes: Following Hainmueller et al. (2019), the figures show the conditional marginal effects from the binning estimator. Both panels presents both the conditional effect estimates from the binning estimator and the standard multiplicative interaction model, as well as the density of the moderator. The binnings are based on terciles of the moderator. In both panels, the outcome variable is $\log \widehat{y}_{i,r,s,t,t+1}$ residualized on age, education, gender for the years t = 2014, 2015, 2016. The standard errors are clustered at the CZ level.

Table A.7: Non-tradable sector aggregation

Non-tradable sector	SIC 2007 code	SIC 2007 name
Electricity, Gas Supply, and Construction	D	Electricity, gas, steam, and air conditioning supply
Electricity, Gas Supply, and Construction	F	Construction
Services	I	Accommodation and food service activities
Services	J	Information and communication
Financial Services	K	Financial and insurance activities
Financial Services	L	Real estate activities
Professional, scientific and technical activities	M	Professional, scientific and technical activities
Financial Services	N	Administration and support service activities
Public administration, Education and Health	O	Public administration, and defense
Public administration, Education, and Health	P	Education
Public administration, Education, and Health	Q	Human health and social work activities
Services	R	Arts, entertainment and recreation
Services	S	Other service activities

Notes: The table shows the sector aggreation to be used in the model estimation and counterfactual simulations. From the left, the columns indicate aggregated sectors used in this paper, the Standard Industrial Classification 2007 (SIC 2007) code of the sub-sectors, and the SIC 2007 name of the sub-sectors. The SIC 2007 sector definitions are defined by Statistics Norway.

Table A.8

	(1)	(2)	(3)
	$\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	$\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	$\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$
$\log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$	4.862	4.782	
	(1.574)	(1.582)	
$\mathbb{I}(\text{Bergen}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			3.790
			(4.127)
$\mathbb{I}(\text{Kristiansand}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			-1.586
			(4.947)
$\mathbb{I}(\text{Oslo}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			3.482
			(4.696)
$\mathbb{I}(\text{Stavanger}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			3.922
			(2.171)
$\mathbb{I}(\text{Tromso}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			9.570
			(2.833)
Implied κ	0.206	0.209	0.0560
R-squared	0.102	0.120	0.144
CZ Fixed Effects	No	Yes	No
Observations	102	102	102

Notes: The regressions in this table estimate Equation (34) for the pre-period 2009 - 2013. The second specification includes CZ fixed effects. Standard errors, clustered at the CZ level, in parentheses.

Table A.9: Estimated σ_s values

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
σ_s	1.085	0.685	1.182	0.867	0.579	0.890	0.839
	(0.09)	(0.08)	(0.13)	(0.10)	(0.08)	(0.08)	(0.07)

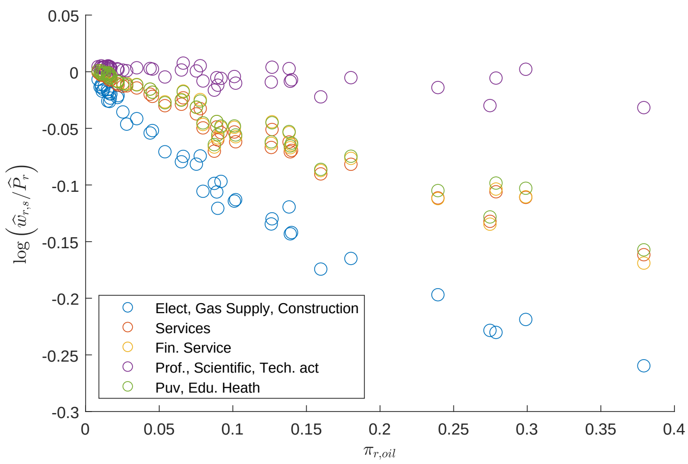
Notes: The table presents calibrated variance parameters σ_s^2 across sectors. Bootstrapped standard errors in parentheses.

Table A.10: Model fit to pre-period moments

	Actual $\pi_{r,k}$	Actual $\frac{\lambda_{r,s,k}}{\pi_{r,k}}$	Actual $\overline{\log y_{r,s}}$
$\pi_{r,k}$	-0.066		
	(0.249)		
$\frac{\lambda_{r,s,k}}{\pi_{r,k}}$		0.033	
		(0.068)	
$\overline{\log y_{r,s}}$			0.394
			(0.075)
Constant	0.152	0.006	0.056
	0.042	0.001	0.014
R^2	0.002	0.001	0.454
Observations	35	210	35

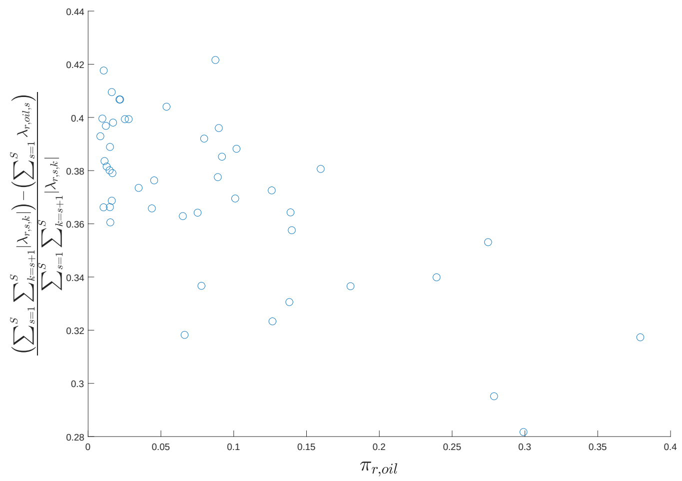
Notes: The table presents the calibrated skill correlation coefficients $\rho_{s,k}$ for all sector pairs. Specifically, the correlation coefficients are the Pearson's correlation coefficient, defined as $\sigma_{i,j}/\sigma_i\sigma_j$, when $\sigma_{i,j}$ is the covariance between sector i and sector j skills, and σ_i and σ_j are the standard deviation of sector i and sector j skills respectively.

Figure A.5: Equilibrium effects across local non-tradable sectors



Notes: The figure shows the impact of the oil price collapse on real wage changes for non-tradable sectors across Norwegian CZs. Specifically, the horizontal axis measures the initial share of workers working in the oil sector for CZs r ($\pi_{r,oil}$), and the vertical axis measures the log real wage change for non-tradable sectors s ($\log(\widehat{w}_{r,s}/\widehat{P}_r)$). The impact measured on the vertical axis times 100 can be interpreted as the approximate percentage change The colors represent different non-tradable sectors.

Figure A.6



Notes: The figure shows the share of worker reallocation between non-oil sectors. Specifically, the horizontal axis measures the total share of sectoral moves minus the moves out of the oil sector, relative to the total share of moves. The vertical axis measures the initial size of the oil sector. Each observation represents a different CZ.

B Estimation details

B.1 Model approximation

Worker i, located in local labor market r, is choosing in which sector s to work by solving the following maximization problem

$$\max_s \{\frac{1}{\kappa} \cdot \log y_{i,s,r} + A_{i,s}\} \tag{28}$$

where $y_{i,s,r}$ is the worker's potential wage, as described in Equation (3), and $A_{i,s}$ is an individual sector specific non-wage draw for sector s. $A_{i,s}$ is i.i.d. extreme value with a mean of zero, consistent with the mixed model presented in Train (2009). I assume κ to be constant across both local labor markets and sectors.

An individual with a vector of potential income y_i, will select into sector s with probability

$$\pi_{i,r,s,t} \equiv \frac{e^{\log y_{i,r,s}/\kappa}}{\sum_s e^{\log y_{i,r,s}/\kappa}}, \tag{29}$$

such that for a local labor market r

$$\pi_{r,s,t} \equiv \frac{1}{N} \sum_{i=1}^{N} \pi_{i,r,s}. \tag{30}$$

$\pi_{r,s,t}$ is an approximation for the pure discrete choice sectoral shares in Equation (6). The smaller is κ, the closer will $\pi_{r,s,t}$ be to Equation (6). On the other hand, as κ increases, more randomness is introduced to the model, and $\pi_{r,s,t}$ moves towards being constant across sectors and equal to $1/S$.

Next, for an individual i with a given vectors of potential income $\boldsymbol{y}$ and $\boldsymbol{y'}$ in the first and second period respectively, the probability of moving from sector s to sector k is

$$\lambda_{i,r,s,k} \equiv \frac{e^{\log y_{i,r,s}/\kappa}}{\sum_s e^{\log y_{i,r,s}/\kappa}} \cdot \frac{e^{\log y'_{i,r,k}/\kappa}}{\sum_s e^{\log y'_{i,r,s}/\kappa}} \tag{31}$$

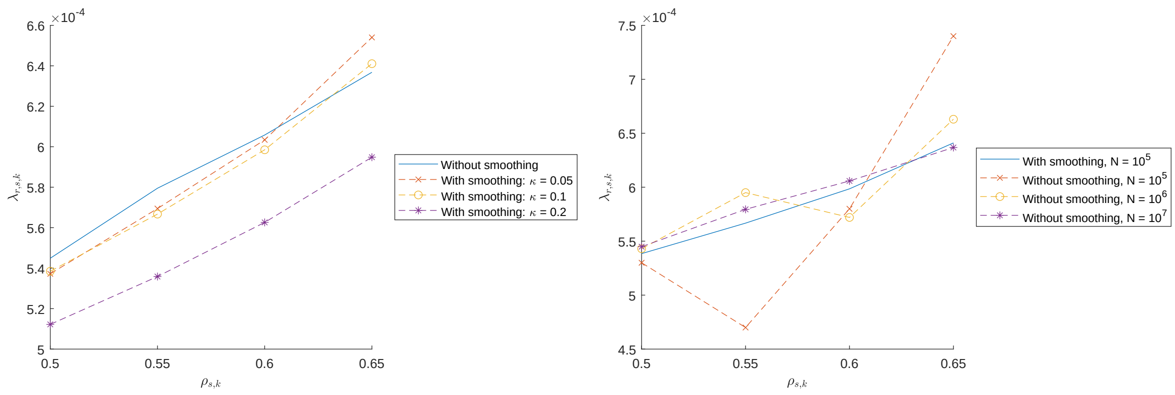
Importantly, the expression is the individual moving probability *conditional* on the worker's potential income for all sectors, in both periods.

For a local labor market r,

$$\lambda_{r,s,k} \equiv \frac{1}{N} \sum_{i=1}^{N} \frac{e^{\log y_{i,r,s}/\kappa}}{\sum_s e^{\log y_{i,r,s}/\kappa}} \cdot \frac{e^{\log y'_{i,r,k}/\kappa}}{\sum_s e^{\log y'_{i,r,s}/\kappa}} \tag{32}$$

As κ is getting closer to zero, the probabilities are moving closer towards the pure discrete choice probabilities in Equation (12), as is demonstrated in Figure A.7. On the other hand, by increasing κ, the probabilities are becoming smooth in the parameters. In fact, Figure A.7 shows the approximated model probabilities are smooth in the parameters with a low number of draws. In contrast, the figure shows that the pure discrete choice model requires a very high number of draws to make the probabilities as smooth.[37]

Figure A.7



(a) (b)

Notes: The figure presents simulated comparative statics exercises. For both panels, the vertical axis represents the probability of moving from sector s to sector k in CZ r ($\lambda_{r,s,k}$). the horizontal axis measures the correlation in skills between sector s and sector k. In Panel (a), the solid line display data simulated using the pure discrete choice Roy model. The dashed lines correspond data simulated with the approximated model for different values of κ. In Panel (b), the solid line display data simulated with the approximated model, while the dashed lines correspond to data simulated with the pure discrete choice Roy model using different numbers of skill draws.

Last, average earnings in a sector s in a local labor market r is

$$\overline{\log y_{r,s}} \equiv \frac{\sum_{i=1}^{N} \log y_{i,r,s} \cdot \pi_{i,r,s}}{\sum_{i=1}^{N} \pi_{i,r,s}}. \tag{33}$$

The approximated model has several advantages. First, the approximated model substantially eases the computational burden of the estimation exercise. Compared to the pure discrete choice model, it increases the speed of the parameter estimation dramatically and at the same time maintain precision. Second, the approximated model puts structure on the error term of the Roy model. In the observed data there is reallocation that is inconsistent with predictions of the Roy model. Specifically, in the data, a share of workers is moving toward sectors with relative declining wages. An advantage of the approximated model is that it has flexibility in terms of allowing for data moments that are inconsistent with the pure discrete choice model, and in particular worker moves that are not in line with the observed sectoral wage changes. Third, there will be an elasticity governing how close the approximated model will be to the pure discrete choice model. The elasticity is interesting in itself, since it can be interpreted as a measure for how important the Roy model is in explaining sectoral reallocation in the data. I will next derive an estimation equation for the elasticity, which I take to the data.

[37] In the same way as for the sectoral shares, a higher κ implies the Roy selection part of the model to be of relatively less importance in the worker maximization problem such that parameters of the skill distribution are less predictive for the worker reallocation.

Estimating κ As already discussed, in contrast to in the pure Roy model, the approximated model generates worker movements in both directions of sector pairs. This is so, because the non-wage draws may make it optimal for some workers to move towards sectors with relatively falling wages. As κ increases, the non-wage draws become more prominent, and the more worker flows there will be in both directions. This contrasts with the pure Roy model, where there will only be movements in one direction of sector pairs. In fact, $1/\kappa$ is an elasticity pinning down the relative importance of the Roy component. Specifically, I solve for the following expression

$$\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}} = \frac{1}{\kappa} \cdot \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}} \tag{34}$$

such that $1/\kappa$ is an elasticity governing the relationship between the share of movers between two sectors relative to the share of movers in the opposite direction, and the relative change in the wage changes of the two sectors. This is an intuitive expression. When there is a relatively large difference in wage changes between two sectors, if κ is low such that the Roy component of the model is strong, then there should be a relatively large share of workers moving in the direction that is in line with the wage change. On the other hand, if the share of workers moving in both directions are similar, then κ must be high, and the relative sectoral wage changes are of less importance to the workers. Details of how the expression is derived follows below.

I take Equation (34) to the data and estimate the elasticity and the implied κ for my setting. I use data on gross movement flows between every sector pair and sectoral wage changes for the set of CZs used in the main estimation exercise.[38] The estimated elasticity implies a κ equal to 0.1. A relatively low κ is in line with the Roy model being important to explain sectoral reallocation. The value ensures enough smoothing to lower the number of draws in the main estimation exercise.

[38] According to the model, this estimation can be conducted using ordinary least squares, and an instrument is not necessary for estimating κ. However, there are arguments outside the model that suggest instrumenting for the wage shocks. I leave this for future research.

Table A.11

	(1) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(2) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(3) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$
$\log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$	9.972	10.50	
	(2.099)	(2.555)	
$\mathbb{I}$(Bergen) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			11.83
			(4.061)
$\mathbb{I}$(Kristiansand) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			16.78
			(4.885)
$\mathbb{I}$(Oslo) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			7.366
			(4.409)
$\mathbb{I}$(Stavanger) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			15.35
			(3.292)
$\mathbb{I}$(Tromso) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			7.042
			(1.939)
Implied κ	0.100	0.0952	0.0974
R-squared	0.328	0.346	0.376
CZ Fixed Effects	No	Yes	No
Observations	103	103	103

Notes: The regressions in this table estimate Equation (34). The second specification includes CZ fixed effects. Standard errors, clustered at the CZ level, in parentheses.

Deriving Equation (34) Recall,

$$\lambda_{i,r,s,k} \equiv \frac{e^{\log y_{i,r,s}/\kappa}}{\sum_s e^{\log y_{i,r,s}/\kappa}} \cdot \frac{e^{\log y'_{i,r,k}/\kappa}}{\sum_s e^{\log y'_{i,r,s}/\kappa}}$$

Then,

$$\frac{\lambda_{i,r,s,k}}{\lambda_{i,r,k,s}} = \frac{\frac{e^{\log y'_{i,r,k}/\kappa}}{\Phi'_{i,r}} \frac{e^{\log y_{i,r,s}/\kappa}}{\Phi_{i,r}}}{\frac{e^{\log y'_{i,r,s}/\kappa}}{\Phi'_{i,r}} \frac{e^{\log y_{i,r,k}/\kappa}}{\Phi_{i,r}}},$$

where

$$\Phi_{i,r} = \sum_s e^{\log y_{i,r,s}/\kappa}.$$

It follows that,

$$\frac{\lambda_{i,r,s,k}}{\lambda_{i,r,k,s}} = \frac{e^{\log y'_{i,r,k}/\kappa} \cdot e^{\log y_{i,r,s}/\kappa}}{e^{\log y'_{i,r,s}/\kappa} \cdot e^{\log y_{i,r,k}/\kappa}},$$

$$\frac{\lambda_{i,r,s,k}}{\lambda_{i,r,k,s}} = e^{\left(\log y'_{i,r,k} + \log y_{i,r,s} - \log y'_{i,r,s} - \log y_{i,r,k}\right)/\kappa}$$

$$\frac{\lambda_{i,r,s,k}}{\lambda_{i,r,k,s}} = e^{(\log \widehat{y}_{i,r,k} - \log \widehat{y}_{i,r,s})/\kappa}$$

$$\frac{\lambda_{i,r,s,k}}{\lambda_{i,r,k,s}} = e^{(\log \widehat{w}_{r,k} - \log \widehat{w}_{r,s})/\kappa}$$

Since the right hand side of the expression is constant across individuals,

$$\frac{\lambda_{r,s,k}}{\lambda_{r,k,s}} = e^{(\log \widehat{w}_{r,k} - \log \widehat{w}_{r,s})/\kappa}$$

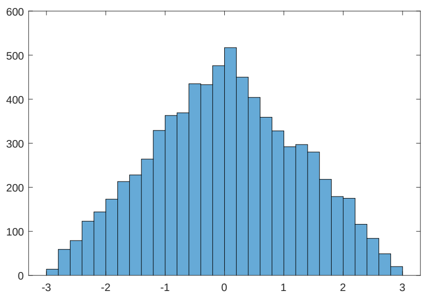
so that,

$$\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}} = \frac{1}{\kappa} \cdot \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}.$$

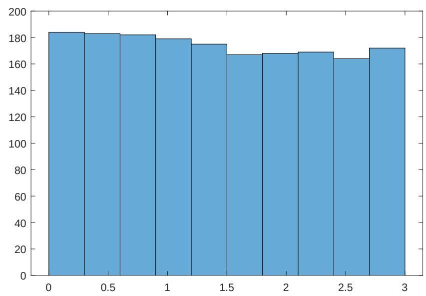
B.2 Monte Carlo simulations

I report Monte Carlo simulation results where I perform the SMM estimation with simulated targeted moments many times. Specifically, I draw random sets of parameters, simulate targets with the model, find SSM estimated parameters, and test whether the estimated parameters differ from the true parameters.[39] The simulations are all ran with the sectoral wage changes as identified in Section 5.4. Histograms of the set of randomly drawn parameters are presented in Figure A.8. Table A.12 presents the results of the Monte Carlo simulations. The table presents the linear fit between the true randomly drawn parameters and the corresponding SMM estimated parameters.

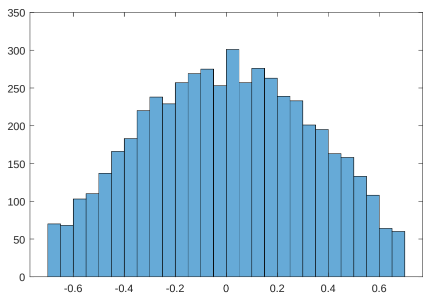
Figure A.8: Monte Carlo simulations: Distriubtion of parameter draws



(a) $\mu_{r,s}$



(b) σ_s^2



(c) $\rho_{r,s}$

Notes: The figure display the distribution of the randomly drawn sets of parameters used to simulate targets for the Monte Carlo simulations. The panels present the distribution of (a) $\mu_{r,s}$, (b) σ_s^2, and (c) $\rho_{r,s}$. The sets of random parameters is restricted to only consider parameter sets such that Σ is a positive semidefinite.

Table A.12: Monte Carlo simulations: Results

	$\mu_{r,s}$	σ_s^2	$\rho_{s,k}$
$\mu_{r,s}^{SSM}$	0.863		
	(0.004)		
$\sigma_s^{2\ SSM}$		0.912	
		(0.009)	
$\rho_{s,k}^{SSM}$			0.939
			(0.009)
Constant	-0.011	0.049	-0.034
	(0.005)	(0.017)	(0.003)
R^2	0.874	0.873	0.742
Observations	7000	1400	4200

Notes: The regressions in this table estimate the SMM estimated parameters on the randomly drawn parameters used to simulate the targets used in the the SMM estimation. From left to right, each specification presents the estimated linear fit coefficient, as well as the constant coefficient for (a) $\mu_{r,s}$; (b) σ_s^2; and (c) $\rho_{r,s}$. Standard errors, in parentheses.

B.3 Bootstrapped Standard Errors

The reported standard errors of the estimated skill distribution parameters reported in Table 1 and Table A.9, as well as the Tables A.15, A.16, A.17, and A.18, are constructed by bootstrap. I contruct the bootstrapped standard errors in the following way. First, I construct 200 boostrap samples. For each CZ seperately, I construct each bootstrap sample by random draw with replacement until the bootstrap sample has the same number of obserservations as in the original data set for the CZ. Second, for each bootstrap sample, I construct bootstrap targeted moments. Third, I estimate the parameters of the model as explained in Section 5 200 times, by using the 200 different sets of bootstrap targeted moments.[40] Forth, I construct the reported standard errors by constructing the standard diviations of the 200 estimated parameters.

B.4 Heterogeneity across education groups

In this Appendix, I perform parameter estimation for heterogeneous groups of workers with different education levels. I divide the sample into two groups: workers with college education and those without.[41] I present the estimated parameters separately for the two groups.

Table A.13 and Table A.14 report the results of the κ estimation for low and high educated workers, respectively. The skill parameter estimates are $\kappa^{LowEdu} = 0.08$ and $\kappa^{HighEdu} = 0.12$. For the low-educated workers, estimated skill parameters are reported in Table A.15 and Table A.17. For high-educated workers, these parameters are reported in Table A.14 and Table A.18. Interestingly, the estimated parameters vary between the two groups. Specifically, low educated workers exhibit more variation in skills across all sectors compared to high educated workers. Additionally, the correlation

[39] The sets of random parameters is be restricted to only consider parameter sets such that Σ is a positive semidefinite. This restriction ensures the exercise to only consider cases that simulate defined moments to be used as targets.

[40] For all these 200 bootstrap estimations, I use the same κ value and estimated wage changes $\widehat{w}_{r,s}$ as in the main parameter estimation. Following, for the standard errors reported in the heterogeneity analysis of Appendix B.4, I use the same κ value and estimated wage changes $\widehat{w}_{r,s}$ for the two eduction groups respectivly.

[41] A small share of the workers (about 1%) transition from no college education to college education between 2013 and 2017. These workers are excluded from the sample used in the following heterogeneity analysis.

structure differs markedly between the two education groups. For many sector pairs, the correlation has opposite signs for the two groups. This is in line with the two groups typically differ in both the magnitude and direction of sectoral reallocation.

Finally, I perform a model fit analysis for the estimated models for the two groups separately. Table A.19 and Table A.20 present the results of these two exercises, where moments simulated by the SMM estimated models are regressed on the targeted moments for low and high educated workers, respectively. The simulated moments significantly predict all the targeted moments, explaining a large share of the variation in the data. For some targeted moments, the fit is even better compared to the main estimation analysis reported in Table 2. This is especially true for the sectoral shares.

Table A.13: Estimating κ: Low education

	(1) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(2) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(3) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$
$\log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$	7.859	8.479	
	(3.277)	(4.104)	
$\mathbb{I}(\text{Bergen}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			18.97
			(4.667)
$\mathbb{I}(\text{Kristiansand}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			18.60
			(7.467)
$\mathbb{I}(\text{Oslo}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			2.559
			(5.587)
$\mathbb{I}(\text{Stavanger}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			13.17
			(3.303)
$\mathbb{I}(\text{Tromso}) \times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			3.352
			(2.106)
Implied κ	0.127	0.118	0.174
R-squared	0.190	0.210	0.305
CZ Fixed Effects	No	Yes	No
Observations	101	101	101

Notes: The regressions in this table estimate Equation (34) for workers without college education. The second specification includes CZ fixed effects. Standard errors, clustered at the CZ level, in parentheses.

Table A.14: Estimating κ: High education

	(1) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(2) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(3) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$
$\log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$	11.73	12.36	
	(1.982)	(2.257)	
$\mathbb{I}$(Bergen) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			5.408
			(4.136)
$\mathbb{I}$(Kristiansand) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			8.314
			(3.160)
$\mathbb{I}$(Oslo) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			13.15
			(4.509)
$\mathbb{I}$(Stavanger) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			24.35
			(4.203)
$\mathbb{I}$(Tromso) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			11.13
			(2.159)
Implied κ	0.0852	0.0809	0.102
R-squared	0.373	0.392	0.447
CZ Fixed Effects	No	Yes	No
Observations	100	100	100

Notes: The regressions in this table estimate Equation (34) for workers with college education. The second specification includes CZ fixed effects. Standard errors, clustered at the CZ level, in parentheses.

Table A.15: Estimated $\rho_{s,k}$ values: Low education

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
Elect & Const	1.000	-0.261	-0.436	-0.256	-0.352	0.800	-0.004
	(-)	(0.19)	(0.12)	(0.22)	(0.19)	(0.10)	(0.25)
Services	-0.261	1.000	0.709	-0.536	0.579	0.183	0.024
	(0.19)	(-)	(0.23)	(0.19)	(0.13)	(0.18)	(0.20)
Financial	-0.436	0.709	1.000	-0.340	0.547	-0.350	-0.372
	(0.12)	(0.23)	(-)	(0.19)	(0.18)	(0.19)	(0.13)
Scient & Tech	-0.256	-0.536	-0.340	1.000	0.163	-0.577	0.485
	(0.22)	(0.19)	(0.19)	(-)	(0.15)	(0.23)	(0.11)
Public	-0.352	0.579	0.547	0.163	1.000	-0.262	0.216
	(0.19)	(0.13)	(0.18)	(0.15)	(-)	(0.21)	(0.17)
Oil	0.800	0.183	-0.350	-0.577	-0.262	1.000	0.108
	(0.10)	(0.18)	(0.19)	(0.23)	(0.21)	(-)	(0.10)
Trade	-0.004	0.024	-0.372	0.485	0.216	0.108	1.000
	(0.25)	(0.20)	(0.13)	(0.11)	(0.17)	(0.10)	(-)

Notes: The table presents the estimatd skill correlation coefficients $\rho_{s,k}$ for all sector pairs. Specifically, the correlation coefficients are the Pearson's correlation coefficient, defined as $\sigma_{i,j}/\sigma_i\sigma_j$, when $\sigma_{i,j}$ is the covariance between sector i and sector j skills, and σ_i and σ_j are the standard deviation of sector i and sector j skills respectively. Bootstrapped standard errors in parentheses.

Table A.16: Estimated $\rho_{s,k}$ values: High education

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
Elect & Const	1.000	-0.222	-0.072	0.172	-0.320	0.341	0.289
	(-)	(0.26)	(0.16)	(0.18)	(0.32)	(0.12)	(0.36)
Services	-0.222	1.000	-0.096	-0.279	-0.329	0.171	0.360
	(0.26)	(-)	(0.23)	(0.20)	(0.22)	(0.16)	(0.19)
Financial	-0.072	-0.096	1.000	0.040	0.380	-0.166	-0.117
	(0.16)	(0.23)	(-)	(0.19)	(0.15)	(0.18)	(0.15)
Scient & Tech	0.172	-0.279	0.040	1.000	0.162	0.234	0.332
	(0.18)	(0.20)	(0.19)	(-)	(0.18)	(0.22)	(0.10)
Public	-0.320	-0.329	0.380	0.162	1.000	0.447	-0.156
	(0.32)	(0.22)	(0.15)	(0.18)	(-)	(0.16)	(0.20)
Oil	0.341	0.171	-0.166	0.234	0.447	1.000	0.421
	(0.12)	(0.16)	(0.18)	(0.22)	(0.16)	(-)	(0.09)
Trade	0.289	0.360	-0.117	0.332	-0.156	0.421	1.000
	(0.36)	(0.19)	(0.15)	(0.10)	(0.20)	(0.09)	(-)

Notes: The table presents the estimatd skill correlation coefficients $\rho_{s,k}$ for all sector pairs. Specifically, the correlation coefficients are the Pearson's correlation coefficient, defined as $\sigma_{i,j}/\sigma_i\sigma_j$, when $\sigma_{i,j}$ is the covariance between sector i and sector j skills, and σ_i and σ_j are the standard deviation of sector i and sector j skills respectively. Bootstrapped standard errors in parentheses.

Table A.17: Estimated σ_s values: Low education

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
σ_s	1.543	1.124	1.540	1.756	1.000	1.492	1.189
	(0.12)	(0.13)	(0.14)	(0.11)	(0.13)	(0.09)	(0.10)

Notes: The table presents calibrated variance parameters σ_s^2 across sectors. Bootstrapped standard errors in parentheses.

Table A.18: Estimated σ_s values: High education

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
σ_s	0.785	0.537	0.849	0.595	0.387	0.603	0.638
	(0.21)	(0.09)	(0.14)	(0.08)	(0.07)	(0.08)	(0.11)

Notes: The table presents calibrated variance parameters σ_s^2 across sectors. Bootstrapped standard errors in parentheses.

Table A.19: Model fit: Low Education

	Actual $\pi_{r,k}$	Actual $\frac{\lambda_{r,s,k}}{\pi_{r,k}}$	Actual $\overline{\log y_{r,s}}$
$\pi_{r,k}$	0.842		
	(0.320)		
$\frac{\lambda_{r,s,k}}{\pi_{r,k}}$		0.920	
		(0.064)	
$\overline{\log y_{r,s}}$			0.856
			(0.080)
Constant	0.023	0.003	0.024
	(0.054)	(0.001)	(0.011)
R^2	0.173	0.497	0.776
Observations	35	210	35

Notes: The table reports the estimated model fit coefficients from regressing the targeted data moments on the corresponding moments simulated by the SMM estimated model for low educated workers. Formally, I run the regression $x^{actual} = \beta_0 + \beta_1 x^{simulated} + \epsilon$, where x^{actual} represents the moments observed in the actual data, $x^{simulated}$ represents the moments simulated by the SMM estimated model, and ϵ is the error term. The specifications, from left to right, evaluate model fit for sectoral shares, movement flows, and average sectoral earnings. Standard errors are reported in parentheses.

Table A.20: Model fit: High Education

	Actual $\pi_{r,k}$	Actual $\frac{\lambda_{r,s,k}}{\pi_{r,k}}$	Actual $\overline{\log y_{r,s}}$
$\pi_{r,k}$	0.962		
	(0.287)		
$\frac{\lambda_{r,s,k}}{\pi_{r,k}}$		0.938	
		(0.049)	
$\overline{\log y_{r,s}}$			0.730
			(0.095)
Constant	0.005	0.004	0.031
	(0.049)	(0.001)	(0.015)
R^2	0.254	0.635	0.640
Observations	35	210	35

Notes: The table reports the estimated model fit coefficients from regressing the targeted data moments on the corresponding moments simulated by the SMM estimated model for high educated workers. Formally, I run the regression $x^{actual} = \beta_0 + \beta_1 x^{simulated} + \epsilon$, where x^{actual} represents the moments observed in the actual data, $x^{simulated}$ represents the moments simulated by the SMM estimated model, and ϵ is the error term. The specifications, from left to right, evaluate model fit for sectoral shares, movement flows, and average sectoral earnings. Standard errors are reported in parentheses.