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Domino Effects: Understanding Sectoral Reallocation and its Wage Implications*

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Abstract

This paper studies how the 2014 collapse in Brent Crude Oil prices propagated through the Norwegian labor market via worker reallocation. Using Norwegian panel data, I show that workers in non-tradable sectors more exposed to inflows of displaced oil workers experienced significant earnings declines and higher rates of sector exit, documenting a key propagation channel that extends the reach of sectoral shocks beyond the directly affected sector. To quantify the full network of equilibrium adjustments, I estimate a multisector Roy model with correlated sectoral skills and mobility costs. Counterfactual simulations show that non-tradable sector wages declined by up to 32% of the oil sector's wage loss. The magnitude of net worker reallocation between non-oil sectors was equivalent to 63% of the net outflow from the oil sector in the median commuting zone. The model shows how a single sectoral shock can trigger economy-wide labor market adjustment through worker movements. The simulations further reveal that the domino reallocation acts as an equalizing force: shutting it down amplifies both mean wage spillovers and wage dispersion within and across commuting zones.

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1 Introduction

How do sector-specific shocks reallocate workers across sectors, and what are the resulting equilibrium effects on the distribution of earnings? A large literature shows that shocks arising from international trade, climate change, or automation lead to substantial worker reallocation.[1] While prior studies show that workers in sectors directly exposed to such shocks experience earnings declines and reallocate across sectors (Walker, 2013; Autor, Dorn, Hanson, & Song, 2014; Dauth, Findeisen, & Suedekum, 2021; Kovak & Morrow, 2025; Costinot, Sarvimäki, & Vogel, 2024), much less is known about how displaced workers affect outcomes in the destination sectors that absorb them, and thereby how shocks propagate through the labor market and generate broader equilibrium effects. The inflow of displaced workers can alter labor supply conditions, compress wages, and trigger further reallocations, even between sectors not directly affected by the shock. Consequently, sector-specific shocks may set off economy-wide adjustments through a cascading chain of labor movements, consistent with evidence of spillovers across sectors and regions (Autor et al., 2013; Hakobyan & McLaren, 2016). This paper traces that propagation path, documenting how displaced workers transmit wage effects far beyond the sector of origin and quantifying the distributional consequences for workers and regions throughout the economy.

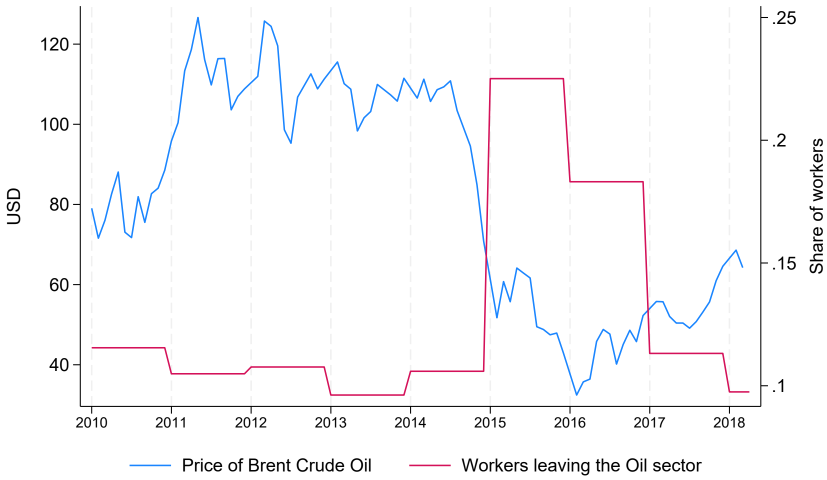
I study the sharp collapse in global oil prices in 2014 (see Figure 1) as a natural experiment for the Norwegian labor market, a shock plausibly exogenous to the domestic economy that directly disrupted oil-sector employment. Norway is well-suited for this analysis: it is a small open economy in which the oil sector is large and geographically concentrated, providing substantial cross-regional variation in exposure, while rich administrative panel data allow me to track individual workers across sectors over time.

The paper proceeds in two steps. I first provide empirical evidence on how the sector-specific shock affected workers in the destination sectors that receive displaced labor. Using Norwegian register data, I exploit variation in pre-shock reallocation patterns to construct a novel measure of exposure to worker inflows across local labor markets and sectors. I find that non-tradable sectors with higher exposure to incoming oil workers experienced relative earnings decline and higher rates of worker exit following the oil price collapse. Comparing the earnings of displaced oil workers to incumbent workers in their destination sectors further reveals positive compositional changes. The positive composition effect and the negative equilibrium wage adjustments jointly shape sectoral earnings, two channels that must be separated to correctly assess distributional impacts.

Building on these empirical findings, I estimate a multisector Roy model with correlated sectoral

[1] Among others, Autor, Dorn, and Hanson (2013) and Dauth, Findeisen, and Suedekum (2014) study import competition; Costinot, Donaldson, and Smith (2016); Cruz (2021); Lyn, Ortiz-Bobea, Rudik, and Tan (2022) climate change; and Dauth, Findeisen, Suedekum, and Woessner (2021); Galle and Lorentzen (2024) automation.

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.

skills and sector-pair movement costs to simulate the full network of reallocation and quantify the equilibrium effects. Counterfactual simulations show that non-tradable sector wages declined on average by 6.2 percent of the oil sector's wage loss, with the effect rising steeply in oil exposure and reaching a maximum of 32 percent across commuting zone–sector pairs. In the median commuting zone, the magnitude of net worker reallocation between non-oil sectors is equivalent to 63 percent of the net outflow from the oil sector, showing that a substantial share of labor market adjustment took place between sectors with no direct exposure to the shock. To examine the role of different adjustment channels, I compare the full equilibrium to counterfactual economies that shut down adjustment channels one at a time. The domino channel, whereby workers in sectors crowded by oil inflows themselves reallocate, turns out to be strongly equilibrating: shutting it down nearly doubles the mean wage spillover and amplifies wage dispersion both within and across commuting zones. Scenarios with more reallocation, on the other hand, generate smaller mean real income losses, more compressed regional outcomes, and in some cases, lead to more within regional differences. These results highlight that understanding the distributional consequences of sectoral shocks requires mapping the entire network of worker movements, not only those originating in the directly exposed sector.

This paper makes three main contributions. First, I provide new empirical evidence on a key propagation channel through which sector-specific shocks affect the broader labor market. By exploiting pre-shock worker mobility patterns to construct a novel exposure measure, I isolate the effect of displaced worker inflows on incumbent workers in destination sectors. I further show that compositional and equilibrium wage effects must be separated to correctly assess how sectoral shocks reshape the earnings distribution. Second, I develop and estimate a multisector Roy model with correlated sectoral skills and sector-pair movement costs. Unlike models that assume i.i.d. Fréchet-distributed skills for tractability, this structure jointly matches observed reallocation flows, sectoral wage changes, and earnings covariances across sectors. Third, I use the estimated model to quantify how the domino channel shapes both the mean and the distribution of wage outcomes: removing it amplifies spillovers and raises wage dispersion within and across commuting zones, while more reallocation compresses the regional income gradient. Together, these contributions highlight that the distributional incidence of sectoral shocks is determined not only by direct exposure but by the full network of cascading worker movements that follows.

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

First, it contributes to the extensive empirical literature on how trade and other sector-specific shocks reshape labor markets. A large body of work documents that import competition and trade integration alter local employment and wage structures (Topalova, 2010; Autor et al., 2013; Dauth et al., 2014; Kovak, 2013; Dix-Carneiro & Kovak, 2017; Bloom, Handley, Kurmann, & Luck, 2019; Kovak & Morrow, 2025; Costinot et al., 2024), and that workers in directly exposed sectors experience large and persistent earnings losses (Autor et al., 2014; Dauth, Findeisen, & Suedekum, 2021; Costinot et al., 2024). This paper extends that literature by tracing the propagation of a sector-specific shock beyond the directly exposed sector, isolating the labor reallocation channel through which the shock transmits to workers in destination sectors. This complements Pierce, Schott, and Tello-Trillo (2026), who document earnings gains for workers outside manufacturing following the China shock through supply-chain linkages, a distinct channel operating through intermediate input markets rather than worker movements. Using the same Norwegian oil price shock studied here, Garnache, Isaksen, and Nareklishvili (2025) documents persistent earnings and employment losses among directly displaced oil workers and examines their transitions across sectors. Bøler, Holtsmark, and Ulltveit-Moe (2025) show that the shock triggered within-firm reallocation of R&D resources toward clean innovation among firms in the oil supply chain. In this paper, I focus on how worker reallocation propagates the shock to workers outside the oil sector, a margin not examined in prior work on this shock, and quantify how this cascading adjustment transmits wage and employment effects across the broader economy.

Second, this paper connects to the structural literature quantifying the effects of trade and sectoral shocks using multisector models with imperfect worker mobility (Artuç, Chaudhuri, & McLaren, 2010; Dix-Carneiro, 2014; Caliendo, Dvorkin, & Parro, 2019; Dix-Carneiro, Pessoa, Reyes-Heroles, & Traiberman, 2023; Galle, Rodríguez-Clare, & Yi, 2022). I build on the Roy model (Roy, 1951; Heckman & Honoré, 1990), a central framework for studying how workers sort across sectors based on comparative advantage (Dix-Carneiro, 2014; Adão, 2016; Kim & Vogel, 2021; Galle et al., 2022). The transferability of skills across sectors, a key determinant of reallocation patterns, has been studied empirically by Gathmann and Schönberg (2010), who show that workers move more readily between occupations with similar task requirements, consistent with the correlated skill structure I estimate. Unlike much of the recent structural literature that assumes i.i.d. Fréchet-distributed skills for tractability (Burstein, Morales, & Vogel, 2019; Hsieh, Hurst, Jones, & Klenow, 2019; Burstein, Hanson, Tian, & Vogel, 2020; Galle et al., 2022; Galle & Lorentzen, 2024), I adopt a multisector log-normal Roy model with correlated sectoral skills and sector-pair-specific movement costs, following Caliendo et al. (2019) and Borusyak, Dix-Carneiro, and Kovak (2022). This structure allows the model to jointly match observed reallocation flows, sectoral wage changes, and earnings covariances, moments that i.i.d. skill models cannot simultaneously fit. My estimation strategy therefore complements and extends models that focus on analytical tractability at the cost of empirical fit (Novy, 2013; Head, Mayer, & Thoenig, 2014; Lind & Ramondo, 2023).

Third, this paper contributes to the literature on the margins of labor market adjustment to sectoral shocks. Earlier work shows that limited worker mobility dampens aggregate gains from trade and slows adjustment (Artuç, Chaudhuri, & McLaren, 2008; Artuç et al., 2010; Dix-Carneiro, 2014; Hakobyan & McLaren, 2016), with most attention focused on how shocks affect workers in directly exposed sectors and how these effects vary across regions. This paper shifts the focus to workers not directly exposed to the shock, and shows that the equilibrium effects of cascading reallocation are unequal not only across regions but also across sectors within the same local labor market. Quantifying this dimension reveals that non-exposed sector reallocation accounts for 63 percent of net worker flows, and that the domino channel equalizes wage and income effects across workers and regions.

Finally, the paper connects to the literature on immigration and local labor market outcomes (Card, 2001; Bratsberg & Raaum, 2012). In both settings, inflows of workers can compress wages and displace incumbents, and the empirical challenge is similar: isolating the wage effect of worker inflows from confounding local demand conditions. The key distinction is that the reallocation studied here is an internally propagated adjustment within the economy, making it a general mechanism through which any sectoral shock can generate economy-wide effects. The Norwegian context makes Bratsberg and Raaum (2012) a particularly natural point of comparison, as they study immigration and wages in the same labor market using similar data.

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

2 Model

The model consists of N workers located across L local labor markets, each comprising a set of tradable and non-tradable sectors. Each local labor market is modeled as a small open economy. Output prices in tradable sectors are determined at the world market and are therefore exogenous to the local economy, while output prices in non-tradable sectors are determined in local equilibrium—meaning that worker inflows into non-tradable sectors affect local wages through both labor supply and goods market channels. Local labor markets are assumed to be independent of one another, consistent with sectoral reallocation dominates geographic reallocation in the data.[2]

The model proceeds in three steps. I first characterize the initial equilibrium, in which workers sort across sectors according to their skills, sectoral wages, and non-pecuniary amenities. I then introduce a shock to the world price of a tradable sector and derive the resulting worker reallocation across sectors. Finally, I characterize the equilibrium real wage changes in non-tradable sectors that arise from the combination of shifting labor supply and falling aggregate demand for non-tradable goods.

2.1 Initial equilibrium

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

$$U_{ir} = \prod_{s=1}^{S} c_{irs}^{\beta_s}$$

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

$$p_{rs} c_{irs} = \beta_s y_{ir}$$

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

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

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

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

[2]This paper performs a before-after analysis without dynamics. The model therefore characterizes the new equilibrium following the shock but abstracts from the transition path.

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

$$\log z_{is} \equiv \widetilde{\mu}_s + v_{is}$$

and v_{is} 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

$$y_{irs} = w_{rs} x_i z_{irs}. \tag{3}$$

where w_{rs} is the local sector-specific wage per effective unit of labor, x_i is observable characteristics of worker i, and $z_{irs} \equiv z_{is}$ denotes the worker's skill in sector s, which does not vary across markets. I assume the observable charateristics to be independent of the sectoral skills. For later use, sector-specific levels within each market are defined as

$$\mu_{rs} \equiv \log w_{rs} + \widetilde{\mu}_s. \tag{4}$$

Moreover, workers make sector-specific non-pecuniary utility draws a_{is}, which are assumed to be independently and identifcally distrubted extreme value with dispersion parameter κ (McFadden, 1989; Train, 2009). The draw a_{is} can be interpreted as a sector-specific amenity, capturing the role of non-wage job characteristics in workers' sectoral choices (Taber & Vejlin, 2020). In the initial equilibrium, workers will choose to work in the sector which is maximizing their individual value

$$\log V_{irs} = \log y_{irs} + a_{is} \tag{5}$$

where y_{irs} is the worker's potential earnings, as described in Equation (3), and a_{is} is the non-pecuniary utility draw. The parameter κ governs the dispersion of idiosyncratic preferences relative to earnings. As κ increases, non-pecuniary preferences become more important relative to wages in workers' sectoral choices. In the limit as $\kappa \to 0$, the model approaches a frictionless Roy model in which workers sort exclusively on the basis of comparative advantage. A worker selects into sector s with probability.

$$\pi_{irs} \equiv \frac{e^{\log y_{irs}/\kappa}}{\sum_k e^{\log y_{irk}/\kappa}}, \tag{6}$$

such that for a local labor market r the share of workers working in a sector is given by

$$\pi_{rs} \equiv \frac{1}{N_r} \sum_{i=1}^{N_r} \pi_{irs}. \tag{7}$$

The shares are independent of observable worker characteristics x_i because x_i enters numerator and denominator of the logit in Equation (5) symmetrically and cancels algebraically. The supply of labor units to a local sector is the total number of sector s specific skill units, adjusted for the observable characteristics, of the workers selecting into sector s in market r

$$Z_{rs} \equiv \sum_{i=1}^{N_r} \pi_{irs} x_i z_{irs}. \tag{8}$$

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

$$F_{rs} = Z_{rs}. \tag{9}$$

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

$$w_{rs} = p_{rs}. \tag{10}$$

Equilibrium For the tradable sectors, p_{rs} 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 (9). Local demand for goods is given as local household expenditures, as in Equation (1). Hence, in equilibrium

$$\beta_s Y_r = p_{rs} F_{rs}. \tag{11}$$

2.2 A shock to the world prices

A shock in the world output 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

$$\widehat{w}_{rs} = \widehat{p}_{rs}. \tag{12}$$

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

Worker reallocation Workers observe sectoral wage changes and decide whether to move to another sector within their region r by maximizing an indirect value function analogous to that in the initial period (Equation (5)). Following Caliendo et al. (2019) and Borusyak et al. (2022), workers face non-pecuniary costs when switching sectors. The post-shock value from working in sector k for a worker previously working in sector s is

$$\log V'_{irsk} = \log y'_{irk} - \log c_{sk} + a'_{ik} \tag{13}$$

where c_{sk} denotes the cost of moving from origin sector s to destination sector k. Movement costs satisfy four assumptions. First, costs are weakly greater than one, $c_{sk} \geq 1$ for all $s \neq k$. Second, they are symmetric, $c_{sk} = c_{ks}$, so that the cost of moving between any two sectors does not depend on the direction of the move. Third, there are no costs associated with remaining in the same sector, $c_{ss} = 1$. Fourth, movement costs are non-pecuniary and therefore do not directly affect individual earnings, only the worker's value of switching sector.[3]

Given these assumptions, worker i moves from origin sector s to destination sector k with probability

$$\lambda_{irsk} = \frac{c_{sk}^{-1/\kappa}}{\sum_{\tilde{s}} c_{s\tilde{s}}^{-1/\kappa} \pi'_{ir\tilde{s}}} \cdot \pi_{irs} \pi'_{irk} \tag{14}$$

where $\pi'_{irk} \equiv e^{\log y'_{ik}/\kappa} / \sum_{\tilde{k}} e^{\log y'_{i\tilde{k}}/\kappa}$ is the probability of selecting sector k in the post-shock equilibrium. Equation (14) has an intuitive interpretation: the probability of moving from s to k is increasing in the post-shock attractiveness of sector k (captured by π'_{irk}), decreasing in the cost of moving to k (captured by $c_{sk}^{-1/\kappa}$), and increasing by the initial probability of being in sector s (captured by π_{irs}). Aggregating over workers, the share of workers in market r moving from sector s to sector k is

$$\lambda_{rsk} = \frac{1}{N} \sum_{i=1}^{N} \frac{c_{sk}^{-1/\kappa}}{\sum_{\tilde{s}} c_{s\tilde{s}}^{-1/\kappa} \pi'_{i\tilde{s}}} \cdot \pi_{irs} \pi'_{irk} \tag{15}$$

where the shares are independent of observable worker characteristics x_i, analogously to the initial sectoral shares. Properties of Equation (15) are discussed in Appendix B: the share of workers moving from s to k decreases in c_{sk}, increases in movement costs to competing destinations, and is unaffected by costs between other sector pairs.[4]

A key object for the structural estimation is the covariance in earnings across sectors for workers who move between them. Define $\log \widetilde{y}_{irs} \equiv \log y_{irs} - \log w_{rs} - \log x_i = \log z_{is}$ as residualized log earnings, i.e. log earnings stripped of the sector wage and observable worker characteristics, leaving only the log skill draw. Since skills are time-invariant, $\log \widetilde{y}'_{irk} = \log z_{ik}$. For workers moving from sector s to sector

[3] When movement costs are absent or invariant to the origin sector, $1/\kappa$ can be interpreted as the elasticity of relative worker flows between any two sectors with respect to their relative wage change, such that $\log(\lambda_{rsk}/\lambda_{rks}) = (1/\kappa)\log(\hat{w}_{rk}/\hat{w}_{rs})$. In the full model with heterogeneous sector-pair movement costs, this relationship holds as an approximation when movement costs are small relative to wage differences, $\log(\lambda_{rsk}/\lambda_{rks}) \approx (1/\kappa)\log(\hat{w}_{rk}/\hat{w}_{rs})$. I will use this approximation to discipline κ directly from the data. See Appendix C.1 for the derivation and estimation results.

[4] Formally, $\partial\lambda_{rsk}/\partial c_{sk} \leq 0$, $\partial\lambda_{rsk}/\partial c_{sq} \geq 0$ for $q \neq k$, and $\partial\lambda_{rsk}/\partial c_{pq} = 0$ for $p \neq s \neq k$ and $q \neq s \neq k$.

k, the λ-weighted covariance of residualized earnings is

$$\text{Cov}^{\text{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) = \frac{\sum_i \lambda_{irsk} \log z_{is} \log z_{ik}}{\sum_i \lambda_{irsk}} - \frac{\left(\sum_i \lambda_{irsk} \log z_{is}\right)\left(\sum_i \lambda_{irsk} \log z_{ik}\right)}{\left(\sum_i \lambda_{irsk}\right)^2} \tag{16}$$

which is the covariance in residualized earnings $\log \widetilde{y}_{irs} = \log z_{is}$ and $\log \widetilde{y}'_{irk} = \log z_{ik}$ for workers moving from sector s to sector k, weighted by the individual probability of moving between the two sectors. This object plays a central role in identifying the skill correlation matrix Σ: workers who move between sectors with highly correlated skills will tend to have positively correlated residualized earnings in origin and destination sectors, while workers moving between sectors with low skill correlations will not. When movement costs are small, this covariance is approximately symmetric across sector pairs, $\text{Cov}^{\text{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) \approx \text{Cov}^{\text{Obs.}}(\log \widetilde{y}_{irk}, \log \widetilde{y}'_{irs})$. Derivations and further discussion are provided in Appendix B.

Finally, the change in effective labor units supplied to sector s in market r following the shock is

$$\hat{Z}_{rs} = \frac{\sum_k \sum_i \lambda_{irks} z_{irs}}{Z_{rs}} \tag{17}$$

where x_i drops out of the expression.[5]

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

$$\log \frac{\widehat{w}_{rs}}{\widehat{P}_r} = \log \frac{\widehat{Y}_r}{\widehat{P}_r} - \log \widehat{Z}_{rs}. \tag{18}$$

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 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 and the movement costs, workers moving from a specific sector will be more likely

[5] Two steps justify this. First, x_i cancels algebraically from the choice probabilities π_{irs} and λ_{irks}, since it enters numerator and denominator of the logit symmetrically. Second, independence of x_i from z_{irs}, assumed above, allows $\mathbb{E}[x_i z_{irs}] = \mathbb{E}[x_i]\mathbb{E}[z_{irs}]$, so that $\mathbb{E}[x_i]$ factors out of both numerator and denominator and cancels.

to move toward certain destination sectors compared to others. Accordingly, there can be variation in $\widehat{Z}_{rs}$ both across and within local labor markets.

3 Data and background

3.1 Data

I use Norwegian register data on individual employment and earnings for the period 2000–2019. The data form an extensive panel in which 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.

Data sources and sample construction. The Norwegian register-based employment records cover all workers each year and provide employment status, sector of employment, and residential municipality. For earnings, from 2000 to 2014 I draw on the yearly wage survey conducted by Statistics Norway, which is carried out each September/October and covers approximately 70% of the private sector and the entire public sector. From 2015 onward, I use wage data from A-ordningen, a coordinated administrative collection of employment and earnings records that replaced the survey. For all years, I use monthly total labor income as my earnings measure, defined as the sum of base salary, bonus, irregular additional salary, and average overtime pay. I further include individual education records containing completed education levels. I restrict the sample to full-time workers of prime working age, defined as those aged 25 to 58 years, who are either employed or self-employed. This excludes young workers such as students and workers approaching retirement. For the small number of workers with multiple full-time job within same year, I assign the one that is highest-paying. I construct control variables by grouping workers into nine age groups with a five-year span and five education groups based on highest completed education: (i) no registered education at high school level or above, (ii) high school, (iii) college or bachelor's degree, (iv) master's degree or equivalent, and (v) Ph.D.

Commuting zone and sector definitions. I follow Bhuller (2009) and construct 46 Norwegian Commuting Zones (CZs) using residential municipality codes, with minor adjustments to account for changes in municipal boundaries over the sample period. I construct sectors based on the Norwegian Standard Industrial Classification (SIC2007), which aligns with the EU's NACE Rev. 2 classification. Following Statistics Norway (2015), I define sectors in which at least 50% of the value of production is related to petroleum as part of the oil sector; this includes both extraction and petroleum supply industries. I define non-tradable (NT) sectors as those in which less than 25% of value added derives from exports.[6] For the empirical analysis, I construct fifteen non-tradable sectors based on the first level of the SIC2007 hierarchy, which provides sufficient granularity to document sector-level reallocation patterns. For the structural exercises, I aggregate to seven sectors — five non-tradable and two tradable — to keep the model computationally tractable while preserving the key distinctions between sector groups.

Additional data inputs. I use the sectoral intermediate input-output table from Statistics Norway for 2013 to construct two additional objects. First, I construct household consumption shares, defined as the value of final household consumption expenditure on a sector as the share of total final household consumption expenditure. These shares enter directly into the model's price index and real income calculations. Second, for each sector I construct the value of sales to the oil sector relative to total use, which I include as a control variable in the empirical specifications to account for demand-side linkages between sectors and the oil industry.

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 in 2013, 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.

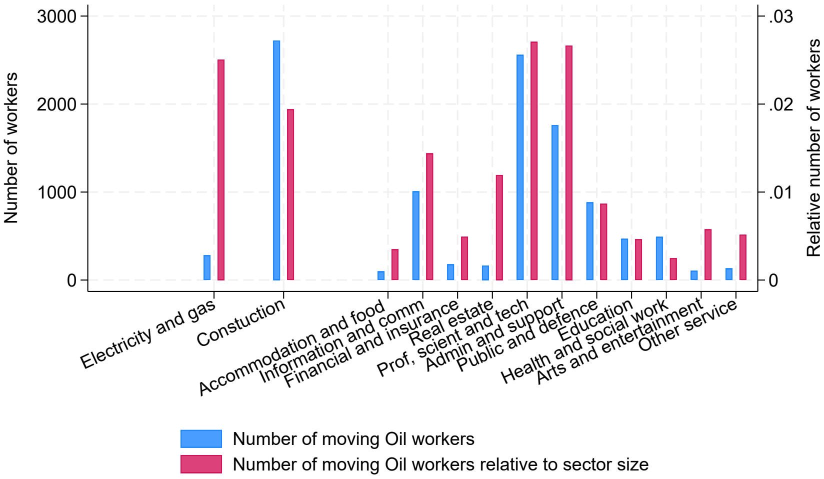
The oil price collapse made oil workers move out of the oil sector. Table A.1 reports that among the workers working in the oil sector in 2013, 14.9% worked in a non-oil sector three years after the shock (2017).[7] By comparing the average moving oil workers to the average oil worker, I find the moving

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

[7] Margins not incorporated in this paper include unemployment, retirement, and exit from the labor market or country. Table A.1 reports that 74.7% 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.

oil workers to be relatively younger, more likely female, and more likely to have a college degree. In fact, 50% of the workers leaving the oil sector had a college education, which is in contrast to 39 % for the initial oil sector and 39% 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 2013. Most of the moving oil workers stayed within their CZ, and the data shows that only 9.3% of the workers that worked in the oil sector in 2013 but in a non-oil sector in 2017, moved to another CZ. For all workers, I find that only 1.5% moved to another CZ over the same period. Figure 2 shows there to be variation in both the number of incoming oil workers and in the 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".[8] 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.

Figure 2: Oil worker inflows to non-tradable sectors



Notes: The figure shows the inflows of oil workers 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 2013 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 in 2013 and 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.

[8] "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.

4 Empirical evidence

As explained by Equation (18), the model predicts that the worker reallocation driven by the oil price collapse affected equilibrium real wages in the NT destination sectors of the moving workers. This, in turn, may have induced 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 increase 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 to the outcomes of interest. 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.

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 in the baseline period, the exposure is defined as

$$\mathbb{Z}_{rs} \equiv \frac{N_{oil,r}}{N_r} \cdot \frac{N_s^{oil}}{N_s}. \tag{19}$$

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, and N_s is the number of workers working in sector s, all constructed for the pre-shock year 2013.[9] 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. 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

[9] I construct the measure for employment spells between the years 2000 and 2012 when computing N_s^{oil}.

previous employment spell in the oil sector at the national level. By measuring the two factors, I find that $N_{oil,r}/N_r$ has a mean of 0.079 across CZs with a standard deviation of 0.070, and N_s^{oil}/N_s has a mean of 0.020 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 94%. 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 64%. 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 movement flows, explaining a large share of the variation in the data. Specifically, it alone accounts for 58% 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. 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. Since the exposure term exploits variations across CZs and destination sectors, it allows for controlling for both CZ-year fixed effects and sector-year fixed effects 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 (18). 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-year 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 secto-year 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 address possible confounding factors at the CZ-sector-year level.

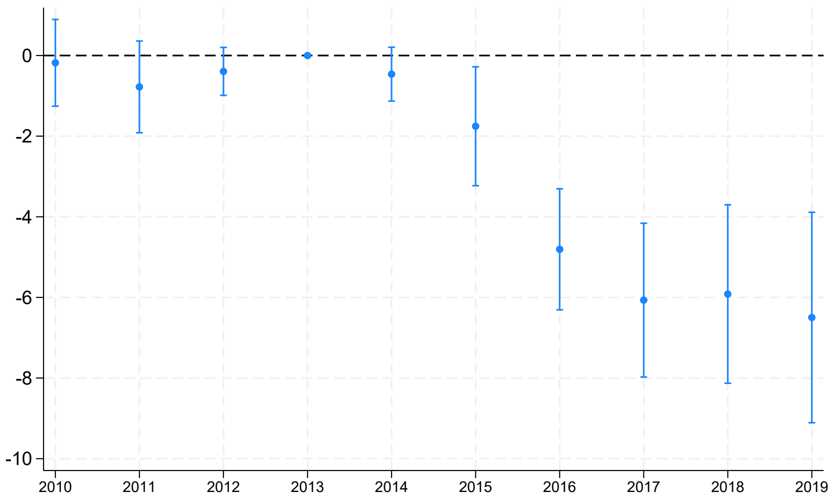
4.2 The effect on equilibrium wages

If inflows of oil workers into NT sectors drive down equilibrium wages, as suggested by Equation (18), we would expect a decline in earnings for stayers in NT sectors. I examine this by estimating the following reduced-form event study

$$\log y_{irst} = \gamma_{rs} + \gamma_{rt} + \gamma_{st} + \gamma_i + \sum_{k \neq 2013} \beta^k \cdot \mathbb{Z}_{rs} \cdot \mathbf{I}(t = k) + \epsilon_{irst} \tag{20}$$

where $\log y_{irst}$ is the log labor income of worker i located in CZ r and working in NT sector s in year t, γ_{rt} and γ_{st} are commuting zone-year and sector-year fixed effects respectively, γ_i is a worker fixed effect, γ_{rs} is a CZ-sector fixed effect, and ϵ_{irst} is the error term. The sample consists of stayers in NT sectors, defined as workers observed in their 2013 baseline sector and CZ in each year from 2013 through 2017, with 2013 as the reference year. Standard errors are clustered at the CZ-sector level. Figure 3

Figure 3: Wages of stayers in non-tradable sectors and oil worker inflows



Notes: The figure reports β^k with 95% confidence intervals for the years 2010 to 2019 by estimating Equation (20). Coefficients are normalized to zero in 2013. The sample includes stayers in NT sectors, defined as workers observed in their baseline sector and CZ in each year from 2013 to 2017. The x-axis measures year t. Included fixed effects are worker, CZ-sector, CZ-year, and sector-year. Standard errors are clustered at the CZ-sector level.

reports the estimated coefficients β^k from Equation (20).[10] The figure shows a sharp and significant decline in log labor income for workers staying NT sectors that are more exposed to oil worker inflows, beginning in 2015 and deepening through 2016 and 2017. After 2017, the income gap relative to the 2013 baseline stabilizes at a persistently lower level, suggesting that the negative wage effect did not

[10] Robustness checks are reported in Appendix Figure A.4, where I present event study estimates under alternative specifications discussed in Section 4.5.

reverse as the oil price shock subsided. This is consistent with a persistent decline in equilibrium wages for NT sectors in response to worker reallocation inflows driven by the oil price collapse, as explained by Equation (18). Figure 3 shows no pre-trends, indicating that there were no systematic differences in log labor income levels for staying workers in NT sectors correlated with the exposure term in the years prior to the shock. The average NT sector staying worker had an exposure of 0.0005 and, by 2017, had income approximately 0.33 percent lower relative to 2013 compared to workers with zero exposure. A worker at the 90th percentile, with an exposure of 0.0032, experienced a 1.93 percent lower income level relative to 2013 by the same year. Because the CZ-year fixed effects absorb any common wage effect across sectors within a CZ, and the sector-year fixed effects absorb any common wage effect across CZs within a sector, the estimated coefficients capture the component of the wage effect driven by the uneven distribution of oil worker inflows across CZ-sector cells, net of these common effects. Section 6 uses the structural model to recover the full equilibrium wage effects, including those absorbed by the fixed effects.

4.3 The change in the average worker composition

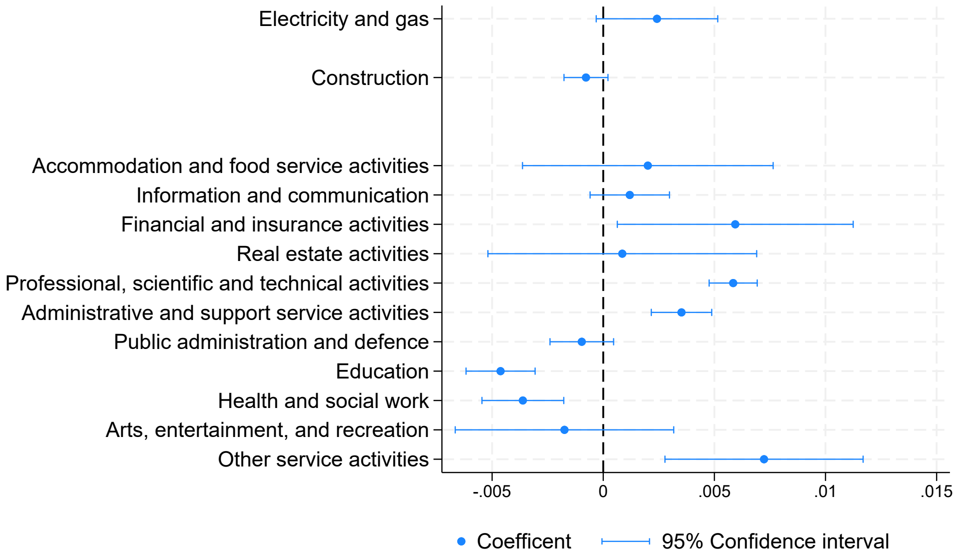
Worker reallocation changes average sectoral earnings for potentially two reasons: changes in the equilibrium wage per effective labor unit and changes in the composition of workers. While Figure 3 presents results consistent with worker reallocation out of the oil sector to have a significantly negative effect on the equilibrium wages, 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 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. Next, for each NT sector, I estimate the following form

$$\log y_{is} = \alpha_s + \beta_s \cdot \mathbb{I}(Oil\ Mover) + \epsilon_{is} \tag{21}$$

where $\log y_{is}$ 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 ϵ_{is} is the error term.

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

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 (21) for each NT sector s separately, for the year 2017. In Equation (21), $\log y_{i,s}$ 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.

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, age group, or CZ.[11]

4.4 The effect on the probability of leaving the baseline sector-CZ

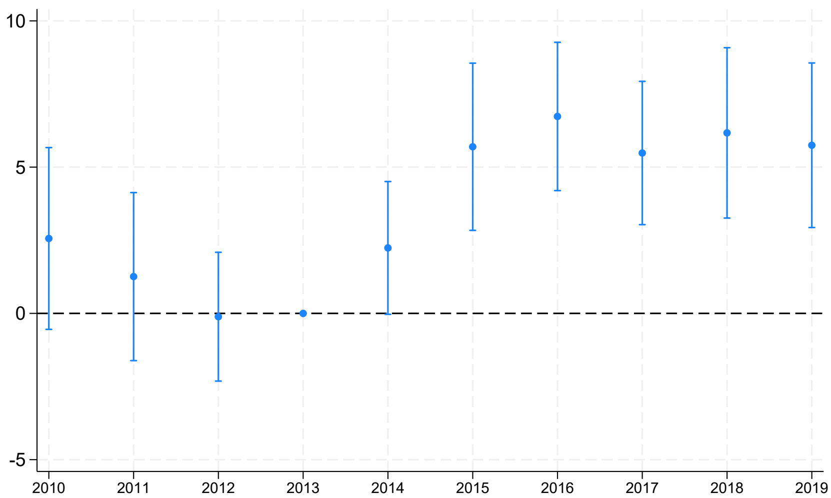
Figure 5 presents the relationship between exposure to inflows of oil workers and the probability that a worker has left her baseline sector and CZ, by estimating the following reduced-form event study

$$D_{irst} = \gamma_{rs} + \gamma_{rt} + \gamma_{st} + \gamma_i + \sum_{k \neq 2013} \beta^k \cdot \mathbb{Z}_{rs} \cdot \mathbf{I}(t = k) + \epsilon_{irst} \tag{22}$$

[11]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.

where D_{irst} is an indicator equal to one if worker i is not observed in her baseline sector s and CZ r in year t, and zero otherwise. γ_{rt} and γ_{st} are CZ-year and sector-year fixed effects, γ_i is a worker fixed effect, γ_{rs} is a CZ-sector fixed effect, and ϵ_{irst} is the error term. The sample consists of all workers in baseline NT sectors, estimated over the period 2010–2019, with 2013 as the reference year. Standard errors are clustered at the CZ-sector level. Figure 5 reports the estimated coefficients β^k from

Figure 5: Probability of leaving the baseline sector-CZ and oil worker inflows



Notes: The figure reports β^k with 95% confidence intervals for the years 2010 to 2019 by estimating Equation (22). Coefficients are normalized to zero in 2013. The sample includes all workers in baseline NT sectors. The outcome D_{irst} equals one if the worker is not observed in her baseline sector and commuting zone in year t. Fixed effects include worker, CZ-sector, CZ-year, and sector-year. Standard errors are clustered at the CZ-sector level.

Equation (22). The figure shows a significant increase in the probability of having left the baseline sector-CZ in the years following the shock for workers more exposed to inflows of oil workers. Moreover, Figure 5 shows no significant pre-trends prior to the shock. These results are consistent with sectoral reallocation driven by the sector-specific shock inducing further reallocation among sectors not directly exposed to the shock, suggesting equilibrium effects throughout the economy. For interpretation, the average worker in NT sectors, with an exposure of 0.0006, had a 0.3 percentage point higher probability of no longer being in her baseline sector-CZ by 2017 compared to workers with zero exposure. A worker at the 90th percentile, with an exposure of 0.0042, had a 2.3 percentage point higher probability of having left her baseline sector-CZ by the same year.[12] As in Section 4.2, the CZ-year fixed effects absorb any factor that varies uniformly across sectors within a CZ, and the sector-year fixed effects absorb any factor that varies uniformly across CZs within a sector, so the estimated coefficients identify only the differential effect on exit probabilities driven by the uneven distribution of oil worker inflows across CZ-sector cells.

[12] These numbers are calculated as the estimated coefficient β^{2017} multiplied by the average and 90th percentile of the exposure term across NT sector workers in 2013, respectively, and scaled by 100 to convert to percentage points.

4.5 Discussion

The identifying assumption underlying the reduced-form event studies (20) and (22) is that, conditional on the included fixed effects, no omitted variable varies at the CZ–sector level over time in a way that is correlated with the exposure term. While CZ-sector fixed effects absorb all time-invariant heterogeneity at the CZ–sector level, and CZ-year and sector-year fixed effects account for differential trends across CZs and sectors, yearly variation at the CZ–sector level that is correlated with the exposure term could confound the interpretation of the estimated patterns. I discuss three potential sources of such variation in turn and provide evidence in line with none of them accounting for the documented patterns.

A first potential confound is the depreciation of the Norwegian krone triggered by the oil price decline. The depreciation raised the competitiveness of all tradable sectors and may have induced worker reallocation from non-tradable sectors toward non-oil tradable sectors. If such outflows are correlated with the inflow exposure measure, the estimated relationship could partly reflect this alternative channel rather than the direct effect of oil worker inflows. To assess this concern, I construct an additional exposure measure capturing each non-tradable sector's exposure to worker flows toward non-oil tradable sectors. A second potential confound is that sectors receiving displaced oil workers may also face demand contractions through local sales linkages to the oil sector. While sector-year fixed effects absorb sales linkages that affect sectors uniformly across CZs, sectors located in CZs with a relatively large oil sector may face differential year-to-year demand contractions that coincide with the pattern of oil worker inflows. To address this, I construct a control variable that interacts each sector's baseline share of total sales to the oil sector with the relative size of the oil sector in the CZ. As reported in Table A.3, neither control is statistically significant when included alongside the main exposure term, and their inclusion does not materially affect the magnitude or significance of the first stage coefficient. As shown in Figures A.4 and A.5, the main coefficients in the reduced-form event studies remain largely unchanged when these controls are included, suggesting that the documented patterns are not driven by exchange-rate-induced reallocation or demand-driven effects operating through input–output linkages.

A third potential confound relates to the construction sector specifically. Construction is both cyclically sensitive and a major destination for displaced oil workers (see Figure 2). A simultaneous demand contraction for construction services in oil-exposed CZs could mean that the documented patterns reflect sector-specific demand effects in construction rather than the consequences of oil worker inflows more broadly. To assess whether the results are driven by the construction sector, I re-estimate the reduced-form specifications in Sections 4.2 and 4.4 excluding construction workers from the sample. As shown in Figures A.4 and A.5, the results are robust to this exclusion, indicating that construction is not the primary driver of the findings.

Taken together, the robustness exercises support the interpretation that the documented patterns reflect the effect of oil worker inflows on workers in destination sectors, operating through the labor reallocation channel, rather than alternative mechanisms related to exchange-rate-induced reallocation, local demand contractions through input–output linkages, or sector-specific demand shocks in the construction sector.

5 Model estimation

The reduced-form evidence in Section 4 establishes that worker inflows from the oil sector reduced labor earnings and increased exit rates among workers in non-tradable destination sectors. However, to recover the full network of reallocation that follows the shock, quantify the aggregate and distributional consequences across all sectors and CZs, and run counterfactuals, I turn to the structural model. I estimate model parameters by using the simulated method of moments (SMM). The estimation uses targeted moments from the initial equilibrium and the reallocation response to the shock: sectoral employment shares, average sectoral earnings, worker movement flows across sector pairs, and earnings covariances for moving workers. The estimated parameters reveal that sectoral skills are correlated across sectors and that movement costs vary across sector pairs. Both shape the magnitude and direction of reallocation, and Section 5.7 demonstrates that the model requires both to jointly fit the observed flows and earnings data.

5.1 Simulated method of moments

I estimate model parameters, including the levels of the skill distribution $\boldsymbol{\mu_r}$, the skill covariance matrix $\boldsymbol{\Sigma}$, and the matrix of movement costs $\boldsymbol{c}$, using SMM. I estimate the parameters jointly for the CZ Stavanger.[13] In this setup, there are $S-1$ levels, $S+(((S\times S)-S)/2)$ covariance matrix parameters, and $(S\times S)-S)/2$ movement costs to be estimated. To obtain the SMM estimates, I solve:

$$\{\boldsymbol{\Sigma}, \boldsymbol{\mu_r}, \boldsymbol{c}\} = \text{argmin} \sum \left(\frac{\boldsymbol{x}^{sim} - \boldsymbol{x}^{obs}}{\overline{\boldsymbol{x}^{obs}}} \right)^2 \tag{23}$$

where the moments included are

$$\boldsymbol{x} = \left\{ \pi_{rs},\ \overline{\log y_{rs}},\ \lambda_{rsk},\ R_{rsk} \right\},$$

conditional on the skill covariance matrix $\boldsymbol{\Sigma}$ being a positive semidefinite. I solve the minimization problem given the set of observed CZ-sector-specific wage changes, $\widehat{w}_{rs}$. These changes are identified using a fixed-effects approach with the set of incumbent workers, as explained in Section 5.4. Standard errors are constructed by drawing 200 bootstrap samples from the micro data, re-constructing the tar-

[13] Stavanger is known as the "centre" of the Norwegian oil industry.

geted moments for each sample, and re-estimating the model parameters for each; the reported standard errors are the standard deviations across these 200 estimates, as described in Appendix C.3. In the expression, π_{rs} is the initial sectoral employment shares, $\overline{\log y_{rs}}$ is the initial average sectoral earnings, λ_{rsk} is the share of workers moving between sector pairs, and $R_{rsk} \equiv \frac{\text{Cov}^{\text{Obs.}}\left(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}\right)}{\sqrt{\text{Var}^{\text{Obs.}}(\log \widetilde{y}_{irs})}\sqrt{\text{Var}^{\text{Obs.}}(\log \widetilde{y}_{irk})}}$ which is the standardized covariance in residualized earnings across the origin and destination sectors for moving workers, relative to the initial period standard deviations of residualized earnings for the two sectors.[14] The simulated moments are constructed as described in Section 2 and Appendix B.1, while the corresponding observed moments are measured in the data as outlined in Section 5.3. Because moment types differ substantially in scale, I normalize each moment's contribution to the objective by its average observed value. Counting the targeted moments, there are $(S-1)$ sectoral shares, $(S-1)$ normalized average sectoral earnings, $((S \times S) - S)$ movement flows, and at most $S(S-1)/2$ standardized covariance moments, since covariances are pooled symmetrically across both directions of each sector pair. To avoid targeting noisy covariance moments, I include R_{rsk} only for sector pairs where $\lambda_{rsk} > 0.005$. The model is overidentified, with more targeted moments than parameters. If the positive semidefiniteness constraint on Σ is active at the optimum, it reduces the effective degrees of freedom even more.

In the estimation exercise, I set $\kappa = 0.13$. Appendix C.1 derives an estimation equation for κ in a setting that approximates the model when movement costs are low. Using this estimation equation, Table A.8 presents results supporting the chosen κ value.[15] The relatively low value indicates that earnings explain a large share of reallocation following changes in sectoral wages, supporting the importance of the Roy model in studying sectoral reallocation in response to shocks.

The estimation exercise draws on two strands of literature modeling sectoral reallocation in response to a trade shock. First, it relates to studies explaining the degree of sectoral reallocation by the dispersion of sectoral skills, as in Galle et al. (2022). Unlike the benchmark model, this paper assumes skills are not distributed independently and identically (iid), thus the structure of the covariance matrix can more precisely explain both the magnitudes and directions of the sectoral worker reallocation. Second, by including sector-specific movement costs, this paper aligns with Caliendo et al. (2019) and Borusyak et al. (2022). As in these studies, the magnitude and directions of the reallocation flows will be explained by the sector pair specific movement costs, which are unrelated to the workers' sectoral skills. I combine these two elements, so that sectoral reallocation is jointly explained by sectoral skills and movement

[14] For the model simulated expression, the numerator is defined as in Equation (16) and is the covariance in residualized earnings across origin sector s and destination sector k, weighted by the probability of moving between the two sectors. For the denominator, $\text{Var}^{\text{Obs.}}(\log \widetilde{y}_{irs})$ is defined as in Equation (37) and is the initial period variance in residualized sector s earnings, weighted by the probability of working in sector s. When measuring the observed counterpart in the data, as discussed in Appendix section B.3, earnings covariances are constructed by using earnings for the workers moving in both directions of the sector pairs, such that the target will be the same for both the pairs s-k and k-s. In Appendix B.3, I show this to be a prediction of the model without movement costs, and is an approximation of earnings covariances close to the model when there are small movement costs.

[15] Specifically, $\kappa = 0.13$ is supported by the 95% confidence intervals in Table A.8. I choose this value over the exact point estimates to ensure sufficient numerical smoothing of the simulated choice probabilities in the SMM estimation.

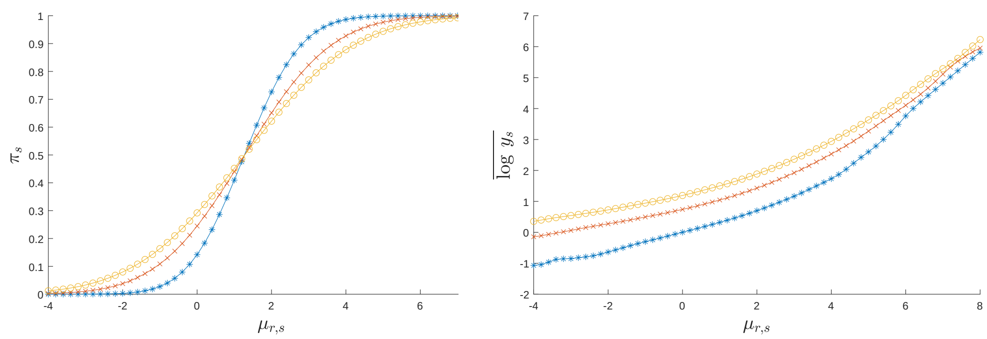
costs. In the estimation exercise, I separate skill correlations from movement costs by targeting both earnings correlations and worker movement flows, which depend on these model elements in different ways. Section 5.7 demonstrates that both correlated skills and movement costs contribute to jointly explaining observed sectoral reallocation and earnings covariances.

The rest of this section presents 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 SMM estimation are presented in Appendix C.2.

5.2 Simulated moments

To provide insight into how moments of the model depend on the parameters to be estimated, 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.[16]

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



(a) Sector share (b) Average earnings

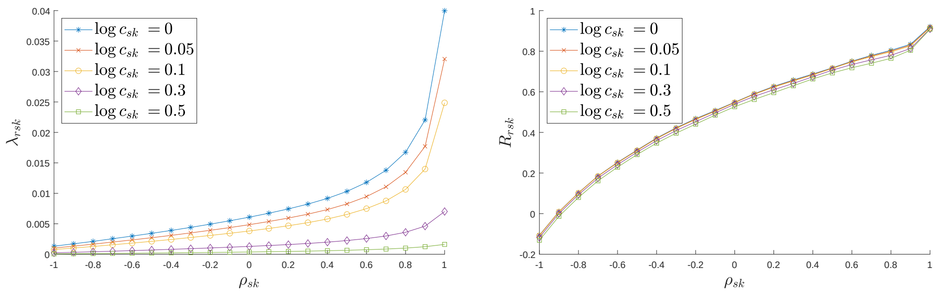
Notes: The figure shows examples of model simulated comparative statics exercises. In both panels, the horizontal axis measures the sector-specific level, μ_{rs}. The vertical axis of panel (a) measures the share of worker working in sector s, and the vertical axis of panel (b) measures the average log 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, μ_{rs}, and the variance parameter, σ_s^2. Panel (a) shows the share of workers selecting into the sector to be increasing in the level. The higher is μ_{rs}, the more workers sort into that sector. By shifting σ_s^2, the

[16]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, ρ_{sk} values are equal to zero, μ_{rs} values are equal to zero, and c_{sk} values are equal to one. Moreover, the set of wage changes $\widehat{w}_{rs}$ identified in Section 5.4 for the CZ Stavanger. Sector s is Oil, and sector k is Financial Services.

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. The degree of selection bias depends on the variation in the sectoral skills. 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 shifts the average earnings upwards, the selection bias is shrinking in the level. As the level is increasing and more workers select into the sector, more of the marginal skill distribution is observed such that average earnings converge toward level at high values of μ_{rs}.

Figure 7: Worker movements: From origin sector s to destination sector k



(a) (b)

Notes: The figure shows an example of a typical model simulated comparative statics exercises. In both panels, the horizontal axis measures values of ρ_{sk}, which is the Pearson's correlation coefficient, defined as $\sigma_{sk}/\sigma_s\sigma_k$, when σ_{sk} 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. In panel (a), the vertical axis measures λ_{rsk}, which is the share of workers in CZ r moving from origin sector s to destination sector k. In panel (b), the vertical axis measures R_{rsk}, which is the standardized covariance in earnings across sectors for workers moving from origin sector s to destinations sector k. The different colors/shapes represent different values of the origin sector s - destination sector k moving costs c_{sk}.

Worker reallocation Figure 7 presents model-simulated comparative exercises for worker reallocation and sectoral earnings covariances of moving workers when there is a negative wage shock in sector s. Given the remaining set of parameters, Panel (a) shows the number of workers moving from the origin sector s to the destination sector k, is increasing in the correlation coefficient for sector s and sector k skills, ρ_{sk}. Thus, for the simulated data presented in the figure, when the two sectors are more correlated in skills, workers are more responsive to a relative wage change between the two sectors. Additionally, the figure shows that for a higher cost of moving between the two sectors, the curve shifts downward and the exercises show less mobility between the two sectors. Panel (b) shows that the earnings of the workers that are moving from origin sector s to destination sector k more positively covary across the two sectors when the two sectors are more correlated in skills. The exercise shows minimal responsiveness to changes in the costs of moving between the two sectors. The results presented in the figure align with the analytical comparative static exercises discussed in Appendix Section B.2.

5.3 Identifying moments in data

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

Sector shares and worker flows π_{rs} is the share of workers selecting into sector s in CZ r, and λ_{rsk} is the share of workers moving from sector s to sector k in CZ r. I use π_{rs} and λ_{rsk} as targets in the estimation exercise, and identify the moments in the data by $\pi_{rs} = \frac{N_{rs}}{N_r}$, and $\lambda_{rsk} = \frac{\Delta N_{rsk}}{N_r}$ where N_{rs} is the number of workers working in sector s in CZ r, N_r is the total number of workers in CZ r, and ΔN_{rsk} is the number of workers moving from origin sector s in CZ r to destination sector k. N_{rs} and N_r are calculated for year 2013, and ΔN_{rsk} is calculated for the time period 2013 to 2017.[17]

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

$$\log y_i = \alpha_0 + \alpha_{rs} + \boldsymbol{X_i'}\beta + \epsilon_{irs} \tag{24}$$

where $\log y_i$ is observed log labor income in the year 2013, α_0 is the constant across workers, α_{rs} is the CZ-sector constant, $\boldsymbol{X_{it}'}$ is the set of observed worker characteristics including age, gender and education level, and ϵ_i is the residual. I define the average sectoral log income used as a targeted moment as

$$\overline{\log y_{rs}} \equiv \alpha_0 + \alpha_{rs} \tag{25}$$

Earnings covariance I construct the observed counterpart of R_{rsk} to be used as target in the SMM estimation. The theoretical object is the covariance of $\log \widetilde{y}_{irs} = \log z_{is}$ (Section 2); its empirical counterpart is the residual from Equation (24), which removes $\log w_{rs}$ via α_{rs} and $\log x_i$ via $\boldsymbol{X_i'}\beta$, leaving a residual that serves as the empirical counterpart to $\log z_{is}$. For the CZ, the earnings distributions for both the year 2013 and 2017 are therefore residualized on initial Mincer controls. Using the residualized earnings distributions, I derive earnings covariances for workers moving across sectors and calculate initial sectoral earnings variances. As discussed in Footnote 14 and in Appendix Section B.3, I include workers moving in both directions of sector pairs, such that the targeted earning covariances are symmetric. As explained in the Appendix Section, this approach approximates the model when movement

[17] Consistent with the model, the sectoral shares and the share of moving workers will be independent of the observed worker characteristics x_i, and I therefore do not control for observed characteristics when computing these targets.

costs are small. At the same time, it ensures that the sample of moving workers used to identify covariances is relatively large for all sector pairs. The covariances are standardized using the standard deviation of residualized sectoral earnings from the initial year of 2013.

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 $\log \widehat{y}_{it} = \log \widehat{w}_{rst}$. 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

$$\log \widehat{y}_{irt,t+1} = \text{FE}_{rst,t+1} + \mathbf{X}'_{it}\beta + \varepsilon_{i,t}, \tag{26}$$

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

$$\log \widehat{w}_{rst,t+1} \equiv \text{FE}_{rst,t+1}. \tag{27}$$

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

$$\log \widehat{w}_{rs} \equiv \sum_{t}^{T-1} \log \widehat{w}_{rst,t+1}. \tag{28}$$

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 Estimation results

The SMM-estimated sectoral skill correlation matrix and movement cost matrix are presented in Tables 1 and 2, respectively. The estimated correlation coefficients confirm that sectoral skills are not independently distributed. Of the 21 unique sector pairs, 13 exhibit positive estimated correlations and 8 exhibit negative correlations, consistent with skills being more often positively correlated than negatively correlated across sectors.

The most pronounced positive correlation is between Financial services and the Oil sector. Further notable positive correlations emerge between Services and Trade, between Electricity, gas supply and construction and Scientific and technical activities, and between Services and Oil. By contrast, the largest negative correlations are estimated between Electricity, gas supply and construction and the Public sector and between Scientific and technical activities and the Public sector. The Public sector also estimated to have a negative skill correlation with Trade. Turning to the movement cost matrix in Table 2, most sector pairs face negligible mobility costs, with estimated costs at or very near unity. However, for certain pairs the estimated costs are higher. The largest estimated costs are between Financial services and the Oil sector, a finding that is noteworthy given that this pair also is estimated to have the highest skill correlation. The co-occurrence of postively correlated skills and a large mobility cost implies that the potential for wage spillovers through worker reallocation between Oil and Financial services is reduced by movement costs. Furthermore, I estimate movement costs for moving between the Public sector and Oil, moving between the Public sector and Trade, between Services and Trade, and between Electricity, gas supply and construction with Scientific and technical activities. At the other hand, there are several sector pairs that face essentially zero movement costs. Table A.5 presents the estimated sector-specific standard deviations of the skill distribution. The results indicate the sectoral skills to have different standard deviations across sectors. Scientific and Technical activities is estimated to have the highest standard deviation, followed by Electricity, gas supply and construction and Financial services. At the other end, Services, Trade, and the Public sector is estimated to have comparatively lower sector-specific standard deviations.

Table 1: Estimated ρ_{sk} values

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
Elect & Const	1.000	0.111	0.282	0.455	-0.732	-0.053	0.113
	(-)	(0.17)	(0.15)	(0.21)	(0.17)	(0.09)	(0.16)
Services	0.111	1.000	0.290	-0.144	0.043	0.390	0.553
	(0.17)	(-)	(0.20)	(0.23)	(0.12)	(0.19)	(0.24)
Financial	0.282	0.290	1.000	0.110	0.072	0.800	-0.032
	(0.15)	(0.20)	(-)	(0.14)	(0.17)	(0.22)	(0.21)
Scient & Tech	0.455	-0.144	0.110	1.000	-0.627	0.014	-0.140
	(0.21)	(0.23)	(0.14)	(-)	(0.10)	(0.26)	(0.17)
Public	-0.732	0.043	0.072	-0.627	1.000	0.310	-0.446
	(0.17)	(0.12)	(0.17)	(0.10)	(-)	(0.23)	(0.22)
Oil	-0.053	0.390	0.800	0.014	0.310	1.000	-0.039
	(0.09)	(0.19)	(0.22)	(0.26)	(0.23)	(-)	(0.16)
Trade	0.113	0.553	-0.032	-0.140	-0.446	-0.039	1.000
	(0.16)	(0.24)	(0.21)	(0.17)	(0.22)	(0.16)	(-)

Notes: The table presents the estimated skill correlation coefficients ρ_{sk} for all sector pairs. Specifically, the correlation coefficients are the Pearson's correlation coefficient, defined as $\sigma_{sk}/\sigma_s\sigma_k$, when σ_{ak} 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. Bootstrapped standard errors are reported in parentheses.

Table 2: Estimated c_{sk} values

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
Elect & Const	1.000	1.003	1.000	1.230	1.000	1.000	1.000
	(-)	(0.01)	(0.02)	(0.07)	(0.05)	(0.06)	(0.00)
Services	1.003	1.000	1.000	1.000	1.221	1.161	1.261
	(0.01)	(-)	(0.05)	(0.06)	(0.03)	(0.02)	(0.06)
Financial	1.000	1.000	1.000	1.008	1.072	1.631	1.000
	(0.02)	(0.05)	(-)	(0.08)	(0.03)	(0.09)	(0.05)
Scient & Tech	1.230	1.000	1.008	1.000	1.049	1.000	1.158
	(0.07)	(0.06)	(0.08)	(-)	(0.04)	(0.00)	(0.04)
Public	1.000	1.221	1.072	1.049	1.000	1.429	1.269
	(0.05)	(0.03)	(0.03)	(0.04)	(-)	(0.05)	(0.05)
Oil	1.000	1.161	1.631	1.000	1.429	1.000	1.093
	(0.06)	(0.02)	(0.09)	(0.00)	(0.05)	(-)	(0.04)
Trade	1.000	1.261	1.000	1.158	1.269	1.093	1.000
	(0.00)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)	(-)

Notes: The table presents the estimated movement costs values c_{sk} for all sector pairs. Bootstrapped standard errors are reported in parentheses. A value equal to one, is equivalent to zero movement costs.

Table 3: Model fit to targeted moments

	Actual π_{rs}	Actual λ_{rsk}	Actual $\overline{\log y_{rs}}$	Actual R_{rsk}
π_{rs}	0.947			
	(0.145)			
λ_{rsk}		1.048		
		(0.044)		
$\overline{\log y_{rs}}$			1.038	
			(0.007)	
R_{rsk}				1.041
				(0.045)
Constant	0.008	-0.000	-0.003	-0.025
	(0.024)	(0.000)	(0.001)	(0.026)
R^2	0.895	0.933	1.000	0.984
Observations	7	42	7	11

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, average sectoral earnings, and the standardized earning covariances. Standard errors are reported in parentheses.

5.6 Model fit

Table 3 presents the results of the model fit exercise in which the targeted moments are regressed on moments simulated by the SMM-estimated model. The simulated moments significantly predict all of the targeted moments and account for close to all the variation in the targeted data moments. In other words, the model explains the data moments used as targets in the SMM estimation very well. The fit is very good for all the four different kinds of targeted moments with both model fit coefficient and R^2 close to one and regression constant close to zero. Furthermore, I test how well the estimated model explains data moments for non-targeted CZs. As expected, Table A.6 demonstrates that the model does not perform as well in predicting data moments for non-targeted CZs, but it performs relatively well, particularly for sectoral shares, movement flows, and average sectoral earnings.

5.7 Discussion

In the model, sectoral reallocation depends both on sectoral skills and movement costs. To shed light on the importance of these two factors for the estimated model, I conduct simulation exercises by removing each element separately. Specifically, in two distinct exercises, I simulate sectoral reallocation without movement costs and with zero correlation in skills across sectors. Table A.7 presents the results of testing how well these modified models explain the actual data on reallocation and earnings covariances. As expected, both models account for less of the observed data compared to the estimated model. Interestingly, the ability of each model in explaining different moments varies. The model without movement costs explains a relatively small share of the variation in sectoral reallocation, and the fit coefficient is low, indicating that the magnitude of reallocation is too high without any costs of moving. Nevertheless, this model accounts for closs to all the variation in earnings covariance for workers moving across sectors. Conversely, the model with zero skill correlations displays the opposite pattern, explaining a relatively higher share of the variation in movement flows. Compared to the estimated model, however, its fit is not as strong, suggesting that both movement costs and skill correlations contribute importantly to explaining the data on movement flows. Moreover, the model without skill correlations poorly accounts for earnings correlations across sectors for moving workers, underscoring the importance of skill correlations in predicting earnings correlations.

6 Counterfactual Simulations

I use the estimated model to simulate worker reallocation following a counterfactual oil price collapse and to quantify the associated impact on sectoral wages and aggregate real income. Between 2013 and 2017, the price of Brent Crude Oil fell by approximately 50 percent (Figure 1), and I set the shock accordingly by setting $\widehat{p}_{\text{oil}} = 0.5$. All simulations use the estimated parameters from Section 5 and are run separately for each of the 46 CZs.[18] To isolate the role of the different adjustment channels, I compare the full equilibrium to three counterfactual economies in which one channel is shut down at a time. Appendix D provides a theoretical characterisation of the mechanisms driving wages and real income across the scenarios. Results for alternative shock sizes of 25 and 75 percent are shown in Appendix Figures A.8–A.11.

6.1 Baseline Results

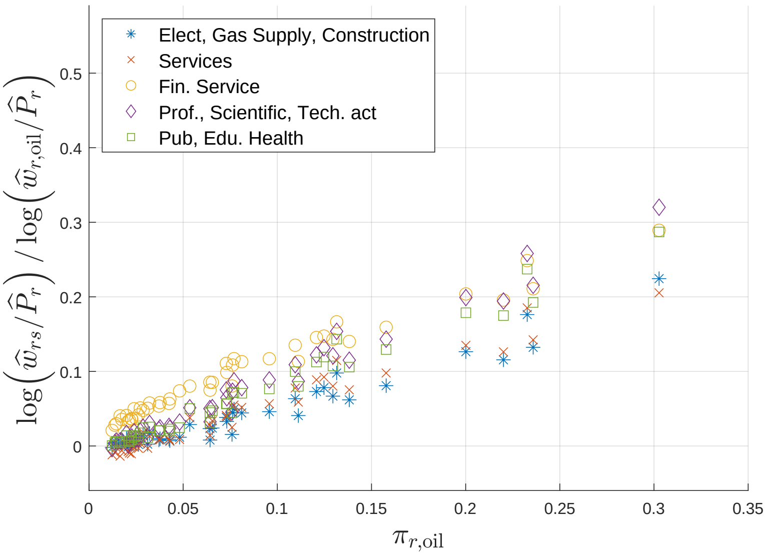
The baseline simulation (scenario A) is the full model equilibrium: workers reallocate optimally given the equilibrium NT wage changes, and aggregate income reflects the full general equilibrium response to the shock.

Equilibrium wage changes. Figure 8 plots the equilibrium real wage changes for each CZ–sector pair, expressed as the change in the non-tradable real wage relative to the oil sector real wage in the same CZ, $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\text{oil}}/\widehat{P}_r)$, against the pre-shock oil employment share $\pi_{r,\text{oil}}$. Values below one indicate that non-tradable real wages fell by less than the oil sector real wage. Two features stand out. First, spillovers are strongly increasing in $\pi_{r,\text{oil}}$: high-oil CZs experience substantially larger non-tradable wage declines, reflecting both the larger inflows of displaced oil workers they absorb and the larger fall in aggregate demand for NT goods. Second, the pattern is heterogeneous across sectors, reflecting the correlated skill structure and sector-pair specific movement costs, and workers do not move uniformly across sectors. At the mean across all CZ–sector pairs, non-tradable wages fall by 6.2% of the oil sector wage decline; the maximum across any single CZ–sector pair reaches 32.0%. Appendix Figure A.6 shows the corresponding log real wage changes $\log(\widehat{w}_{rs}/\widehat{P}_r)$. Consistent with equation (18), these patterns reflect three channels. First, the shock induces reallocation out of the oil sector, increasing labor supply to the destination sectors of moving oil workers and reducing NT wages there. In CZs with a larger oil sector, more workers move and the downward pressure is greater. Second, falling oil income reduces aggregate demand for NT goods, leading to a uniform demand-driven wage decline within each CZ. Third, in response to declining NT wages, workers in non-oil sectors reallocate out of their intial sector, which is the domino channel, partially offsetting the labor supply shock.

Sectoral reallocation. The pattern across sectors reflects the estimated skill correlation and movement cost structure. Services and Trade receive the largest overall inflows. For Services, this reflects both a positive skill correlation with Oil (0.39, Table 1) and relatively low movement costs (Table 2).

[18]For the counterfactual simulations, I define CZ-specific level parameters. Specifically, for each CZ, I find the sector-specific level parameters to match the observed initial sectoral shares.

Figure 8: Impact of the oil price collapse on non-tradable sector real wage changes



Notes: Full counterfactual (scenario A). Each point is a CZ–sector pair. The five non-tradable sectors are distinguished by color and marker. The x-axis is the pre-shock oil employment share $\pi_{r,\text{oil}}$ and the y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\text{oil}}/\widehat{P}_r)$.

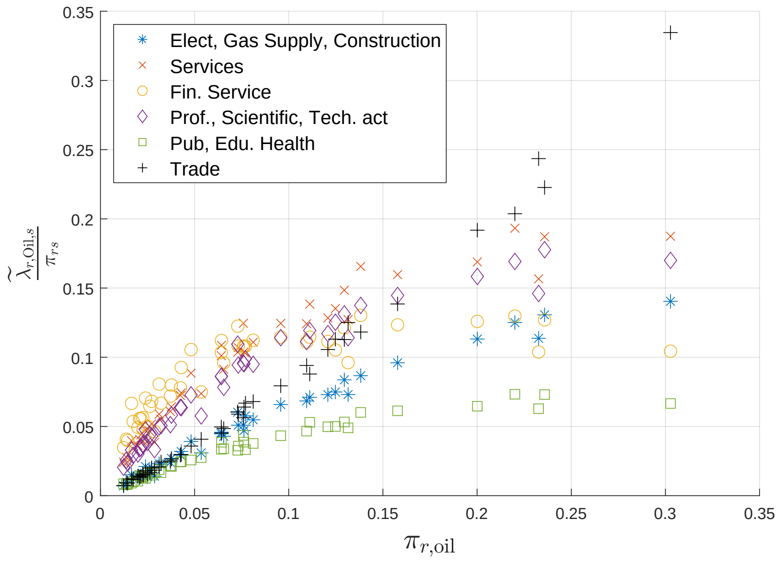
For Trade, low movement costs drive the large inflows despite a slightly negative skill correlation with Oil (-0.04, Table 1), and since wages in tradable sectors are pinned down by world prices, Trade remains relatively attractive as NT wages fall. Scientific and Technological activities also receives large inflows driven by very low movement costs ($c_{sk} = 1.00$, Table 2), despite a low skill correlation of 0.01 (Table 1). By contrast, the highest skill correlation is between Oil and Financial Services (0.80), but the large movement cost between these two sectors (1.63) substantially dampens mobility between them. As shown in Figure 9b, sectors receiving the largest oil inflows exhibit net outflows of non-oil workers, confirming the equilibrating mechanism: Services, which receives the largest NT oil inflows, also sees the largest non-oil outflows, while Trade similarly attracts non-oil workers as falling NT wages make the tradable sector relatively more attractive. The net equilibrating counterflow from non-oil sectors amounts to a median of 63% of the net oil worker reallocation across the 46 CZs (Table 4).

6.2 Counterfactual Scenarios

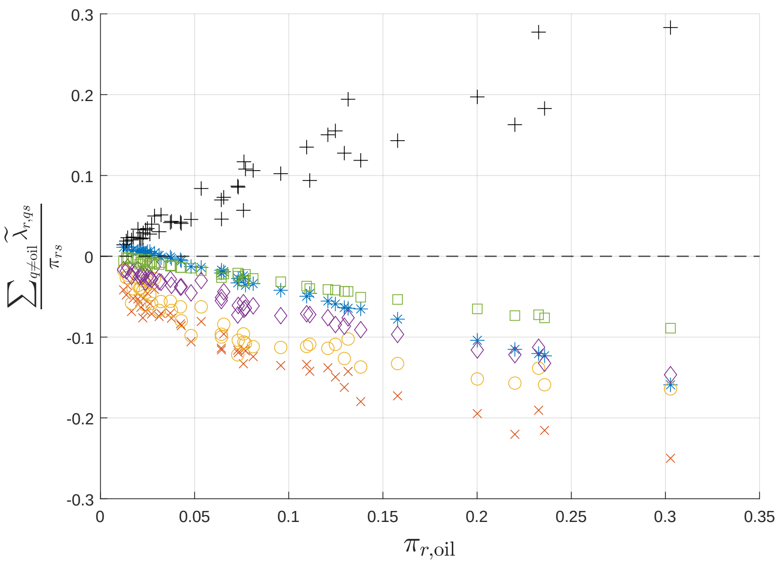
To understand the mechanisms driving the baseline results, I compare the full equilibrium to three counterfactual economies, each shutting down one adjustment channel. Figure A.7 presents the wage spillover patterns for all four scenarios side by side, and Table 4 collects summary statistics.

Scenario (B): Oil worker reallocation only. In this scenario the domino channel is shut down: non-oil workers are constrained to remain in their initial sector while oil workers continue to optimise freely and the demand channel remains active. The results reveal that the domino channel is strongly

Figure 9: Sectoral reallocation following the oil price collapse



(a) Oil worker movements



(b) Non-oil worker movements

Notes: Full counterfactual (scenario A). Panel (a) shows the shift in employment due to net inflows of moving oil workers ($\widetilde{\lambda}_{r,\mathrm{Oil},s}/\pi_{rs}$). Panel (b) shows the shift in employment due to net inflows from all non-oil sectors ($\sum_{q\neq \mathrm{oil}} \widetilde{\lambda}_{r,qs}/\pi_{rs}$); negative values indicate net outflows. The horizontal axis measures the initial oil employment share $\pi_{r,\mathrm{oil}}$ and each observation is a CZ–sector pair.

equilibrating. Comparing column (B) to column (A) in Table 4, shutting down the domino channel nearly doubles the mean relative spillover, from 6.2% to 11.4%, and raises the maximum from 32.0% to 49.2%. When non-oil workers can move, those who leave sectors crowded by oil inflows partially restore labor market balance, attenuating the wage compression in their origin sector. When this channel is absent, oil worker inflows into NT sectors are not offset by non-oil outflows, so the net increase in NT labor supply is larger and the resulting wage compression is more severe.[19] The between-CZ standard deviation of log real NT wage changes rises from 0.033 to 0.048 and the within-CZ standard deviation rises from 0.015 to 0.021: without domino reallocation, wage outcomes vary more both across and within CZs, as the equalising force of non-oil outflows is absent.[20]

Table 4: Counterfactual Simulations: Summary Statistics

	(A) Full	(B) Oil moves	(C) No reallocation	(D) Frictionless
Wage spillovers				
Mean NT wage change rel. to oil	0.062	0.114	0.072	0.053
Max NT wage change rel. to oil	0.320	0.492	0.352	0.571
Log real income change ($\log \widehat{Y}_r - \log \widehat{P}_r$)				
Mean across CZs	-0.017	-0.016	-0.042	-0.001
Std. dev. across CZs	0.032	0.034	0.040	0.025
Dispersion in log real NT wage changes (std. dev. of $\log(\widehat{w}_{rs}/\widehat{P}_r)$*)*				
Total	0.036	0.051	0.040	0.058
Within CZ (across sectors)	0.015	0.021	0.000	0.050
Between CZ	0.033	0.048	0.040	0.031
Worker reallocation				
Non-oil/oil net moves (median)	0.631	0.000	—	0.801

Notes: Results for a 50% oil price decline across all 46 Norwegian commuting zones. (A) Full counterfactual: all workers reallocate optimally given estimated movement costs. (B) Oil workers only: oil workers optimise freely, non-oil workers remain in their sector, shutting down the domino channel. (C) No reallocation: wages adjust only through the aggregate demand channel. (D) Frictionless: same as (A) but with movement costs set to zero. NT wage changes are expressed relative to the oil sector wage change in the same CZ. Log real income change is $\log \widehat{Y}_r - \log \widehat{P}_r$. Within-CZ dispersion is exactly zero under scenario (C) by construction. Dispersion in log real NT wage changes is decomposed into within-CZ (mean standard deviation across the five NT sectors within a CZ) and between-CZ (standard deviation of the CZ-mean log real NT wage change across the 46 commuting zones) components. The worker reallocation row reports the median across the 46 commuting zones of the ratio of non-oil to oil net moves; undefined under scenario (C) and reported as "—" since no workers move and the ratio is not defined; exactly zero under scenario (B) since non-oil workers are constrained to remain in their initial sector.

Scenario (C): No reallocation. In this scenario all workers are constrained to remain in their initial sector. Non-tradable wages adjust only through the aggregate demand channel: the fall in oil income reduces expenditure on non-tradable goods, lowering wages in all NT sectors uniformly within each CZ. Column (C) in Table 4 shows that the demand channel alone generates a mean relative spillover of

[19] The comparison of (A) and (B) does not deliver a clean additive attribution of the domino channel. Because non-oil workers are absent from the reallocation market in scenario (B), the equilibrium wages that oil workers face differ from those in the baseline, so the oil worker flows themselves change. The gap between (A) and (B) should therefore be read as quantifying the total general equilibrium contribution of the domino channel, with the oil worker reallocation response held endogenous.

[20] Appendix Figures A.8–A.11 repeat all four scenarios for oil price declines of 25 and 75 percent. The qualitative ordering is preserved at all shock sizes: scenario (B) consistently generates larger spillovers than the baseline (A), confirming that the equilibrating role of the domino channel is not specific to the 50 percent shock. The gap between scenarios (A) and (B) is particularly pronounced at the 25 percent shock, and appears more compressed at the 75 percent shock, suggesting that the equilibrating role of the domino channel may be relatively more important for moderate disruptions.

7.2%, somewhat larger than the baseline of 6.2%. Since no workers move, the demand channel shifts all NT wages by the same proportional amount within each CZ, so within-CZ dispersion is exactly zero by construction. The between-CZ standard deviation of 0.040 exceeds the baseline of 0.033: without reallocation, the cross-CZ variation in oil exposure translates more directly into wage dispersion across regions.

Scenario (D): Frictionless reallocation. In this scenario all movement costs are set to zero. Column (D) in Table 4 shows that removing frictions reduces the mean relative spillover from 6.2% to 5.3% but substantially amplifies the maximum from 32.0% to 57.1%. The within-CZ standard deviation of log real NT wage changes rises markedly from 0.015 in the baseline to 0.050, while between-CZ dispersion falls slightly from 0.033 to 0.031. As discussed in Appendix D, the direction of the within-CZ effect is theoretically ambiguous, but the simulations show that in the Norwegian context removing frictions amplifies rather than compresses cross-sector wage differences within CZs. Overall, the estimated movement frictions have modest average effects but matter significantly for the distributional pattern.[21]

Real income across scenarios. The mean log real income loss is largest under scenario (C) at -4.2% and smallest under scenario (D) at -0.1%, with the baseline (A) and scenario (B) both intermediate. The standard deviation of log real income changes across CZs follows the reverse ordering, largest under scenario (C) at 0.040 and smallest under scenario (D) at 0.025, with (A) and (B) in between. More reallocation thus compresses the cross-CZ income gradient, while the absence of any adjustment under scenario (C) allows oil exposure to map directly into income dispersion across regions.[22]

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 earnings 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 aggregate and distributional effects of sector specific shocks more accurately than existing models. Through counterfactual simulations, the model reveals

[21] Appendix Figure A.11 shows the frictionless scenario (D) across shock sizes. The mean spillover relative to the baseline (A) is broadly stable, but within-CZ dispersion under scenario (D) is somehow larger at smaller shock sizes.

[22] As shown in Appendix D, the real income difference between any two scenarios decomposes into an income channel and a price relief channel. For the B vs. C comparison, the price relief term is non-negative since oil worker inflows raise NT labor supply and lower NT prices, but the income term is not unconditionally signed. All comparison rankings are verified by the simulations for all 46 Norwegian CZs.

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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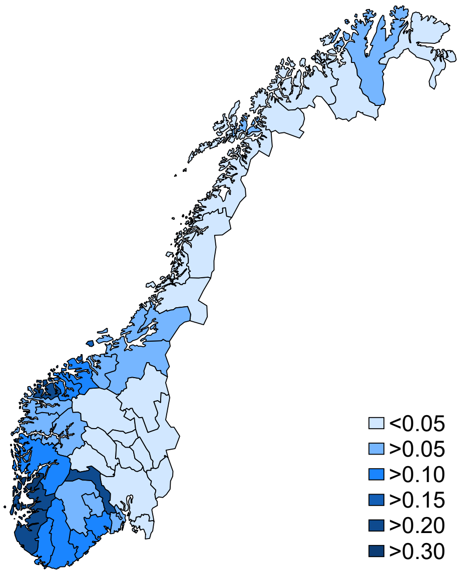
Appendices

A Supplementary figures and 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	41.644	41.445	41.380	37.581
Female	0.552	0.455	0.185	0.236
College education	0.391	0.546	0.391	0.504
log $y_{i,r,s}$	0.000	-0.006	0.235	0.149
log $y_{i,r,s}$, residualised	0.000	-0.019	0.180	0.114
Moving across sectors	0.063	0.118	0.149	1.000
Moving across CZs	0.015	0.031	0.031	0.093
Moving across sectors and CZs	0.005	0.010	0.013	0.093
Remaining fulltime employed	0.375	0.712	0.747	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 minus average log earnings for all workers in 2013; average log residualized earnings minus average log residualized earnings 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	37.581	0.236	0.504
Elect. and gas supply	44.199	0.229	0.456
Construction	40.640	0.063	0.122
Accommodation, food service	38.592	0.493	0.228
Information and communication	40.159	0.277	0.654
Financial and insurance act.	42.541	0.461	0.614
Real estate activities	42.480	0.318	0.456
Prof., scientific, tech. act.	40.800	0.390	0.703
Admin., support service	40.171	0.370	0.291
Public adm., defence, soc. security	43.125	0.470	0.655
Education	42.569	0.612	0.871
Human health, social work	41.698	0.768	0.645
Arts, entertainment and recreation	41.247	0.425	0.547
Other service act.	41.931	0.626	0.387

Notes: The first row presents characteristics of workers who moved from the oil sector to non-tradable sectors between 2013 and 2017 (oil movers). The remaining rows present average characteristics of all full-time employed or self-employed workers in each non-tradable sector in 2013, provided for comparison with the incoming oil movers. 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.

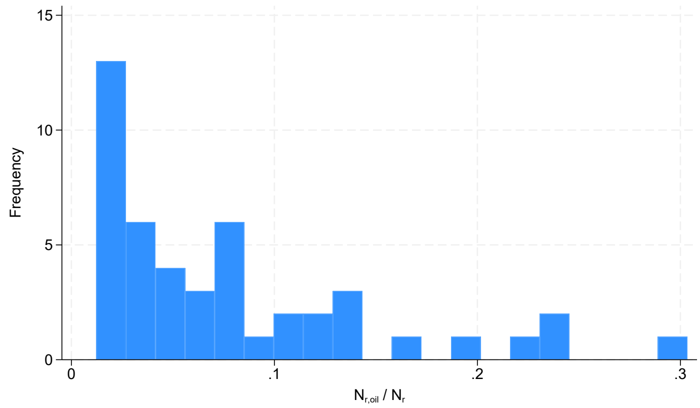
Table A.3: Relevance: Exposure and oil worker inflows

	(1)	(2)	(3)
	$\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$	$\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$	$\log \frac{N_{r,s}+\Delta N_{r,oil,s}}{N_{r,s}}$
$\mathbb{Z}_{r,s}$	5.945	4.330	4.180
	(0.206)	(0.375)	(0.409)
$\mathbb{Z}_{r,s}^{Trade}$			0.000287
			(0.0507)
Sales to local oil sector			0.254
			(0.274)
R-squared	0.583	0.660	0.661
Fixed effects	No	Yes	Yes
Observations	598	598	598

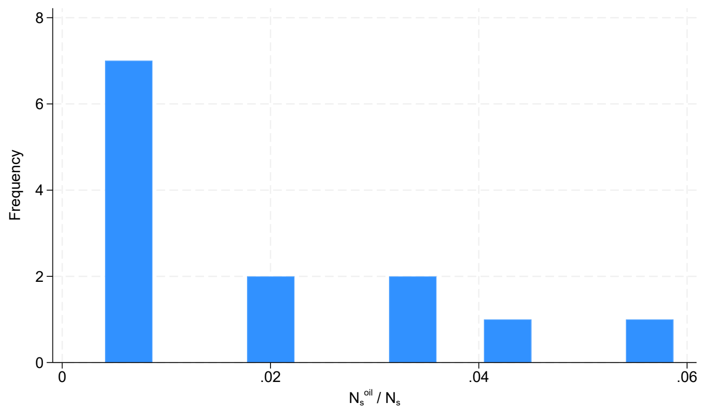
Notes: $\Delta N_{r,oil,s}$ is the number of workers moving from the oil sector to sector s in commuting zone r over the period 2013–2017. $\mathbb{Z}_{r,s}^{Trade} = \frac{N_{Trade,r}}{N_r} \cdot \frac{N_s^{Trade}}{N_s}$, where *Trade* includes all tradable sectors except the oil sector. *Sales to local oil sector* is 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 CZ. All variables are measured in the baseline year 2013. Columns (2) and (3) include sector and CZ fixed effects. Standard errors in parentheses.

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

(a) Across CZs



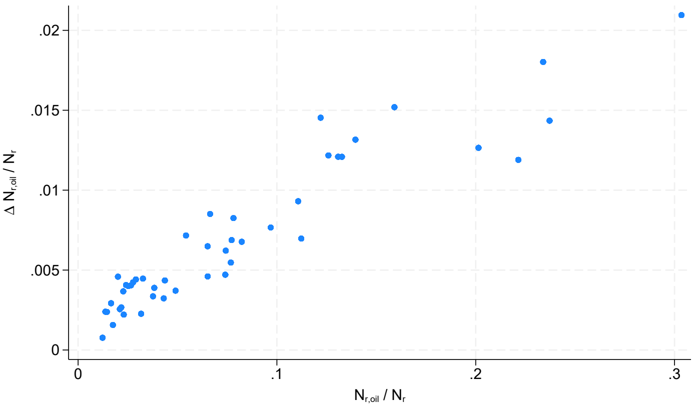
(b) Across sectors



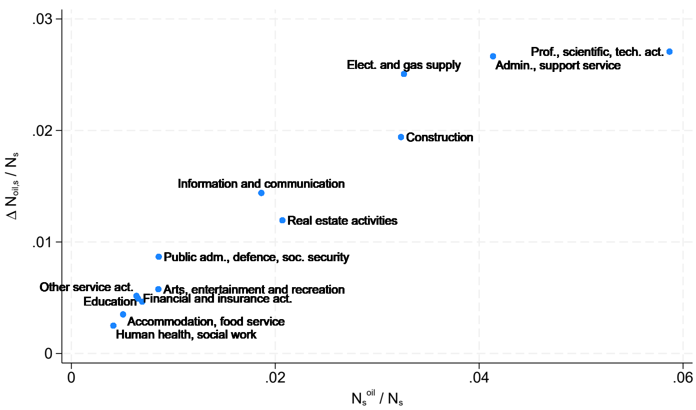
Notes: Panel (a) reports the frequency of $N_{oil,r}/N_r$ across CZs. Panel (b) reports the frequency N_s^{oil}/N_s across sectors. $N_{oil,r}$ is the number of workers working in the oil sector in commuting zone r, N_r the number of workers located in commuting zone r, N_s^{oil} is the number of workers 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.

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

(a) Variation across CZs

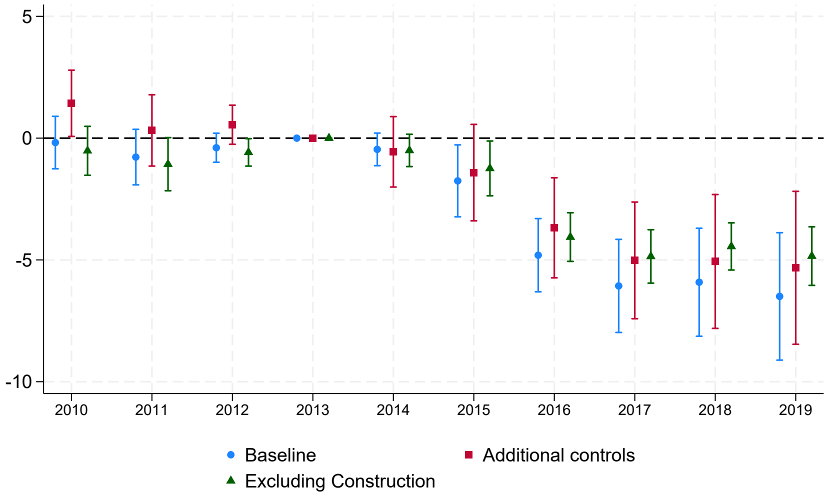


(b) Variation across sectors



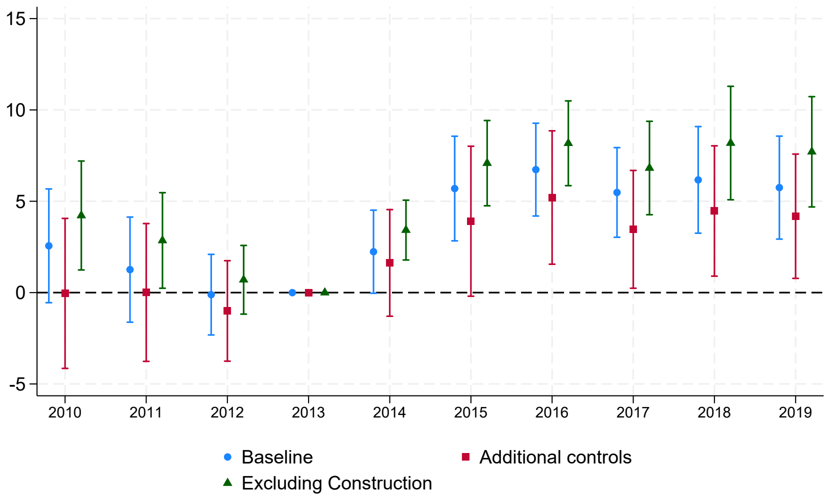
Notes: In panel A.3a the horizontal axis measures the share of workers working in the oil sector in the pre-period 2013. $N_{oil,r}$ is the number of workers working in the oil sector in CZ r, and N_r is the number of workers located in CZ r. The vertical axis measures the share of workers moving out 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.

Figure A.4: Log wages for stayers in non-tradable sectors: robustness across specifications



Notes: The figure reports β^k with 95% confidence intervals for the years 2010 to 2019 by estimating Equation (20) under three specifications. The baseline specification (blue) is identical to that reported in Figure 3. The additional controls specification (red) augments the baseline with two controls, each interacted with year indicators so that they vary at the CZ-sector-year level and are not absorbed by the CZ-sector fixed effects: (i) the trade-flow exposure measure $\mathbb{Z}_{r,s}^{Trade}$, where $\mathbb{Z}_{r,s}^{Trade} = \frac{N_{Trade,r}}{N_r} \cdot \frac{N_s^{Trade}}{N_s}$; and (ii) a variable interacting each sector's initial share of sales to the oil sector with the relative size of the oil sector in the CZ. The excluding construction specification (green) re-estimates the baseline excluding construction workers from the sample. Coefficients are normalized to zero in 2013. The sample includes stayers in NT sectors, defined as workers observed in their baseline sector and commuting zone in each year from 2013 to 2017. The x-axis measures year t. Included fixed effects are worker, CZ-sector, commuting zone-year, and sector-year. Standard errors are clustered at the CZ-sector level.

Figure A.5: Probability of leaving the baseline sector-CZ and oil worker inflows: robustness across specifications



Notes: The figure reports β^k with 95% confidence intervals for the years 2010 to 2019 by estimating Equation (22) under three specifications. The baseline specification (blue) is identical to that reported in Figure 5. The additional controls specification (red) augments the baseline with two controls, each interacted with year indicators so that they vary at the CZ-sector-year level and are not absorbed by the CZ-sector fixed effects: (i) the trade-flow exposure measure $\mathbb{Z}_{r,s}^{Trade}$, where $\mathbb{Z}_{r,s}^{Trade} = \frac{N_{Trade,r}}{N_r} \cdot \frac{N_s^{Trade}}{N_s}$; and (ii) a variable interacting each sector's initial share of sales to the oil sector with the relative size of the oil sector in the CZ. The excluding construction specification (green) re-estimates the baseline excluding construction workers from the sample. Coefficients are normalized to zero in 2013. The sample includes all workers in baseline NT sectors. The outcome $D_{i,r,s,t}$ equals one if the worker is not observed in her baseline sector and commuting zone in year t. Fixed effects include worker, CZ-sector, CZ-year, and sector-year. Standard errors are clustered at the CZ-sector level.

Table A.4: 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.5: Estimated σ_s values

Sector	Elect & Const	Services	Financial	Scient & Tech	Public	Oil	Trade
σ_s	0.932	0.552	0.915	0.996	0.623	0.777	0.621
	(0.10)	(0.10)	(0.18)	(0.13)	(0.10)	(0.12)	(0.09)

Notes: The table presents estimated sectoral skill standard deviation parameters σ_s, computed as the square root of the estimated variance parameters. Bootstrapped standard errors in parentheses.

Table A.6: Model fit to non-targeted moments

	Actual π_{rs}	Actual λ_{rsk}	Actual $\overline{\log y_{rs}}$	Actual R_{rsk}
π_{rs}	1.614			
	(0.125)			
λ_{rsk}		0.814		
		(0.047)		
$\overline{\log y_{rs}}$			0.918	
			(0.142)	
R_{rsk}				0.235
				(0.148)
Constant	-0.078	0.000	0.034	0.529
	(0.021)	(0.000)	(0.016)	(0.076)
R^2	0.884	0.645	0.656	0.067
Observations	24	168	24	37

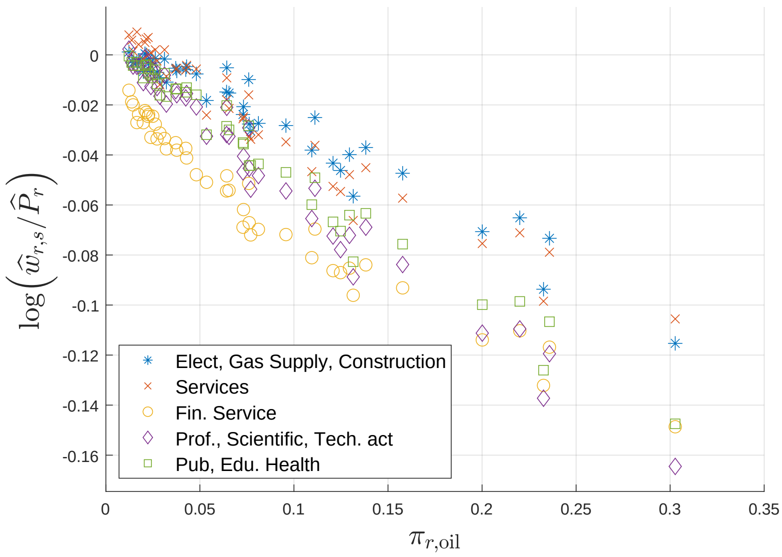
Notes: The table reports the estimated model fit coefficients from regressing the data moments measured in the data on the moments simulated by the SMM estimated model for non-targeted CZs. For the initial sectoral shares, the CZ-specific level parameters μ_{rs} are calibrated to each CZ, but the remaining structural parameters (σ_s^2, ρ_{sk}, c_{sk}) are fixed at the Stavanger estimates. 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, average sectoral earnings, and the standardized earning covariances. Standard errors are reported in parentheses.

Table A.7: Discussion Table

	No Move Costs		Zero skill correlations	
	λ_{rsk}	R_{rsk}	λ_{rsk}	R_{rsk}
λ_{rsk}	0.329		1.036	
	(0.056)		(0.121)	
R_{rsk}		1.005		0.608
		(0.045)		(2.262)
Constant	0.001	0.005	-0.000	0.234
	(0.000)	(0.026)	(0.001)	(1.244)
R^2	0.462	0.982	0.647	0.008

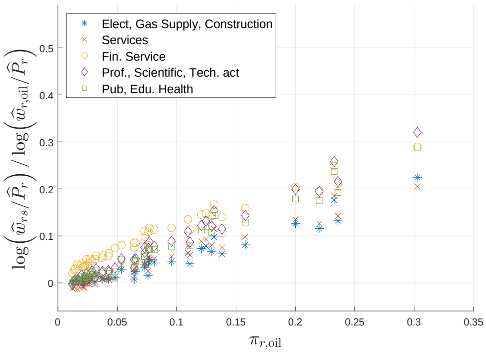
Notes: The table shows results from estimating alternative models on the targeted data used in the SMM exercies. Specifically, the two first collumns present results when regressing moments simulated by the model but with zero movement costs on the observed targeted data moments. The following two collumns present results when regressing moments simulated by the model but with zero skill correlations on observed targeted data moments. Standard errors in parentheses.

Figure A.6: Equilibrium effects across local non-tradable sectors

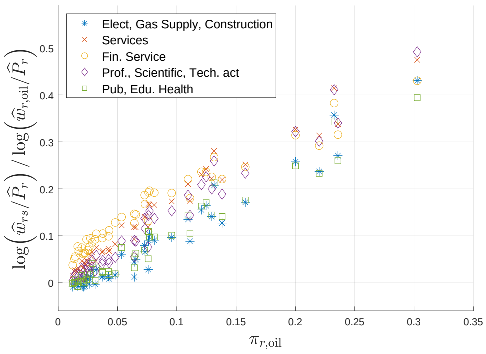


Notes: The figure shows the impact of the oil price collapse on real wage changes for non-tradable sectors across Norwegian CZs. Specifically, the horizontal axis measures the initial share of workers working in the oil sector for CZs r ($\pi_{r,oil}$), and the vertical axis measures the log real wage 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.

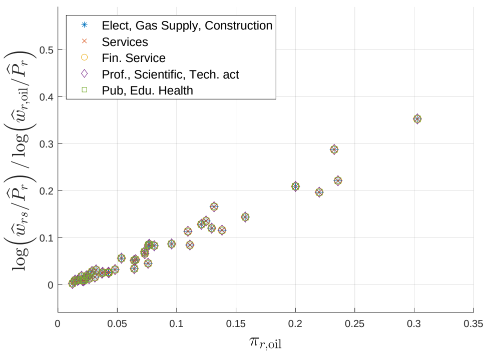
Figure A.7: Non-tradable real wage changes across counterfactual scenarios



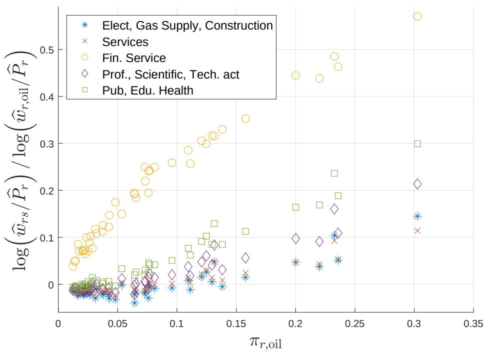
(a) Full counterfactual



(b) Oil workers only



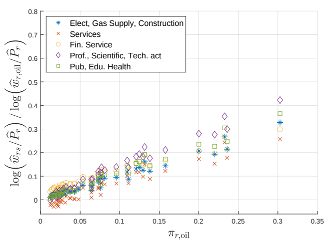
(c) No reallocation



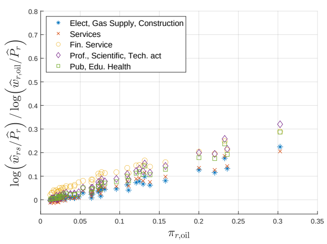
(d) Frictionless

Notes: Each point is a CZ–sector pair. The y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\mathrm{oil}}/\widehat{P}_r)$; the x-axis is $\pi_{r,\mathrm{oil}}$. Axis limits are identical across all panels. A 50 percent oil price decline. Scenario (A): full counterfactual with estimated movement costs. Scenario (B): only oil workers reallocate. Scenario (C): no reallocation; wages adjust through the demand channel only. Scenario (D): frictionless reallocation.

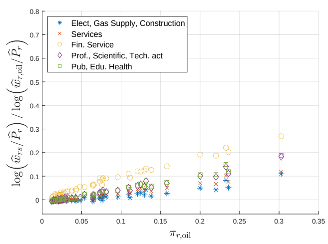
Figure A.8: Robustness to shock size: scenario (A) full counterfactual



(a) 25% decline



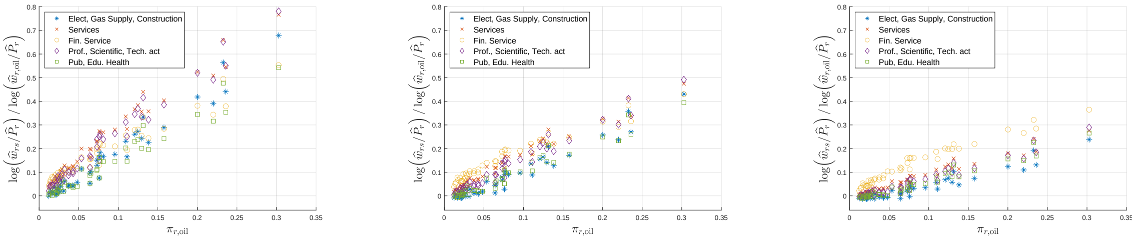
(b) 50% decline



(c) 75% decline

Notes: Full counterfactual (scenario A): all workers reallocate optimally given estimated movement costs. The y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\mathrm{oil}}/\widehat{P}_r)$ and the x-axis is $\pi_{r,\mathrm{oil}}$. Each point is a CZ–sector pair. Axis limits are common across all panels in Figures A.8–A.11.

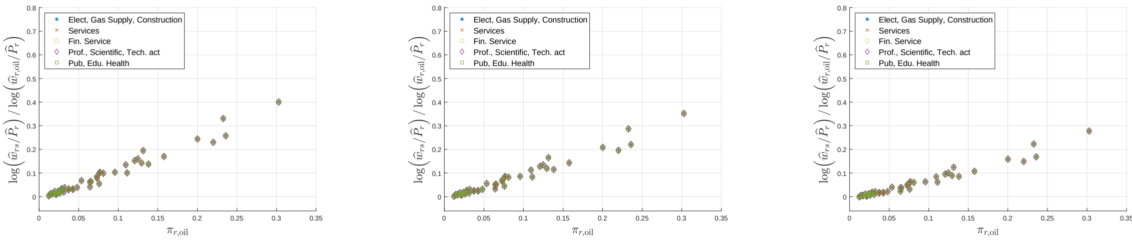
Figure A.9: Robustness to shock size: scenario (B) oil workers only



(a) 25% decline (b) 50% decline (c) 75% decline

Notes: Oil workers only (scenario B): oil workers reallocate optimally given estimated movement costs; non-oil workers are constrained to their initial sector, shutting down the domino channel. The y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\text{oil}}/\widehat{P}_r)$ and the x-axis is $\pi_{r,\text{oil}}$. Each point is a CZ–sector pair. Axis limits are common across all panels in Figures A.8–A.11.

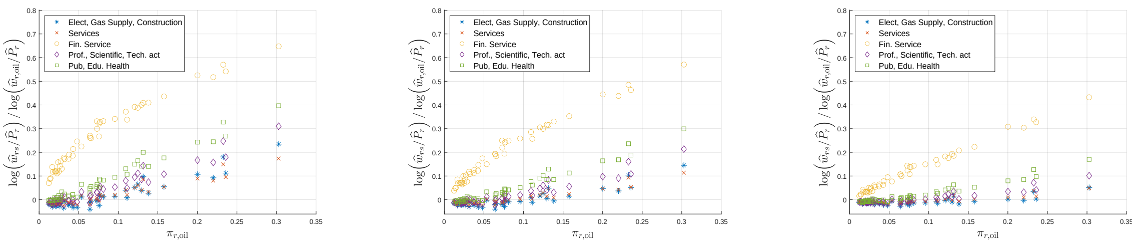
Figure A.10: Robustness to shock size: scenario (C) no reallocation



(a) 25% decline (b) 50% decline (c) 75% decline

Notes: No reallocation (scenario C): all workers remain in their initial sector and wages adjust through the aggregate demand channel only. The y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\text{oil}}/\widehat{P}_r)$ and the x-axis is $\pi_{r,\text{oil}}$. Each point is a CZ–sector pair. Axis limits are common across all panels in Figures A.8–A.11.

Figure A.11: Robustness to shock size: scenario (D) frictionless



(a) 25% decline (b) 50% decline (c) 75% decline

Notes: Frictionless reallocation (scenario D): same as scenario (A) but with all movement costs set to zero. The y-axis is $\log(\widehat{w}_{rs}/\widehat{P}_r)/\log(\widehat{w}_{r,\text{oil}}/\widehat{P}_r)$ and the x-axis is $\pi_{r,\text{oil}}$. Each point is a CZ–sector pair. Axis limits are common across all panels in Figures A.8–A.11.

B Model details

B.1 Deriving expressions

Sectoral shares A worker with a vector of potential income $\boldsymbol{y}_{ir}$, selects into sector s with probability

$$\pi_{irs} \equiv \frac{e^{\log y_{is}/\kappa}}{\sum_k e^{\log y_{ik}/\kappa}}, \tag{29}$$

such that for a local labor market r the share of workers working in a sector is given by

$$\pi_{rs} \equiv \frac{1}{N_r} \sum_{i=1}^{N_r} \pi_{irs}. \tag{30}$$

Initial average sectoral earnings

$$\overline{\log y}_s = \frac{\sum_i \pi_{irs} \log y_{is}}{\sum_i \pi_{irs}} \tag{31}$$

Probability of moving

$$\begin{aligned}
\lambda_{irod} &= \frac{e^{\log y_{iro}/\kappa}}{\sum_s e^{\log y_{irs}/\kappa}} \cdot \frac{e^{\left(\log y'_{ird} - \log c_{od}\right)/\kappa}}{\sum_s e^{\left(\log y'_{irs} - \log c_{os}\right)/\kappa}} \\
&= \pi_{iro} \cdot \frac{c_{od}^{-1/\kappa} \cdot e^{\left(\log y'_{ird}\right)/\kappa}}{\sum_s c_{os}^{-1/\kappa} \cdot e^{\left(\log y'_{irs}\right)/\kappa}} \\
&= \pi_{iro} \cdot \frac{c_{od}^{-1/\kappa} \cdot \pi'_{ird}}{\sum_s c_{os}^{-1/\kappa} \cdot \pi'_{i,s}} \\
&= \frac{c_{od}^{-1/\kappa}}{\sum_s c_{os}^{-1/\kappa} \pi'_{irs}} \cdot \pi_{iro} \cdot \pi'_{ird}
\end{aligned} \tag{32}$$

Then,

$$\lambda_{rod} = \frac{1}{N} \sum_{i=1}^{N} \frac{c_{od}^{-1/\kappa}}{\sum_s c_{os}^{-1/\kappa} \pi'_{irs}} \cdot \pi_{iro} \pi'_{ird} \tag{33}$$

The individual moving probabilities from origin sector o sum over destination sectors to the individual probability of selecting origin sector o in the initial period:

$$\begin{aligned}\sum_d \lambda_{irod} &= \sum_d \frac{c_{od}^{-1/\kappa}}{\sum_s c_{os}^{-1/\kappa}\pi'_{irs}} \cdot \pi_{iro} \cdot \pi'_{ird} \\ &= \pi_{iro} \cdot \sum_d \frac{c_{od}^{-1/\kappa}}{\sum_s c_{os}^{-1/\kappa}\pi'_{irs}} \cdot \pi'_{ird} \\ &= \pi_{iro} \cdot \frac{\sum_d c_{od}^{-1/\kappa}\pi'_{ird}}{\sum_s c_{os}^{-1/\kappa}\pi'_{irs}} \\ &= \pi_{iro}\end{aligned} \tag{34}$$

Earnings covariance Since $\log \widetilde{y}_{irs} = \log z_{is}$ and $\log \widetilde{y}'_{irk} = \log z_{ik}$ (skills are time-invariant), the λ-weighted covariance of residualized earnings for workers moving from sector s to sector k is defined directly as

$$\text{Cov}^{\text{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) \equiv \frac{\sum_i \lambda_{irsk} (\log z_{is} - \bar{z}_s)(\log z_{ik} - \bar{z}_k)}{\sum_i \lambda_{irsk}} \tag{35}$$

where $\bar{z}_s = \frac{\sum_i \lambda_{irsk} \log z_{is}}{\sum_i \lambda_{irsk}}$ and $\bar{z}_k = \frac{\sum_i \lambda_{irsk} \log z_{ik}}{\sum_i \lambda_{irsk}}$ are the λ-weighted means. Expanding (35) gives the equivalent form used in the estimation:

$$\text{Cov}^{\text{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) = \frac{\sum_i \lambda_{irsk} \log z_{is} \log z_{ik}}{\sum_i \lambda_{irsk}} - \frac{(\sum_i \lambda_{irsk} \log z_{is})(\sum_i \lambda_{irsk} \log z_{ik})}{(\sum_i \lambda_{irsk})^2} \tag{36}$$

which is identical to Equation (16) in the main text.

The initial sector-specific earnings variances, used to standardize the covariance into R_{rsk}, are defined as the π-weighted variance of residualized earnings:

$$\text{Var}^{\text{Obs.}}(\log \widetilde{y}_{irs}) \equiv \frac{\sum_i \pi_{irs} (\log z_{is} - \bar{z}_s^{\pi})^2}{\sum_i \pi_{irs}} \tag{37}$$

where $\bar{z}_s^{\pi} = \frac{\sum_i \pi_{irs} \log z_{is}}{\sum_i \pi_{irs}}$ is the π-weighted mean of log skills in sector s.

B.2 Comparative statics w.r.t. movement costs

I provide analytical expressions for how the probability of moving between sectors and the observed sectoral earnings correlations depend on the costs of moving between sectors.

$$
\begin{aligned}
\frac{\partial\lambda_{irod}}{\partial c_{od}} &= \frac{-\frac{1}{\kappa}\, c_{od}^{\frac{-(1+\kappa)}{\kappa}} \left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right) - c_{od}^{-1/\kappa}\left(-\frac{1}{\kappa}\right) c_{od}^{\frac{-(1+\kappa)}{\kappa}}\pi'_{ird}}{\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right)^2}\pi_{iro}\pi'_{ird} \\
&= \frac{-\frac{1}{\kappa} c_{od}^{\frac{-(1+\kappa)}{\kappa}}\left[\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right) - c_{od}^{-1/\kappa}\pi'_{ird}\right]}{\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right)^2}\pi_{iro}\pi'_{ird} \\
&= \frac{-\frac{1}{\kappa} c_{od}^{-1}\left[\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right) - c_{od}^{-1/\kappa}\pi'_{ird}\right]}{\sum_s c_{os}^{-1/\kappa}\pi'_{irs}}\lambda_{irod} \\
&= -\frac{1}{\kappa}\left(1-\frac{\lambda_{irod}}{\pi_{iro}}\right)\frac{\lambda_{irod}}{c_{od}} \leq 0
\end{aligned}
\tag{38}
$$

$$
\begin{aligned}
\frac{\partial\lambda_{irod}}{\partial c_{ok}} &= \frac{-c_{od}^{-1/\kappa}\left(-\frac{1}{\kappa}\right) c_{ok}^{-\frac{1+\kappa}{\kappa}}\pi'_{irk}}{\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right)^2}\pi_{iro}\pi'_{ird} \\
&= \frac{\frac{1}{\kappa} c_{ok}^{-\frac{1+\kappa}{\kappa}}\pi'_{irk}}{\left(\sum_s c_{os}^{-1/\kappa}\pi'_{irs}\right)}\lambda_{irod} \\
&= \frac{1}{\kappa}\frac{\lambda_{irok}}{\pi_{iro}}\frac{\lambda_{irod}}{c_{ok}} \geq 0
\end{aligned}
\tag{39}
$$

$$
\frac{\partial\lambda_{irod}}{\partial c_{sk}} = 0 \;\text{ for }\; s \neq o \neq d \;\text{ and }\; k \neq o \neq d \tag{40}
$$

Expressions (38) show that the individual probability of moving from origin sector o to destination sector d is decreasing in the cost of moving between the two sectors, c_{od}, increasing in the cost of moving from the same origin sector to a different destination sector, c_{os}, and unaffected by the cost of moving between any other sector pair c_{sk}.

$$
\begin{aligned}
\frac{\partial \mathrm{Cov}^{\mathrm{Obs.}}\left(\log\widetilde{y}_{irs}, \log\widetilde{y}'_{irk}\right)}{\partial c_{sk}} = {} & \frac{1}{(N\lambda_{rsk})^2}\Bigg[\left(\sum_i \frac{\partial\lambda_{irsk}}{\partial c_{sk}}\log z_{is}\log z_{ik}\right)N\lambda_{rsk} \\
& -N\frac{\partial\lambda_{rsk}}{\partial c_{sk}}\left(\sum_i \lambda_{irsk}\log z_{is}\log z_{ik}\right)\Bigg] \\
& -\frac{1}{(N\lambda_{rsk})^4}\Bigg((N\lambda_{rsk})^2\Bigg[\\
& \left(\sum_i \frac{\partial\lambda_{irsk}}{\partial c_{sk}}\log z_{is}\right)\left(\sum_i \lambda_{irsk}\log z_{ik}\right) \\
& +\left(\sum_i \lambda_{irsk}\log z_{is}\right)\left(\sum_i \frac{\partial\lambda_{irsk}}{\partial c_{sk}}\log z_{ik}\right) \\
& -2N\lambda_{rsk}\frac{\partial\lambda_{rsk}}{\partial c_{sk}}N\left(\sum_i \lambda_{irsk}\log z_{is}\right)\left(\sum_i \lambda_{irsk}\log z_{ik}\right)\Bigg]\Bigg)
\end{aligned}
\tag{41}
$$

B.3 Earnings covariance and symmetry

The expression for earnings covariance for moving workers can be rewritten as

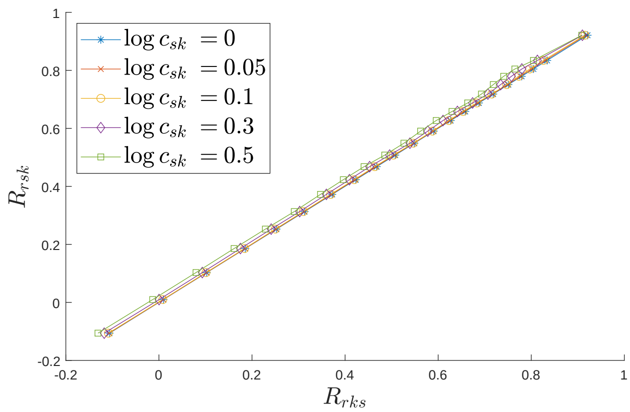
$$\mathrm{Cov}^{\mathrm{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) = \frac{\sum_i \frac{\lambda_{irsk}}{\lambda_{irks}} \lambda_{irks} \log z_{is} \log z_{ik}}{\sum_i \frac{\lambda_{irsk}}{\lambda_{irks}} \lambda_{irks}} - \frac{\left(\sum_i \frac{\lambda_{irsk}}{\lambda_{irks}} \lambda_{irks} \log z_{is}\right)\left(\sum_i \frac{\lambda_{irsk}}{\lambda_{irks}} \lambda_{irks} \log z_{ik}\right)}{\left(\sum_i \frac{\lambda_{irsk}}{\lambda_{irks}} \lambda_{irks}\right)^2} \tag{42}$$

In Appendix C.1, I show that for zero or constant movement costs across sectors, $\lambda_{irsk}/\lambda_{irks}$ is constant across workers and equal to $\lambda_{rsk}/\lambda_{rks}$. Hence, for low movement costs, the earnings covariance can be approximated as symmetric across sector pairs:

$$\mathrm{Cov}^{\mathrm{Obs.}}(\log \widetilde{y}_{irs}, \log \widetilde{y}'_{irk}) \approx \mathrm{Cov}^{\mathrm{Obs.}}(\log \widetilde{y}_{irk}, \log \widetilde{y}'_{irs}) \,.$$

This is a particularly useful result, as it allows for measuring the observed earnings covariance in the data by pooling workers moving in both directions of a sector pair, which increases precision when measuring moments. Figure A.12 shows a model simulation of the relationship.

Figure A.12: Symmetry of R_{rsk}



Notes: The figure displays the relationship of R_{rsk} and R_{rks} for different values of movement costs. The values are increasing as the skill correlation between the two sectors ρ_{sk} is changing. The set of wage changes $\widehat{w}_{rs}$ identified in Section 5.4 for the CZ Stavanger. Sector s is Oil, and sector k is Financial Services. Other parameters than those presented are fixed as follows: σ_s^2 values are equal to one, ρ_{sk} values are equal to zero, μ_{rs} values are equal to zero, and c_{sk} values are equal to one.

C Estimation details

C.1 Estimating κ

Due to idiosyncratic non-wage utility draws and finite movement costs, the model allows for worker reallocation in both directions between any pair of sectors, including movements toward sectors with relatively lower wage growth. The parameter κ governs the dispersion of the idiosyncratic non-wage utility component. As κ increases, idiosyncratic preferences become more important relative to wages in workers' sectoral choices, leading to larger gross flows in both directions of sector pairs. This contrasts with a frictionless Roy model without idiosyncratic utility components or mobility frictions, in which workers move exclusively toward sectors experiencing relative wage increases. In this appendix section, I show how κ can be disciplined using observed relative sectoral wage changes and the relative magnitude of worker flows across sector pairs.

When movement costs are absent or invariant to the origin sector, the model implies the following relationship:

$$\log \frac{\lambda_{rsk}}{\lambda_{rks}} = \frac{1}{\kappa} \log \frac{\widehat{w}_{rk}}{\widehat{w}_{rs}}, \tag{43}$$

where λ_{rsk} denotes the share of workers moving from sector s to sector k within region r, and $\widehat{w}_{rs}$ denotes the proportional wage change in sector s. Equation (43) holds with equality in a model without movement costs, and more generally when movement costs are invariant to the origin sector, i.e., $c_{kq} = c_{sq}$ for all destination sectors q. When movement costs vary across origin sectors but are small relative to wage differences, Equation (43) continues to hold as an approximation. Details of the derivation are provided below. The expression shows that $1/\kappa$ can be interpreted as an elasticity linking relative worker flows between two sectors to relative sectoral wage changes. When wage changes differ substantially across sectors, a low value of κ, which corresponds to a strong Roy component, implying a large imbalance in worker flows toward the higher-wage sector. Conversely, when worker flows are similar in both directions despite large wage differentials, κ must be large, indicating that idiosyncratic non-wage utility plays a more prominent role in shaping sectoral reallocation. Thus, $1/\kappa$ summarizes the relative importance of the Roy component of the model.

I take Equation (43) 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 a set of 5 CZs.[23] I set $\kappa = 0.13$, a value above the point estimates but within the 95% confidence intervals of all specifications in Table A.8, to ensure sufficient numerical smoothing of the simulated choice probabilities

[23]Equation (43) holds exactly under absent or origin-invariant movement costs. With heterogeneous movement costs, it holds as an approximation when costs are small relative to wage differences, and OLS identifies κ under this approximation rather than as an exact implication of the full model.

Table A.8

	(1) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(2) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$	(3) $\log \frac{\lambda_{r,s,k}}{\lambda_{r,k,s}}$
$\log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$	11.54	12.28	
	(3.307)	(4.200)	
$\mathbb{I}$(Bergen) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			19.81
			(4.950)
$\mathbb{I}$(Kristiansand) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			26.91
			(6.008)
$\mathbb{I}$(Oslo) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			7.671
			(4.270)
$\mathbb{I}$(Stavanger) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			19.60
			(4.215)
$\mathbb{I}$(Tromso) $\times \log \frac{\widehat{w}_{r,k}}{\widehat{w}_{r,s}}$			7.389
			(2.034)
Implied κ	0.0866	0.0814	0.0809
R-squared	0.324	0.337	0.428
CZ Fixed Effects	No	Yes	No
Observations	104	104	104

Notes: The regressions in this table estimate Equation (43). The second specification includes CZ fixed effects. Standard errors, clustered at the CZ level, in parentheses.

in the SMM estimation.

Deriving Equation (43) I derive the relationship between relative worker flows and relative sectoral wage changes implied by the model. Let λ_{irsk} denote the probability that worker i in region r moves from origin sector s to destination sector k. Using the multinomial logit choice probabilities implied by Equation (5), the ratio of movement probabilities across a sector pair can be written as

$$\frac{\lambda_{irsk}}{\lambda_{irks}} = \frac{\frac{c_{sk}^{-1/\kappa}}{\sum_q c_{sq}^{-1/\kappa}\,\pi'_{iq}}}{\frac{c_{ks}^{-1/\kappa}}{\sum_q c_{kq}^{-1/\kappa}\,\pi'_{iq}}} \cdot \frac{\frac{\exp(\log y'_{irk}/\kappa)}{\Phi'_{ir}}\,\frac{\exp(\log y_{irs}/\kappa)}{\Phi_{ir}}}{\frac{\exp(\log y'_{irs}/\kappa)}{\Phi'_{ir}}\,\frac{\exp(\log y_{irk}/\kappa)}{\Phi_{ir}}}, \tag{44}$$

where

$$\Phi_{ir} = \sum_s \exp\left(\frac{\log y_{irs}}{\kappa}\right)$$

denotes the pre-shock wage aggregator, and Φ'_{ir} is defined analogously for post-shock wages.

Simplifying Equation (44) yields

$$\begin{aligned}
\frac{\lambda_{irsk}}{\lambda_{irks}} &= \frac{\sum_q c_{kq}^{-1/\kappa}\,\pi'_{iq}}{\sum_q c_{sq}^{-1/\kappa}\,\pi'_{iq}} \cdot \frac{\exp(\log y'_{irk}/\kappa)\exp(\log y_{irs}/\kappa)}{\exp(\log y'_{irs}/\kappa)\exp(\log y_{irk}/\kappa)} \\
&= \frac{\sum_q c_{kq}^{-1/\kappa}\,\pi'_{iq}}{\sum_q c_{sq}^{-1/\kappa}\,\pi'_{iq}} \cdot \exp\left(\frac{\log y'_{irk} + \log y_{irs} - \log y'_{irs} - \log y_{irk}}{\kappa}\right) \\
&= \frac{\sum_q c_{kq}^{-1/\kappa}\,\pi'_{iq}}{\sum_q c_{sq}^{-1/\kappa}\,\pi'_{iq}} \cdot \exp\left(\frac{\log \widehat{y}_{irk} - \log \widehat{y}_{irs}}{\kappa}\right) \\
&= \frac{\sum_q c_{kq}^{-1/\kappa}\,\pi'_{iq}}{\sum_q c_{sq}^{-1/\kappa}\,\pi'_{iq}} \cdot \exp\left(\frac{\log \widehat{w}_{rk} - \log \widehat{w}_{rs}}{\kappa}\right),
\end{aligned} \tag{45}$$

where $\widehat{y}_{irs} \equiv y'_{irs}/y_{irs}$ and $\widehat{w}_{rs}$ denotes the corresponding sector-level wage change.

Equation (45) shows that the ratio of worker flows across a sector pair depends on both relative wage changes and a mobility-cost term. When movement costs are absent, or when they are invariant to the origin sector such that $c_{kq} = c_{sq}$ for all destination sectors q, the mobility-cost term cancels out and Equation (45) simplifies to

$$\frac{\lambda_{rsk}}{\lambda_{rks}} = \exp\left(\frac{\log \widehat{w}_{rk} - \log \widehat{w}_{rs}}{\kappa}\right).$$

When movement costs vary across origin sectors but are small relative to wage differences, this expression continues to hold as an approximation. Taking logs yields

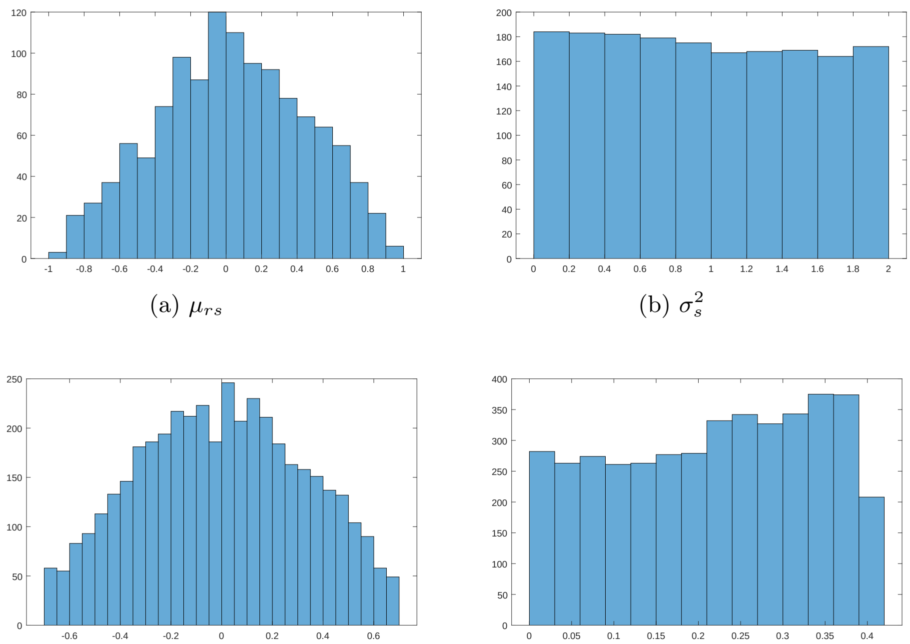
$$\log \frac{\lambda_{rsk}}{\lambda_{rks}} \approx \frac{1}{\kappa} \log \frac{\widehat{w}_{rk}}{\widehat{w}_{rs}},$$

which corresponds to Equation (43).

C.2 Monte Carlo simulations

I report Monte Carlo simulation results where I draw random sets of parameters, simulate targeted moments from the model, re-estimate parameters by SMM, and test how well the estimated parameters recover the true ones.[24] The simulations use the sectoral wage changes identified in Section 5.4. The randomly drawn parameters span a wide range of the parameter space, as shown in Figure A.13. Table A.9 reports the linear fit between true and estimated parameters for the full simulation sample. Figure A.14 shows that as the sample is restricted to simulations achieving a low value of the objective function at the minimum, the fit coefficient approaches one, the constant approaches zero, and R^2 approaches one across all parameter types. This indicates that imprecise recovery in the full sample is driven by simulations that do not reach the minimum rather than by a failure of identification.

Figure A.13: Monte Carlo simulations: Distribution of parameter draws



(a) μ_{rs} (b) σ_s^2

(c) ρ_{sk} (d) $\log c_{sk}$

Notes: The figure reports the linear fit coefficient, constant, and R^2 between true and SMM estimated parameters as the sample is progressively restricted to simulations achieving a lower value of the objective function at the minimum (the log residual). Results are shown separately for each parameter type.

As a complementary exercise, I simulate moments from the actual SMM estimates and test whether re-estimating the model on these moments recovers the original parameters. Table A.10 reports the results. The model recovers all parameters reasonably well, with particularly close recovery for the level and dispersion parameters, consistent with the larger bootstrap standard errors for the skill correlations

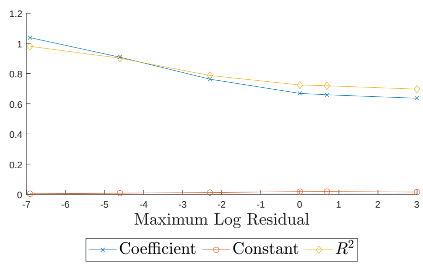
[24]The parameter draws are restricted to sets such that Σ is positive semidefinite, ensuring that all draws produce well-defined simulated moments.

Table A.9: Monte Carlo simulations

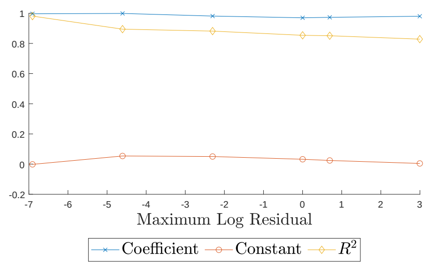
	$\mu_{r,s}$	σ_s^2	$\rho_{s,k}$	$c_{s,k}$
$\mu_{r,s}^{SSM}$	0.637			
	(0.012)			
$\sigma_s^{2\ SSM}$		0.984		
		(0.014)		
$\rho_{s,k}^{SSM}$			0.758	
			(0.016)	
$c_{s,k}^{SSM}$				0.554
				(0.009)
Constant	0.015	-0.008	0.002	0.562
	(0.006)	(0.016)	(0.004)	(0.012)
R^2	0.665	0.771	0.361	0.467
Observations	1400	1400	4200	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) μ_{rs}, (b) σ_s^2, (c) ρ_{rs}, and (d) c_{sk}. Standard errors, in parentheses.

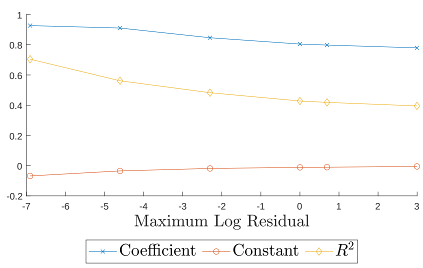
Figure A.14: Monte Carlo simulations: Results by degree of convergence



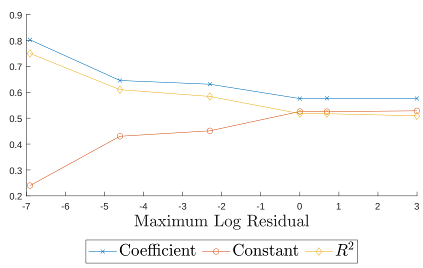
(a) μ_{rs}



(b) σ_s^2



(c) ρ_{sk}



(d) c_{sk}

Notes: The figure display the results of the Monte Carlo simulation when SMM simulations are exculded based on the log residual, which is the log value of the objective function at the minimum. The figure display the results of the different parameter types separately.

and movement costs reported in Tables 1 and 2.

Table A.10: Finding back to the estimated parameters

	μ_{rs}	σ_s^2	ρ_{sk}	c_{sk}
μ_{rs}^{SSM}	1.264			
	(0.211)			
$\sigma_s^{2\ SSM}$		1.192		
		(0.148)		
ρ_{sk}^{SSM}			0.705	
			(0.140)	
c_{sk}^{SSM}				0.412
				(0.131)
Constant	0.024	-0.058	-0.009	0.652
	(0.131)	(0.100)	(0.051)	(0.149)
R^2	0.900	0.928	0.571	0.342
Observations	6	7	21	21

Notes: The regressions in this table estimate the SMM estimated parameters on the estimated 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) μ_{rs}, (b) σ_s^2, (c) ρ_{rs}, and (d) c_{sk}. Standard errors, in parentheses.

C.3 Bootstrapped Standard Errors

The reported standard errors of the estimated skill distribution parameters reported in Table 1, 2, and Table A.5 are constructed by bootstrap. I contruct the bootstrapped standard errors in the following way. First, I construct 200 boostrap samples in the micro data. 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. For all these 200 bootstrap estimations, I use the same κ value and estimated wage changes $\widehat{w}_{rs}$ as in the main parameter estimation. Forth, I construct the reported standard errors by constructing the standard diviations of the 200 estimated parameters.

D Theoretical Characterisation of the Scenarios

This appendix derives analytical predictions from the model on changes in sectoral real wages, aggregate nominal income, aggregate real income, and wage dispersion across the four counterfactual scenarios: (A) full counterfactual with estimated movement costs; (B) only oil workers reallocate; (C) no reallocation; (D) frictionless reallocation. The predictions identify which comparisons are signed by model structure alone and which depend on empirical conditions that the simulations verify.

D.1 Sectoral Real Wages

The equilibrium real wage change for a non-tradable sector s in CZ r follows directly from equation (18):

$$\log \frac{\widehat{w}_{rs}}{\widehat{P}_r} = \log \frac{\widehat{Y}_r}{\widehat{P}_r} - \log \widehat{Z}_{rs}.$$

A fall in total real income in market r lowers demand for non-tradable goods and reduces NT wages uniformly within the CZ, while any change in the supply of effective labor units $\widehat{Z}_{rs}$ generates additional variation across sectors within the CZ. To decompose these forces, I substitute the price index $\log \widehat{P}_r = \sum_s \beta_s \log \widehat{w}_{rs}$ and use the fact that for tradable sectors $\widehat{w}_{rj} = \widehat{p}_{rj}$. Substituting and rearranging yields:

$$\begin{aligned} \log \widehat{w}_{rs} - \log \widehat{P}_r &= \log \widehat{Y}_r - \log \widehat{Z}_{rs} - \sum_{j \in \mathrm{NT}} \beta_j (\log \widehat{Y}_r - \log \widehat{Z}_{rj}) - \sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj} \\ &= \beta_{\mathrm{T}} \log \widehat{Y}_r - \log \widehat{Z}_{rs} + \sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj} - \sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj}, \end{aligned} \tag{46}$$

where $\beta_{\mathrm{T}} = \sum_{j \in \mathrm{T}} \beta_j = 1 - \beta_{\mathrm{NT}}$. The four terms have distinct economic interpretations. The first, $\beta_{\mathrm{T}} \log \widehat{Y}_r$, is the income channel: a fall in nominal income lowers NT wages one-for-one, but also lowers the NT price index by $\beta_{\mathrm{NT}} \log \widehat{Y}_r$ since NT goods receive weight β_{NT} in the price index. The net real wage effect is therefore scaled by β_{T}: workers are compensated on their NT expenditure share through lower prices but bear the full loss on the tradable expenditure share whose prices do not adjust in equilibrium. The second, $-\log \widehat{Z}_{rs}$, is the own labor supply effect: inflows into sector s compress wages there specifically. This is the only term that varies across NT sectors within a CZ, so it is the sole source of cross-sector wage dispersion within a CZ. The third, $\sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj}$, is the price relief channel: worker inflows into NT sectors broadly lower NT prices, benefiting all consumers. The fourth, $-\sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj}$, captures changes in tradable prices, which are common across all scenarios and cancel in all comparisons.

The expenditure shares govern the relative importance of each channel in (46). A larger β_{T} increases the weight on the income channel $\beta_{\mathrm{T}} \log \widehat{Y}_r$ relative to the price relief term, so tradable sector labor allocation becomes more important for real wages. Conversely, a smaller β_{T} shifts the balance toward the price relief channel, so NT labor supply changes, including those generated by the domino channel, feed through more strongly to real wages.

D.2 Aggregate Nominal Income

Aggregate nominal income in CZ r equals total earnings across all sectors:

$$Y_r = \sum_s w_{rs} Z_{rs}. \tag{47}$$

Using the NT goods market equilibrium condition $\beta_s Y_r = w_{rs} Z_{rs}$ for all $s \in \mathrm{NT}$:

$$Y_r = \beta_{\mathrm{NT}} Y_r + \sum_{s \in \mathrm{T}} w_{rs} Z_{rs}. \tag{48}$$

Solving for Y_r:

$$Y_r = \frac{1}{\beta_{\mathrm{T}}} \sum_{s \in \mathrm{T}} w_{rs} Z_{rs}. \tag{49}$$

Aggregate nominal income depends only on earnings in the tradable sectors. NT sector earnings are always exactly $\beta_{\mathrm{NT}} Y_r$ by the equilibrium condition. Workers who move from oil to NT sectors therefore affect $\widehat{Y}_r$ only through the oil sector term. Their departure reduces $\widehat{Z}_{\mathrm{oil},r}$ and hence oil earnings, while their arrival in NT sectors does not directly raise Y_r'.

Defining the initial income share of tradable sector s as $\phi_s \equiv w_{rs} Z_{rs} / Y_r$, so that $\sum_{s \in \mathrm{T}} \phi_s = \beta_{\mathrm{T}}$, the change in nominal income is:

$$\widehat{Y}_r = \frac{\sum_{s \in \mathrm{T}} \phi_s \widehat{w}_{rs} \widehat{Z}_{rs}}{\beta_{\mathrm{T}}}. \tag{50}$$

Since Y_r is the same across all scenarios and tradable wages $\widehat{w}_{rs}$ are exogenously set and identical across scenarios, comparing nominal income across scenarios X and Y in levels gives:

$$\widehat{Y}_r^X - \widehat{Y}_r^Y = \frac{1}{\beta_{\mathrm{T}}} \sum_{s \in \mathrm{T}} \phi_s \widehat{w}_{rs} \left(\widehat{Z}_{rs}^X - \widehat{Z}_{rs}^Y \right), \tag{51}$$

and in logs:

$$\log \widehat{Y}_r^X - \log \widehat{Y}_r^Y = \log \frac{\sum_{s \in \mathrm{T}} \phi_s \widehat{w}_{rs} \widehat{Z}_{rs}^X}{\sum_{s \in \mathrm{T}} \phi_s \widehat{w}_{rs} \widehat{Z}_{rs}^Y}. \tag{52}$$

The nominal income difference between scenarios depends only on tradable sector labor input changes. The log difference (52) does not simplify further since the log of a ratio of weighted sums cannot be decomposed into separate sector contributions.

D.3 Aggregate Real Income

Substituting the price index into $\log(\widehat{Y}_r/\widehat{P}_r) = \log \widehat{Y}_r - \log \widehat{P}_r$ and splitting into NT and tradable sectors gives:

$$\log(\widehat{Y}_r/\widehat{P}_r) = \beta_{\mathrm{T}} \log \widehat{Y}_r + \sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj} - \sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj}. \tag{53}$$

The three terms mirror those in (46): the income effect $\beta_{\mathrm{T}} \log \widehat{Y}_r$, where $\widehat{Y}_r$ is determined by tradable sector labor allocation through (50); the price relief from NT labor supply changes $\sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj}$; and the tradable price term, which is common across all scenarios. Since the tradable price term cancels when comparing any two scenarios:

$$\log(\widehat{Y}_X/\widehat{P}_X) - \log(\widehat{Y}_Y/\widehat{P}_Y) = \beta_{\mathrm{T}}(\log \widehat{Y}_r^X - \log \widehat{Y}_r^Y) + \sum_{j\in\mathrm{NT}} \beta_j(\log \widehat{Z}_{X,rj} - \log \widehat{Z}_{Y,rj}). \tag{54}$$

This decomposition separates two channels: the income channel $\beta_{\mathrm{T}}(\log \widehat{Y}_r^X - \log \widehat{Y}_r^Y)$, characterised by (52) and driven by tradable sector labor allocation, and the price relief channel $\sum_{j\in\mathrm{NT}} \beta_j(\log \widehat{Z}_{X,rj} - \log \widehat{Z}_{Y,rj})$, driven by NT sector labor allocation. A larger β_{T} amplifies the income channel relative to price relief; a larger β_{NT} does the opposite. Neither term is generally signed without additional structure: the income term depends on whether tradable sector inflows dominate the loss from oil workers both facing a lower wage and leaving the sector, and the price relief term depends on the direction and magnitude of NT labor reallocation across scenarios. The rankings across all four scenarios are therefore verified empirically rather than derived analytically.

D.4 Comparing Scenarios: Aggregate Real Income

Applying (54) to each pairwise comparison, the real income difference between any two scenarios decomposes into an income channel and a price relief channel. For the B vs C comparison, the price relief term is non-negative since $\widehat{Z}_{B,rj} \geq 1$ for all NT sectors receiving oil worker inflows, while $\widehat{Z}_{C,rj} = 1$ for all j: oil worker inflows raise NT labor supply, lowering NT prices and benefiting consumers. The income term depends on whether the gain from oil-to-tradable moves outweighs the loss from oil workers both facing a lower wage and leaving the sector, which is not unconditionally signed. For the A vs B comparison, the difference in the expenditure-weighted price relief term, $\sum_{j\in\mathrm{NT}} \beta_j(\log \widehat{Z}_{rj}^A - \log \widehat{Z}_{rj}^B)$, reflects the full general equilibrium difference in NT labor reallocation between the two scenarios, including both the domino channel and the endogenous response of oil workers to changed NT wages. The sign depends on the β_j weights of the sectors gaining and losing workers under scenario A relative to B, and is not unconditionally signed. For the D vs A comparison, both terms are ambiguous for the same reasons. All three rankings, B vs C, A vs B, and D vs A, are verified by simulations.

D.5 Wage and Income Dispersion

Within-CZ dispersion in NT real wages. Within-CZ dispersion is $\mathcal{W}_r = \mathrm{sd}_s(\log \widehat{w}_{rs} - \log \widehat{P}_r)$, the standard deviation of log real wage changes across NT sectors within CZ r. The statistic reported in Table 4 is the mean of $\mathcal{W}_r$ across the 46 CZs, $\frac{1}{|\mathrm{CZ}|}\sum_r \mathcal{W}_r$. Since only the second term in (46) varies across sectors within a CZ:

$$\mathcal{W}_r = \mathrm{sd}_s\Big(\log \widehat{w}_{rs} - \log \widehat{P}_r\Big) = \mathrm{sd}_s\Big(\log \widehat{Z}_{rs}\Big), \quad s \in \mathrm{NT}. \tag{55}$$

Within-CZ dispersion equals the cross-sector standard deviation of log labor input changes. All terms in (46) that are common across sectors cancel exactly.

Under scenario C, $\widehat{Z}_{C,rs} = 1$ for all s and r, so $\mathcal{W}_r^C = 0$ exactly: all NT wages move proportionally within each CZ and there is no cross-sector dispersion. Under scenario B, oil worker inflows are not uniform across sectors, since the skill correlation structure and movement costs direct more workers into some sectors than others, so $\mathcal{W}_r^B = \mathrm{sd}_s(\log \widehat{Z}_{B,rs}) \geq 0$ and $\mathcal{W}_r^B \geq \mathcal{W}_r^C = 0$ unconditionally. Under scenario A, domino movers partially offset the oil inflows in the most compressed sectors; the net effect on within-CZ dispersion relative to B is ambiguous and depends on whether domino moves are concentrated in the sectors with the largest oil inflows or spread more broadly. Under scenario D, frictionless mobility allows workers to respond more fully to wage differences, tending to compress dispersion, but sharper sorting by comparative advantage concentrates inflows and amplifies dispersion.

Between-CZ dispersion in NT real wages. To characterise between-CZ dispersion, define $\bar{w}_r$ as the simple mean of the log real wage change across NT sectors within CZ r:

$$\bar{w}_r \equiv \frac{1}{|\mathrm{NT}|} \sum_{s \in \mathrm{NT}} \left(\log \widehat{w}_{rs} - \log \widehat{P}_r \right). \tag{56}$$

Taking the mean of (46) across NT sectors, terms 1, 3, and 4 pass through unchanged while term 2 averages to $-\overline{\log \widehat{Z}}_r \equiv -\frac{1}{|\mathrm{NT}|} \sum_{s \in \mathrm{NT}} \log \widehat{Z}_{rs}$. Combining the resulting NT terms gives:

$$\bar{w}_r = \beta_{\mathrm{T}} \log \widehat{Y}_r + \sum_{j \in \mathrm{NT}} \left(\beta_j - \frac{1}{|\mathrm{NT}|} \right) \log \widehat{Z}_{rj} - \sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj}. \tag{57}$$

Between-CZ dispersion is $\mathcal{B} = \mathrm{sd}_r(\bar{w}_r)$. Since the tradable price term is common across CZs it drops out, giving:

$$\mathcal{B} = \mathrm{sd}_r \left(\beta_{\mathrm{T}} \log \widehat{Y}_r + \sum_{j \in \mathrm{NT}} \left(\beta_j - \frac{1}{|\mathrm{NT}|} \right) \log \widehat{Z}_{rj} \right). \tag{58}$$

The expression has two components. The first, $\beta_{\mathrm{T}} \log \widehat{Y}_r$, is the income channel, which varies across CZs through differences in tradable sector labor allocation. The second, $\sum_{j \in \mathrm{NT}} (\beta_j - \frac{1}{|\mathrm{NT}|}) \log \widehat{Z}_{rj}$, is a weighted sum of NT labor input changes with weights $(\beta_j - \frac{1}{|\mathrm{NT}|})$, which are positive when $\beta_j > \frac{1}{|\mathrm{NT}|}$ and zero or negative otherwise. Between-CZ dispersion is large when either component has large cross-CZ variance, or when the two components covary positively across CZs.

Under scenario C, $\widehat{Z}_{C,rj} = 1$ for all j and r, so the NT term vanishes and (58) reduces to $\mathcal{B}^C = \beta_{\mathrm{T}} \cdot \mathrm{sd}_r(\log \widehat{Y}_{C,r})$: between-CZ dispersion reflects only cross-CZ variation in nominal income, which under scenario C is driven entirely by differences in oil exposure across CZs. Under scenarios B and A, reallocation introduces cross-CZ variation in the second term. Whether this raises or lowers $\mathcal{B}$ relative to scenario C depends on the variance of the second term and its covariance with the income channel, both of which depend on how unevenly worker inflows are distributed across CZs and whether the sectors receiving the most uneven inflows have β_j above or below $\frac{1}{|\mathrm{NT}|}$. This is an empirical question verified by the simulations.

Dispersion in aggregate real income. The standard deviation of aggregate real income changes across CZs is $\mathcal{R} = \mathrm{sd}_r(\log(\widehat{Y}_r/\widehat{P}_r))$. Since the tradable price term in (53) is common across CZs it drops out, giving:

$$\mathcal{R} = \mathrm{sd}_r\left(\beta_{\mathrm{T}} \log \widehat{Y}_r + \sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj}\right). \tag{59}$$

Comparing (59) to (58), the two statistics differ in the weight on NT labor input changes: $\mathcal{R}$ uses the full expenditure weights β_j, while $\mathcal{B}$ uses the re-centered weights $(\beta_j - \frac{1}{|\mathrm{NT}|})$. Using (57) and noting that the tradable price term drops out of the standard deviation:

$$\beta_{\mathrm{T}} \log \widehat{Y}_r + \sum_{j \in \mathrm{NT}} \beta_j \log \widehat{Z}_{rj} = \bar{w}_r + \overline{\log \widehat{Z}}_r + \sum_{j \in \mathrm{T}} \beta_j \log \widehat{p}_{rj}, \tag{60}$$

so $\mathcal{R} = \mathrm{sd}_r(\bar{w}_r + \overline{\log \widehat{Z}}_r)$: the dispersion in aggregate real income equals the dispersion of the CZ mean NT real wage plus the mean NT labor input change. Under scenario C, $\widehat{Z}_{C,rj} = 1$ for all j, so (59) reduces to $\mathcal{R}^C = \beta_{\mathrm{T}} \cdot \mathrm{sd}_r(\log \widehat{Y}_{C,r})$, identical to $\mathcal{B}^C$: without reallocation the two statistics coincide since $\overline{\log \widehat{Z}}_r = 0$. Under scenarios B and A they diverge as reallocation introduces cross-CZ variation in $\overline{\log \widehat{Z}}_r$.