Trapped or Transferred: Worker Mobility and Labor Market Power in the Energy Transition

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November 20, 2025

Abstract

Using matched employer-employee data covering 1.35 million US workers separated from the fossil fuel extraction industry between 1999 and 2019, I estimate how local fossil fuel labor demand shocks affect employment and earnings. Employment probabilities fall markedly after exposure, and earnings decline gradually over the first seven years with only partial recovery by ten years since exposure to the shocks. Workers who remain in the fossil fuel sector, disproportionately men in sector-specific roles, experience nearly twice the earnings losses of those who switch sectors, possibly due to limited occupational mobility. Among non-switchers, losses are larger in labor markets with high employer concentration, indicating that scarce outside options translate into lower reemployment wages and weaker bargaining positions. Geographic movers fare worse than stayers, reflecting negative selection (younger, lower-earning) and relocation to metropolitan areas where fossil fuel or low-skilled service sectors remain highly concentrated, leaving monopsony power intact. (*JEL* Q32, R11, J31, J60, J42)

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1 Introduction

In many advanced and emerging economies, labor markets are being reshaped by the combined forces of automation, trade liberalization, and decarbonization policies, often reducing demand for narrowly defined tasks in specific regions. These shocks are most damaging when two conditions coincide: skills are highly sector-specific and a small set of employers dominates hiring. When demand falls, workers struggle to redeploy their human capital, and the few remaining employers can set wages below productivity. This pair of frictions (skill immobility and monopsony power) arises where tasks are highly specialized and employment is concentrated among a few firms. It is especially salient in fossil fuel (FF) production regions, including coal mining and oil and gas extraction, where production is tied to immovable resources and a small number of operators set pay. Understanding how these frictions interact is essential for policy that aims to protect workers during large industrial transitions. This is particularly relevant for the energy transition, which delivers global environmental gains while concentrating job-loss risk in communities long dependent on FF employment.[1]

In this paper, I bring new evidence to this broader question about how worker mobility and local employer concentration jointly shape post-separation employment and earnings. Using the Longitudinal Employer-Household Dynamics (LEHD) data, I track nearly the universe of US fossil fuel extraction workers from 1999 to 2019. The matched worker-firm histories let me observe whether displaced workers switch sectors, move regions, or both, and then quantify how their earnings trajectories depend on the portability of their skills and the competitiveness of the destination labor market. Where prior work has documented average earnings declines after plant closures (Jacobson et al., 1993), import surges (Autor et al., 2014), or environmental regulation (Walker, 2013), I ask how limited sectoral portability and

[1]Empirical estimates of earnings losses in carbon-intensive sectors include Curtis (2018), Deschenes (2010), Greenstone (2002), and Walker (2013).

monopsony power contribute to the observed earnings impact.[2] That distinction is pivotal for policy: if monopsony dominates, antitrust or new-entrant incentives may be key; if skill immobility dominates, retraining or mobility subsidies take center stage.

FF extraction provides a useful empirical setting for this analysis. Because FF extraction is tied to immovable resource deposits and relies on large, site-specific capital, firms cannot relocate when prices or regulations change. Employment is therefore clustered among a small number of local employers, and when local extraction contracts, adjustment is geographically concentrated: workers face scarce comparable jobs nearby and must either move to other FF regions or switch into non-FF industries. Tasks in FF extraction, such as operating drilling rigs, maintaining longwall systems, and managing high-pressure completions, require specialized, equipment-specific skills with limited transferability to other industries, mirroring the specificity of many tasks.[3]

This paper analyzes the short- and long-run impacts of local FF labor demand shocks on individual workers' employment and earnings after separation. To capture market- or commuting zone (CZ)-level exposure to these shocks, I construct a Bartik-style variable defined as the growth in national FF employment (excluding the CZ itself) multiplied by each market's predetermined geological potential for FF extraction. This measure exploits variation in markets' economic reliance on fossil fuels and their vulnerability to sectoral fluctuations: regions with higher geological potential typically have more FF-dependent economies, making them particularly sensitive to demand shocks.

Matched worker-firm histories allow me to classify separated workers along two margins: (i) sectoral mobility (whether they leave the FF sector), and (ii) geographic mobility (whether they leave their origin market). Using detailed worker and firm-level data from the LEHD

[2]I disentangle the effects of skill-specific human capital from employer monopsony power by estimating the same labor-demand-shock regressions within mutually exclusive subsamples defined by mobility group (e.g., workers who leave both the FF sector *and* their local labor market) and high- vs. low-monopsony areas. By holding local concentration fixed when comparing sectoral switchers to non-switchers, and skill portability fixed when comparing high- and low-monopsony markets, the differences in coefficients isolate how each friction independently contributes to earnings losses after separation.

[3]See, for example, Autor et al. (2014) on China-trade shocks and Acemoglu and Restrepo (2020) on automation.

and the Longitudinal Business Database, I compare earnings outcomes across these worker groups to reveal how both worker selection and local monopsony power jointly influence earnings recovery.

In the full sample of about 1.35 million workers, a 1% decline in national FF employment lowers exposed workers' employment probability by 0.3 p.p. and annual earnings by 0.16% on average. The earnings effects are small immediately after separation, plausibly reflecting temporary factors such as severance or brief reemployment. In the medium term, earnings decline steadily as adjustment costs accumulate, job matches shift toward lower pay, or nonemployment spells lengthen, with only partial recovery after ten years.

To identify the specific causes of job separations, I construct a *mass-layoff* sample that includes workers separated from employers that either closed or experienced job cuts exceeding 30%. The findings from the mass-layoff sample align closely with those from the full sample, suggesting that layoffs are the primary driver of the observed earnings losses. Evidence from the mass-layoff subsample and the tight co-movement of employment and earnings points to longer nonemployment spells as the primary channel. At the same time, when I restrict to observations with positive earnings and hold the worker sample fixed, the patterns are similar. This implies that losses also occur among the employed, consistent with lower wages or hours in new matches; therefore, intensive margins likely contribute as well.[4]

Workers who remain in the FF sector after separation ("Nonswitchers") experience deeper and more persistent losses, consistent with selection into roles with limited portability. In drilling, roughly 75% of positions are FF-specific, meaning a significant portion of jobs are in occupations that are rarely found outside FF industries, whereas oil-and-gas extraction employs a more transferable mix of tasks and occupations. I find that separated drilling workers, who are disproportionately male, rarely switch and incur the largest losses, while women in more transferable roles exit at higher rates and face milder setbacks. Workers who leave their local labor markets after separation ("Movers") display larger short-run losses

[4]Because conditioning on positive earnings selects on post-treatment employment, interpret this evidence as suggestive rather than a full decomposition.

than Nonmovers. Stylized facts and subgroup estimates point to two forces: a composition effect—the affected group is disproportionately younger, with shorter tenure and lower pre-separation earnings—and the costs of match rebuilding after displacement.

I measure destination markets' concentration in two ways: FF-specific HHI (within-FF bargaining conditions) and all-sector HHI (overall outside options). For Nonswitcher-Nonmovers, high FF-HHI yields large, persistent losses, while low FF-HHI workers nearly return to their baseline earnings in the long run; using all-sector HHI, the same group shows modest losses in high-HHI markets and sizable gains in low-HHI markets. For Switcher-Nonmovers, FF-specific HHI is largely uninformative since jobs are outside FF, whereas all-sector HHI remains decisive (modest losses at high HHI and modest gains at low HHI). These results indicate that, when outside options are scarce, incumbent FF employers capture much of the switching surplus. By contrast, in more competitive markets the availability of non-FF job offers strengthens workers' bargaining power, even for Nonswitchers who remain in the FF sector.

Among Nonswitcher-Movers, high FF-specific HHI is associated with large long-run losses and low FF-HHI with only modest losses; with all-sector HHI, high-HHI destinations produce large losses and competitive destinations modest gains. For Switcher-Movers, FF concentration does not price wages, but overall concentration still matters: modest losses in high-HHI markets and approximately zero effects in low-HHI markets. Given that Movers predominantly relocate from rural to urban areas, the estimates imply that the FF niche often remains highly concentrated even in urban labor markets. Consequently, mobility does not automatically improve bargaining conditions; meaningful gains from geographic arbitrage arise mainly when the destination has low overall employer concentration.

My first contribution revisits the classic job-displacement debate through the lens of two explicit *cushions* that normally soften a lay-off: the skill cushion, representing the ease of transferring displaced workers' human capital, and the competition cushion, reflecting the degree of local employer competition that supports workers' outside options. Seminal studies such as Jacobson et al. (1993) document large and persistent earnings losses but implicitly presume that at least one cushion is thick, either because general skills travel well or because post-displacement pay is set in competitive markets.[5] Instead, I show that when both cushions are thin, as in resource-dependent enclaves where tasks are highly specialized and employment is dominated by a handful of firms, earnings losses are roughly twice what we would predict from skill mismatch alone. This analysis builds on recent evidence showing that displacement scars arise from distinct sources such as loss of match-specific human capital (Lachowska et al., 2020), reduced bargaining leverage in monopsonistic markets (Berger et al., 2022), and diminished outside-option rents (Jarosch, 2023). To my knowledge, however, this paper is the first to explicitly quantify how limited employer competition significantly amplifies earnings losses in contexts where skill transferability is already low.[6] In doing so, it connects the job-loss and monopsony literatures and highlights promoting employer competition as a distinct policy tool, separate from traditional retraining programs.

A second contribution extends the literature on reallocation frictions by showing that earnings losses are compounded when workers face constraints on both geographic and sectoral adjustment. Earlier work has tended to isolate one margin: trade-shock work emphasizes regional stickiness even when industry switching is possible (Autor et al., 2013); migration models stress moving costs that mute geographic responses to wage differentials (Kennan & Walker, 2011); and macro-spatial models of structural change treat industry switching with fixed mobility parameters (Caliendo et al., 2019). Closer to my approach, a few papers (Colmer et al., 2024; Walker, 2013) study earnings conditional on both sector and location. I contribute to this literature by unpacking mechanisms on two fronts: first, I doc-

[5]Prior research has documented that displacement leads to persistent earnings losses (Davis & Wachter, 2011; Schmieder et al., 2023), attributing these to factors such as the loss of firm-specific wage premiums and productivity (Couch & Placzek, 2010), limited mobility over the life cycle (Jung & Kuhn, 2019), and skill mismatches in re-employment (Farber, 2017).

[6]Yi et al. (2024) study German male manufacturing workers, attributing post-shock earnings losses solely to regional industry composition and sectoral proximity. My analysis extends this by incorporating actual observed worker mobility—across sectors and regions—and local employer concentration. I show that limited employer competition approximately doubles the earnings losses already stemming from poor skill transferability, an amplification channel not captured by Yi et al. (2024)'s absorptiveness index.

ument selection into sector switching and relocation using observable worker characteristics; second, I link the cross-group dispersion in earnings losses to features of destination labor markets. These patterns help reconcile why large local shocks leave permanent employment gaps (Yagan, 2019) and suggest that skill-transfer barriers (Kambourov & Manovskii, 2009; Parent, 2000) and monopsony power[7] interact with traditional frictions such as migration costs or housing constraints.

Last but not least, this paper contributes to the emerging literature on the labor market impacts of decarbonization in two distinct ways. First, I examine the entire FF supply chain—including coal mining, oil and gas extraction, drilling, and related support services —rather than focusing solely on specific worker groups (e.g., coal miners[8]) or aggregate employment measures at the industry or regional level (Allcott & Keniston, 2018; Bartik et al., 2019; Feyrer et al., 2017). This broader approach demonstrates that skill- and location-specific scarring effects observed in coal mining generalize across the FF sector as a whole. Second, I provide the first causal estimates illustrating how simultaneous sectoral decline and local employer concentration jointly suppress wages and employment opportunities. In this regard, the paper complements prior work by Walker (2013), which focused on regulated manufacturing plants, by specifically quantifying reallocation costs within industries directly targeted by the energy transition. Thus, my results yield granular evidence to inform policy design, highlighting the importance of promoting worker retraining, geographic mobility, and competitive labor markets in regions.

The rest of the article is structured as follows: Section 2 provides an overview of the FF extraction industry in the US. Section 3 outlines the theoretical framework for labor reallocation under frictions, and Section 4 describes the data used in this study. Section 5 presents descriptive findings on the sectoral and geographic mobility of FF workers. Section 6 and Section 7 explain the empirical strategy and reports the results, respectively. Section 8

[7]A handful of studies show that monopsony power suppresses wages in concentrated labor markets (Azar et al., 2022; Schubert et al., 2024; Thoresson, 2024).

[8]Previous studies have examined job losses and earnings declines among individual coal mining workers in the US (Colmer et al., 2024) and the United Kingdom (Rud et al., 2024).

discusses the policy implications. Section 9 concludes.

2 Background on the Fossil Fuel Industry

The cyclical nature of FF extraction employment underscores the sector's pronounced sensitivity to external economic and regulatory shocks, creating a highly volatile employment environment.[9] The top-left panel of Figure 1 illustrates significant fluctuations in FF employment in the US over recent decades, driven largely by geopolitical events and environmental regulations. These disruptions frequently trigger large-scale, geographically concentrated layoffs (Black et al., 2005; Marchand, 2012; Rud et al., 2024).[10]

The bottom-left panel plots annual series for all separations, employer-driven job losses (firm-level net employment reductions), and layoffs from 2000 to 2019. Periods when national FF employment falls, such as 2008-09 and 2014-15, line up with sharp increases in employer-initiated separations and layoffs. This comovement indicates that downturn spikes in total separations are driven mainly by involuntary exits. The surge in layoffs shows how external shocks translate into heightened job instability in the FF sector.

Local FF labor markets are highly concentrated and spatially immobile, which gives employers substantial wage-setting power and makes reallocation costly. The top-right panel in Figure 1 documents this concentration: 30% of commuting zones have fewer than 10 FF employers, compared with 2% in construction and 6% in manufacturing; at the county level, about one third of US counties have fewer than five FF employers (versus 3% in construction and 6% in manufacturing). The mechanism is geographic: extraction is tied to fixed resource deposits, so production cannot relocate when prices or regulations change. Employment therefore clusters where reserves are abundant, as shown by the strong spatial correlation

[9] Hereafter, FF extraction refers to the following NAICS 6-digit industries: Crude Petroleum Extraction (211120); Natural Gas Extraction (211130); Bituminous Coal and Lignite Surface Mining (212111); Bituminous Coal Underground Mining (212112); Anthracite Mining (212113); Drilling Oil and Gas Wells (213111); Support Activities for Oil and Gas Operations (213112); Support Activities for Coal Mining (213113).

[10] Notable events include the Clean Air Act Amendments, the Great Recession, and OPEC's decision to maintain high oil supply alongside intensified EPA standards during 2012-2016, causing sharp employment declines. Between 2014 and 2017 alone, FF employment dropped by approximately 30%.

between reserves and employment intensity (Figure A.4). When local extraction contracts, comparable jobs nearby are scarce, and workers either move to other labor markets or switch out of fossil fuels locally, often at lower pay.[11]

The capital intensity of FF extraction is a direct corollary of resource immobility. Because production occurs where deposits are located, firms make large, sunk investments in site-specific infrastructure (e.g., drilling pads, mine pits, processing and transport assets), which ties activity to place and makes relocation infeasible (Figure A.5). This creates a challenging situation where workers with specialized FF skills may need to either relocate to other FF regions or transition to different industries entirely, as the location-dependent nature of FF resources inherently restricts the geographic flexibility of FF employment opportunities.

Sector-specific roles in the FF sector show notably lower occupational mobility than similar roles in other sectors (bottom-right panel in Figure 1). Highly specialized positions dominant in the FF sector, such as roustabouts and mining machine operators,[12] typically have substantially lower Outside Options Index (OOI) values (Caldwell & Danieli, 2024; Schubert et al., 2024), indicating fewer alternative employment opportunities for workers. Although general occupations with higher skill transferability, such as managers or office clerks, exist within the sector, they account for only a small portion of the workforce. This pronounced specialization among most FF occupations severely restricts workers' transitions to non-FF industries, especially during industry downturns.[13] Consequently, when contractions occur, FF workers frequently encounter severe skill mismatches, prolonging unemployment spells or compelling them to accept positions that poorly align with their expertise.

[11]This is consistent with the relatively high share of FF workers citing job-related reasons for moving (Figure A.3) and with FF wages exceeding those in nearby alternatives such as manufacturing and construction (Figure A.2).

[12]See Figure A.6 for the distribution of major occupations in the FF sector.

[13]Figure A.1 shows that occupations such as derrick operators, continuous mining machine operators, and wellhead pumpers show nearly 100% concentration in the FF sector. In contrast, major occupations in other sectors are often more widely distributed and can be found in multiple industries outside their primary sector. This suggests that FF workers possess highly specialized skills that are almost entirely applicable within the FF industry, creating significant barriers to transferring their skills when seeking employment in other sectors.

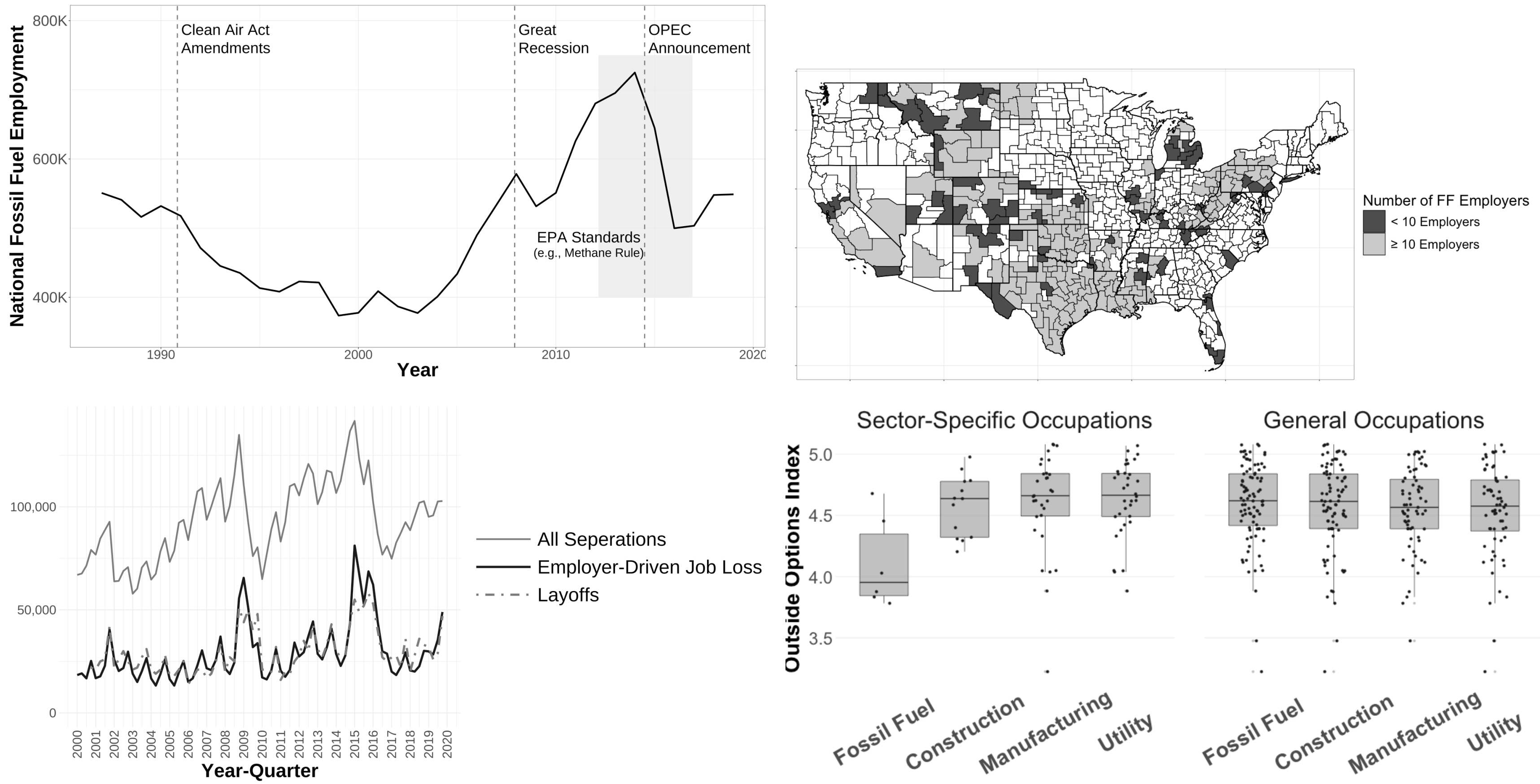


Figure 1: National Fossil Fuel Employment (Top-Left) and Employer-Driven Job Loss (Bottom-Left), and CZ-Level Fossil Fuel Employers (Top-Right) and Outside Options Index, Sector-Specific vs. General Occupations by Sector (Bottom-Right)

Notes: The *top-left* panel shows annual US fossil fuel employment, defined as total employment in oil and gas extraction, coal mining, and mining support activities (collectively classified under NAICS code 21; Quarterly Census of Employment and Wages, US BLS). Shaded area (March 2012-December 2016) highlights the period of intensified Environmental Protection Agency (EPA) standards. "OPEC Announcement" indicates the Organization of the Petroleum Exporting Countries (OPEC)'s decision to maintain oil supply, triggering an oil price collapse. The *bottom-left* panel presents quarterly data on total job separations and employer-driven job losses (Longitudinal Employer-Household Dynamics, US Census Bureau), along with layoffs (Job Openings and Labor Turnover Survey, US BLS). Employer-driven job losses represent the "net" reduction in employment at firms experiencing declines during a given quarter. This measure excludes separations offset by immediate hiring, thereby filtering out routine quits that firms quickly replace. The *top-right* panel illustrates the number of employers in the FF sector in each CZ in 2019. The *bottom-right* panel compares occupational mobility between sector-specific and general occupations across four sectors: Fossil Fuel, Construction, Manufacturing, and Utility. Examples of sector-specific occupations include derrick operators in Fossil Fuel, carpenters in Construction, team assemblers in Manufacturing, and power-line mechanics in Utility. The Outside Options Index (OOI), based on Shannon entropy, measures the diversity of workers' potential employment transitions. Each boxplot shows the distribution of OOI across occupations, with the box representing the interquartile range, the line indicating the median, and dots showing individual occupations. Lower OOI suggests more limited mobility and fewer viable outside options. Data source: Quarterly Census of Employment and Wages, County Business Patterns, US BLS, and Schubert et al. (2024).

3 Conceptual Framework

3.1 Individual Skill Transferability and Labor Allocation

To study worker reallocation after a shock, I build a two-period model with two sectors —fossil fuel (F) and non-fossil fuel (N)—and two local labor markets, A (the origin) and B (a potential destination). In period 1, both markets $k \in \{A, B\}$ are in steady state, with $n_1^{F,k}$ fossil fuel workers and $n_1^{N,k}$ non-fossil fuel workers. At the start of period 2, a negative, sector-specific shock hits market A' s fossil fuel industry, leaving market B essentially unaffected.[14] For simplicity, all fossil fuel workers in market A ($n_1^{F,A}$, the "AF" group) are separated from their employers.

I make the following assumptions for reallocation with frictions:

1. **Worker heterogeneity and eligibility.** Each worker i has skill transferability $\theta_i \in [0, 1]$ (fraction of F productivity that carries to N), time-invariant and uniformly distributed. An eligibility threshold $\theta^* \in (0, 1)$ governs access to N: workers with $\theta \geq \theta^*$ are "high-type"; otherwise "low-type". Low types cannot access N anywhere.

2. **Assignment.** Conditional on being high-type, a worker switches locally to AN with probability $P(\theta)$. If not, the worker either relocates to B's F or N with probabilities $M^F(\theta)$ and $M^N(\theta)$ (residual probability is staying in AF). Low types may move only to BF. These probabilities summarize frictions such as licensing, information, and networks.[15] Figure 2 illustrates these assignments.

3. **Effective labor and portability.** In the N sector, a worker produces θ in A and

[14]This one-market assumption mirrors many resource shocks in practice (e.g., coal in Appalachia vs. the Powder River Basin). Allowing small spillovers to B would not change the qualitative results but would burden notation.

[15]The model focuses on the reallocation of these displaced AF workers; all other workers (AN, BF, and BN) are held fixed after the shock. Thus, it is a model of *net* flows out of AF rather than gross two-way "cross-hauling" of labor that often occurs in the data. Background churn between sectors and regions can be several times larger than net flows. Abstracting from it isolates the displacement margin of interest. It is also deliberately *not* a Roy model: AF workers do not choose the best sector. Instead, their period-2 destinations are generated by reduced-form probabilities that depend on worker type θ and origin market A. This design isolates displacement and frictions without solving a full selection problem.

$\psi(\theta) \leq \theta$ in B capturing imperfect portability of N-relevant skills across markets; in sector F, productivity is normalized to 1 in both markets.[16]

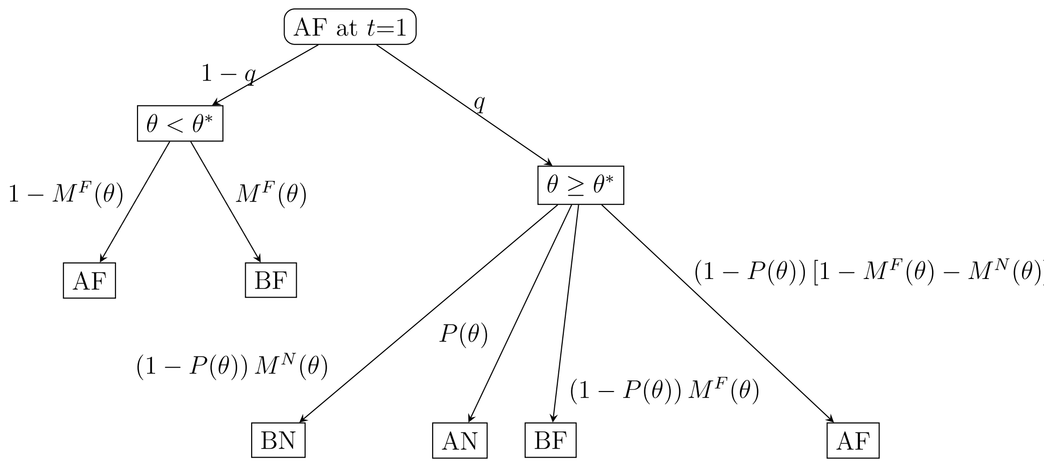


Figure 2: Post-Shock Assignment of Displaced Fossil Fuel Workers in Market A by Type

3.2 Equilibrium Wages under Market Power

In each sector j and local market k, employers collectively face an upward-sloping labor-supply schedule, so the sector–market wage needed to employ L workers rises with L. I model the sector–market inverse labor-supply as

$$w^{j,k}(L) \;=\; \chi^{j,k}\, L^{1/\varepsilon^{j,k}}, \qquad \varepsilon^{j,k} > 0, \tag{1}$$

where $w^{j,k}(L)$ is the wage required to employ L workers in (j, k), $\chi^{j,k}$ captures local conditions, and $\varepsilon^{j,k}$ is the elasticity of labor supply to the market. Thus, a *higher* $\varepsilon^{j,k}$ means a more elastic supply and *less* wage-setting power; lower values indicate more restrictive labor supply and stronger market power.

[16] By definition, θ can be interpreted as a worker attribute that matters in sector N (e.g., proficiency in tasks outside fossil fuel). The mapping $\psi(\cdot)$ is weakly increasing with $\psi(\theta) \leq \theta$ and represents losses from geographic mismatch or missing local complements in B. I normalize productivity in F to 1 everywhere and absorb any relocation/search frictions for F into other terms, so the model isolates productivity and match losses associated with moving from F into N.

Profit maximization equates the marginal revenue product of labor (MRPL) with the marginal expenditure on labor. Under (1), marginal expenditure is $ME = w^{j,k}(1 + 1/\varepsilon^{j,k})$, implying a markdown of wages relative to MRPL (Berger et al., 2022):

$$\mu^{j,k} \;\equiv\; \frac{w^{j,k}}{\mathrm{MRPL}^{j,k}} \;=\; \frac{\varepsilon^{j,k}}{1+\varepsilon^{j,k}} \;\in\; (0,1]. \tag{2}$$

When $\mu^{j,k}=1$, the market is competitive; smaller $\mu^{j,k}$ indicates a larger wedge and stronger wage-setting power. I interpret $\mu^{j,k}$ as a *market-level markdown* that summarizes all sources of wage wedges in (j,k) (e.g., employer market power, recruiting frictions, coordination), without requiring a single-firm monopsony.

Assuming that each sector in each market produces goods using a Cobb-Douglas production function, wages in each sector–market pair are determined by the marginal product of labor. To isolate the effects of labor supply and sectoral price shifts on wages, I simplify the model by normalizing both total factor productivity and capital to one. With these normalizations, the equilibrium wage equation becomes

$$w_t^{j,k} = \mu^{j,k}\alpha^j p_t^j (L_t^{j,k})^{\alpha^j-1} \tag{3}$$

where α^j is the labor share of output. p_t^j is the price in each sector j's product, which is assumed to be market-neutral.

3.3 Framework Implications

Wages in a sector–market pair reflect two forces: a *markdown* term μ (capturing monopsony) and a *congestion* term that depends on effective labor. With $\alpha \in (0,1)$, holding prices and μ fixed, a larger effective labor pool lowers the wage; holding effective labor fixed, a larger μ (weaker monopsony) raises the wage. The sign results below therefore hinge on two objects: (i) differences in markdowns across sectors and markets and (ii) differences in effective labor generated by the assignment primitives (P, M^F, M^N, ψ). See Appendix A for the formal definitions of $\tilde{L}_2^{j,k}$, integrals over θ, micro sufficient conditions for the congestion comparisons, and proofs.

- **Proposition 1 (Switchers vs. nonswitchers in A).** Suppose (i) $p_2^F \leq 1$ (a nontrivial negative F price shock) and (ii) $\mu^{N,A} \geq \mu^{F,A}$. If, in addition, the assignment primitives imply a thinner effective N pool than the F pool in A (formal sufficient congestion conditions in Appendix Prop. A.1), then

$$w_2^{N,A} > w_2^{F,A}.$$

  The switcher premium is larger when local switch success $P(\theta)$ is low, relocation favors BF over BN, and A's N incumbents are small (all reduce $\tilde{L}_2^{N,A}/\tilde{L}_2^{F,A}$).

- **Proposition 2 (Switchers vs. nonswitchers in B).** Under the same logic, if (i) $\mu^{N,B} \geq \mu^{F,B}$ and (ii) assignment primitives put more effective labor into BF than BN (Appendix Prop. A.2), then

$$w_2^{N,B} > w_2^{F,B}.$$

  Congestion tends to be stronger in BF because both low- and high-types can end up in F, while only high-types can reach BN and are discounted by $\psi(\theta) \leq \theta$.

- **Proposition 3 (Mover penalty in F).** If the destination F market is at least as monopsonistic as the origin ($\mu^{F,B} \leq \mu^{F,A}$) and the assignment primitives generate a larger effective F pool in B than in A (Appendix Prop. A.3), then

$$w_2^{F,B} < w_2^{F,A}.$$

  The penalty grows with the mass of low-type movers (M^F on L), with high-type nonswitchers who relocate to BF (large M^F on H), and with a large F incumbent base in B.

- **Proposition 4 (Mover penalty in N).** If the destination N market is sufficiently more monopsonistic than the origin ($\mu^{N,B} < \mu^{N,A}$) and effective N labor in B is thick relative to A (Appendix Prop. A.4), then

$$w_2^{N,B} < w_2^{N,A}.$$

The penalty is larger when local switch success is low (small $P(\theta)$, which keeps AN thin), when relocation into BN among eligibles is common (large $M^N(\theta)$ on $[\theta^*, 1]$), when portability is strong ($\psi(\theta)$ close to θ), and when B has a larger incumbent N base.

4 Data

4.1 Matched Employer-Employee Data

This study utilizes data from the US Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program spanning 1999 to 2019. The LEHD is a comprehensive quarterly dataset that links employer and employee records, covering over 95% of private-sector jobs in the US. The dataset includes information on worker earnings, primarily sourced from confidential state Unemployment Insurance (UI) earnings data,[17] as well as key demographic characteristics such as age and sex.

The LEHD provides key employer-level characteristics, including industry classification (6-digit NAICS codes), age, employment size, and ownership type. Using the LEHD's employer-state identifier (SEIN), I match each job to the Employer Characteristics File (ECF). To supplement this, I incorporate a restricted-use Longitudinal Business Database (LBD) data, which covers all states and tracks firm dynamics, including parent-child relationships between *employers* and overarching firms. In this study, I define *employers* as

[17] Earnings data encompass gross wages, bonuses, stock options, and similar compensation types.

individual business units (e.g., a mine site, field office, or drilling yard). The LBD also tracks business entry and exit, allowing me to determine whether a business unit remains operational or shuts down over time.

I use the LEHD from 29 states,[18] which collectively represents approximately 80% of national fossil fuel employment (Figure A.7). This coverage provides a robust foundation for analyzing fossil fuel workers. While I can track the earnings history of business units and their workers only in the 29 LEHD-approved states, this study leverages a restricted-use dataset, which provides annual records with residential geography at the census tract level for workers in *all* states, regardless of the LEHD approval status. This granularity enables precise measurement of migration rates within the US. It also allows me to determine whether a worker's earnings record disappears due to relocation to a non-approved state or because they have left the US labor market entirely due to retirement or emigration.

Using these datasets, I construct a worker-level panel that captures annual earnings, place of residence, individual demographics, and employer characteristics. If a worker is employed by multiple employers in a given year, the employer providing the highest earnings is designated as the worker's main employer (Lamadon et al., 2022; Sorkin, 2018). This comprehensive framework enables a detailed analysis of labor dynamics across both fossil fuel and non-fossil fuel sectors, while also tracking individual worker relocation decisions, such as whether they moved to a different CZ.

4.2 Sample Selection for Separated Fossil Fuel Workers

To identify separated workers from the fossil fuel (FF) sector, I follow this data sampling procedure: First, I restrict the sample to workers who were employed in the FF sector for more than four consecutive quarters, ensuring the selection of workers reasonably attached to the industry. Second, I include only workers who were separated from their FF employer

[18] The states that approved my project for accessing the LEHD are listed in abbreviations: AZ, CA, CO, CT, DE, IA, IN, KS, MD, ME, MT, ND, NE, NM, NJ, NV, OR, OH, OK, PA, SC, SD, TN, TX, UT, VA, WA, WI, and WY.

during the sample period. To exclude separations due to firm restructuring rather than layoffs, I do not count moves between different employers within the same firm as separations. Third, I focus on workers born between 1945 and 1995, ensuring they spent at least ten years between the ages of 15 and 65 during the sample period. Finally, I adjust all earnings to the 2010 Personal Consumption Expenditures Price Index and exclude workers whose average non-zero quarterly earnings fell below the federal minimum wage threshold of $3,260 per quarter (as of 2010). These steps yield a sample of approximately 1.35 million workers, equal to about 1.0% of US employment and 1.3% of the national wage bill.

5 Stylized Facts

Summary. The LEHD data reveal five stylized facts:

1. Following separation, FF workers exhibit unusually high geographic mobility: about 20.7% leave their CZ within one year and 38.2% by year seven, well above comparable sectors.

2. Relocation tends to facilitate sector switching, but this effect is much weaker in the FF sector, where even movers are far less likely to leave the sector than other sectors.

3. Drilling-wells workers are 5-10 p.p. more likely to remain in FF jobs than those from extraction or coal mining, consistent with more FF-specific occupations.

4. Movers are younger (the under-35 share is 12 p.p. higher), implying shorter tenure and lower pre-separation earnings, while sex, race, and education are similar across groups.

5. Net flows show out-migration from rural resource regions (e.g., Wyoming, West Texas, Appalachia) and in-migration to not only other FF-rich parts but also metropolitan CZs in Texas, the Mid-Atlantic, and California, consistent with relocation toward thicker urban labor markets.

5.1 Worker Classification by Mobility Status

To analyze the sectoral and geographic mobility of workers, I examine individuals' employment and residence history for seven years following their separation from the fossil fuel (FF) sector. For residence, I track an individual's county of residence and assign them to a commuting zone (CZ) based on 2010 delineations.[19] CZs serve as the unit of local labor markets in this study. For instance, a worker employed in the FF sector in 2009 would have one of three employment statuses in 2010: employed by another FF employer, employed outside the FF sector, or missing earnings.[20] In this context, 2010 is defined as the first year of post-separation.

I classify workers into four mutually exclusive groups based on their mobility status after separation, considering both sectoral and geographic reallocation. These groups are defined by whether a worker left the FF sector and whether they left their CZ within seven years of separation. Workers are considered to have left the FF sector if they worked in the non-FF sector for more than two years during this period. Similarly, workers are classified as having left their CZ (based on their residence location) if they moved out of the CZ where they were separated and did not return. Workers who left both the FF sector and their CZ are grouped as *Switcher-Mover*. Those who left the FF sector but remained in or returned to their original CZ are classified as *Switcher-Nonmover*. The remaining two groups—*Nonswitcher-Nonmover* and *Nonswitcher-Mover*—are defined in the same way, considering workers who stayed in the FF sector. Additionally, I define broader groups based on single dimensions: for example, workers who left their CZ, regardless of whether they left the FF sector or not, are referred to as the *Mover* group.

[19]This study uses 2010 CZ delineations, as they represent the midpoint of the sample period. The 625 CZs are clusters of counties with strong internal commuting ties, determined using commuter flow data from the 1990 and 2000 Decennial Censuses and the 2006–2010 American Community Survey (Fowler et al., 2016).

[20]If a worker has missing earnings and resides in a non-LEHD-approved state, that worker-year observation is excluded.

5.2 Employment Transition Patterns of Fossil Fuel Workers

5.2.1 Geographic and Sectoral Mobility

The top-left panel of Figure 3 shows the geographic mobility of separated workers from the FF sector and three comparison sectors following job separation.[21] Geographic mobility is measured by the share of workers who left the CZ where they were previously employed. FF workers exhibit markedly higher rates of out-migration compared to their counterparts in other sectors. Specifically, 20.7% of FF workers had relocated out of their original CZ just one year after separation, and this share increases steadily to 38.2% by the seventh year. This level of geographic mobility stands out in contrast to patterns observed in other sectors and broader labor market trends.[22] These findings underscore the particularly high geographic mobility of FF workers following job loss. This pattern aligns with the inherently immobile nature of FF jobs described in the background section and reflects the distinct employment structure and regional concentration of the FF industry.

The top-right panel of Figure 3 plots, by years since separation, the difference between the share of switchers among Movers and among Nonmovers across different sectors. The series are positive throughout and jump in the first year before flattening, implying that relocation generally facilitates sector switching by exposing workers to a wider set of vacancies and lowering search or retraining frictions. The FF line is much lower—about 3 to 4 percentage points, compared with 7 to 12 in construction, manufacturing, and utilities—showing that even movers from FF jobs are less likely to leave the sector. This is consistent with sector-specific skills and licensing that transfer more readily across FF regions than

[21] To compare FF workers' mobility with that of workers in other sectors, I construct analogous groups for individuals separated from the construction, manufacturing, and utility sectors. For each of these sectors, I follow the same sampling and classification procedure used for FF workers. This consistent approach allows for direct comparison of both geographic and sectoral mobility across sectors that are similar in skill requirements, physical demands, and wage levels.

[22] For example, Horn et al. (2022) calculate the share of workers who found a new job in a different MSA by the end of their sample period (the fourth quarter of 2014) using LEHD data from 2002 to 2014. They find that only 19.2% of workers separated from mass-layoff establishments across all industries eventually left their metropolitan statistical areas (MSAs) over the long run, a mobility rate that closely mirrors the patterns observed among separated construction, manufacturing, and utility workers in my data.

into other industries. Taken together, the patterns point to a high-pay but low-opportunity trade-off for FF workers: staying means few local openings and repeated disruptions, while switching often requires giving up the FF wage premium and does not fully eliminate earnings losses, making stable long-term employment difficult under either path. Consistent with this interpretation, Movers show slightly lower nonemployment than Nonmovers across industries (Figure A.8), indicating that mobility can aid reattachment, although a nontrivial subset still faces prolonged nonemployment.

5.2.2 Observable Selection across Worker Groups

The bottom-left panel of Figure 3 plots the share of Nonswitchers by pre-separation subsector within the FF industry, separately for Nonmovers and Movers. In both mobility groups, workers from the drilling-wells subsector are 5 to 10 p.p. more likely to remain in FF employment than workers from oil and gas extraction or coal mining. The gap persists even among Movers, indicating that drilling workers tend to stay in FF jobs after relocating. This pattern aligns with the occupational mix documented in Figure A.18 and discussed in Section 2: drilling roles are highly FF-specific, which limits the portability of skills and reduces occupational mobility outside the industry.

Age differences are also notable (bottom-right panel of Figure 3). A larger share of Movers are young: the under-35 share is about 12 p.p. higher than for Nonmovers. Given the positive age–tenure relationship, this composition suggests Movers tend to have shorter job tenure, and it aligns with their lower pre-separation earnings (Figure A.9). In contrast, demographic characteristics such as sex, race, and educational attainment show little variation between Movers and Nonmovers (Figure A.10). Across all groups, the share of female workers fluctuates by only 5–6 p.p., while White workers consistently make up about 88% of each group. Likewise, the proportion of workers with at least a bachelor's degree remains stable at around 18–21%.

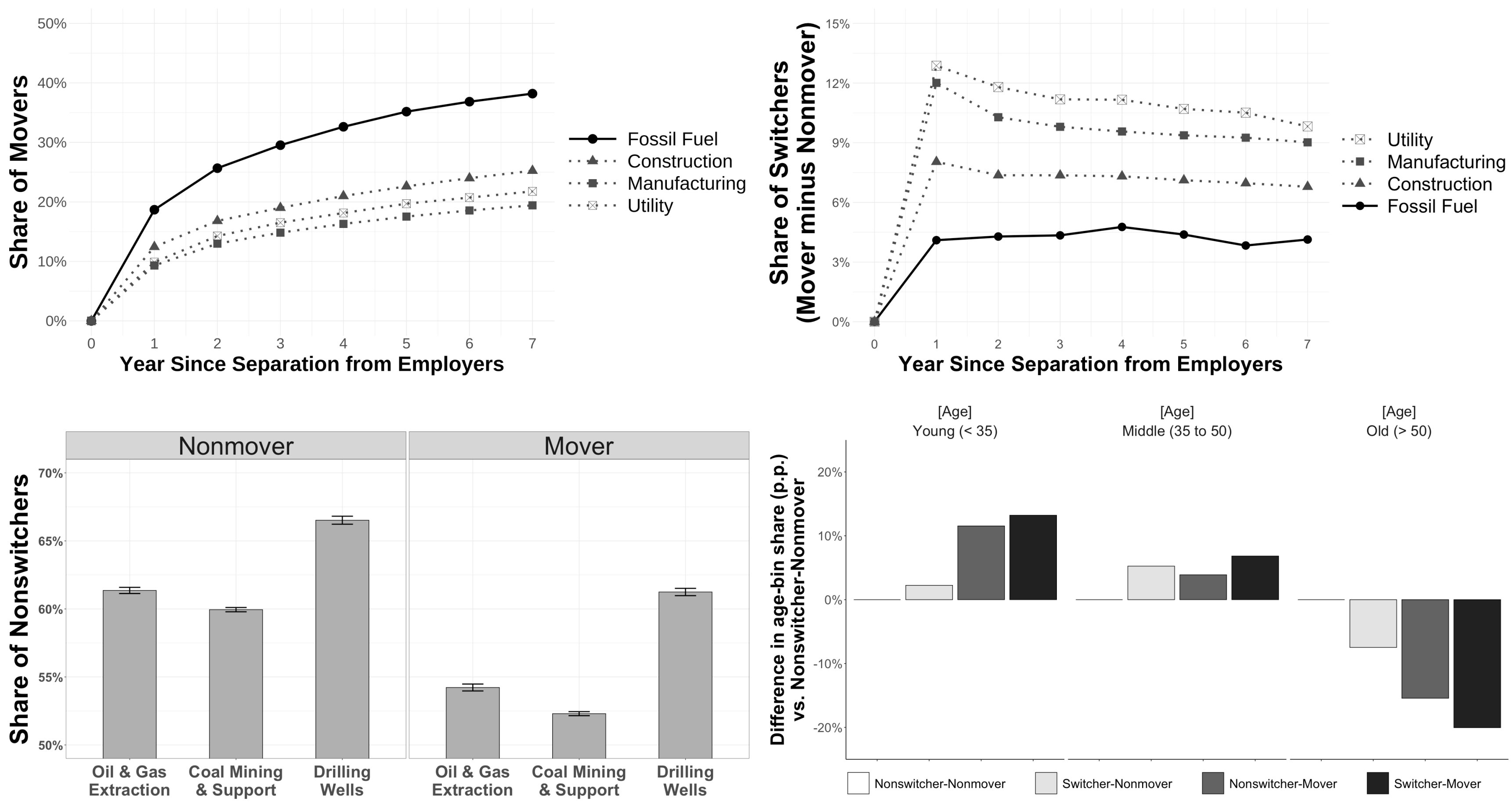


Figure 3: Geographic Mobility (Top-Left) and Sectoral Mobility (Top-Right) by Sector, and Conditional Probability of Staying the FF Sector by Pre-Separation Subsector (Bottom-Left) and Age Composition Differences across Worker Groups (Bottom-Right)

Notes: The bottom-right plot distinguishes sectoral nonswitchers from switchers. The right plot compares geographic nonmovers to movers. Year 0 denotes the year of job separation. Each bar in the bottom-right panel represents the percentage-point difference in the share of workers within an age bracket for each group. Data source: LEHD.

5.2.3 Migration Pattern of Movers

Geographic reallocation underscores the important role that urban areas play as labor market hubs, offering FF workers access to more diverse employment opportunities and potentially greater economic stability. Figure 4 presents the net migration patterns of workers who separated from the FF sector. Striped and dotted regions represent areas with negative net migration, and solid, pattern-free regions mark positive net migration. Large, predominantly rural CZs such as Wyoming, West Texas, and parts of Appalachia show substantial net outflows, indicating that separations in these areas often trigger exits from resource-dependent regions. Net inflows concentrate in two destination types: FF-rich rural CZs experiencing expansions (for example, North Dakota during the shale boom) and geographically small, high-density metropolitan CZs. Notable urban destinations include centers in Texas, the Mid-Atlantic, and California. Taken together, the pattern suggests that after job loss, FF workers reallocate either to new FF frontiers in rural areas or to diversified urban labor markets with broader opportunities and more resilient demand.

Figure 4: Net Migration Flows of Separated Fossil Fuel Workers Across US Regions

Notes: Data source: LEHD.

6 Methodology

To understand how workers adjust to labor demand shocks in the FF sector across CZs, I construct a measure of exposure to these shocks. My objective is to estimate the short-run and long-run impacts of plausibly exogenous local labor demand shocks on individual workers' earnings. Following the approach of Hanson (2023), the exposure to FF labor demand shocks in CZ c in year t is defined as:[23]

$$FFShock_{ct} = \Delta \log \left(\sum_{c' \neq c} Emp^{FF}_{c',t} \right) \times Depth_c \tag{4}$$

where $\Delta \log(\sum_{c' \neq c} Emp^{FF}_{c',t})$ represents the log change in leave-one-out national FF employment, which directly captures labor demand conditions in the FF sector.[24] This approach aligns with the rationale for using national industry employment growth rates as exogenous shocks to estimate regional labor supply elasticities (Bartik, 1991). As discussed in Section 2, changes in national FF employment are largely driven by external factors, such as global oil price fluctuations, which are plausibly exogenous and unlikely to be influenced by local labor market conditions. Because the identifying variation arises from large negative national demand shocks, which primarily represent involuntary, employer-driven layoffs, any voluntary separations occurring during unrelated boom periods (e.g., due to family or career reasons) could introduce classical measurement error.[25]

I incorporate cross-sectional variation in CZs' sensitivity to shocks to identify differential exposure to common labor demand shocks. Specifically, I use a single resource-depth mea-

[23]In the regression analysis, the shock in Eq. (4) is multiplied by -1 to simplify interpretation, allowing higher values of the exposure measure to represent larger negative changes.

[24]It is reasonable to believe that total FF employment is a noisy proxy for coal employment, as coal faces secular, policy-driven declines while oil and gas fluctuates primarily with oil prices. However, Figure A.11 shows a positive short-run correlation between annual changes in national coal and total FF employment, reflecting shared macroeconomic and energy-demand shocks, regional labor market spillovers, and synchronized investment cycles. This suggests that total FF employment reasonably captures relevant short-run variation in coal employment.

[25]This would bias the estimate toward zero, not create spurious evidence of earnings losses.

sure from the national geological survey that covers both oil and coal-bed gas formations.[26][27] This geological measure is advantageous for three reasons. First, it is predetermined using data from the 1970s, decades before my sample period, making it plausibly exogenous and unlikely to be influenced by contemporaneous local labor supply conditions like population composition or local amenities.[28] Second, regions with deeper resources historically developed more FF-dependent economies, as deeper resources are associated with more intensive extraction activities for oil and gas formations and coal seams (Luppens et al., 2009). Third, deeper resources generally entail higher extraction (e.g., drilling or well completion) costs (U.S. EIA, 2016), making these sites among the first to close during fossil fuel price downturns and thus more vulnerable to demand shocks.[29][30]

Figure 5 illustrates the relationship between the depth of resources and both the share and l4evel of FF employment in each CZ in 1990. The statistically significant positive correlations indicate that areas with deeper FF resources historically became more FF-dependent. Accordingly, CZs with greater resource depth tended to exhibit higher employment shares in FF activity and were more likely exposed to sectoral downturns than shallower-resource

[26] The data source is the 1995 National Assessment of United States Oil and Gas Resources, conducted by the US Geological Survey. For further details, refer to the report available at the following link: https://pubs.usgs.gov/circ/1995/1118/report.pdf.

[27] I normalize depth by dividing the raw measure by the sample maximum, yielding a unit-free index that preserves cross-sectional ranking. Under this scaling, the distributed-lag path traces the response to a one-unit national shock for high-exposed versus low-exposed locations.

[28] The depth measure comes from the USGS geologic-input file for undiscovered resources. It is set by burial history and seismic mapping before any economic screening; whether a trap ever becomes commercially viable is evaluated only later in the "economic module." Hence depth is a fixed geologic parameter, not an equilibrium or extractability measure. See Allcott and Keniston (2018) for an example of employing USGS geological estimates of undiscovered reserves as a measure of local oil and gas endowment within a Bartik-style analysis.

[29] The approach relies solely on monotonicity, meaning greater depth raises extraction costs in both oil and coal sectors, without requiring identical cost functions across these sectors. The cost functions need not share a common functional form (linear, quadratic, etc.), nor must depth affect labor intensity uniformly across fuels; these differences influence only the magnitude of estimated effects, not their validity.

[30] Another geological candidate is net thickness, but depth may more directly reflect local vulnerability to demand shocks due to its relationship with drilling costs, such as rig time, casing requirements, and high-pressure completions. In contrast, net thickness primarily indicates resource volume, which might be less sensitive to marginal changes in extraction activity and employment.

areas.[31]

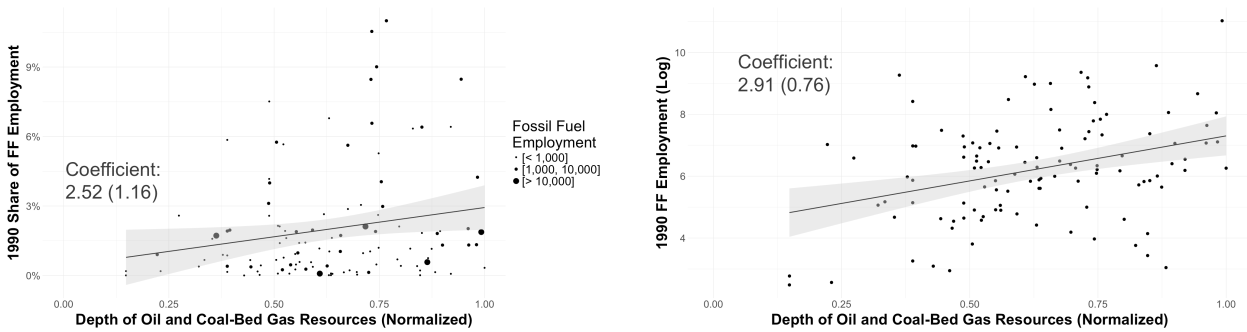


Figure 5: Depth of Fossil Fuel resources and 1990 Fossil Fuel Employment Share (Left) and Employment Level (Right)

Notes: In the left panel, the size of each point reflects the total FF employment in the CZ. Data source: Quarterly Census of Employment and Wages, US BLS and US Geological Survey.

To confirm that my exposure measure specifically captures fossil fuel shocks rather than acting as a general industrial share reflecting multiple unobserved sectoral shocks, I conduct a sectoral-independence (exogeneity) test, shown in Figure A.13. For each industry, I regress 1990 sectoral shares of total employment (top panels) and log employment levels (bottom panels) on the depth measure, indicating no systematic relationship between resource depth and pre-treatment industrial structure outside the FF sector. Because depth is therefore uncorrelated with outcomes through alternative industry channels, it satisfies the "tailored-share" requirement emphasized by Borusyak et al. (2025): exposure should mediate only the specific treatment shock (here, fossil fuel demand) rather than a broad set of potential shocks that could violate parallel trends.[32]

To further support the share-exogeneity condition underlying credible exposure measures inspired by shift-share designs, Figure A.14 tests whether the depth measure is correlated

[31] Figure A.12 shows a positive correlation between the depth and the lagged coal mining employment share (1990) across CZs, though the relationship is observed in a relatively small number of CZs. This correlation suggests that resource depth also serves as a useful predictor of exposure to common labor demand shocks in the coal mining industry, which has experienced a substantial decline since the late 2000s.

[32] Because my shock measure assumes share exogeneity, one concern might be negative Rotemberg weights, which could (i) invalidate the interpretation of the average treatment effect as a convex average of local effects, or (ii) allow a few markets with large but opposing weights to dominate the results (Goldsmith-Pinkham et al., 2020). In my setting, however, these issues do not arise. My shock measure relies on a leave-one-out national series for the *single* sector and strictly positive, time-invariant geological shares, ensuring Rotemberg weights remain strictly non-negative and well-dispersed. See Appendix B for details.

with labor-supply fundamentals. Across CZs, depth exhibits statistically insignificant correlations with key socioeconomic indicators, including the 1990 share of young workers, share of adults with at most a high-school diploma, median household income, and unemployment rate. Given that demographic structure, baseline earning capacity, and labor-market slack represent major potential confounders influencing workers' ability or willingness to adjust to shocks, these insignificant relationships suggest that depth does not proxy for unobserved labor-supply heterogeneity.

For the regression specification using matched employer-employee data, I begin with a model incorporating worker and firm fixed effects (Abowd et al., 1999). To focus on the variation in shocks over time, I first-difference the model, following the approaches of Autor et al. (2013) and Borusyak et al. (2022). This isolates temporal variation in the exposure to shocks and estimates the impact of these shocks on *changes* in outcomes, rather than levels, to mitigate concerns that shares are equilibrium objects likely codetermined with outcome levels (Goldsmith-Pinkham et al., 2020).

For worker i employed by employer j in industry m in CZ c in year t, I estimate the following regression model, where worker fixed effects (FEs) are eliminated through first-differencing:

$$\Delta y_{ict} = \sum_{k=-4}^{10} \beta_k FFShock_{c,t-k} + \gamma_{j(i,t)} + \delta_{1,s(c)t} + \delta_{2,m(j)t} + \varepsilon_{ict} \tag{5}$$

where y_{ict} is the outcome of my interest, such as an employment indicator (interpreted as the probability of employment), or log annual earnings.[33] Thus, Δy_{ict} is either the change in the employment indicator (entry or exit) or year-over-year log-earnings growth, and expressing outcomes in changes makes effect sizes comparable across workers and horizons. $\gamma_{j(i,t)}$ represents employer FEs, which control for time-invariant characteristics specific to each employer. Additionally, I include state-by-year FEs ($\delta_{1,s(c)t}$) to account for time-varying shocks at the state level, such as policy changes or shifts in macroeconomic conditions. Industry-

[33] Earnings are transformed as $\log(earnings + 1)$ to accommodate zero-earnings observations.

by-year FEs ($\delta_{2,m(j)t}$), where industry is defined at the 6-digit NAICS level, are also included to capture time-varying shocks specific to industries. ε_{ict} is the error term. Standard errors are clustered at the employer and state-by-year levels[34] to account for heteroskedasticity and autocorrelation: potential correlation in errors within the same employer, which could arise from firm-specific shocks or policies, and within the same state and year, which could result from regional economic conditions or state-level policy changes.

I include the lead and lag terms of the exposure measure ($FFShock_{c,t-k}$) in the model, with β_k as the coefficients of interest. This structure creates a distributed-lag model, enabling the estimation of both short-term and long-term effects of labor demand shocks on individual workers' earnings.[35] This approach offers two key advantages over the standard difference-in-differences method typically used in displacement studies. First, by relying only on exogenous variation in shocks across similar local markets, the identification strategy captures involuntary separations, thereby eliminating the upward bias caused by selection (i.e., more productive workers remaining employed), a common issue in comparisons with non-displaced incumbents. Second, the annual lagged coefficients track the full dynamic response of earnings, highlighting when losses stabilize or intensify. This approach implicitly incorporates general-equilibrium effects such as crowd-out (increased competition among displaced workers) and crowd-in (creation of non-FF job vacancies).[36]

[34] See, e.g., Hummels et al. (2014) and Rose and Shem-Tov (2023) for similar clustering choices.

[35] Although my regression estimates earnings growth, the ten-year cumulative coefficient represents the long-run log-level change when the lag length is sufficiently large (see Appendix C for proof). Consequently, empirical comparisons using $\sum_{k=0}^{10} \hat{\beta}_k$ correspond directly to comparisons between equilibrium wages in the theoretical model.

[36] Previous studies rely on cumulative annual earnings or cohort-level averages: for example, Autor et al. (2014) calculate cumulative worker outcomes on a rolling annual basis for each year in their sample period, and Walker (2013) simplifies the computational demands of working with the LEHD by aggregating data into annual cohort earnings, where cohorts are defined based on county and industry. My approach avoids aggregation and selection bias by directly examining year-by-year impacts at the individual level. By explicitly incorporating lead terms, the model also accounts for potential anticipatory effects, offering a comprehensive view of the timing and magnitude of shocks on worker outcomes.

7 Results

7.1 Market-Level Analysis of Fossil Fuel Labor Demand Shocks

I begin by examining labor market dynamics through nonemployment rates in each local labor market. The individual-level analysis, captured in the worker-year panel, focuses on workers' direct exposure to labor demand shocks, while CZ-level nonemployment rates provide insights into aggregate local labor market conditions.

I define the FF nonemployment rate for CZ c in year t as the share of workers employed in FF industries in $t-1$ who report zero earnings in t.[37] Expressing the measure as a rate normalizes for CZ size and the initial scale of the local FF workforce, making outcomes comparable across places and over time. Although this measure is restricted to the FF labor force, it is locally consequential: a rise in it lengthens job-search durations, shifts wage-setting, and triggers migration responses that affect both displaced and incumbent workers.

This CZ-level indicator is informative about general-equilibrium adjustment: increases in FF nonemployment propagate to local wages, search frictions, spending, and reallocation into non-FF activities. To isolate these local dynamics, I relate the rate to the same FF labor demand shock used in the main specification while including CZ and industry-year fixed effects; these absorb time-invariant CZ attributes and common industry-wide movements, so remaining variation reflects local spillovers and reallocation tied to the shock. Formally,

$$\Delta NonempRate_{cmt} = \sum_{k=-4}^{10} \beta_k FFShock_{c,t-k} + \delta_{1,c} + \delta_{2,mt} + \varepsilon_{cmt} \tag{6}$$

[37] Formally, nonemployment rate is defined as:

$$NonempRate_{cmt} = \frac{\sum_{i \in c} \mathbb{1}(E_{i,t-1} > 0, E_{i,t} = 0)}{\sum_{i \in c} \mathbb{1}(E_{i,t-1} > 0)}$$

where $E_{i,t}$ denotes the earnings of worker i in year t, who resides in CZ c and is employed in industry m (defined at the 6-digit NAICS level). To avoid misclassifying retirees or those who exit the workforce, I exclude workers above retirement age and account for potential migration by checking whether they reappear in the residence history after a gap.

where $\delta_{1,c}$ is CZ-level fixed effects and $\delta_{2,mt}$ is industry-by-year fixed effects. Standard errors are clustered at the CZ level.

Figure 6 plots coefficients for the FF nonemployment rate, where k indexes years relative to the onset of the local FF labor demand shock ($k = 0$ is the exposure year). It shows no significant pre-trend in the nonemployment rate for FF workers: the lead coefficients (k=-4 to -1) are near zero with tight confidence intervals. Beginning at $k = 0$ the cumulative effect turns positive; within one year ($k = 1$) the cumulative effect is about 0.1 p.p. It then flattens between years 1 and 3, hovering around 0.25 pp, which is consistent with a short-run adjustment in which some displaced workers find temporary jobs or rely on severance/savings before a second wave of separations. After year 3, the effect grows steadily, reaching roughly 0.5 p.p. by year 6 and exceeding 1 p.p. by year 10. The widening gap is consistent with scarring: prolonged FF contractions depress local job creation, weaken search effectiveness, and deter in-migration, leaving a rising share of the original FF workforce nonemployed.

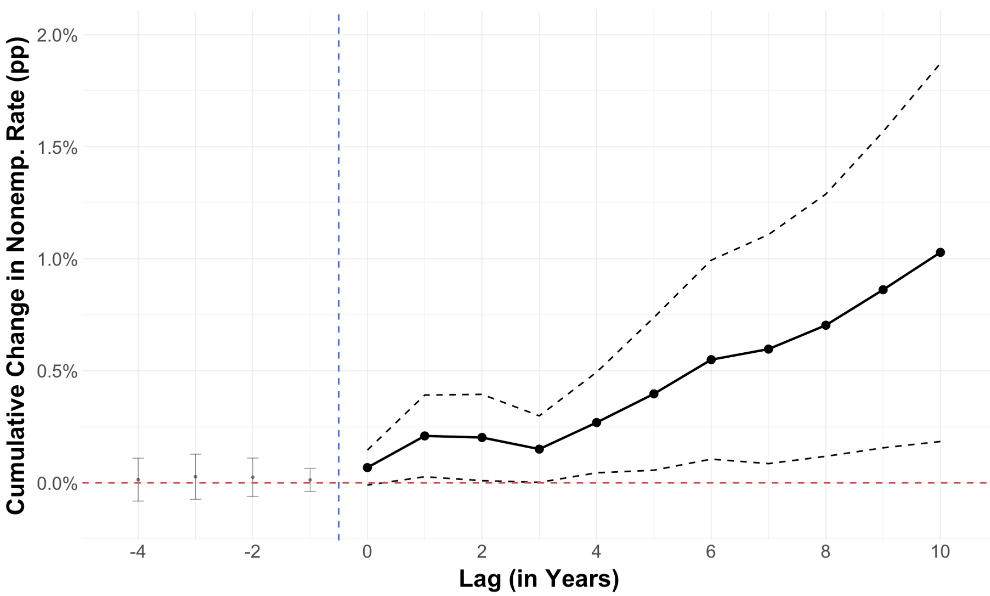


Figure 6: Fossil Fuel Labor Demand Shocks and CZ-Level Nonemployment Rate

Notes: This figure presents estimated coefficients (gray points) and 95% confidence intervals (gray error bars) for lead terms ($FFShock_{c,t-k}$, k=–4 to –1), representing pre-exposure effects. The solid black line shows the cumulative effects of local fossil fuel labor demand shocks from year 0 through year 10 since exposure (k=0 to 10). The dashed black lines indicate the corresponding 95% confidence intervals for these cumulative effects, computed from the variance-covariance matrix. A detailed summary of all estimates can be found in Table A.2.

7.2 Worker-Level Analysis of Fossil Fuel Labor Demand Shocks

7.2.1 Effects on Probability of Employment

I next examine worker-level annual *employment* using Eq. (5) in the full worker sample. The outcome is an employment indicator equal to 1 if the worker has any quarter with positive earnings in year t (0 otherwise).[38] The left panel of Figure 7 shows flat pre-trends and then a steady decline after exposure: the employment probability falls in the first two years, continues to drop through about year 8, and shows only a small partial rebound thereafter. By year 10, the estimated level effect is -0.30: an exposed worker is 30 p.p. less likely to have at least one quarter with positive earnings in that year. Put simply, relative to a comparable worker in a less-exposed market, roughly three more out of every ten record no earnings that year.

7.2.2 Effects on Annual Earnings

The right panel in Figure 7 visualizes the cumulative β_k coefficients (labeled as 'Full Sample') from k=0, illustrating the short-term and long-term impacts of the shocks on annual *earnings*. The lead coefficients are statistically indistinguishable from zero, confirming the absence of pre-trends. Table 1 summarizes the estimated impacts, presenting three specifications: individual-period effects (β_k; column 1), cumulative effects until n years ($\sum_{k=0}^{n} \beta_k$; column 2), and cumulative effects adjusted with a discount factor ($\delta = 0.96$; column 3) to account for worker's time preferences.

Initially, the impact on earnings is relatively modest and shows mixed patterns, possibly due to short-term factors such as severance payments, residual wages from previous employment, or temporary support mechanisms. During the medium term (years 3–6), earnings consistently decline, signaling growing adjustment costs and difficulties such as lower-paying

[38] As a robustness check, I use a stricter employment definition: an indicator equal to 1 only if the worker has positive earnings in at least two quarters of year t. This captures sustained attachment and filters out one-off, seasonal, or noisy spells that can inflate the "any-quarter" measure; Figure A.15 shows similar estimates under both definitions, indicating the results reflect genuine changes in employment attachment after FF demand shocks rather than timing-within-year artifacts.

reemployment or extended periods of nonemployment. In the long term (years 7–10), the effects stabilize, with earnings cumulatively declining by approximately 0.16% annually in response to a 1% decline in national FF employment for a CZ at the sample mean depth. When incorporating the discount factor ($\delta = 0.96$), the time-discounted estimates suggest an annual earnings decline of about 0.14%. Furthermore, my estimates show that an interquartile range (IQR) difference in exposure (6.37%) results in annual earnings losses of approximately 2.5%, consistent with prior findings examining individual worker earnings.[39] The parallel movement of employment probability and earnings indicates that persistent earnings losses are driven by FF-shock–induced job separations, indicating that adjustment occurs mainly on the extensive margin.

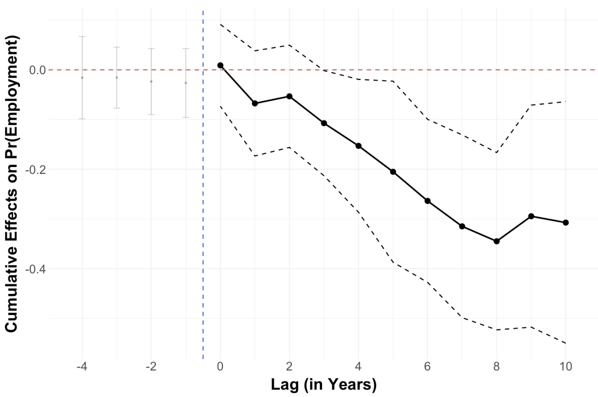
While I define separations as changes between parent firms rather than movements between individual business units (to rule out cases of firm restructuring), it still remains possible that some separations represent temporary leaves rather than true displacement. To mitigate this concern, I construct a *mass-layoff* sample, following the sampling framework used in previous job displacement studies (Davis & Wachter, 2011; Yagan, 2019). The mass-layoff sample includes workers who separated in year t from employers that either: (1) closed between t–1 and t, or (2) had at least 50 employees in t–1 and experienced job cuts exceeding 30% between t–1 and t.[40] The results from the mass-layoff sample are quantitatively similar to those of the full sample (Figure 7), suggesting that the main findings are likely driven by layoffs rather than other types of job separations. This aligns with the findings on nonemployment duration, where job losses correspond closely to earnings declines.

To examine the intensive margin of worker adjustment (e.g., the change in hours or pay when workers switch to a new employer), I keep the same set of workers as in the main sample but restrict the post-separation panel to worker-years with positive annual

[39]For comparison, Autor et al. (2014) reports annual earnings losses of 2.6% for US manufacturing workers due to import penetration; Yagan (2019) finds 1.3% losses for US workers across sectors following Great Recession local shocks; and Kovak and Morrow (2024) reports 2.3% losses for Canadian manufacturing workers after industry-specific shocks (Canadian traiff cuts).

[40]This refined sample consists of about 751,800 workers.

earnings, so comparisons reflect outcomes among the employed.[41] This approach eliminates the influence of transitions into nonemployment while maintaining a meaningful comparison of earnings changes among employed workers. The right panel in Figure 7 shows that the results from the nonzero-earnings sample also remain similar in magnitude to the full sample estimates. This implies that transitions into nonemployment are a central channel, with similar patterns among positive-earnings observations providing suggestive evidence that reduced wage premia or hours in new matches also contribute on the intensive margin.



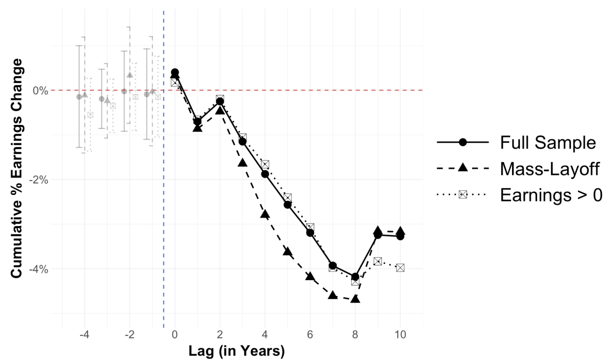


Figure 7: Cumulative Effects on Probability of Employment and Earnings

Notes: The left panel presents estimated coefficients (gray points) and 95% confidence intervals (gray error bars) for lead terms ($FFShock_{c,t-k}$, k=–4 to –1), representing pre-exposure effects. The solid black line shows the cumulative effects of local fossil fuel labor demand shocks from year 0 through year 10 since exposure (k=0 to 10). The dashed black lines indicate the corresponding 95% confidence intervals for these cumulative effects, computed from the variance-covariance matrix. The right panel shows the cumulative effects from k=0 to 10 only. A detailed summary of all estimates can be found in Table A.3 and Table A.4.

7.2.3 Effects on Nonemployment Duration

Columns 4 to 5 in Table 1 present the individual-period and cumulative impacts on nonemployment duration, measured by the number of zero-earning quarters at the worker level. This variable leverages the quarterly earnings records in the LEHD, capturing within-year unemployment spells with greater precision. Similar to the earnings results, the cumulative effects up to 10 years after exposure to shocks are visualized in Figure A.16. The duration of nonemployment exhibits an inverse pattern to earnings losses: the number of

[41]Since the outcome variable is the log change in earnings, excluding cases where earnings drop from a nonzero amount in year $t-1$ to zero in year t prevents sharp declines that would otherwise result in large negative log changes due to differencing.

zero-earnings quarters begins to increase significantly in the short term and intensifies during the medium term, reaching its highest point about 8 years after initial exposure. At this peak, an interquartile range (IQR) difference in the exposure measure corresponds to an average annual increase of approximately 10 weeks in workers' nonemployment. In the long term, the cumulative effect begins to decline, indicating partial recovery as workers either re-enter the labor market or exit entirely (e.g., through retirement).

Table 1: Earnings and Nonemployment Responses to Fossil Fuel Labor Demand Shocks

	Earnings			Nonemployment Duration	
lag (k)	(1)	(2)	(3)	(4)	(5)
-4	-0.149			-0.040	
	(0.583)			(0.174)	
-3	-0.196			-0.008	
	(0.339)			(0.116)	
-2	-0.026			-0.120	
	(0.458)			(0.138)	
-1	-0.092			-0.100	
	(0.518)			(0.151)	
0	0.400	0.400	0.400	-0.212	-0.212
	(0.498)	(0.498)	(0.498)	(0.147)	(0.147)
1	-1.105*	-0.705	-0.660	0.230	0.019
	(0.567)	(0.736)	(0.719)	(0.158)	(0.214)
2	0.454	-0.251	-0.242	-0.082	-0.063
	(0.679)	(0.658)	(0.620)	(0.171)	(0.199)
3	-0.907***	-1.157	-1.044	0.229**	0.166
	(0.294)	(0.724)	(0.675)	(0.090)	(0.215)
4	-0.739**	-1.896**	-1.672**	0.374***	0.540**
	(0.350)	(0.830)	(0.761)	(0.119)	(0.251)
5	-0.704	-2.599**	-2.245**	0.207	0.748**
	(0.585)	(1.132)	(1.006)	(0.173)	(0.342)
6	-0.649	-3.248***	-2.753***	0.120	0.868***
	(0.652)	(1.080)	(0.922)	(0.207)	(0.328)
7	-0.761	-4.009***	-3.325***	0.152	1.020***
	(0.691)	(1.247)	(1.026)	(0.221)	(0.351)
8	-0.259	-4.268***	-3.512***	0.035	1.055***
	(0.596)	(1.148)	(0.900)	(0.177)	(0.351)
9	0.971*	-3.297**	-2.839***	-0.338**	0.717*
	(0.522)	(1.404)	(1.097)	(0.141)	(0.396)
10	-0.031	-3.328**	-2.860**	-0.264	0.453
	(0.521)	(1.521)	(1.171)	(0.182)	(0.467)
Estimate	Indiv.	Cumul.	Cumul. (δ=0.96)	Indiv.	Cumul.
Obs.	21,520,000	21,520,000	21,520,000	21,520,000	21,520,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. For the time-discounted cumulative estimates, standard errors are computed using the delta method. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

7.3 Earnings Losses by Sectoral and Geographic Mobility

In response to labor demand shocks, workers may adjust by moving between industries and/or regions to mitigate earnings losses. These adjustments can have significant long-term impacts on workers' earnings, depending on their reallocation choices. The left panel in Figure 8 shows the earnings impact of FF labor demand shocks over time using the full sample, disaggregated by the four worker reallocation groups defined in Section 5. At k=0, Nonswitcher-Nonmovers exhibit the largest initial earnings gains. These gains are likely driven by short-term factors such as severance payments, residual pay, or bonuses tied to continued employment in the FF sector. In contrast, Switcher-Nonmovers experience smaller initial earnings gains, reflecting their transition out of the FF sector and the absence of such sector-specific benefits during this process.

Interestingly, Nonswitcher-Movers experience greater earnings losses compared to Nonswitcher-Nonmovers. This gap likely reflects the added costs and disruption of moving while staying in a volatile sector; by contrast, exiting the FF sector can place workers in more stable industries. Over the medium and long run, Nonswitcher-Nonmovers show moderate cumulative declines, whereas Switcher-Nonmovers exhibit the most stable paths, consistent with successful local sectoral transitions. Even so, Switcher-Nonmovers experience modest long-run losses, consistent with losing employer premia (Schmieder et al., 2023) or match-specific rents (Lachowska et al., 2020) at displacement. Table A.7 reports pairwise tests of differences in the 10-year cumulative effect ($\sum_{k=0}^{10} \hat{\beta}_k$) across groups: pooling over mobility status, Nonswitchers incur about statistically significant 44% larger cumulative earnings losses than Switchers. Finally, workers who change CZs experience the largest losses regardless of switching status; Movers' cumulative losses are roughly 2.2 times those of Nonmovers, underscoring the substantial costs of geographic adjustment.

I re-estimate worker-group effects in the *mass-layoff* subsample to test whether the full-sample patterns persist in a setting dominated by involuntary separations. The right panel of Figure 8 shows estimates that closely track the full-sample results, strengthening the credibility of the baseline and supporting the interpretation that the main effects are primarily driven by involuntary job loss from FF labor demand shocks.

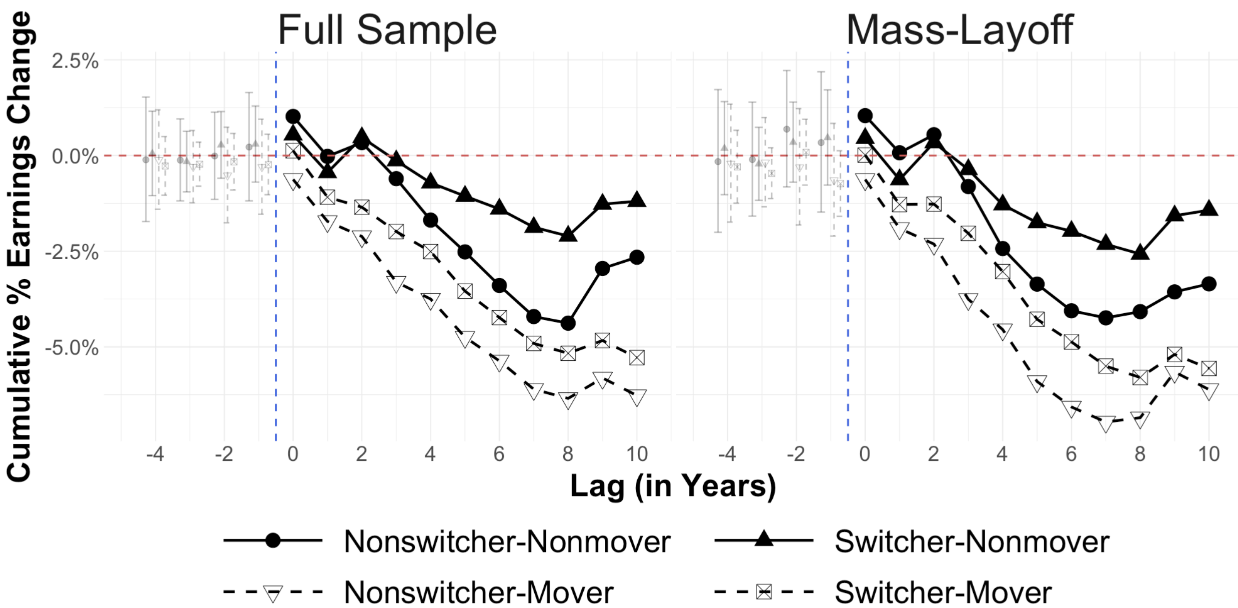


Figure 8: Fossil Fuel Labor Demand Shocks and Earnings Impact by Reallocation Margins

Notes: A detailed summary of all estimates can be found in Table A.5 and Table A.6.

7.3.1 Selection into Switching: Greater Occupational Mobility Among Switchers

A consistent empirical finding is that Nonswitchers suffer larger and more persistent earnings losses than Switchers. Classic sector-specific human capital models (e.g., Topel, 1991; Walker, 2013) would predict the opposite if the sector remained viable, because leaving a sector destroys specific capital. My findings are not driven by secular decline per se as the design differences out worker fixed effects and includes rich controls, so it reflects how local FF shocks translate into earnings. The shock may lower the relative price of FF-specific tasks, reducing the return to FF-specific capital and making staying associated with lower pay even without switching. I explore several mechanisms that reconcile the result.

Evidence on transferability by subsector. Because LEHD does not report occupations, I proxy the specificity of workers' pre-separation skill bundles using 6-digit NAICS subsectors. Employers in *Oil and Gas Extraction* typically have a lower share of highly specialized FF roles (approximately 30%), reflecting a mix of extraction with sales, logistics, and administrative functions; by contrast, *Drilling Wells* often exceeds 75% in FF-specific positions.[42] Consistent with higher specificity, separations from drilling subsectors are disproportionately followed by *not* switching out of FF, as discussed in Section 5.2.2.

The left panel of Figure 9 illustrates cumulative earnings losses for FF workers by their pre-separation subsectors: Oil & Gas Extraction, Coal Mining, Support Activities, and Drilling Wells. The results indicate that workers from subsectors with more specialized and FF-specific skill requirements experience notably larger and more persistent earnings declines after separation. In contrast, workers from the Oil & Gas Extraction subsector, which typically involves broader and more transferable skill sets, suffer relatively minor earnings losses over time. This supports the argument that limited occupational mobility imposes significant long-term costs, as workers with highly specialized skills lose substantial skill premiums when transitioning out of the FF sector. Given the narrow applicability of their expertise in non-FF industries, these specialized workers are frequently forced into positions with lower bargaining power and diminished earning potential, which explains the persistence of their earnings losses.

Cross-sectional corroboration by sex. Task content also varies systematically by sex. Female workers in the FF sector tend to exhibit higher occupational mobility, largely because they often hold roles with more transferable skills, such as accounting or administrative support (Figure A.19). In contrast, male workers predominantly fill mining-specific positions, such as heavy vehicle technicians or derrick operators, which involve fewer transferable skills. This difference in skill transferability aligns with evidence that female workers are more likely to switch sectors, whether or not they relocate geographically (Table A.1). Consequently, as shown in the right panel of Figure 9, female workers experience significantly smaller earnings losses compared to their male counterparts, suggesting that limited job mobility contributes

[42] Figure A.18 details the distribution of FF-specific roles by subsector.

to higher adjustment costs following economic shocks.

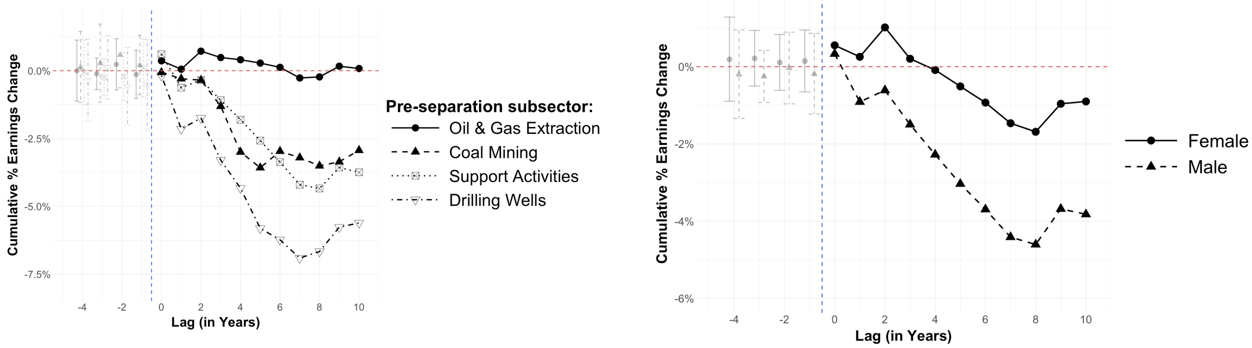


Figure 9: Fossil Fuel Labor Demand Shocks and Earnings Impact by Subsector (Left) and by Sex (Right)

Notes: A detailed summary of all estimates can be found in Table A.8.

The positive-selection result is informative for two main reasons. First, my empirical design isolates a single FF employment shock while holding labor-demand conditions fixed, demonstrating that re-employment outcomes systematically depend on workers' skill portability. This provides direct evidence that previous displacement studies that combine multiple shocks and industries could not separately identify (Autor et al., 2014; Lachowska et al., 2020). Second, although I do not explicitly control for job tenure, first-differencing removes worker-level fixed effects, absorbing permanent wage determinants such as general experience, match quality, and much of the tenure effect. The remaining earnings gap between Switchers and Nonswitchers thus underscores sectoral skill portability as an independent margin of adjustment beyond what those permanent factors alone can explain.

7.3.2 Selection into Moving: Shorter-Tenure and Lower-Earning Workers Are More Likely to Relocate

At first glance, it may seem surprising that Movers experience larger earnings losses than Nonmovers, as standard models typically predict relocation only if expected lifetime benefits outweigh the costs (Greenwood, 1975; Kennan & Walker, 2011). However, two considerations help reconcile this finding.

Negative selection on tenure and human capital portability. First, Movers experience larger earnings losses than nonmovers not simply because they are younger, but because relocation destroys firm-specific and place-specific capital and forces reentry at lower rungs of the job ladder. The left panel in Figure 10 shows that low-tenure workers lose more than high-tenure workers. This pattern is consistent with a composition effect: low-tenure workers are more likely to move (as discussed in Section 5), Movers lose substantially more on average, and the pooled tenure gradient combines Mover and Nonmover outcomes.

Age-mobility patterns indicate that older Nonmovers fare worse in stagnant local markets, consistent with Autor et al. (2014) and Jacobson et al. (1993), whereas younger Movers experience larger losses as they rebuild matches after relocating (Figure A.21). Among Movers, tenure likely raises the threshold for relocation: seniority, firm- and place-specific networks, and job-ladder positions make moving costly, so only high-tenure workers with strong destination prospects choose to move, creating positive selection. Consequently, high-tenure Movers tend to incur smaller losses than low-tenure Movers, who move with weaker options and higher adjustment costs. This sorting reconciles the facts: Movers have larger losses on average than Nonmovers, and the pooled data show a low-tenure penalty even though, within Nonmovers, losses rise with age.

Negative selection on pre-separation earnings and liquidity. Second, Movers are negatively selected on pre-separation earnings: descriptive evidence in Section 5 shows that, even before separation, they earn less on average than Nonmovers. The right panel in Figure 10 documents that workers in the bottom quartile of the pre-separation earnings distribution experience the largest post-separation losses. Lower initial earnings plausibly correlate with tighter liquidity constraints, limiting the ability to finance lengthy searches or retraining and pushing workers toward quicker, lower-paying acceptances. This channel is consistent with displacement settings where shocks reduce demand disproportionately in lower-skill tasks (Autor et al., 2014).

These findings point to a previously overlooked negative selection within the exposed

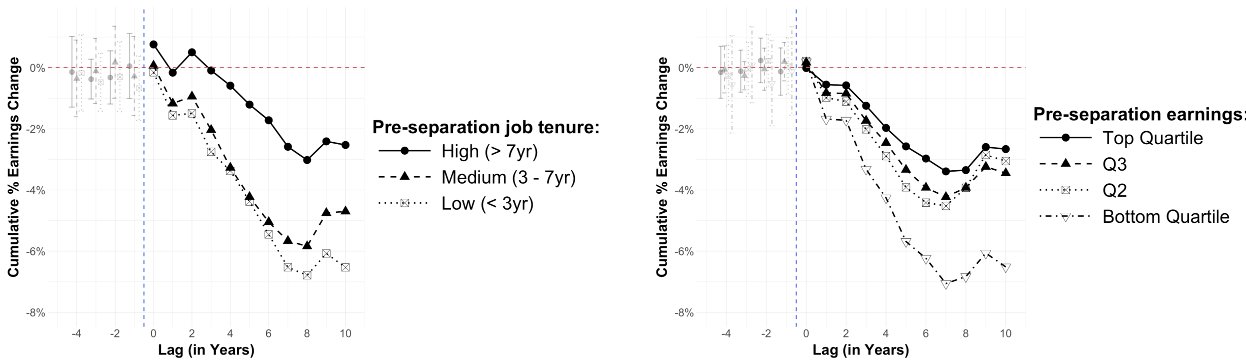


Figure 10: Fossil Fuel Labor Demand Shocks and Earnings Impact by Job Tenure (Left) and by Pre-Separation Earnings (Right)

Notes: A detailed summary of all estimates can be found in Table A.9.

workforce: *involuntary* mobility driven by economic necessity. This stands in contrast to classic migration models, which view relocation as a deliberate, optimizing choice made mainly by higher-skill workers seeking wage gains, which is a view supported by evidence on voluntary moves (Borjas et al., 1992; Collins & Wanamaker, 2014; Kennan & Walker, 2011). In a nationwide FF contraction, however, relocation is better characterized as push-driven: workers move primarily because local opportunities collapse, not because of unobserved destination pull. The frequent shifts from rural to urban areas that I observed in Figure 4 are consistent with this interpretation, as cities offer thicker labor markets and broader fallback options; these moves mitigate losses rather than pursue new gains.

7.3.3 Employer Concentration: Wage-Setting Conditions

As discussed in Section 2, FF employment is typically concentrated among a small number of local employers, consistent with substantial monopsony power in the sector. Limited employer competition restricts workers' bargaining power and makes alternative employment options scarce, effectively trapping workers in the declining FF industry, akin to the experience of displaced manufacturing workers (Autor et al., 2014). Combined with limited information about employment prospects outside their industry and overly optimistic expectations about sector recovery, workers may underestimate the potential benefits of switching sectors. Consequently, they remain in the FF sector, incurring prolonged earnings losses as their local labor markets offer few comparable or better-paying alternatives.

To quantify FF employer concentration within local labor markets, I construct a sector-specific Herfindahl-Hirschman Index (HHI) using the LBD. A simple Cournot-oligopsony model provides the intuition for using concentration as a proxy for monopsony. With multiple employers in the same sector and local market facing an upward-sloping market labor supply, each firm internalizes that hiring one more worker raises the wage paid to all existing employees. This increases the firm's marginal hiring cost, and the size of that increase is proportional to the firm's employment share in the market. Aggregating across firms yields a *market-level* markdown μ that is *smaller* (a deeper wedge) when employer concentration is higher and *larger* when market labor supply is more elastic. Hence, more concentrated FF markets feature a lower μ and, via Eq. (3), lower wages holding prices and effective labor fixed. Appendix D formalizes this mapping and its comparative statics.

Let $m = 1, ..., M$ index 6-digit NAICS FF subsectors and $j = 1, ..., J_m$ index firms in subsector m.[43] Specifically, the HHI^{FF} for CZ c in year t is defined as:

$$HHI_{ct}^{FF} = \underbrace{\sum_{m=1}^{M} \left(\frac{E_{mct}}{E_{ct}}\right)}_{\substack{\text{Emp. share} \\ \text{of subsector}}} \times \underbrace{\sum_{j=1}^{J_m} s_{jmct}^2}_{\substack{\text{Concentration} \\ \text{within subsector}}} \tag{7}$$

where E_{mct} is employment in subsector m and E_{ct} is total FF employment in CZ c at year t; $s_{jmct} = E_{jmct}/E_{mct}$ is firm j's employment share *within* its subsector. Both the subsector employment weight (outer term) and the firm-level concentration measure (inner term) are expressed as shares, ensuring the composite index ranges between 0 and 1 and facilitating comparability across CZs with different subsector compositions. Weighting subsector-level concentration by its local employment share captures both firm-specific monopsony power

[43] Firm-level employment shares thus provide a direct, ex-ante proxy for local monopsony power (Benmelech et al., 2022). Although this approach does not explicitly capture job-entry dynamics, it provides a robust proxy for monopsony conditions, particularly in industries experiencing limited hiring activity or declining employment.

and subsectoral dominance,[44] reflecting the wage-setting environment faced by workers.

Motivated by the fact that many Movers relocate to diversified urban labor markets in Section 5.2.3, I construct an all-sector concentration measure, HHI^{All}, using firm-level employment shares across all 6-digit NAICS subsectors within a CZ (analogous to Eq. 7). This metric captures overall employer concentration, which reflects the breadth of outside options and wage-setting conditions regardless of whether a worker remains in FF or switches sectors. To ensure this measure is predetermined and unaffected by subsequent employment shocks, I fix each CZ's HHI at its average value from 1990-1994, at least four years prior to my analysis window of worker separations. I classify each separated worker's *destination* labor market, defined as the CZ where the worker's subsequent job is located, as a high-concentration one (e.g., high-HHI^{FF}) if the HHI of that CZ lies above the median of the HHI distribution across all CZs in the data; otherwise, I classify it as a low-concentration market.

Nonswitcher-Nonmover. Panel A in Figure 11 shows stark divergence under HHI^{FF}: workers in high-concentration FF markets suffer large, persistent losses, whereas those in low-concentration FF markets experience a mid-run dip followed by near recovery in the long run. Panel B reveals the broader mechanism: under HHI^{All}, high-concentration destinations still depress long-run earnings (modest losses), but in low-concentration destinations the same workers realize large gains. Even without switching, abundant cross-sector outside options force FF employers to bid up pay over time. Taken together, HHI^{FF} isolates within-sector labor market power, while HHI^{All} shows how overall market competitiveness can more than offset that force. It suggests that sectoral reallocation is not the only route to recovery: in sufficiently competitive overall markets, even sector stayers can more than claw back losses as the job ladder steepens via non-FF offers. Where the whole market is concentrated, the same human capital is priced under stronger markdowns and gains are muted.

Switcher-Nonmover. Under HHI^{FF}, long-run effects are null in both high and

[44] For instance, oil extraction dominance in the Permian Basin or coal mining prominence in Appalachia.

low bins, as expected once workers no longer sell FF-priced skills. Panel B shows where wage-setting power re-enters: under HHI^{All}, high-concentration destinations yield modest losses, while low-concentration destinations yield modest gains. This pattern aligns tightly with the selection evidence in Section 7.3.1: switching creates surplus through transferable skills, but whether that surplus is paid out depends on the competitiveness of the overall local market. In dynamic models with on-the-job search, the steady-state wage rises with the arrival rate and quality of alternative offers. High HHI^{All} compresses these outside options, either via fewer potential bidders or lower recruiting intensity, so the firm captures the switching surplus; low HHI^{All} lets workers climb the local job ladder and realize gains, indicating that the same human-capital redeployment yields opposite earnings paths depending solely on market power at destination.

Nonswitcher-Mover. Moving into a destination with high HHI^{FF} leads to *large* long-run losses, whereas moving into a low-HHI^{FF} destination attenuates the damage to modest losses. This is consistent with FF employers at destination continuing to price these workers' FF-specific skills: when few FF rivals can poach, the within-FF job ladder is flat and markdowns persist; when many FF rivals are present, poaching is stronger and losses are smaller. Panel B emphasizes the role of overall employer power: high-HHI^{All} destinations yield large losses, while low-HHI^{All} destinations deliver modest gains. Because the worker stays in FF, the destination's FF concentration still governs the relevant offer arrival rate within FF. At the same time, general competition in the broader market (low HHI^{All}) raises the background threat point, since even non-FF firms can credibly bid for the worker. Mobility arbitrages geography only if it lands workers in competitive overall markets. Relocation resets the match, but the long-run path is shaped by poaching rates at destination, and low HHI^{All} can overturn the common mover penalty documented in Section 7.3.2.

Switcher-Mover. Panel A shows modest long-run losses in both HHI^{FF} bins, as expected because FF-sector concentration no longer prices Switcher-Movers once they leave FF. Panel B shows that HHI^{All} is decisive: high-concentration destinations yield modest losses, while low-concentration destinations deliver approximately zero long-run effects. This pattern aligns with dynamic monopsony: in competitive markets (low HHI^{All}), higher offer arrival rates and stronger poaching steepen the job ladder and neutralize mover frictions; in concentrated markets (high HHI^{All}), low poaching and larger markdowns prevent workers from fully capitalizing on the switching surplus. Re-skilling therefore cushions mobility costs, but only competitive destinations fully offset them; where overall concentration is high, even switchers retain modest long-run losses.

How these results relate to the migration pattern of Movers. Urbanization typically lowers overall employer concentration, so destinations more often have low HHI^{All}; in my estimates, this corresponds to modest gains for Nonswitcher-Movers and approximately zero long-run effects for Switcher-Movers. Even in urban areas, the FF niche may remain highly concentrated, and HHI^{FF} can remain high even when HHI^{All} is low because a few FF firms may dominate the subsector. Consistent with this, Nonswitcher-Movers still incur large losses in high-HHI^{FF} destinations, since their pay is set within FF. By contrast, after switching, HHI^{FF} no longer prices Switcher-Movers; their outcomes depend almost entirely on HHI^{All}, with modest losses in high-HHI^{All} markets and near-neutral effects where HHI^{All} is low. Thus, rural to urban migration is a useful proxy for lower HHI^{All}, not for lower HHI^{FF}, which could explain why Nonswitcher-Movers are shaped by both indices while Switcher-Movers are governed mainly by HHI^{All}.

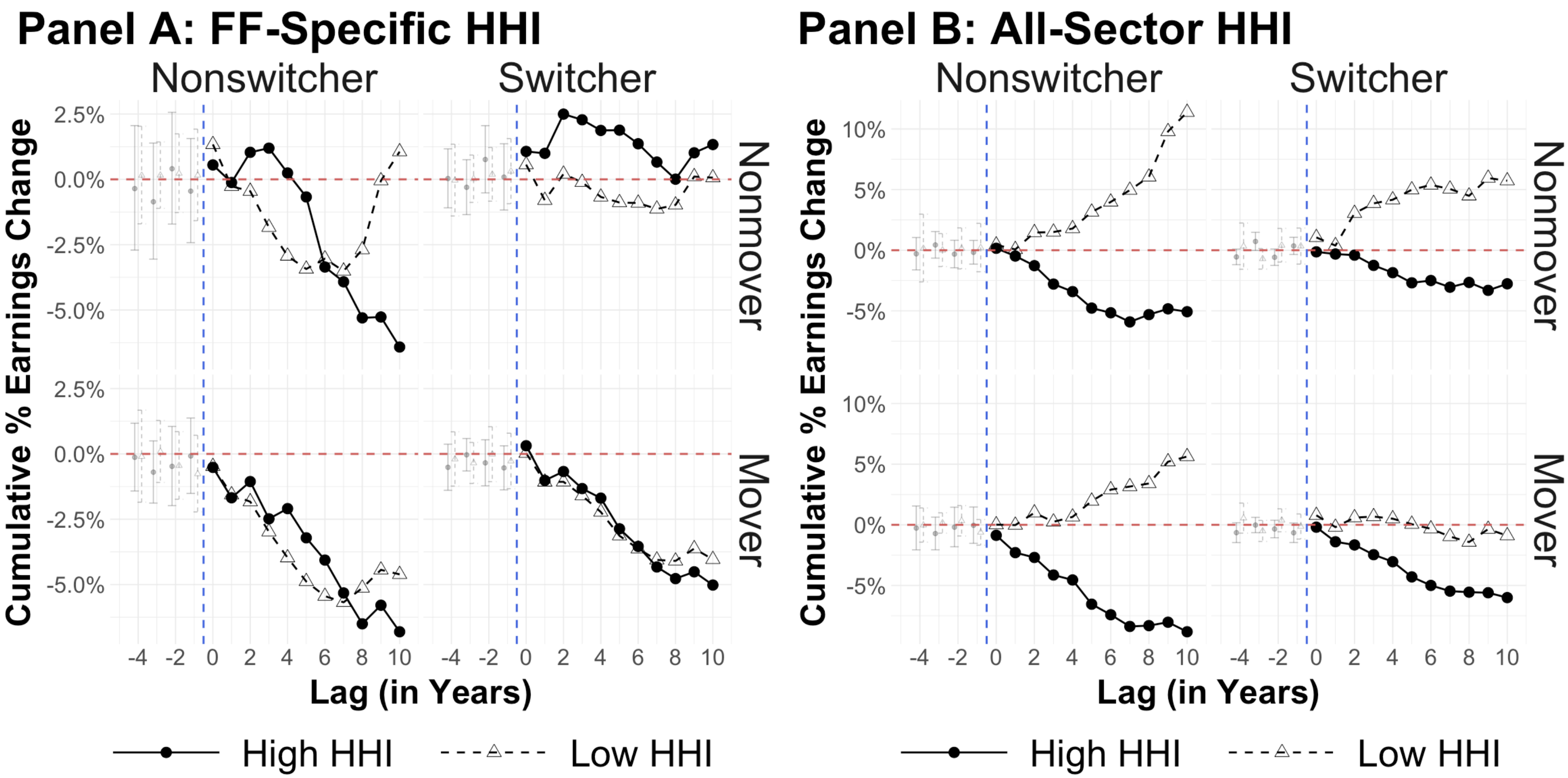


Figure 11: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Destination Markets

Notes: A detailed summary of all estimates can be found in Table A.11 and Table A.12.

One concern is that Movers self-select out of high- versus low-concentration origins and that unobserved characteristics tied to origin HHI could drive the gaps. To probe this, I re-index Movers by their *origin* (pre-separation) HHI within each of the four worker groups. Figure A.22 shows that long-run earnings impacts are statistically indistinguishable between high- and low-origin HHI bins across all groups. Given the main specification with a bunch of fixed effects, any origin-based selection influencing post-shock slopes would be expected to show up in this split. The absence of such differences serves as a suggestive falsification-style check against origin-driven selection and is consistent with destination market forces, such as monopsony markdowns and congestion, playing an important role in the observed heterogeneity.

7.3.4 Linking Empirical Results to the Framework

The earnings impact ranking follows from the interaction of the price channel, destination-side monopsony, and selection on effective labor discussed in Section 3. The price channel is not common across groups: after the aggregate FF shock, remaining in the FF sector mechanically tilts wages down relative to switching. Conditional on prices, destination gaps load on the markdown factor and congestion. Positive selection into switching (higher P_H) feeds more high types into AN and drains AF. Switchers then outperform Nonswitchers even before differences in μ are considered. Negative selection into moving and match rebuilding shift congestion the other way across locations: low-type movers into BF (M_L^F) and high types who fail to switch locally but still enter BF (M_H^F), together with a larger BF incumbent base. Entrants to BN contribute fewer effective units than local switchers to AN because their productivity is scaled by potential geographic frictions such as moving costs or losses of place-specific capital. These assignment patterns generate a common mover penalty in F and much smaller congestion in N.

The employer concentration patterns are the empirical footprint of how $\mu^{j,k}$ and $\tilde{L}^{j,k}$ in the framework move across groups. (i) For Nonswitcher-Nonmovers, strong FF-side employer power at destination implies small $\mu^{F,\cdot}$ and persistent losses, while weaker FF-side power permits near recovery. When overall concentration is stronger, $\mu^{F,\cdot}$ becomes larger from stronger outside options and a smaller $\tilde{L}^F$ as higher probability of switching (P_H) reallocates high types to N, producing the large gains observed. (ii) For Nonswitcher-Movers, small $\mu^{F,B}$ in concentrated destinations combines with higher BF from M_L^F, M_H^F, and incumbents to yield large losses; where overall concentration is low, $\mu^{F,B}$ improves and the mover penalty is partially offset, producing modest gains. (iii) For Switcher-Nonmovers, FF-side power no longer prices pay, so outcomes sort on $\mu^{N,\cdot}$. Large $\mu^{N,\cdot}$ in competitive destinations allows the switching surplus to appear as modest gains, with P_H simultaneously thinning $\tilde{L}^F$. (iv) For Switcher-Movers, wages depend on $\mu^{N,B}$ and the effective contribution of entrants to BN. When overall concentration keeps $\mu^{N,B}$ small and entrants' productivity is scaled by ψ_H^N, modest losses remain, whereas in competitive destinations a large $\mu^{N,B}$ neutralizes mover frictions and long-run effects are approximately zero.

7.4 Robustness Checks

7.4.1 Additional Age Controls

To verify that life-cycle earnings profiles are not driving the baseline effects, I re-estimate the baseline specification adding time-varying age and age squared as controls.[45] As shown in Figure A.23, the series with age controls closely overlaps the baseline estimates: pre-trends remain near zero, the post-shock decline and subsequent trajectory are virtually unchanged, and confidence intervals largely coincide across horizons. Minor deviations are unsystematic and within sampling error, indicating that the main effects reflect FF labor-demand shocks rather than differential aging or shifts in age composition.

[45]Because the model is estimated in first differences and already includes rich state-year and industry-year controls, making the age terms mechanically collinear with time variation and thus potentially over-controlling. For this reason, I keep the parsimonious specification as the baseline and treat the age-augmented version as a robustness check.

7.4.2 Different Clustering Choices

Figure A.24 keeps the point estimates fixed and varies only how standard errors are clustered. When the cluster is broadened to CZ, employer and CZ, or employer and state, the intervals widen enough that zero occasionally falls just inside the 95 percent band, yet the estimates remain statistically different from zero at the 10 percent level (90 percent bands exclude zero). Thus, the earnings decline is still economically meaningful and at least marginally significant under alternative clustering rules.[46]

7.4.3 Asymmetry of Earnings Responses

I test whether FF labor demand shocks affect workers' earnings asymmetrically, such as downturns having a more harmful impact than the beneficial effects of upturns, by introducing a quadratic term into the baseline distributed-lag model (Notowidigdo, 2020).[47] Figure A.25 shows that all confidence intervals comfortably include zero, indicating that the squared shock term is neither statistically nor economically meaningful at any horizon. Thus, the earnings response appears effectively linear and symmetric: the magnitude of a worker's earnings change depends only on the size, not the direction, of the FF employment shock. This result supports the baseline specification by confirming that modeling shocks linearly captures the full earnings impact without overlooking important nonlinear effects.

[46] Notably, the two-way employer and state cluster is more conservative than the baseline, but the employer and state-year specification is conceptually preferable because it captures within-state, within-year shocks (e.g., regional demand swings or policy changes) that could induce correlation in worker-year errors.

[47] Formally, I estimate the following regression:

$$\Delta y_{ict} = \sum_{k=-4}^{10} \beta_k^{(1)} FFShock_{c,t-k} + \sum_{k=-4}^{10} \beta_k^{(2)} FFShock_{c,t-k}^2 + \gamma_{j(i,t)} + \delta_{1,s(c)t} + \delta_{2,m(j)t} + \varepsilon_{ict}$$

. Figure A.25 presents the estimated coefficients $\beta_k^{(2)}$ and their 95% confidence intervals across k.

8 Discussion

8.1 Additional Factors Affecting Worker Adjustment Costs

8.1.1 Industry-Cycle Phase at Separation

I examine additional factors beyond adjustment margins that influence workers' earnings. I start with sectoral demand conditions at the time of separation, which change the mix of exits: in boom years, most separations are quits or quick switches, whereas in bust years, they are largely employer-initiated layoffs. Accordingly, I split workers by separation year into a boom cohort (separations through 2011, when the shale revolution expanded the sector) and a bust cohort (2012 onward, when the oil price plunge and stricter EPA standards reduced fossil fuel demand). This comparison isolates how the industry cycle at separation shapes subsequent earnings. Figure A.26 shows similar earnings paths for the two cohorts through about five years after exposure. After year five, the paths diverge: the post-2012 bust cohort experiences a steeper and more persistent decline, ending with long-run cumulative losses roughly twice those of the pre-2012 boom cohort. This pattern is consistent with deeper scarring from layoffs in weak local labor markets, including lower reemployment rates and poorer matches, relative to the largely voluntary separations in the boom (Katovich et al., 2025).

8.1.2 Job Discrimination

Figure A.27 shows the earnings and nonemployment impacts of FF labor demand shocks across racial groups. In the top panel, Black workers experience significantly larger cumulative earnings losses compared to White workers and workers of races other than White and Black, with losses peaking at more than twice the magnitude of their counterparts. One possible explanation is racial discrimination in hiring, which may exacerbate adjustment costs for marginalized groups (Bertrand & Mullainathan, 2004; Giuliano et al., 2009). The bottom panel shows that Black workers also endure disproportionately higher nonemployment durations, peaking at over two quarters, while White and other workers face relatively smaller increases. These disparities suggest that structural barriers, including bias in hiring processes and limited access to reemployment opportunities, disproportionately burden Black workers.

8.1.3 Unionization

Figure A.28 depicts the earnings impacts disaggregated by the age and size of workers' previous FF employers. Workers displaced from old firms experience significantly greater cumulative earnings losses compared to those from young firms, with the gap widening in the medium to long term. Similarly, workers from large firms face steeper earnings declines than those from small firms, with losses peaking after several years. Unionization may explain some of these differences in earnings losses (Kuhn & Sweetman, 1999; Lee & Mas, 2012). Old mining firms often have a long-standing tradition of unionization[48] and union density tends to be higher in large firms.[49] Union benefits, such as higher wages, severance pay, and job protection, may make workers more reliant on unionized environments, leading to larger earnings losses when they are displaced and can no longer benefit from these protections. For Movers, the absence of union influence in new regions could exacerbate their earnings losses, as they lose access to the wage premiums and protections typically associated with unionized jobs.

8.2 Leveraging Machine Learning for Policy Interventions

To draw policy-relevant lessons, I estimate treatment-effect heterogeneity with a causal random forest (CRF). CRF scales to large datasets and flexibly captures nonlinearities and interactions without pre-specifying them: it partitions observations by X_i into locally similar

[48] It can be exemplified by organizations like the United Mine Workers of America (founded in 1890) and the International Union of Operating Engineers (founded in 1896).

[49] For union density by firm size, see the following link: https://www.oecd.org/content/dam/oecd/en/publications/reports/2017/06/oecd-employment-outlook-2017_g1g7934d/empl_outlook-2017-en.pdf

groups and estimates the average effect within each group.[50] Formally,

$$\Delta y_i = \beta(X_i) FFShock_i + f(X_i) + \varepsilon_i, \tag{8}$$

where Δy_i is the difference in average earnings before and after separation. $\beta(X_i)$ is the conditional average treatment effect (CATE), and $f(X_i)$ absorbs baseline outcome heterogeneity. The characteristics X_i include both *people*-level variables such as job tenure, pre-separation earnings, sex, and education, and *place*-level variables such as origin/destination local employer concentration (HHI^{All}), pre-separation unemployment rate, industry diversity index, and median income.[51]

To summarize what drives heterogeneity in earnings losses from exposure, I use two complementary summaries of the CRF in Eq. (8). First, *permutation importance*, which is a model-agnostic diagnostic of the fitted forest, ranks each covariate in X_i by its contribution to predicting treatment-effect heterogeneity (Davis & Heller, 2020). I randomly permute that variable in the out-of-bag sample, recompute $\hat{\beta}(X)$), and record the increase in out-of-bag mean-squared error; larger increases signal greater importance.

Second, a *precision-weighted linear projection* provides direction and magnitude. I regress the forest's CATE predictions $\hat{\tau}_i = \hat{\beta}(X_i)$ on X_i using weights $w_i = 1/\widehat{\mathrm{Var}}(\hat{\tau}_i)$. The coefficients show how predicted earnings impacts covary with each factor, holding others fixed, so they describe patterns of heterogeneity.[52]

Permutation importance diagnostics show that job tenure is the single most influential moderator (the left panel of Figure 12). Among pre-separation place covariates, local unemployment, industry diversity, and median income rank next in that order. Employer concentration (HHI) also shows nontrivial importance, indicating that concentration is a rel-

[50] CRF uses sample-splitting ("honesty") and out-of-bag prediction to guard against overfitting, so patterns in $\beta(X)$ generalize beyond the training sample.

[51] I cluster by the commuting zone where each worker finds a new job, ensuring that standard errors reflect within-CZ correlations and spatial clustering of shock exposures. See Appendix E for additional details on the CRF estimation.

[52] See Appendix E for details on permutation importance and the precision-weighted projection.

evant correlate of heterogeneity on either side of the move. Among people covariates, age and pre-separation earnings carry a modest signal, whereas education and female contribute little.[53][54]

The right panel of Figure 12 depicts how the predicted earnings response to an IQR increase in exposure varies with people- and place-level characteristics. One SD increase in job tenure is associated with the largest shift (−3.46%), and higher median income in the local area is similarly associated with a smaller predicted response (−2.38%).[55] By contrast, higher unemployment rate (1.76%) and greater employer concentration (0.9%) are associated with larger predicted responses, with industry diversity showing a smaller positive association. Pre-separation earnings and age have a modest negative association, while female and above-high-school education are not statistically distinguishable from zero.

Both diagnostics point to job tenure as the primary moderator. Conditional on tenure, the remaining variation in the model's predicted earnings response is more closely linked to place-based conditions than to the observed individual demographics. This should be treated as hypothesis-generating: permutation importance is a relative, correlation-sensitive ranking, and the linear projection is a model-based descriptive summary of the fitted forest, not a doubly robust causal inference. At most, these patterns can help prioritize where to pilot or scale market-level services, subject to pre-specified robustness checks and out-of-sample validation.

8.3 A Back-of-the-Envelope Estimate of Earnings Losses

I provide a back-of-the-envelope calculation of the cost of the energy transition in terms of foregone earnings for displaced FF workers. Using my main regression estimates, a 1% decline in national FF employment leads to a cumulative earnings loss of roughly $14,157

[53] Permutation importance is a relative, nonadditive diagnostic and is sensitive to correlation across covariates; accordingly, I do not aggregate importances into people versus place totals and instead summarize by ranks and top-K counts.

[54] The small negative for female reflects sampling noise.

[55] See Table A.20 for the summary statistics of the covariates.

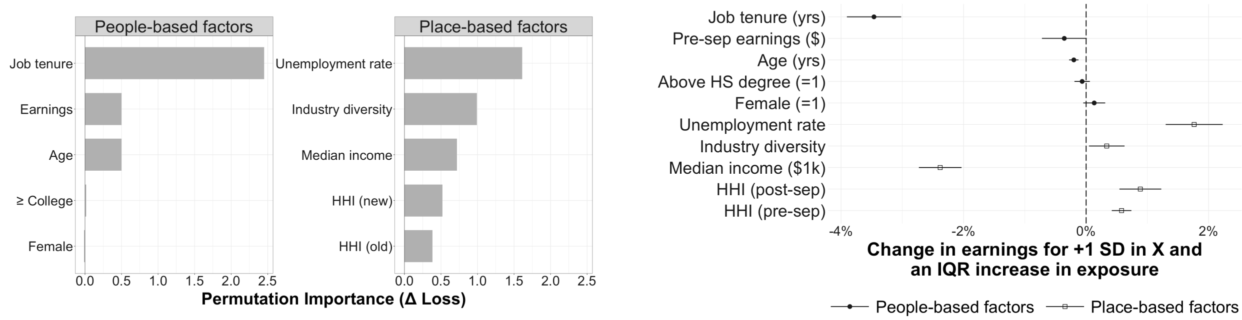


Figure 12: Causal Random Forest: Permutation Importance (Left) and Linear Projection (Right)

Notes: A detailed summary of all estimates can be found in Table A.21.

per worker over 11 years. Multiplying this loss by my sample of 1.35 million FF workers implies an aggregate earnings reduction of approximately $23.9 billion.[56]

This study focuses narrowly on the reallocative costs to FF workers and employs a partial equilibrium approach.[57] However, it is instructive to benchmark these worker-level losses against broader economic gains, notably from job creation in clean energy sectors. The clean-energy industry has rapidly grown, adding about 100,000 jobs annually, comparable in wages to FF jobs. Over 11 years, this growth implies roughly 1.1 million new jobs and about $664 billion in cumulative earnings (U.S. Department of Energy, 2024). Assuming displaced FF workers represent about 0.5% of transitions from "brown" to "green" jobs,[58] the earnings specifically attributable to re-employment of former FF workers would amount to around $3.2 billion. This figure is substantially below the estimated $23.9 billion in earnings losses, highlighting the distinct and substantial economic hardships faced by FF workers, despite broader gains from clean-energy job growth.

Several limitations qualify this comparison. First, the estimates are partial-equilibrium

[56]This calculation assumes a discounted annual cumulative earnings decline of 2.3%. Because my sample covers approximately 80% of national FF employment, this estimate reasonably approximates the national impact. For context, this figure exceeds by more than fourfold the reallocative costs ($5.4 billion) borne by manufacturing workers affected by the 1990 Clean Air Act Amendments (Walker, 2013), underscoring the significant economic burden of the energy transition on FF workers.

[57]Thus, it does not capture broader macroeconomic adjustments such as spillover effects, productivity changes, or secondary employment impacts across other industries.

[58]This assumption aligns with empirical estimates from worker-level transition studies (Colmer et al., 2023; Curtis et al., 2024).

and they scale an 80% sample to a national total under linear, homogeneous responses. General-equilibrium feedbacks such as local multipliers, wage re-leveling, migration, and price effects could raise or reduce the measured losses. Second, the clean-energy benchmark is not directly comparable to the counterfactual for displaced FF workers. It reports gross earnings, it combines temporary construction jobs with permanent operations jobs, and it depends on uncertain transition shares. These features mean that the benefits cannot be netted one-for-one against the estimated losses. Nevertheless, this simple comparison remains useful as an order-of-magnitude yardstick that helps gauge the scale of potential adjustment costs and the need for targeted policy, even though it is not a net welfare measure.

9 Conclusion

The evidence assembled in this study underscores how unusually volatile and geographically concentrated the US fossil fuel extraction sector has been over the past three decades. FF employment swings sharply with commodity-price cycles and regulatory shocks, and the jobs themselves are tied to fixed resource locations and highly specialized occupations. As a result, separation from an FF employer typically triggers far more mobility than in other blue-collar industries: one year after displacement, 20% of workers have already moved to a new labor market, a share that rises to almost 40% within seven years, and roughly one-half have switched out of the sector altogether. Yet these moves involve significant costs. Workers who remain in FF roles face intense monopsony power in sparsely populated resource hubs, whereas those who exit the sector must accept substantial reductions in earnings due to the limited transferability of drilling and mining skills to other industries.

The causal estimates show that local labor-demand shocks in the FF sector translate into persistent losses for both places and people. A 1% decline in national FF employment lifts the non-employment rate of the local FF workforce by about one p.p. within a decade and reduces individual annual earnings by roughly 0.16% on average, which is equivalent to a 2.5% hit for workers in CZs at the 75th versus the 25th percentile of exposure. These losses operate through both extensive and intensive margins: displaced workers accumulate roughly ten additional weeks without earnings over the ten-year window, and those who do find new jobs accept lower wage premiums.

Heterogeneity analyses reveal stark asymmetries. Nonswitcher-Nonmover who remain in FF jobs in the same locality absorb the largest scarring, owing to monopsonistic wage-setting and the collapse in sector-specific skill prices, while Switcher-Nonmovers enjoy the most stable paths after reallocating to non-FF work close to home. Movers, despite incurring the costs of relocation, often fare worse than stayers because they are disproportionately younger, lower-tenure and concentrated in destinations where FF employment is dominated by a handful of firms. Sub-sector and gender splits corroborate these mechanisms: workers from drilling and support activities, and male workers in highly specialized roles, endure the steepest long-run declines.

Taken together, these findings suggest that a successful energy transition may need to address three linked frictions: limited sectoral skill transferability, geographic immobility, and local labor-market power. Policies that subsidize re-training into adjacent high-demand occupations, streamline recognition of prior experience, and provide targeted relocation or commuting assistance could lower the private costs of moving out of declining resource enclaves. In parallel, measures that enhance competition in destination labor markets, including careful merger oversight, support for small and medium-sized clean-energy firms, and greater transparency around prevailing wages, may reduce monopsony rents and help displaced workers receive compensation closer to their marginal productivity. Finally, wage-insurance or time-limited earnings top-ups tied to re-employment could cushion the medium-term income losses observed in the estimates without materially weakening search incentives. Addressing these margins within a broader "just transition" policy framework may help mitigate earnings losses for current FF workers and promote a more widely shared distribution of the gains from decarbonization.

References

Abowd, J. M., Kramarz, F., & Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, *67*(2), 251–333.

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, *128*(6), 2188–2244.

Allcott, H., & Keniston, D. (2018). Dutch disease or agglomeration? the local economic effects of natural resource booms in modern america. *Review of Economic Studies*, *85*(2), 695–731.

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, *103*(6), 2121–2168.

Autor, D. H., Dorn, D., Hanson, G. H., & Song, J. (2014). Trade adjustment: Worker-level evidence. *Quarterly Journal of Economics*, *129*(4), 1799–1860.

Azar, J., Marinescu, I., & Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, *57*(S), S167–S199.

Bartik, A., Currie, J., Greenstone, M., & Knittel, C. R. (2019). The local economic and welfare consequences of hydraulic fracturing. *American Economic Journal: Applied Economics*, *11*(4), 105–55.

Bartik, T. J. (1991). *Who benefits from state and local economic development policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Benmelech, E., Bergman, N. K., & Kim, H. (2022). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, *57*(S), S200–S250.

Berger, D., Herkenhoff, K., & Mongey, S. (2022). Labor market power. *American Economic Review*, *112*(4), 1147–1193.

Bertrand, M., & Mullainathan, S. (2004). Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *American Economic Review*, *94*(4), 991–1013.

Black, D., McKinnish, T., & Sanders, S. (2005). The economic impact of the coal boom and bust. *The Economic Journal*, *115*(503), 449–476.

Borjas, G. J., Bronars, S. G., & Trejo, S. J. (1992). Self-selection and internal migration in the united states. *Journal of Urban Economics*, *32*(2), 159–185.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Review of Economic Studies*, *89*(1), 181–213.

Borusyak, K., Hull, P., & Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, *39*(1), 181–204.

Caldwell, S., & Danieli, O. (2024). Outside options in the labour market. *Review of Economic Studies*, *91*(6), 3286–3315.

Caliendo, L., Dvorkin, M., & Parro, F. (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica*, *87*(3), 741–835.

Collins, W. J., & Wanamaker, M. H. (2014). Selection and economic gains in the great migration of african americans: New evidence from linked census data. *American Economic Journal: Applied Economics*, *6*(1), 220–252.

Colmer, J., Krause, E., Lyubich, E., & Voorheis, J. (2024). Transitional costs and the decline in coal: Worker-level evidence. *CEP Discussion Papers* (*CEPDP2049*).

Colmer, J., Lyubich, E., Voorheis, J., & Addison, K. (2023). Nice work if you can get it? the distribution of employment and earnings during the early years of the clean energy transition. *Working Paper*.

Couch, K. A., & Placzek, D. W. (2010). Earnings losses of displaced workers revisited. *American Economic Review*, *100*(1), 572–589.

Curtis, E. M. (2018). Who loses under cap-and-trade programs? the labor market effects of the nox budget trading program. *Review of Economics and Statistics*, *100*(1), 151–166.

Curtis, E. M., O' Kane, L., & Park, R. J. (2024). Workers and the green-energy transition: Evidence from 300 million job transitions. *Environmental and Energy Policy and the Economy*, *5*(1), 127–161.

Davis, J. M., & Heller, S. B. (2020). Rethinking the benefits of youth employment programs: The heterogeneous effects of summer jobs. *Review of economics and statistics*, *102*(4), 664–677.

Davis, S. J., & Wachter, T. v. (2011). Recessions and the cost of job loss. *NBER Working Paper 17638*.

Deschenes, O. (2010). Climate policy and labor markets. *NBER Working Paper 16111*.

Farber, H. S. (2017). Employment, hours, and earnings consequences of job loss: Us evidence from the displaced workers survey. *Journal of Labor Economics*, *35*(S1), S235–S272.

Feyrer, J., Mansur, E. T., & Sacerdote, B. (2017). Geographic dispersion of economic shocks: Evidence from the fracking revolution. *American Economic Review*, *107*(4), 1313–34.

Flood, S., King, M., Rodgers, R., Ruggles, S., Warren, J. R., Backman, D., Chen, A., Cooper, G., Richards, S., Schouweiler, M., & Westberry, M. (2024). IPUMS CPS: Version 12.0 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V12.0

Fowler, C. S., Rhubart, D. C., & Jensen, L. (2016). Reassessing and revising commuting zones for 2010: History, assessment, and updates for us 'labor-sheds' 1990–2010. *Population Research and Policy Review*, *35*, 263–286.

Giuliano, L., Levine, D. I., & Leonard, J. (2009). Manager race and the race of new hires. *Journal of Labor Economics*, *27*(4), 589–631.

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, *110*(8), 2586–2624.

Greenstone, M. (2002). The impacts of environmental regulations on industrial activity: Evidence from the 1970 and 1977 clean air act amendments and the census of manufactures. *Journal of Political Economy*, *110*(6), 1175–1219.

Greenwood, M. J. (1975). Research on internal migration in the united states: A survey. *Journal of Economic Literature*, 397–433.

Hanson, G. H. (2023). Local labor market impacts of the energy transition: Prospects and policies. *NBER Working Paper 30871*.

Horn, K., Pollakowski, H., Zabel, J., & Chance, J. (2022). The geography of worker adaptation to unanticipated job losses. *2022 APPAM Fall Research Conference*.

Hummels, D., Jørgensen, R., Munch, J., & Xiang, C. (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, *104*(6), 1597–1629.

Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 685–709.

Jarosch, G. (2023). Searching for job security and the consequences of job loss. *Econometrica*, *91*(3), 903–942.

Jung, P., & Kuhn, M. (2019). Earnings losses and labor mobility over the life cycle. *Journal of the European Economic Association*, *17*(3), 678–724.

Kambourov, G., & Manovskii, I. (2009). Occupational mobility and wage inequality. *The Review of Economic Studies*, *76*(2), 731–759.

Katovich, E., Parker, D., & Poelhekke, S. (2025). Timing is everything: Labor market winners and losers during boom-bust cycles. *Journal of the Association of Environmental and Resource Economists*.

Kennan, J., & Walker, J. R. (2011). The effect of expected income on individual migration decisions. *Econometrica*, *79*(1), 211–251.

Kovak, B. K., & Morrow, P. M. (2024). The long-run labour market effects of the canada-us free trade agreement. *Review of Economic Studies*, rdae113.

Kuhn, P., & Sweetman, A. (1999). Vulnerable seniors: Unions, tenure, and wages following permanent job loss. *Journal of Labor Economics*, *17*(4), 671–693.

Lachowska, M., Mas, A., & Woodbury, S. A. (2020). Sources of displaced workers' long-term earnings losses. *American Economic Review*, *110*(10), 3231–3266.

Lamadon, T., Mogstad, M., & Setzler, B. (2022). Imperfect competition, compensating differentials, and rent sharing in the us labor market. *American Economic Review*, *112*(1), 169–212.

Lee, D. S., & Mas, A. (2012). Long-run impacts of unions on firms: New evidence from financial markets, 1961–1999. *Quarterly Journal of Economics*, *127*(1), 333–378.

Luppens, J. A., Rohrbacher, T. J., Osmonson, L. M., & Carter, M. D. (2009). Coal resource availability, recoverability, and economic evaluations in the united states—a summary. *The National Coal Resource Assessment Overview, USGS, US Geological Survey Professional Paper*.

Marchand, J. (2012). Local labor market impacts of energy boom-bust-boom in western canada. *Journal of Urban Economics*, *71*(1), 165–174.

Notowidigdo, M. J. (2020). The incidence of local labor demand shocks. *Journal of Labor Economics*, *38*(3), 687–725.

Parent, D. (2000). Industry-specific capital and the wage profile: Evidence from the national longitudinal survey of youth and the panel study of income dynamics. *Journal of Labor Economics*, *18*(2), 306–323.

Rose, E. K., & Shem-Tov, Y. (2023). How replaceable is a low-wage job? *NBER Working Paper 31447*.

Rud, J.-P., Simmons, M., Toews, G., & Aragon, F. (2024). Job displacement costs of phasing out coal. *Journal of Public Economics*, *236*, 105167.

Ruggles, S., Flood, S., Sobek, M., Backman, D., Chen, A., Cooper, G., Richards, S., Rodgers, R., & Schouweiler, M. (2024). IPUMS USA: Version 15.0 [dataset]. Minneapolis, MN: IPUMS. https://doi.org/10.18128/D010.V15.0

Schmieder, J. F., Wachter, T. v., & Heining, J. (2023). The costs of job displacement over the business cycle and its sources: Evidence from germany. *American Economic Review*, *113*(5), 1208–1254.

Schubert, G., Stansbury, A., & Taska, B. (2024). Employer concentration and outside options. *Available at SSRN 3599454*.

Sorkin, I. (2018). Ranking firms using revealed preference. *The Quarterly Journal of Economics*, *133*(3), 1331–1393.

Thoresson, A. (2024). Employer concentration and wages for specialized workers. *American Economic Journal: Applied Economics*, *16*(1), 447–479.

Topel, R. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy*, *99*(1), 145–176.

U.S. Department of Energy. (2024). 2024 U.S. Energy & Employment Jobs Report. https://www.energy.gov/sites/default/files/2024-10/USEER%202024_COMPLETE_1002.pdf

U.S. EIA. (2016). Trends in U.S. Oil and Natural Gas Upstream Costs. https://www.eia.gov/analysis/studies/drilling/pdf/upstream.pdf

Walker, W. R. (2013). The transitional costs of sectoral reallocation: Evidence from the clean air act and the workforce. *Quarterly Journal of Economics*, *128*(4), 1787–1835.

Yagan, D. (2019). Employment hysteresis from the great recession. *Journal of Political Economy*, *127*(5), 2505–2558.

Yi, M., Müller, S., & Stegmaier, J. (2024). Industry mix, local labor markets, and the incidence of trade shocks. *Journal of Labor Economics*, *42*(3), 000–000.

Appendix

A Details and Proofs for the Conceptual Framework

A.1 Effective labor (definitions moved from main text)

Let $q \equiv \Pr(\theta \geq \theta^*)$, and for any function $X(\theta)$ define

$$\overline{X_H} \equiv \sup_{\theta\in[\theta^*,1]} X(\theta), \quad \underline{X_H} \equiv \inf_{\theta\in[\theta^*,1]} X(\theta), \quad \overline{X_L} \equiv \sup_{\theta\in[0,\theta^*)} X(\theta), \quad \underline{X_L} \equiv \inf_{\theta\in[0,\theta^*)} X(\theta).$$

Effective labor at $t=2$:

$$\tilde{L}_2^{N,A} = \underbrace{n_1^{N,A}}_{\text{incumbents}} + \underbrace{n_1^{F,A}\int_{\theta^*}^{1} P(\theta)\,\theta\,d\theta}_{\text{switchers from AF}}, \tag{A.1}$$

$$\tilde{L}_2^{F,A} = \underbrace{n_1^{F,A}\int_0^{\theta^*}\big[1-M^F(\theta)\big]\,d\theta}_{\text{low-type nonswitchers stay in AF}} + \underbrace{n_1^{F,A}\int_{\theta^*}^{1}\big[1-P(\theta)\big]\big[1-M^F(\theta)-M^N(\theta)\big]\,d\theta}_{\text{high-type nonswitchers stay in AF}}, \tag{A.2}$$

$$\tilde{L}_2^{N,B} = \underbrace{n_1^{N,B}}_{\text{incumbents}} + \underbrace{n_1^{F,A}\int_{\theta^*}^{1}\big[1-P(\theta)\big]\,M^N(\theta)\,\psi(\theta)\,d\theta}_{\text{movers from AF to BN}}, \tag{A.3}$$

$$\tilde{L}_2^{F,B} = \underbrace{n_1^{F,B}}_{\text{incumbents}} + \underbrace{n_1^{F,A}\int_0^{\theta^*} M^F(\theta)\,d\theta}_{\text{low-type movers to BF}} + \underbrace{n_1^{F,A}\int_{\theta^*}^{1}\big[1-P(\theta)\big]\,M^F(\theta)\,d\theta}_{\text{high-type movers to BF}}. \tag{A.4}$$

A.2 Wage equations

With $p_2^N \equiv 1$ and common $\alpha \in (0,1)$:

$$\frac{w_2^{N,k}}{w_2^{F,k}} = \frac{\mu^{N,k}}{\mu^{F,k}} \cdot \frac{1}{p_2^F} \cdot \left(\frac{\tilde{L}_2^{N,k}}{\tilde{L}_2^{F,k}}\right)^{\alpha-1}, \tag{A.5}$$

$$\frac{w_2^{j,B}}{w_2^{j,A}} = \frac{\mu^{j,B}}{\mu^{j,A}} \cdot \left(\frac{\tilde{L}_2^{j,B}}{\tilde{L}_2^{j,A}}\right)^{\alpha-1}. \tag{A.6}$$

A.3 Micro sufficient conditions for congestion comparisons

Within A (switchers vs. nonswitchers). A mean-based sufficient condition for $\tilde{L}_2^{F,A} > \tilde{L}_2^{N,A}$ is

$$\underbrace{\theta^*\left(1-\overline{M_L^F}\right)}_{\text{low-type nonswitchers in } AF} + \underbrace{q\left(1-\overline{P_H}\right)\underline{s_H}}_{\text{high-type nonswitchers in } AF} > \underbrace{\frac{n_1^{N,A}}{n_1^{F,A}}}_{AN \text{ incumbents (scaled)}} + \underbrace{q\,\overline{P_H}\,\overline{\theta}_H}_{\text{high-type switchers to } AN}, \tag{A.7}$$

where $s_H(\theta) \equiv 1 - M^F(\theta) - M^N(\theta)$.

Within B (switchers vs. nonswitchers). A sufficient condition for $\tilde{L}_2^{F,B} > \tilde{L}_2^{N,B}$ is

$$\underbrace{\theta^*\,\underline{M_L^F}}_{\text{low-type movers to } BF} + \underbrace{q\left(1-\overline{P_H}\right)\underline{M_H^F}}_{\text{high-type movers to } BF} + \underbrace{\frac{n_1^{F,B}-n_1^{N,B}}{n_1^{F,A}}}_{\text{incumbent advantage of } BF} > \underbrace{q\left(1-\underline{P_H}\right)\overline{M_H^N}\,\overline{\psi_H}}_{\text{movers to } BN}. \tag{A.8}$$

Note: Low types cannot reach N, so the supremum on M^N is over H.

Within F (movers vs. nonmovers). A sufficient condition for $\tilde{L}_2^{F,B} \geq \tilde{L}_2^{F,A}$ is

$$\underbrace{\frac{n_1^{F,B}}{n_1^{F,A}}}_{BF \text{ incumbents (scaled)}} + \underbrace{\theta^*\,\underline{M_L^F}}_{\text{low-type movers}} + \underbrace{q\left(1-\overline{P_H}\right)\underline{M_H^F}}_{\text{high-type movers}} \geq \underbrace{\theta^*\left(1-\underline{M_L^F}\right)}_{\text{low-type stayers}} + \underbrace{q\left(1-\underline{P_H}\right)\overline{s_H}}_{\text{high-type stayers}}. \tag{A.9}$$

Within N (movers vs. nonmovers). A sufficient condition for $\tilde{L}_2^{N,B} \geq \tilde{L}_2^{N,A}$ is

$$\underbrace{q\left(1-\overline{P_H}\right)\underline{M_H^N}\,\underline{\psi_H}}_{\text{movers to } BN} + \underbrace{\frac{n_1^{N,B}-n_1^{N,A}}{n_1^{F,A}}}_{N \text{ incumbent gap favoring } B} \geq \underbrace{q\,\overline{P_H}\,\overline{\theta}_H}_{\text{switchers to } AN}. \tag{A.10}$$

A.4 Proofs

All results use $\alpha \in (0,1)$ so that, holding μ and prices fixed, higher effective labor reduces the sector–market wage.

Proposition 1. Under (A.7), $\tilde{L}_2^{N,A}/\tilde{L}_2^{F,A} < 1$. With $p_2^F \leq 1$ and $\mu^{N,A} \geq \mu^{F,A}$, (A.5) implies $w_2^{N,A} > w_2^{F,A}$. Strictness follows if at least one inequality is strict.

Proposition 2. Under (A.8), $\tilde{L}_2^{N,B}/\tilde{L}_2^{F,B} < 1$. With $\mu^{N,B} \geq \mu^{F,B}$, (A.5) (with $k{=}B$) yields $w_2^{N,B} > w_2^{F,B}$.

Proposition 3. Under (A.9), $\tilde{L}_2^{F,B} \geq \tilde{L}_2^{F,A}$. If additionally $\mu^{F,B} \leq \mu^{F,A}$, then (A.6) with $j{=}F$ implies $w_2^{F,B} \leq w_2^{F,A}$.

Proposition 4. Under (A.10), $\tilde{L}_2^{N,B} \geq \tilde{L}_2^{N,A}$. If $\mu^{N,B} \leq \mu^{N,A}$, then (A.6) with $j{=}N$ gives $w_2^{N,B} \leq w_2^{N,A}$. Strong portability ($\psi(\theta)$ close to θ), low local switch success, high relocation into BN among eligibles, and a larger N incumbent base in B strengthen (A.10) by increasing $\tilde{L}_2^{N,B}$.

A.5 Comparative statics (corollaries)

1. $\partial\left(w_2^{N,A}/w_2^{F,A}\right)/\partial P_H < 0$: higher local switch success increases $\tilde{L}_2^{N,A}$ and lowers the switcher premium in A.
2. $\partial\left(w_2^{F,B}/w_2^{F,A}\right)/\partial M^F(\cdot) > 0$ for the denominator and < 0 for the numerator: more relocation to BF raises $\tilde{L}_2^{F,B}$ and deepens the mover penalty in F.
3. $\partial w_2^{N,B}/\partial\psi(\cdot) < 0$: better portability raises $\tilde{L}_2^{N,B}$ and reduces $w_2^{N,B}$ (all else equal).
4. If $\mu^{N,k}/\mu^{F,k}$ rises or p_2^F falls, $w_2^{N,k}/w_2^{F,k}$ rises (direct markdown/price effects).

B Rotemberg Weights for the Fossil Fuel Labor Demand Shock Measure

In a conventional Bartik setting with multiple industry-specific shocks, Rotemberg weights arise because each local industry's share is multiplied by the covariance between that industry's national shock and the overall composite shock. Since these covariances can differ in sign, some localities receive negative weights, meaning they actually reduce the first-stage variation identifying the two-stage least squares (2SLS) estimates.

In contrast, my instrument uses only a single time-invariant geological measure ($Depth_c$) combined with a leave-one-out national series for the single sector ($\Delta\log(\sum_{c'\neq c} Emp_{c',t}^{FF})$). Mathematically, the Rotemberg weights simplify to

$$\alpha_c = \frac{Depth_c^2 Var(\Delta log(Emp_{-c,t}^{FF}))}{\sum_r Depth_r^2 Var(\Delta log(Emp_{-r,t}^{FF}))}.$$

Because the square of depth is always non-negative, these weights are guaranteed non-negative, sum to one by construction, and thus cannot become negative through offsetting shocks, unlike traditional multi-industry Bartik instruments. Consequently, problems highlighted by Goldsmith-Pinkham et al. (2020) as identification being driven by a few large but cancelling weights—are mathematically ruled out in my single-sector framework.

Remaining concerns about local-average-treatment-effect (LATE) biases and omitted variables are further minimized by the geological nature of depth, established millions of years before current settlement patterns. To bias the estimates, any omitted socioeconomic characteristic would need to correlate strongly with depth squared and move consistently with national fossil employment cycles. Commuting-zone fixed effects and extensive state-year controls effectively neutralize static correlations with historical coal prosperity, union strength, or demographics.

C Proof of Equivalence Between Cumulative Elasticity from First-Difference Distributed-Lag Model and Long-Run Elasticity from Level-Based Model

Proof. Consider a standard level-based log-log partial-adjustment model:

$$\log(y_t) = \gamma \log(x_t) + \rho \log(y_{t-1}) + u_t, \quad |\rho| < 1. \tag{A.1}$$

In this specification, the long-run elasticity (level-to-level elasticity) is defined as:

$$\beta_{LR} = \frac{\gamma}{1-\rho}. \tag{A.2}$$

Taking the first difference of the level-based model, I explicitly derive:

$$\Delta \log(y_t) = \gamma \Delta \log(x_t) + \rho \Delta \log(y_{t-1}) + \Delta u_t. \tag{A.3}$$

Now, iteratively substituting lagged differences in earnings growth ($\Delta \log(y_{t-1})$) explicitly, I express the model purely in terms of current and past changes in $\log(x_t)$:

$$\Delta \log(y_t) = \gamma \Delta \log(x_t) + \rho \left[\gamma \Delta \log(x_{t-1}) + \rho \Delta \log(y_{t-2}) + \Delta u_{t-1}\right] + \Delta u_t \tag{A.4}$$

$$= \gamma \Delta \log(x_t) + \gamma\rho \Delta \log(x_{t-1}) + \gamma\rho^2 \Delta \log(x_{t-2}) + \cdots + \rho^k \Delta \log(y_{t-k}) + (\text{error terms}). \tag{A.5}$$

Continuing substitution infinitely, and assuming stationarity and stability ($|\rho| < 1$), I obtain the infinite distributed-lag representation clearly in terms of changes in x only:

$$\Delta \log(y_t) = \gamma \Delta \log(x_t) + \gamma\rho \Delta \log(x_{t-1}) + \gamma\rho^2 \Delta \log(x_{t-2}) + \cdots + \varepsilon_t. \tag{A.6}$$

In the distributed-lag first-difference specification estimated empirically, I truncate this infinite series at lag K:

$$\Delta \log(y_t) = \sum_{k=0}^{K} \beta_k \Delta \log(x_{t-k}) + \varepsilon_t, \tag{A.7}$$

where the cumulative elasticity is the sum of all estimated distributed-lag coefficients:

$$\sum_{k=0}^{K} \beta_k. \tag{A.8}$$

If the lag length K is sufficiently large for full adjustment, I can explicitly equate this cumulative elasticity from the truncated first-difference distributed-lag model to the infinite geometric series above:

$$\sum_{k=0}^{K} \beta_k \approx \gamma(1+\rho+\rho^2+\dots) = \frac{\gamma}{1-\rho}. \tag{A.9}$$

I show the cumulative elasticity obtained from the first-difference distributed-lag specification directly equals the standard long-run elasticity from the level-based specification (Eqn. (A.2)). Thus, it follows:

$$\sum_{k=0}^{K} \beta_k \approx \beta_{LR} \tag{A.10}$$

This equivalence explicitly clarifies that the cumulative elasticity from the estimated first-difference log-log distributed-lag model is interpretable as the familiar long-run elasticity from the standard, no-difference, level-based log-log model.

■

D Cournot–oligopsony microfoundation and the HHI–markdown map

Consider sector j in local market k with N employers. The *market* inverse labor supply is

$$w(L) = \chi\, L^{1/\varepsilon}, \qquad \varepsilon > 0, \tag{A.11}$$

so $w'(L) = \frac{w(L)}{\varepsilon L}$. Let firm i choose L_i with total employment $L = \sum_{i=1}^{N} L_i$ and share $s_i \equiv L_i/L$. The firm's marginal expenditure on labor is

$$ME_i = w(L) + L_i\, w'(L) = w(L)\Big(1 + \frac{s_i}{\varepsilon}\Big). \tag{A.12}$$

With marginal revenue product of labor MRPL_i, the first-order condition is

$$\text{MRPL}_i = ME_i = w(L)\Big(1 + \frac{s_i}{\varepsilon}\Big), \tag{A.13}$$

which implies a firm-level markdown

$$\mu_i \equiv \frac{w(L)}{\text{MRPL}_i} = \frac{1}{1+\frac{s_i}{\varepsilon}} \in (0,1]. \tag{A.14}$$

Define $\text{HHI} \equiv \sum_{i=1}^{N} s_i^2$. Define the *market-level* markdown as the ratio of the common wage to the employment-weighted average MRPL:

$$\mu^{\text{market}} \equiv \frac{w(L)}{\sum_{i=1}^{N} s_i \text{MRPL}_i}. \tag{A.15}$$

Using the first-order condition ($\mathrm{MRPL}_i = w(L)(1 + s_i/\varepsilon)$),

$$\sum_{i=1}^{N} s_i \mathrm{MRPL}_i = w(L) \sum_{i=1}^{N} s_i \Big(1 + \frac{s_i}{\varepsilon}\Big) = w(L)\Big(1 + \frac{\mathrm{HHI}}{\varepsilon}\Big), \tag{A.16}$$

so we obtain the exact HHI–markdown map

$$\mu^{\text{market}} = \frac{1}{1 + \frac{\mathrm{HHI}}{\varepsilon}}. \tag{A.17}$$

Hence $\partial \mu^{\text{market}}/\partial \mathrm{HHI} < 0$ and $\partial \mu^{\text{market}}/\partial \varepsilon > 0$. Under symmetry ($s_i = 1/N$ so $\mathrm{HHI} = 1/N$),

$$\mu^{\text{market}} = \frac{1}{1 + \frac{1}{N\varepsilon}} = \frac{N\varepsilon}{1 + N\varepsilon}. \tag{A.18}$$

Remark. If instead one averages firm-level markdowns,

$$\sum_{i=1}^{N} s_i \mu_i = \sum_{i=1}^{N} \frac{s_i}{1 + \frac{s_i}{\varepsilon}}, \tag{A.19}$$

a first-order expansion $1/(1 + x) \approx 1 - x$ gives $\sum_i s_i \mu_i \approx 1 - \mathrm{HHI}/\varepsilon$. Moreover, by the weighted AM-HM inequality,

$$\sum_{i=1}^{N} \frac{s_i}{1 + \frac{s_i}{\varepsilon}} \geq \frac{1}{\sum_{i=1}^{N} s_i (1 + \frac{s_i}{\varepsilon})} = \frac{1}{1 + \frac{\mathrm{HHI}}{\varepsilon}} = \mu^{\text{market}}, \tag{A.20}$$

with equality under symmetry.

Connecting to the main text, equilibrium wages in sector j and market k satisfy

$$w_t^{j,k} = \mu_t^{j,k} \alpha_j p_{j,t} \big(\tilde{L}_{j,k,t}\big)^{\alpha_j - 1}, \tag{A.21}$$

so, holding $p_{j,t}$ and $\tilde{L}_{j,k,t}$ fixed, higher concentration (larger HHI) reduces $\mu_t^{j,k}$ and therefore wages. The textbook monopsony with a single employer ($N = 1$) is the special case $\mu = \varepsilon/(\varepsilon + 1)$.

E Causal Random Forest Estimation

In my causal random forest estimation, I set the number of trees to 1500. Given the substantial sample size of approximately 1.35 million workers, employing a large number of trees is particularly reasonable, as it ensures the stability and accuracy of the estimates by averaging predictions across many independently trained models. With such extensive data, having many trees helps exploit the dataset's full informational content without introducing excessive computational burden.

I specified the minimum node size as 500 to ensure that each subgroup identified by the forest contains enough observations to produce reliable, precise estimates of the treatment effect, significantly reducing noise from random fluctuations in small sub-samples. Given the vast size of the dataset, this node size strikes a balance between detailed subgroup differentiation and the statistical reliability needed for valid policy implications.

Additionally, I set the sample fraction at 0.1, meaning each tree uses a random subsample of roughly 135,000 workers. This large subsample size maintains computational efficiency without sacrificing predictive accuracy, as it remains sufficiently large to detect meaningful patterns in the data. The honesty option with a 60% split further protects against overfitting by clearly separating the data used for identifying subgroup structures from the data used to estimate subgroup-specific effects.

Details on permutation importance calculation. Permutation importance quantifies how crucial each covariate is to the causal forest's prediction accuracy. First, a baseline mean squared error (MSE) is computed between the forest's predictions and the observed pseudo-outcomes on a subset of evaluation data. To enhance computational speed, predictions use a randomly chosen "subforest" of up to 500 trees instead of the full model.

Next, the procedure tests each covariate individually. It randomly shuffles the values of one covariate at a time and recalculates the MSE after each shuffle. This process is repeated three times for each covariate. Shuffling removes the relationship between that covariate and the outcomes; therefore, an increase in MSE above the baseline indicates that the covariate significantly contributes to prediction accuracy. Finally, the average increase in MSE over the three shuffles provides the measure of permutation importance: higher values mean the covariate is more important for explaining differences in outcomes.

Details on precision-weighted linear projection of forest predictions. After estimating a causal forest for

$$\Delta y_i \;=\; \beta(X_i)\,\text{Exposure}_{c(i)} + f(X_i) + \varepsilon_i,$$

I obtain for each worker i the predicted individual effect $\hat{\tau}_i = \hat{\beta}(X_i)$ and its prediction variance $\widehat{\text{Var}}(\hat{\tau}_i)$. To summarize how the *fitted* heterogeneity varies with people- and place-level covariates X_i, I run the precision-weighted linear projection

$$\hat{\tau}_i \;=\; \alpha + X_i^\top \gamma + u_i,$$

estimated by WLS with weights $w_i = 1/\widehat{\text{Var}}(\hat{\tau}_i)$ and standard errors clustered at the CZ level. This regression should be interpreted as a descriptive, model-based summary of the heterogeneity learned by the forest: the coefficient γ_j is the change in the *predicted* effect (per one unit of the exposure) associated with a one-unit difference in covariate A_{ij}, holding other covariates fixed.

Appendix Tables

Table A.1: Summary Statistics of Workers and Subgroups by Sectoral and Geographic Mobility

	All Workers (1)	Nonswitcher-Nonmover (2)	Switcher-Nonmover (3)	Nonswitcher-Mover (4)	Switcher-Mover (5)
Variable (Dummy)					
Young (< 35)	0.292	0.236	0.258	0.351	0.368
Middle (35−50)	0.377	0.339	0.391	0.378	0.407
Old (> 50)	0.331	0.425	0.351	0.271	0.225
Female	0.176	0.186	0.210	0.134	0.147
Male	0.825	0.814	0.790	0.867	0.853
White	0.877	0.881	0.870	0.884	0.877
Black	0.056	0.052	0.064	0.051	0.054
Other Races	0.067	0.067	0.066	0.066	0.070
< High School	0.178	0.170	0.171	0.188	0.188
High School	0.314	0.313	0.306	0.319	0.320
College	0.310	0.305	0.314	0.306	0.312
> College	0.199	0.211	0.208	0.187	0.180
Number of Workers	1,349,500	398,900	385,000	251,500	324,100

Notes: Each cell, except those in the last row, displays the average value for the corresponding variable. The numbers are rounded in line with Census disclosure rules. Data source: LEHD.

Table A.2: Fossil Fuel Labor Demand Shocks and Nonemployment Rate

	Nonemployment Rate	
lag (k)	(1)	(2)
-4	0.014	
	(0.049)	
-3	0.027	
	(0.051)	
-2	0.025	
	(0.044)	
-1	0.013	
	(0.026)	
0	0.068*	
	(0.040)	
1	0.141**	0.210**
	(0.060)	(0.093)
2	-0.007	0.202**
	(0.023)	(0.098)
3	-0.052	0.151**
	(0.037)	(0.076)
4	0.119***	0.269**
	(0.046)	(0.115)
5	0.128**	0.397**
	(0.065)	(0.174)
6	0.152**	0.550**
	(0.061)	(0.226)
7	0.047	0.597**
	(0.044)	(0.261)
8	0.107**	0.704**
	(0.047)	(0.299)
9	0.158**	0.862**
	(0.069)	(0.360)
10	0.167**	1.029**
	(0.077)	(0.431)
Estimate	Indiv.	Cumul.
Obs.	18,000	18,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by commuting zone are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.3: Fossil Fuel Labor Demand Shocks and Employment Impact

	Indicator for Employment		Indicator for Short-Term Employment	
lag (k)	(1)	(2)	(3)	(4)
-4	0.016		0.017	
	(0.042)		(0.054)	
-3	0.016		0.019	
	(0.031)		(0.033)	
-2	0.024		0.003	
	(0.034)		(0.038)	
-1	0.026		0.000	
	(0.035)		(0.044)	
0	-0.009	-0.009	-0.020	-0.020
	(0.042)	(0.042)	(0.044)	(0.044)
1	0.077**	0.068	0.115**	0.095
	(0.038)	(0.054)	(0.055)	(0.070)
2	-0.014	0.053	-0.085	0.010
	(0.038)	(0.052)	(0.070)	(0.056)
3	0.054*	0.107**	0.077***	0.087
	(0.029)	(0.054)	(0.024)	(0.064)
4	0.046	0.153**	0.090***	0.176**
	(0.038)	(0.068)	(0.033)	(0.071)
5	0.052	0.205**	0.061	0.237**
	(0.054)	(0.093)	(0.057)	(0.097)
6	0.059	0.264***	0.037	0.274***
	(0.052)	(0.084)	(0.059)	(0.092)
7	0.051	0.315***	0.062	0.336***
	(0.050)	(0.094)	(0.059)	(0.102)
8	0.030	0.346***	0.024	0.360***
	(0.043)	(0.091)	(0.052)	(0.103)
9	-0.051	0.295***	-0.073	0.287**
	(0.041)	(0.114)	(0.048)	(0.127)
10	0.013	0.308**	-0.009	0.278**
	(0.044)	(0.124)	(0.052)	(0.141)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	21,520,000	21,520,000	21,520,000	21,520,000

Notes: For columns 1 and 2, the outcome is an employment indicator equal to 1 if the worker has any quarter with positive earnings in year t (0 otherwise). For columns 3 and 4, the outcome is an employment indicator equal to 1 if the worker has more than one quarter with positive earnings in year t (0 otherwise). The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.4: Fossil Fuel Labor Demand Shocks and Earnings Impact with Full, Mass-Layoff, and Nonzero-Earnings Sample

	Baseline		Mass-Layoffs		Nonzero Earnings	
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)
-4	-0.149		-0.117		-0.553	
	(0.583)		(0.664)		(0.418)	
-3	-0.196		-0.242		-0.351	
	(0.339)		(0.428)		(0.308)	
-2	-0.026		0.330		-0.151	
	(0.458)		(0.549)		(0.387)	
-1	-0.092		-0.030		-0.147	
	(0.518)		(0.625)		(0.463)	
0	0.400		0.335		0.170	
	(0.498)		(0.583)		(0.385)	
1	-1.105*	-0.705	-1.204*	-0.869	-0.835*	-0.665
	(0.567)	(0.736)	(0.680)	(0.840)	(0.492)	(0.598)
2	0.454	-0.251	0.392	-0.477	0.469	-0.196
	(0.679)	(0.658)	(0.780)	(0.771)	(0.579)	(0.600)
3	-0.907***	-1.157	-1.181***	-1.658*	-0.871***	-1.067
	(0.294)	(0.724)	(0.336)	(0.876)	(0.262)	(0.685)
4	-0.739**	-1.896**	-1.175***	-2.833***	-0.607*	-1.674**
	(0.350)	(0.830)	(0.438)	(1.028)	(0.316)	(0.814)
5	-0.704	-2.599**	-0.867	-3.700***	-0.762	-2.435**
	(0.585)	(1.132)	(0.699)	(1.399)	(0.558)	(1.134)
6	-0.649	-3.248***	-0.579	-4.279***	-0.685	-3.120***
	(0.652)	(1.080)	(0.768)	(1.343)	(0.577)	(1.190)
7	-0.761	-4.009***	-0.443	-4.722***	-0.938	-4.058***
	(0.691)	(1.247)	(0.802)	(1.516)	(0.575)	(1.311)
8	-0.259	-4.268***	-0.089	-4.811***	-0.320	-4.378***
	(0.596)	(1.148)	(0.660)	(1.433)	(0.462)	(1.322)
9	0.971*	-3.297**	1.600**	-3.211*	0.470	-3.908**
	(0.522)	(1.404)	(0.677)	(1.731)	(0.445)	(1.537)
10	-0.031	-3.328**	-0.013	-3.223*	-0.151	-4.059**
	(0.521)	(1.521)	(0.618)	(1.838)	(0.434)	(1.664)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	21,520,000	21,520,000	11,880,000	11,880,000	17,830,000	17,830,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.5: Fossil Fuel Labor Demand Shocks and Earnings Impact by Reallocation Margins (Full Sample)

	Nonswitcher-Nonmover		Switcher-Nonmover		Nonswitcher-Mover		Switcher-Mover	
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-4	-0.111		0.050		-0.112		-0.274	
	(0.830)		(0.562)		(0.663)		(0.392)	
-3	-0.120		-0.162		-0.294		-0.227	
	(0.547)		(0.405)		(0.483)		(0.294)	
-2	-0.013		0.274		-0.518		-0.165	
	(0.581)		(0.444)		(0.640)		(0.378)	
-1	0.221		0.295		-0.300		-0.237	
	(0.721)		(0.506)		(0.635)		(0.404)	
0	1.016		0.540		-0.626		0.126	
	(0.731)		(0.435)		(0.759)		(0.387)	
1	-1.038	-0.022	-0.985*	-0.445	-1.109	-1.735*	-1.219***	-1.093**
	(0.725)	(1.003)	(0.506)	(0.683)	(0.740)	(0.959)	(0.429)	(0.556)
2	0.359	0.337	0.915*	0.470	-0.403	-2.138**	-0.266	-1.359***
	(0.910)	(0.919)	(0.533)	(0.678)	(0.831)	(0.874)	(0.472)	(0.497)
3	-0.943**	-0.606	-0.605*	-0.135	-1.222**	-3.360***	-0.647***	-2.006***
	(0.436)	(1.007)	(0.321)	(0.787)	(0.492)	(0.918)	(0.236)	(0.541)
4	-1.096**	-1.702	-0.580*	-0.715	-0.462	-3.822***	-0.535	-2.541***
	(0.502)	(1.177)	(0.331)	(0.886)	(0.660)	(1.131)	(0.351)	(0.670)
5	-0.848	-2.550	-0.352	-1.067	-1.040	-4.862***	-1.065**	-3.606***
	(0.778)	(1.614)	(0.519)	(1.170)	(0.919)	(1.446)	(0.504)	(0.871)
6	-0.905	-3.455**	-0.340	-1.407	-0.655	-5.517***	-0.721	-4.327***
	(0.945)	(1.466)	(0.601)	(1.163)	(0.757)	(1.388)	(0.484)	(0.883)
7	-0.844	-4.299**	-0.485	-1.892	-0.785	-6.301***	-0.708	-5.035***
	(0.928)	(1.769)	(0.608)	(1.280)	(0.809)	(1.548)	(0.529)	(0.954)
8	-0.180	-4.479***	-0.235	-2.127*	-0.255	-6.557***	-0.272	-5.306***
	(0.795)	(1.563)	(0.449)	(1.234)	(0.823)	(1.567)	(0.511)	(0.941)
9	1.484**	-2.995	0.849*	-1.278	0.569	-5.988***	0.352	-4.954***
	(0.650)	(1.858)	(0.465)	(1.440)	(0.735)	(1.951)	(0.410)	(1.145)
10	0.302	-2.693	0.075	-1.203	-0.488	-6.476***	-0.471	-5.425***
	(0.652)	(2.023)	(0.531)	(1.646)	(0.723)	(2.067)	(0.385)	(1.219)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	6,338,000	6,338,000	6,699,000	6,699,000	3,590,000	3,590,000	4,897,000	4,897,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.6: Fossil Fuel Labor Demand Shocks and Earnings Impact by Reallocation Margins (Mass-Layoff Sample)

	Nonswitcher-Nonmover		Switcher-Nonmover		Nonswitcher-Mover		Switcher-Mover	
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-4	-0.158		0.186		-0.210		-0.297	
	(0.953)		(0.619)		(0.788)		(0.487)	
-3	-0.105		-0.222		-0.181		-0.466	
	(0.760)		(0.488)		(0.596)		(0.340)	
-2	0.687		0.344		-0.305		0.084	
	(0.770)		(0.532)		(0.777)		(0.439)	
-1	0.338		0.463		-0.646		-0.737*	
	(0.932)		(0.632)		(0.756)		(0.440)	
0	1.037	1.037	0.451	0.451	-0.627	-0.627	0.012	0.012
	(0.896)	(0.896)	(0.493)	(0.493)	(0.868)	(0.868)	(0.480)	(0.480)
1	-0.965	0.072	-1.082*	-0.631	-1.296*	-1.923*	-1.301**	-1.289*
	(0.932)	(1.206)	(0.568)	(0.790)	(0.784)	(1.043)	(0.513)	(0.662)
2	0.471	0.543	0.968	0.337	-0.418	-2.341**	0.012	-1.276**
	(1.074)	(1.152)	(0.644)	(0.813)	(0.892)	(0.964)	(0.566)	(0.630)
3	-1.357***	-0.814	-0.702*	-0.364	-1.487**	-3.828***	-0.778***	-2.054***
	(0.517)	(1.316)	(0.405)	(0.976)	(0.586)	(1.098)	(0.278)	(0.694)
4	-1.646**	-2.460	-0.929**	-1.294	-0.827	-4.655***	-1.026***	-3.080***
	(0.714)	(1.605)	(0.413)	(1.125)	(0.858)	(1.373)	(0.397)	(0.826)
5	-0.957	-3.417	-0.474	-1.768	-1.430	-6.085***	-1.292**	-4.372***
	(0.996)	(2.175)	(0.619)	(1.471)	(1.081)	(1.675)	(0.576)	(1.095)
6	-0.724	-4.141**	-0.229	-1.997	-0.711	-6.796***	-0.620	-4.992***
	(1.213)	(1.993)	(0.680)	(1.504)	(0.883)	(1.649)	(0.546)	(1.104)
7	-0.193	-4.334*	-0.349	-2.346	-0.420	-7.216***	-0.668	-5.660***
	(1.155)	(2.249)	(0.717)	(1.710)	(0.855)	(1.824)	(0.605)	(1.172)
8	0.170	-4.164**	-0.261	-2.606	0.121	-7.096***	-0.314	-5.974***
	(1.008)	(1.954)	(0.500)	(1.712)	(0.853)	(1.866)	(0.556)	(1.184)
9	0.536	-3.629	1.021*	-1.585	1.275	-5.821***	0.637	-5.337***
	(0.859)	(2.213)	(0.612)	(1.991)	(0.956)	(2.244)	(0.507)	(1.411)
10	0.218	-3.411	0.147	-1.438	-0.488	-6.309***	-0.388	-5.725***
	(0.823)	(2.366)	(0.654)	(2.249)	(0.882)	(2.369)	(0.442)	(1.467)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	3,522,000	3,522,000	3,527,000	3,527,000	2,127,000	2,127,000	2,705,000	2,705,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.7: Cumulative Coefficient Differences between Stayers and Leavers

$\sum_{k=0}^{10} \hat{\beta}_k^{Nonswitcher} - \sum_{k=0}^{10} \hat{\beta}_k^{Switcher}$	-1.499***
	(0.667)
$\sum_{k=0}^{10} \hat{\beta}_k^{Nonmover} - \sum_{k=0}^{10} \hat{\beta}_k^{Mover}$	3.016***
	(0.610)

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.8: Fossil Fuel Labor Demand Shocks and Earnings Impact by Pre-Separation Subsector and Sex

	Pre-Separation Subsector				Sex	
	Oil & Gas Extraction	Coal Mining	Support Activites	Drilling Wells	Female	Male
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)
-4	-0.002	0.130	-0.059	-0.350	0.189	-0.202
	(0.574)	(0.665)	(0.608)	(0.769)	(0.555)	(0.585)
-3	-0.114	0.271	-0.242	0.122	0.215	-0.255
	(0.297)	(0.731)	(0.352)	(0.597)	(0.366)	(0.345)
-2	0.231	0.579	-0.221	-0.587	0.108	-0.038
	(0.481)	(0.618)	(0.456)	(0.733)	(0.368)	(0.473)
-1	-0.141	0.204	0.086	-0.523	0.145	-0.188
	(0.454)	(0.556)	(0.554)	(0.849)	(0.407)	(0.534)
0	0.364	-0.062	0.604	-0.181	0.552*	0.332
	(0.443)	(0.459)	(0.586)	(0.821)	(0.306)	(0.528)
1	0.056	-0.297	-0.625	-2.170*	0.255	-0.915
	(0.734)	(0.704)	(0.788)	(1.259)	(0.521)	(0.757)
2	0.717	-0.349	-0.343	-1.761	1.011*	-0.613
	(0.772)	(0.771)	(0.750)	(1.193)	(0.586)	(0.673)
3	0.484	-1.321	-1.096	-3.350**	0.205	-1.509**
	(0.752)	(0.877)	(0.818)	(1.344)	(0.656)	(0.735)
4	0.405	-3.043**	-1.820**	-4.424***	-0.087	-2.303***
	(0.932)	(1.184)	(0.910)	(1.488)	(0.794)	(0.839)
5	0.280	-3.640***	-2.609**	-5.982***	-0.512	-3.081***
	(1.133)	(1.348)	(1.204)	(1.966)	(1.029)	(1.166)
6	0.125	-3.011**	-3.426***	-6.433***	-0.935	-3.765***
	(1.210)	(1.374)	(1.157)	(1.909)	(1.040)	(1.120)
7	-0.267	-3.256**	-4.292***	-7.153***	-1.475	-4.513***
	(1.531)	(1.467)	(1.312)	(1.960)	(1.170)	(1.273)
8	-0.229	-3.569**	-4.437***	-6.894***	-1.700	-4.713***
	(1.627)	(1.619)	(1.222)	(1.783)	(1.177)	(1.170)
9	0.166	-3.413*	-3.634**	-5.937***	-0.966	-3.751**
	(1.852)	(1.929)	(1.490)	(2.297)	(1.303)	(1.458)
10	0.081	-2.977	-3.814**	-5.772**	-0.905	-3.897**
	(1.902)	(2.205)	(1.620)	(2.562)	(1.412)	(1.576)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$					
Obs.	5,598,000	1,219,000	11,420,000	3,290,000	3,765,000	17,760,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.9: Fossil Fuel Labor Demand Shocks and Earnings Impact by Pre-Separation Job Tenure and Earnings

	Pre-Separation Job Tenure			Pre-Separation Earnings			
	High (>7yr)	Medium (3−7yr)	Low (<3yr)	Q1	Q2	Q3	Q4
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
-4	-0.143	-0.359	-0.179	-0.560	-0.263	-0.061	-0.154
	(0.589)	(0.641)	(0.636)	(0.817)	(0.509)	(0.392)	(0.434)
-3	-0.376	-0.117	-0.480	0.087	-0.056	-0.265	-0.117
	(0.333)	(0.544)	(0.486)	(0.635)	(0.452)	(0.236)	(0.351)
-2	-0.323	0.169	-0.304	-0.515	0.217	-0.052	0.234
	(0.445)	(0.599)	(0.586)	(0.716)	(0.438)	(0.352)	(0.370)
-1	0.050	-0.284	-0.677	-0.117	0.044	0.194	-0.131
	(0.542)	(0.662)	(0.540)	(0.743)	(0.474)	(0.320)	(0.395)
0	0.757	0.068	-0.152	0.191	0.213	0.170	-0.013
	(0.572)	(0.628)	(0.580)	(0.852)	(0.591)	(0.362)	(0.368)
1	-0.164	-1.178	-1.574*	-1.697	-0.986	-0.830*	-0.556
	(0.805)	(0.899)	(0.834)	(1.071)	(0.749)	(0.470)	(0.554)
2	0.501	-0.946	-1.505**	-1.734*	-1.115	-0.848*	-0.581
	(0.760)	(0.819)	(0.722)	(1.018)	(0.733)	(0.479)	(0.519)
3	-0.092	-2.056**	-2.789***	-3.380***	-2.039**	-1.748***	-1.254**
	(0.832)	(0.916)	(0.768)	(1.161)	(0.826)	(0.570)	(0.555)
4	-0.590	-3.324***	-3.433***	-4.351***	-2.936***	-2.488***	-1.990***
	(0.909)	(1.072)	(1.021)	(1.385)	(1.023)	(0.693)	(0.758)
5	-1.215	-4.318***	-4.478***	-5.854***	-3.993***	-3.396***	-2.608***
	(1.181)	(1.496)	(1.367)	(1.740)	(1.422)	(0.968)	(0.980)
6	-1.736	-5.180***	-5.611***	-6.438***	-4.514***	-4.002***	-3.017***
	(1.188)	(1.273)	(1.317)	(1.736)	(1.292)	(1.062)	(0.948)
7	-2.621*	-5.833***	-6.753***	-7.321***	-4.627***	-4.321***	-3.452***
	(1.339)	(1.385)	(1.482)	(1.745)	(1.283)	(1.124)	(1.236)
8	-3.067**	-6.019***	-7.031***	-7.078***	-4.006***	-4.002***	-3.409***
	(1.229)	(1.184)	(1.422)	(1.784)	(1.285)	(1.166)	(1.287)
9	-2.441*	-4.871***	-6.267***	-6.256***	-2.893*	-3.296**	-2.630*
	(1.476)	(1.507)	(1.728)	(2.164)	(1.538)	(1.319)	(1.460)
10	-2.562	-4.815***	-6.756***	-6.737***	-3.101*	-3.510***	-2.699*
	(1.584)	(1.665)	(1.841)	(2.419)	(1.694)	(1.331)	(1.396)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$						
Obs.	10,340,000	6,878,000	4,307,000	4,684,000	5,214,000	5,585,000	6,041,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.10: Fossil Fuel Labor Demand Shocks and Earnings Impact by Age

	Nonmover			*Mover*		
	Young	Middle	Old	Young	Middle	Old
	(< 35)	(35−50)	(> 50)	(< 35)	(35−50)	(> 50)
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)
-4	-0.116	-0.062	-0.172	-0.633	-0.658	-0.418
	(0.788)	(0.650)	(0.623)	(0.472)	(0.497)	(0.694)
-3	-0.276	-0.225	0.200	-0.238	-0.258	0.154
	(0.562)	(0.438)	(0.387)	(0.354)	(0.393)	(0.451)
-2	-0.300	-0.016	0.462	-0.635	-0.130	-0.118
	(0.606)	(0.430)	(0.472)	(0.470)	(0.450)	(0.605)
-1	0.301	0.142	0.257	-0.503	-0.899*	-0.384
	(0.697)	(0.599)	(0.444)	(0.431)	(0.522)	(0.574)
0	0.761	0.681	0.079	-0.628	-0.188	0.126
	(0.724)	(0.573)	(0.390)	(0.481)	(0.587)	(0.649)
1	-0.379	-0.392	-1.041	-1.922***	-1.691**	-0.401
	(0.950)	(0.808)	(0.700)	(0.635)	(0.771)	(0.916)
2	0.351	0.031	-1.139	-2.048***	-1.536**	-0.496
	(0.947)	(0.826)	(0.694)	(0.614)	(0.752)	(0.879)
3	-0.579	-0.547	-2.324***	-3.095***	-2.301***	-1.435
	(1.048)	(0.910)	(0.735)	(0.688)	(0.788)	(0.941)
4	-1.773	-1.394	-3.496***	-3.748***	-3.026***	-2.107*
	(1.205)	(1.014)	(0.856)	(0.824)	(1.006)	(1.144)
5	-2.434	-2.051	-4.499***	-5.116***	-4.072***	-2.704**
	(1.680)	(1.313)	(1.082)	(1.130)	(1.267)	(1.186)
6	-3.057*	-2.566**	-5.215***	-5.600***	-4.939***	-2.963**
	(1.647)	(1.265)	(1.042)	(1.172)	(1.251)	(1.180)
7	-4.008**	-3.165**	-5.607***	-6.416***	-5.589***	-3.504***
	(1.778)	(1.482)	(1.212)	(1.223)	(1.324)	(1.320)
8	-4.108**	-3.143**	-5.567***	-6.590***	-5.433***	-3.459**
	(1.656)	(1.368)	(1.274)	(1.252)	(1.373)	(1.398)
9	-2.958	-1.934	-4.437***	-6.458***	-4.841***	-2.412
	(1.922)	(1.649)	(1.527)	(1.442)	(1.680)	(1.776)
10	-2.792	-1.728	-4.165***	-7.082***	-5.455***	-1.954
	(2.120)	(1.876)	(1.550)	(1.512)	(1.771)	(2.003)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$					
Obs.	4,835,000	4,553,000	3,648,000	4,361,000	2,816,000	1,310,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.11: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Destination Markets (FF-Specific HHI)

	Nonswitcher-Nonmover		Switcher-Nonmover		Nonswitcher-Mover		Switcher-Mover	
	High	Low	High	Low	High	Low	High	Low
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-4	-0.355	0.148	0.032	-0.038	-0.130	-0.103	-0.514	-0.198
	(1.219)	(0.951)	(0.576)	(0.701)	(0.662)	(0.900)	(0.452)	(0.531)
-3	-0.862	0.154	-0.305	0.020	-0.700	0.086	-0.034	-0.348
	(1.143)	(0.647)	(0.538)	(0.462)	(0.611)	(0.605)	(0.317)	(0.402)
-2	0.405	0.225	0.757	0.188	-0.477	-0.450	-0.342	-0.014
	(1.087)	(0.767)	(0.651)	(0.524)	(0.776)	(0.664)	(0.451)	(0.536)
-1	-0.452	0.154	0.086	0.306	-0.079	-0.767	-0.537	-0.275
	(1.021)	(0.893)	(0.646)	(0.634)	(0.737)	(0.754)	(0.433)	(0.543)
0	0.550	1.329	1.063*	0.562	-0.517	-0.474	0.313	0.029
	(0.948)	(0.821)	(0.588)	(0.602)	(0.832)	(0.834)	(0.426)	(0.510)
1	-0.122	-0.267	0.991	-0.806	-1.692	-1.571	-1.019*	-1.080
	(1.392)	(1.102)	(0.843)	(0.901)	(1.125)	(1.040)	(0.579)	(0.765)
2	1.029	-0.455	2.466***	0.204	-1.064	-1.845*	-0.676	-1.073
	(1.441)	(1.213)	(0.920)	(0.919)	(1.172)	(0.985)	(0.603)	(0.674)
3	1.187	-1.853	2.253**	-0.112	-2.515**	-3.025***	-1.335**	-1.610**
	(1.514)	(1.425)	(1.025)	(1.014)	(1.238)	(1.082)	(0.649)	(0.733)
4	0.243	-2.979*	1.854	-0.676	-2.116	-4.053***	-1.707**	-2.249**
	(1.686)	(1.580)	(1.219)	(1.250)	(1.461)	(1.416)	(0.793)	(0.983)
5	-0.676	-3.492*	1.865	-0.891	-3.264*	-5.006***	-2.908***	-3.183**
	(2.198)	(1.917)	(1.476)	(1.699)	(1.763)	(1.695)	(0.935)	(1.259)
6	-3.413	-3.084	1.352	-0.911	-4.148**	-5.596***	-3.603***	-3.698***
	(2.571)	(2.046)	(1.579)	(1.740)	(1.783)	(1.577)	(0.973)	(1.300)
7	-4.000	-3.572	0.659	-1.141	-5.468***	-5.846***	-4.423***	-4.141***
	(2.461)	(2.266)	(1.615)	(1.879)	(1.934)	(1.705)	(1.040)	(1.406)
8	-5.447**	-2.727	0.007	-0.983	-6.724***	-5.269***	-4.890***	-4.181***
	(2.505)	(2.117)	(1.547)	(1.974)	(1.889)	(1.777)	(0.935)	(1.557)
9	-5.412	-0.052	1.011	0.106	-5.965***	-4.538**	-4.618***	-3.691**
	(3.313)	(2.352)	(1.687)	(2.186)	(2.266)	(2.230)	(1.105)	(1.817)
10	-6.632*	1.054	1.323	0.065	-7.049***	-4.719*	-5.149***	-4.120**
	(3.888)	(2.427)	(1.986)	(2.293)	(2.439)	(2.521)	(1.206)	(1.906)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$							
Obs.	2,129K	4,208K	2,524K	4,175K	1,409K	2,181K	2,105K	2,792K

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.12: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Destination Markets (All-Sector HHI)

	Nonswitcher-Nonmover		Switcher-Nonmover		Nonswitcher-Mover		Switcher-Mover	
	High	Low	High	Low	High	Low	High	Low
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-4	-0.294	0.144	-0.553*	0.320	-0.272	-0.029	-0.649	0.546
	(0.682)	(1.423)	(0.330)	(0.969)	(0.925)	(0.720)	(0.420)	(0.629)
-3	0.437	0.004	0.721*	-0.713	-0.723	0.150	-0.018	-0.510
	(0.555)	(0.692)	(0.380)	(0.436)	(0.692)	(0.428)	(0.323)	(0.445)
-2	-0.321	0.138	-0.581*	0.402	-0.193	0.325	-0.346	0.372
	(0.579)	(0.862)	(0.347)	(0.706)	(0.836)	(0.637)	(0.370)	(0.482)
-1	-0.173	0.202	0.356	0.333	-0.041	-0.627	-0.658	-0.143
	(0.499)	(1.015)	(0.360)	(0.756)	(0.764)	(0.544)	(0.414)	(0.529)
0	0.162	0.444	-0.134	1.052	-0.870	0.013	-0.195	0.782
	(0.722)	(1.034)	(0.393)	(0.644)	(0.967)	(0.711)	(0.451)	(0.630)
1	-0.481	0.065	-0.314	0.386	-2.320**	-0.021	-1.407**	-0.190
	(0.837)	(1.563)	(0.584)	(0.976)	(1.135)	(1.117)	(0.575)	(0.881)
2	-1.280	1.448	-0.404	3.003***	-2.728***	0.988	-1.673***	0.592
	(0.791)	(1.691)	(0.572)	(1.121)	(1.056)	(1.158)	(0.549)	(0.871)
3	-2.830***	1.490	-1.257**	3.791***	-4.227***	0.246	-2.494***	0.677
	(0.951)	(2.066)	(0.628)	(1.411)	(1.064)	(1.372)	(0.600)	(1.014)
4	-3.471***	1.772	-1.868**	4.080**	-4.653***	0.652	-3.091***	0.503
	(1.070)	(2.172)	(0.764)	(1.645)	(1.348)	(1.621)	(0.718)	(1.279)
5	-4.888***	3.106	-2.724***	4.872***	-6.767***	1.941	-4.388***	0.052
	(1.300)	(2.272)	(1.009)	(1.882)	(1.616)	(2.026)	(0.911)	(1.555)
6	-5.294***	3.906	-2.528**	5.241**	-7.704***	2.858	-5.126***	-0.330
	(1.386)	(2.552)	(1.133)	(2.251)	(1.650)	(2.153)	(0.939)	(1.710)
7	-6.092***	4.838	-3.095**	4.930*	-8.752***	3.107	-5.621***	-0.970
	(1.403)	(3.083)	(1.220)	(2.706)	(1.755)	(2.258)	(0.989)	(1.903)
8	-5.453***	5.870**	-2.691**	4.388	-8.678***	3.349	-5.714***	-1.432
	(1.428)	(2.983)	(1.350)	(2.872)	(1.844)	(2.369)	(0.986)	(2.032)
9	-4.951***	9.342***	-3.363**	5.779*	-8.371***	5.073*	-5.763***	-0.357
	(1.897)	(3.369)	(1.587)	(3.171)	(2.473)	(2.617)	(1.308)	(2.253)
10	-5.201***	10.775***	-2.806	5.574	-9.231***	5.477**	-6.188***	-0.899
	(1.972)	(3.792)	(1.716)	(3.500)	(2.785)	(2.713)	(1.426)	(2.474)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$							
Obs.	3,314K	3,023K	3,461K	3,238K	2,305K	1,285K	3,259K	1,638K

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.13: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Origin Markets

	Nonswitcher-Mover				*Switcher-Mover*			
	FF-Specific HHI		All-Sector HHI		FF-Specific HHI		All-Sector HHI	
	High	Low	High	Low	High	Low	High	Low
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
-4	-0.036	-0.135	-0.372	-0.016	-0.702	-0.069	-0.304	-0.179
	(0.684)	(0.794)	(0.658)	(0.690)	(0.430)	(0.456)	(0.442)	(0.480)
-3	-0.230	-0.471	-0.356	-0.290	-0.178	-0.270	-0.229	-0.128
	(0.580)	(0.564)	(0.465)	(0.501)	(0.406)	(0.356)	(0.368)	(0.330)
-2	-0.453	-0.597	-0.420	-0.471	-0.303	-0.054	-0.324	-0.069
	(0.705)	(0.696)	(0.695)	(0.655)	(0.468)	(0.413)	(0.370)	(0.398)
-1	-0.595	-0.125	-0.257	-0.589	-0.137	-0.188	-0.519	-0.369
	(0.706)	(0.707)	(0.602)	(0.665)	(0.426)	(0.483)	(0.411)	(0.459)
0	-0.542	-0.715	-0.705	-0.374	0.210	0.136	-0.315	0.628
	(0.805)	(0.863)	(0.783)	(0.845)	(0.494)	(0.450)	(0.356)	(0.430)
1	-1.244	-2.147**	-1.961*	-1.291	-1.059	-1.146*	-1.652***	-0.317
	(1.123)	(1.027)	(1.009)	(1.090)	(0.670)	(0.629)	(0.533)	(0.658)
2	-1.143	-2.139**	-2.138**	-1.065	-1.191*	-0.960*	-1.489***	-0.548
	(1.085)	(0.951)	(0.983)	(1.102)	(0.665)	(0.580)	(0.467)	(0.693)
3	-2.358**	-3.383***	-3.385***	-2.278**	-1.771**	-1.732***	-2.256***	-0.986
	(1.201)	(0.988)	(1.115)	(1.115)	(0.708)	(0.645)	(0.522)	(0.790)
4	-2.651*	-3.981***	-3.806***	-2.524*	-2.179**	-2.384***	-2.760***	-1.355
	(1.358)	(1.327)	(1.292)	(1.410)	(0.866)	(0.814)	(0.683)	(0.925)
5	-3.607**	-5.071***	-4.383***	-3.447*	-3.283***	-3.551***	-3.716***	-2.393**
	(1.633)	(1.636)	(1.450)	(1.829)	(1.030)	(1.111)	(0.880)	(1.162)
6	-4.281**	-5.736***	-5.097***	-3.643*	-3.856***	-4.358***	-4.362***	-3.032**
	(1.711)	(1.538)	(1.505)	(1.859)	(1.079)	(1.086)	(0.837)	(1.348)
7	-5.520***	-6.280***	-5.322***	-4.386**	-4.665***	-4.932***	-4.915***	-3.841**
	(1.697)	(1.793)	(1.541)	(2.098)	(1.178)	(1.142)	(0.875)	(1.506)
8	-5.968***	-6.336***	-5.452***	-4.456*	-5.228***	-4.976***	-4.991***	-4.071***
	(1.649)	(1.897)	(1.438)	(2.323)	(1.110)	(1.213)	(0.877)	(1.563)
9	-5.315**	-5.623**	-4.298**	-3.843	-4.864***	-4.541***	-4.849***	-3.459**
	(2.087)	(2.238)	(1.782)	(2.715)	(1.355)	(1.385)	(1.118)	(1.743)
10	-5.601**	-6.188**	-4.927***	-4.037	-5.334***	-5.033***	-5.394***	-3.820**
	(2.288)	(2.406)	(1.911)	(2.842)	(1.471)	(1.475)	(1.276)	(1.823)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$							
Obs.	1,106K	2,484K	1,838K	3,059K	1,757K	1,834K	2,610K	2,287K

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.14: Fossil Fuel Labor Demand Shocks and Earnings Impact: Baseline vs. Specifications with Age Controls

	Full Sample		Full Sample with Age Controls	
lag (k)	(1)	(2)	(3)	(4)
-4	-0.149		-0.241	
	(0.583)		(0.587)	
-3	-0.196		-0.266	
	(0.339)		(0.377)	
-2	-0.026		-0.119	
	(0.458)		(0.472)	
-1	-0.092		-0.163	
	(0.518)		(0.536)	
0	0.400	0.400	0.287	0.287
	(0.498)	(0.498)	(0.526)	(0.526)
1	-1.105*	-0.705	-1.161*	-0.874
	(0.567)	(0.736)	(0.600)	(0.762)
2	0.454	-0.251	0.373	-0.501
	(0.679)	(0.658)	(0.724)	(0.673)
3	-0.907***	-1.157	-0.953***	-1.454**
	(0.294)	(0.724)	(0.317)	(0.733)
4	-0.739**	-1.896**	-0.827**	-2.282***
	(0.350)	(0.830)	(0.382)	(0.858)
5	-0.704	-2.599**	-0.790	-3.072***
	(0.585)	(1.132)	(0.635)	(1.190)
6	-0.649	-3.248***	-0.708	-3.780***
	(0.652)	(1.080)	(0.686)	(1.098)
7	-0.761	-4.009***	-0.813	-4.593***
	(0.691)	(1.247)	(0.706)	(1.256)
8	-0.259	-4.268***	-0.252	-4.845***
	(0.596)	(1.148)	(0.601)	(1.137)
9	0.971*	-3.297**	0.912*	-3.933***
	(0.522)	(1.404)	(0.532)	(1.402)
10	-0.031	-3.328**	-0.060	-3.993***
	(0.521)	(1.521)	(0.549)	(1.515)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	21,520,000	21,520,000	21,520,000	21,520,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.15: Fossil Fuel Labor Demand Shocks and Earnings Impact by Different Clustering Choices

lag (k)	Employer (1)	State-Year (2)	CZ (3)	Employer and CZ (4)	Employer and State (5)
-4	-0.149	-0.149	-0.149	-0.149	-0.149
	(0.130)	(0.600)	(0.222)	(0.211)	(0.219)
-3	-0.196	-0.196	-0.196	-0.196	-0.196
	(0.123)	(0.353)	(0.150)	(0.138)	(0.124)
-2	-0.026	-0.026	-0.026	-0.026	-0.026
	(0.150)	(0.467)	(0.162)	(0.156)	(0.199)
-1	-0.092	-0.092	-0.092	-0.092	-0.092
	(0.141)	(0.527)	(0.287)	(0.272)	(0.148)
0	0.400***	0.400	0.400	0.400	0.400
	(0.144)	(0.508)	(0.310)	(0.301)	(0.477)
1	-0.705***	-0.705	-0.705*	-0.705*	-0.705**
	(0.197)	(0.750)	(0.372)	(0.366)	(0.357)
2	-0.251	-0.251	-0.251	-0.251	-0.251
	(0.239)	(0.663)	(0.507)	(0.489)	(0.630)
3	-1.157***	-1.157	-1.157*	-1.157*	-1.157
	(0.270)	(0.728)	(0.642)	(0.621)	(0.937)
4	-1.896***	-1.896**	-1.896**	-1.896**	-1.896*
	(0.333)	(0.832)	(0.857)	(0.831)	(1.010)
5	-2.599***	-2.599**	-2.599**	-2.599**	-2.599**
	(0.402)	(1.139)	(1.196)	(1.164)	(1.263)
6	-3.248***	-3.248***	-3.248**	-3.248**	-3.248**
	(0.448)	(1.072)	(1.527)	(1.493)	(1.376)
7	-4.009***	-4.009***	-4.009**	-4.009**	-4.009***
	(0.495)	(1.237)	(1.813)	(1.782)	(1.545)
8	-4.268***	-4.268***	-4.268**	-4.268**	-4.268**
	(0.516)	(1.125)	(1.926)	(1.896)	(1.882)
9	-3.297***	-3.297**	-3.297*	-3.297*	-3.297
	(0.562)	(1.396)	(1.890)	(1.858)	(2.316)
10	-3.328***	-3.328**	-3.328*	-3.328*	-3.328
	(0.584)	(1.520)	(1.785)	(1.748)	(2.385)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$				
Obs.	21,520,000	21,520,000	21,520,000	21,520,000	21,520,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors are shown in parentheses and are clustered at the level indicated in the first row. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.16: Quadratic Terms of Fossil Fuel Labor Demand Shocks and Earnings Impact

lag (k)	$FFShock^2$ (1)
-4	-0.060
	(0.817)
-3	0.087
	(0.635)
-2	-0.115
	(0.716)
-1	-0.117
	(0.743)
0	0.191
	(0.852)
1	-0.088
	(0.764)
2	-0.038
	(0.811)
3	-0.646
	(0.507)
4	-0.371
	(0.714)
5	-0.503
	(1.156)
6	-0.584
	(1.057)
7	-0.183
	(0.930)
8	0.244
	(0.706)
9	0.222
	(0.723)
10	-0.480
	(0.810)
Estimate	Indiv.
Obs.	21,520,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.17: Fossil Fuel Labor Demand Shocks and Earnings Impact by Separation Year

	Separation year: ≤ 2011		Separation year: ≥ 2012	
lag (k)	(1)	(2)	(3)	(4)
-4	-0.300		-0.105	
	(0.538)		(0.712)	
-3	0.002		-0.015	
	(0.403)		(0.351)	
-2	0.156		-0.303	
	(0.467)		(0.462)	
-1	-0.270		0.396	
	(0.530)		(0.549)	
0	0.194	0.194	0.062	0.062
	(0.419)	(0.419)	(0.676)	(0.676)
1	-1.285**	-1.091	-0.550	-0.489
	(0.574)	(0.702)	(0.514)	(0.877)
2	0.777	-0.314	0.194	-0.294
	(0.776)	(0.613)	(0.403)	(0.929)
3	-0.958***	-1.272*	-0.704***	-0.999
	(0.319)	(0.689)	(0.251)	(1.026)
4	-0.763*	-2.035***	-0.622*	-1.621
	(0.391)	(0.780)	(0.324)	(1.172)
5	-0.350	-2.385**	-1.259**	-2.880**
	(0.554)	(1.044)	(0.496)	(1.438)
6	-0.354	-2.739***	-0.922*	-3.802***
	(0.658)	(0.934)	(0.530)	(1.428)
7	-0.301	-3.040***	-1.243*	-5.045***
	(0.648)	(1.054)	(0.736)	(1.628)
8	-0.117	-3.157***	-0.263	-5.308***
	(0.572)	(0.856)	(0.664)	(1.453)
9	1.171**	-1.986*	0.983*	-4.325**
	(0.552)	(1.113)	(0.526)	(1.718)
10	0.187	-1.799	-0.141	-4.467**
	(0.603)	(1.377)	(0.382)	(1.778)
Estimate	Indiv.	Cumul.	Indiv.	Cumul.
Obs.	12,420,000	12,420,000	9,107,000	9,107,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.18: Fossil Fuel Labor Demand Shocks and Earnings Impact by Race

	White		Black		Other Races	
	Earnings	Nonemp.	Earnings	Nonemp.	Earnings	Nonemp.
lag (k)	(1)	(2)	(3)	(4)	(5)	(6)
-4	-0.168	-0.032	0.159	-0.025	0.675	-0.320
	(0.573)	(0.171)	(1.067)	(0.294)	(0.780)	(0.298)
-3	-0.154	-0.031	-0.427	0.016	0.135	0.020
	(0.317)	(0.103)	(0.713)	(0.307)	(0.574)	(0.251)
-2	-0.078	-0.096	0.601	-0.309	0.380	-0.158
	(0.448)	(0.130)	(0.761)	(0.204)	(0.784)	(0.272)
-1	-0.176	-0.113	0.181	-0.182	0.474	0.099
	(0.492)	(0.143)	(1.030)	(0.283)	(0.801)	(0.282)
0	0.344	-0.203	0.690	-0.221	0.737	-0.327
	(0.488)	(0.144)	(0.916)	(0.235)	(0.601)	(0.218)
1	-0.709	0.018	-1.898	0.335	-0.124	-0.272
	(0.729)	(0.211)	(1.311)	(0.323)	(0.986)	(0.343)
2	-0.280	-0.056	-1.114	0.442	0.360	-0.326
	(0.653)	(0.202)	(1.435)	(0.375)	(1.114)	(0.372)
3	-1.138	0.161	-2.048	0.646	-1.075	-0.044
	(0.713)	(0.215)	(1.611)	(0.432)	(1.328)	(0.434)
4	-1.794**	0.502**	-3.901**	1.366**	-1.834	0.362
	(0.808)	(0.246)	(1.932)	(0.578)	(1.532)	(0.545)
5	-2.413**	0.716**	-5.270**	1.734**	-2.118	0.159
	(1.101)	(0.327)	(2.474)	(0.746)	(1.878)	(0.664)
6	-3.020***	0.794**	-6.441**	2.199***	-2.222	0.388
	(1.078)	(0.330)	(2.551)	(0.711)	(2.124)	(0.695)
7	-3.752***	0.923***	-7.724***	2.431***	-2.878	0.793
	(1.233)	(0.355)	(2.909)	(0.812)	(2.282)	(0.692)
8	-4.035***	0.960***	-8.459***	2.468***	-2.882	0.739
	(1.160)	(0.358)	(2.950)	(0.863)	(2.033)	(0.644)
9	-3.104**	0.630	-7.226**	2.195**	-1.489	0.343
	(1.421)	(0.402)	(3.209)	(0.856)	(2.303)	(0.726)
10	-3.160**	0.374	-7.212**	1.755**	-0.733	0.013
	(1.519)	(0.461)	(3.433)	(0.891)	(2.560)	(0.864)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$					
Obs.	18,960,000	18,960,000	1,184,000	1,184,000	1,384,000	1,384,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.19: Fossil Fuel Labor Demand Shocks and Earnings Impact by Firm Age and Size

	Firm Age		Firm Size	
	Young	Old	Small	Large
	(< 15)	(≥ 15)	(Emp $<$ 1,000)	(Emp $\geq$ 1,000)
lag (k)	(1)	(2)	(3)	(4)
-4	-0.019	-0.163	-0.162	-0.134
	(0.565)	(0.536)	(0.460)	(0.637)
-3	-0.139	-0.056	0.045	-0.314
	(0.327)	(0.342)	(0.248)	(0.420)
-2	-0.106	0.154	-0.164	0.252
	(0.444)	(0.470)	(0.382)	(0.514)
-1	0.024	-0.174	0.060	-0.135
	(0.499)	(0.474)	(0.379)	(0.577)
0	0.472	0.203	0.320	0.279
	(0.522)	(0.413)	(0.397)	(0.582)
1	-0.528	-0.938	-0.622	-0.914
	(0.708)	(0.667)	(0.536)	(0.884)
2	-0.288	-0.560	-0.600	-0.316
	(0.664)	(0.594)	(0.506)	(0.802)
3	-0.986	-1.847***	-1.426**	-1.489*
	(0.745)	(0.649)	(0.579)	(0.886)
4	-1.556*	-2.823***	-1.881***	-2.607**
	(0.815)	(0.826)	(0.642)	(1.082)
5	-2.051*	-3.647***	-2.515***	-3.477**
	(1.138)	(1.109)	(0.859)	(1.439)
6	-2.444**	-4.378***	-2.896***	-4.122***
	(1.077)	(1.108)	(0.869)	(1.396)
7	-2.977***	-5.075***	-3.362***	-4.899***
	(1.123)	(1.301)	(0.921)	(1.604)
8	-2.832***	-5.404***	-3.081***	-5.260***
	(1.092)	(1.252)	(0.936)	(1.556)
9	-2.150	-4.123***	-2.607**	-3.704**
	(1.344)	(1.503)	(1.145)	(1.785)
10	-2.287	-3.949**	-2.800**	-3.458*
	(1.470)	(1.580)	(1.221)	(1.862)
	Estimate: Individual until $k = 0$ and cumulative since $k > 0$			
Obs.	10,060,000	11,470,000	11,050,000	10,480,000

Notes: The numbers are rounded in line with Census disclosure rules. Standard errors clustered by employer and state-by-year are shown in parentheses. Standard errors for the cumulative coefficients are calculated based on the variance-covariance matrix. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table A.20: Summary Statistics of Covariates Used in the CRF Estimation

	Mean (1)	Median (2)	Std. Dev. (3)
Job tenure (pre-sep.)	7.871		5.817
Earnings (pre-sep.) [$K]	41,500	26,500	66,500
Age (pre-sep.)	37.36		11.63
Unemployment rate (pre-sep.) [%]	4.73	4.199	1.984
Industry diversity index (pre-sep.)	-0.8696	-0.88	0.4061
Median income (pre-sep.) [$K]	50.51	50.15	3.347
HHI (post-sep.)	0.2614	0.2507	0.1212
HHI (pre-sep.)	0.2631	0.2511	0.1221

Notes: The numbers are rounded in line with Census disclosure rules. The median values are pseudo-percentiles in line with Census disclosure rules. The pseudo-percentile values are computed as the mean of a symmetric window of ordered observations centered on the target quantile, with at least five observations on each side (a minimum of 11 observations in total). Data source: LEHD.

Table A.21: Causal Random Forest: Permutation Importance and Linear Projection

Group	Variable	Permutation Importance	Linear Projection
People-based factors	Job tenure (pre-sep.)	2.451	-3.463
			[-3.905, -3.019]
People-based factors	Earnings (pre-sep.)	0.500	-0.356
			[-0.721, 0.010]
People-based factors	Age (pre-sep.)	0.498	-0.201
			[-0.277, -0.124]
People-based factors	Above HS degree (pre-sep.)	0.018	-0.065
			[-0.190, 0.061]
People-based factors	Female (pre-sep.)	-0.011	0.132
			[-0.047, 0.312]
Place-based factors	Unemployment rate (pre-sep.)	1.612	1.763
			[1.299, 2.230]
Place-based factors	Industry diversity index (pre-sep.)	0.993	0.336
			[0.046, 0.627]
Place-based factors	Median income (pre-sep.)	0.720	-2.382
			[-2.730, -2.034]
Place-based factors	HHI (post-sep.)	0.519	0.885
			[0.544, 1.227]
Place-based factors	HHI (pre-sep.)	0.384	0.579
			[0.418, 0.739]

Notes: The numbers are rounded in line with Census disclosure rules. Bracketed values denote 95% confidence intervals, reported as [lower, upper]. Data source: LEHD.

Appendix Figures

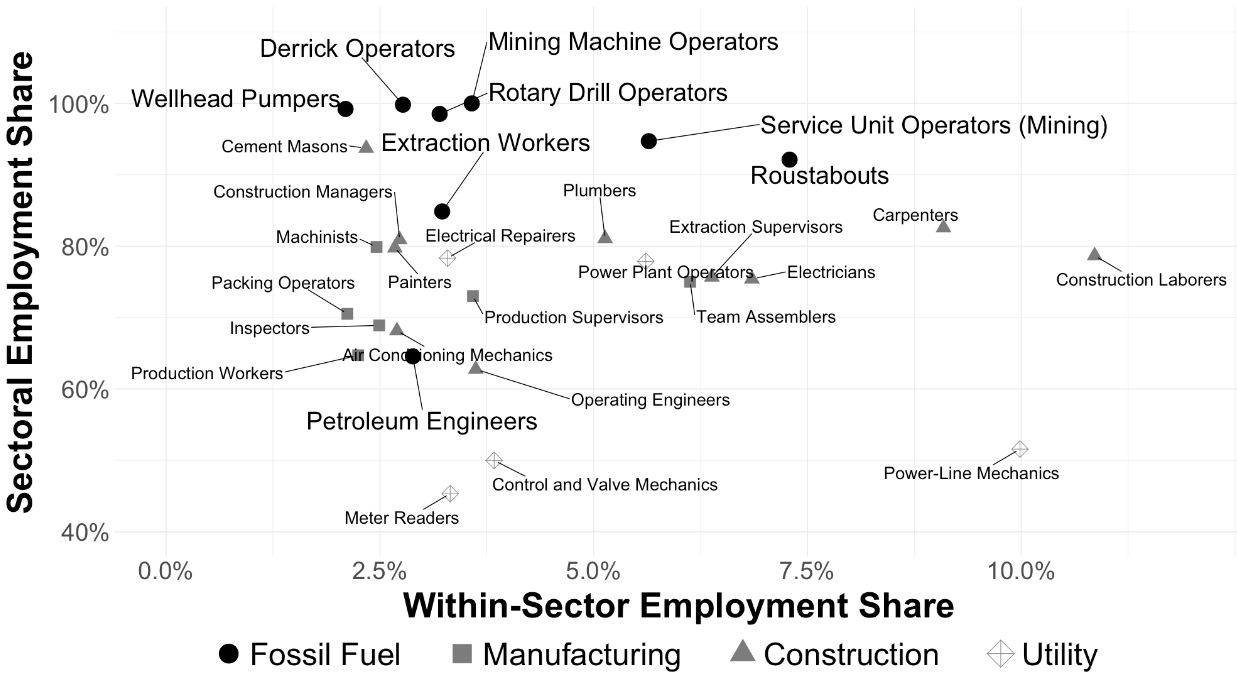


Figure A.1: Skill Transferability of Sector-Specific Occupations

Notes: This figure demonstrates the limited transferability of FF workers' skills to other industries by analyzing national occupation-sector employment data from 2010. The sectoral employment share of an occupation is calculated as $\frac{E_{o_i,s_j}}{\sum_{j=1}^{J} E_{o_i,s_j}}$, where E_{o_i,s_j} represents the number of workers employed in occupation $o_i \in \{o_1,\ldots,o_I\}$ within sector $s_j \in \{s_1,\ldots,s_J\}$. This measure reflects the proportion of a specific occupation's total employment that is concentrated in a single sector. A high sectoral employment share suggests that an occupation's skills are primarily utilized within one sector, indicating limited transferability to other industries. The within-sector employment share of an occupation is defined as $\frac{E_{o_i,s_j}}{\sum_{i=1}^{I} E_{o_i,s_j}}$. This measure indicates how common a specific occupation is within a given sector, providing insight into its prevalence relative to other occupations in that sector. Data source: Occupational Employment and Wage Statistics (2010), U.S. BLS.

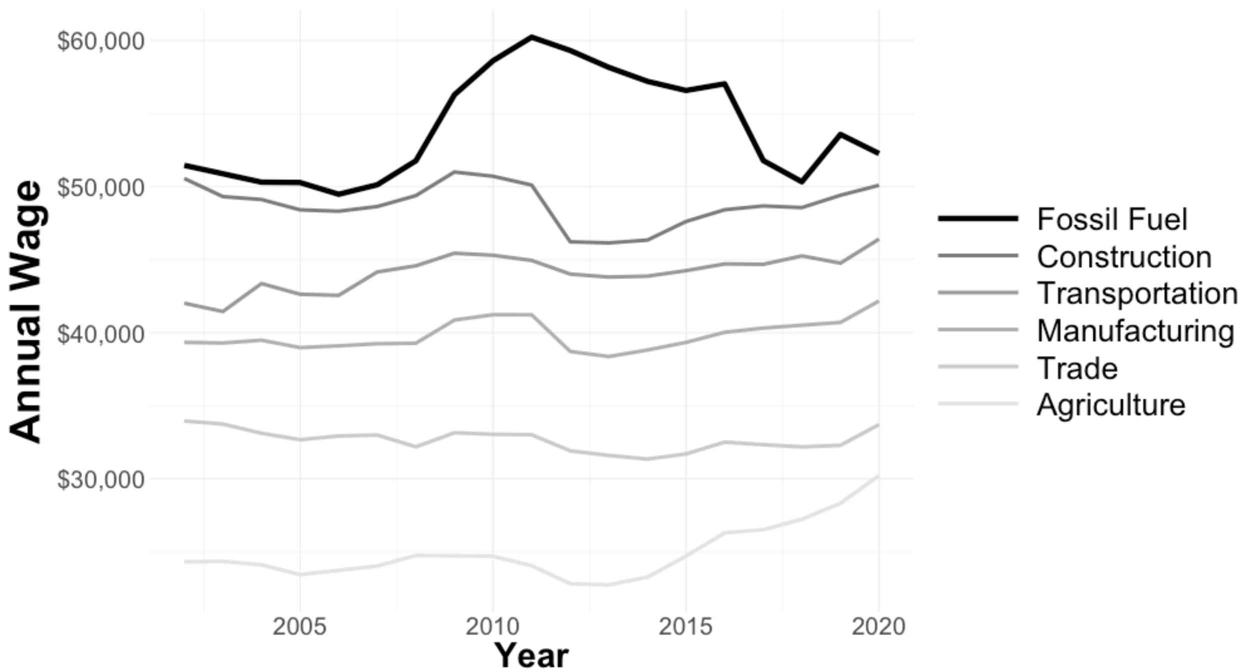


Figure A.2: Annual Wage by Sector

Notes: Data source: Quarterly Census of Employment and Wages, U.S. BLS.

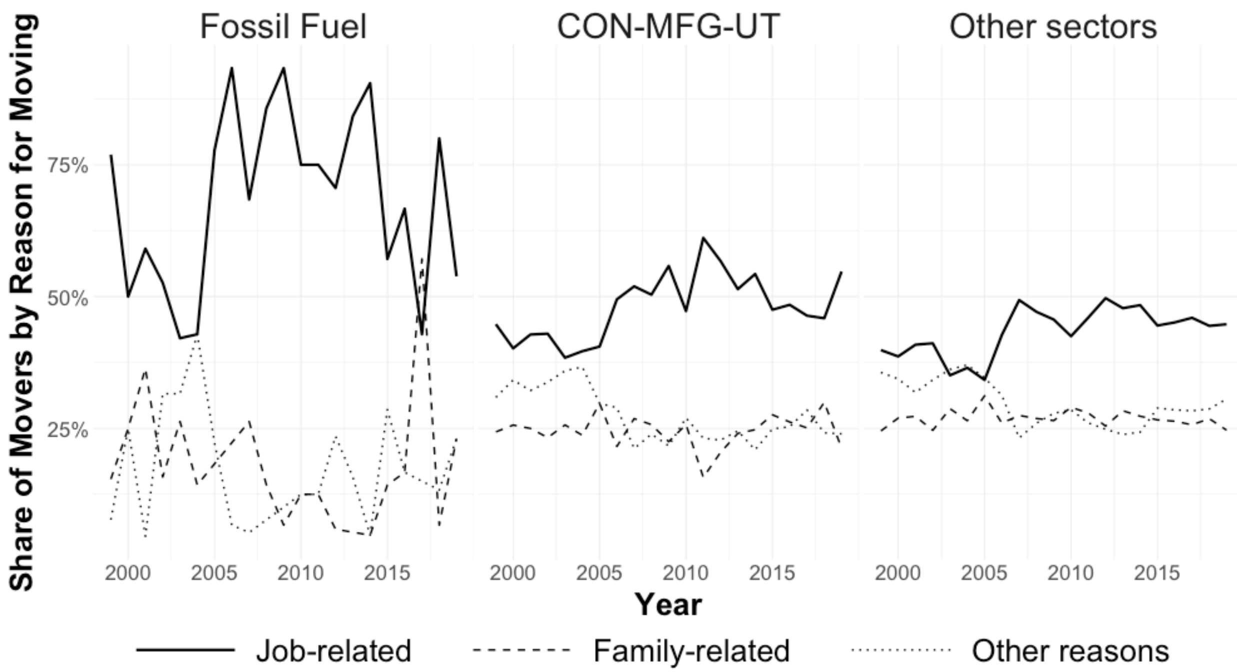


Figure A.3: Interstate Mobility by Reason for Moving Across Sectors

Notes: 'CON', 'MFG', and 'UT' represent the construction, manufacturing, and utility sectors, respectively. Job-related reasons include starting a new job, job transfer, job loss, or seeking employment, as well as an easier commute. Family-related reasons include changes in marital status, establishing a new household, or other family-related factors. Other reasons include housing-related factors (e.g., moving for a new, better, or more affordable home), climate change, health concerns, natural disasters, or other unspecified reasons. Data source: The Annual Social and Economic (ASEC) supplement to the Current Population Survey (CPS), provided by the Integrated Public Use Microdata Series (Flood et al., 2024).

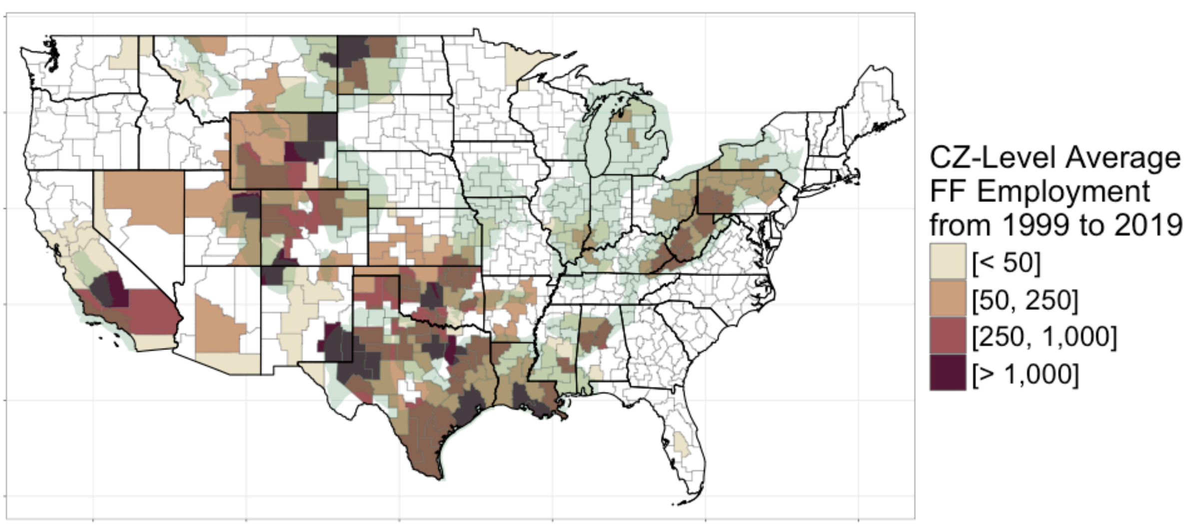


Figure A.4: Fossil Fuel Reserves and CZ-Level Fossil Fuel Employers

Notes: The figure illustrates the CZ-level average employment in the FF sector, 1999-2019. The shaded green area denotes the fossil fuel reserves. Data source: Quarterly Census of Employment and Wages.

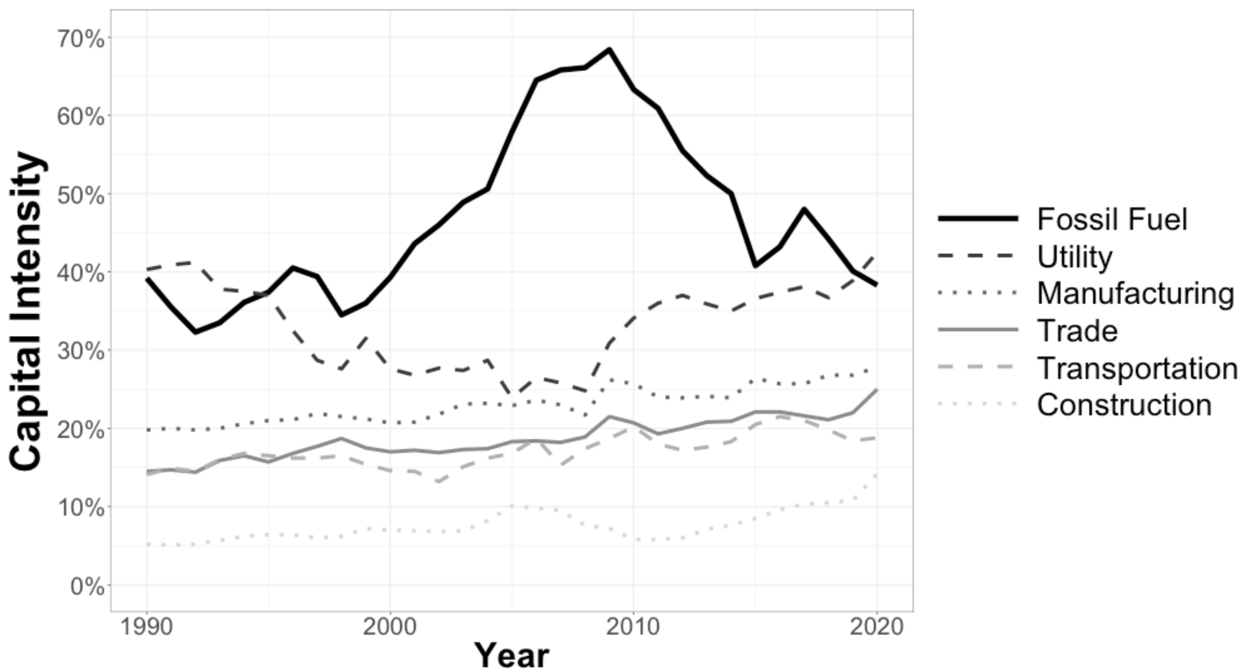


Figure A.5: Capital Intensity by Sector

Notes: Data source: U.S. BLS.

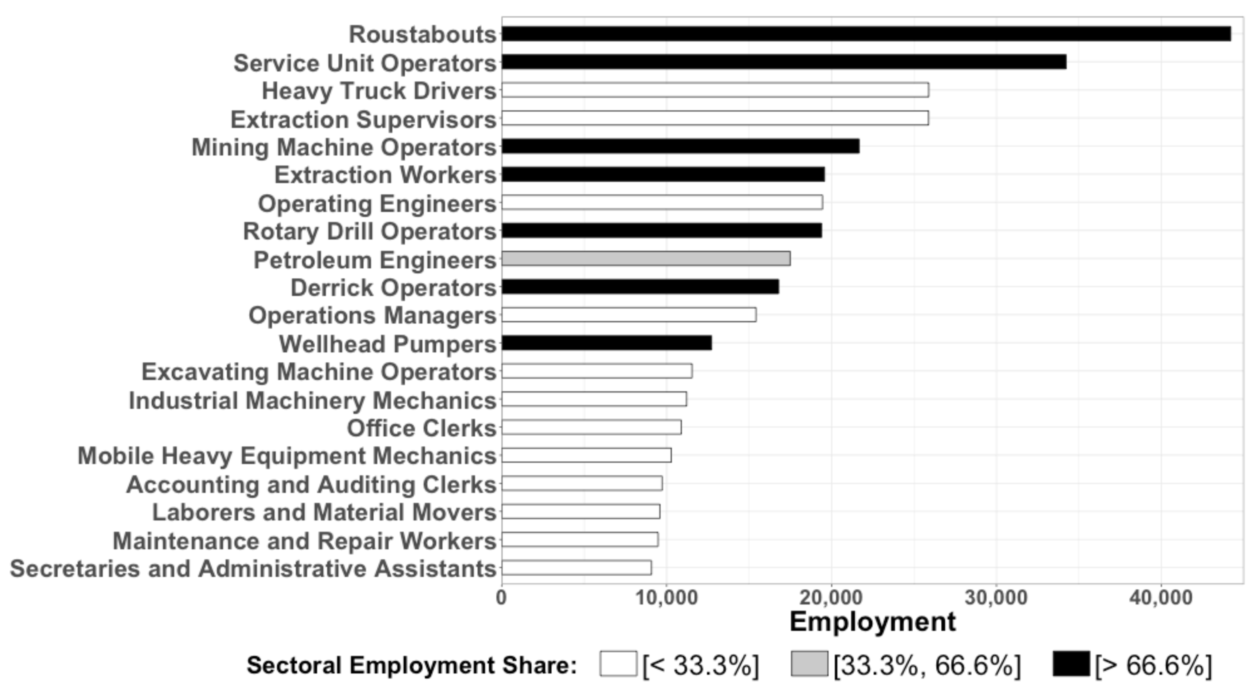


Figure A.6: Distribution of Fossil Fuel Occupations

Notes: Data source: Occupational Employment and Wage Statistics, U.S. BLS.

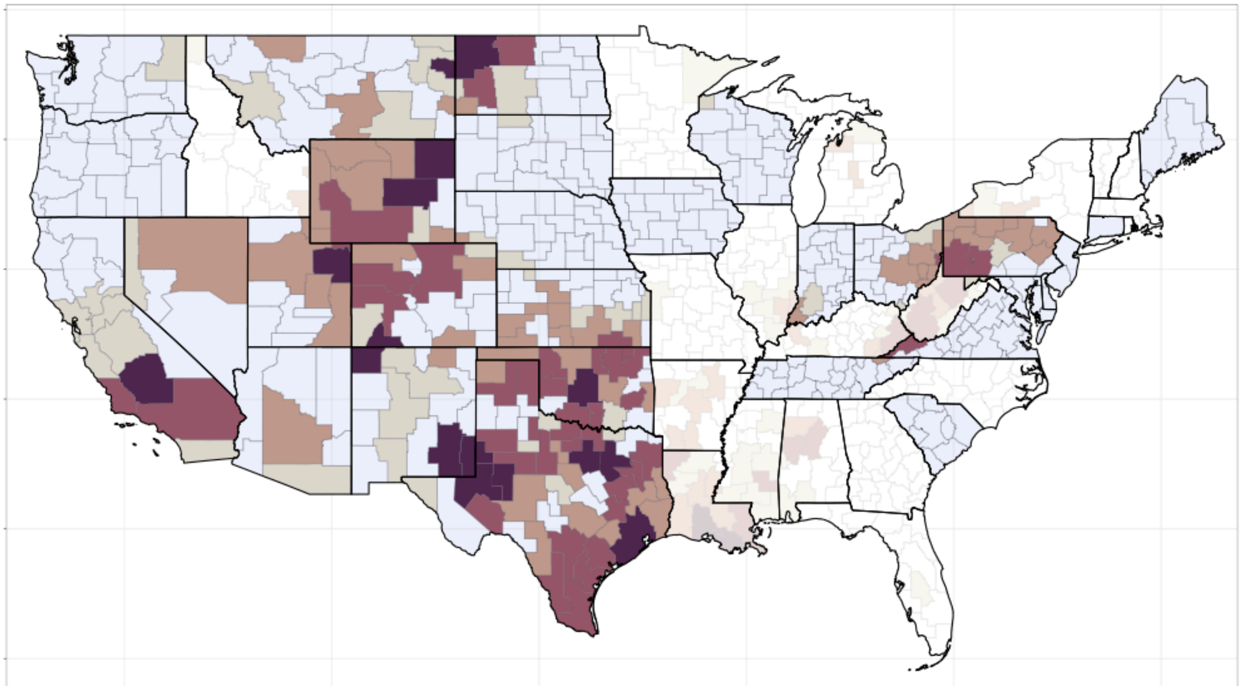


Figure A.7: Fossil Fuel Employment in LEHD-Approved States

Notes: The light blue shaded areas indicate localities where LEHD access is approved. Data source: Quarterly Census of Employment and Wages, U.S. BLS.

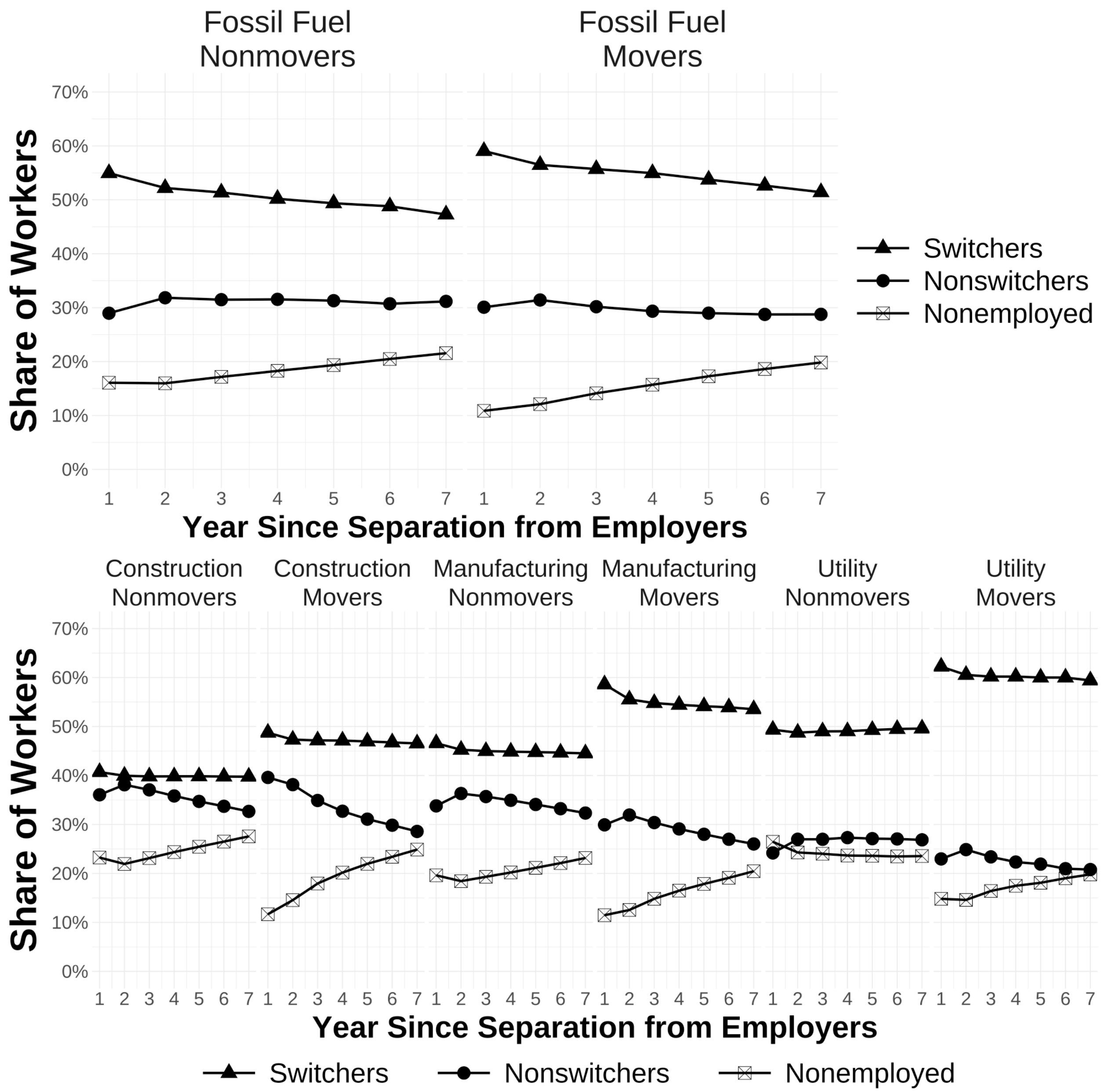


Figure A.8: Sectoral Employment Transitions Conditional on Geographic Reallocation

Notes: The top and bottom panels show the distribution of separated workers from the fossil fuel sector and other comparison sectors, respectively, based on their post-separation sectoral transitions. Data source: LEHD.

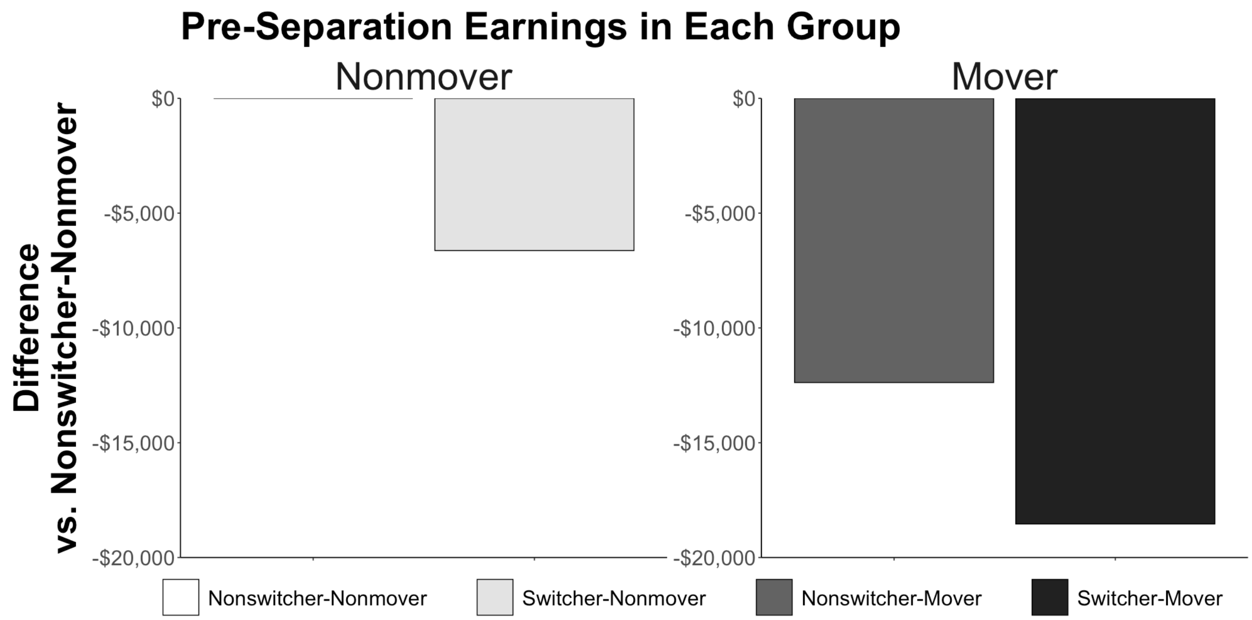


Figure A.9: Differences in Pre-Separation Earnings across Worker Groups

Notes: Each bar represents the difference in the average earnings before separation for each group. Data source: LEHD.

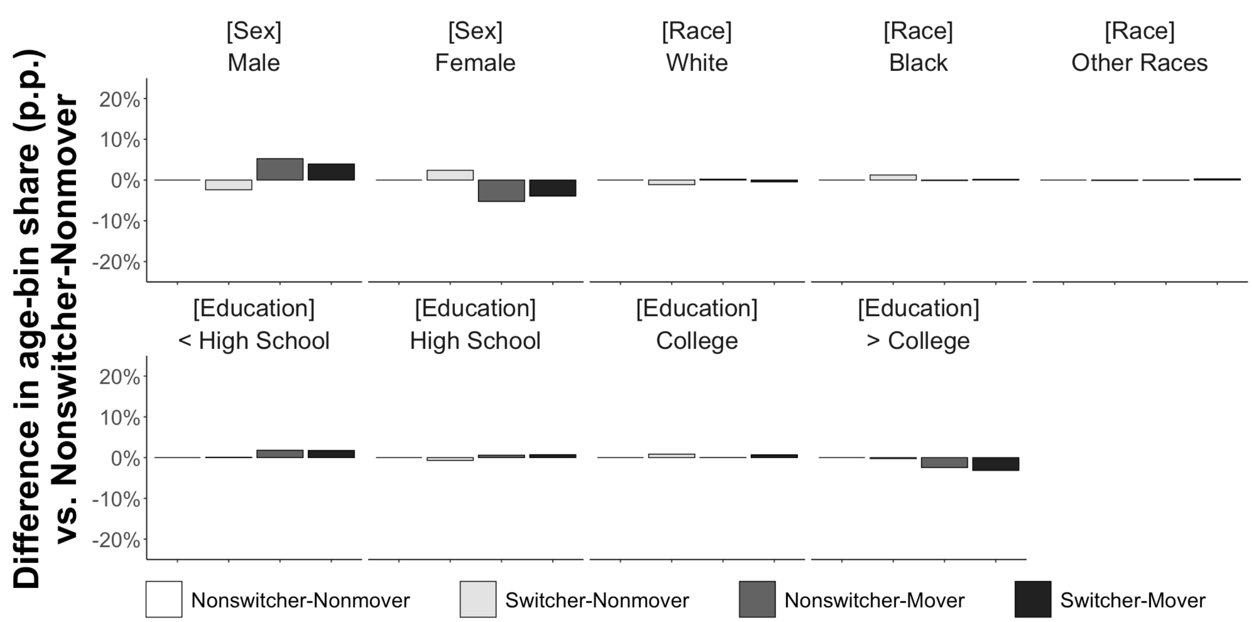


Figure A.10: Sex, Race, and Education Level Composition Differences across Worker Groups

Notes: Each bar represents the percentage-point difference in the share of workers within each sex, race, or education category for each group. Data source: LEHD.

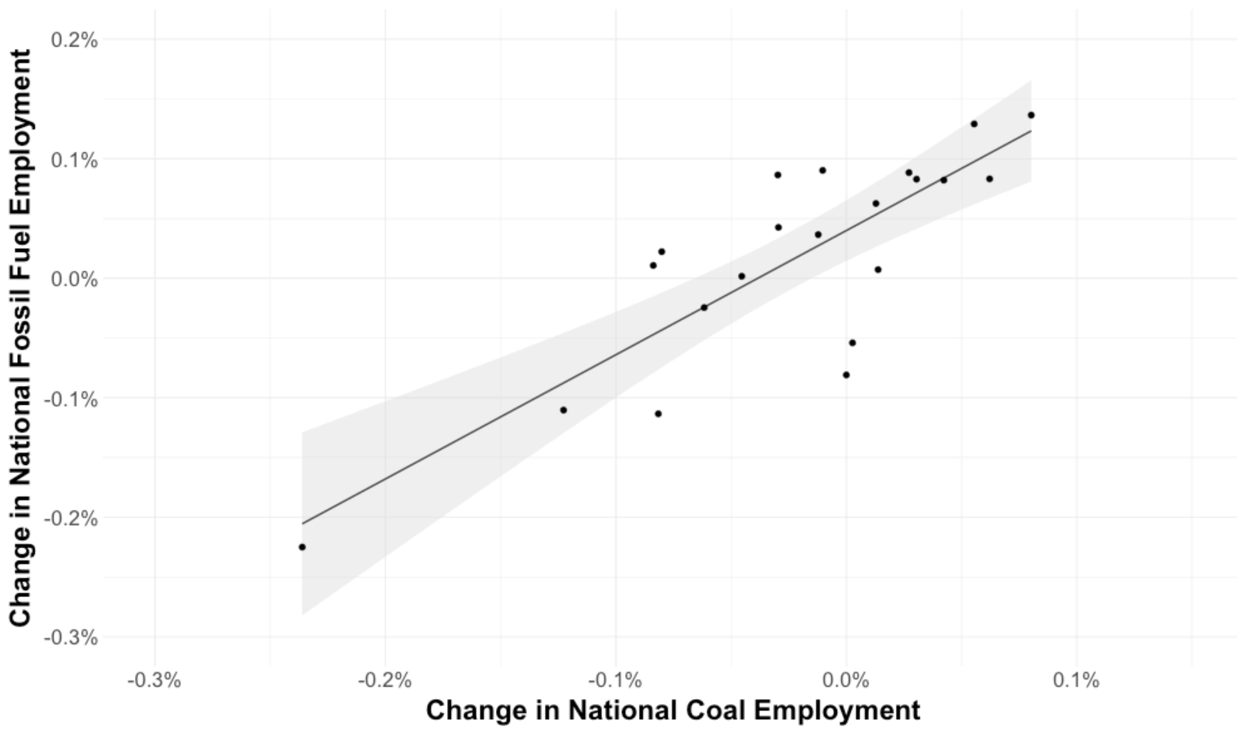


Figure A.11: Annual Change in National Fossil Fuel and Coal Employment

Notes: Data source: Quarterly Census of Employment and Wages.

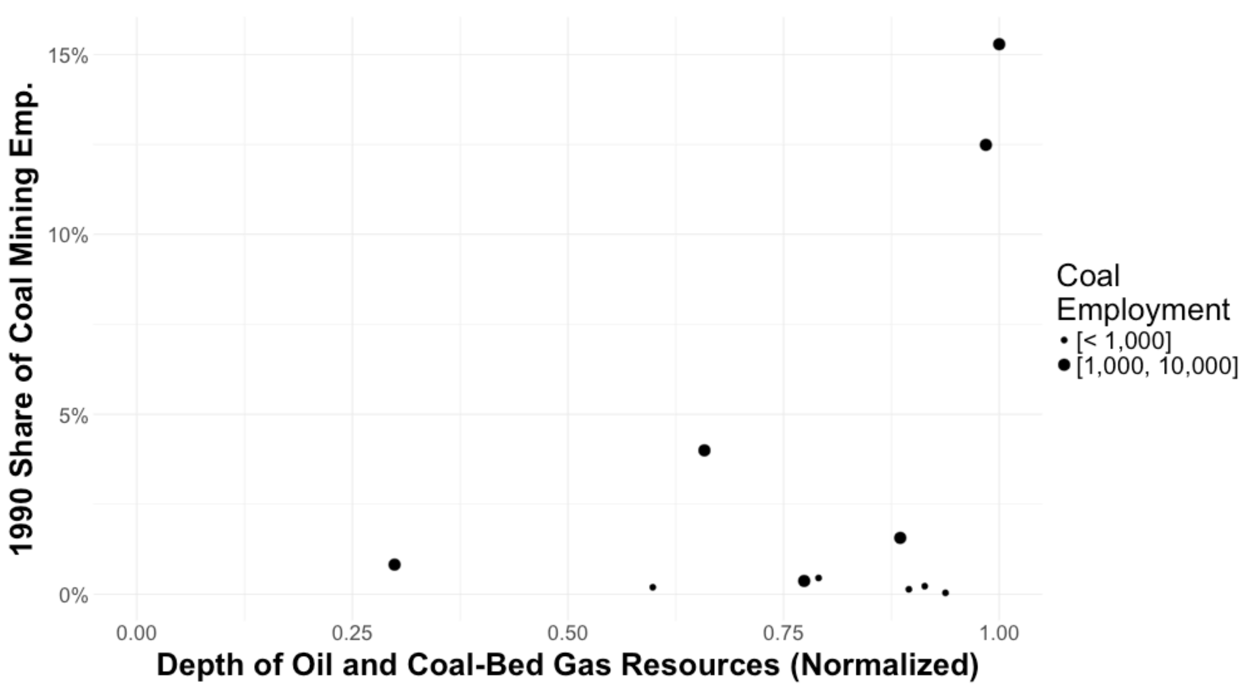


Figure A.12: Lagged Coal Mining Employment Share (1990) and Depth of Fossil Fuel Reserves

Notes: Data source: Quarterly Census of Employment and Wages, U.S. BLS and U.S. Geological Survey.

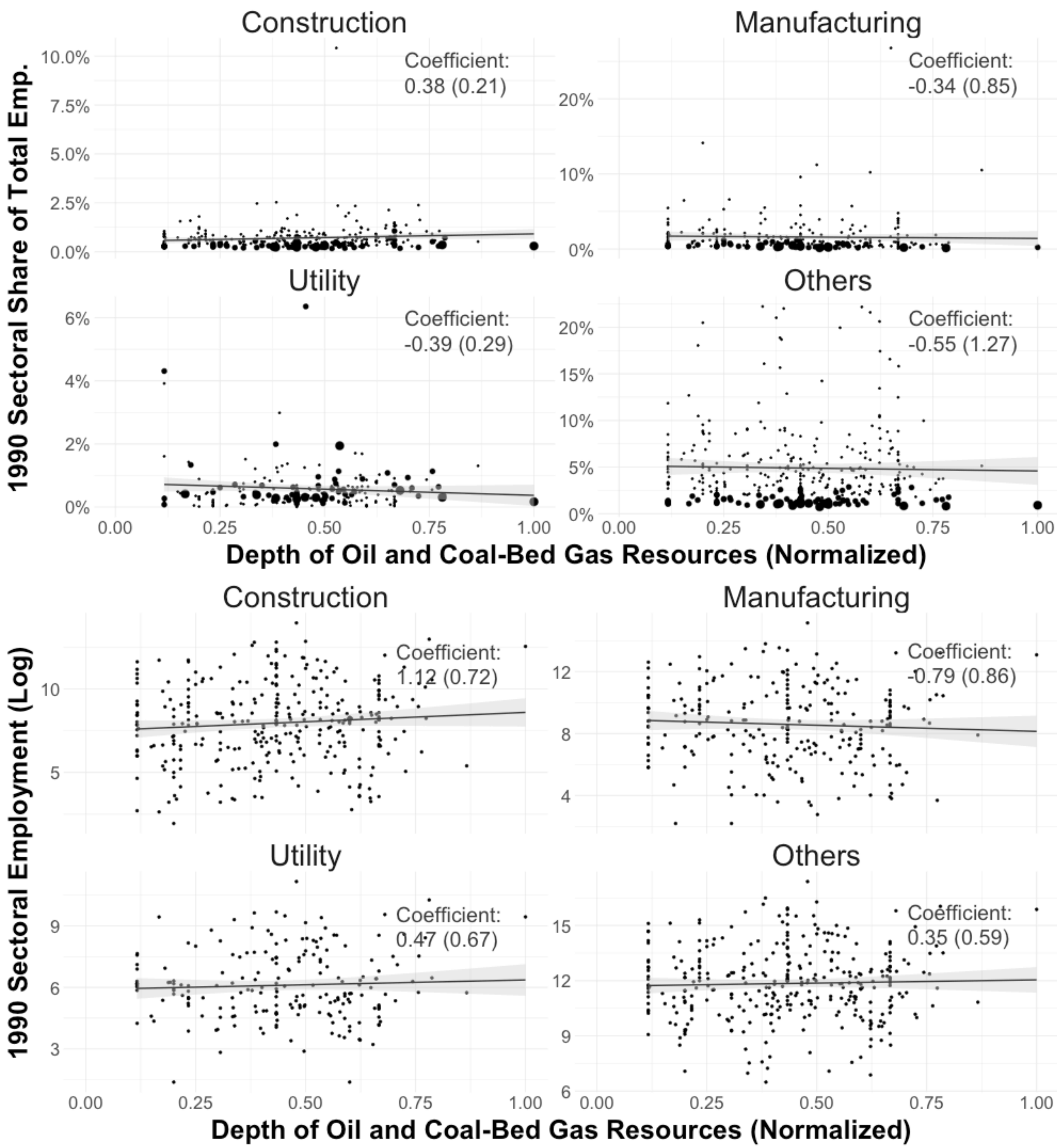


Figure A.13: Exogeneity of the FF Labor Demand Shock Variable: Sectoral Employment Share (Top) and Level (Bottom)

Notes: Data source: Quarterly Census of Employment and Wages, U.S. BLS and U.S. Geological Survey.

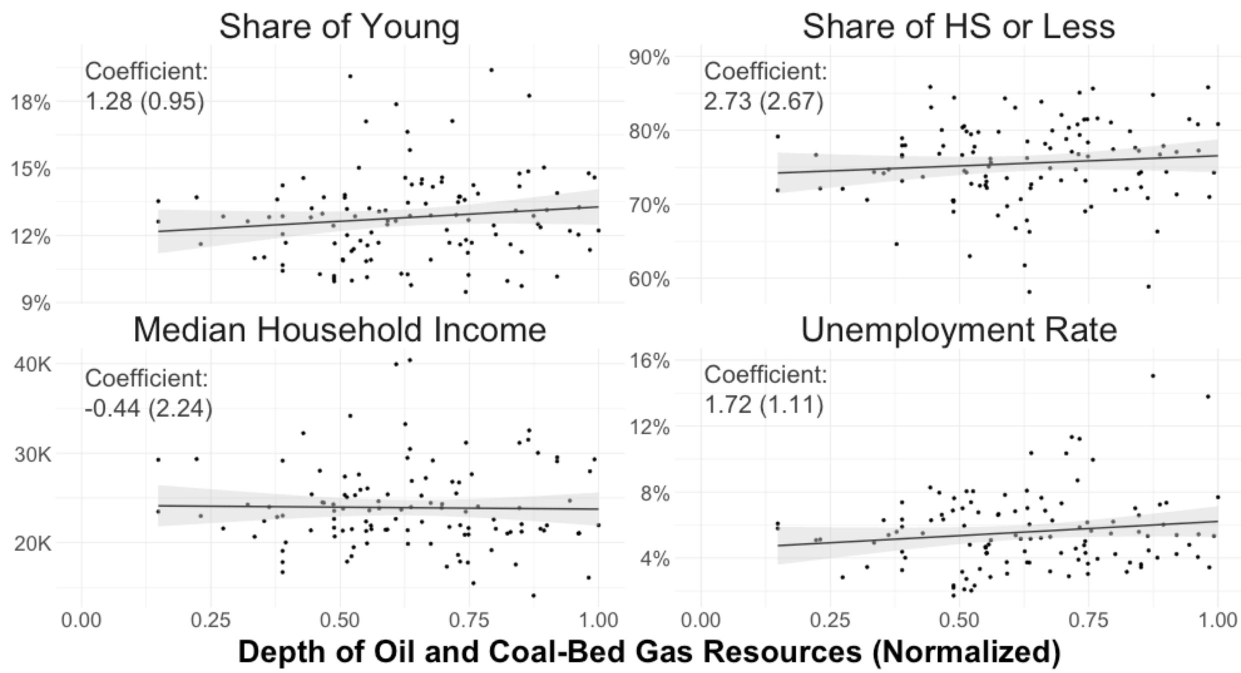


Figure A.14: Exogeneity of the FF Labor Demand Shock Variable: Socioeconomic Indicators

Notes: Data source: U.S. Census Bureau and U.S. BLS.

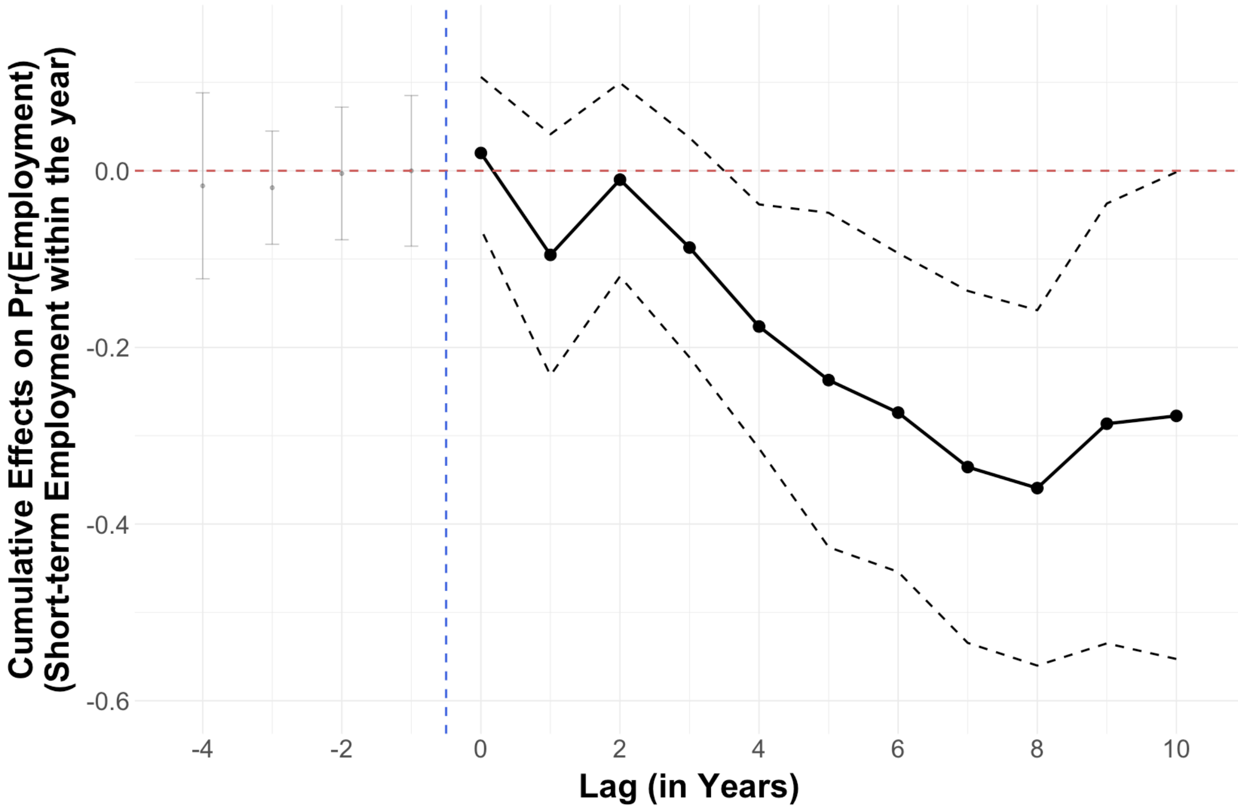


Figure A.15: Fossil Fuel Labor Demand Shocks and Probability of Short-Term Employment

Notes: The outcome is an employment indicator equal to 1 if the worker has more than one quarter with positive earnings in year t (0 otherwise). A detailed summary of all estimates can be found in Table A.3.

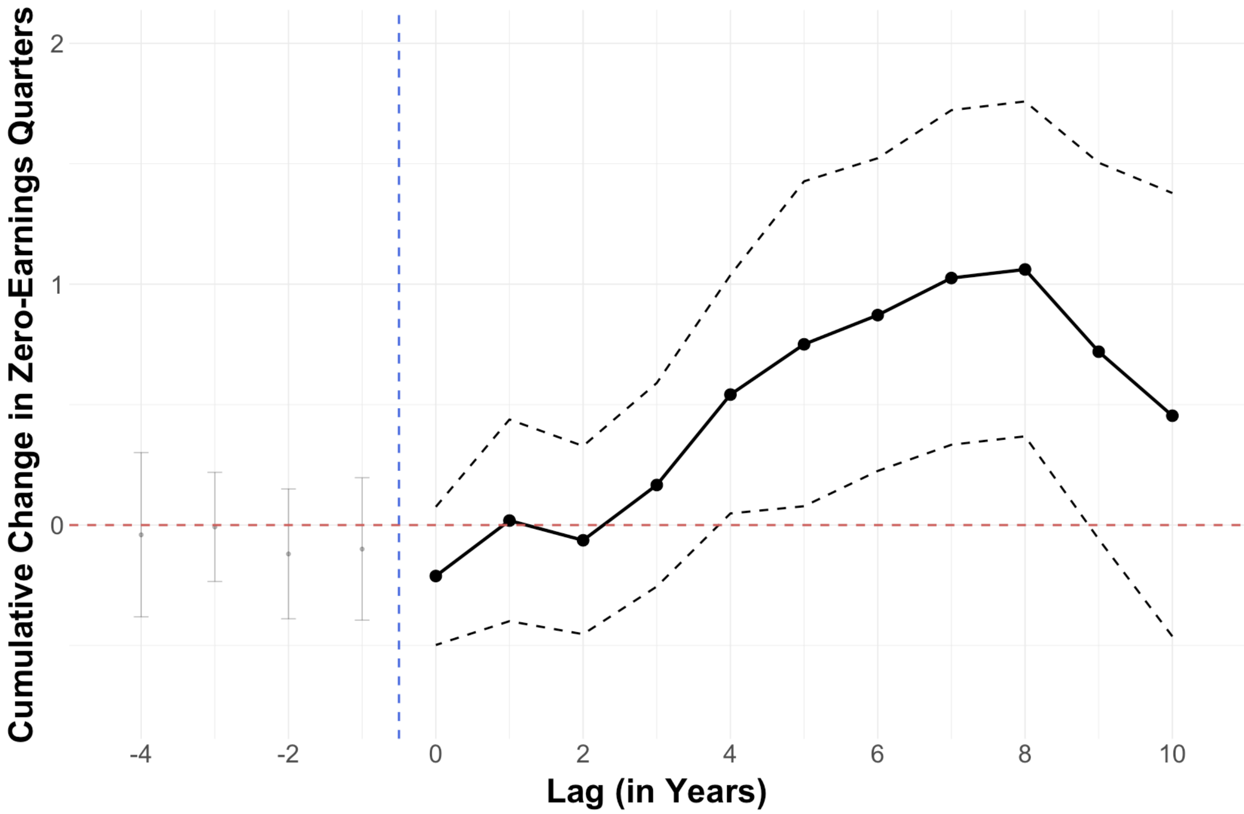


Figure A.16: Fossil Fuel Labor Demand Shocks and Nonemployment Duration

Notes: A detailed summary of all estimates can be found in Table 1.

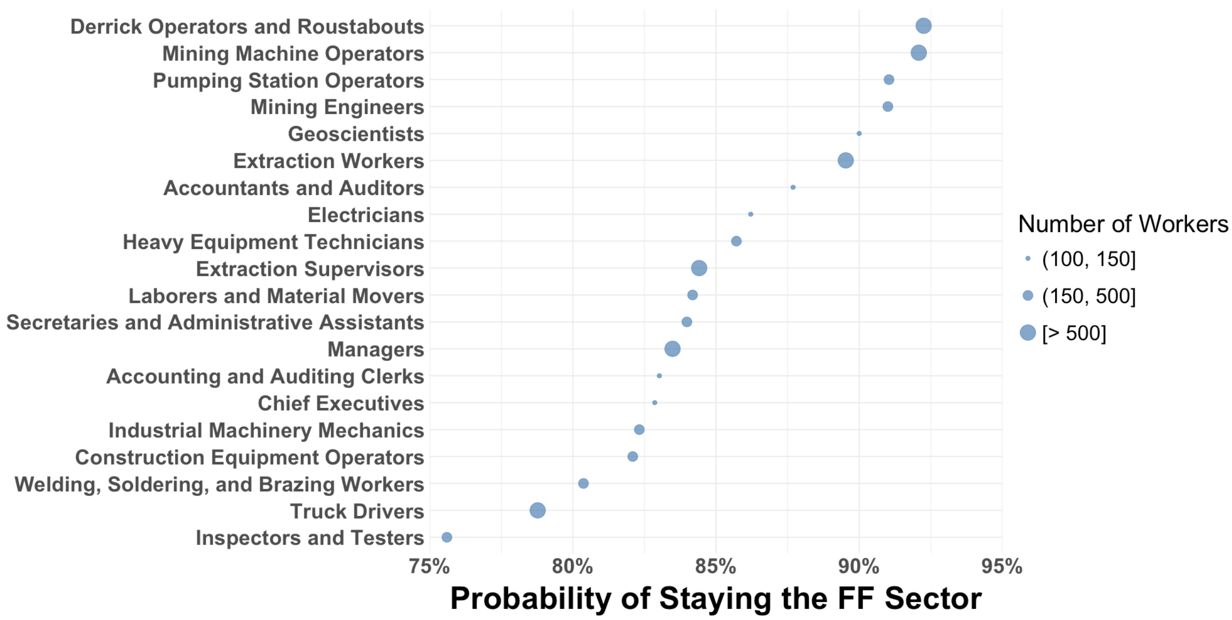


Figure A.17: Probability of Staying the FF Sector

Notes: Data source: Current Population Survey (U.S. Census Bureau).

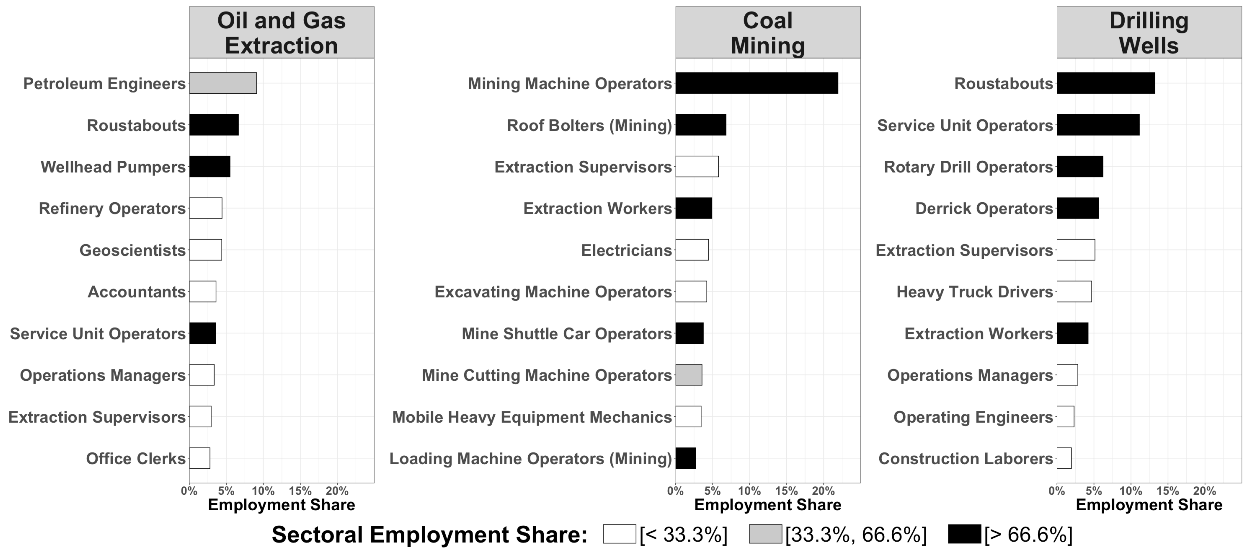


Figure A.18: Distribution of Fossil Fuel Occupations by Subsector

Notes: Data source: Occupational Employment and Wage Statistics, U.S. BLS.

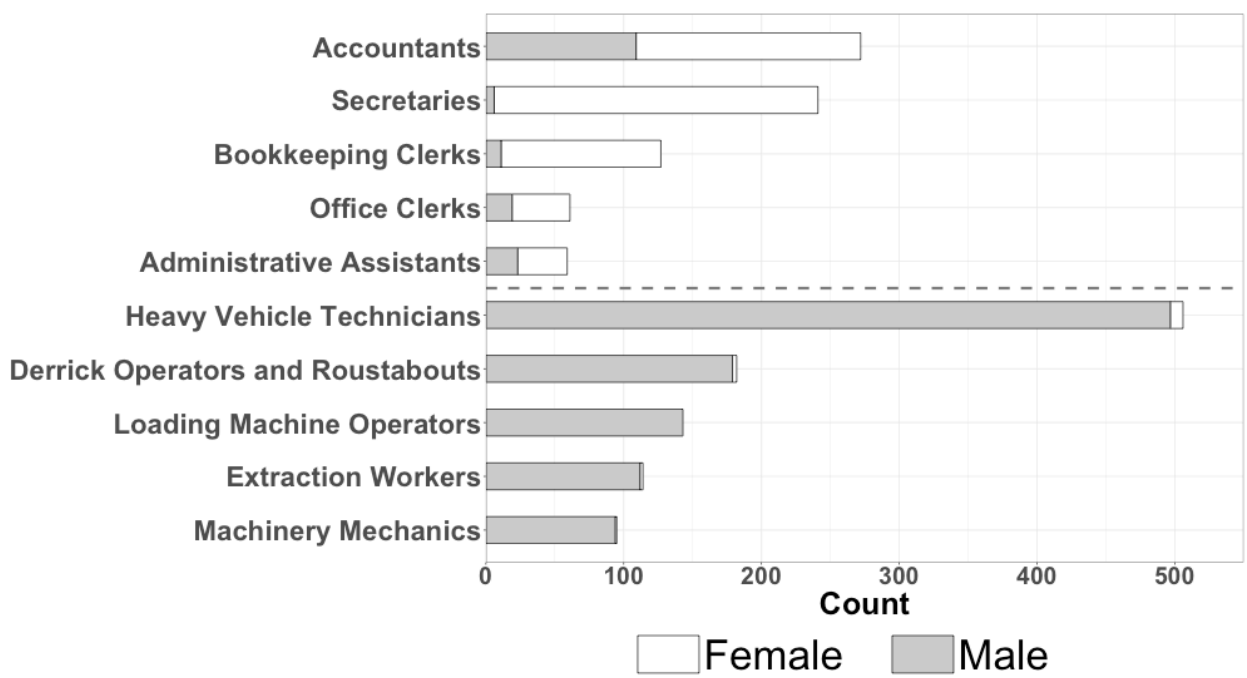


Figure A.19: Distribution of Fossil Fuel Occupations by Sex

Notes: Data source: Decennial Census (2000) and American Community Survey (2006, 2011, and 2016), provided by the Integrated Public Use Microdata Series (Ruggles et al., 2024).

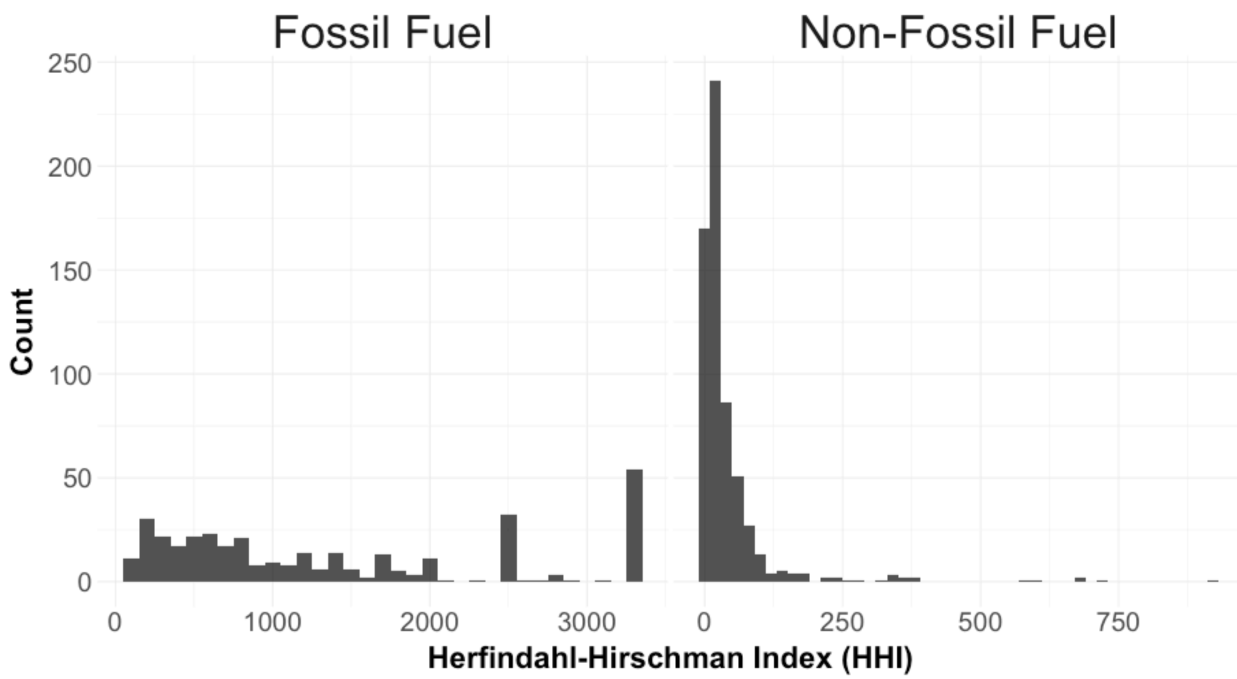


Figure A.20: CZ-Level Fossil Fuel Employer Concentration

Notes: I construct the Herfindahl–Hirschman Index (HHI) of labor market concentration using County Business Patterns (CBP) data. For each commuting zone (CZ) and sector (Fossil Fuel or Non-Fossil Fuel), I approximate employment per establishment using midpoint values from CBP-reported size categories. The HHI is calculated as the sum of squared firm employment shares (weighted by establishment counts) multiplied by 10,000, where higher HHI values reflect greater local market concentration and lower competition. However, this measure has important caveats: it relies on midpoint approximations rather than actual firm-level employment data, potentially understating or overstating true market concentration. Additionally, it assumes uniform firm sizes within each employment-size category, ignoring within-category variations. Nevertheless, this measure remains a useful proxy for local monopsony power because it provides a systematic and consistent method to capture geographic variation in employer concentration across CZs using publicly available data.

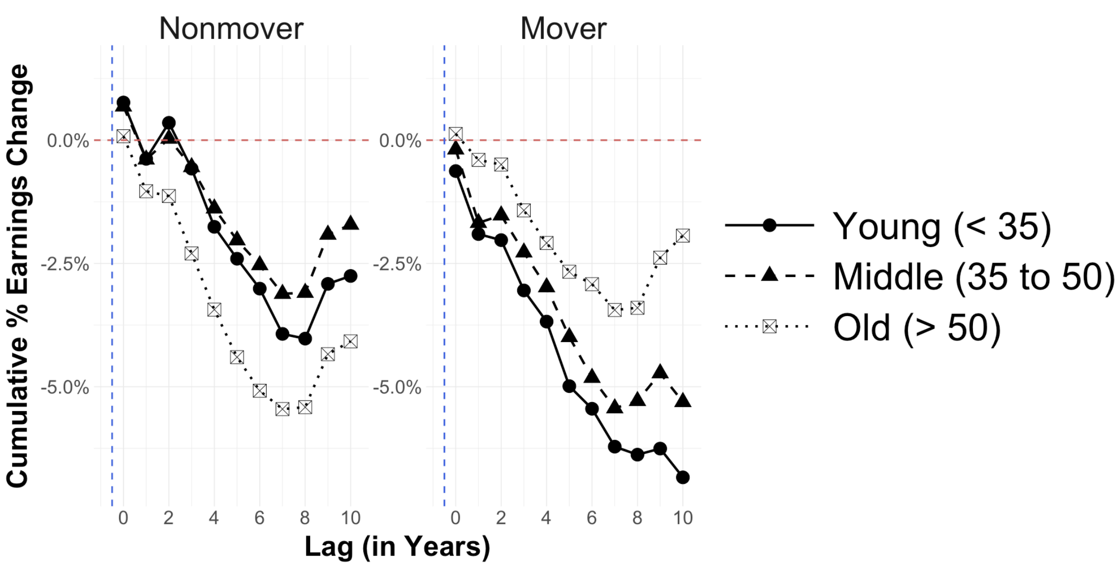


Figure A.21: Fossil Fuel Labor Demand Shocks and Earnings Impact by Age

Notes: A detailed summary of all estimates can be found in Table A.10.

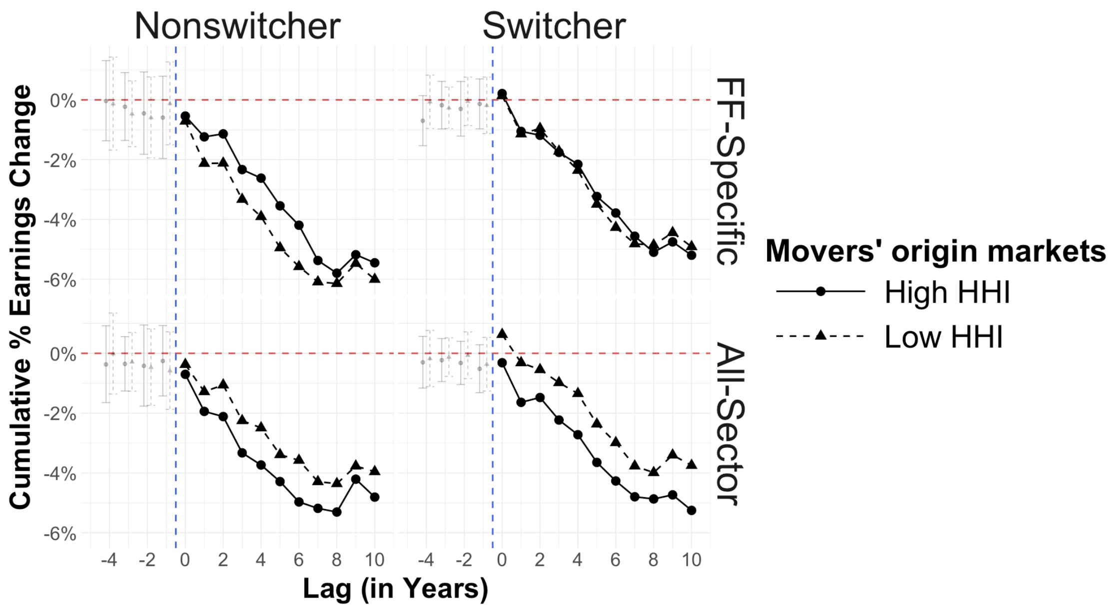


Figure A.22: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Origin Markets

Notes: A detailed summary of all estimates can be found in Table A.13.

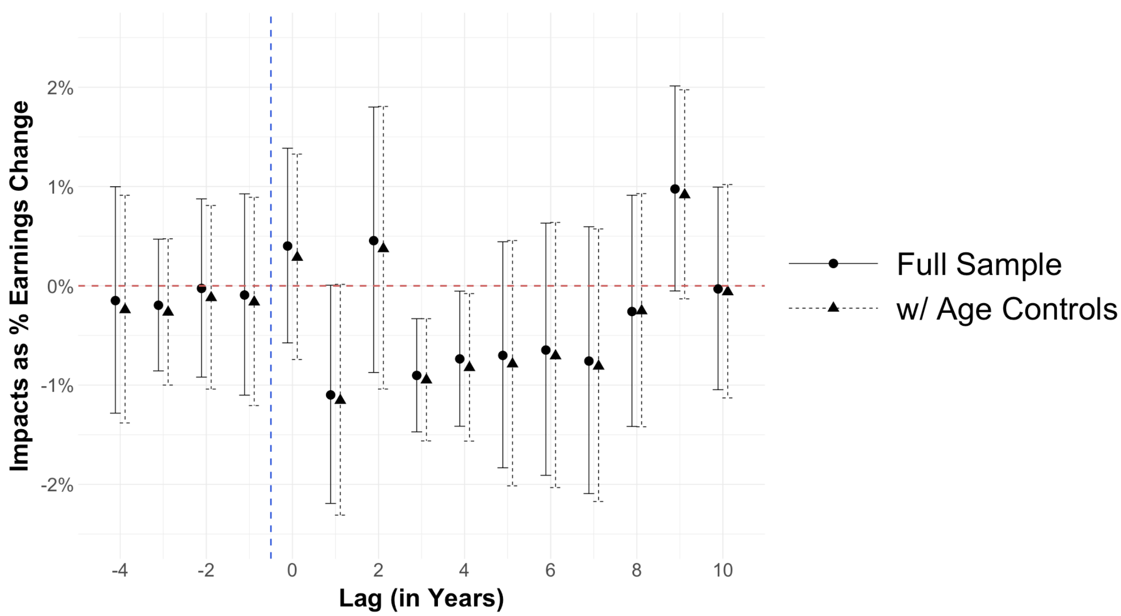


Figure A.23: Fossil Fuel Labor Demand Shocks and Earnings Impact: Baseline vs. Specifications with Age Controls

Notes: A detailed summary of all estimates can be found in Table A.14.

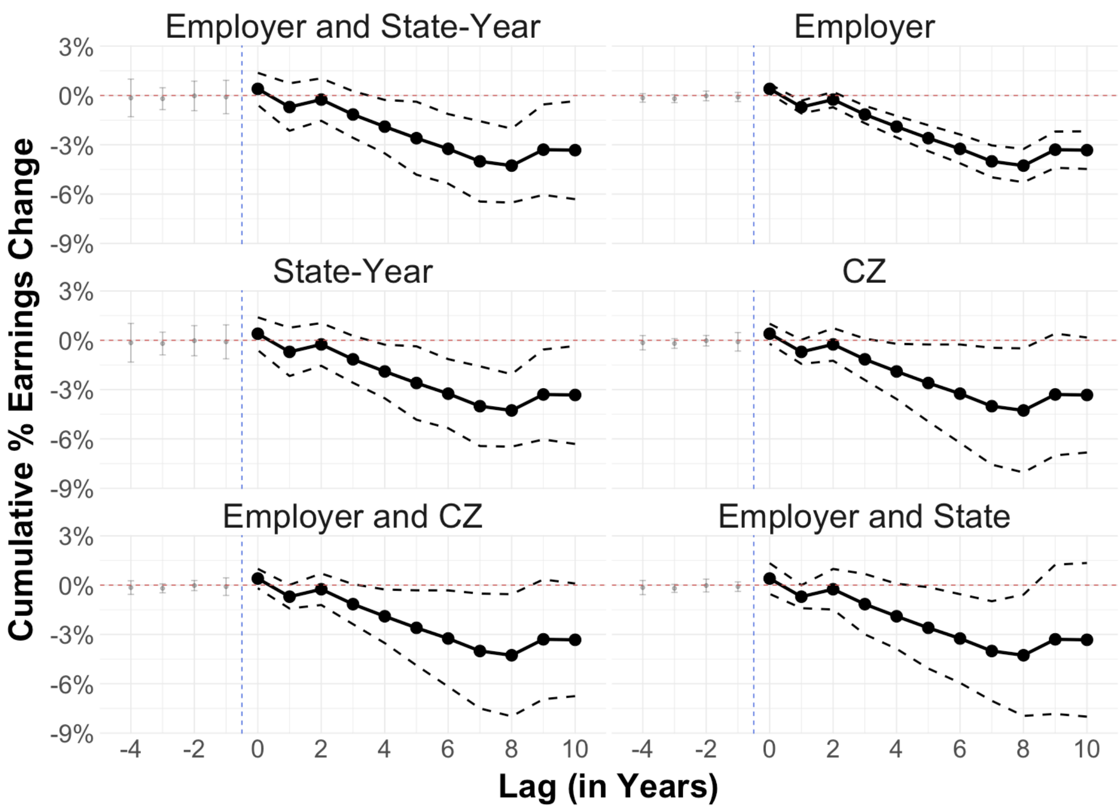


Figure A.24: Fossil Fuel Labor Demand Shocks and Earnings Impact by Different Clustering Choices

Notes: A detailed summary of all estimates can be found in Table A.15.

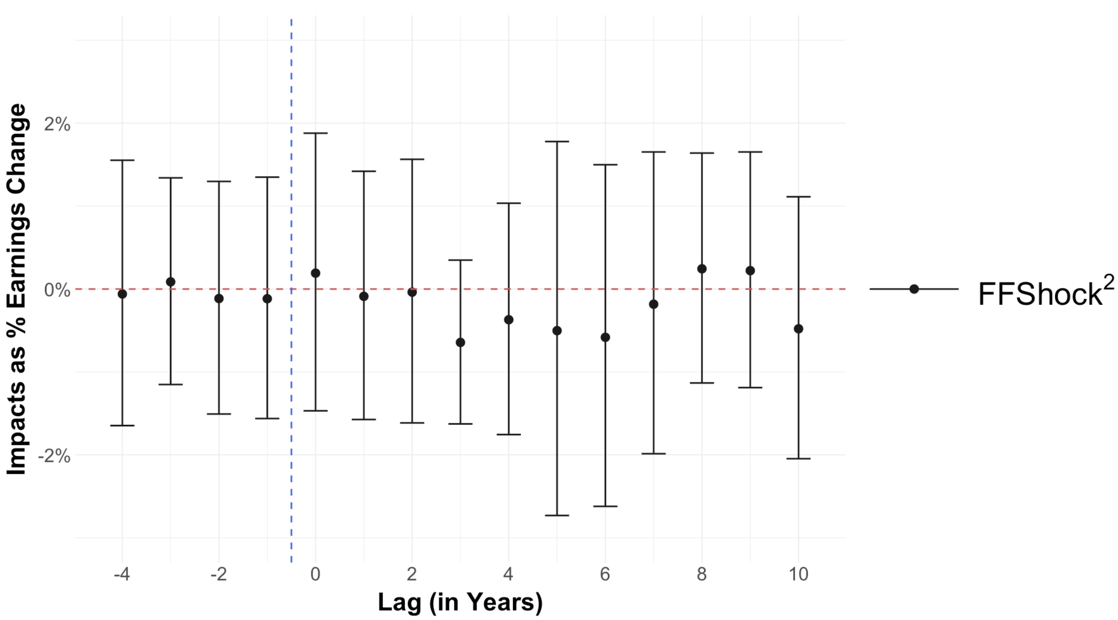


Figure A.25: Coefficient Estimates of Quadratic Terms of Fossil Fuel Labor Demand Shocks

Notes: A detailed summary of all estimates can be found in Table A.16.

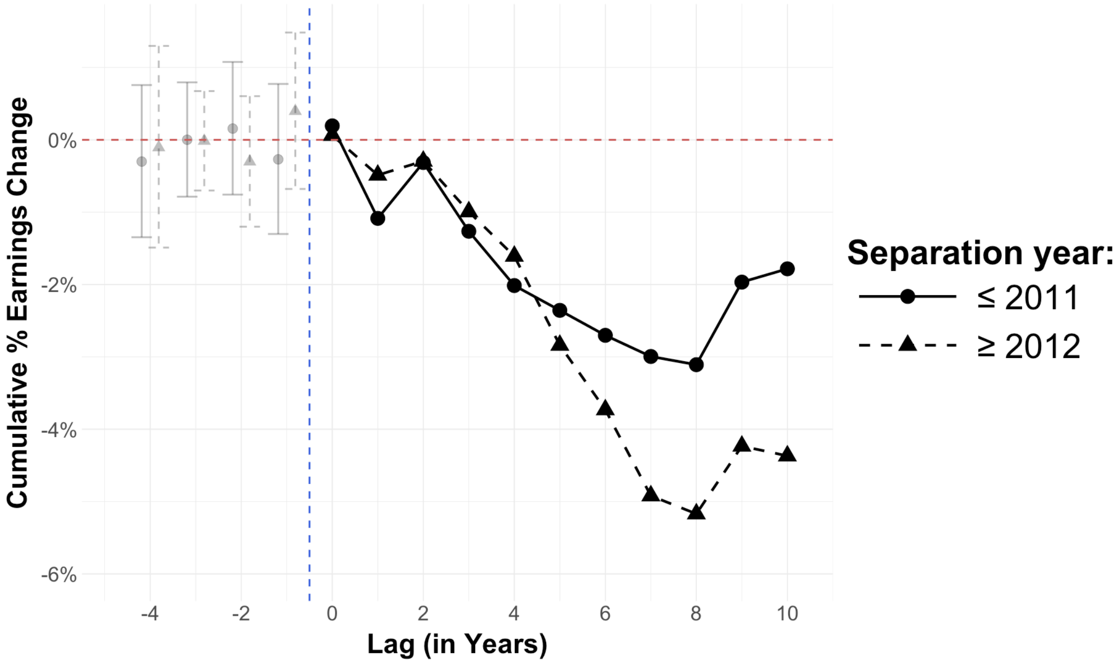


Figure A.26: Fossil Fuel Labor Demand Shocks and Earnings Impact by Separation Year

Notes: A detailed summary of all estimates can be found in Table A.17.

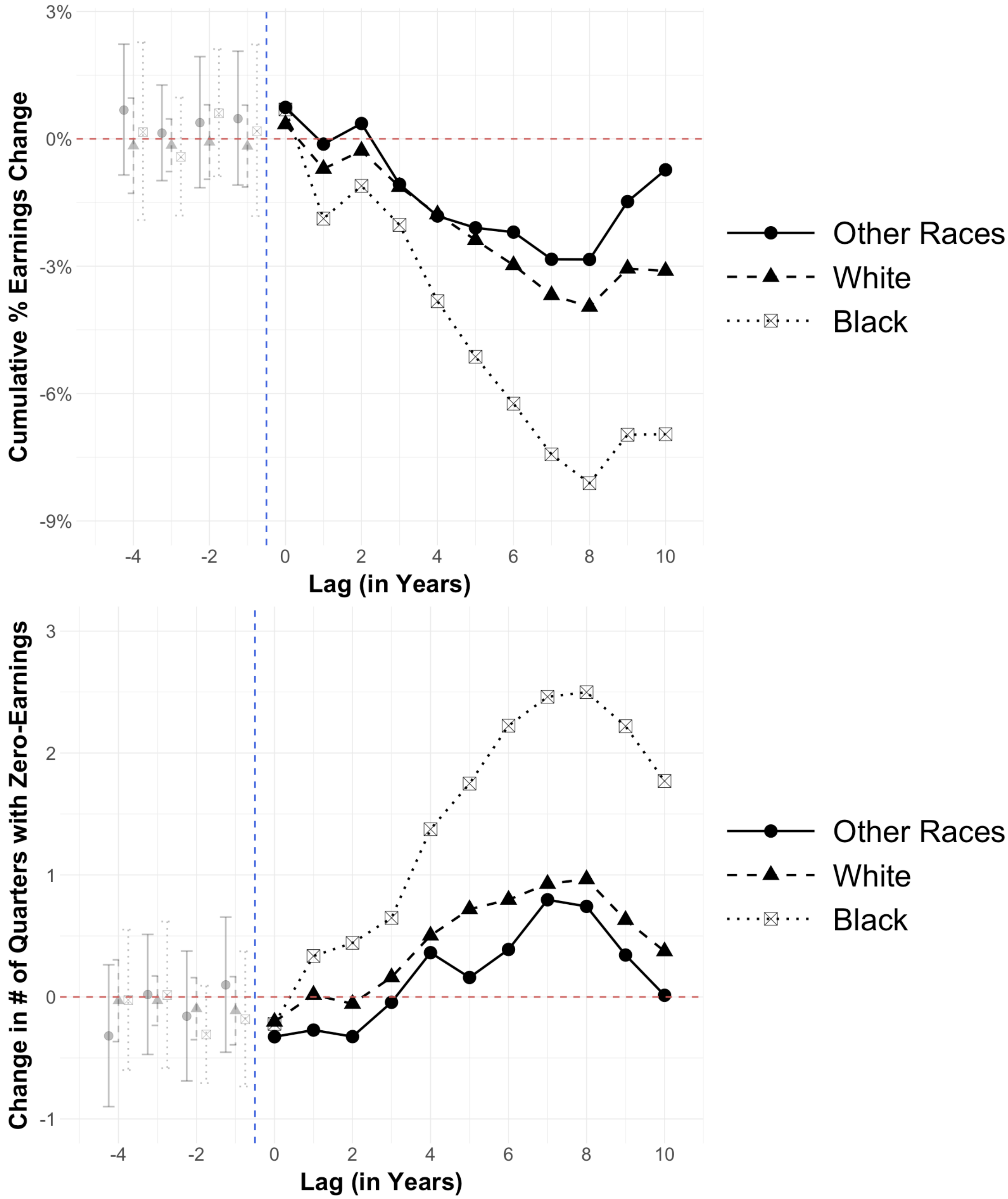


Figure A.27: Fossil Fuel Labor Demand Shocks and Earnings (Top) and Nonemployment Duration (Bottom) Impact by Race

Notes: A detailed summary of all estimates can be found in Table A.18.

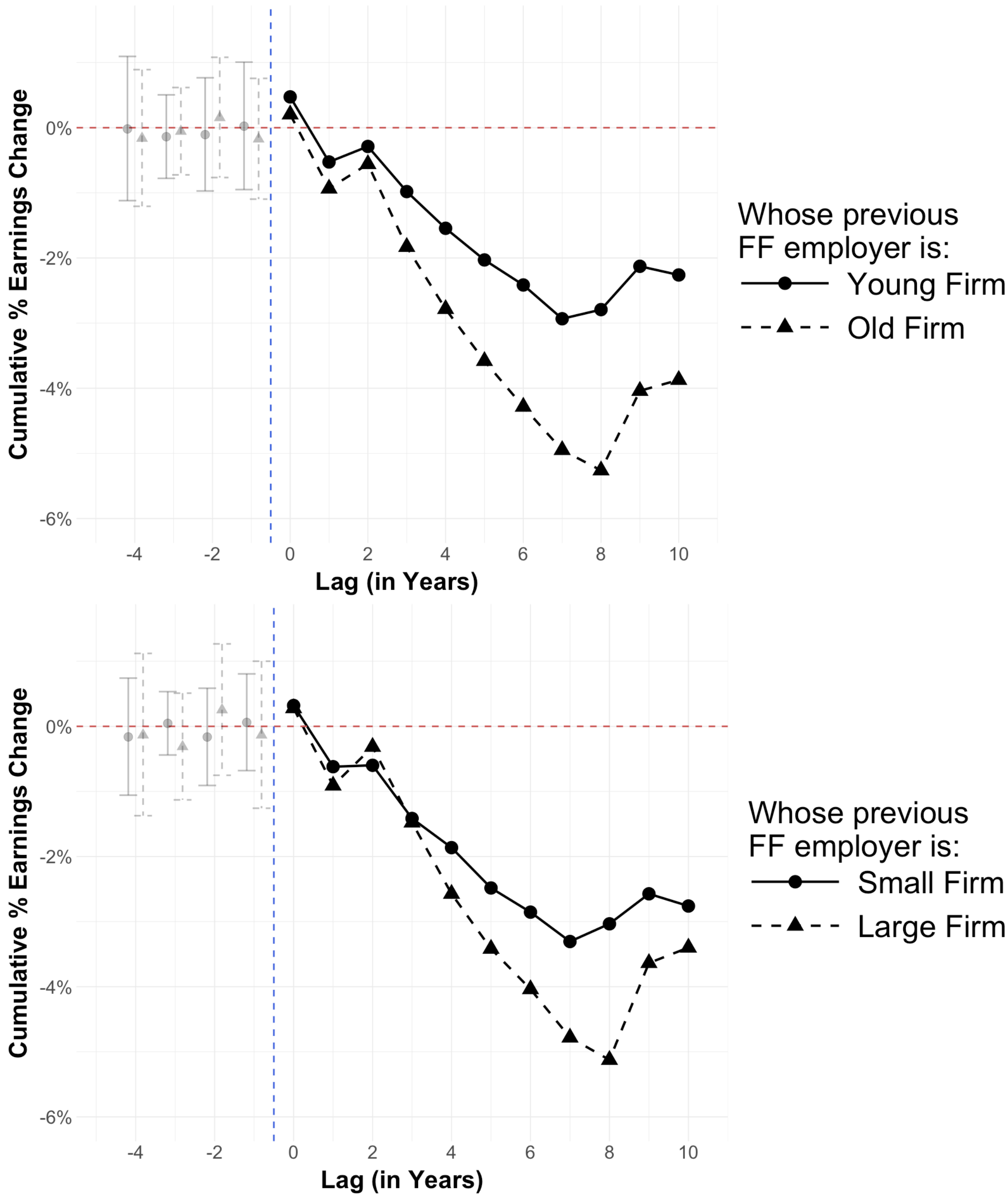


Figure A.28: Fossil Fuel Labor Demand Shocks and Earnings Impact by Firm Age (Top) and Size (Bottom)

Notes: A detailed summary of all estimates can be found in Table A.19.