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Essays on the Economics of the Energy Transition

A dissertation submitted in partial satisfaction

of the requirements for the degree

Doctor of Philosophy

in

Economics

by

Minwoo Hyun

Committee in charge:

Professor Kyle Meng, Chair

Professor Olivier Deschênes

Professor Peter Kuhn

June 2026

The Dissertation of Minwoo Hyun is approved.

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May 2026

Essays on the Economics of the Energy Transition

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by

Minwoo Hyun

In memory of my grandfather, who mined the dark of South Korean coal pits to kindle a light of education that guides his five children and me.

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I owe my deepest gratitude to my advisor, Kyle Meng. He was unfailingly supportive, providing both funding and guidance with remarkable responsiveness and kindness. Beyond the technical, Kyle taught me that true scholarship requires creativity and rigor over mere diligence. He has been the model of an exceptional mentor and person, and I am profoundly grateful for his impact on my life and work.

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I also carry with me the legacy of my grandfather, Seungtae Cho. A survivor of the Korean War, he spent decades working in the coal mines of eastern Korea to provide for his five children, including my mother. While he could not pursue higher education himself, his enduring dream for his grandchildren to seek knowledge and live as "lights to the world" became the spiritual compass for my own journey. His resilience, sacrifice, and vision are the deepest roots of this achievement.

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Curriculum Vitæ

Minwoo Hyun

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Presentations

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Abstract

Essays on the Economics of the Energy Transition

by

Minwoo Hyun

This dissertation examines how changes in fossil fuel activity reshape labor markets, youth outcomes, and local public finances in the United States.

Chapter 1 uses matched employer-employee data on 1.35 million workers separated from fossil fuel extraction (1999-2019) to estimate the impacts of local fossil fuel labor demand shocks. Employment probabilities fall sharply after exposure, and earnings drift down for seven years with only partial recovery by year ten. Workers who remain in fossil fuels, disproportionately men in sector-specific roles, lose nearly twice as much as sector switchers, consistent with limited occupational mobility. Among non-switchers, losses are largest in markets with high employer concentration, indicating monopsony depresses reemployment wages. Geographic movers fare worse than stayers, reflecting negative selection and moves into metropolitan niches where fossil fuel or low-skill services remain highly concentrated.

Chapter 2 links coal production, county arrest records, and school-finance data to examine community effects of coal busts. Declines raise arrests across ages, with larger proportional increases among juveniles, especially for status offenses like truancy. Busts coincide with school-revenue shortfalls and cuts to operational spending, notably reductions in instructional aides and non-classroom support. Policing resources and family/child-abuse measures show little movement, supporting a school-finance mechanism for the juvenile effects.

Chapter 3 analyzes how coal contraction affects local government budgets using plau-

sibly exogenous variation from geology and staggered shale-play activations. Coal declines shrink own-source revenues and, counter to insurance, also reduce intergovernmental transfers, chiefly state general-purpose aid. Governments cut spending on housing/community development, workforce programs, and education; neighboring non-coal counties also lose revenue and spending. Calibrations show that a welfare-maximizing rule can undercompensate small but highly exposed places, whereas an equalization rule stabilizes proportional shocks and targets aid to the hardest-hit and affected neighbors. Observed transfers were procyclical and diverged from both benchmarks.

JEL Codes: Q32, R11, J31, J60, J42, K42, H75, I22, O13, H77, I38

Contents

Curriculum Vitae **vii**

Abstract **ix**

Introduction **1**

1 Trapped or Transferred: Worker Mobility and Labor Market Power in the Energy Transition **4**
1.1 Introduction 4
1.2 Background on the Fossil Fuel Industry 11
1.3 Conceptual Framework 15
1.4 Data 19
1.5 Stylized Facts 21
1.6 Methodology 28
1.7 Results 33
1.8 Discussion 55
1.9 Conclusion 61

2 Industrial Decline Raises Juvenile Antisocial Behavior: Evidence from US Coal Communities **63**
2.1 Introduction 63
2.2 Background and Data 67
2.3 Methods 71
2.4 Results 76
2.5 Robustness Checks 94
2.6 Conclusion 98

3 Fossil Fuels and Fiscal Federalism: How Intergovernmental Transfers Respond to Local Coal Industry Declines **100**
3.1 Introduction 100
3.2 Background 106
3.3 Empirical Strategy 108

3.4 Results . . . 115
3.5 Robustness Check . . . 128
3.6 Mechanisms . . . 133
3.7 Simulating IGT Rules and Policy Discussion . . . 137
3.8 Conclusion . . . 149

4 Beyond Extraction: A Research Agenda for the Decarbonization of the Industrial Economy 150
4.1 Synthesis of the Dissertation . . . 150
4.2 Advanced Labor Market Dynamics and Reallocation Frictions . . . 152
4.3 The Resilience of Public Finance . . . 154
4.4 Political Economy and Institutional Consequences . . . 156

A Appendix to Chapter 1 158
A.1 Details and Proofs for the Conceptual Framework . . . 158
A.2 Rotemberg Weights for the Fossil Fuel Labor Demand Shock Measure . . . 160
A.3 Proof of Equivalence Between Cumulative Elasticity from First-Difference Distributed-Lag Model and Long-Run Elasticity from Level-Based Model 161
A.4 Cournot–Oligopsony Microfoundation . . . 163
A.5 Causal Random Forest Estimation . . . 164

B Appendix to Chapter 2 207

C Appendix to Chapter 3 218
C.1 SW-Optimal IGT Responsiveness . . . 218
C.2 Alternative Fiscal Equalization Rule . . . 219
C.3 Temporal Variation in the First Successful Fracking across the Shale Plays 220
C.4 Parameter Recovery . . . 221

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Introduction

The global transition away from fossil fuels is a defining environmental and economic imperative of the twenty-first century. While the long-run climate and macroeconomic benefits of decarbonization are well documented, the localized costs of this transition remain far less understood. Fossil fuel communities bear the brunt of these costs because their local economies are often highly specialized, geographically isolated, and fundamentally anchored by extraction industries. These sectors historically provided a rare combination of high-wage employment for workers without college degrees and robust tax revenues for local governments. When these legacy industries experience a structural decline, the resulting economic shock does not easily dissipate into the broader macroeconomy. Instead, it triggers a localized downward spiral of depressed wages, shrinking municipal tax bases, and out-migration that heavily burdens the workers, families, and local institutions left behind.

Previous economics literature provides a critical foundation for understanding these localized impacts, primarily by studying historical trade, technology, and resource shocks. Foundational work on local labor markets demonstrates that displaced workers face severe adjustment frictions and limited spatial mobility, leading to persistent, long-term earnings losses following structural economic shifts (Autor et al., 2013). Within the specific context of natural resources, economists have shown that energy booms and busts generate extreme local volatility, fundamentally altering regional employment and

non-tradable sector spillovers (Black et al., 2005; Feyrer et al., 2017; Allcott and Keniston, 2018). However, the permanent, policy-driven nature of the current energy transition poses unique challenges that extend beyond temporary commodity cycles, requiring a deeper examination of how structural decay cascades into multi-generational community well-being and local public finance.

These empirical gaps are currently at the forefront of urgent policy debates surrounding the "Just Transition." Policymakers are actively debating how to design effective place-based interventions, wage insurance, and fiscal equalization transfers to prevent the economic collapse of legacy energy communities. Yet, the design of these transfer rules and community investments often relies on aggregate labor statistics, lacking precise micro-level evidence on the multidimensional costs of industrial contraction. To address these gaps, this dissertation examines how changes in fossil fuel activity reshape labor markets, youth outcomes, and local public finances in the United States.

The first chapter focuses on *individual workers* by using matched employer-employee data on 1.35 million workers separated from fossil fuel extraction between 1999 and 2019 to estimate the impacts of local labor demand shocks. Employment probabilities fall sharply after exposure, and earnings drift down for seven years with only partial recovery by year ten, largely because high employer concentration depresses reemployment wages and limited occupational mobility severely penalizes those who remain in sector-specific roles. The second chapter shifts the focus to *our children* by linking coal production, county arrest records, and school-finance data to examine the community-level spillover effects of coal busts. This analysis reveals that industrial declines coincide with severe school-revenue shortfalls and cuts to operational spending, which systematically drive increases in juvenile arrests, especially for status offenses like truancy. The third chapter examines *local community services* by analyzing how coal contraction affects local government budgets using plausibly exogenous variation from geology and staggered shale-play activations.

The findings demonstrate that coal declines not only shrink own-source revenues but also reduce intergovernmental transfers, ultimately highlighting the need for welfare-maximizing equalization rules to stabilize proportional shocks and target aid to the hardest-hit municipalities.

The final chapter of this dissertation charts a forward-looking research agenda that extends the empirical frameworks developed in the preceding sections. While the first three chapters established a comprehensive understanding of the multi-dimensional costs of the energy transition within fossil fuel communities, my future work pivots toward the broader industrial landscape. I plan to expand this transition risk framework to encompass other carbon-intensive sectors beyond extraction, where structural changes are increasingly driven by a complex intersection of endogenous market forces and exogenous environmental policy. By integrating my ongoing research into the firm-level mediators of labor costs with new inquiries into the political economy and institutional consequences of industrial decay, this concluding chapter outlines how my future research will contribute the precise, micro-level evidence necessary for managing the equitable reallocation of human and fiscal capital across the global economy.

Chapter 1

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

1.1 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 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

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

[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.

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 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

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

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 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

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

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 and 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 (Walker, 2013; Colmer et al., 2024a) study earnings conditional on both sector and location. I contribute to this literature by unpacking mechanisms on two

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

fronts: first, I document 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 (Parent, 2000; Kambourov and Manovskii, 2009) 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 (Feyrer et al., 2017; Allcott and Keniston, 2018; Bartik et al., 2019). 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.

[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., 2024a) and the United Kingdom (Rud et al., 2024).

1.2 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 1.1 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 1.1 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

[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%.

change. Employment therefore clusters where reserves are abundant, as shown by the strong spatial correlation 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 1.1). 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 and 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

[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.

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.

[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.

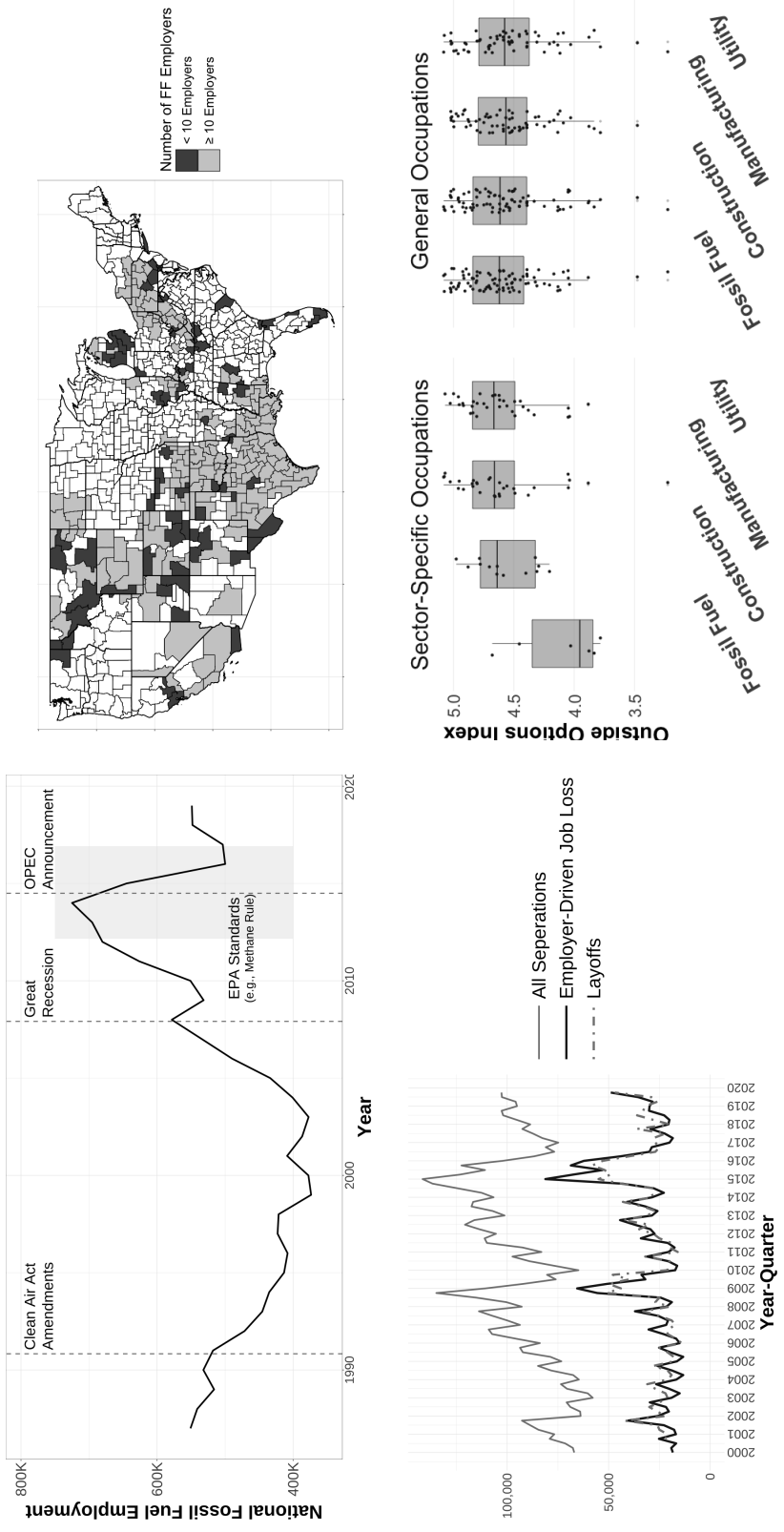


Figure 1.1: National Fossil Fuel Employment (Top-Left) and Employer-Driven Job Loss (Bottom-Left), and CZ-Level Fossil Fuel Employers (Top-Right) and Outside Options Index, Sector-Specific vs. General Occupations by Sector (Bottom-Right)

Notes: **Top-left**: Annual US fossil fuel (FF) employment (NAICS 21; QCEW). Shading denotes intensified EPA standards (2012–2016); "OPEC" marks the supply-driven price collapse. **Bottom-left**: Quarterly separations and layoffs (LEHD, JOLTS). "Employer-driven" losses represent net firm-level employment reductions, excluding routine quits replaced by immediate hiring. **Top-right**: 2019 FF employer counts by commuting zone. **Bottom-right**: Occupational mobility across four sectors. The Outside Options Index (OOI) uses Shannon entropy to quantify the diversity of potential job transitions; lower OOI indicates more limited mobility and fewer viable outside options. Data: QCEW, CBP, JOLTS, LEHD, and Schubert et al. (2024).

1.3 Conceptual Framework

1.3.1 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 1.2 illustrates these assignments.

[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.

3. **Effective labor and portability.** In the N sector, a worker produces θ in A and $\psi(\theta) \leq \theta$ in B capturing imperfect portability of N-relevant skills across markets; in sector F, productivity is normalized to 1 in both markets.[16]

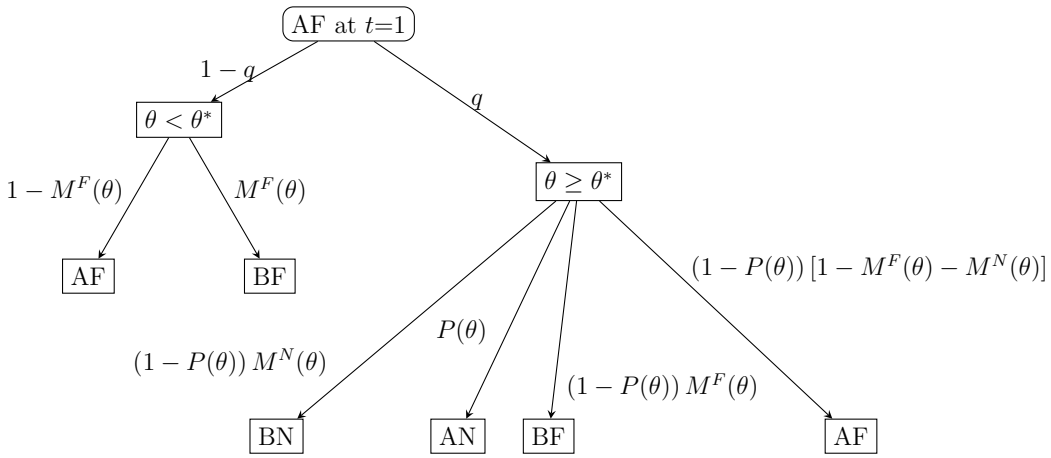


Figure 1.2: Post-Shock Assignment of Displaced Fossil Fuel Workers in Market A by Type

1.3.2 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

$$w^{j,k}(L) \;=\; \chi^{j,k}\, L^{1/\varepsilon^{j,k}}, \qquad \varepsilon^{j,k} > 0, \tag{1.1}$$

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 $\varepsilon^{j,k}$

[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.

means a more elastic supply and less wage-setting power; lower values indicate more restrictive labor supply and stronger market power.

Profit maximization equates the marginal revenue product of labor (MRPL) with the marginal expenditure on labor. Under (1.1), marginal expenditure is $ME = w^{j,k}(1+1/\varepsilon^{j,k})$, implying a markdown of wages relative to MRPL (Berger et al., 2022):

$$\mu^{j,k} \equiv \frac{w^{j,k}}{\text{MRPL}^{j,k}} = \frac{\varepsilon^{j,k}}{1+\varepsilon^{j,k}} \in (0,1]. \tag{1.2}$$

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

$$w_t^{j,k} = \mu^{j,k}\alpha^j p_t^j (L_t^{j,k})^{\alpha^j - 1} \tag{1.3}$$

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.

1.3.3 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.1 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.

1.4 Data

1.4.1 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 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

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

[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.

is employed by multiple employers in a given year, the employer providing the highest earnings is designated as the worker's main employer (Sorkin, 2018; Lamadon et al., 2022). 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.

1.4.2 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 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.

1.5 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.

1.5.1 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

[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).

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.

1.5.2 Employment Transition Patterns of Fossil Fuel Workers

Geographic and Sectoral Mobility

The top-left panel of Figure 1.3 shows the geographic mobility of separated workers from the FF sector and three comparison sectors following job separation.[21] Geographic

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

[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.

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 1.3 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 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

[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.

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.

Observable Selection across Worker Groups

The bottom-left panel of Figure 1.3 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 1.2: 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 1.3). 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%.

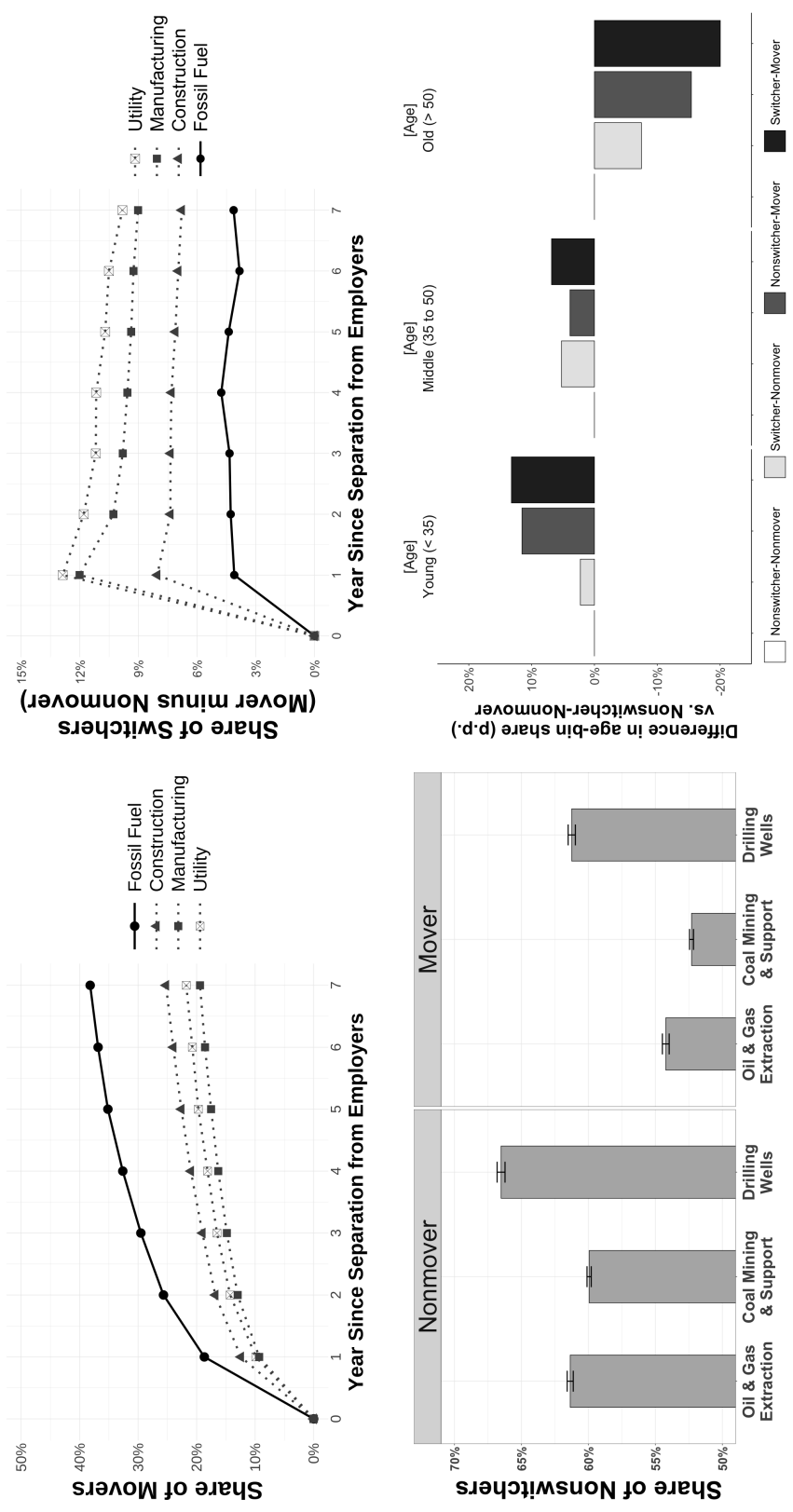


Figure 1.3: Geographic Mobility (Top-Left) and Sectoral Mobility (Top-Right) by Sector, and Conditional Probability of Staying the FF Sector by Pre-Separation Subsector (Bottom-Left) and Age Composition Differences across Worker Groups (Bottom-Right)

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.

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 1.4 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.

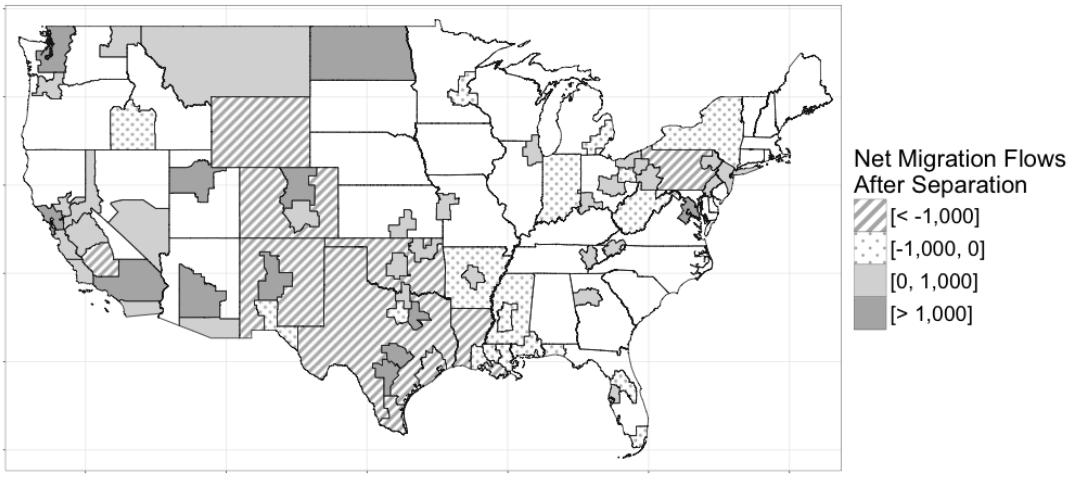


Figure 1.4: Net Migration Flows of Separated Fossil Fuel Workers Across US Regions

Notes: Data source: LEHD.

1.6 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]

$$FFShock_{ct} = \Delta \log \Big(\sum_{c' \neq c} Emp^{FF}_{c',t} \Big) \times Depth_c \tag{1.4}$$

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 1.2, 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]

[23] In the regression analysis, the shock in Eq. (1.4) 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.

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 measure 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 1.5 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

[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.

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 areas.[31]

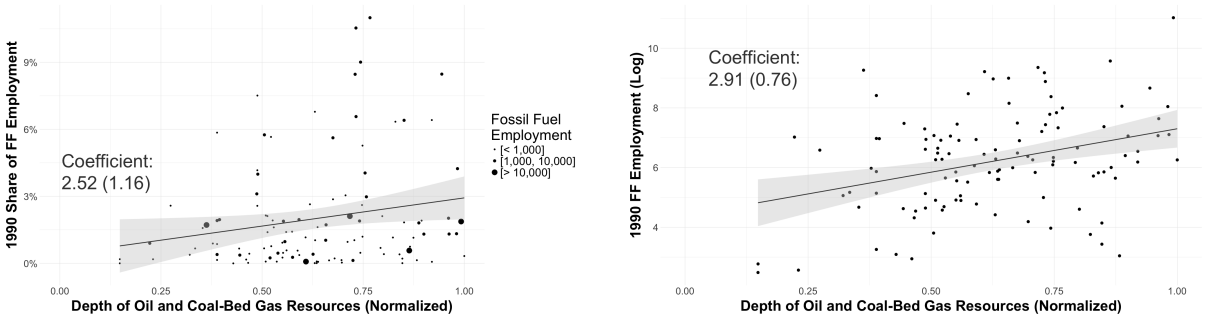


Figure 1.5: Depth of Fossil Fuel resources and 1990 Fossil Fuel Employment Share (Left) and Employment Level (Right)

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

[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.

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 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

[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 A.2 for details.

first-differencing:

$$\Delta y_{ict} = \sum_{k=-4}^{10} \beta_k FFShock_{c,t-k} + \gamma_{j(i,t)} + \delta_{1,s(c)t} + \delta_{2,m(j)t} + \varepsilon_{ict} \tag{1.5}$$

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-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

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

[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 A.3 for proof). Consequently, empirical comparisons using $\sum_{k=0}^{10} \hat{\beta}_k$ correspond directly to comparisons between equilibrium wages in the theoretical model.

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]

1.7 Results

1.7.1 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

[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.

[37] Formally, nonemployment rate is defined as:

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

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,

$$\Delta NonempRate_{cmt} = \sum_{k=-4}^{10} \beta_k FFShock_{c,t-k} + \delta_{1,c} + \delta_{2,mt} + \varepsilon_{cmt} \tag{1.6}$$

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 1.6 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

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.

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.

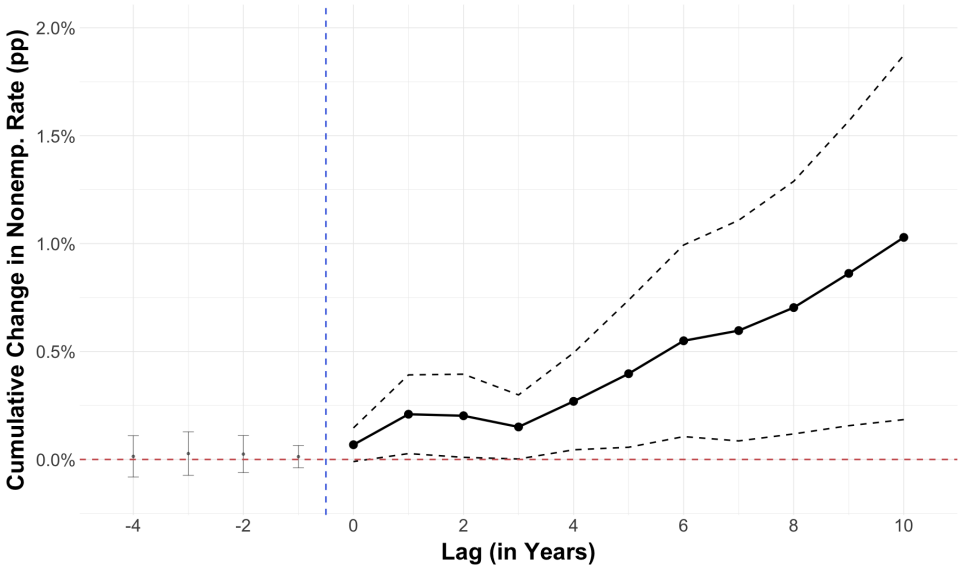


Figure 1.6: Fossil Fuel Labor Demand Shocks and CZ-Level Nonemployment Rate

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.

1.7.2 Worker-Level Analysis of Fossil Fuel Labor Demand Shocks

Effects on Probability of Employment

I next examine worker-level annual *employment* using Eq. (1.5) 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 1.7 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.

Effects on Annual Earnings

The right panel in Figure 1.7 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 1.1 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 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

[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.

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 and 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 1.7), 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

[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.

annual 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 1.7 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.

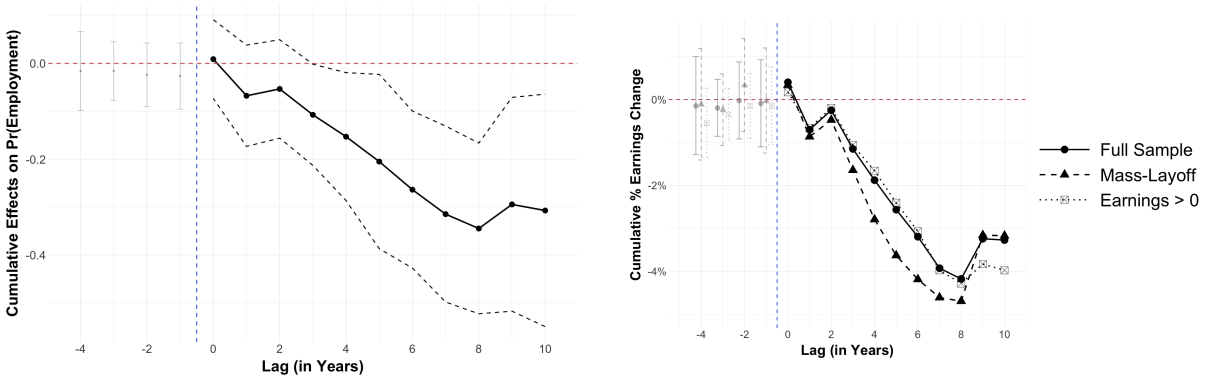


Figure 1.7: Cumulative Effects on Probability of Employment and Earnings

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.

Effects on Nonemployment Duration

Columns 4 to 5 in Table 1.1 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,

[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.

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 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 1.1: 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.

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 1.8 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 1.5. 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 1.8 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.

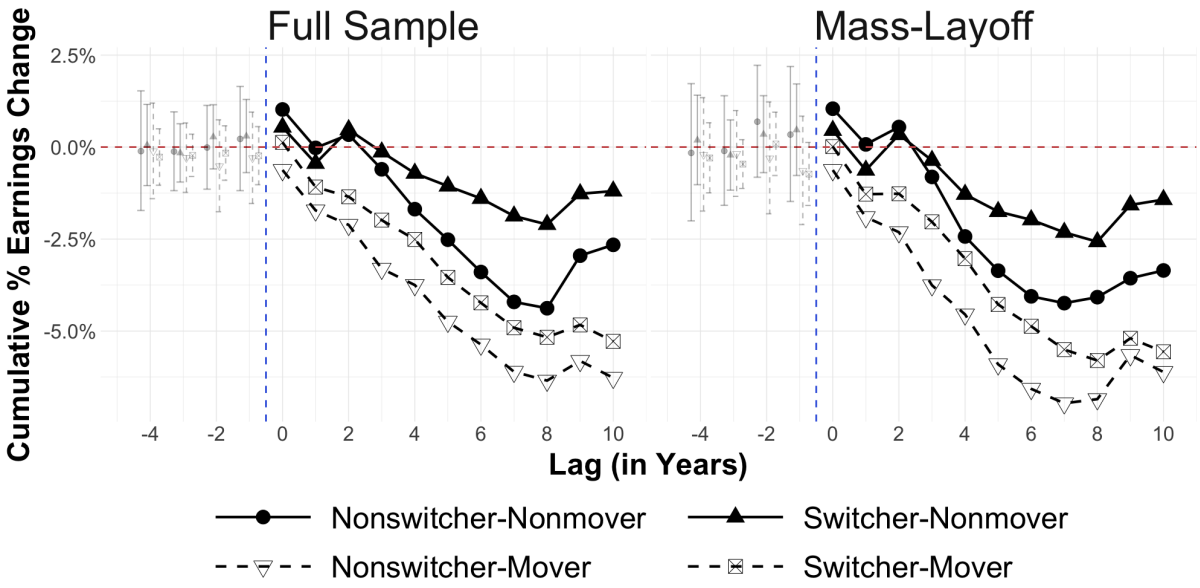


Figure 1.8: Fossil Fuel Labor Demand Shocks and Earnings Impact by Reallocation Margins

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

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 1.5.2.

The left panel of Figure 1.9 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,

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

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 1.9, female workers experience significantly smaller earnings losses compared to their male counterparts, suggesting that limited job mobility contributes to higher adjustment costs following economic shocks.

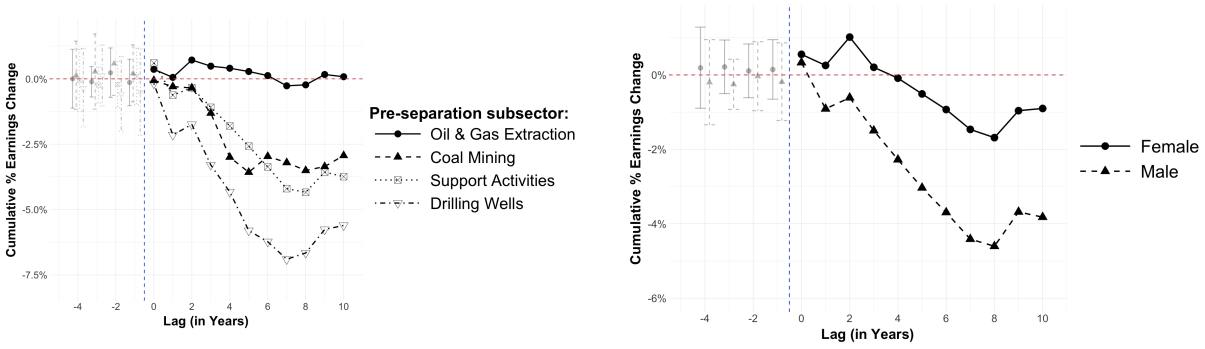


Figure 1.9: Fossil Fuel Labor Demand Shocks and Earnings Impact by Subsector (Left) and by Sex (Right)

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.

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 and 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 1.10 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 1.5), 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 Jacobson et al. (1993); Autor et al. (2014), 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 1.5 shows that, even before separation, they earn less on average than Nonmovers. The right panel in Figure 1.10 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).

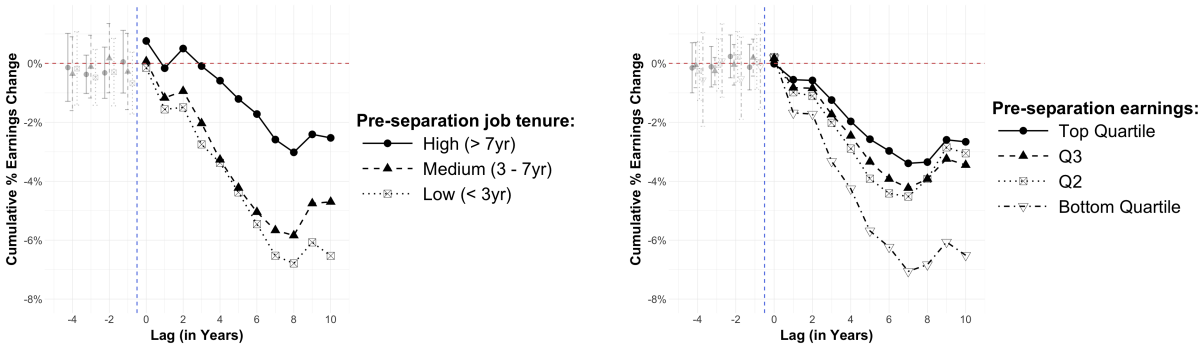


Figure 1.10: Fossil Fuel Labor Demand Shocks and Earnings Impact by Job Tenure (Left) and by Pre-Separation Earnings (Right)

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

These findings point to a previously overlooked negative selection within the exposed 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; Kennan and Walker, 2011; Collins and Wanamaker, 2014). 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 1.4 are consistent with this interpretation, as cities offer thicker labor markets and broader fallback options; these moves mitigate losses rather than pursue new gains.

Employer Concentration: Wage-Setting Conditions

As discussed in Section 1.2, 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. (1.3), lower wages holding prices

and effective labor fixed. Appendix A.4 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:

$$HHI_{ct}^{FF} = \underbrace{\sum_{m=1}^{M} \left(\frac{E_{mct}}{E_{ct}}\right)}_{\substack{\text{Emp. share} \\ \text{of subsector}}} \times \underbrace{\sum_{j=1}^{J_m} s_{jmct}^2}_{\substack{\text{Concentration} \\ \text{within subsector}}} \tag{1.7}$$

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 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 1.5.2, 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. 1.7). 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

[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.

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

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 1.11 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 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 1.7.3: 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 1.7.3.

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}.

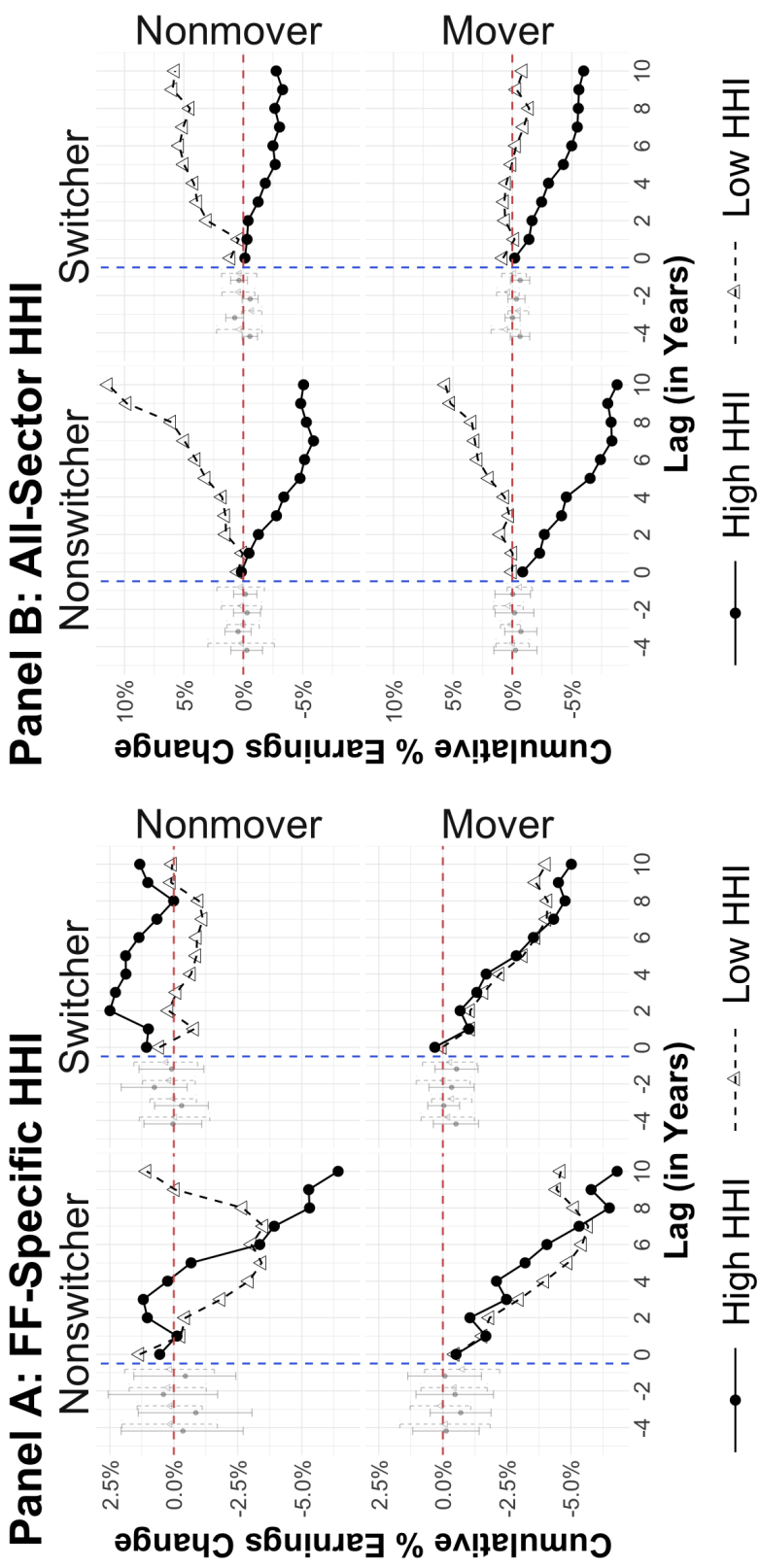


Figure 1.11: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Destination Markets

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.

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 1.3. 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.

1.7.4 Robustness Checks

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

[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.

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.

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]

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

[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.

employment shock. This result supports the baseline specification by confirming that modeling shocks linearly captures the full earnings impact without overlooking important nonlinear effects.

1.8 Discussion

1.8.1 Additional Factors Affecting Worker Adjustment Costs

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).

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 and 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.

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 and Sweetman, 1999; Lee and 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

[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`

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.

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

$$\Delta y_i = \beta(X_i) FFShock_i + f(X_i) + \varepsilon_i, \tag{1.8}$$

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. (1.8). First, *permutation importance*, which is a model-agnostic diagnostic of the fitted forest, ranks each covariate in X_i by

[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 A.5 for additional details on the CRF estimation.

its contribution to predicting treatment-effect heterogeneity (Davis and 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 1.12). 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 relevant 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 1.12 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

[52]See Appendix A.5 for details on permutation importance and the precision-weighted projection.

[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.

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.

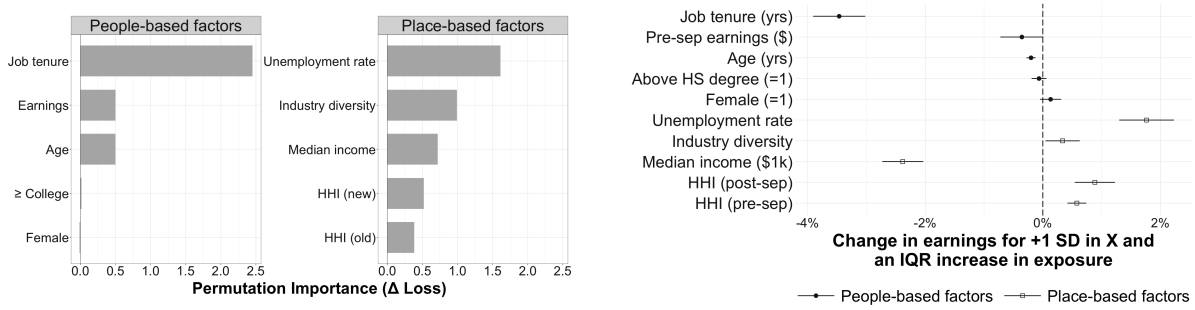


Figure 1.12: Causal Random Forest: Permutation Importance (Left) and Linear Projection (Right)

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

1.8.3 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 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 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

[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).

adjustment costs and the need for targeted policy, even though it is not a net welfare measure.

1.9 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.

Chapter 2

Industrial Decline Raises Juvenile Antisocial Behavior: Evidence from US Coal Communities

2.1 Introduction

Communities have long been shaped by the rise and fall of dominant local industries. Historically, cities reliant on single industries, such as steel production in Rust Belt cities or textile mills in New England, have suffered significantly when these industries declined. More recently, globalization and automation have intensified these effects, with import competition from China severely reducing manufacturing employment across many American communities, often leaving lasting economic distress (Autor et al., 2016). Local industry downturns weaken community support systems by eroding local governments' fiscal bases, leading to reduced public goods and services precisely when they are most needed (Feler and Senses, 2017).

Economists have extensively studied how adverse economic shocks contribute to

increased crime, emphasizing mechanisms such as diminished labor market opportunities and heightened family instability (Becker, 1968; Gould et al., 2002; Rege et al., 2011). Schools, particularly vulnerable to such revenue shortfalls due to their dependence on local taxes, are often forced to cut staffing, increase class sizes, and reduce extracurricular programming, with potential consequences for youth engagement, academic support, and socialization. Declining school resources can directly foster student disengagement, notably through increased truancy, which may precede more serious delinquent behavior (Garry, 1996; Jacob and Lefgren, 2003).[1] Thus, local economic shocks appear to create community-wide distress affecting both youth and adults, with schools serving as one important, though not exclusive, channel from fiscal stress to juvenile outcomes.

This setting is particularly salient in communities dependent on fossil fuel extraction, such as coal-producing regions, where industry contractions quickly affect local fiscal capacity. Unlike typical downturns, the collapse of fossil fuel production directly reduces revenue streams that finance a sizable share of local school budgets, covering roughly 40% on average (Jackson et al., 2021; Raimi et al., 2023). As coal production declines, schools in these communities face tighter operating budgets and constraints on student-facing services (Deming, 2011; Jacob and Lefgren, 2003).

I examine how a major local industry downturn influences juvenile antisocial behavior, using the recent decline of the US coal mining industry as a case in point. Between the late 2000s and 2019, US coal production fell approximately 45%, devastating counties reliant on coal extraction. I exploit this sharp downturn to analyze its impact on youth outcomes by assembling county-level data on juvenile arrest rates and school finances. To identify exogenous variation in local coal production, I construct an instrumental variable (IV) leveraging the fracking boom's impact on coal demand, combining temporal

[1]According to the Office of Juvenile Justice and Delinquency Prevention, students who are habitually truant are significantly more likely to engage in serious antisocial behaviors, including drug use, theft, and vandalism.

variations from shale gas development with cross-sectional differences in coalbed thickness across counties. This IV captures how advancements in drilling technology made coal less competitive, significantly reducing demand faced by coal mines.

My IV estimates reveal that coal production declines are associated with increases in arrests across age groups, with disproportionately larger proportional responses among juveniles. The largest juvenile effects arise for status offenses (e.g., truancy), which expand more than disorderly conduct or property offenses. At the same time, adult arrests also rise, indicating a broader crime response in distressed communities rather than a pattern unique to minors. I interpret the concentration in status offenses as suggestive of school-linked dynamics operating alongside other forces.

To explore mechanisms, I document that a 1-million-short-ton (Mst) annual decline in coal production (24% of the sample mean) is associated with a $91 decline in total school revenue per student and a $136 decline in operational spending per student (about 1.2% of average per-pupil spending). Federal aid rises but does not fully offset state and local revenue losses. A complete cessation of coal production could imply annual reductions of roughly $612 per student, comparable in magnitude to moderate recession-induced budget cuts discussed in the literature (Jackson et al., 2021).[2] These fiscal contractions provide a plausible channel through which coal declines could exacerbate juvenile antisocial behavior.

Consistent with this channel, expenditure patterns point to selective cuts in instruction-related resources, including reductions in instructional aides and student-support staff, and a measurable decline in class attendance. I find limited evidence supporting alternative mechanisms, such as changes in policing, parental employment, or household victimization, lending suggestive support to school-centered explanations.

[2]Jackson et al. (2021) report average Great Recession cuts of roughly $700–$1,000 per pupil (≈7%). My back-of-the-envelope estimate for a complete local cessation implies $563-$612 per pupil (≈5%).

Finally, heterogeneity by pre-period exposure to coal-linked school revenues is consistent with the idea that fiscal erosion magnifies juvenile impacts, while adult effects show less systematic variation along this dimension. Overall, the evidence indicates a broader community-level increase in crime with additional juvenile-specific responses consistent with (but not limited to) school-finance pressures.

My findings contribute to the literature examining the relationship between fossil fuel extraction and crime or school outcomes. Several studies focus on the effects of the fracking boom on school-related outcomes, such as school finances and test scores (Marchand and Weber, 2020), high school dropout rates and per-pupil spending (Cascio and Narayan, 2022), class attendance and graduation rates (Kovalenko, 2023), and school enrollment (Zuo et al., 2019).[3] Other research highlights that some oil-rich regions experienced increases in crime due to the rapid expansion of oil and natural gas production during the fracking boom (Andrews and Deza, 2018; Bartik et al., 2019; James and Smith, 2017; Komarek, 2018). While these studies primarily examine the effects of booming oil and gas industries, my work shifts the focus to coal-rich communities, where coal mining industries were negatively impacted by the fracking boom, and investigates the resulting effects on crime and school outcomes.

Existing literature examines the effects of policies that increase school spending per pupil to examine whether "money does matter" for student success. Some studies find improvements in outcomes such as test scores or college-going rates (Hyman, 2017; Abott et al., 2020; Baron, 2022), while others highlight the impact of school spending cuts driven by economic downturns (Jackson et al., 2021).[4] Compared to academic performance metrics, school spending impacts on non-achievement or behavioral outcomes such as student absenteeism or criminal activity have been understudied. One related work is

[3]Acuna et al. (2024) also explore the impact of oil royalties on school completion.

[4]See Jackson (2020) and Jackson and Mackevicius (2024) for existing quasi-experimental literature on the effects of school spending on student outcomes.

Baron et al. (2024), which assesses whether increased school funding changes arrest rates in adulthood. Complementing Noghanibehambari (2022), who show that reforms raising per-pupil spending reduced juvenile arrests, I provide suggestive evidence that spending *cuts* are associated with higher juvenile antisocial behavior.

This paper also enriches the literature on the economics of education and crime. Previous research shows that juvenile antisocial behavior is influenced by various school-related factors, such as time spent in school (Jacob and Lefgren, 2003; Berthelon and Kruger, 2011; Bell et al., 2022), dropout rates (Anderson, 2014; Cook and Kang, 2016), and socioemotional skills (Jackson et al., 2020). Deming (2011) highlights the role of school quality, measured by peer and teacher inputs, in shaping adult crime outcomes, using data on felony and other arrests observed seven years after random assignment in public school choice lotteries. Building on this literature, I present evidence consistent with a school-linked mechanism, via staffing and attendance, operating alongside broader community distress following coal declines.

2.2 Background and Data

2.2.1 US Coal Declines and School Finances in Coal-Rich Regions

Since the late 2000s, the United States has experienced a significant decline in coal production, dropping from 1,200 Mst to approximately 700 Mst by 2019. During this period, the majority of 143 coal-producing counties saw declines in coal production exceeding 40% (Figure 2.1). This trend is largely attributed to a reduction in coal-fired electricity generation, driven primarily by a sharp decrease in natural gas prices rather than by environmental regulations or renewable energy mandates (Coglianese et al., 2020).

The decline in natural gas prices resulted from technological advancements in hydraulic fracturing (commonly known as fracking), which created an exogenous economic shock and serves as the basis for the empirical context of this study.

Public schools in the fossil fuel-rich regions exhibit heavy fiscal reliance on the mining industry for the following reasons. First, fossil fuel extraction companies pay different types of local taxes such as property tax, which account for approximately 40% of the total revenue sources for school districts (Jackson et al., 2021). Second, a significant portion of the fossil fuel revenues collected by state governments flow into education trust funds, which are typically used to support public schools (Newell and Raimi, 2018b). Third, declines in the fossil fuel industry would erode not only the tax bases for school districts but other local aid sources such as county and city governments or other neighboring school districts. Figure 2.1 shows the residualized[5] per-student school revenue in coal-producing and non-coal-producing counties, suggesting that school revenue in coal communities follows declines in coal production since 2010.

[5]By focusing on residuals, I highlight deviations from expected school revenue after removing county and state-year fixed effects to allow for clearer comparisons across groups (coal and non-coal counties). The raw school revenue may be influenced by national trends or structural differences across counties.

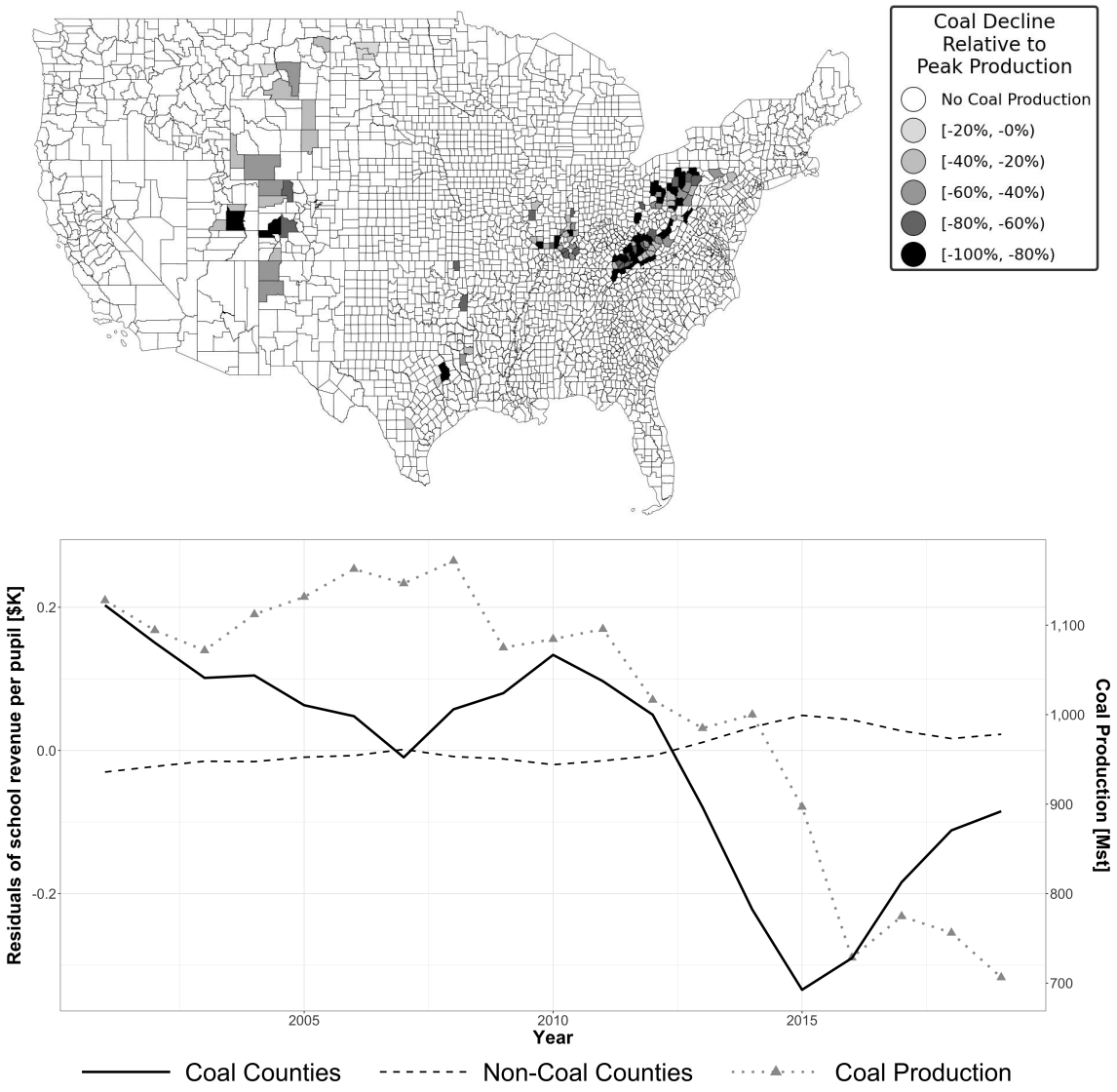


Figure 2.1: County-Level Coal Declines (Top) and Per-Student School Revenue in Coal and Non-Coal Counties (Bottom)

Notes: The coal production data in the top panel comes from the Annual Survey of Coal Production and Preparation. The school revenue data in the bottom panel comes from the Annual Survey of School System Finances. The top panel depicts the county-level coal decline measure, which is a percentage change of cumulative coal production in the recent five years (2016 to 2020) relative to the sum of the top five annual coal production during the 20-year sample period. To obtain the residuals for the bottom panel, I run a regression using school revenue as the dependent variable, controlling for county and state-year fixed effects where the sample includes all coal and non-coal counties in coal-producing states, isolating deviations in school revenue that cannot be explained by these fixed effects.

2.2.2 Data Sources

The Annual Survey of Coal Production and Preparation (EIA-7A) provides annual coal production data for all coal mines covering the years from 2000 at the county level. Crime-related data are from the Federal Bureau of Investigation (FBI) and the National Center for Juvenile Justice (NCJJ). The FBI's Uniform Crime Reporting (UCR) program provides data on arrests by age[6] and crime category and the number of officers reported by each police enforcement agency. This study also uses county juvenile court cases provided by NCJJ. The juvenile court data contain delinquency and status offense cases regardless of being charged in a petition. To obtain a precise measure for the arrest rate by age (especially for juvenile ages), county-level age-specific population data provided by the Easy Access to Juvenile Populations is employed in this paper.

All the school-related data used in this study applies exclusively to public K-12 schools in the US.[7] School finance data including revenue, expenditure, and debt comes from the Annual Survey of School System Finances provided by the Census Bureau. It contains revenue in elementary and secondary schools from different sources: federal (e.g., Title 1) and state (e.g., general formula) aids, and local tax revenue (e.g., property tax). For school expenditure items, the data includes school operational spending (e.g., teacher salaries), capital outlay, and payments to other levels of governments (e.g., support for other schools). I aggregate the school district-level finance data up to the county-level by identifying each school district's associated county.[8] By leveraging the number of K-12 pupil count in each county, I calculate dollar per student which is typically used in

[6]The age profiles are 10–12, 13–14, 15, 16, 17, 18–20, and five-year intervals after age 20 (e.g., 21–25).

[7]The trends in the share of private school students in coal counties closely mirror those in non-coal counties and the national average, as shown in Figure B.1. However, private school enrollment in coal counties is consistently lower than in non-coal counties and the national average. This suggests that private schools in coal counties are unlikely to have a distinctive effect on my outcomes, given their similar trends and smaller presence.

[8]The crosswalk between school district and county is provided by the Census Bureau: https://www.census.gov/programs-surveys/saipe/guidance-geographies/districts-counties.html

literature on the effects of school spending (Abott et al., 2020; Jackson et al., 2016, 2021). All dollar values are adjusted to the 2015 Consumer Price Index (CPI) level.

Non-financial school data such as staffing is obtained from administrative sources. This study uses the teacher-student ratio and the number of school personnel for all school districts in the US, provided by the National Center of Education Statistics (NCES). For non-achievement school outcomes (e.g., class attendance) and teacher qualification metrics (e.g., years of teacher experience), I collect school district-level data from each state school authority (e.g., Kentucky Department of Education). This dataset does not fully cover all the coal-rich parts of the US, but it includes seven out of the top 10 coal-producing states and the coal production in the counties (where the hand-collected school districts are located) accounts for about 85% of the total coal production.

2.3 Methods

To estimate the causal effects of coal decline on local crime or school outcomes, this study leverages county-level data which are available every year during a 20-year sample period. To identify counties where they have steadily relied on coal mining industry, I rule out the counties that produced coal for less than ten consecutive years. This restriction also ensures that "coal decline" is defined relative to a meaningful baseline industry and that the identifying variation in annual coal production reflects economically salient changes rather than sporadic, volatile production. As a result, the 143 counties with 4,104 mines remain in my sample.[9]

I construct a two-way fixed effects (TWFE) model to estimate the impact of coal

[9]See Table B.13 for name and coal-rich region of each county. It is worth to be noted that the counties in my sample collectively produced 92.4% of the total national coal output between 2000 and 2020.

production ($Coal_{it}$) in county i at year t on the outcomes of interest (Y_{it}) as follows:

$$Y_{it} = \beta_1 Coal_{it} + X_{it}^{'}\theta + \alpha_i + \delta_t + \varepsilon_{it} \tag{2.1}$$

where α_i denotes county fixed effects, year fixed effects (δ_t) are used to capture time-specific shocks, and ε_{it} is the error term. Y_{it} is an economic outcome such as arrest rates or school finance.[10] The main coefficient of interest is β_1, which provides the parameter estimates for the impact of coal declines on the outcomes. To facilitate the discussion of declines in coal production, the reported estimated coefficients of β_1 are multiplied by -1. $X_{it}^{'}$ is socioeconomic and demographic controls.[11] For the main results, standard errors are clustered by county to account for potential intra-county correlations, as observations within the same county may share unobserved local economic conditions that could bias my estimates.

Coal production may be endogenous for several reasons. First, changes in the local labor market within coal-rich regions can influence coal production levels. Second, unobserved factors correlated with outcomes, such as school bond elections, may not be fully captured by the controls. To address this issue, I construct a "coal-bust potential" variable as an instrument for local coal production. This variable leverages two key elements: (1) the impact of the fracking boom on coal demand in the electricity sector over time, and (2) a geological feature of coal mining. The rationale behind this instrument is that declines in coal production were an unintended consequence of the shale boom.

[10]Non-coal counties might help pin down broad year fixed effects, but in a TWFE design with a continuous treatment the parameter β_1 is identified by within-county changes in coal production intensity. Counties that never produce coal contribute no such within-county variation. They mainly shape the common year effects, which may be unrepresentative of the macro shocks facing coal-reliant counties.

[11]The socioeconomic controls include local per-capita income, unemployment rate, and poverty rate. Data on per-capita income and unemployment rate are sourced from the US Bureau of Economic Analysis, while the poverty rate is obtained from the US Census Bureau. The demographic controls include the proportion of non-White residents, the share of the population under 25 years of age, and population density, all sourced from the US Census Bureau.

Advances in drilling technology drove a rapid expansion of natural gas wells, which reduced local natural gas prices. This price decline made coal relatively more expensive, thereby reducing its demand.

Temporal Variation

For a source of time-series variation in the instrumental variable, I employ the initiation of fracking activity in shale gas plays, which are natural gas accumulations sharing similar geological features. As discussed in Section 2.2, the effects of the modern technological advances in gas and oil production on natural gas prices explain the majority of the decline in coal production. One notable feature of the shale gas plays is that they have different timelines for which the first successful horizontal wells became public knowledge from press releases or investor calls, which would attract more natural gas producers to explore the play (Bartik et al., 2019). This fact allows me to exploit temporal variation in play-specific shocks to demand for coal in the electricity sector by the following procedure. First, I identify power plants that purchase coal from a given county. Second, I sum an indicator for whether a calendar year is no earlier than the first year of successful fracking in individual shale gas play over all major plays in the US. The indicator is then inversely weighted by the distance between the play and the power plant.[12] Third, I sum up the time-varying fracking initiation measures at the plant level for each county. Thus, the sum of the indicators represents the growing effects of shale gas plays on coal-producing counties via the steam coal market over time.

Cross-Sectional Variation

[12]This study takes advantage of novel data on the fracking initiation date for each play from Bartik et al. (2019). They also provide the fracking prospectivity score which is measured by the Rystad Energy, an oil and gas consulting firm. I test the robustness of my instrument by using the product of the shale play initiation indicator and the prospectivity score.

While the fracking initiation measures provide plausibly exogenous time-series variation, the cross-sectional variation across coal-producing counties would not be sufficiently explained by them. As the US natural gas spot market is highly integrated, the coal-bust potential instrument would be needed to capture spatially heterogeneous coal supply responses to demand shocks that are induced by the natural gas price changes via the wholesale electricity market. To address this concern, I use a predetermined coal deposit thickness as an exogenous variable for the geological coal potential of each county. The US Geological Survey operates a nationwide database of coal quality such as coal seam depth and thickness for over 13,000 samples that were collected between 1973 and 1989.[13] It is noteworthy that the survey was conducted over 15 years ahead of the sample period in this study. Since the thickness of coalbeds determines the efficiency of underground and surface mining,[14] it can serve as a measure of "coal extraction prospectiveness."

The rationale for how coal-bed thickness relates to vulnerability to coal demand shocks is as follows. Thicker coal beds enable more efficient mining, lowering per-unit costs, attracting greater investment, and leading to higher overall production. When demand declines, mines in thick-bed regions remain profitable longer, whereas those in thin-bed areas face higher costs and are more likely to shut down. This justifies the use of inverse thickness in the instrument in Eqn. (3.2), as it effectively captures the greater vulnerability of thin-bed regions to coal production declines during demand shocks. Figure B.2 illustrates that counties with thicker coal beds tend to have higher coal production, supporting the idea that thicker coal beds reduce marginal extraction costs and help sustain production even in periods of declining demand. This suggests that coal-bed thickness provides exogenous cross-sectional variation, serving as a meaningful measure of coal mining productivity across different counties.

[13]The database is known as COALQUAL.

[14]To understand how average coal seam thickness is related to mining productivity, see the following article published by EIA: https://www.eia.gov/todayinenergy/detail.php?id=35232

Yet, my instrument may suffer from an exclusion restriction violation if the shale gas boom had direct labor market effects on nearby local communities, drawing workers away from coal towards natural gas production.[15] One important fact is that the gas and oil extraction industry has an extremely small share of employment compared to coal (and other mineral) mining in the coal-rich counties (Figure B.3), indicating that geographic spillovers of the shale boom would be negligible in this setting. Nevertheless, I restrict the estimating sample to counties that are located over 150 miles away from each shale play to address this concern. This sample restriction enables variations in coal demand that are sufficiently far away as to have minimal direct impacts on the local labor market. In addition, even though coal power plants where locations have similar distances from the shale gas plays, the impact of fracking potential on the plants would differ by the intensity of local gas transport infrastructure. For example, coal plants in a state that has a high density of intrastate and interstate gas pipelines (e.g., Texas) would be more affected by the fracking boom. The IV incorporates gas pipeline capacity in the year of 2000 in each state which is computed using the annual announced pipeline projects dataset provided by the EIA.

Let CP_{it} be a prospect of a coal bust with demand shocks in county i at time t, which is the instrumental variable used in this study. Intuition on how this instrument works is that local coal production would decrease more as the fracking-driven demand shocks are greater, and the shale boom impacts would be more intensive with thinner coalbed. Formally, define $\mathcal{J}_i$ as the set of coal-fired power plants j that are matched to county i based on coal procurement links, meaning plants in $\mathcal{J}_i$ purchase coal from county i. CP_{it}

[15] New gas production could generate spillover impacts in neighboring areas within 100 miles of the fracking sites (Feyrer et al., 2017).

is specified as:

$$CP_{it} = \underbrace{\frac{1}{Thickness_i}}_{\substack{\text{Cross-Sectional} \\ \text{Variation}}} \times \underbrace{\sum_{j \in \mathcal{J}_i} \Big[\sum_{k} \mathbb{1}(Play_{kt} \geq \bar{t}_k) \times \varphi_{jk} \Big] G_j}_{\text{Temporal Variation}} \tag{2.2}$$

where $Thickness_i$ is the average thickness of coalbeds in county i, the main exogenous cross-sectional variation in the instrument. $\bar{t}_k$ denotes play-specific announcement date of successful fracking and $\mathbb{1}(Play_{kt} \geq \bar{t}_k)$ is an indicator equal to 1 after play k is announced. φ_{jk} is the inverse distance between plant j and play k, so plants closer to an activated play receive a larger shock. G_j is the natural gas pipeline density around plant j in 2000, which scales the shock by pre-determined infrastructure.

Thus, the first-stage regression using the coal-bust potential instrument is summarised as:

$$Coal_{it} = \gamma_1 CP_{it} + X_{it}^{'}\kappa + \xi_i + \phi_t + u_{it} \tag{2.3}$$

where the estimated coefficient of γ_1 is expected to be negative since coal-rich regions, which are more exposed to fracking-driven coal demand shocks and have thinner coalbeds, are likely to experience a greater decline in coal production. In Section 2.5.1, I analyze the results of the first-stage equation (3.3) under various specifications of the instrument.

2.4 Results

2.4.1 Coal Declines and Crime

My empirical analysis begins by estimating the reduced-form relationship between local coal declines and juvenile criminal activity which is measured using the number of arrests per 1,000 individuals in each county. The left panel in Figure 2.2 presents the

results from the estimation of a 2SLS equation (3.1), where arrest rates are modeled as a function of a 1-million-short-ton (Mst) decline in coal production. The findings show that the effects are evident for both juveniles and adults. In Figure 2.2's right panel (coefficients as a percent of each cohort's mean), juvenile groups (ages 10-17) show larger proportional increases by about 9-16%, while adult cohorts also rise by roughly 3–7% (with little change at 60+). Thus, juveniles appear disproportionately affected, but the pattern is consistent with a broader community-wide increase in arrests rather than a response unique to minors.

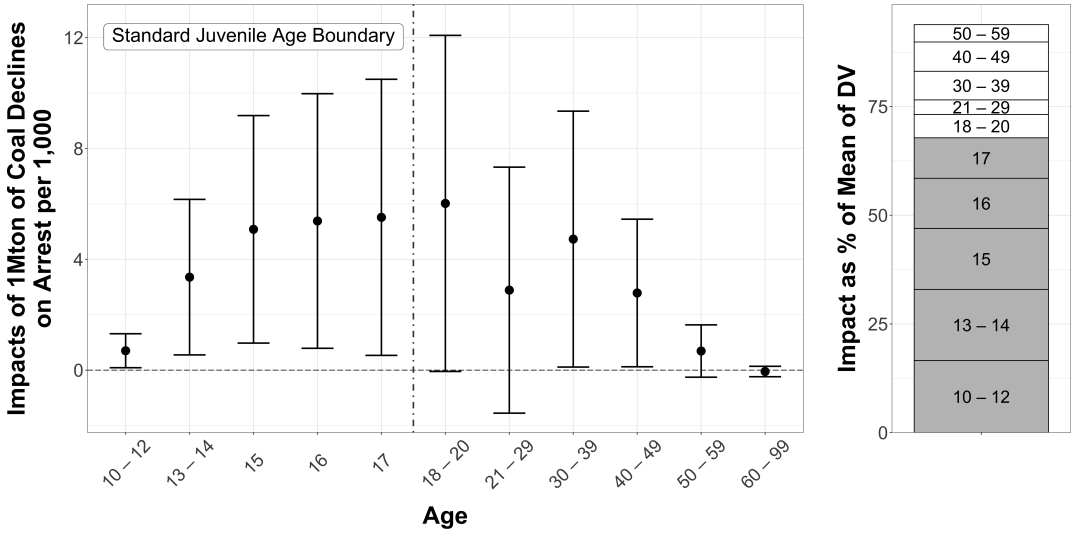


Figure 2.2: Impact of Coal Declines on Arrest Rates by Age

Notes: The left panel illustrates the estimated coefficients (represented by dots) along with their corresponding 95% confidence intervals (depicted as error bars). The x-axis indicates the age of the cohorts, with the dependent variable being the arrest rates. The right panel presents a stacked bar chart where the estimated coefficients are expressed as percentages of the mean of the dependent variable, with the bars stacked by age group. A detailed summary of all estimates can be found in Appendix (Table B.5).

Table 2.1 presents the estimated impact of coal declines on juvenile (ages 10–17) arrest rates per 1,000 individuals, broken down by crime type.[16] The first-stage results demonstrate the strong instrument relevance, with F-statistics ranging from 140 to 220

[16]See Table B.12 for a detailed breakdown of offenses under each crime category.

across all types of arrests, mitigating concerns about weak instrument bias. Columns (1) to (3) present the overall impact of coal declines on juvenile arrest rates, with each specification incorporating different levels of control variables. The coefficient estimates indicate that declines in coal production are associated with significant increases in total juvenile arrests, with effect sizes ranging from 2.7 to 3.3 arrests per 1,000 individuals. These estimates correspond to 10.5% to 12.9% of the mean arrest rate, suggesting a meaningful rise in youth criminal activity in response to economic downturns in coal-dependent areas.

Column (4) shows that the effect on violent crime arrests is not statistically significant, with a coefficient of 0.046. In contrast, Columns (5) and (6) reveal statistically significant increases in arrests for disorderly conduct and property crimes. The coefficient for sex offense arrests in column (8), while not precisely estimated, accounts for 13.0% of the mean, indicating a notable impact on this crime type. Arrests for drug abuse exhibit no significant effects (column 9). Interestingly, this contrasts with findings for adults (ages 30 and above), where statistically significant impacts are observed for sex offenses and drug abuse only (Table B.2).

In column (7), coal declines have the largest effect on status offenses (offenses only for minors, such as truancy or curfew violations): the estimate is 23.5% of the mean, about 1.5 to 2 times the impacts on disorderly conduct and property crimes. Given that truancy accounts for approximately 75% of status offense cases,[17] this suggests that schools play a critical role in shaping juvenile behavior. Coal declines may lead to reductions in school funding, adversely affecting the quality of education and school resources. These disruptions could weaken schools' ability to engage students effectively, thereby increasing their vulnerability to antisocial behavior. This underscores the importance of examining the impact of coal declines on school outcomes, particularly in terms of revenue and

[17]To determine how much truancy contributes to status offense cases, please refer to the following link: https://www.ojjdp.gov/ojstatbb//court/qa06602.asp?qaDate=2021

expenditure sources, as a channel potentially influencing youth crime.

One potential concern is that the empirical design does not sufficiently connect the results on juvenile crime with the proposed schooling mechanism, given that coal declines also affect adult crime rates. To further explore whether this school-linked mechanism operates alongside a general community-wide shock, I examine heterogeneity based on counties' pre-treatment reliance on coal property taxes for K-12 revenue (detailed further in Section 2.5.3). The results suggest that in counties with greater exposure to this fiscal dimension, juvenile arrests tend to show larger increases. In contrast, adult arrest rates do not appear to exhibit a similar systematic differential response. This pattern provides suggestive evidence consistent with a school funding channel, indicating that the erosion of the local tax base may create an additional pathway that disproportionately affects juvenile offending alongside broader community distress.

2.4.2 Coal Declines and School Finances

Table 2.2 presents the regression results on the impact of coal declines on school finances, measured in dollars per student across various dimensions of revenue, expenditure, and debt. Columns (1) to (4) show that coal declines significantly reduce total revenue per student, with the largest effect observed in local revenue, reflecting the heavy fiscal reliance of U.S. public schools on local property taxes paid by fossil fuel extraction companies. The 2SLS estimates consistently show a negative and statistically significant impact, indicating that local coal declines erode the tax base that forms a major source of school district funding.

Columns (5) to (8) report that coal declines also lead to reductions in total and operational expenditures, with the largest impact on operational expenditures, suggesting that resource constraints may hinder the day-to-day functioning of schools. A decline

Table 2.1: Impact of Coal Declines on Juvenile (10–17) Arrest Rates by Crime Type

	All Crime (1)	All Crime (2)	All Crime (3)	Violent Crime (4)	Disorderly Conduct (5)	Property Crime (6)	Status Offense (7)	Sex Offense (8)	Drug Abuse (9)	Other Offenses (10)
DV: Arrest per 1,000										
Coal Decline	2.685**	3.109**	3.274**	0.046	0.736**	0.590**	1.234**	0.042	0.023	0.614**
	(1.081)	(1.256)	(1.378)	(0.040)	(0.338)	(0.287)	(0.493)	(0.028)	(0.069)	(0.309)
Mean of DV	25.459	25.459	25.459	0.653	5.204	5.888	5.241	0.323	2.109	4.280
Impact [%]	10.5	12.2	12.9	7.0	14.1	10.0	23.5	13.0	1.1	14.3
F-statistic	262.3	223.0	219.1	206.8	215.4	213.3	215.2	149.6	216.8	218.2
Observations	1,943	1,943	1,943	1,849	1,925	1,912	1,926	1,605	1,921	1,930
Controls										
Local economy		X	X	X	X	X	X	X	X	X
Demographic			X	X	X	X	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

of 1 Mst of coal production reduces school operation expenditure by $136 per student, which is about 1.2% of the mean spending per student ($11,073). To contextualize the magnitude of this effect, consider the widely studied China import shock. Feler and Senses (2017) found that a $1,000 per-worker increase in Chinese imports led to a 0.9% decline in local per capita educational spending. In contrast, the estimated 1.2% decline implies an even larger fiscal shock, particularly relevant in coal-dependent regions. For a typical community producing 4.5 Mst annually, a complete production halt could cut per-student operational funding by roughly $612 each year.

The final two columns of the table demonstrate mixed effects on school district debt, with coal declines significantly reducing retired debt but showing no significant impact on issued debt. This pattern suggests that coal declines strain school district finances, limiting their ability to pay off existing debt while preventing them from taking on additional debt. This may be because reduced revenues from coal-related taxes erode the financial capacity needed to retire debt, while fiscal uncertainty discourages new borrowing. Overall, the results show that coal industry contraction imposes severe fiscal pressure on local school systems, comparable in scale to other major economic shocks, with potential long-run costs for educational quality and equity.

Figure 2.3 shows the impact of coal declines on school revenue sources, broken down into federal, state, and local funding categories. It indicates that federal support increases as coal declines, with significant positive effects observed for rural and low-income funding and other federal support, consistent with the expectation that federal aid aims to cushion the financial shocks in coal-dependent communities. However, these increases in federal aid are insufficient to offset the declines in state and local revenues. State general formula funding shows a significant decline, while capital outlay support from

Table 2.2: Impact of Coal Declines on School Finances

	Revenue				Expenditure				Debt	
	Total	Total	Total	Local	Total	Total	Total	Operation	Issued	Retired
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DV: $K per student										
Coal Decline	-0.091	-0.077	-0.093	-0.137**	-0.125*	-0.071	-0.080	-0.136**	0.001	-0.073*
	(0.055)	(0.056)	(0.063)	(0.068)	(0.072)	(0.068)	(0.072)	(0.059)	(0.042)	(0.039)
Mean of DV	10.703	10.703	10.703	4.123	11.073	11.073	11.073	9.682	0.828	0.629
F-statistic	329.3	270.8	270.6	270.6	329.3	270.8	270.6	270.6	270.6	270.6
Observations	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322
Controls										
Local economy		X	X	X		X	X	X	X	X
Demographic			X	X			X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

state governments increases as coal declines.[18] It highlights the vulnerability of state-level funding mechanisms tied to coal-related tax bases.[19]

Moreover, local revenue sources, such as tax revenue and fees and sales, also experience significant reductions. This reflects the erosion of property taxes and other local contributions as coal-rich communities experience economic decline, emphasizing the close connection between the coal industry and local school revenue sources. Property taxes from coal-related businesses constitute a significant portion of school district funding, making schools particularly vulnerable to the industry's downturn. Despite increased federal support, the reductions in state and local revenues create a substantial funding gap, underlining the challenges faced by schools in maintaining financial stability and service quality as coal declines.

[18]This aligns with the fact that state governments often prioritize infrastructure investments in economically distressed areas to support recovery efforts and sustain public services.

[19]One might interpret this concurrent drop in state funding as indicative of a broader, state-wide macroeconomic shock. As discusses in Section 2.2.1, however, significant portions of state education trust funds in many fossil-fuel-producing states are generated directly from industry-specific severance taxes and royalties. Thus, a localized contraction in coal production directly shrinks the state-level revenue pool distributed back to those districts, manifesting as a localized industry shock rather than a state-wide business cycle phenomenon. Furthermore, to address any remaining concerns regarding unobserved state-level correlations, I demonstrate in Table B.10 that the main findings remain robust when standard errors are clustered at the county and state-year level, as well as two-way clustered by state and year.

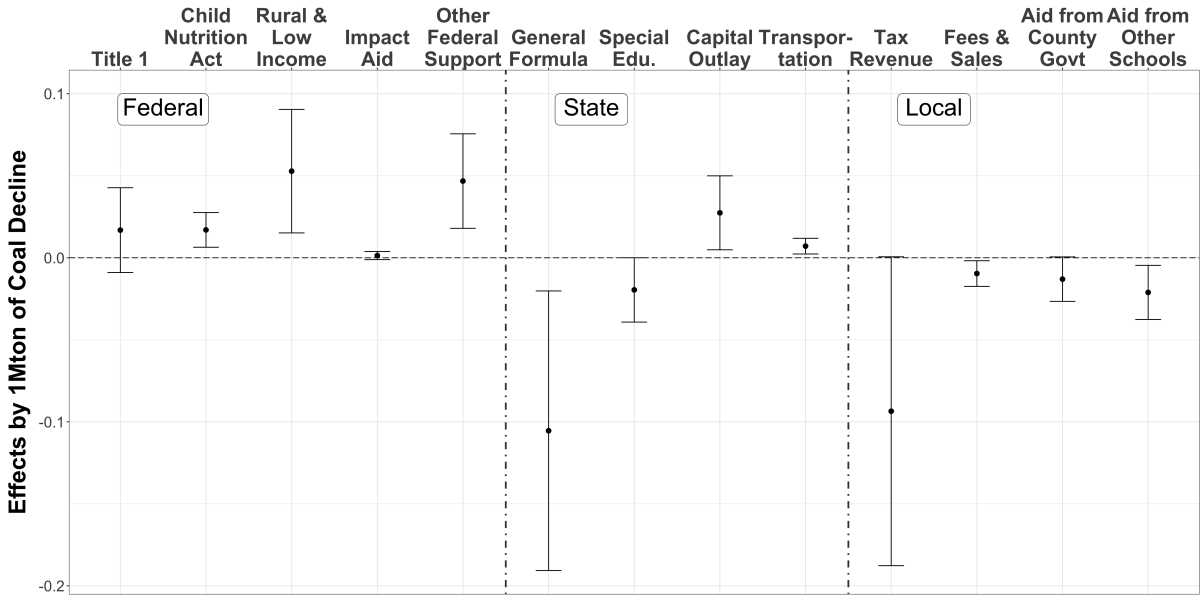


Figure 2.3: Impact of Coal Declines on School Revenue by Sources

Notes: This figure illustrates the estimated coefficients (represented by dots) along with their corresponding 95% confidence intervals (depicted as error bars). The top x-axis labels funding sources; the outcome is annual per-pupil school revenue. A detailed summary of all estimates can be found in Appendix (Table B.6).

How do schools respond to coal-decline-induced revenue shocks? Table 2.3 shows the impact of coal declines on school expenditures per student, broken down by expenditure categories. Column (1) shows a significant reduction ($144 per student) in salaries and benefits for school personnel, including regular teachers and student support services, which account for the majority of school spending cuts. In contrast, columns (2) and (3) show no significant impact on operational staffing (e.g., plant operations, student transportation) or support programs (e.g., food and community services), suggesting that budget cuts are primarily focused on teaching-related expenditures. For capital outlay, column (4) shows a positive but insignificant effect on construction and lands, while column (5) highlights a significant reduction in spending on instructional equipment, with a decline of $13 per student, further emphasizing cuts to resources essential for teaching and learning. Columns (6) shows no significant effects on payments to state and local

governments but a small, significant reduction in payments to other schools (column 7). In sum, schools respond to revenue losses caused by declining coal production by reducing spending on instruction-related items, potentially affecting the quality of education they provide.

Table 2.3: Impact of Coal Declines on School Expenditure by Item Category

	Operation			*Capital Outlay*		Payments to	
	School Personnel	Operational Staff	Non-Instr. Programs	Construction and Lands	Instr. Equipment	State & Local Gov'ts	Other Schools
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV: $K per student							
Coal Decline	-0.144**	-0.001	0.009	0.080	-0.013**	0.002	-0.013*
	(0.058)	(0.010)	(0.006)	(0.049)	(0.006)	(0.016)	(0.008)
Mean of DV	7.222	1.968	0.637	0.828	0.242	0.103	0.219
F-statistic	270.6	270.6	270.6	270.6	270.6	270.6	270.6
Observations	2,322	2,322	2,322	2,322	2,322	2,322	2,322
Controls							
Local economy	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

2.4.3 Intermediate Step: School Staffing and Student Outcomes

Having established that declines in coal production lead to a significant reduction in teachers' salaries and benefits, I turn to estimating the impact of coal decline on school staffing. Table 2.4 presents the impact of coal declines across various staffing roles. Columns (1) and (2) show negative but statistically insignificant effects on the number of regular teachers and school administrators. This lack of significant impact may be explained by the relative stability and tenure associated with these roles, which

often shield them from immediate budgetary cuts. Additionally, administrative positions are critical for maintaining school operations, making them less likely to be targeted during periods of financial strain. Similarly, school counselors and librarian/media support staff exhibit no significant changes in response to coal decline (columns 4 and 5). Their specialized responsibilities, such as providing essential academic and emotional support or managing educational resources, are often viewed as indispensable, even during fiscal constraints. This stability may also reflect a strategic prioritization by schools to preserve core instructional and administrative functions, which are important for minimizing short-term disruptions to classroom activities and institutional management.

The burden of staffing reductions appears to fall more heavily on support staff categories, which could create challenges in maintaining a comprehensive support system for students. Coal declines are associated with notable reductions in instructional aides (column 3). Instructional aides often play a crucial role in the classroom by assisting teachers with instructional tasks, providing one-on-one support for struggling students, and monitoring disruptive behavior. Reductions in these roles may lead to less supervision and fewer opportunities for tailored interventions, potentially increasing the risk of disengagement or behavioral issues among vulnerable students.

The potential impact extends beyond the classroom, as column (6) suggests a decline in student support service staff. Unlike school counselors, these staff members typically manage extracurricular programs and other non-classroom activities, such as after-school programs and truancy prevention efforts. These services can provide structure and mentorship for students, particularly those who may otherwise lack such support. A reduction in these roles might limit the availability of structured after-school activities, which could result in fewer opportunities to engage students positively during critical hours thereby reducing the "incapacitation" effect, whereby structured activities physically prevent delinquent behavior (Jacob and Lefgren, 2003). This could, in turn, increase

the likelihood of disengagement or truancy, although the extent of this effect may vary depending on the specific context.

In addition, column (7) highlights reductions in other support services, which include essential roles such as administrative assistance and technical support. While these positions do not interact directly with students, they contribute to the smooth operation of schools and help reduce the workload of teaching staff. A decrease in these roles may add strain to the remaining staff, potentially limiting their ability to provide individualized attention to students. Combined with reductions in instructional aides and student support staff, these changes may affect the overall support available to students, particularly those at higher risk.

Taken together, these staffing reductions diminish the school's capacity to foster a safe and supportive environment, leaving vulnerable students more exposed to antisocial behavior, truancy, and potentially criminal activities. This pattern aligns with the observed increase in truancy-related arrest rates in Table 2.1. Finally, column (8) reports a decline in the teacher-student ratio, though it is not statistically significant (t-statistic ≈ -1.67) in the 2SLS estimation. While the impact on individualized attention appears modest, the broader reductions in support staff underscore the significant risks staffing cuts pose to student behavior and educational outcomes in coal-dependent communities.

Table 2.4: Impact of Coal Declines on School Staffing

	Regular Teacher	School Admin.	Instr. Aides	School Counselor	Library & Media Support	Student Support Service	Other Support Service	Teacher-Student Ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coal Decline	-0.883	-2.132	-6.261**	-0.006	0.149	-4.827*	-9.592*	-0.040
	(4.589)	(1.780)	(2.960)	(0.182)	(0.334)	(2.566)	(5.378)	(0.024)
Mean of DV	589	141	125	21	17	49	269	6.933
Impact [%]	0.1	1.5	5.0	0.0	0.9	9.9	3.6	–
F-statistic	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6
Observations	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322
Controls								
Local economy	X	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X	X

Notes: 'School Admin.' refers to school administrative staff, and 'Instr. Aids' refers to instructional aides. The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 2.5 shows the impact of coal declines on student absenteeism, dropouts, and teacher qualification metrics. Columns (1) to (3) demonstrate a significant reduction in class attendance rates, with a decline of 0.38 percentage points after accounting for both the local economy and demographic controls, which amounts to roughly 25% of the standard deviation (1.73%). Considering the high baseline attendance rate of 94.72%, this decrease represents a notable disruption to school participation in coal-dependent communities. This finding aligns with earlier evidence of increased truancy behavior among students, highlighting the broader impact of coal production declines on educational outcomes. I find no significant impact on dropout rates, suggesting that coal declines may not directly affect overall dropout behavior within the observed timeframe (column 4 to 6). Columns (7) to (9) analyze teacher qualification metrics, including years of

experience and the proportion of teachers with bachelor's or master's degrees, and find no statistically significant effects. These results highlight the critical role of class attendance as a non-achievement school outcome influenced by economic shocks, further linking coal declines to student disengagement and truancy-related behaviors.

Table 2.5: Impact of Coal Declines on Student Absenteeism, Dropouts, and Teacher Outcomes

	Non-Achievement School Outcomes						*Teacher Qualification Metrics*		
	Class Attendance Rate			Dropout Rate			Years of Experience	Bachelor's Degree	Master's Degree
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coal Decline	-0.428***	-0.400***	-0.383***	-0.052	-0.065	-0.025	0.178	1.290	-0.953
	(0.108)	(0.101)	(0.098)	(0.057)	(0.073)	(0.066)	(0.445)	(0.963)	(2.500)
Mean of DV	94.72 [%]	94.72 [%]	94.72 [%]	1.15 [%]	1.15 [%]	1.15 [%]	13.74	73.37 [%]	41.41 [%]
F-statistic	784.7	699.2	748.8	278.3	180.7	155.3	36.9	28.7	32.0
Observations	3,498	3,498	3,498	4,528	4,528	4,528	2,537	2,032	2,581
Controls									
Local economy		X	X		X	X	X	X	X
Demographic			X			X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

2.4.4 Do Family and Community Factors Matter?

I examine whether family-related factors influence juvenile crimes in coal-dependent communities, as economic distress could potentially lead to increased child neglect or domestic conflicts, which in turn might contribute to higher juvenile arrest rates. Table 2.6 shows the impact of coal declines on arrest rates for offenses against family and children across various age categories. The coefficients for all age groups, including juveniles (column 1), young adults (columns 2 and 3), and older age groups (columns 4–7), are statistically insignificant, indicating no measurable effect of coal declines on family-related

offenses in any age category.

I also investigate the impact of coal declines on child abuse and neglect cases, as well as out-of-home placements, using both the total number of cases (columns 1 and 2 in Table B.7) and cases per 1,000 juveniles (columns 3 and 4). Across all specifications, the coefficients are statistically insignificant, indicating no measurable effect of coal declines on either child abuse and neglect or out-of-home placements, which serve as a proxy for child abuse. These findings suggest that the family channel is unlikely to play a significant role in shaping juvenile antisocial behavior in this context, reinforcing the conclusion that school-related factors may be more relevant in explaining the observed increase in juvenile crime following declines in coal production.

Table 2.6: Impact of Coal Declines on Arrest Rates for Family Offense Cases

	Offenses Against Family and Children						
	10–17	18–20	21–29	30–39	40–49	50–59	Over 60
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coal Decline	0.020	0.019	-0.019	0.036	0.028	0.009	0.004
	(0.037)	(0.044)	(0.050)	(0.049)	(0.028)	(0.011)	(0.004)
Mean of DV	0.174	0.677	1.166	1.356	0.647	0.188	0.033
F-statistic	174.6	174.6	174.6	174.6	174.6	174.6	174.6
Observations	1,517	1,517	1,517	1,517	1,517	1,517	1,517
Controls							
Local economy	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). All dependent variables are measured per 1,000 people. County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Although I find no evidence that coal declines impact family offenses or child abuse, juvenile crimes may still be influenced by changes in the broader local community, which is adversely affected by coal declines. For instance, the number of police officers might increase in response to anticipated rises in crime rates as coal-dependent communities collapse or, conversely, decrease due to reductions in local public revenues. Increased police presence might lead to stricter enforcement and higher arrest rates, while reduced enforcement, possibly due to budget cuts from declining local revenues, could result

in fewer arrests. Using county-level police enforcement data from the FBI, I perform regressions with dependent variables that include the number of sworn officers, civilian officers, and the number of officers per 1,000 juveniles. Across all specifications, the coefficients are statistically insignificant, indicating no measurable effect of coal declines on police staffing levels, including sworn officers (columns 1 and 4), civilian officers (columns 2 and 5), or total officers (columns 3 and 6). These findings suggest that coal declines do not significantly alter police enforcement resources in coal-dependent communities.

If declines in coal production negatively impact the youth labor market, it could affect the likelihood of juveniles engaging in criminal activity. A strong labor market may have an incapacitation effect by keeping youth occupied and reducing their exposure to delinquent behavior, particularly if employment provides a greater deterrent effect than school enrollment. To investigate this potential link, I examine the impact of coal production declines on youth labor market outcomes, focusing on employment and job separation for individuals aged 14–18. The data is sourced from the Quarterly Workforce Indicators (QWI) provided by the U.S. Census Bureau. Table B.8 shows that the estimated effects of coal declines on job separation across all sectors (columns $1-3$), job separation in the mining sector (columns $4-6$), and mining employment (columns $7-9$) are statistically insignificant. These results suggest that changes in juvenile arrest rates are unlikely to be influenced by enforcement practices, youth labor market participation, or job stability. Instead, they reinforce the importance of other mechanisms, such as school-related factors, in shaping juvenile antisocial behavior in this context.

Table 2.7: Impact of Coal Declines on Police Enforcement

	Number of Police Officers			*Officer per 1,000 Juveniles*		
	Sworn	Civilian	Total	Sworn	Civilian	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Coal Decline	2.478	1.338	3.816	0.281	0.004	0.285
	(1.804)	(1.204)	(2.877)	(0.193)	(0.118)	(0.270)
Mean of DV	104	36	141	15	6	20
F-statistic	274.8	274.8	274.8	274.8	274.8	274.8
Observations	2,192	2,192	2,192	2,192	2,192	2,192
Controls						
Local economy	X	X	X	X	X	X
Demographic	X	X	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

2.4.5 Other Potential Mechanisms: Demand for Education and Outmigration

One factor driving the increase in youth arrests following coal declines is the shifting demand for high school degree completion. Historically, coal mining provided well-paying jobs that required little formal education, making early labor force entry a viable alternative to high school completion. As coal jobs disappear, the opportunity cost of staying in school declines, leading to higher school enrollment and graduation rates, as confirmed by the statistically significant increases in both enrollment and graduation rates following coal declines (Table B.3). While the increase in school enrollment and graduation rates suggests that more students are staying in school and completing their education, it does not necessarily lead to improved social behavior among youth. In this context, higher school attendance may be occurring alongside school resource challenges, which could contribute to the rise in youth arrest rates. This aligns with my main findings, which indicate that in coal-dependent areas, declining local tax revenues may strain school budgets, making it more difficult to support a growing student population. As a result,

schools could experience larger class sizes, understaffing, and reduced student support services, potentially leading to more disciplinary issues and an increased reliance on law enforcement to manage student behavior.

Another potential mechanism is the compositional effect of outmigration. As coal-dependent communities lose employment opportunities, some families may relocate in search of work, potentially altering the demographic and economic composition of those who remain. However, limited public data make it difficult to track individual migrants from coal-rich counties, particularly families with school-aged children. To address this, I use the American Community Survey (ACS), which, while not ideal for studying individual migration decisions (e.g., limited sample size at the county level), is valuable for identifying broader migration patterns and assessing shifts in family characteristics over time.

Figure B.6 presents the average family income of stayers and leavers from coal-rich counties, focusing on households with at least one child aged 5 to 17 in a given survey year (2006, 2011, and 2016). The figure shows that while leavers tend to have lower family incomes than stayers, the income gap appears relatively stable over time. Despite the sharp coal downturn from 2011 to 2016, family income among stayers continued to increase. This pattern suggests that coal decline may not have disproportionately led to the outmigration of higher-income families, making it less likely that selective outmigration is the main driver of rising youth arrest rates. Instead, the findings point toward changes affecting those who remain in coal-dependent communities as a potentially more important factor, though further research is needed to fully understand the role of migration dynamics.

2.5 Robustness Checks

2.5.1 First-Stage Results and Robustness of IV

I examine the relationship between the coal-bust potential IV and coal declines in the first stage equation. Table B.1 shows that the estimated coefficients across all specifications are negative and statistically significant, confirming that greater exposure to coal bust predicts larger coal declines. Columns 1-5 report the estimates with varying the distance radius. These specifications change the radius within which plays are allowed to influence a coal-buying plant while keeping the inverse-distance kernel and equal weights on plays. Intuitively, this probes the spatial decay of the fracking shock: if identification hinged on an arbitrary cutoff (very local vs. more regional), estimates would move sharply as the radius changes. The coefficient remains negative and significant throughout, indicating that the timing-distance channel is not sensitive to how wide the market area is defined.

I examine whether transport capacity is essential for identification or primarily an amplifier. The estimate remains negative and highly significant (column 6). Because removing rescales the instrument, coefficient magnitudes are not directly comparable across columns; the key fact is that the sign and strength persist, indicating that pipelines amplify but do not create the identifying variation.

Instead of equal-weighting plays, I weight each by its prospectivity score, giving greater weight to geologically promising plays.[20] Column 7 uses the maximum prospectivity among nearby plays (a "dominant-play" channel), while column 8 uses the mean (a "diffuse exposure" channel). Both yield negative, significant coefficients, showing that the first stage is robust to how fracking intensity across plays is aggregated.

[20]Prospectivity is an index of potential productivity across sub-areas of shale plays, constructed by the Rystad Energy as a nonlinear function of the geological inputs used by Bartik et al. (2019).

2.5.2 Placebo-Style Diagnostic for IV

To assess whether the IV reflects exposure to staggered shale-play activations (scaled by pre-determined weights) rather than proxying macro conditions, including the Great Recession, I implement a placebo-style diagnostic. The top row of Figure B.4 plots within-county binned scatters of coal production on the IV as I add fixed effects: year, state-by-year, and county-specific linear trends. The slopes are similar across specifications, suggesting the instrument is not simply capturing aggregate or regional cycles. The bottom row repeats my default specification (county and year FEs) separately before 2007, during 2007–2009, and after 2009. The association is statistically indistinguishable from zero in the first two periods but becomes strongly negative thereafter. Because year fixed effects purge aggregate macro conditions common to all counties, this timing is inconsistent with a business-cycle story and is consistent with the coal-bust instrument capturing exposure to staggered shale-play activations.

2.5.3 Heterogeneity in Coal Decline Impacts

To further investigate whether school funding may mediate the effect of coal decline on juvenile crime, I examine heterogeneity along two pre-treatment fiscal exposure margins. First, I use each county's pre-period share of K-12 revenue funded by coal property taxes to gauge reliance on the coal tax base. Second, because coal produced on federal lands is generally not locally taxable, I use the ownership mix of coal reserves (federal vs. nonfederal) as a predetermined proxy for the scope of local tax loss. Figure B.5 indicates that the estimates have the expected signs and are generally statistically significant: effects tend to be larger in counties with higher coal-tax reliance and smaller where federal ownership is greater. In higher-exposure counties, coal declines are associated with larger reductions in school revenue and staffing and with larger increases in juvenile arrest rates,

while adult arrest rates show no systematic differential response. Overall, the results suggest that coal declines affect both juvenile and adult crime, but erosion of the local tax base appears to create an additional pathway that disproportionately increases juvenile offending.

2.5.4 Juvenile Court Cases

As mentioned in Section 2.2, I collect the administrative data on county-level juvenile court cases by crime type. Both single-year case numbers and three-year rolling sums are used as dependent variables to account for the time lag in juvenile court petitions, providing a more comprehensive measure of the impact of coal declines on juvenile court cases. Table B.4 shows the impact of coal declines on juvenile court cases per 1,000 individuals. Delinquency cases (columns 1 and 2) include criminal acts such as theft, assault, or property damage committed by juveniles. The results show a significant increase in delinquency cases, with a 7.0% impact relative to the mean for baseline values and 7.8% for the three-year rolling sum. In contrast, status offense cases (columns 3 and 4), which include habitual truancy, exhibit even larger effects. The impact on status offenses is 33.7% of the mean for baseline values and 28.0% for the three-year rolling sum. These pronounced effects on status offenses align with earlier findings on arrest rates by crime type, supporting the conclusion that coal declines disproportionately affect behaviors tied to school engagement and implying economic shocks on juvenile court involvement, particularly for status offenses.

2.5.5 Robustness Checks on the Main Results

Since data availability varies across sources, the number of county–year observations differs across outcomes in the main tables. To ensure differences are not driven by sample

composition, I re-estimate the effects on key outcomes using a balanced panel restricted to the maximal common sample of 1,926 county-year observations used across all columns. Table B.9 confirms the core findings: coal decline raises juvenile arrests for both all crime and status offenses (cols. 1–2), and modestly increases adult arrests (col. 3). In the school-finance and staffing outcomes (cols. 4–10), the pattern matches the main sample: local revenue declines, operating budgets shrink, the amount of debt retired falls, and student-support staffing contract. The only difference is instructional aides: in the balanced panel, the estimate is not statistically significant, whereas it is statistically significant in the main sample. These balanced-panel results mirror the main sample, indicating that patterns across outcomes reflect the impact of coal decline rather than shifts in the underlying sample.

Table B.10 presents regression results for the impact of coal declines on juvenile arrest rates under different clustering choices for standard errors. Clustering at the county level (column 1) is appropriate given that the data spans 20 years and the analysis is conducted at the county level, capturing within-county correlation over time. Another preferred inference clusters by county and state–year (col. 2), which allows arbitrary serial correlation within counties and contemporaneous correlation across counties within the same state–year cell, yielding a large number of clusters and avoiding few-cluster concerns. Columns 3-7 provide robustness to alternative correlation structures: county and CZ–year (col. 3) to capture local labor-market shocks; county and year (col. 4) for common annual shocks; CZ and year (col. 5) when commuting zones define the relevant geography; CZ alone (col. 6) for within-CZ correlation over time; and state and year (col. 7) as a benchmark that clusters on two dimensions with relatively few groups. The consistent statistical significance across all these specifications ensures that the observed effects are not sensitive to the choice of clustering method.

To ensure the robustness of the findings over time, I analyze the main results on

juvenile arrest rates across different time periods: 2000–2019, 2005–2019, and 2010–2019. The choice of different time periods reflects the timeline of coal declines in the US, which began to intensify in the mid-2000s as described in Section 2.2. Table B.11 shows that the estimated coefficients for coal decline are consistent and statistically significant across all timeframes, indicating robust results. It suggests that the relationship between coal declines and juvenile arrest rates is stable over time, regardless of the specific period analyzed. Focusing the analysis on shorter, more recent periods further confirms the robustness of the results, strengthening the validity of the findings across different economic and policy contexts.

2.6 Conclusion

This study finds that coal's post-mid-2000s collapse is associated with higher juvenile arrest rates in coal-dependent localities in the US. The largest increases appear for status offenses, with effects about 1.5 times greater than those for other crimes, which is consistent with truancy acting as a precursor to more serious offending (Garry, 1996). This pattern points toward school-linked dynamics around attendance and supervision.

One plausible mechanism is a school-finance channel. In the data, revenue shortfalls and limited debt capacity coincide with pressure on operating budgets and noticeable cuts to school support personnel (instructional and non-instructional aides). These staff are the adults most involved in day-to-day supervision, behavior monitoring, and attendance follow-up, so their loss could plausibly raise truancy and related status offenses. Consistent with this story, I observe declines in class attendance. At the same time, I do not find statistically significant effects on dropout rates or core teacher staffing metrics, suggesting that broad staffing or teacher quantity is not the primary margin of adjustment.

I investigate alternative explanations and find little support for them. Coal declines

are not associated with changes in family offense arrests or child abuse/neglect cases. Shifts in police staffing and youth labor market participation also do not appear to drive the results in reduced-form tests. Still, I cannot fully rule out other influences, such as peer effects or local norms, that might amplify antisocial behavior during community downturns (Damm and Dustmann, 2014). Overall, the weight of evidence is consistent with reduced adult supervision and guidance in schools being one important contributor among several.

Policy responses might prioritize keeping youth supervised and supported. In schools, districts could consider temporarily restoring aides, counselors, and attendance supports; outside school, expanding after-school and community programs may help. For criminal-justice stakeholders, some juvenile offenses in these settings may reflect economic and educational disruption rather than intent, suggesting that remediation and diversion could be more effective rather than intensified enforcement alone. More broadly, energy-transition policy could aim to cushion children in revenue-dependent regions by supplementing school aid during busts, bolstering mental-health services, and funding engagement programs. Such steps may help limit longer-run social costs and make the transition fairer for younger residents.

Chapter 3

Fossil Fuels and Fiscal Federalism: How Intergovernmental Transfers Respond to Local Coal Industry Declines

3.1 Introduction

Local governments play a crucial role in providing public services and buffering economic risks in their communities, but their ability to self-insure against major downturns is limited. In federal systems like the US, higher-level governments step in via intergovernmental transfers (IGTs) to redistribute resources, helping to equalize fiscal disparities and cushion local revenue shocks. Indeed, roughly 40% of US local government revenues come from state or federal transfers (Wildasin, 2010). When a locality dominated by a single industry suffers an economic collapse, these transfers are meant to support the affected government and stabilize public finances. Historical episodes such as the collapse of the

steel industry in Pennsylvania (Deitrick and Briem, 2007) and the decline of automobile manufacturing in Detroit (Owens et al., 2020) illustrate the stakes: both events eroded local tax bases and strained municipal budgets. Even broader trade shocks like the surge of Chinese imports in the 2000s forced cutbacks in local public spending Feler and Senses (2017). This backdrop poses a central public finance problem: designing intergovernmental transfers that respond to localized shocks and stabilize local economies and budgets.

Although IGTs are often promoted as automatic stabilizers, their real-world ability to insure local governments against negative shocks is limited. Two institutional features reduce responsiveness. First, general-purpose aid is commonly allocated by rigid formulas or statutory rules that do not adjust to sudden revenue losses. Second, many transfers are earmarked for specific programs, which prevents local officials from moving funds to the most urgent needs during a downturn. As a result, aid flows only weakly track local economic conditions and may arrive in spite of local distress rather than because of it. This misalignment is especially concerning given the tight fiscal interdependence between US states and their local governments. It underscores the need to evaluate not only how much aid is provided, but also whether it adjusts to community needs when conditions deteriorate.

This paper examines this issue by analyzing the downturn of the US coal industry. Coal production experienced a dramatic and prolonged downturn in the 2010s, driven by technological changes and environmental pressures, with severe impacts concentrated in a handful of regions. Several features make this an informative case for how well the IGT system responds. First, coal's geographic concentration means the shock is highly localized: a coal-producing county faces a sharp loss, while nearby non-coal counties can serve as comparisons. Second, coal revenues are fiscally salient for local governments. A coal bust drains local income and employment, which in turn shrinks property and sales tax bases, and it diminishes revenues like mining royalties and fees that resource-rich

counties rely on. For example, as coal activity contracts, local property values and retail sales fall, directly reducing tax collections (Raimi et al., 2023). Third, the shock propagates to higher tiers: states lose severance taxes and leasing fees from coal extraction, potentially tightening state budgets for aid. This means a coal region's fiscal trauma can reverberate through state finances, imperiling IGT flows that might otherwise help.

Another important aspect of the coal decline is its regional spillovers. A body of evidence shows that resource booms and busts propagate across county lines as firms, workers, and landowners pass gains or losses along supply chains (Feyrer et al., 2017). When a coal county contracts, nearby areas face weaker demand for local suppliers, outmigration, and erosion of shared tax bases. Because these spillovers link local finances, higher-level fiscal policy should aid both directly affected places and their neighbors. This prompts a key question: do existing intergovernmental transfers offset or equalize the resulting fiscal shocks? The answer reveals whether the current federalism framework stabilizes local budgets or needs reform.

I study the early-2010s collapse in coal production using plausibly exogenous variation in coal dependence driven by geological endowments and the timing of the shale revolution. The design identifies causal effects on two fronts. First, I estimate how coal declines affect local economic outcomes and the fiscal health of county and city governments. Second, I quantify fiscal spillovers to neighboring counties that do not produce coal. This approach clarifies both the direct impacts on resource-dependent communities and the broader regional consequences that arise through interconnected local economies.

The empirical findings show how a localized industry shock spreads through local economies and budgets. In coal-exposed counties, local GDP, employment, and personal income fall. The contraction erodes the tax base: property taxes, sales taxes, and other own-source revenues decline as jobs and earnings disappear. Coal-reliant local governments therefore face sizable losses in locally generated revenue after the shock.

This mechanical link from a smaller economy to weaker collections sets the stage for a test of fiscal federalism: higher-tier transfers should rise to offset these local shortfalls.

I find that intergovernmental transfers fell rather than rose after the coal bust. Per capita aid to affected localities declined, indicating pro-cyclical support in the face of fiscal distress. The drop was driven largely by cuts in state general-purpose aid, consistent with states tightening budgets as severance and other resource-based revenues fell. Coal-reliant counties therefore faced a compounded shock: own-source revenues shrank while external assistance weakened. Local governments cut spending across housing and community development, workforce programs, and education. Spillovers extended to neighbors, where employment, income, and local revenues also fell. Overall, a major industry collapse depressed regional economies and public finances, and the existing transfer system provided little fiscal insurance.

Beyond documenting how IGTs actually responded to the coal decline, this paper asks how they should respond from a normative standpoint. I develop two benchmark rules on a common set of primitives and a shared budget. The first is a social-welfare-maximizing (SW-max) rule in which a benevolent planner allocates transfers to maximize total welfare subject to a budget constraint. This rule takes into account factors like the marginal utility of public spending, differences in communities' baseline fiscal capacity, and cross-county spillovers in economic outcomes. Because it concentrates funds where aggregate welfare gains are largest, it can leave small but severely hit communities undercompensated when pre-existing disparities or strong spillovers are present, keeping highly exposed places fiscally fragile.

A purely welfare-optimal rule might concentrate resources where they yield the highest aggregate welfare gains, which could mean that severely affected but small communities are not fully compensated if the planner deems funds more productive elsewhere. The second rule targets fiscal equalization (FE). It allocates transfers so that each county bears

a similar proportional revenue shock regardless of size or initial tax base. In practice, this directs more per-capita aid to the hardest-hit, resource-dependent places to offset larger losses. I derive the rule to equalize marginal fiscal shocks and calibrate it using estimated revenue declines and measured spillovers. Because both rules face the same budget and economic environment, differences in recommended transfers reflect objectives rather than assumptions. This comparison makes the efficiency-equity trade-off explicit and shows how alternative goals would reshape aid in the face of the coal bust.

The contribution of this paper is three-fold. First, it extends a stream of literature on the impacts of geographically concentrated shocks on the local economy. While many studies examined the local labor market and migration outcomes (Autor et al., 2013, 2014; Greenland et al., 2019; Feyrer et al., 2017; Allcott and Keniston, 2018), the public fiscal effects of localized economic shocks have been understudied. This study conducts an empirical investigation of local government finance affected by localized coal shocks and the consequent local economic responses. Previous literature on the local fiscal conditions of resource-dependent communities focuses on gas and oil-producing regions (Newell and Raimi, 2018a,b; Bartik et al., 2019) in most cases. Some studies that document coal-related fiscal rupture examine public (Haggerty et al., 2018; Morris et al., 2021) or household finance (Blonz et al., 2023). While previous studies rely on a long-difference approach or focus on limited coal-rich localities only, this paper investigates short-term coal decline shocks on the local economy and how this effect persists in coal-producing counties across all regions in the US. In addition, it examines the impact of coal production on the local public finance, which has rarely been scrutinized by resource economics literature.

Second, this paper contributes to the literature on fiscal federalism and intergovernmental risk sharing. Theory predicts that decentralized finance underprovides insurance and public goods when jurisdictions create cross-border externalities or when people and tax bases are immobile (Tiebout, 1956; Buchanan and Goetz, 1972; Gordon, 1983; Oates,

1999). Reduced-form evidence from the United States shows that local shocks do not self-correct through migration, leaving distressed places with persistent job and income losses and shrinking tax bases (Autor et al., 2013; Feler and Senses, 2017), while federal and state systems smooth only a fraction of idiosyncratic regional shocks (Asdrubali et al., 1996). Yet we have limited evidence on whether state-to-local transfers stabilize such places in real time, how transfers move by grant type, and whether aid or fiscal stress spills over to neighbors. This study fills that gap by providing causal evidence on how state-to-local transfers respond to a concentrated sectoral downturn, the coal bust, and by showing that general-purpose IGTs are procyclical rather than stabilizing, compounding own-source revenue losses. It also quantifies fiscal spillovers onto neighboring non-coal counties in both revenues and spending, an interjurisdictional channel the empirical literature has largely overlooked.

My third contribution is to the literature on empirically grounded optimal transfer design in federations. Normative work distinguishes SW-max rules that internalize spillovers and target high marginal social value from FE rules that pursue horizontal equity, defined as comparable services at comparable tax effort (Buchanan, 1950; Boadway and Flatters, 1982; Persson and Tabellini, 1996; Bordignon et al., 2001). Empirical welfare analyses show that real-world formulas can be neither fully efficient nor fully equitable (Albouy, 2012), and quantitative spatial work demonstrates how estimated spillovers and mobility frictions tilt welfare-optimal allocations toward distressed, low-wage areas (Fajgelbaum and Gaubert, 2020). I advance this literature by operationalizing a head-to-head SW-max versus FE comparison calibrated with reduced-form estimates from the coal decline, explicitly incorporating measured cross-county spillovers into both rules and showing how their prescriptions diverge from realized US allocations. The exercise provides a transferable template that links optimal-policy formulas to empirically identified parameters, yielding implementable guidance for designing intergovernmental

transfers under spatial externalities.

3.2 Background

3.2.1 Coal Decline and the Shale Boom in the US

Since the late 2000s, US coal output fell from about 1,100 to about 500 million short tons by 2020. The decline is driven mainly by reduced coal-fired generation as cheaper natural gas displaced coal, rather than by environmental rules or renewable mandates (Coglianese et al., 2020). The shale boom, enabled by drilling innovations, expanded gas production, lowered local gas prices, made coal relatively expensive (Figure C.1), and reduced coal demand. Coal exports did not rise enough to offset falling domestic demand, and production continued to drop (Figure C.2). Figure 3.1 maps county-level declines, showing large but spatially varied losses in coal-rich communities.

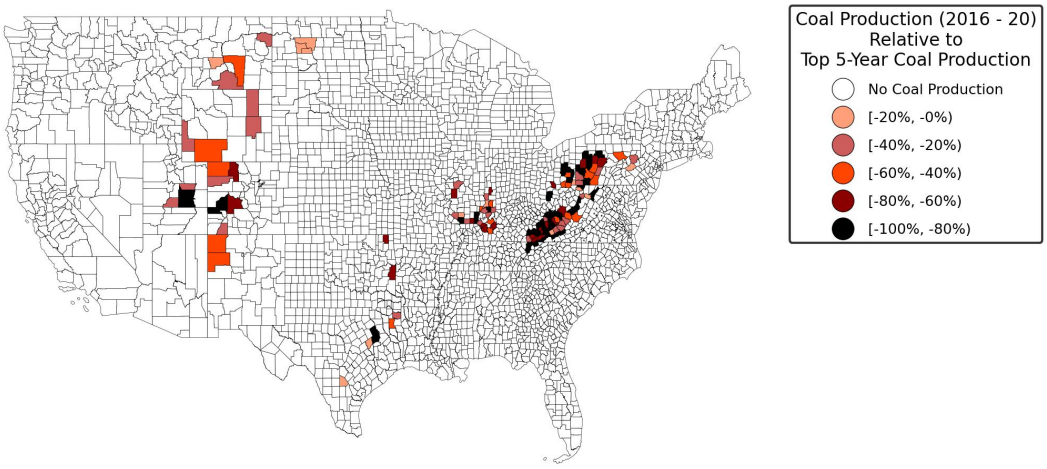


Figure 3.1: County-Level Coal Decline

Notes: It depicts the county-level coal decline measure, which is a percentage change of cumulative coal production in the recent five years (2016 to 2020) relative to the sum of the top five annual coal production during the 20-year sample period.

3.2.2 Local Fiscal Flows in the US Coal-Rich Communities

Coal production contributes substantially to public finances. At the federal level, revenues include lease bonuses, annual rents of $3 per acre before production, royalties of 8.0–12.5% of production value, abandoned mine land fees of $0.12–0.28 per ton, and an excise tax ($0.55–1.10 per ton or 4.4% of sales) that supports coal-related health programs such as the Black Lung Program. Only a small share (about 2%) is ultimately disbursed to producing localities due to two-stage transfers (federal to landowning states, then states to local governments), and because revenues also flow to other federal funds and to under-resourced groups such as Native American tribes (Raimi et al., 2023).

States add their own fiscal layers. Severance taxes may be value-based (around 4.5 of gross value) or volume-based (about $0.2 to $1 per ton). Proceeds can support state general funds or be earmarked for development, infrastructure, and services in producing counties. Severance taxes alone are an incomplete measure of coal-related public revenue because they exclude local taxes. Local governments also collect own-source revenue via sales and use taxes tied to extraction activity and property taxes on coal reserves, land, and equipment.

During 2000 to 2019, coal communities rarely received targeted federal assistance programs[1] even though most are disadvantaged and rural.[2] As a result, these communities faced substantial fiscal risk from the coal collapse and relied more on state aid, since direct federal-to-local transfers were uncommon.

[1]Examples include the Partnerships for Opportunity and Workforce and Economic Revitalization (POWER) Initiative and Assistance to Coal Communities. Roemer and Haggerty (2021) finds limited effectiveness, in part due to declining participation in retraining programs.

[2]About 70% of coal-producing counties are outside Metropolitan Statistical Areas in 2010.

3.3 Empirical Strategy

3.3.1 Data Description

The Annual Survey of Coal Production and Preparation (EIA-7A) provides mine-level coal output, employment, and labor hours; mine coordinates come from the Mine Safety and Health Administration (MSHA). I aggregate mines to the county level. To focus on continuously active producers selling to power plants, I keep mines that appear in fuel-receipts data and drop counties with fewer than ten consecutive years of production. The final sample contains 4,104 mines in 143 counties (Table C.15).[3]

For local public finance, I use the Census of Governments, which surveys direct revenues and expenditures for state and local governments every five years (years ending in 2 and 7). I sum county and municipal governments to the county level and convert all amounts to 2015 US$ using the CPI.

This study takes advantage of county-level economic outcomes from several sources: US Bureau of Economic Analysis (BEA) for GDP, net earnings, the Internal Revenue Service (IRS) for wages and salaries, dividends and interest, and the Quarterly Workforce Indicators (QWI) for sectoral employment and earnings per worker. IRS measures income by residence, whereas QWI reflects activity at establishments located in the county.[4] Data on the number of business establishments (firms) comes from the County Business Patterns (CBP), which provides reliable counts for firm entry and exit at the county level.

[3]Sample counties account for 92.4% of coal production among all coal-producing counties between 2000 and 2020.

[4]See Feyrer et al. (2017) on this distinction.

3.3.2 Econometric Specification

Interesting parameters to recover are the causal effects of one unit decrease in coal production on local economic outcomes such as employment and income. To do so, this study leverages county-level administrative data which are available every year during a 20-year sample period. I construct a two-way fixed effects model to estimate the impact of coal production ($Coal_{it}$) in county i at year t on the outcomes of interest (Y_{it}) as follows:

$$Y_{it} = \beta_1 log(Coal_{it}) + \alpha_i + \delta_t + \varepsilon_{it} \tag{3.1}$$

where α_i denotes county fixed effects, year fixed effects (δ_t) are used to capture time-specific shocks on the local economy, and ε_{it} is the error term. To account for spatial correlations in the outcome variables and correlations over time, standard errors are two-way clustered by commuting zone[5] and year for the main results. Y_{it} is an economic outcome such as the local GDP, employment, and income. The main coefficient of interest is β_1, which delivers the parameter estimates for coal decline impact on the economic outcomes.

Reverse causality is a central concern when estimating the impact of coal production on local labor market outcomes: changes in the labor market within a coal-rich region could alter its coal production. Thus, it is reasonable to believe that $log(Coal_{it})$ is endogenous as coal may be extracted more when mining companies hire new workers (Figure C.2).

3.3.3 Instrumental Variables Approach

To address this concern, I construct a "coal-bust potential" variable as an instrument for local coal production. This variable leverages two key elements: (1) the impact of the

[5]As with prior literature on the local economic impacts (Walker, 2013; David and Dorn, 2013; Autor et al., 2014), this clustering choice accounts for correlations within a commuting zone, which consists of county clusters based on journey-to-work data and then approximates the concept of local labor markets.

fracking boom on coal demand in the electricity sector over time, and (2) a geological feature of coal mining. The rationale behind this instrument is that declines in coal production were an unintended consequence of the shale boom. Advances in drilling technology drove a rapid expansion of natural gas wells, which reduced local natural gas prices. This price decline made coal relatively more expensive, thereby reducing its demand.

Temporal Variation

For a source of time-series variation in the instrumental variable, I employ the initiation of fracking activity in shale gas plays, which are natural gas accumulations sharing similar geological features. This study takes advantage of novel data on the fracking initiation date for each play from Bartik et al. (2019). As discussed in Section 3.2, the effects of the modern technological advances in gas and oil production on natural gas prices explain the majority of the decline in coal production. And one notable feature of the shale gas plays is that they have different timelines for which the first successful horizontal wells became public knowledge from press releases or investor calls, which would attract more natural gas producers to explore the play (Figure C.4). This fact allows me to exploit temporal variation in play-specific shocks to demand for coal in the electricity sector by the following procedure. First, I identify power plants that purchase coal from a given county ((j, i) which is described above).[6] Second, I sum an indicator for whether a calendar year is no earlier than the first year of successful fracking in individual shale gas play over all major plays in the US. The indicator is then inversely weighted by

[6]I use the dataset of plant-level fuel receipts provided by the US Energy Information Administration (EIA). The Form EIA-923/423 data includes a quantity of fuel received, quality (e.g., average heat content), and fuel cost. The noteworthy feature of this data is that it allows me to identify "mine-plant" pairs of each purchase.

the distance between the play and the power plant.[7] Third, I sum up the time-varying fracking initiation measures at the plant level for each county. Thus, the sum of the indicators represents the growing effects of shale gas plays on coal-producing counties via the steam coal market over time.

Cross-Sectional Variation

While the fracking initiation measures provide plausibly exogenous time-series variation, the cross-sectional variation across coal-producing counties would not be sufficiently explained by them. As the US natural gas spot market is highly integrated, the coal-bust potential instrument would be needed to capture heterogeneous coal supply responses to demand shocks that are induced by the natural gas price changes via the wholesale electricity market at a given year. To address this concern, I use a predetermined coal deposit thickness as an exogenous variable for the geological coal potential of each county. The US Geological Survey operates a nationwide database (COALQUAL) of coal quality such as coal seam depth and thickness for over 13,000 samples that were collected between 1973 and 1989. It is noteworthy that the survey was conducted over 15 years ahead of the sample period in this study. Since the thickness of coalbeds determines the efficiency of underground and surface mining[8], it can serve as a measure of "coal extraction potential." As expected, there is a strong positive correlation between the coalbed thickness and coal production (Figure 3.2), indicating that the thickness measure exhibits exogenous cross-sectional variation to represent coal mining productivity across different counties.

[7] Bartik et al. (2019)'s dataset archive also provides the fracking prospectivity score which is measured by the Rystad Energy, an oil and gas consulting firm. I test the robustness of my instrument by using the product of the shale play initiation indicator and the prospectivity score.

[8] To understand how average coal seam thickness is related with mining productivity, see a following article published by EIA: `https://www.eia.gov/todayinenergy/detail.php?id=35232`

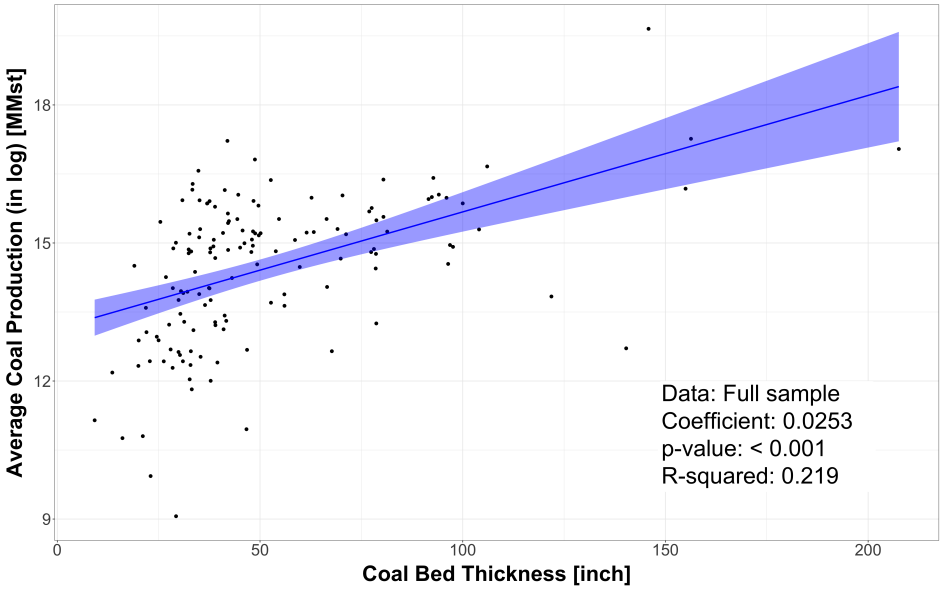


Figure 3.2: Coalbed Thickness as a Strong Predictor for Coal Production

Notes: Observations are the average thickness of coalbeds recorded between 1973 and 1989 and annual coal production from 2000 to 2020 for each county.

Addressing Potential Exclusion Restriction Violations

Yet, my instrument may suffer from an exclusion restriction violation if the shale gas boom had direct labor market effects on nearby local communities, drawing workers away from coal towards natural gas production—Feyrer et al. (2017) find that new gas production generates spillover impacts in neighboring areas within 100 miles of the fracking sites. One important fact is that the gas and oil extraction industry has an extremely small share of employment compared to coal (and other mineral) mining in the coal-rich counties (Figure C.3), indicating that geographic spillovers of the shale boom would be negligible in this setting. Nevertheless, I restrict the estimating sample to counties that are located over 150 miles away from each shale play to address this concern (see Figure C.5 for illustration). This sample restriction enables variations in coal demand that are sufficiently far away as to have minimal direct impacts on the local labor market. In addition, even though coal power plants where locations have similar distances from

the shale gas plays, the impact of fracking potential on the plants would differ by the intensity of local gas transport infrastructure. For example, coal plants in a state that has a high density of intrastate and interstate gas pipelines (e.g., Texas) would be more affected by the fracking boom. The IV incorporates gas pipeline capacity in the year of 2000 in each state which is computed using the annual announced pipeline projects dataset provided by the EIA (see Section C.3 for more details).

Formally, let CP_{it} be a prospect of a coal bust with demand shocks, which is the instrumental variable used in this study. Intuition on how this instrument works is that local coal production would decrease more as the fracking-driven demand shocks are greater, and the shale boom impacts would be more intensive with thicker coalbed. CP_{it} is specified as:

$$CP_{it} = \frac{1}{Thickness_i} \times \sum_{j \in (j,i)} \Big[\sum_{k} \mathbb{1}(Play_{kt} \geq \bar{t}_k) \times \varphi_{jk} \Big] G_j \tag{3.2}$$

where $Thickness_i$ is the average thickness of coalbeds in county i, the main exogenous cross-sectional variation in the instrument. $\bar{t}_k$ denotes play-specific announcement date of successful fracking and $\mathbb{1}(Play_{kt} \geq \bar{t}_k)$ is an indicator equal to 1 after play k is announced. φ_{jk} is the inverse distance between plant j and play k.[9] Natural gas pipeline density in 2000 is G_j. I show the robustness of the IV with different choices of the county-play distances, the fracking score, and the gas pipeline variable in Section 3.4.

This empirical strategy may require additional clarifications for three concerns. First, some mines might export a significant portion of coal in response to a decrease in domestic coal demand. It would then attenuate local economic shocks due to coal decline. However, the past and recent trends in coal supply and trade suggest that net exports of coal have not remarkably changed over time (Figure C.2). Furthermore, it is also clear that coal

[9]For details on the notations, see Appendix.

production itself has declined significantly in the last few years. Second, the IV approach of this paper using the mine-plant pairs would not be valid if either many coal mines and power plants are owned by one company or they have long-term coal contracts. The fuel receipts data for coal shows that there are only two mine-plant pairs owned by the same utility out of total 7,214 pairs, indicating that the ownership structure in the coal mining industry is not a critical concern in this study. In addition, contracts with more than five years only account for roughly 15% of coal deliveries to US power plants in the 2010s.[10] Third, if many coal-fueled plants decided to locate "far" away from the shale plays in order to avoid the expected rapid growth of local gas production, it would be not appropriate to use the location of the plants for identification strategy. Yet, only about 3.5% of the coal power plants were built after 2005, for which most shale gas plays initiated innovative fracking activity, and there is no visual evidence on strategic siting of the plants (Figure C.6).

Thus, the first-stage regression using the fracking potential instrument is summarised as:

$$log(Coal_{it}) = \gamma_1 CP_{it} + \alpha_i + \delta_t + u_{it} \tag{3.3}$$

where α_i denotes county fixed effects, δ_t is year fixed effects, and u_{it} is the error term. I expect that the estimated coefficient of γ_1 is negative since coal-rich regions that are more exposed to fracking-driven coal demand shocks and thicker coalbeds would experience a larger decrease in coal production.

As described in Section 3.3.1, the local government finance data, one of the main outcomes of interest, is not available every year. Given the lack of data on detailed sources of fiscal flows in the public sector and the complexity of intergovernmental transfers, it is difficult to identify how local government finances respond to changes in the coal industry

[10]Source: S&P Global Market Intelligence (LINK)

(Morris et al., 2021). Yet, it is still interesting to compare changes in public revenue and spending in coal-rich parts with non-coal-producing ones due to coal decline. Since the coal production in 2016-17 is reduced to about two-thirds of the 2011-12 level, I estimate a long-difference model of the change between 2012 and 2017[11]:

$$\Delta Y_i = \beta_1 \Delta log(Coal_i) + \varepsilon_i \tag{3.4}$$

where ΔY_i is the change of local public revenue and expenditure (or in per-capita) in coal-producing county i. Similarly, I instrument for the decline in coal production using changes in the coal-bust potential (ΔCP_i). I report heteroskedasticity-robust standard errors.

3.4 Results

3.4.1 Effects on Local Labor Market Outcomes

Table 3.1 shows that coal declines have significant negative effects on local labor market outcomes. These impacts become even more pronounced when endogeneity is addressed using IV estimation. A 1% decline in coal activity leads to a 0.36% reduction in local real GDP (column 1), which translates to a loss of approximately $9.8 million based on the mean real GDP of $2.8 billion. This highlights how central coal production is to local economic activity, as a small percentage decline in coal activity leads to a disproportionately large loss in overall economic productivity. It also results in a 0.16% decline in the number of firms, equivalent to a loss of approximately 2 firms (column 2).

[11]Although the individual local government unit data on previous years (e.g., 2002 and 2007) are available, the survey item classification is not consistent between 2000s and 2010s. For example, interlocal transfers data is available in 2012 and 2017 surveys, while it is not in 2002 and 2007. The survey questionnaires in 2012 and 2017 are very consistent, allowing me to match government finance activities at the question item level.

Similarly, there is a 0.25% drop in total employment, or about 53 fewer jobs out of the mean of 21,272 (column 3).

For gross income, the reduction is 0.21%, translating to a loss of about $3 million out of the mean gross income of $1.4 billion (column 4). Per-capita net earnings and royalty income decline by 0.1% (columns 4 and 5). The OLS estimates, while slightly smaller, also reveal consistent negative effects. These findings indicate that coal declines have a ripple effect on local labor markets, causing coal-dependent industries and related sectors, such as transportation, retail, and services, to shut down or cut jobs as economic activity slows down. Table C.4 presents evidence of significant cross-industry spillover effects from coal declines, with consistent negative impacts observed across several non-coal sectors. The estimated coefficients for establishments, employment, and wages are generally negative and statistically significant in industries such as construction, manufacturing, transportation, and services.[12] These effects are not limited to sectors directly tied to coal but extend to broader local industries, suggesting that coal declines trigger adverse general equilibrium effects in local labor markets.

[12]For instance, a 1% decline in coal activity is associated with a 0.52% decline in construction employment and a 0.4% decline in manufacturing employment. Notably, education and health appear sectors relatively insulated from these spillovers, with small and statistically insignificant coefficients.

Table 3.1: Impact of Coal Declines on Local Labor Market Outcomes

	Local Real GDP (BEA)	Total Firms (CBP)	Total Employment (QWI)	Gross Income (IRS)	Per-Capita Earnings (BEA)	Per-Capita Royalty Inc. (IRS)
	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
log(Coal Decline)	-0.054***	-0.004**	-0.019***	-0.015***	-0.014***	-0.007**
	(0.006)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
IV						
log(Coal Decline)	-0.355***	-0.162***	-0.249***	-0.213***	-0.095***	-0.106***
	(0.043)	(0.020)	(0.033)	(0.028)	(0.019)	(0.030)
F-statistic	49.4	50.4	50.5	50.4	49.4	50.4
Observations	2,367	2,385	2,369	2,385	2,367	2,385
Mean of DV	2,767 [$M]	1,390	21,272	1,403 [$M]	20,200 [$]	12,973 [$]

Notes: Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. All dependent variables are measured in logarithmic terms. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

3.4.2 Effects on Local Government Finance

Coal declines significantly reduce local government revenue and expenditures while having mixed effects on debt issuance (Table 3.2). Although per-capita dollar values offer valuable information, my interpretation of the results centers on outcomes in log values given the non-uniform distribution of revenues and expenditures across the population (Feler and Senses, 2017). Using IV estimates for clarity, a 1% decline in coal activity leads to a 0.09% reduction in per-capita local (own-source) revenue (column 1), amounting to approximately $21 per person. This finding highlights local governments' dependence on coal-related economic activities as they directlythe lose revenue they generate (e.g., from local taxes or fees) when coal activity declines. Notably, intergovernmental transfers

experience a larger decline of 0.3% (column 2), translating to a $33 reduction per capita, accounting for about 9% of the mean transfer amount of $376. It indicates that coal-dependent counties also lose funding from higher levels of government as coal activity declines, likely because these transfers are tied to economic output or resource royalties.

On the expenditure side, specific expenditures decrease by 0.084% (column 5), or roughly $55 per capita, while general expenditures decline by 0.087% (column 6), equivalent to a $40 reduction per capita. As coal-related revenues decline, spending on targeted programs, such as infrastructure projects, and broader discretionary areas, like administrative costs, is reduced. This likely lowers the quality or availability of essential services and creates financial strain across all areas of local government operations. Overall, total expenditures decline by 0.087%, which corresponds closely to a 0.082% decrease in total revenue per capita (columns 3 and 7). Debt issuance does not show a statistically significant impact (column 4), suggesting the broader fiscal challenges brought about by coal declines, which diminish local governments' capacity to generate revenue and support essential expenditures.

Table 3.2: Impact of Coal Declines on Local Government Finance

	Revenue			Debt	*Expenditure*		
	Local	IGT	All	Issued	Specific	General	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV: log($ per capita)							
log(Coal Decline)	-0.091*	-0.304***	-0.082**	0.104	-0.084*	-0.087	-0.087**
	(0.052)	(0.086)	(0.038)	(0.463)	(0.043)	(0.059)	(0.037)
DV: $ per capita							
log(Coal Decline)	-20.64	-32.83***	-53.47	9.66	-55.47**	-39.90	-95.37**
	(29.71)	(11.49)	(33.24)	(44.62)	(27.43)	(24.97)	(40.56)
Mean of DV [$]	805	376	1,181	107	879	358	1,237
F-statistic	36.9	36.9	36.9	36.9	36.9	36.9	36.9
Observations	128	128	128	128	128	128	128

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.4). Heteroskedasticity-robust standard errors are reported in parentheses, and the Kleibergen Paap F-statistic is included to assess instrument relevance. The mean of the dependent variable (DV) is calculated based on each item's value in 2012. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

3.4.3 Effects on Local Government Revenue and Expenditure by Sub-Items

I disaggregate local government revenue sources to identify the specific channels through which coal declines affect public finances, as shown in the top panel of Table 3.3. Three key points emerge from this analysis for the own-source revenue items. First, as expected, coal declines have the most significant impact on local rents and royalties (column 1). Local governments in coal-rich areas face substantial revenue losses as coal production decreases, directly reducing their ability to fund services that rely heavily on these revenues. Second, coal industry collapses also have notable indirect fiscal effects on revenue sources like sales tax (column 2) and charges and license fees (column 4). This is consistent with the negative income shocks associated with coal declines, as shown

in Table 3.1. The resulting economic downturn reduces individual consumption of local goods and payments for public services, leading to declines in sales tax revenue, charges for public services (e.g., highways or utilities), and license fees (e.g., motor vehicles). Third, on a percentage basis, coal declines have no significant impact on property tax revenue (column 3). One possible explanation is that assessed property values, which determine property tax revenue, may not respond immediately to coal declines or that housing values adjust to economic downturns with a time lag. Additionally, local governments may adjust property tax rates to mitigate fiscal risks, helping stabilize this revenue source even during economic challenges.

The IV results for columns 5, 6, and 7 highlight how coal declines impact intergovernmental transfers in various ways. For matching grants (column 5), a 1% decline in coal activity reduces these grants by 0.152%, although the impact in dollar-per-capita terms is relatively small and subject to some variability (Table 3.3). This suggests that local governments in coal-dependent regions struggle to secure matching grants, as their reduced revenues make it harder to meet the funding requirements for such programs, limiting access to external funds for projects like infrastructure and education. Strikingly, general-purpose transfers (column 6) face a much larger impact, with a 1% coal decline leading to a 0.54% reduction, or a per-capita loss of approximately $31 from the mean of $133. These unrestricted funds are vital for addressing fiscal gaps and funding essential services, and their significant decline exacerbates the financial strain on local governments. The large reduction in these transfers also highlights the cascading effect of coal production declines, reducing funds available not just from local sources but also from higher levels of government. I explore the potential mechanisms driving the significant reduction in general-purpose intergovernmental transfers in more detail in Section 3.6.

Transfers from other local governments (column 7) show an estimated 0.164% decline, but the result is statistically insignificant. This suggests that inter-local transfers, such

as shared funding agreements, remain relatively stable despite coal production declines. However, these transfers have played only a limited role in offsetting public revenue losses, possibly because neighboring localities are also affected by the economic shocks caused by coal declines and face similar fiscal challenges. Together, these findings emphasize how coal declines not only erode local revenue but also disrupt critical funding streams from higher government levels, further limiting the ability of coal-dependent communities to sustain public services and infrastructure.

The bottom panel of Table 3.3 shows how the coal-rich localities make spending decisions in local public services. The coal decline led to modest spending cuts in specific-purpose works except for public safety (column 9): housing development (column 8), public transit (column 10), and local welfare services (column 11). Not only specific-purpose services but general-purpose ones are decreased by coal-induced revenue declines, which is consistent with the sharp reduction in general-purpose grants from state governments. It also suggests that county and city governments are likely to "sacrifice" themselves by cutting down their own activities to keep appropriate levels of provisions of specific-purpose public services in response to a significant budget deficit. The most pronounced reduction among all expenditure items was made for general government-wide services such as local economic development (e.g., job training) or premiums for insurance (column 12), while they rarely cut spending in core administration (column 13; e.g., operation of tax assessment agency or the mayor's office) or general public buildings (column 14; e.g., city halls).

Table 3.3: Impact of Coal Declines on Local Government Revenue and Expenditure Items

Panel A: Revenue

	Local (Own-Source)				*Intergovernmental Transfer*		
	Rents & Royalties	Sales Tax	Property Tax	Charges & Fees	Matching Grant	General Purpose	Other Locals
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(Coal Decline)	-0.417**	-0.146**	0.029	-0.166*	-0.152***	-0.540**	-0.164
	(0.210)	(0.067)	(0.037)	(0.087)	(0.059)	(0.189)	(0.148)
Mean of DV [$]	34	164	383	229	198	133	46
F-statistic	30.2	36.9	36.9	36.9	36.9	36.9	36.9
Observations	107	128	128	128	128	128	128

Panel B: Expenditure

	Specific Purpose				*General Purpose*		
	Housing & Enviro.	Local Safety	Public Transit	Health & Welfare	General Service	Central Staff	Public Building
	(8)	(9)	(10)	(11)	(12)	(13)	(14)
log(Coal Decline)	-0.173**	-0.108*	-0.142	-0.056	-0.262*	0.007	-0.176
	(0.087)	(0.060)	(0.102)	(0.103)	(0.144)	(0.049)	(0.129)
Mean of DV [$]	202	248	226	109	165	159	35
F-statistic	36.9	36.9	36.9	36.9	36.9	36.9	32.8
Observations	128	128	128	128	128	128	120

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.4). Heteroskedasticity-robust standard errors are reported in parentheses, and the Kleibergen Paap F-statistic is included to assess instrument relevance. All dependent variables are measured as the logarithm of dollars per capita. The mean of the dependent variable (DV) is calculated based on each item's value in 2012. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

3.4.4 Fiscal Spillover Effects

To estimate the fiscal spillover effects of coal declines, I replace the outcome variable with the average per-capita revenue or expenditure of local governments in neighboring

counties. Following the geographical spillover range of natural resource booms outlined by Feyrer et al. (2017), I define neighboring counties as those located within a 100-mile radius of the centroid of each coal-rich county within the same state, excluding counties that also produce coal. To ensure the robustness of these spillover estimates, I also provide results using different buffer distances for defining neighboring counties.

Figure 3.3 illustrates that a 1% decline in coal activity has consistently negative effects on neighboring non-coal counties across all buffer distances, with small but measurable reductions. Neighboring non-coal counties experience declines in local output, the number of businesses, and employment, with the impacts being more pronounced in areas closer to coal-producing counties. Income losses also ripple out to neighboring counties, but these effects are strongest within close proximity to coal-producing areas. In contrast, the spillover effects on per-capita net earnings and royalty income in neighboring non-coal counties are relatively modest, showing smaller declines compared to other outcomes. These findings highlight the concentrated nature of coal's economic impact and the limited, though notable, regional spillovers that affect neighboring areas.

Panel A of Figure 3.4 presents the results of the spatial spillover effects on local government revenue. As expected, non-coal counties do not experience declines in local rents and royalties linked to coal production, as these revenues are directly tied to coal extraction activities, leaving neighboring non-coal counties largely unaffected. Similarly, sales tax and charge revenues in neighboring non-coal counties show minimal impacts, reflecting the fact that their economies and demand for public services are less directly influenced by coal production. Property tax revenue exhibits only modest effects across neighboring counties, with slightly positive estimates at larger buffer distances. This suggests that property taxes are less sensitive to declines in coal production, as property values and assessed taxes tend to remain stable or are adjusted to mitigate revenue losses. This pattern aligns with the behavior of coal-rich counties, which adjust property tax

collections to compensate for reductions in intergovernmental transfers (IGT).

For general-purpose intergovernmental transfers, neighboring counties experience non-trivial and statistically significant declines across all buffer distances. When coal production declines, state-level revenue streams would shrink, reducing the overall pool of funds available for distribution to local governments, including neighboring non-coal counties. This demonstrates how the fiscal impacts of coal declines extend beyond coal-producing counties, indirectly affecting the broader allocation of state resources. In contrast, matching grants to neighboring non-coal counties remain largely unaffected, with estimates clustering near zero, indicating that these counties' ability to secure funding for specific projects like infrastructure or education is not impacted. The lack of significant changes in transfers from other local governments highlights the stability of interlocal funding arrangements, even during coal-related economic disruptions.

Expenditures in neighboring non-coal counties exhibit varying patterns across categories and buffer distances, as shown in Panel B of Figure 3.4. Spending on housing and environmental services shows mixed patterns, with both positive and negative changes depending on the distance, suggesting that these expenditures are influenced by localized needs or policy priorities rather than a uniform response to coal-related disruptions. In contrast, spending on local safety, such as police and fire services, increases significantly, likely driven by the need to address safety concerns associated with an influx of migrants from coal-rich counties (Table 3.4) experiencing economic decline. Health and welfare expenditures show small declines in counties closer to coal-rich areas but stabilize at greater distances, indicating a limited spillover effect on social services. Public transit expenditures, on the other hand, remain largely unaffected across all distances, likely because these services involve fixed costs that are not immediately impacted by local economic changes.

In contrast, there are modest declines in general-purpose expenditures, possibly in

response to reductions in general-purpose IG transfers caused by state-level revenue losses tied to coal production, as shown in Panel A. If the declines in general-purpose expenditures were solely due to state-level revenue losses, the effects would likely be consistent across all distances from coal-rich counties. However, the fact that the effects decrease with distance suggest that state-level revenue losses alone cannot fully explain the observed pattern. Instead, localized spillover effects likely play a significant role. Counties closer to coal-producing areas are more directly impacted by the economic downturn due to stronger economic linkages, such as shared supply chains, labor markets, or consumer demand. These closer counties may also experience greater demographic spillovers, such as an influx of migrants from coal-rich counties seeking better opportunities, which increases fiscal strain and necessitates resource reallocation, potentially reducing general-purpose expenditures.

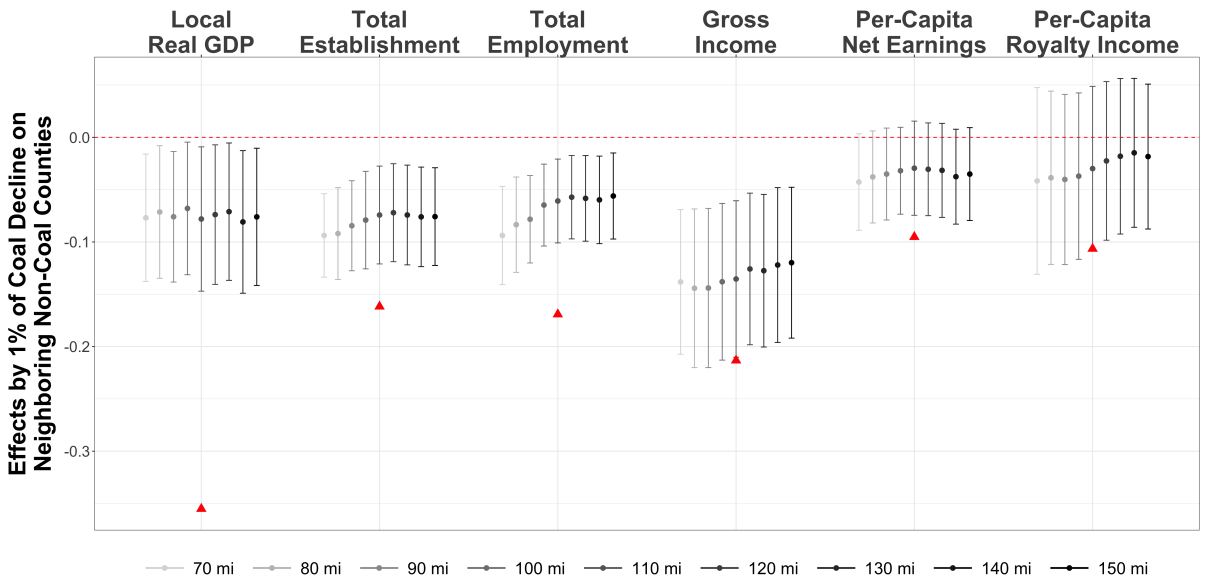


Figure 3.3: Spillover Effects of Coal Declines on Local Economy

Notes: The estimates are obtained from a two-stage least squares (2SLS) estimation, using the coal-bust potential as an instrumental variable. This approach is based on equation (3.4), where the dependent variable is measured in logarithmic terms. The dots and error bars represent the estimated coefficients and their 90 percent confidence intervals, respectively. Red triangles indicate the parameter estimates for the impacts on coal-producing counties presented in Table 3.1. Grey-scale colors indicate different distances from the centroid of each coal-rich county. A detailed summary of all estimates can be found in Appendix Table C.4.

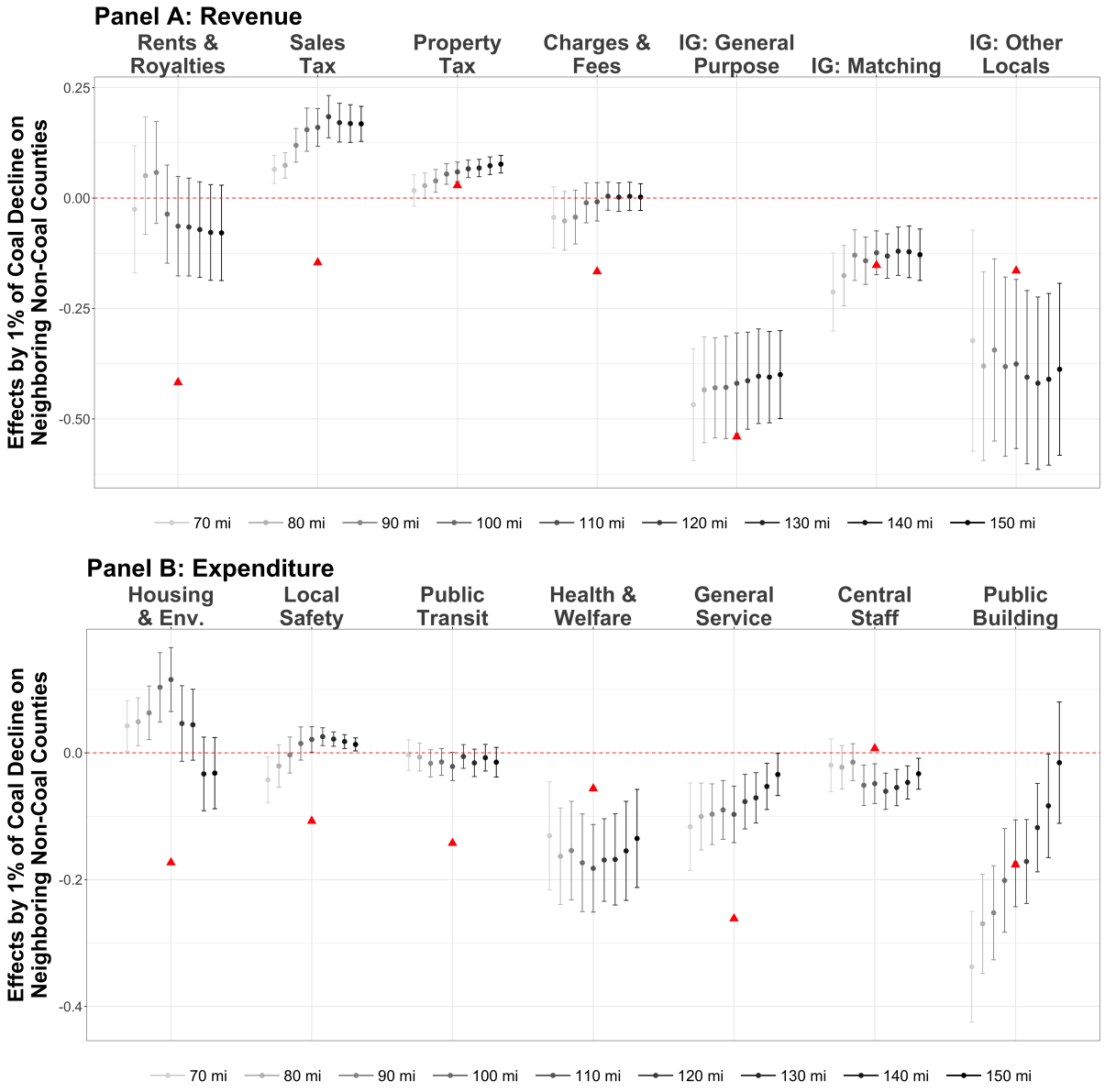


Figure 3.4: Spillover Effects of Coal Declines on Local Government Finance

Notes: The estimates are obtained from a two-stage least squares (2SLS) estimation, using the coal-bust potential as an instrumental variable. This approach is based on equation (3.4), where the dependent variable represents the logarithm of the average per-capita revenue or expenditure of local governments in neighboring counties. The dots and error bars represent the estimated coefficients and their 90 percent confidence intervals, respectively. Red triangles indicate the parameter estimates for the impacts on coal-producing counties presented in Table 3.3. Grey-scale colors indicate different distances from the centroid of each coal-rich county. A detailed summary of all estimates can be found in Appendix Table C.5.

3.5 Robustness Check

3.5.1 Alternative Specification

The long-difference IV that uses the coal-bust potential instrument can be underpowered because it relies only on cross-sectional variation across coal-producing counties. To improve efficiency, I recast the analysis as difference-in-differences (DiD) with nonparametric preprocessing. The design uses 2012 as the pre-period and 2017 as the post-period, consistent with the IV setup. A key step is to form a control group that closely resembles the treated coal counties. I implement nearest-neighbor matching from a donor pool that excludes all coal-producing counties and, within the same state, excludes counties that border a coal county or lie within two degrees of proximity. These screens reduce the risk of in-state geographic spillovers from coal declines. After applying them, the donor pool falls from 2,887 to 2,340 counties, supporting cleaner matches for the DiD.

Similarity is measured by distances in propensity scores. I estimate the propensity score using baseline covariates from the 2000 Census: log population, log marriages, share white, share age 65 and older, share with a college degree or higher, log per-capita income, log median home value, log gross rent, and the unemployment rate. Matching on these characteristics yields control counties that are well balanced at baseline relative to treated counties. This preprocessing strengthens identification and improves precision while preserving the 2012–2017 long-difference structure.

Table C.6 compares the variables used in the matching procedure across treatment and control counties, suggesting that covariates of both groups are well-balanced for ratios of controls to treated in the sample. I report the main results with a 2:1 match where population size in control counties is the most similar to that in treatment ones, nevertheless, the results with a 1:1 or 3:1 match are also presented for the robustness check. Matching *without* replacement is chosen as the primary method to ensure more

robust statistical inference.[13] The estimating equation is then specified as follows:

$$\Delta Y_{j,2012-2017} - \Delta Y_{k,2012-2017} = \beta_1 \mathbb{1}[\text{Coal-Producing}]_j + \varepsilon_j \tag{3.5}$$

where j denotes treated (coal-producing) counties and k is control (matched) ones. ε_j is error term. β_1 is a mean shift estimate of the effect of coal decline on local government revenue and spending. I report the standard errors clustered by the matched set for main inference and also the conventional heteroskedasticity-robust standard errors to support variance robustness.

The matching results closely align with those from the IV estimation used in the main analysis (Figure C.7). While the estimates for total revenue are slightly higher than those obtained from the IV model, the expenditure estimates are very similar to the IV results presented in Table 3.2. Both own-source revenue and intergovernmental transfers show significant declines compared to non-coal-producing counterparts, yet coal-rich local governments do not appear to offset these revenue losses through debt financing. Additionally, Figure C.11 further supports the comparability of the local public finance results when using the matching method *with* replacement within the DiD framework, confirming the robustness of the findings.

[13]Nonparametric preprocessing in matching procedures has generally not raised significant concerns regarding methods for estimating uncertainty, such as standard errors (Ho et al., 2007). However, Abadie and Spiess (2022) emphasize that valid statistical inference requires matching without replacement and clustering standard errors at the level of the matched set. This approach minimizes potential bias in variance estimation, which can occur due to correlations between the matching variables and the regression covariates. Nonetheless, matching without replacement can introduce bias in estimating the average treatment effect on the treated (ATT), as noted by Colmer et al. (2024b). In contrast, matching with replacement reduces bias by allowing control units with greater similarity (e.g., smaller distance measures) to be selected multiple times. To address the trade-off between bias and variance, this study presents results using both matching with and without replacement.

3.5.2 Tests for the Intrumental Variable and the Main Results

To support my instrumental variable (IV) rationale, I conduct various analyses. First, the coal-bust instrument exhibits strong predictive power for changes in coal production, as shown in Figure C.8. The scatter plot illustrates a significant negative relationship between the coal-bust instrument and changes in coal production, with a t-statistic of -5.85, confirming the statistical strength of the instrument. Additionally, Table C.7 provides robust evidence across various model specifications. For example, the instrument's estimated coefficient remains consistently negative and statistically significant depending on the specification. The models include county and year-fixed effects, ensuring that the results account for unobserved heterogeneity and time-invariant factors. Furthermore, the high F-statistics across specifications indicate strong instrument relevance, exceeding the critical thresholds for weak instrument concerns. The robustness of the instrument is further supported by adjustments for distance thresholds and pipeline availability, demonstrating its stability under different exclusion criteria. Furthermore, coal demand by power plants also shows a negative response to the instrument, as presented in Table C.8. It reveals consistently negative and statistically significant coefficients across varying model specifications depending on the distance threshold. These results indicate that the coal-bust potential strongly predicts reductions in coal demand, further validating the instrument's relevance.

Additionally, Figure C.9 demonstrates the results of weak instrument tests, using the Kleibergen-Paap F-statistic, to evaluate the strength of the coal-bust instrument across varying distances ($\bar{d}$) between coal-producing counties and shale gas plays. The F-statistic initially exceeds the critical thresholds (red and blue dashed lines) at smaller distances, confirming a strong instrument when a limited geographical buffer is applied. However, as the distance increases and more shale gas plays are excluded, the F-statistic

declines, eventually falling below the rule-of-thumb threshold of 10. This pattern indicates that the instrument becomes weaker as the effects of the shale boom on coal production diminish with greater geographical exclusion. These findings support the IV rationale by demonstrating how the instrument's strength relies on the indirect impact of the shale boom on coal production through wholesale electricity market competition. The results underscore the importance of maintaining geographical proximity in the analysis to ensure a valid and strong instrumental variable.

Second, it is possible that local labor market frictions exhibit sluggish dynamics and that measurement errors are inherent in coal storage for mined products. To address these potential concerns, Table C.9 presents results using two-year and three-year moving averages of coal production to smooth out short-term fluctuations. The estimates for key labor market outcomes are consistent with those from the baseline specifications. For example, the impact of coal declines on local real GDP remains significant, with coefficients of -0.3770 (two-year moving average) and -0.4145 (three-year moving average), both statistically significant at the 1% level. These findings suggest that the results are not driven by short-term measurement errors or temporary storage adjustments, and they provide additional confidence in the robustness of the analysis.

Third, the main IV results are consistent with the results obtained after excluding counties with extreme levels of coal production, as shown in Table C.10.[14] These findings confirm that the results are not driven by extreme cases and are representative of broader patterns. Table C.11 demonstrates that the main IV results are robust to different clustering choices for standard errors. Whether clustering by county, county-year, commuting zone-year, or state-year, the estimated effects remain consistent across all labor market outcomes. The consistency across clustering choices reinforces the robustness of

[14]I exclude six counties with extremely low coal production (less than 1 million short tons) and Campbell County, WY, an exceptionally large coal producer (over 1,000 million short tons).

the IV results and ensures that they are not sensitive to alternative methods of addressing spatial or temporal correlations in the data.

I conduct placebo and falsification tests to further support evidence of coal decline impacts on local public finance. One such test involves estimating the effect of changes in coal production during a "placebo" preceding period on the outcome variables of interest. Table C.12 presents regression results where I replace the IV with its 10-year lagged counterpart ($\Delta CP_{i,t-10}$) or substitute the explanatory variable with 10-year lagged coal production ($\Delta Coal_{i,t-10}$), representing coal production during 2002–2007. The results show no statistically significant effects of the lagged coal production variables on local public finance outcomes, as seen in the consistently small and insignificant coefficients across both revenue and expenditure categories. This placebo demonstrates that the results are unlikely driven by spurious relationships, historical trends, or earlier unrelated changes in coal production, which remained relatively stable in the preceding period (Figure C.2).

For a falsification test, I estimate the main public finance outcomes using the propensity-score-matched counties, as described in Section 3.5.1. The underlying assumption is that coal declines should have no direct effect on the public finance outcomes of counties that share similar characteristics with coal-producing counties but are not connected to coal extraction or production. This provides a baseline for evaluating whether the observed associations in the main analysis are due to actual coal-related dynamics or spurious correlations. Table C.13 presents the results for public finance outcomes across three matched sets of counties. The estimates are consistently small and statistically insignificant across all matches. It indicates that the observed relationships are likely driven by coal-related economic dynamics and not by general local characteristics or unobserved confounding factors.

3.6 Mechanisms

In this section, I explore possible explanations for my findings on the decline in intergovernmental transfers (IGTs) to coal-rich communities during downturns. The result is unexpected given the countercyclical purpose of IGTs: to stabilize local governments, reduce fiscal disparities, and support distressed areas. In principle, transfers should rise when own-source revenues drop, yet in coal-dependent counties they decline despite sharp revenue losses, rising poverty, and out-migration. This pattern suggests that current transfer systems do not account for volatile coal revenues or the specific needs of these communities, weakening their role as stabilizing and equitable instruments.

3.6.1 State Budget Constraints and Coal Revenue Redistribution

A plausible channel is a reduction in state severance-tax revenue when coal output falls. Figure C.12 shows severance collections for the seven largest coal-producing states, defined as taxes on natural-resource extraction, mainly fossil fuels.[15] Revenues appear to decline after the early 2010s, broadly tracking the drop in coal production. Texas is a partial exception because severance receipts there are driven more by oil and gas than by coal. These patterns suggest that coal is an important part of the severance base in several states, so budgets linked to this base can be sensitive to coal activity. When the base contracts, the pool available for state-funded aid may also contract, since severance revenues often supplement formula funding for local governments.

Revenue-sharing arrangements may then transmit the shock. Allocations typically account for production levels, mining employment or earnings, and local impacts of extraction, with equity considerations layered on top. In West Virginia, about 75% of

[15]Pennsylvania has no severance tax and is excluded.

severance proceeds go to coal-producing counties, and roughly 25% go to all counties and municipalities based on population. In Kentucky, about 50% of severance revenue flows to a local government fund distributed to coal counties using measures such as tonnage or mining statistics, while the other 50% goes to the state general fund. In Wyoming, severance taxes and federal mineral royalties are returned to local governments through direct appropriations, with grant and loan programs that often prioritize coal counties for infrastructure and community projects. Taken together, these designs indicate that when statewide severance revenue falls, transfers to coal communities can decline as well, although the magnitude likely depends on statutory formulas, annual appropriations, and broader budget conditions.

3.6.2 State-to-Local Grant Allocation

The decline in IGTs to coal-dependent communities can be linked to reductions not only in coal-related revenues, but also in more general state aid. US county and city governments typically receive two types of IGTs: specific-purpose grants (matching grants) and general-purpose grants, with about 90% of these funds appropriated by state governments (US Census of Governments 2017).[16] Matching grants reimburse local governments for expenditures on specific services like highways and often include spending requirements. As shown in the left panel of Figure 3.5, matching grants do not appear to be sensitive to changes in local income levels.

In contrast, general-purpose grants are allocated based on factors such as population and local economic performance, including contributions to state-imposed taxes. The right panel of Figure 3.5 shows a positive relationship between general-purpose grant allocations and per-capita income, indicating that these grants are closely tied to local

[16]Furthermore, a very small proportion of federal policies is explicitly oriented towards regions associated with fossil fuel extraction (see `https://media.rff.org/documents/Report_22-12_AxXwJqy.pdf`).

economic conditions. This *payback-as-you-go* principle implies that significant economic contractions in coal-rich communities result in reduced general-purpose grants, as these areas contribute less to state budgets and coal-related revenues. Consequently, coal-rich communities facing severe income declines receive less general-purpose aid, further exacerbating their fiscal challenges.

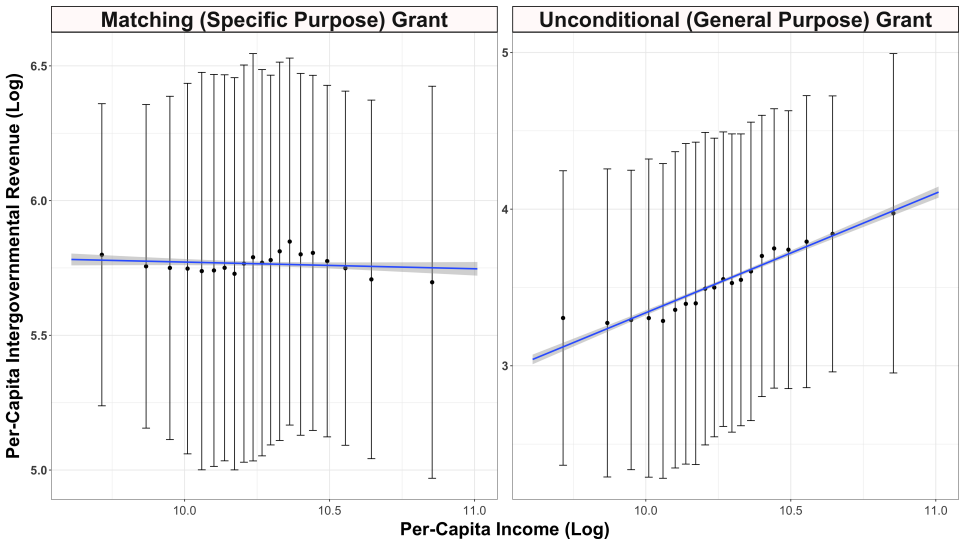


Figure 3.5: Per-Capita Income and IGTs

Notes: The dots and error bars represent the mean and mean plus one standard deviation of log per-capita IG revenue in each log per-capita income bin (divided into 20 bins). The dataset covers CPI-adjusted IGTs at the county level across all local government units in the US surveyed from 1972 to 2012. Controlling for county and year fixed effects, the regression coefficient of log per-capita income on log per-capita IG revenue from general-purpose grants is 0.236 with a t-value of 3.944. Data source: US Census of Governments

3.6.3 Out-Migration and Political Prioritization

Population loss can directly reduce allocations because population size is a key factor in the distribution formulas for IGTs. Table 3.4 highlights the impact of coal declines

on total population and internal migration flows in coal-rich communities.[17] The IV estimates reveal that a 1% decline in coal production leads to a 0.096% decrease in total population (column 1), driven primarily by out-migration (columns 4 and 5). More residents leave coal communities, both within the state and across state lines, suggesting that coal declines not only disrupt local economies but also trigger significant demographic shifts. At the same time, reduced in-migration further exacerbates the population loss (columns 2 and 3). This shrinking population base plays a critical role in explaining the decline in IGTs to coal-dependent areas, as smaller populations translate into lower state funding allocations and reduced local political and economic influence.

The rise in out-migration resulting from coal declines offers insight into why IGTs to coal-rich communities might decrease. First, the reduction in population directly impacts IGT allocation formulas, particularly for general-purpose grants that are typically based on population size. As the population of coal-dependent communities shrinks, their share of state-distributed funds also decreases, regardless of their increasing need for fiscal support. In addition, the increase in poverty (column 6) reflects worsening economic conditions and a reduced local contribution to state tax revenues, which further weakens the basis for state-funded transfers under the *payback-as-you-go* principle. This dual impact—shrinking populations and rising poverty—exacerbates the decline in IGTs, even as these communities face greater fiscal and social challenges.

Second, out-migration may dilute the voting power of coal communities and, with it, their influence in statewide decisions. As populations shrink, these areas can lose electoral salience relative to larger or faster-growing regions, so policy attention and resources may

[17] I collect population and poverty estimates from the Census Bureau. The Census Bureau provides single-year estimates of county-level population estimates by age, sex, and race, and single-year estimates of poverty headcount and rate for all ages produced in the Small Area Income and Poverty Estimates (SAIPE) Program. I use IRS-provided annual county-to-county migration flow data to make internal migration variables. For in-migration and out-migration count variables, I leverage the number of tax return exemptions flowed into or out of the same or different (or both) origin/destination states.

tilt toward urban centers. Economic decline and rising poverty could also make these counties appear less viable for long-term investment, encouraging states to deprioritize them in intergovernmental transfers.

Table 3.4: Impact of Coal Declines on Internal Migration and Poverty

	Total Population	In-Migrants per 100 from		Out-Migrants per 100 into		Poverty Rate
		Same State	*Diff. State*	*Same State*	*Diff. State*	
	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
log(Coal Decline)	-0.005***	-0.013*	0.007	0.019***	0.008	0.109**
	(0.001)	(0.008)	(0.009)	(0.006)	(0.007)	(0.046)
IV						
log(Coal Decline)	-0.096***	0.045	-0.114**	0.187***	0.119**	1.11***
	(0.012)	(0.057)	(0.054)	(0.051)	(0.054)	(0.404)
F-statistic	50.0	49.6	48.4	49.9	46.0	50.0
Mean of DV	59,616	2.306	1.472	2.386	1.475	18.0%
Observations	2,385	2,378	2,361	2,377	2,361	2,385

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable. Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

3.7 Simulating IGT Rules and Policy Discussion

3.7.1 Normative Design of Intergovernmental Transfer Rules

This section develops a simple normative framework for IGT design by mapping the reduced-form estimates into two benchmark rules built on the same primitives and a common budget. The first benchmark is a social-welfare-maximizing rule. A benevolent planner allocates transfers to maximize total welfare subject to the program budget. The

allocation reflects the marginal utility of public spending, differences in baseline fiscal capacity, and cross-county spillovers, so funds flow to places that raise aggregate welfare the most. This objective can concentrate resources where aggregate gains are largest, leaving small but severely affected communities undercompensated if funds are more productive elsewhere.

The second benchmark is a fiscal equalization (FE) rule. Transfers are set so that each county experiences a similar proportional revenue shock regardless of population or initial tax base. In practice, this implies higher per-capita aid for the hardest-hit, resource-dependent places to offset larger losses. I derive the rule to equalize marginal fiscal shocks across counties and calibrate it using the estimated revenue declines and measured spillovers.

IGT Rules under Objective for Social-Welfare Maximization

There are two counties $i \in \{H, L\}$. County H produces coal in quantity q_H; county L does not, but it is exposed through the state economy and regional linkages. Let total income and population respond linearly to q_H:

$$y_H(q_H) = \bar{y}_H + m_H q_H, \qquad y_L(q_H) = \bar{y}_L + m_L q_H, \qquad n_i(q_H) = \bar{n}_i + \mu_i q_H, \tag{3.6}$$

where $m_H \equiv \partial y_H / \partial q_H$ is the within-county income effect of coal, $m_L \equiv \partial y_L / \partial q_H$ is the cross-county income spillover, and $\mu_i \equiv \partial n_i / \partial q_H$ captures migration responses.

State IGT budget and fiscal spillovers of transfers. The pool for state-to-local aid is co-funded by coal-specific and broad tax bases:

$$G(q_H) = \tau^s \, q_H + \sigma^s \big[y_H(q_H) + y_L(q_H) \big] - E, \tag{3.7}$$

where τ^s denotes a coal-specific tax rates (e.g., severance tax), σ^s an effective state tax on non-coal income, and E state expenditures not passed to local governments. The state allocates a share $\gamma_H \in [0,1]$ to H (hence $\gamma_L = 1-\gamma_H$). To internalize the fiscal spillovers of transfers, I let the effective service shares be

$$s_H(\gamma_H) = \phi_H + (1-\phi_H)\gamma_H, \qquad s_L(\gamma_H) = 1-(1-\phi_L)\gamma_H, \tag{3.8}$$

where $\phi_H < 1$ is constant and the spillover intensity onto L varies with coal activity through a general function

$$\phi_L : \mathbb{R}_+ \to [0,1], \qquad q_H \mapsto \phi_L(q_H). \tag{3.9}$$

When coal activity is high, transfers to H more effectively ease service pressures in L because demand spills across jurisdictions via shared or mobile services (e.g., roads, housing) and regional input-output linkages; when coal contracts, these spillovers attenuate.

Aggregate consumption and preferences. Aggregate consumption in county i combines private income and the local public service flow financed by IGTs:

$$c_i(q_H, \gamma_H) = y_i(q_H) \; + \; n_i(q_H)\, \rho\, G(q_H)\, s_i(\gamma_H). \tag{3.10}$$

where ρ maps one dollar of IGT into per-capita public-consumption units measured in private-good units.

I focus on interregional insurance as the core role of IGTs. Individuals have constant relative risk aversion (CRRA) preferences

$$u(c) = \frac{c^{1-\eta}-1}{1-\eta} \quad (\eta > 0),$$

and the state government maximizes a Pareto-weighted utilitarian social welfare function

$$W = \sum_{i \in \{H,L\}} \lambda_i \, u\Big(c_i(q_H, \gamma_H)\Big), \tag{3.11}$$

where $\lambda_i > 0$ are Pareto weights. Concavity of u embeds the planner's aversion to dispersion in consumption, delivering insurance across places: higher η increases the planner's weight on smoothing temporary income shocks across counties.

Planner's problem and characterization. Let the social marginal value of \$1 in county i be $\omega_i(c_i) \equiv \lambda_i \, u'(c_i)$. Using $\gamma_L = 1 - \gamma_H$ and the fact that $\partial c_H / \partial \gamma_H = n_H \, \rho \, G(1 - \phi_H)$ and $\partial c_L / \partial \gamma_H = -n_L \, \rho \, G(1 - \phi_L)$, the spillover-aware first-order condition (FOC) for γ_H is

$$(1 - \phi_H) \, n_H(q_H) \, \omega_H\big(c_H(q_H, \gamma_H)\big) = (1 - \phi_L) \, n_L(q_H) \, \omega_L\big(c_L(q_H, \gamma_H)\big). \tag{3.12}$$

With $u'' < 0$ ($\eta > 0$), $\omega_i'(c_i) = \lambda_i u''(c_i) < 0$. Hence $\partial F / \partial \gamma_H < 0$, implying a unique interior solution for $\gamma_H \in [0, 1]$ whenever $G > 0$, $n_i > 0$, and $\rho > 0$. I denote this solution by the SW-optimal level rule $\gamma_H^*(q_H)$. Although γ_H^* is computed numerically, its closed-form slope $d\gamma_H^* / dq_H$ delivers transparent comparative statics (Appendix C.1).

IGT Rules under Objective for Equalizing Fiscal Shocks Across Localities

As a complementary benchmark, I study a rule that equalizes the marginal fiscal shock across counties, while preserving the same primitives $(q_H, y_i(\cdot), n_i(\cdot))$ and the same state budget $G(q_H)$ from Eq. (3.6)–(3.7). This ensures differences between the two rules reflect the objective, not the environment.

County revenues with economic spillovers. Let total county revenue be own-source plus its share of the state IGT pool:

$$R_{i,\text{Total}}(q_H) = R_{i,\text{Own}}(q_H) + R_{i,\text{IG}}(q_H). \tag{3.13}$$

Own-source revenue comprises a coal-specific base (for H) and non-coal activity:

$$R_{i,\text{Own}}(q_H) = \tau_i^l \, q_i + \sigma_i^l \, z_i(q_H), \qquad q_L \equiv 0, \tag{3.14}$$

where τ_i^l is a coal-specific local instrument (royalties, fees), σ_i^l is an effective local tax on non-coal activity, and $z_i(q_H)$ is non-coal output. To parsimoniously embed the reduced-form spillovers, I let

$$z_i(q_H) = \bar{z}_i + m_i q_H, \tag{3.15}$$

so that m_H captures cross-industry impacts in H and m_L captures cross-border impacts in L. The IG revenue is the county's share of the common pool:

$$R_{i,\text{IG}}(q_H) = G(q_H) \, \gamma_i(q_H), \qquad \gamma_H(q_H) + \gamma_L(q_H) = 1, \tag{3.16}$$

with $G(\cdot)$ given by Eq. (3.7).

Equalization condition and closed-form rule. The FE objective chooses $\gamma_H(\cdot)$ such that marginal revenue shocks are equalized:

$$\frac{dR_{H,\text{Total}}}{dq_H} = \frac{dR_{L,\text{Total}}}{dq_H}. \tag{3.17}$$

Using (3.13)–(3.16) with (3.15), the condition (3.17) reduces to a first-order linear ordinary differential equation in $\gamma_H(q_H)$ whose unique solution under the innocuous boundary

$\gamma_H(0)=0.5$ is

$$\hat{\gamma}_H(q_H) = \frac{1}{2}\left[1 - \frac{(\tau_H^l + \sigma_H^l m_H - \sigma_L^l m_L)\, q_H}{(\tau^s + \sigma^s(m_H + m_L))\, q_H + \sigma^s(\bar{z}_H + \bar{z}_L) - E}\right]. \tag{3.18}$$

See Section C.2 in Appendix for derivation. The numerator summarizes how strongly H's own bases move with coal relative to L. The denominator transmits the *state-budget sensitivity*, $dG/dq_H = \tau^s + \sigma^s(m_H + m_L)$, and the *baseline pool*, $\sigma^s(\bar{z}_H + \bar{z}_L) - E$, to both counties. Intuitively, when coal contracts (q_H decreases), H's own bases fall (large τ_H^l and $\sigma_H^l m_H$), so the rule prescribes a higher share for H (countercyclical $\hat{\gamma}_H$) unless the neighbor exposure ($\sigma_L^l m_L$) is comparably large.

3.7.2 Model Calibration

I discipline all shared primitives with reduced-form estimates obtained from Section 3.4 or observed policy parameters: $\{\bar{y}_i, \bar{n}_i, m_i, \mu_i, \tau^s, \sigma^s, E, \rho, \phi_H\}$. First, I recover m_H, m_L, and μ_H using the estimates of local income and population effects, while assuming $\mu_L = 0$ for simplicity.[18] Second, I assume the effective non-coal tax rates for state governments are 5%, consistent with the median state income tax rate ($\sigma^s = 0.05$). Third, I assume that 20% of total state general revenue is allocated to local transfers, based on data from the U.S. Census of Governments, which implies, which implies $E \approx \$95.5\text{M}$. I normalize the per-capita conversion factor to unity, $\rho = 1$.[19]

[18] See Section C.4 for details on parameter recovery.

[19] Under my linear technology, ρ only scales G and drops out of the FOC for the optimal transfer share; hence this normalization is without loss of generality. It coincides with the canonical fungibility benchmark for general-purpose intergovernmental aid (unconditional grants are equivalent to lump-sum income) and with standard practice in the inter-regional insurance and optimal redistribution literatures (Bordignon et al., 2001; Lucas Jr, 2003).

Simulating the SW-Maximization Rule

Consistent with evidence that resource booms and busts comove with cross-jurisdictional service burdens and non-tradable activity (Allcott and Keniston, 2018; Black et al., 2005), I parameterize the non-coal county spillover as linear in the cycle proxy q around a reference level $q_\circ$:

$$\phi_L(q) \;=\; \phi_{L0} \;+\; \phi_{L1}\,\frac{q - q_\circ}{q_\circ}.$$

I fix the baseline level at $\phi_{L0} \approx -0.5$ using reduced-form elasticities of genera-purpose IGT,[20] and center the cycle at $q_\circ$. ϕ_{L1} then captures the cycle sensitivity of the spillover and is calibrated in two complementary ways. First, for out-of-sample analysis I re-fit the spillover slope to match the 2012 allocation for each candidate curvature and then assess the 2017 policy implication without re-targeting, which isolates the model's insurance prescription in the downturn. Second, I report a single baseline obtained by jointly fitting curvature and the spillover slope to the 2012 and 2017 allocations, which pins down one normative share curve used throughout the historical and forward-looking exercises.

I use two *realized* allocations[21] in 2012 and 2017 as external moments: $(\tilde{q}_{2012}, \tilde{\gamma}_{2012}) =$ (932, 0.391) and $(\tilde{q}_{2017}, \tilde{\gamma}_{2017}) =$ (686, 0.349).[22] I then treat 2012 as the anchor and evaluate 2017 out of sample. For each risk-aversion parameter (η) on a normative grid $[0.5, 2.5]$, re-estimate the cycle-varying spillover slope $\phi_{L1}(\eta)$ to satisfy $\gamma^*_H(\tilde{q}_{2012};\, \eta, \phi_{L1}(\eta)) = \tilde{\gamma}_{2012}$, which matches the observed allocation. Holding that re-anchored environment fixed, I calculate the consumption-equivalent welfare (CEV) loss from using the observed share

[20] I recover the baseline non-coal spillover level ϕ_{L0} from the reduced-form estimates of spillovers in local revenue and expenditure: $\phi_L = \frac{|\beta_L^{GS}|\cdot GS_L - |\beta_L^{IG}|\cdot IG_L}{|\beta_H^{IG}|\cdot IG_H} = \frac{(0.0926*325.17)-(0.278*325.24)}{0.304*376} \approx -0.53$ where β_L^{GS} is the (neighbor) elasitcity of general-service expenditure, β_L^{IG} is the (neighbor) elasitcity of general-purpose IGT, and β_H^{IG} is the (coal-county) elasitcity of general-purpose IGT. The quantities GS_L, IG_L, and IG_H are baseline per-capita levels used to convert elasticities to derivatives.

[21] The actual shares of IGTs allocated to coal-producing counties are calculated using state-level data from the Census of Governments.

[22] Thus, $q_\circ = \frac{932+686}{2} = 809$.

instead of the SW-optimal share as the uniform consumption scaling κ that equalizes welfare across counties:

$$\sum_{i\in\{H,L\}} u((1+\kappa)\, c_i(\tilde{q}_{2017}, \tilde{\gamma}_{2017})) = \sum_{i\in\{H,L\}} u(c_i(\tilde{q}_{2017}, \gamma^*_{2017}))\,,$$

and report $100\times\kappa$ in percent.

Figure 3.6 shows how the model links social preferences over inter-county risk to optimal transfers and their welfare implications. In the left panel, the SW-optimal coal-county IGT share in 2017 rises concavely with the risk-sharing parameter η: higher η implies stronger redistribution toward distressed coal counties. The dashed line marks the actual 2017 allocation, and its intersection with the optimal curve occurs around $\eta\approx 1.4$, suggesting that if the legislature's choices are rationalized by a standard isoelastic social welfare function, the enacted rule is close to first best for a moderate, empirically plausible degree of inequality aversion. The right panel translates this into welfare space by plotting the consumption-equivalent loss from using the observed 2017 share. The resulting U-shape suggests that the current IGT formula is robustly near-optimal for a wide range of moderate risk-sharing preferences but would look substantially too generous (for low η) or too stingy (for high η) under more extreme views about inter-county inequality.

Simulating the Fiscal Equalization Rule

To provide a preference-light, implementable alternative that targets the shock directly, I simulate the fiscal-equalization IGT rule derived in Eq. (3.18). One additional parameter to set is the local coal and non-coal tax rates. I derive $\tau^l_H \approx \$0.19/ton$ using the estimates on the local own-source revenue effects, and assume that $\sigma^l_i = 0.01$ for simplicity.

By incorporating these parameters into the fiscal equalization framework, the alter-

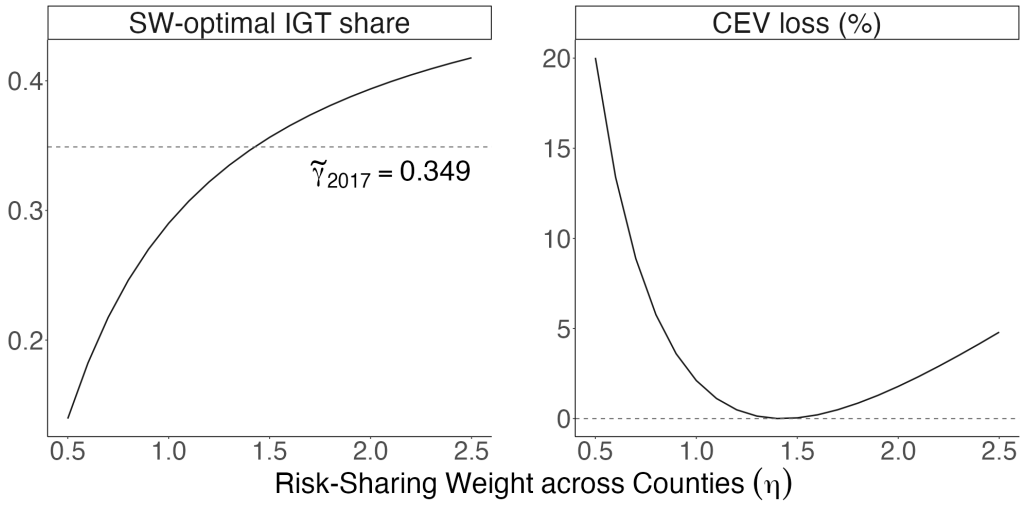


Figure 3.6: SW-Optimal IGT Shares and Welfare Losses Across Risk-Sharing Preferences

Notes: The dashed line marks the realized 2017 share $\tilde{\gamma}_{2017} = 0.349$; its intersection with the optimal curve indicates the value of η under which the observed allocation is SW-optimal.

native rule for sharing the IG transfer fund for a coal-producing county (H) is given by:

$$\hat{\gamma}_H(q_H) = \frac{4.3}{3.8q_H + 23.9} + 0.32 \tag{3.19}$$

This alternative rule highlights the relationship between coal production (q_H) and the optimal IGT share for coal-producing counties, reflecting how aid adjusts to coal production levels. It provides a benchmark for evaluating whether past IGT allocations achieved fiscal equalization and offers a theoretically grounded alternative for state governments to consider.

Figure 3.7 shows the SW-optimal IGT shares ($\gamma^*_H(q_H)$) over historical coal production since 2000 and the reazlied IGT shares $\tilde{\gamma}_H$ for each available survey year (2002, 2007, 2012, and 2017). Despite a steady decline in coal production during the 2010s, the redistribution share in 2012 ($\tilde{\gamma}_H(q_{H,2012}) = 0.391$) remained nearly identical to the share in 2007 (0.395). Strikingly, the transfer share to coal-producing counties significantly decreased from 2012 to 2017 ($\tilde{\gamma}_H(q_{H,2017}) = 0.349$), even as coal production fell sharply from 932 million tons in 2012 to 686 million tons in 2017.

This observed decrease in transfer share contradicts the recommendation of my alternative rule, which suggests that the share in 2017 ($\hat{\gamma}_H(q_{H,2017})$) should have been increased to 0.402 to better account for the sharp decline in coal production. This comparison suggests a possible misalignment between the historical policy and the fiscal equalization framework, indicating that a more responsive transfer system might better address economic shocks in coal-dependent communities.

Using the annually predicted coal production values from the Inflation Reduction Act (IRA) High-Uptake scenario, ranging from 539 million tons in 2025 to 249 million tons in 2050, I calculate how the alternative policy ($\hat{\gamma}_H$) would evolve under a long-term coal phase-down plan. The redistribution share is computed using the fiscal equalization rule in Eq. (3.18), assuming baseline parameters for tax rates and income effects. To explore the impact of changes in these parameters, I consider four alternative scenarios: (i) doubling the state coal tax rate (τ^s; Scenario A), (ii) doubling the state non-coal tax rate (σ^s; Scenario B), (iii) doubling the local non-coal tax rate ($\sigma^l = \sigma^l_H = \sigma^l_L$; Scenario C), or (iv) doubling the local income effect of coal production (m_H; Scenario D), while keeping all other parameters unchanged.

Figure 3.7 plots the SW-optimal redistribution share for coal counties, $\gamma^*_H(q_{H,t})$, along the historical path of coal production since 2000, together with the realized IGT shares $\tilde{\gamma}_H$ in survey years 2002, 2007, 2012, and 2017. The calibration matches the levels of historical transfers closely: in each survey year the observed share is near its SW-optimal counterpart. The temporal pattern of $\gamma^*_H(q_{H,t})$ is, however, distinctly cyclical. The optimal share rises during the coal boom of the early 2000s, peaks in the late 2000s, and then declines sharply through the 2010s as coal production contracts. From an interregional insurance perspective, this pattern is undesirable: coal counties receive a smaller fraction of the transfer pool precisely when their tax base is shrinking. An IGT system designed to insure region-specific commodity shocks would instead exhibit countercyclical behavior,

with the redistribution share to coal counties increasing as q_H falls.

To impose this countercyclical property, I introduce a fiscal-equalization rule, $\hat{\gamma}_H(q_H)$, defined in Eq. (3.18). Under this rule, the coal county's transfer share is mechanically linked to its relative revenue shortfall, so that a negative coal shock (a decline in q_H) increases $\hat{\gamma}_H$. Applied to the 2012–2017 downturn, the FE rule would have prescribed a higher redistribution share in 2017, indicating a misalignment between the historical general-purpose IGT system and its insurance objective.

Using the annually projected coal production path from the Inflation Reduction Act (IRA) High-Uptake scenario, which declines from 539 million tons in 2025 to 249 million tons in 2050, I then simulate how the FE policy, $\hat{\gamma}_H$, would evolve under a long-run coal phase-down. The right-hand portion of Figure 3.7 reports the resulting redistribution shares. Under the baseline parameterization, the FE rule starts from a substantially higher redistribution share than the continuation of the SW-optimal rule and increases gradually as coal production declines, before flattening once coal output becomes small. This delivers precisely the countercyclical pattern of support that is absent under the historical IGT formula.

To examine how different revenue instruments shape this countercyclical insurance, I consider four alternative FE scenarios: (A) doubling the local coal tax rate in the coal county ($2\times\tau_H^l$); (B) doubling the state non-coal tax rate ($2\times\sigma^s$); (C) doubling the local non-coal tax rate in the non-coal county ($2\times\sigma_L^l$); and (D) doubling the local income effect of coal production ($2\times m_H$), holding all other parameters fixed. Scenarios B and, in particular, C yield the highest redistribution shares over the transition, because strengthening non-coal tax bases, either at the state level or in the diversified county, enlarges the revenue pool that the FE rule directs to coal counties to equalize fiscal capacity. By contrast, Scenarios A and D reduce the redistribution share relative to the FE baseline: higher local coal taxes or a larger coal income multiplier increase own-source

revenue in the coal county and thus narrow the equalization gap to be filled by IGTs.

Taken together, these results yield several implications for IGT design during a coal phase-down. First, although the calibrated SW-optimal rule can account for the average level of historical transfers, its cyclical behavior is inconsistent with the insurance role of intergovernmental aid. Second, an explicit fiscal-equalization rule can restore countercyclical support by raising the transfer share for coal counties as their tax base erodes. Third, broadening non-coal tax bases, particularly in more diversified parts of the state, is especially effective for financing countercyclical redistribution while reducing reliance on the shrinking coal base. A combination of these instruments can deliver a more robust and equitable system of interregional insurance as the economy transitions away from coal.

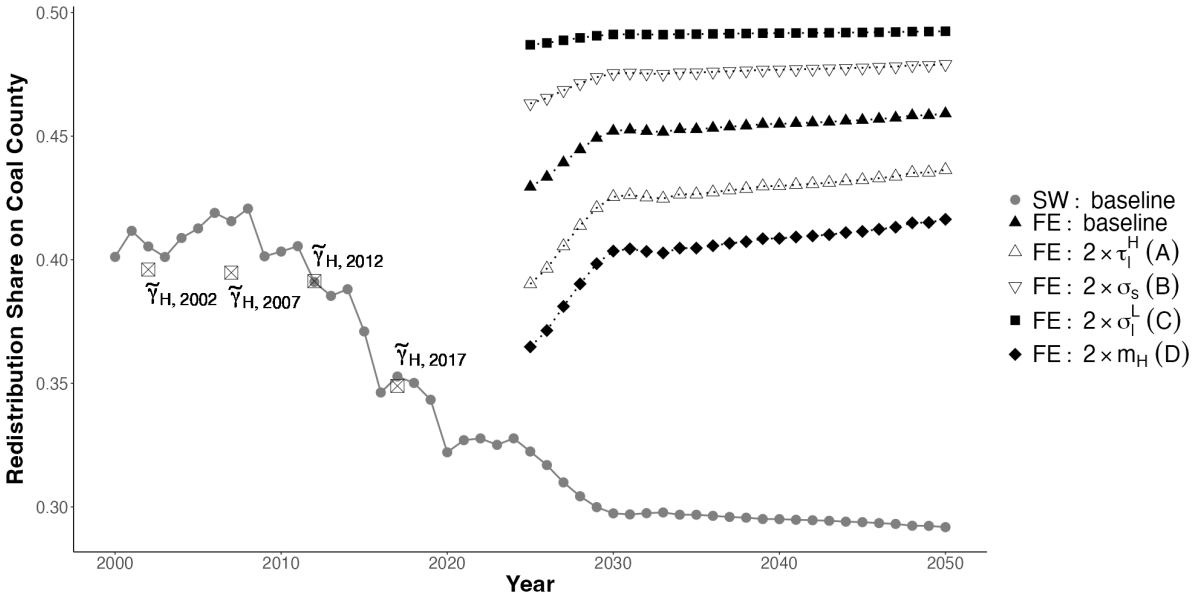


Figure 3.7: Fiscal-Equalization Policy with the IRA Coal Production Scenario

Notes: The dashed line is the historical coal production in MMst. The solid line represents the prediction for coal production in the IRA High-Uptake scenario.

3.8 Conclusion

The decline of the coal industry has sharply reduced local revenues from royalties, severance taxes, and related sources in coal-dependent communities in the US. Economic activity slows, jobs and people leave, and incomes fall, worsening fiscal stress. Intergovernmental transfers (IGTs) are not fully responsive, so spending on core services and infrastructure is cut. I find that coal declines also spill over to neighboring non-coal counties. Output, employment, and firm counts drop, with effects that fade with distance. General-purpose IGTs fall across buffers, while project-specific matching grants (e.g., infrastructure, education) remain stable. Spending shifts toward safety services, with smaller declines in health and welfare close to coal areas; public transit is largely unchanged. Falling IGTs to coal counties reflect shrinking state revenues from coal taxes, allocation formulas tied to local income and population, and out-migration that erodes political influence. Together these forces reduce transfers just as needs rise.

A social-welfare planner might prioritize coal counties that face large income and population losses, although this could create trade-offs with broader equity and efficiency objectives. The fiscal-equalization (FE) rule adjusts redistribution shares with production and may offer a more responsive mechanism; expanding non-coal tax bases can increase the capacity to support coal communities while maintaining statewide equity. Policy design could combine targeted federal assistance with state reforms that make IGT formulas more shock-responsive (for example, triggers based on distress or population loss). Energy-transition policies might also include provisions to ensure coal communities can access opportunities in renewables and related industries.

Chapter 4

Beyond Extraction: A Research Agenda for the Decarbonization of the Industrial Economy

4.1 Synthesis of the Dissertation

The global transition toward a net-zero economy represents a fundamental restructuring of the industrial landscape. The preceding chapters have empirically documented that the phase-out of legacy fossil fuel industries is not merely a frictionless technological substitution; rather, it imposes severe, localized frictions that cascade across generations and institutions. By examining the socioeconomic incidence of industrial shifts, this research has shown that displaced workers in extraction sectors suffer persistent earnings scars driven by the loss of highly specific human capital and severe spatial mobility constraints. Furthermore, these labor market frictions are inextricably linked to intergenerational consequences. As local economic opportunities evaporate, youth in fossil fuel-dependent communities face distinct educational scarring and behavioral health impacts, trapped in

the crosshairs of a localized resource curse. Compounding these individual and family-level burdens, the fiscal resilience of local governments is severely tested by the volatility of royalty revenues and the looming threat of municipal debt overhangs accumulated during prior energy booms.

Together, these findings construct a comprehensive "transition risk" framework. They reveal that the true economic cost of decarbonization cannot be fully captured by aggregate employment statistics alone. Instead, evaluating the welfare impacts of the energy transition requires precise, micro-level evidence on how the decay of localized extraction sectors triggers a downward spiral of depressed wages, eroding public services, and demographic out-migration. However, the dynamics uncovered in fossil fuel extraction communities represent only the initial frontier of the climate transition. As the global push to mitigate climate change accelerates, the mandate to decarbonize will inevitably permeate the broader industrial economy, threatening to destabilize a much wider array of legacy sectors.

The purpose of this concluding chapter is to pivot from the immediate findings of this dissertation toward a forward-looking empirical research agenda. If policymakers are to design effective, place-based interventions and fiscal equalization transfers, which are often summarized under the umbrella of a *Just Transition*, the economics literature need to deepen and broaden its understanding of industrial decay. Future research can expand the transition risk framework beyond extraction-anchored communities to encompass downstream, carbon-intensive manufacturing sectors that face parallel, yet structurally distinct, economic shocks. Furthermore, it is critical for future empirical work to rigorously disentangle the specific drivers of this decline, distinguishing between the endogenous market forces of technological change and the exogenous, permanent shocks of environmental policy. By outlining these frontiers across labor dynamics, public finance, and political economy, this chapter charts a course for the next wave of literature on the

socioeconomic costs of the energy transition.

4.2 Advanced Labor Market Dynamics and Reallocation Frictions

In Chapter 1, I documented the severe earnings scars and prolonged unemployment spells experienced by displaced fossil fuel workers. My empirical findings revealed that these transitional costs were largely driven by the highly specific nature of human capital in extractive industries and the profound geographic isolation of these resource-dependent communities. As my research agenda expands to encompass the decarbonization of downstream, carbon-intensive manufacturing, a central objective of my future work is to evaluate how these advanced labor market dynamics evolve in fundamentally different industrial contexts. Workers in sectors such as steel production, petrochemicals, or internal combustion automotive manufacturing possess unique skill sets that may exhibit entirely different transferability profiles compared to coal miners or oil rig operators. I plan to empirically test whether the skills acquired in heavy manufacturing offer a smoother transition into the emerging green economy, or if these workers face a similarly devastating depreciation of their human capital premiums.

To explore these reallocation frictions, I intend to leverage detailed occupational task data alongside linked employer-employee administrative records to map the precise skill distances between legacy manufacturing jobs and growing low-carbon occupations. While a fossil fuel extraction worker's expertise is intrinsically tied to geologic resource recovery, an automotive assembly worker or a chemical plant technician frequently utilizes mechanical, electrical, and process engineering skills. These competencies might seamlessly translate into electric vehicle manufacturing, advanced battery production, or wind turbine

assembly. By estimating the elasticity of these skills across different sectors, my future research will assess the efficacy of worker retraining initiatives. I aim to uncover whether the broader labor market naturally reabsorbs these displaced manufacturing workers without significant friction, or if the loss of highly tenured, often unionized positions inevitably leads to permanent downward wage mobility.

Crucially, these labor reallocations do not occur in a vacuum; they are dictated by employer behavior. To that end, my ongoing project expands this framework by examining the direct role of firms in mediating the labor costs of the energy transition. Utilizing firm-level finance data combined with matched worker-firm administrative records, I am analyzing how companies respond to regulatory shocks, specifically using the Clean Air Act as an empirical setting. Examining the firm side is a highly compelling frontier because the firm is the actual agent absorbing the environmental compliance cost. While traditional transition literature focuses heavily on worker-side characteristics, such as age, tenure, or skill, it often treats the employer as a black box. In reality, a firm's financial health, capital structure, and market power fundamentally determine how a regulatory shock is processed. For instance, a financially constrained firm might be forced to respond to new environmental regulations with immediate mass layoffs, whereas a well-capitalized firm might absorb the compliance costs, invest in abatement technology, or internally reallocate its workforce to greener production lines. By linking corporate financial frictions to individual worker outcomes, this project reveals how the precise nature of labor scarring is engineered at the firm level.

Beyond skill specificity and firm-level behavior, the spatial distribution of these economic shocks represents another vital dimension of my upcoming research. Fossil fuel extraction is typically constrained to rural or remote regions, meaning displaced workers face immense spatial frictions; to find equivalent employment, they frequently have to uproot their families and migrate away from established social safety nets. Conversely,

carbon-intensive manufacturing facilities are often embedded within larger, more diversified urban or suburban labor markets. I plan to investigate how this spatial proximity to alternative employment opportunities mitigates or alters the nature of reallocation frictions. By modeling localized labor market dynamics, I will analyze whether the density of a metropolitan economy provides an adequate buffer against the closure of a major industrial plant. This spatial analysis will allow me to identify exactly how place-based policies and wage insurance programs can be optimally tailored to fit the distinct geographic realities of various industrial hubs navigating the energy transition.

4.3 The Resilience of Public Finance

In Chapters 2 and 3, I highlighted the precarious nature of local public finance in fossil fuel extraction communities, demonstrating how reliance on volatile royalty payments and the accumulation of municipal debt create severe transition risks. As I pivot my research toward downstream carbon-intensive manufacturing sectors, I plan to explore how this fiscal vulnerability manifests in deeply rooted industrial hubs. Unlike extraction colonies, legacy manufacturing cities do not typically rely on severance taxes or direct natural resource royalties. Instead, their fiscal health is inextricably tethered to massive commercial property valuations, corporate tax receipts, and the robust sales and income taxes generated by a dense, historically unionized workforce. My future research will investigate the structural erosion of these distinct revenue streams when heavy manufacturing facilities, such as legacy steel mills or internal combustion engine assembly plants, face market-driven or policy-induced closures.

A central component of this upcoming work will involve quantifying the *stranded asset* phenomenon and its cascading impact on municipal balance sheets. When a heavy industrial plant shutters, it leaves behind a massive, highly specialized, and

often environmentally compromised footprint that cannot be easily repurposed by local developers. I aim to empirically measure how this sudden collapse in commercial property value contracts the local tax base. This dynamic creates a dangerous fiscal trap: while tax revenues plummet, a municipality's fixed financial obligations, including debt servicing for previously built utility infrastructure and pension liabilities for public workers, remain rigidly in place. To capture this mechanism, I plan to utilize municipal bond market data to assess exactly how institutional investors price this specific transition risk. I will explore whether the looming threat of industrial decay artificially inflates local borrowing costs and paralyzes civic investment long before a factory actually halts production.

Finally, this research trajectory is designed to critically evaluate the efficacy of modern place-based policies and fiscal equalization frameworks in a non-extractive context. Current federal initiatives, such as the advanced manufacturing tax credits in the Inflation Reduction Act, frequently target support toward designated "Energy Communities." I will analyze whether these transfer rules, which were heavily influenced by the immediate distress of coal and oil regions, adequately serve the distinct fiscal architecture of legacy manufacturing hubs. By econometric modeling of various revenue replacement strategies, my goal is to provide actionable, micro-level evidence on how to design intergovernmental transfers that prevent the fiscal collapse of industrial cities. Understanding how to cushion this unique revenue shock is essential to ensuring that these communities retain the civic capacity to invest in schools, public health, and the economic diversification required for their long-term survival.

4.4 Political Economy and Institutional Consequences

In the preceding chapters of my dissertation, I documented how localized economic shocks in fossil fuel communities create deep social and fiscal scars. However, economic decay does not occur in a political vacuum. When workers lose sector-specific premiums, youth face severe educational scarring, and municipalities confront crippling debt overhangs, these concentrated economic losses inevitably spill over into the political arena. My future research agenda will explore these political economy and institutional consequences. The energy transition presents a uniquely fascinating setting to study these dynamics because it represents a structural shift where the macroeconomic and climate benefits are globally diffuse, but the economic costs are intensely local and geographically concentrated. This stark asymmetry creates powerful local incentives for political resistance, making the energy transition an ideal laboratory to observe how structural economic decline reshapes voter preferences and institutional power dynamics.

A critical institutional dimension I plan to investigate is the impact of industrial decline on collective bargaining power and union density. Chapter 1 highlighted the severe earnings scars caused by the loss of specific human capital among extraction workers. Moving forward, I will apply this lens to carbon-intensive manufacturing hubs, such as legacy steel or automotive cities, where these jobs have historically served as the bedrock of organized labor. As market forces and environmental regulations cause these facilities to downsize, the resulting loss of unionized jobs threatens to fundamentally erode regional labor power. I aim to empirically test how this institutional decay affects not only the displaced workers but the broader local labor market. By analyzing wage spillover effects and changes in local political mobilization, I will explore whether the transition to a greener economy inadvertently weakens the institutional structures that have historically

protected worker welfare and advocated for equitable labor policies.

Furthermore, I intend to study the electoral feedback loops generated by these concentrated transition costs. Chapter 3 demonstrated how municipal fiscal crises severely constrain local governance and the provision of public goods. When communities face this simultaneous loss of economic opportunity and civic capacity, they become highly vulnerable to political polarization. As domestic manufacturing faces new competitive frictions from international climate policies like Carbon Border Adjustment Mechanisms, local economies become acutely sensitive to global trade dynamics. I will investigate how these concentrated economic losses translate into shifting political preferences at the ballot box. Specifically, I plan to analyze whether voters in heavily impacted industrial hubs increasingly support protectionist trade policies or populist platforms as a defensive response to perceived regulatory overreach.

Understanding these political feedback mechanisms is essential for the broader economics literature. If the distributional costs of the energy transition are continuously concentrated in politically pivotal regions, the resulting electoral backlash could easily stall or reverse ambitious climate targets. By mapping the political geography of industrial decline, my goal is to provide empirical insights into how policymakers can design transition assistance programs that not only alleviate economic distress but also sustain the political consensus required for a lasting green transition.

Appendix A

Appendix to Chapter 1

A.1 Details and Proofs for the Conceptual Framework

A.1.1 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:

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

$$\tilde{L}_2^{F,A} = \underbrace{n_1^{F,A} \int_{0}^{\theta^*} \left[1 - M^F(\theta)\right] d\theta}_{\text{low-type nonswitchers stay in AF}} + \underbrace{n_1^{F,A} \int_{\theta^*}^{1} \left[1 - P(\theta)\right] \left[1 - M^F(\theta) - M^N(\theta)\right] d\theta}_{\text{high-type nonswitchers stay in AF}}, \tag{A.2}$$

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

$$\tilde{L}_2^{F,B} = \underbrace{n_1^{F,B}}_{\text{incumbents}} + \underbrace{n_1^{F,A} \int_{0}^{\theta^*} M^F(\theta)\, d\theta}_{\text{low-type movers to BF}} + \underbrace{n_1^{F,A} \int_{\theta^*}^{1} \left[1 - P(\theta)\right] M^F(\theta)\, d\theta}_{\text{high-type movers to BF}}. \tag{A.4}$$

A.1.2 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.1.3 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

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

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.1.4 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.1.5 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).

A.2 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 ($\Delta \log(\sum_{c' \neq c} Emp^{FF}_{c',t})$). Mathematically, the Rotemberg weights simplify to

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

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.

A.3 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 ($\Delta \log(y_{t-1})$) ex-

plicitly, I express the model purely in terms of current and past changes in $\log(x_t)$:

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

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:

$$\Delta \log(y_t) = \gamma \Delta \log(x_t) + \gamma\rho \Delta \log(x_{t-1}) + \gamma\rho^2 \Delta \log(x_{t-2}) + \cdots + \varepsilon_t. \tag{A.5}$$

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

$$\Delta \log(y_t) = \sum_{k=0}^{K} \beta_k \Delta \log(x_{t-k}) + \varepsilon_t, \tag{A.6}$$

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

$$\sum_{k=0}^{K} \beta_k. \tag{A.7}$$

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:

$$\sum_{k=0}^{K} \beta_k \approx \gamma(1 + \rho + \rho^2 + \dots) = \frac{\gamma}{1-\rho}. \tag{A.8}$$

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:

$$\sum_{k=0}^{K} \beta_k \approx \beta_{LR} \tag{A.9}$$

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.

■

A.4 Cournot–Oligopsony Microfoundation

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

$$w(L) = \chi\, L^{1/\varepsilon}, \qquad \varepsilon > 0, \tag{A.10}$$

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

$$ME_i = w(L) + L_i\, w'(L) = w(L)\Big(1 + \frac{s_i}{\varepsilon}\Big). \tag{A.11}$$

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

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

which implies a firm-level markdown

$$\mu_i \equiv \frac{w(L)}{\mathrm{MRPL}_i} = \frac{1}{1 + \frac{s_i}{\varepsilon}} \in (0, 1]. \tag{A.13}$$

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

$$\mu^{\text{market}} \equiv \frac{w(L)}{\sum_{i=1}^{N} s_i \mathrm{MRPL}_i}. \tag{A.14}$$

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

$$\sum_{i=1}^{N} s_i \mathrm{MRPL}_i = w(L) \sum_{i=1}^{N} s_i \Big(1 + \frac{s_i}{\varepsilon}\Big) = w(L)\Big(1 + \frac{\mathrm{HHI}}{\varepsilon}\Big), \tag{A.15}$$

so I obtain the HHI–markdown map

$$\mu^{\text{market}} = \frac{1}{1 + \frac{\mathrm{HHI}}{\varepsilon}}. \tag{A.16}$$

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

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

Remark. If instead one averages firm-level markdowns,

$$\sum_{i=1}^{N} s_i \mu_i = \sum_{i=1}^{N} \frac{s_i}{1 + \frac{s_i}{\varepsilon}}, \tag{A.18}$$

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

$$\sum_{i=1}^{N} \frac{s_i}{1 + \frac{s_i}{\varepsilon}} \geq \frac{1}{\sum_{i=1}^{N} s_i (1 + \frac{s_i}{\varepsilon})} = \frac{1}{1 + \frac{\text{HHI}}{\varepsilon}} = \mu^{\text{market}}, \tag{A.19}$$

with equality under symmetry.

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

$$w_t^{j,k} = \mu_t^{j,k} \alpha_j p_{j,t} \big(\tilde{L}_{j,k,t}\big)^{\alpha_j - 1}, \tag{A.20}$$

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 $\mu = \varepsilon/(\varepsilon + 1)$.

A.5 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.

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	
lag (k)	Oil & Gas Extraction (1)	Coal Mining (2)	Support Activites (3)	Drilling Wells (4)	Female (5)	Male (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)				
lag (k)	(1)	(2)	(3)	Q1 (4)	Q2 (5)	Q3 (6)	Q4 (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)
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)
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)
	(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: $\leq$ 2011		Separation year: $\geq$ 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 ≥ 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.

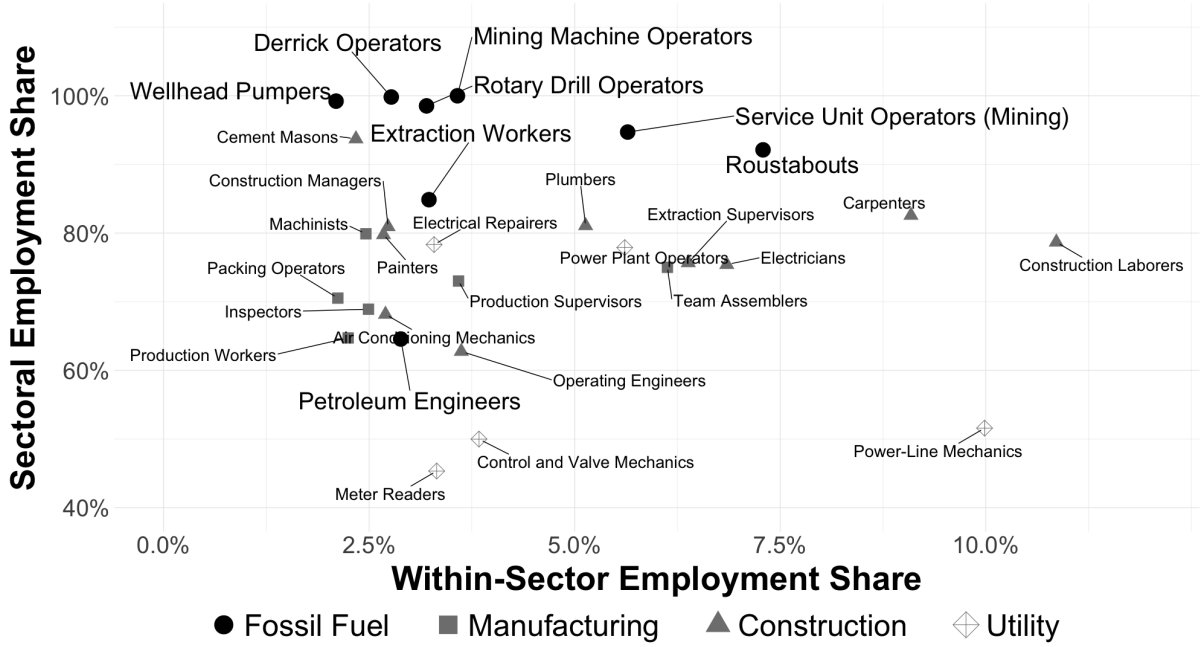


Figure A.1: Skill Transferability of Sector-Specific Occupations

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.

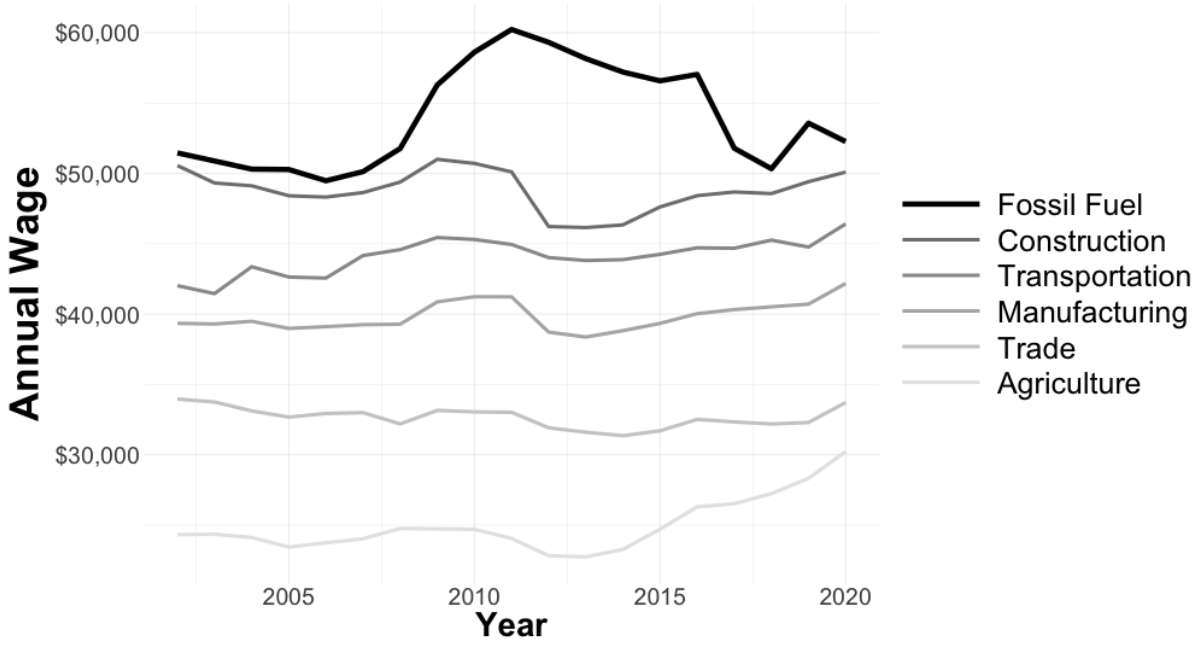


Figure A.2: Annual Wage by Sector

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

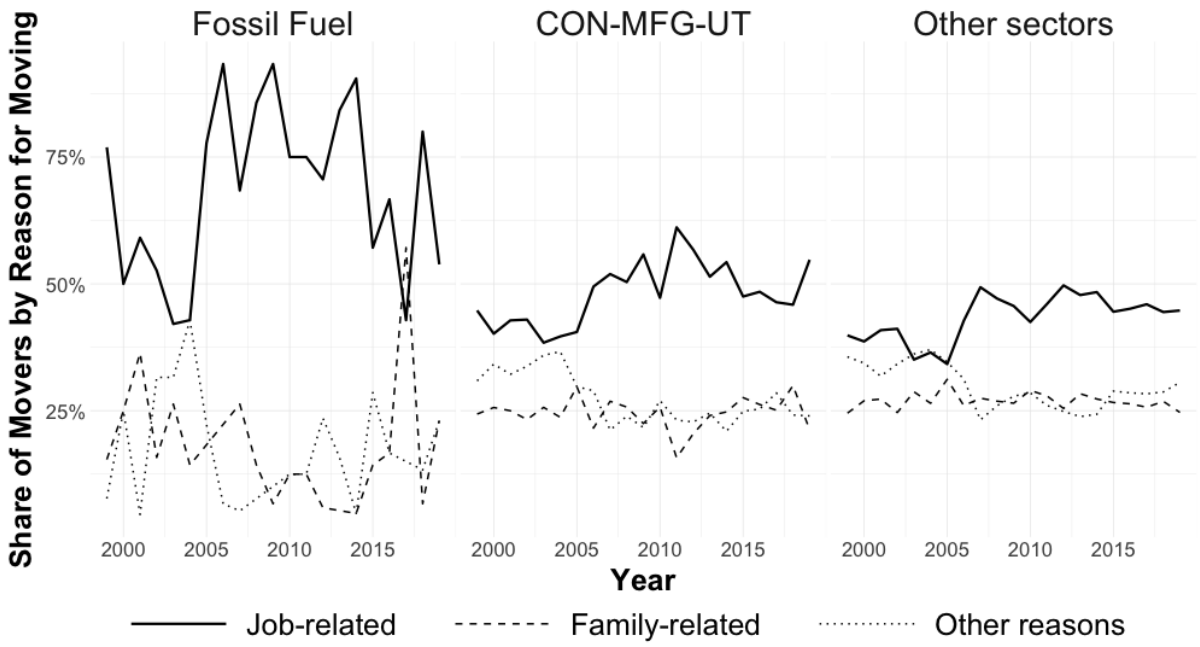


Figure A.3: Interstate Mobility by Reason for Moving Across Sectors

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).

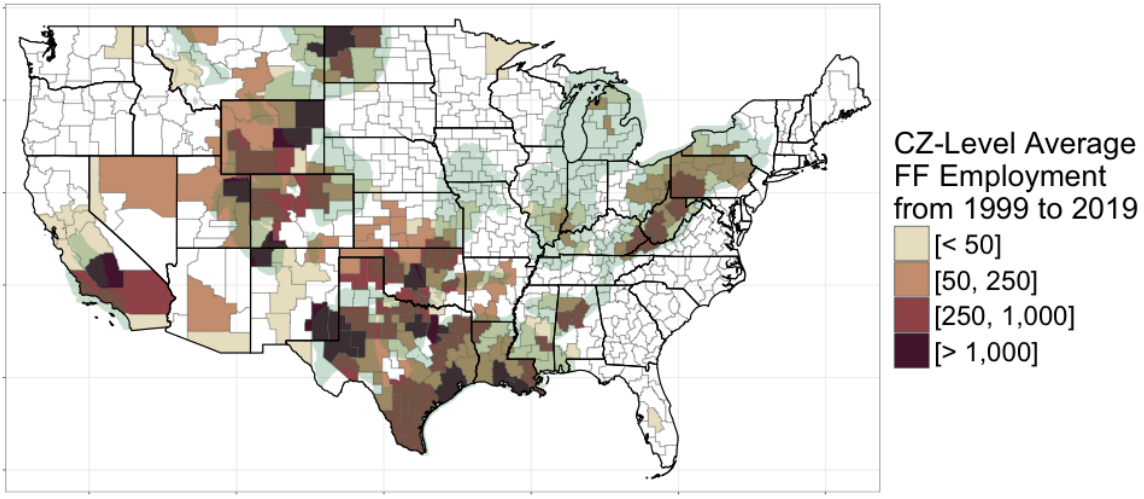


Figure A.4: Fossil Fuel Reserves and CZ-Level Fossil Fuel Employers

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.

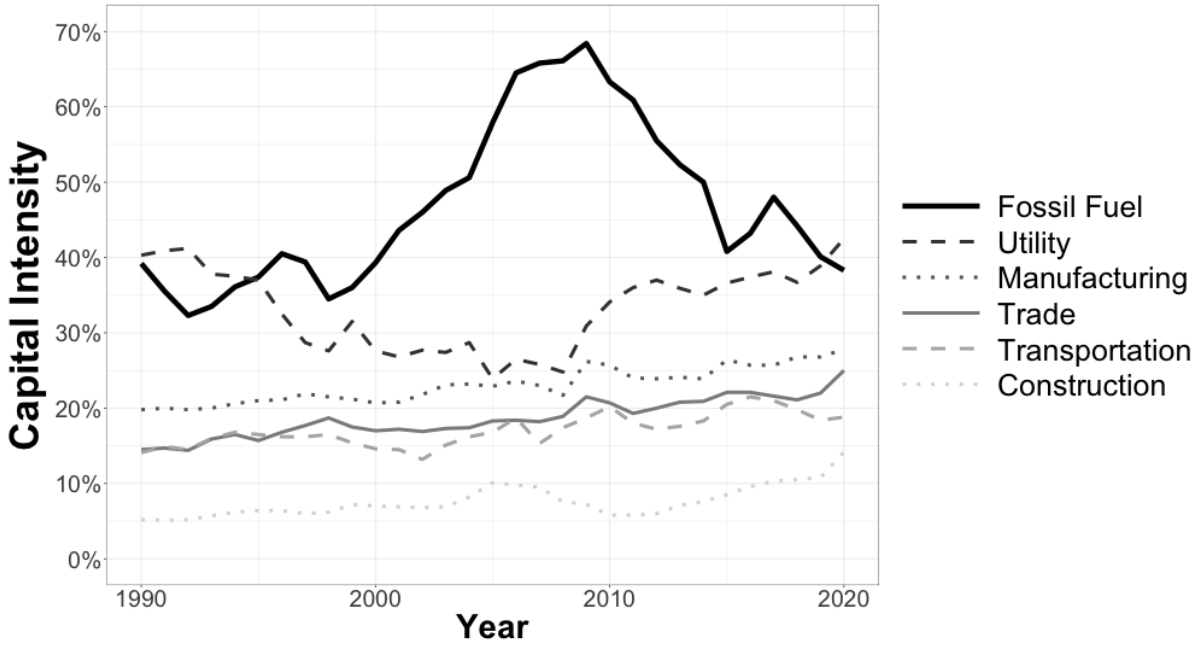


Figure A.5: Capital Intensity by Sector

Notes: Data source: U.S. BLS.

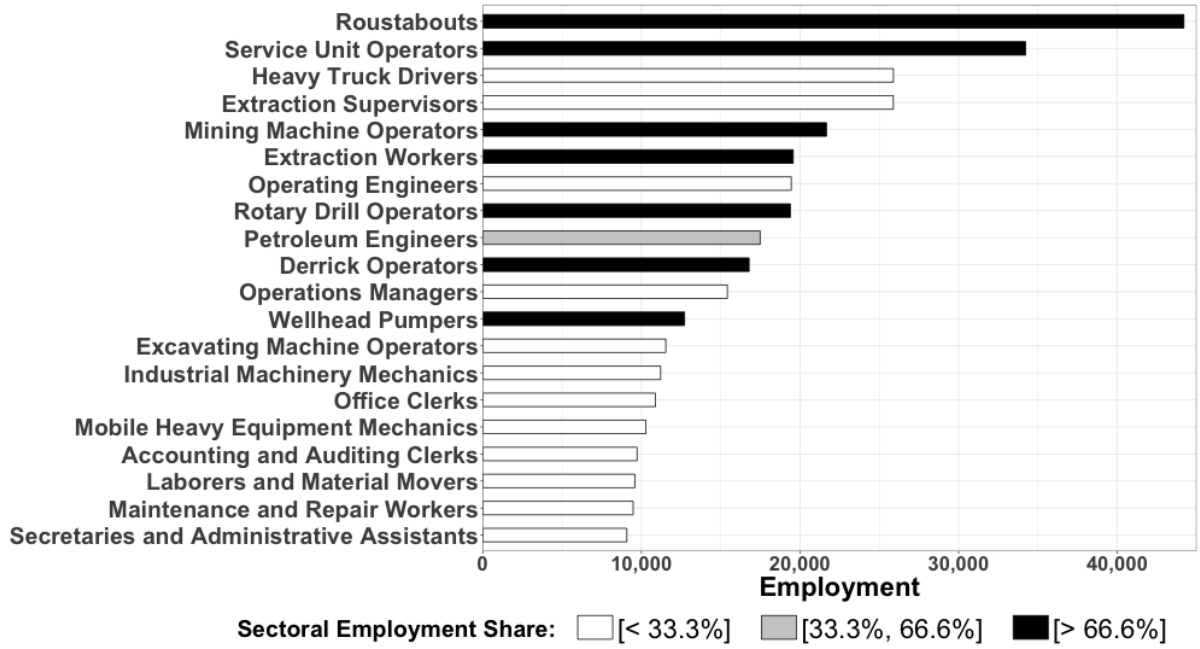


Figure A.6: Distribution of Fossil Fuel Occupations

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

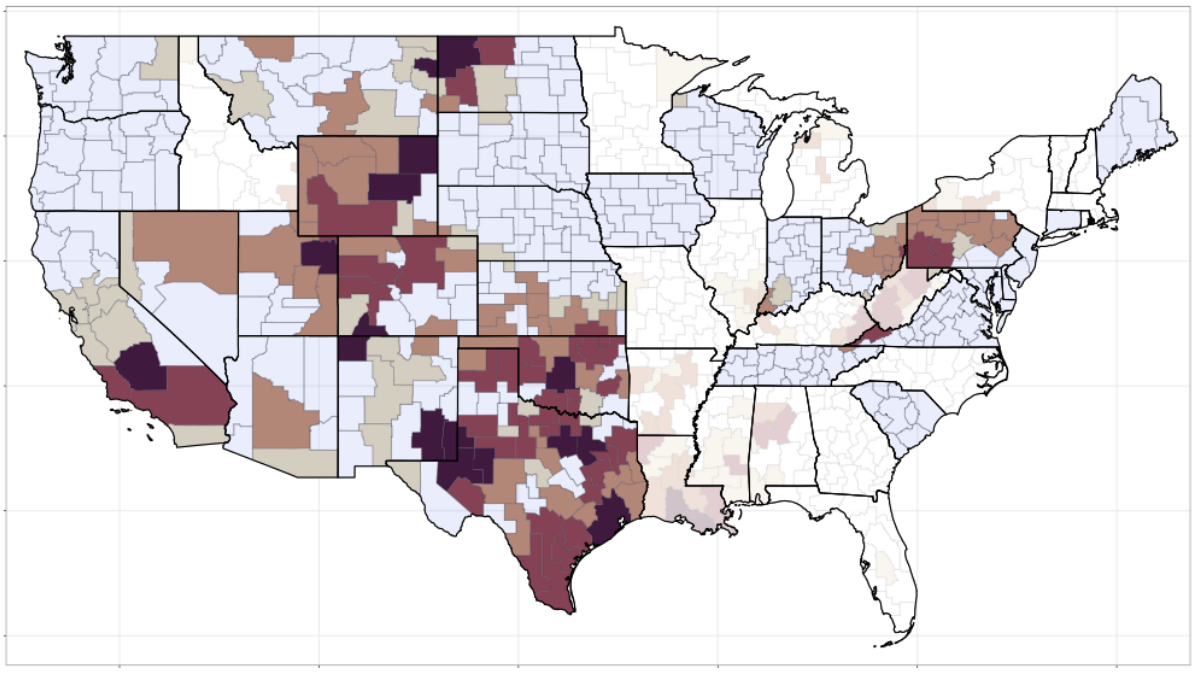


Figure A.7: Fossil Fuel Employment in LEHD-Approved States

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

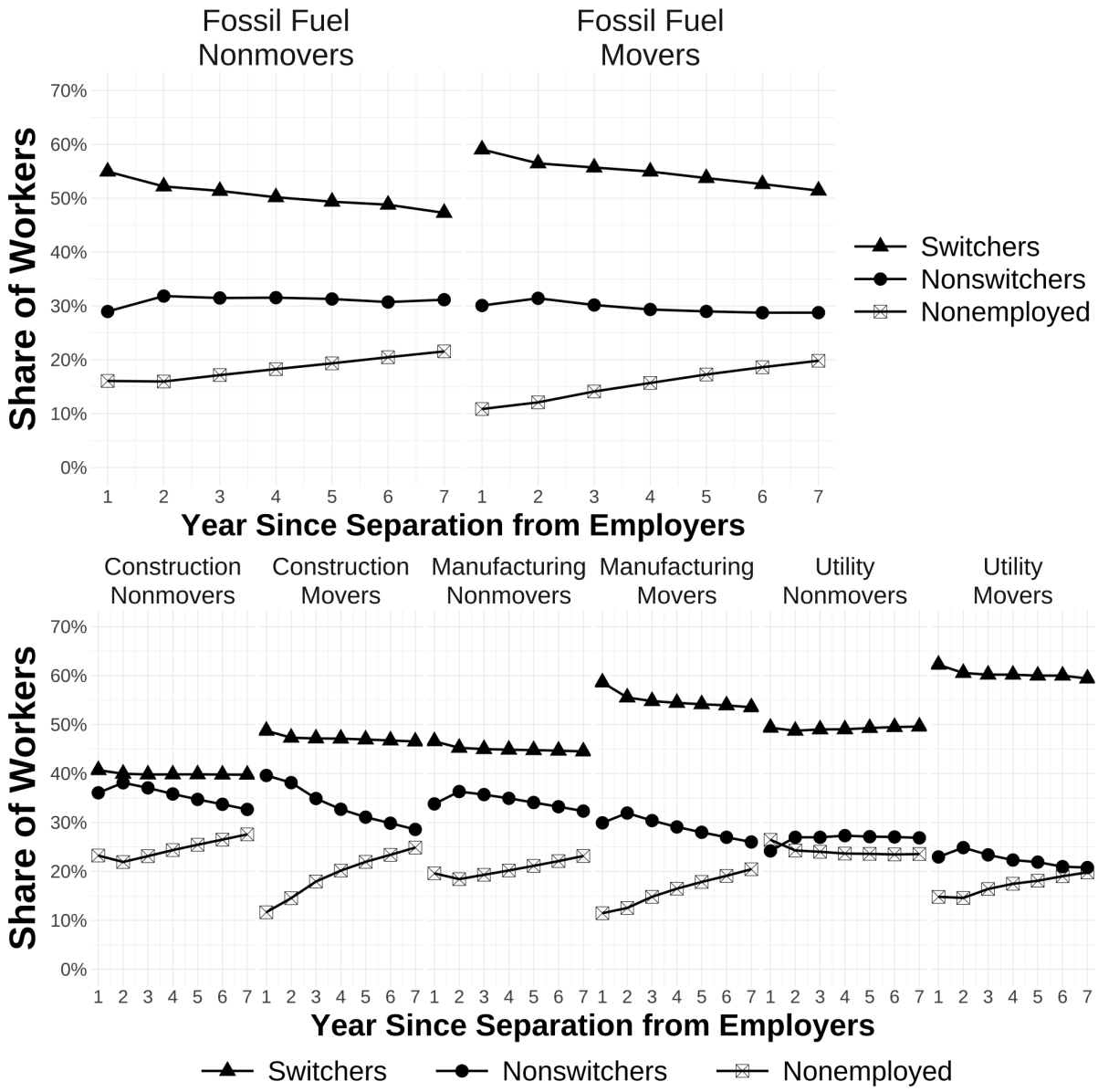


Figure A.8: Sectoral Employment Transitions Conditional on Geographic Reallocation

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.

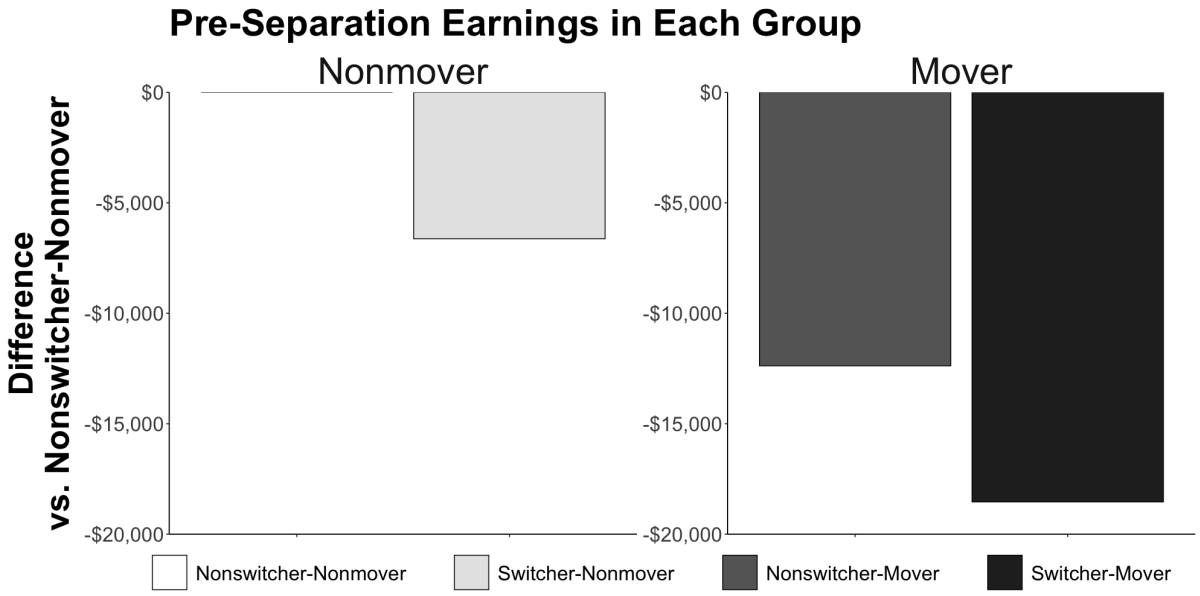


Figure A.9: Differences in Pre-Separation Earnings across Worker Groups

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

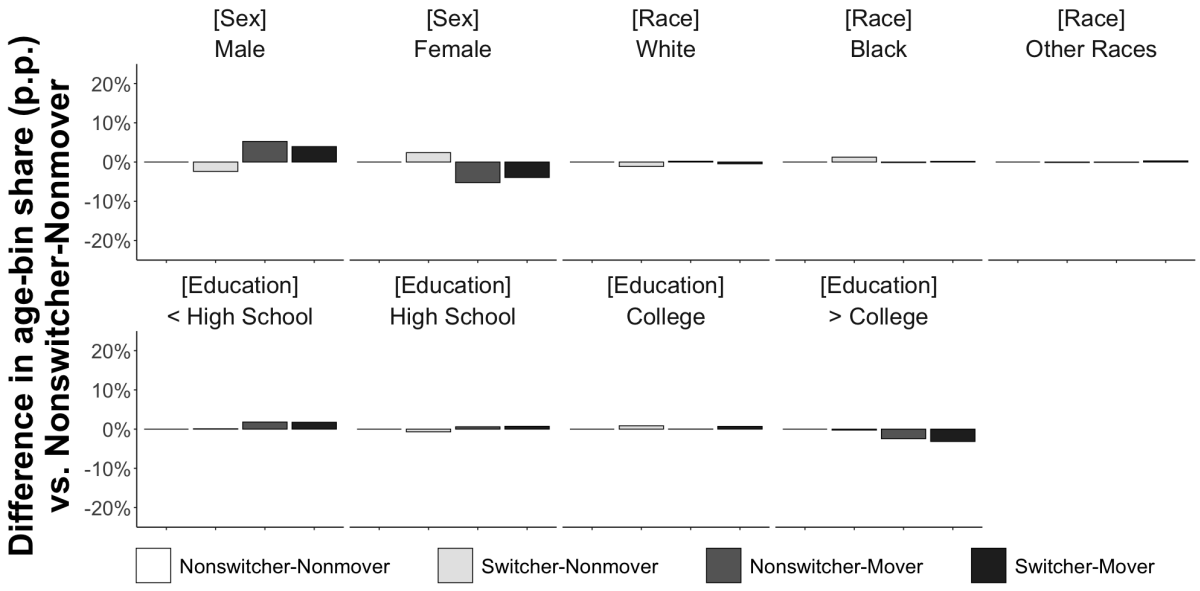


Figure A.10: Sex, Race, and Education Level Composition Differences across Worker Groups

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.

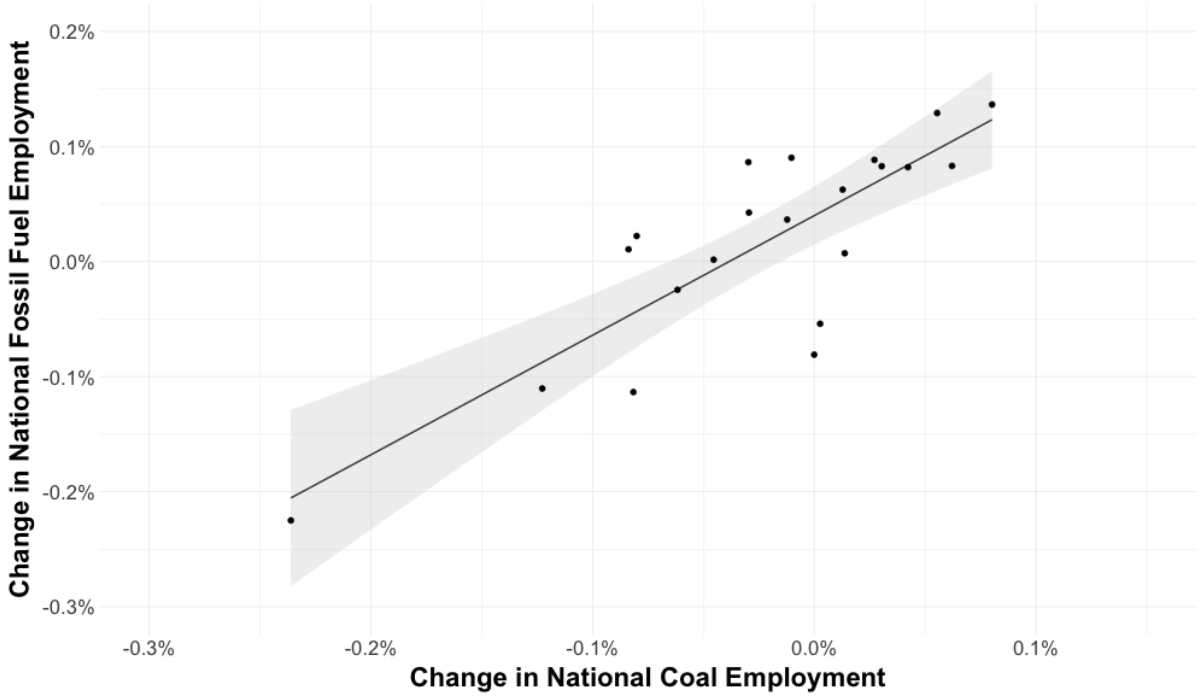


Figure A.11: Annual Change in National Fossil Fuel and Coal Employment

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

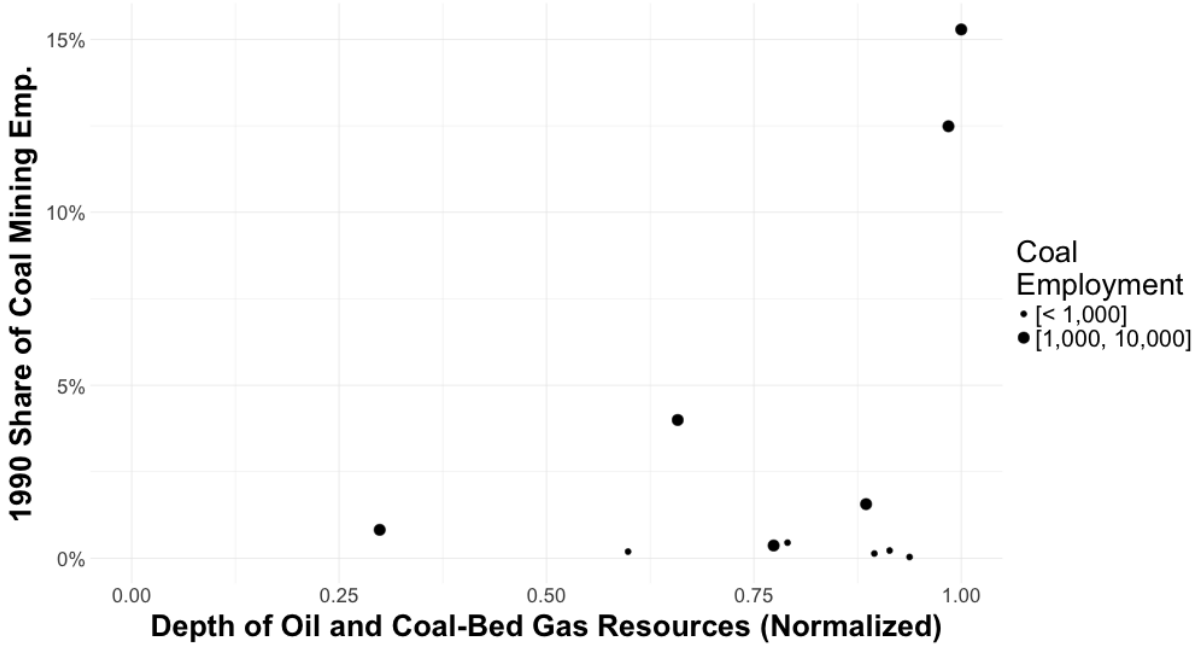


Figure A.12: Lagged Coal Mining Employment Share (1990) and Depth of Fossil Fuel Reserves

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

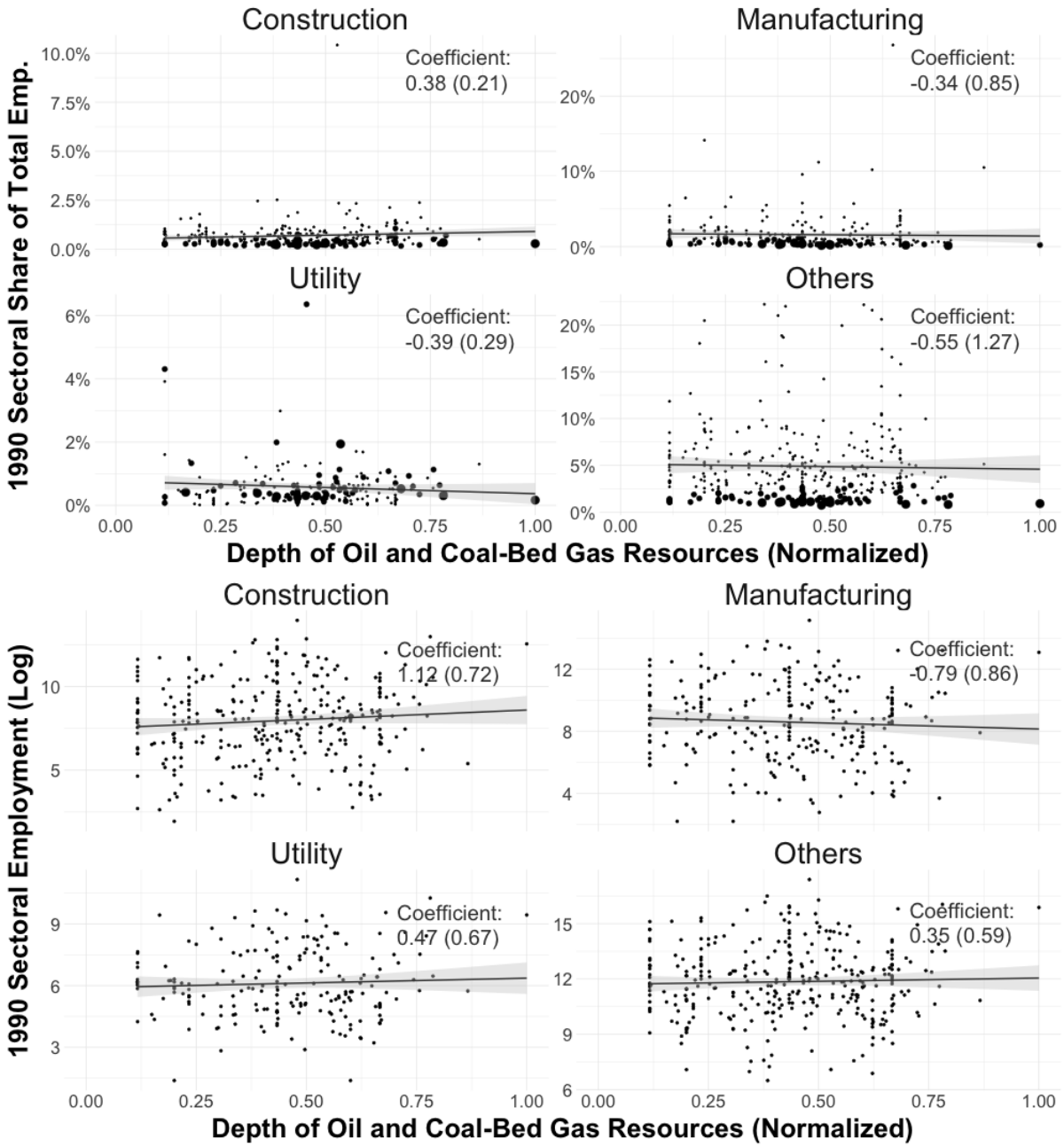


Figure A.13: Exogeneity of the FF Labor Demand Shock Variable: Sectoral Employment Share (Top) and Level (Bottom)

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

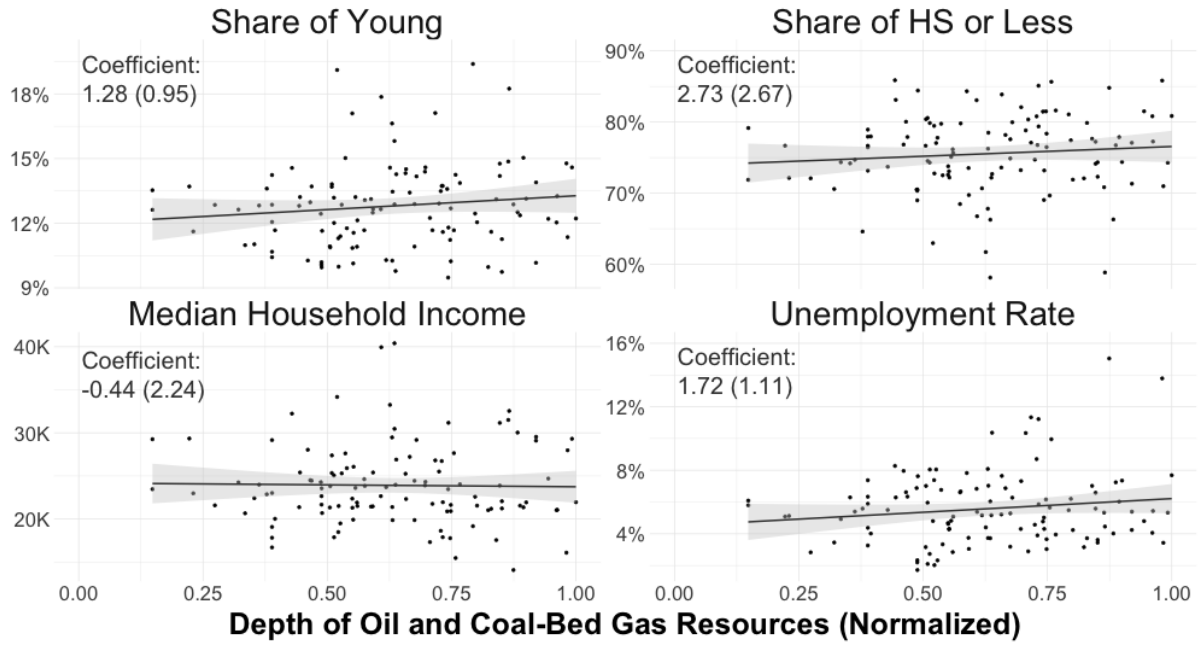


Figure A.14: Exogeneity of the FF Labor Demand Shock Variable: Socioeconomic Indicators

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

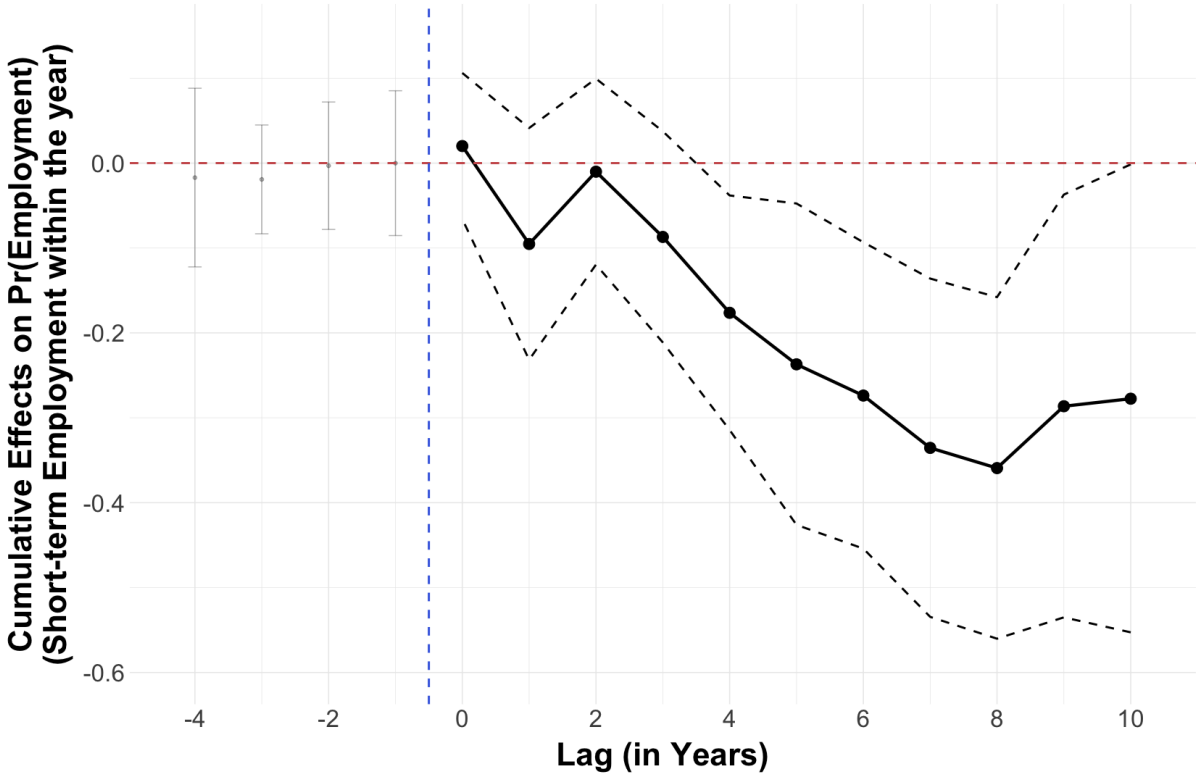


Figure A.15: Fossil Fuel Labor Demand Shocks and Probability of Short-Term Employment

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.

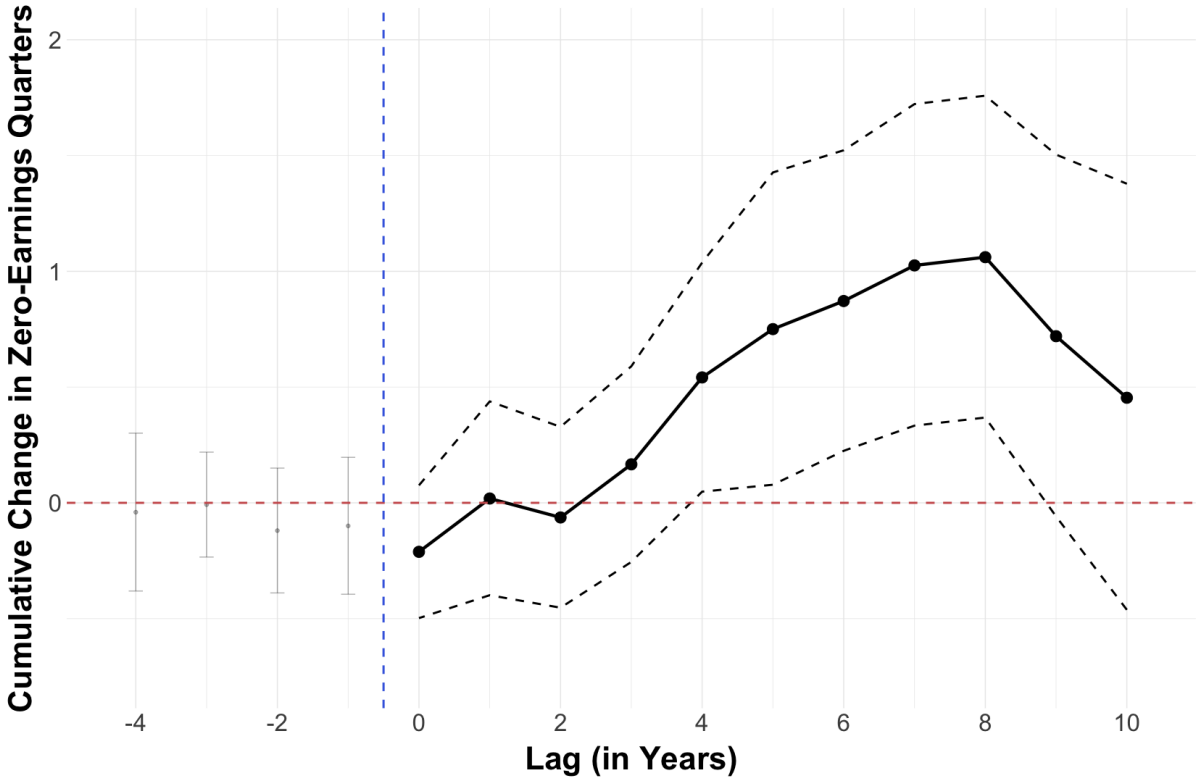


Figure A.16: Fossil Fuel Labor Demand Shocks and Nonemployment Duration

Notes: A detailed summary of all estimates can be found in Table 1.1.

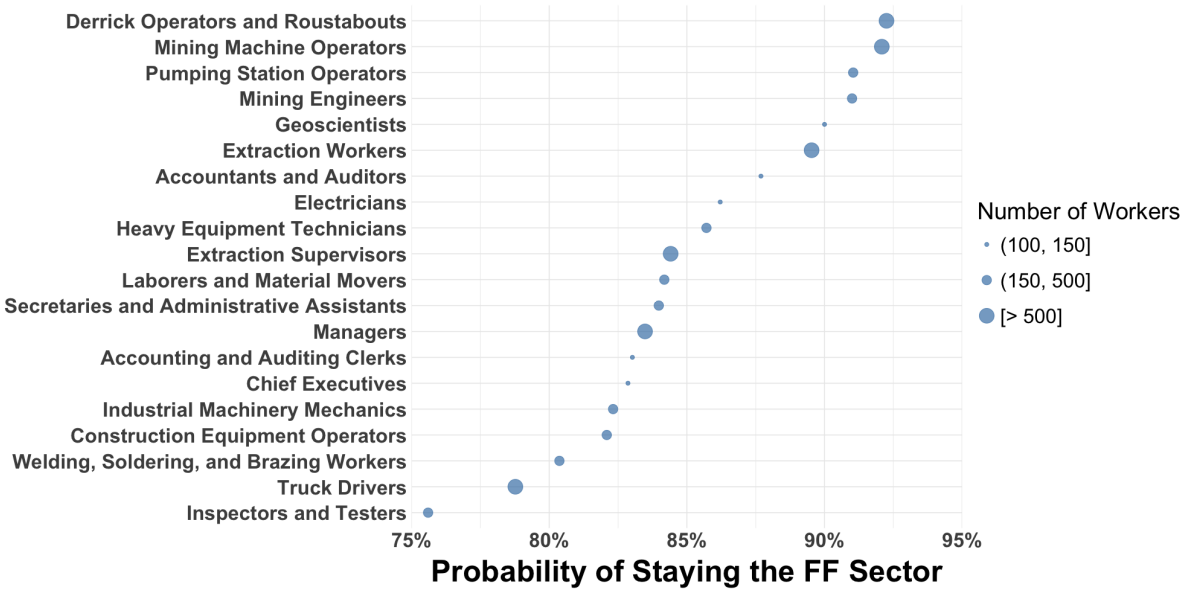


Figure A.17: Probability of Staying the FF Sector

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

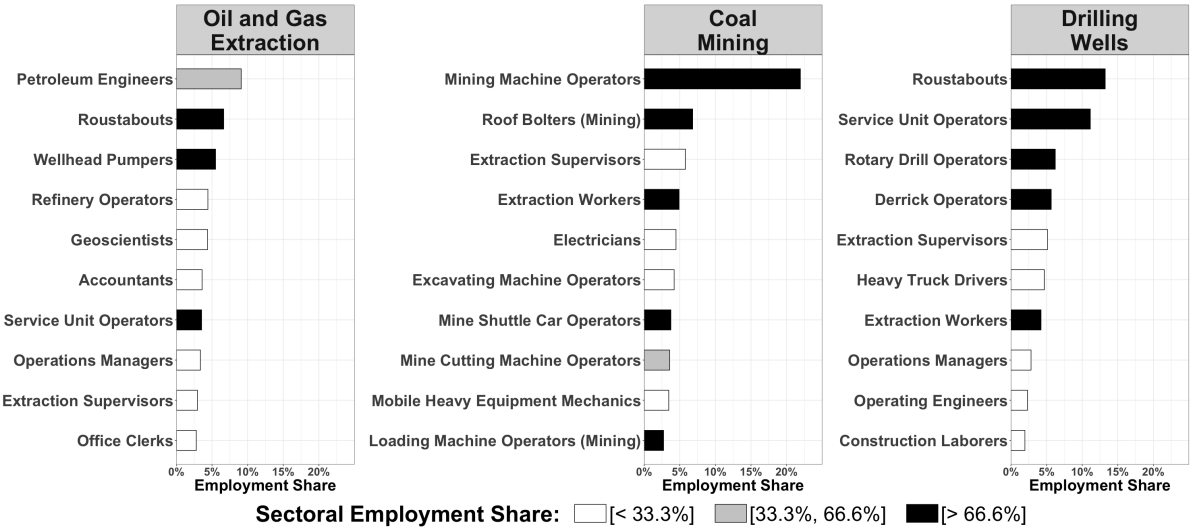


Figure A.18: Distribution of Fossil Fuel Occupations by Subsector

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

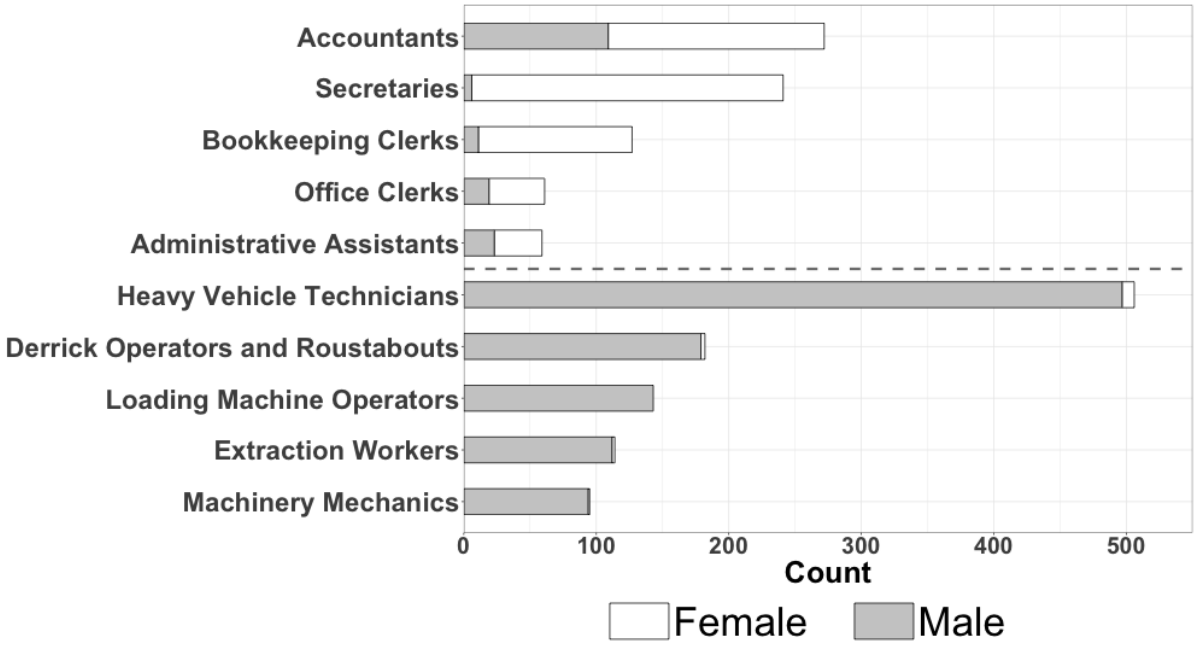


Figure A.19: Distribution of Fossil Fuel Occupations by Sex

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).

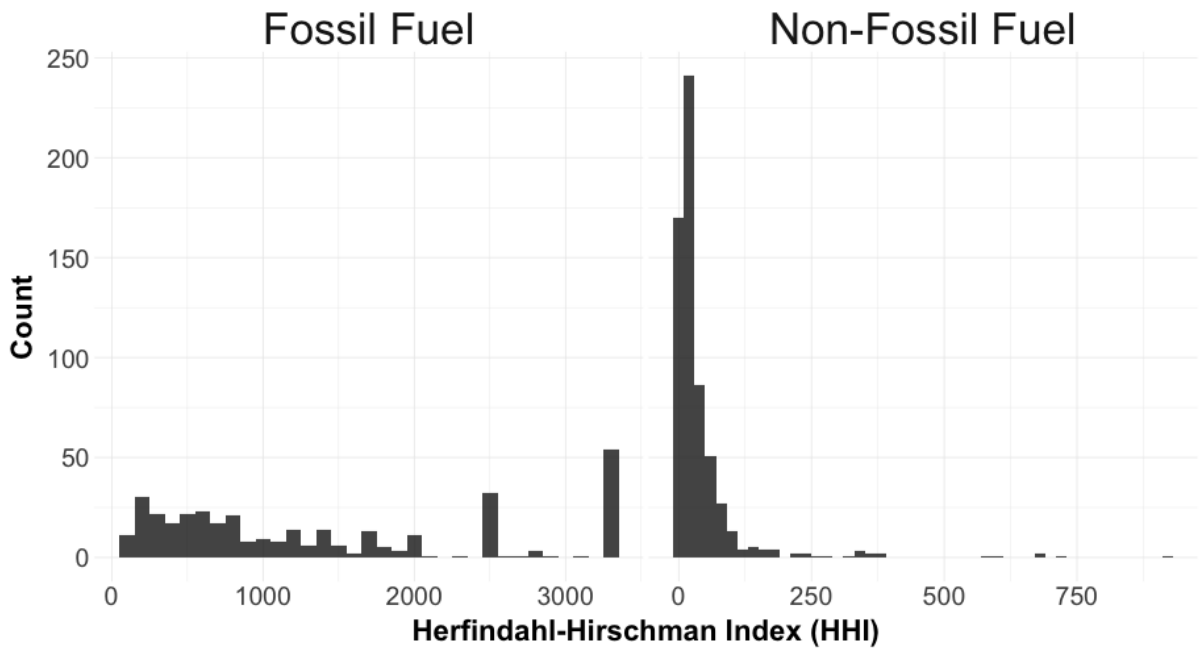


Figure A.20: CZ-Level Fossil Fuel Employer Concentration

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.

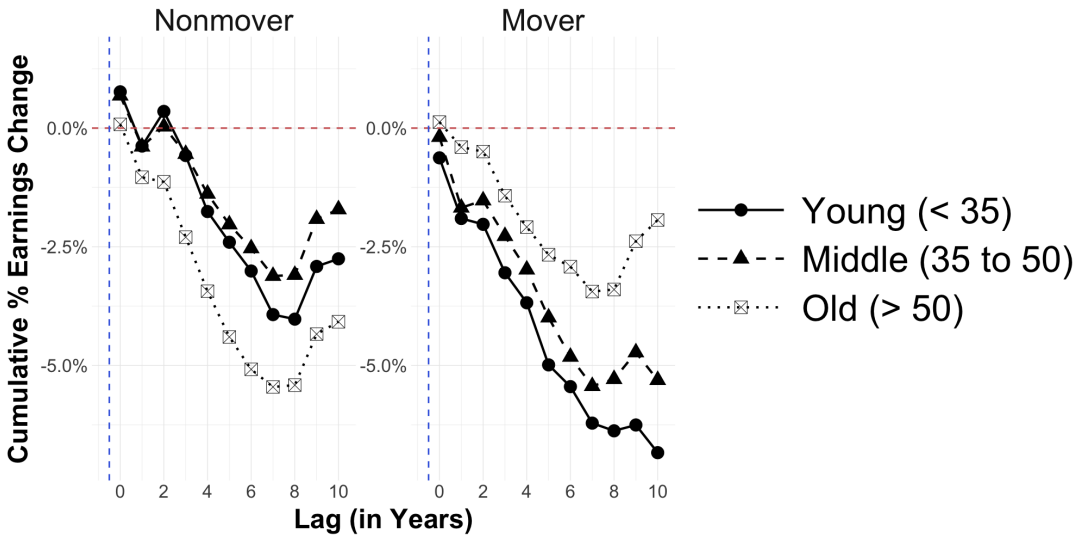


Figure A.21: Fossil Fuel Labor Demand Shocks and Earnings Impact by Age

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

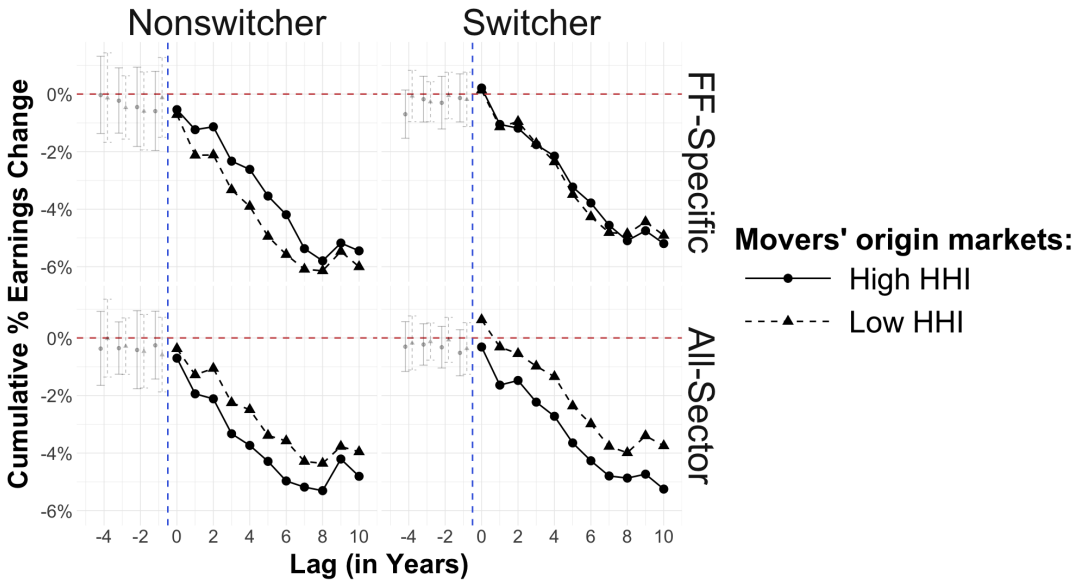


Figure A.22: Fossil Fuel Labor Demand Shocks and Earnings Impact by Employer Concentration in Origin Markets

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

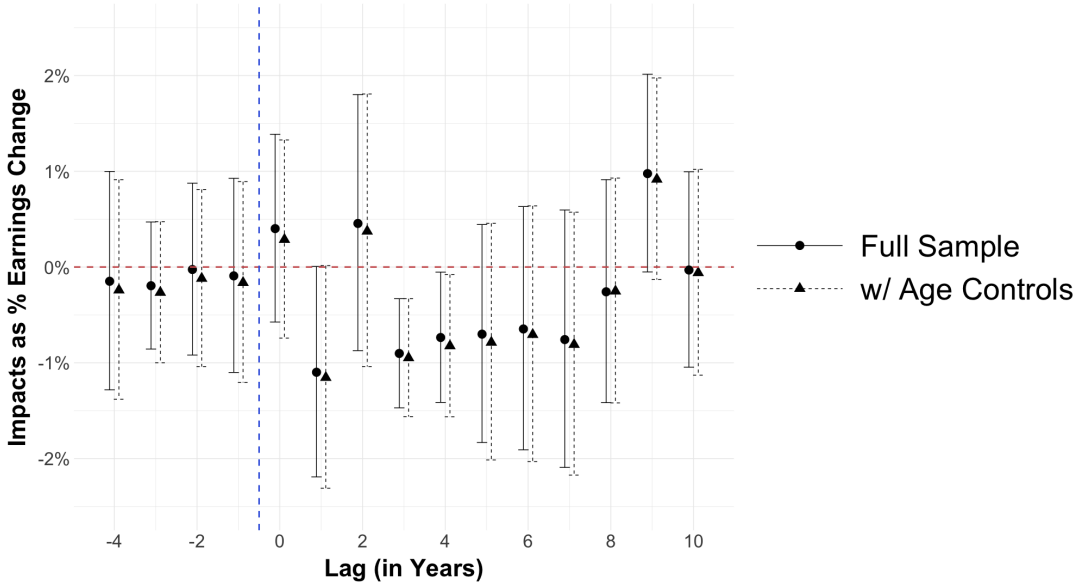


Figure A.23: Fossil Fuel Labor Demand Shocks and Earnings Impact: Baseline vs. Specifications with Age Controls

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

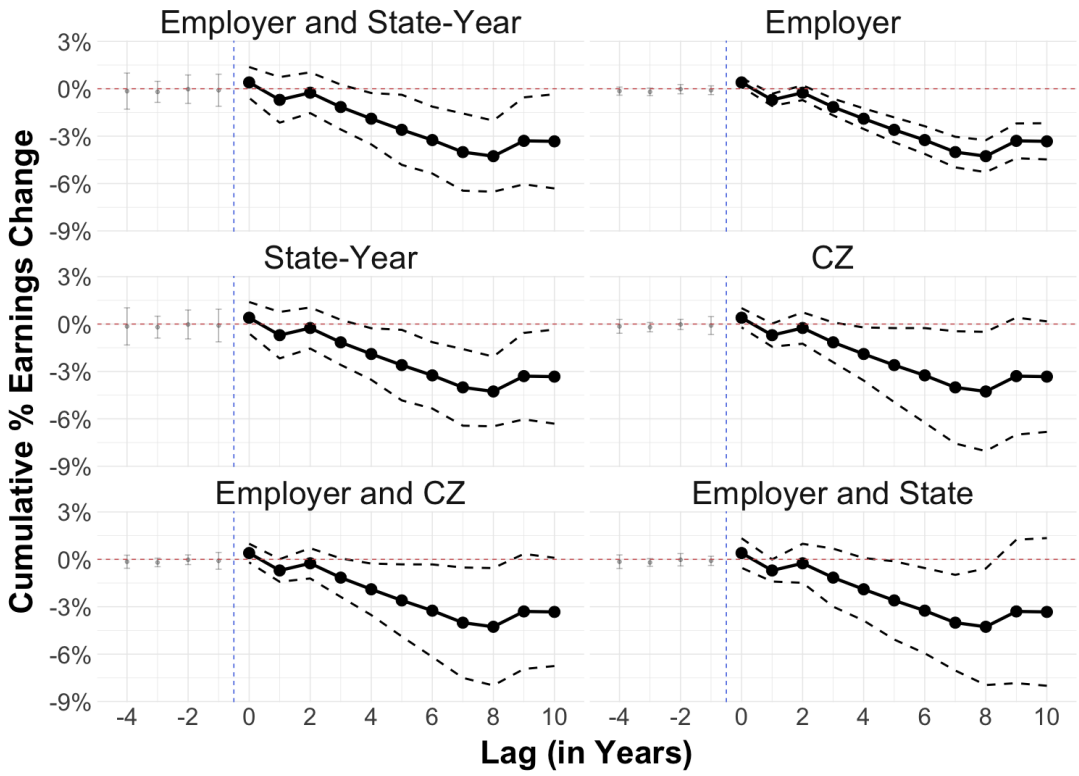


Figure A.24: Fossil Fuel Labor Demand Shocks and Earnings Impact by Different Clustering Choices

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

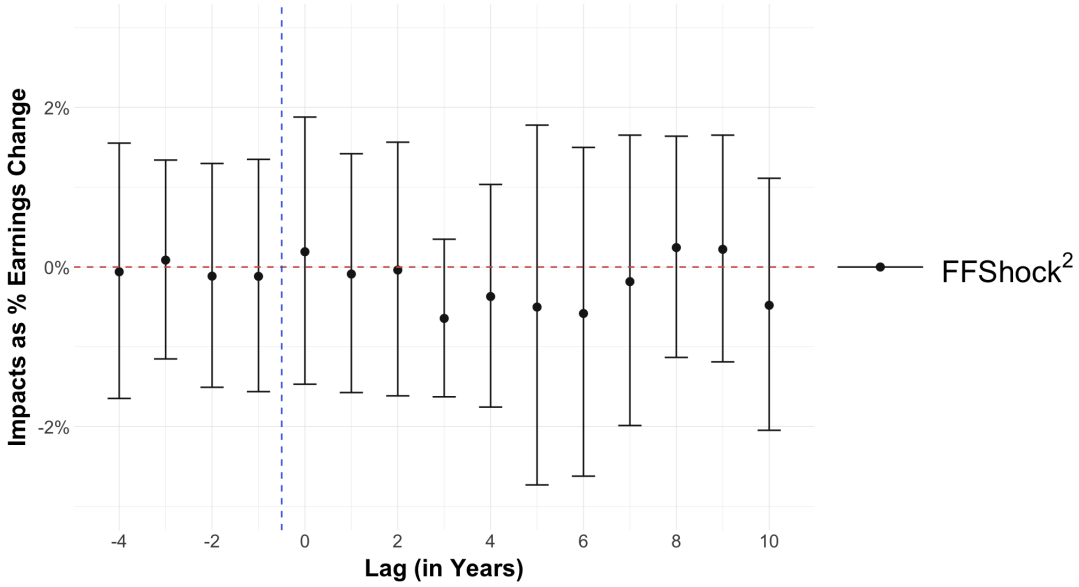


Figure A.25: Coefficient Estimates of Quadratic Terms of Fossil Fuel Labor Demand Shocks

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

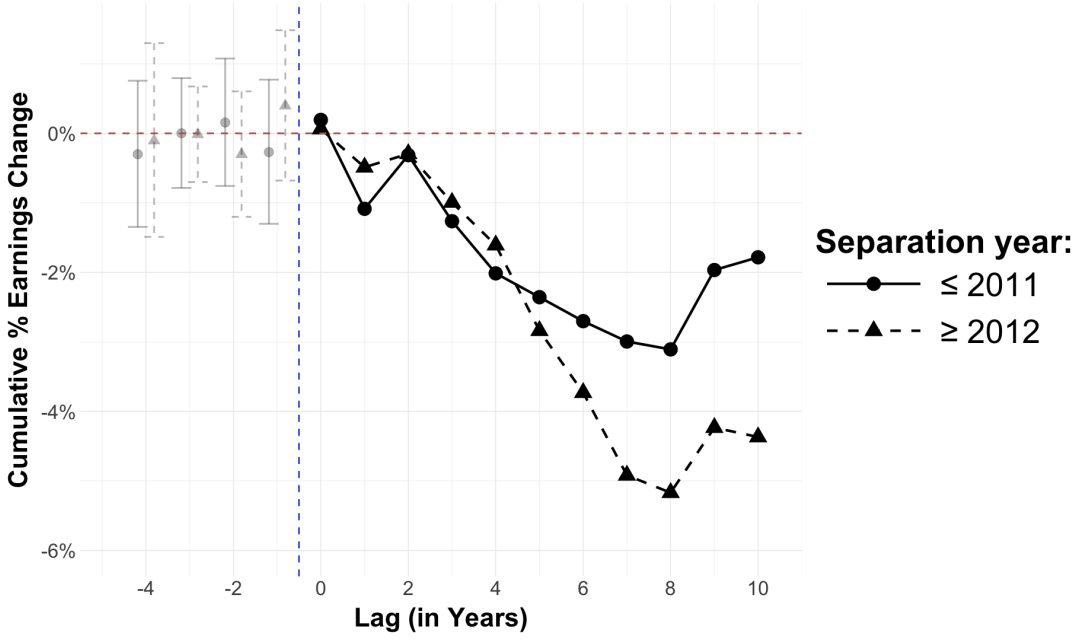


Figure A.26: Fossil Fuel Labor Demand Shocks and Earnings Impact by Separation Year

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

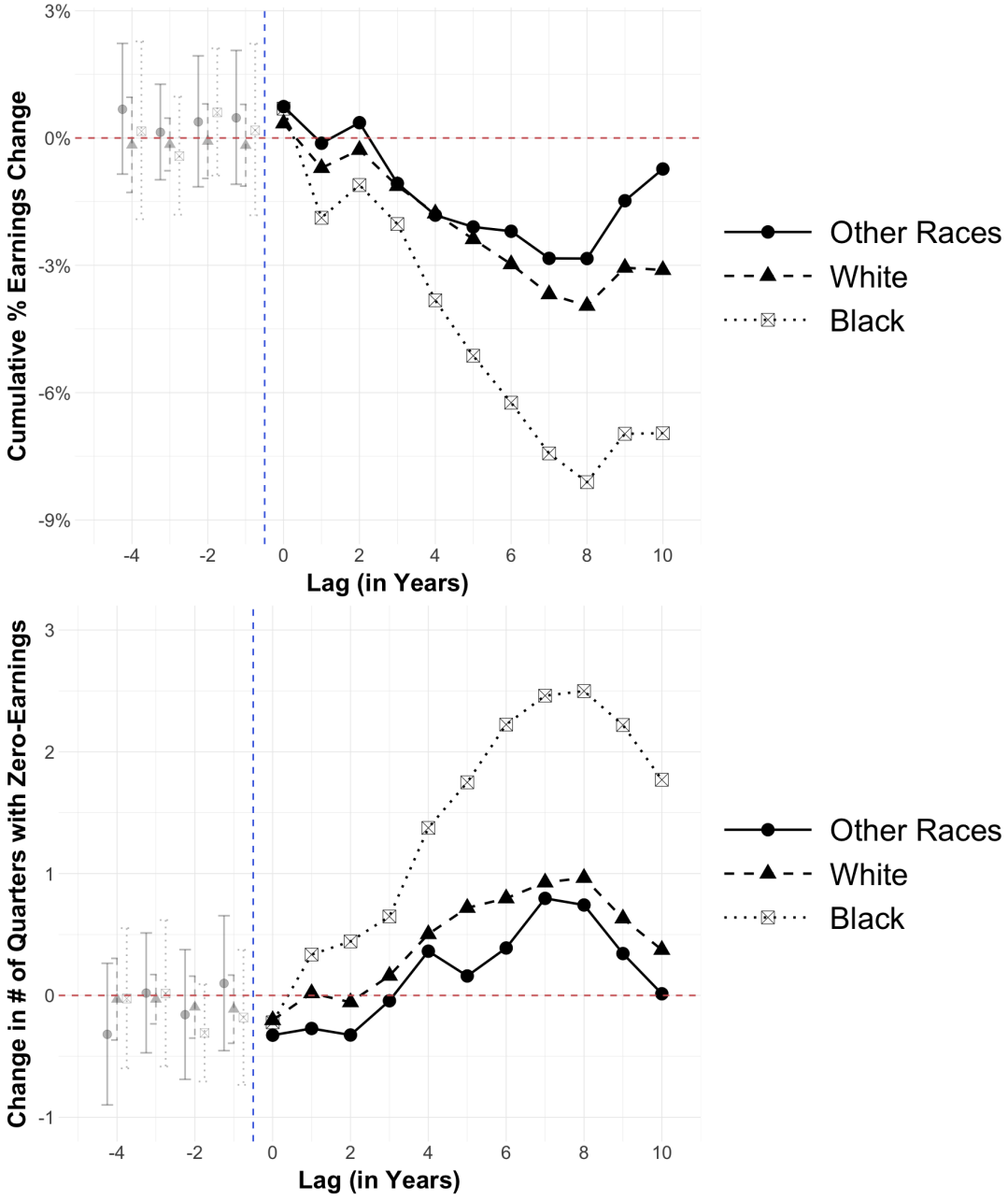


Figure A.27: Fossil Fuel Labor Demand Shocks and Earnings (Top) and Nonemployment Duration (Bottom) Impact by Race

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

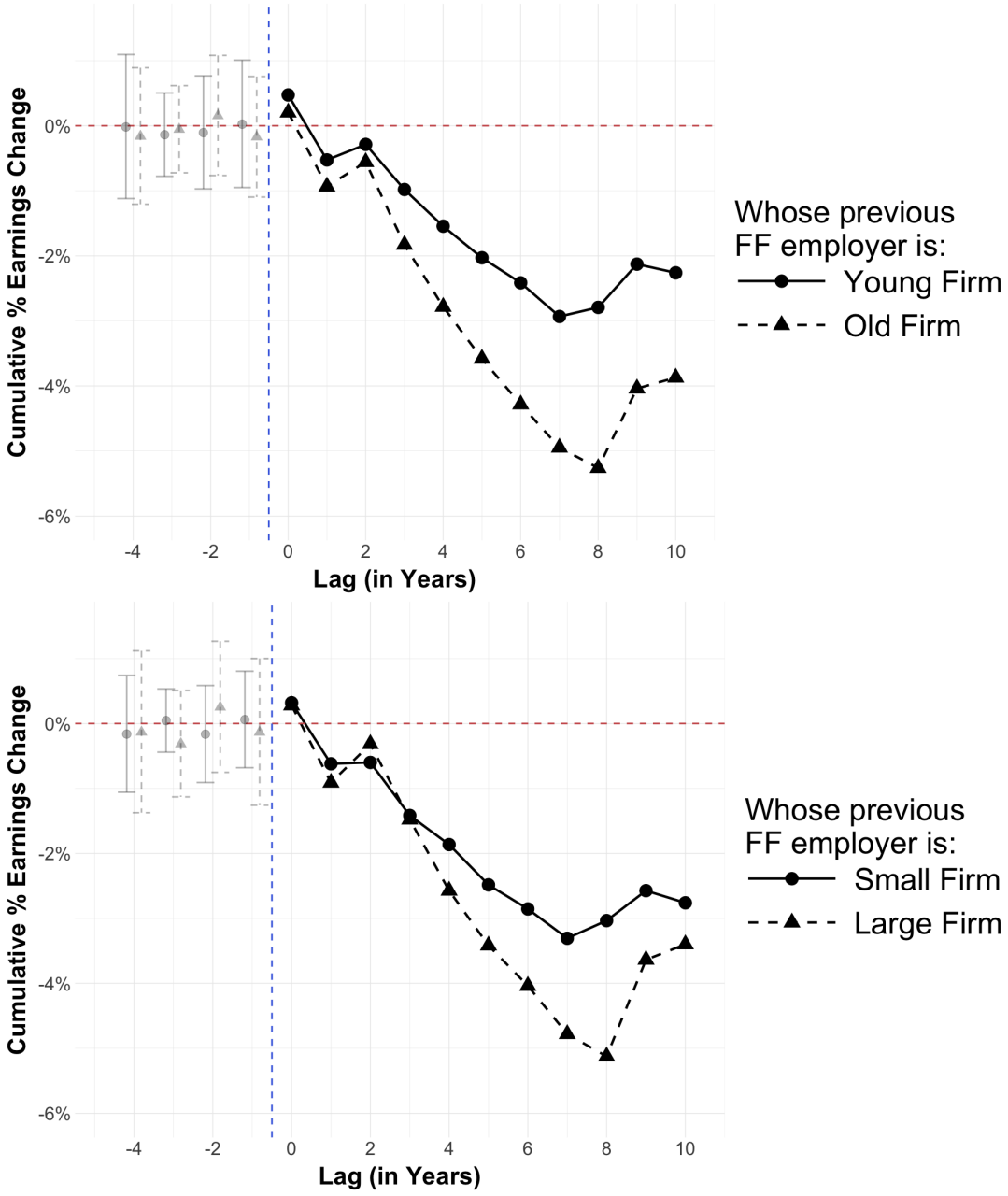


Figure A.28: Fossil Fuel Labor Demand Shocks and Earnings Impact by Firm Age (Top) and Size (Bottom)

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

Appendix B

Appendix to Chapter 2

Table B.1: Coal Demand Response to Coal-Bust Potential (Instrument Relevance)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coal-Bust Potential	-1.935***	-2.745***	-2.931***	-2.922***	-2.919**	-0.695***	-0.766***	-1.027***
	(0.605)	(0.870)	(0.921)	(1.002)	(1.318)	(0.190)	(0.248)	(0.343)
F-statistic	66.6	69.3	70.3	69.4	65.5	72.6	69.0	68.0
Distance [miles]	50	100	130	150	200	130	130	130
Fracking Score	one	one	one	one	one	one	max	mean
Pipeline (2000)	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Observations	2,367	2,367	2,367	2,366	2,360	2,367	2,367	2,367
R^2	0.887	0.891	0.893	0.891	0.885	0.896	0.891	0.889
Fixed-effects								
County	X	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X	X

Notes: "Distance" is the shortest distance ($\bar{d}$) between county i and shale gas play k, assuming a spherical earth. County-clustered standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.2: Impact of Coal Declines on Adult (30–99) Arrest Rates by Crime Type

	Violent Crime (1)	Disorderly Conduct (2)	Property Crime (3)	Alcohol Offense (4)	Sex Offense (5)	Drug Abuse (6)	Other Offenses (7)	All Crime (8)
DV: Arrest per 1,000								
Coal Decline	0.112	0.059	0.169	0.246	0.018*	0.318*	0.332	1.598**
	(0.070)	(0.130)	(0.112)	(0.200)	(0.009)	(0.172)	(0.335)	(0.803)
Mean of DV	0.771	3.697	2.508	6.120	0.162	2.680	8.350	27.414
Impact [%]	14.5	1.6	6.7	4.0	10.9	11.9	4.0	5.8
F-statistic	206.8	215.4	213.3	215.2	149.6	216.8	218.2	219.1
Observations	1,849	1,925	1,912	1,926	1,605	1,921	1,930	1,943
Controls								
Local economy	X	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.3: Impact of Coal Declines on Enrollment and Graduation Rates

	Enrollment rate			*Graduation rate*		
	(1)	(2)	(3)	(4)	(5)	(6)
Coal Decline	0.947**	0.940**	0.969**	2.795**	3.589**	3.414**
	(0.370)	(0.388)	(0.399)	(1.090)	(1.602)	(1.612)
Mean of DV	84.86	84.86	84.86	89.46	89.46	89.46
F-statistic	329.3	270.8	270.6	222.9	144.1	130.3
Observations	2,322	2,322	2,322	4,538	4,538	4,538
Controls						
Local economy		X	X		X	X
Demographic			X			X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.4: Impact of Coal Declines on Juvenile Court Cases

	Juvenile Court Cases per 1,000			
	Delinquency		*Status Offense*	
	Baseline	3-yr sum	Baseline	3-yr sum
	(1)	(2)	(3)	(4)
Coal Decline	1.967**	6.272**	2.735***	6.736***
	(0.835)	(2.613)	(1.037)	(2.108)
Mean of DV	27.969	80.931	8.111	24.023
Impact [%]	7.0	7.8	33.7	28.0
F-statistic	195.1	195.1	209.6	209.6
Observations	1,799	1,799	1,504	1,504
Controls				
Local economy	X	X	X	X
Demographic	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.5: Impact of Coal Declines on Arrest Rates by Age

	10 – 12 (1)	13 – 14 (2)	15 (3)	16 (4)	17 (5)	18 – 20 (6)	21 – 29 (7)	30 – 39 (8)	40 – 49 (9)	50 – 59 (10)	Over 60 (11)
DV: Arrest per 1,000											
OLS											
Coal Decline	0.084	0.358	0.385	0.580	0.397	-0.377	-0.581	0.128	0.168	-0.069	-0.028
	(0.087)	(0.311)	(0.478)	(0.555)	(0.624)	(0.977)	(0.640)	(0.512)	(0.271)	(0.125)	(0.027)
2SLS											
Coal Decline	0.701**	3.356**	5.081**	5.382**	5.514**	6.016*	2.887	4.728**	2.784**	0.690	-0.049
	(0.313)	(1.431)	(2.094)	(2.344)	(2.541)	(3.094)	(2.264)	(2.355)	(1.358)	(0.482)	(0.096)
Mean of DV	4.427	21.008	37.035	47.502	59.837	111.220	83.718	69.950	40.000	16.722	3.312
F-statistic	219.1	219.1	219.1	219.1	219.1	219.1	219.1	219.1	219.1	219.1	219.1
Observations	1,943	1,943	1,943	1,943	1,943	1,943	1,943	1,943	1,943	1,943	1,943

Notes: County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. The specification includes controls for local economic conditions and demographics. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.6: Impact of Coal Declines on School Revenue by Sources

	Federal					*State*				*Local*			
	Title1 (1)	Child Nutrition Act (2)	Rural & Low Income (3)	Impact Aid (4)	Other Federal Support (5)	General Formula (6)	Special Education (7)	Capital Outlay (8)	Transportation (9)	Tax Revenue (10)	Fees & Sales (11)	Aid from County Gov't (12)	Aid from Other Schools (13)
DV: $K per student													
OLS													
Coal Decline	-0.001	0.003**	0.003	0.002	0.003	0.010	-0.007	0.001	0.001*	-0.058**	0.000	-0.005	-0.008**
	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.017)	(0.004)	(0.004)	(0.001)	(0.026)	(0.001)	(0.003)	(0.004)
2SLS													
Coal Decline	0.017	0.017***	0.053**	0.001	0.047***	-0.105**	-0.020	0.027**	0.007**	-0.094	-0.010**	-0.013	-0.021**
	(0.016)	(0.006)	(0.023)	(0.002)	(0.018)	(0.052)	(0.012)	(0.014)	(0.003)	(0.057)	(0.005)	(0.008)	(0.010)
Mean of DV	0.313	0.296	0.439	0.080	0.253	4.417	0.436	0.208	0.137	3.449	0.278	0.171	0.224
F-statistic	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6	270.6
Observations	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322	2,322

Notes: County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. The specification includes controls for local economic conditions and demographics. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.7: Impact of Coal Declines on Child Abuse

	Number of Cases		*Cases per 1,000 Juveniles*	
	Child Abuse and Neglect	Out-Of-Home Placement	Child Abuse and Neglect	Out-Of-Home Placement
	(1)	(2)	(3)	(4)
Coal Decline	0.322	0.193	0.182	0.055
	(0.558)	(0.174)	(0.186)	(0.055)
Mean of DV	7.150	1.011	1.125	0.190
F-statistic	100.0	76.5	100.0	76.5
Observations	1,552	1,318	1,552	1,318
Controls				
Local economy	X	X	X	X
Demographic	X	X	X	X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

Table B.8: Impact of Coal Declines on Youth (14–18) Separation and Employment

	Separation (All)			Separation (Mining)			Employment (Mining)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coal Decline	-0.301	1.284	0.853	-0.034	0.022	0.028	-0.112	0.059	0.083
	(0.900)	(1.184)	(1.133)	(0.032)	(0.050)	(0.050)	(0.100)	(0.140)	(0.147)
Mean of DV	67.731	67.731	67.731	0.378	0.378	0.378	1.510	1.510	1.510
F-statistic	329.3	270.8	270.6	328.2	269.1	268.9	328.2	269.1	268.9
Observations	2,313	2,313	2,313	2,322	2,322	2,322	2,313	2,313	2,313
Controls									
Local economy		X	X		X	X		X	X
Demographic			X			X			X

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.1). All dependent variables are measured per 1,000 people aged 14–18. County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Data source: Quarterly Workforce Indicator (QWI). Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.9: Impact of Coal Declines on Key Outcome Variables (Balanced Panel)

	All Crime (Juvenile)	Status Offense (Juvenile)	All Crime (Adult)	*School Revenue*		*School Expenditure*		Debt Retired	Instr. Aides	Student Support Service
	(1)	(2)	(3)	Total (4)	Local (5)	Total (6)	Oper. (7)	(8)	(9)	(10)
Coal Decline	3.337**	1.234**	1.577*	-0.094	-0.133*	-0.071	-0.127**	-0.087**	-3.625	-5.108*
	(1.404)	(0.493)	(0.804)	(0.067)	(0.072)	(0.082)	(0.057)	(0.044)	(2.342)	(2.818)
Mean of DV	25.100	5.006	27.892	11.112	4.394	11.417	9.963	0.685	138	52
Impact [%]	13.3	24.7	5.7	0.8	3.0	0.6	1.3	12.7	2.6	9.8
F-statistic	215.2	215.2	215.2	215.2	215.2	215.2	215.2	215.2	215.2	215.2
Observations	1,926	1,926	1,926	1,926	1,926	1,926	1,926	1,926	1,926	1,926
Controls										
Local economy	X	X	X	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X	X	X	X

Notes: 'Oper.' denotes schools' operating expenditures and corresponds to column (8) of Table 2.2. County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. The specification includes controls for local economic conditions and demographics. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.10: Results with Different Clustering Choices for Standard Errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DV: Juvenile arrest rates							
Coal Decline	3.274**	3.274**	3.274**	3.274**	3.274***	3.274***	3.274*
	(1.378)	(1.386)	(1.382)	(1.343)	(1.042)	(1.112)	(1.566)
F-statistic	219.1	219.1	219.1	221.0	206.1	204.1	221.0
Observations	1,943	1,943	1,943	1,943	1,943	1,943	1,943
Cluster	County	County and State-Year	County and CZ-Year	County and Year	CZ and Year	CZ	State and Year
Controls							
Local economy	X	X	X	X	X	X	X
Demographic	X	X	X	X	X	X	X

Notes: 'CZ' stands for commuting zone, a geographic unit based on the 2000 definition that represents regional labor markets determined by commuting patterns. Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.11: Results Across Different Time Periods

	2000–2019			2005–2019			2010–2019		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DV: Juvenile arrest rates									
Coal Decline	2.685**	3.109**	3.274**	2.764**	3.440**	3.782**	2.442***	2.810***	2.874***
	(1.081)	(1.256)	(1.378)	(1.137)	(1.428)	(1.626)	(0.851)	(0.970)	(1.041)
F-statistic	262.3	223.0	219.1	201.7	158.4	152.3	169.2	136.9	122.4
Observations	1,943	1,943	1,943	1,649	1,649	1,649	1,112	1,112	1,112
Controls									
Local economy		X	X		X	X		X	X
Demographic			X			X			X

Notes: County-clustered standard errors are shown in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table B.12: Classification of Crime Reported

Category of Crime	Description of Offenses
Violent Crime	Aggravated assault, manslaughter, murder, and robbery
Disorderly Conduct	Fighting, threatening, making unreasonable noise, etc.
Property Crime	Arson, burglary, larceny, motor theft, vandalism, and stolen property
Status Offense	Truancy, curfew and loitering law violations, and runaways
Alcohol Offense	Driving under the influence, drunkenness, and liquor laws
Sex Offense	Rape and other sex offenses
Drug Abuse	Drug sale and possession
Family offense	Offenses against family and children
Other offenses	Embezzlement, gambling, suspicion, vagrancy, and unclassified offenses

Table B.13: List of 143 Sample Counties

	County Name	State		County Name	State
1	Bell County	Kentucky	73	Greenbrier County	West Virginia
2	Breathitt County	Kentucky	74	Harrison County	West Virginia
3	Clay County	Kentucky	75	Kanawha County	West Virginia
4	Daviess County	Kentucky	76	Lincoln County	West Virginia
5	Floyd County	Kentucky	77	Logan County	West Virginia
6	Harlan County	Kentucky	78	McDowell County	West Virginia
7	Henderson County	Kentucky	79	Marion County	West Virginia
8	Hopkins County	Kentucky	80	Marshall County	West Virginia
9	Johnson County	Kentucky	81	Mineral County	West Virginia
10	Knott County	Kentucky	82	Mingo County	West Virginia
11	Knox County	Kentucky	83	Monongalia County	West Virginia
12	Laurel County	Kentucky	84	Nicholas County	West Virginia
13	Lawrence County	Kentucky	85	Preston County	West Virginia
14	Leslie County	Kentucky	86	Raleigh County	West Virginia
15	Letcher County	Kentucky	87	Tucker County	West Virginia
16	Magoffin County	Kentucky	88	Upshur County	West Virginia
17	Martin County	Kentucky	89	Wayne County	West Virginia
18	Muhlenberg County	Kentucky	90	Webster County	West Virginia
19	Ohio County	Kentucky	91	Wyoming County	West Virginia
20	Owsley County	Kentucky	92	Delta County	Colorado
21	Perry County	Kentucky	93	Gunnison County	Colorado
22	Pike County	Kentucky	94	La Plata County	Colorado
23	Union County	Kentucky	95	Moffat County	Colorado
24	Webster County	Kentucky	96	Montrose County	Colorado
25	Whitley County	Kentucky	97	Rio Blanco County	Colorado
26	Belmont County	Ohio	98	Routt County	Colorado
27	Carroll County	Ohio	99	Gallatin County	Illinois
28	Columbiana County	Ohio	100	Jackson County	Illinois
29	Harrison County	Ohio	101	Macoupin County	Illinois
30	Jackson County	Ohio	102	Perry County	Illinois
31	Jefferson County	Ohio	103	Randolph County	Illinois
32	Mahoning County	Ohio	104	Saline County	Illinois
33	Monroe County	Ohio	105	Sangamon County	Illinois
34	Muskingum County	Ohio	106	Wabash County	Illinois
35	Noble County	Ohio	107	White County	Illinois
36	Perry County	Ohio	108	Williamson County	Illinois
37	Stark County	Ohio	109	Clay County	Indiana
38	Tuscarawas County	Ohio	110	Daviess County	Indiana
39	Vinton County	Ohio	111	Dubois County	Indiana
40	Allegheny County	Pennsylvania	112	Gibson County	Indiana
41	Armstrong County	Pennsylvania	113	Knox County	Indiana
42	Beaver County	Pennsylvania	114	Pike County	Indiana
43	Butler County	Pennsylvania	115	Sullivan County	Indiana
44	Cambria County	Pennsylvania	116	Vigo County	Indiana
45	Clarion County	Pennsylvania	117	Warrick County	Indiana
46	Clearfield County	Pennsylvania	118	Big Horn County	Montana
47	Elk County	Pennsylvania	119	Musselshell County	Montana
48	Fayette County	Pennsylvania	120	Richland County	Montana
49	Greene County	Pennsylvania	121	Rosebud County	Montana
50	Indiana County	Pennsylvania	122	McKinley County	New Mexico
51	Jefferson County	Pennsylvania	123	San Juan County	New Mexico
52	Luzerne County	Pennsylvania	124	McLean County	North Dakota
53	Lycoming County	Pennsylvania	125	Mercer County	North Dakota
54	Schuylkill County	Pennsylvania	126	Oliver County	North Dakota
55	Somerset County	Pennsylvania	127	Craig County	Oklahoma
56	Venango County	Pennsylvania	128	Haskell County	Oklahoma
57	Washington County	Pennsylvania	129	Le Flore County	Oklahoma
58	Westmoreland County	Pennsylvania	130	Atascosa County	Texas
59	Anderson County	Tennessee	131	Freestone County	Texas
60	Campbell County	Tennessee	132	Harrison County	Texas
61	Claiborne County	Tennessee	133	Leon County	Texas
62	Buchanan County	Virginia	134	Robertson County	Texas
63	Dickenson County	Virginia	135	Rusk County	Texas
64	Lee County	Virginia	136	Titus County	Texas
65	Russell County	Virginia	137	Carbon County	Utah
66	Tazewell County	Virginia	138	Emery County	Utah
67	Wise County	Virginia	139	Sevier County	Utah
68	Barbour County	West Virginia	140	Campbell County	Wyoming
69	Boone County	West Virginia	141	Converse County	Wyoming
70	Clay County	West Virginia	142	Lincoln County	Wyoming
71	Fayette County	West Virginia	143	Sweetwater County	Wyoming
72	Grant County	West Virginia			

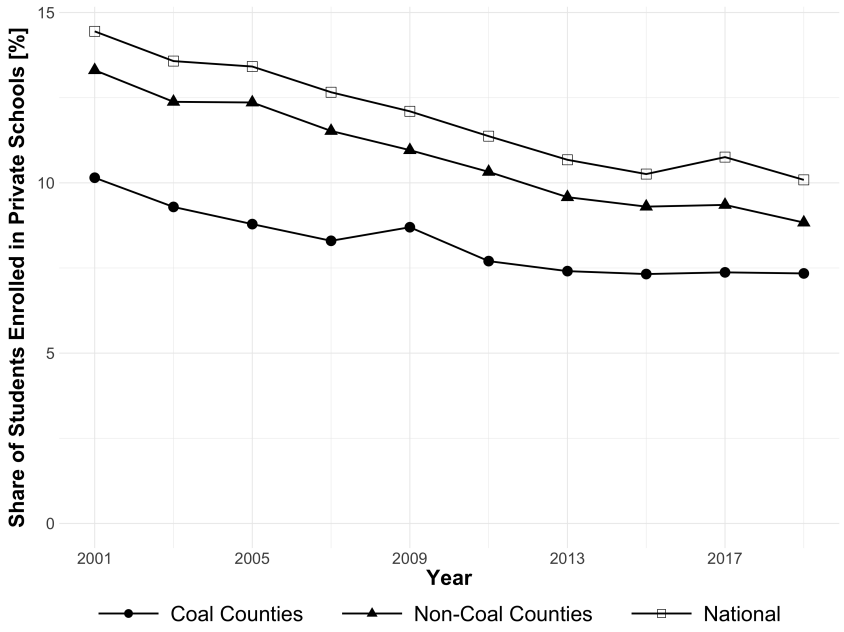


Figure B.1: Share of Students Attending Private Schools in Coal and Non-Coal Counties

Notes: Data source: Private School Universe Survey (PSS) from the National Center for Education Statistics

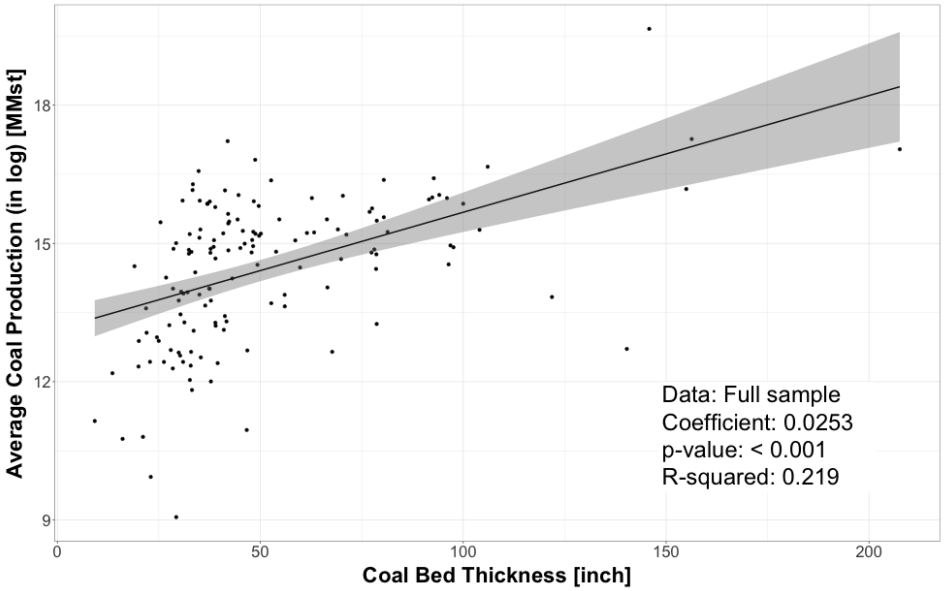


Figure B.2: Coal-bed Thickness as a Strong Predictor for Coal Production

Notes: Observations are the average thickness of coalbeds recorded between 1973 and 1989 and annual coal production from 2000 to 2020 for each county. Data source: EIA-7A (coal production) and USGS (coal bed thickness).

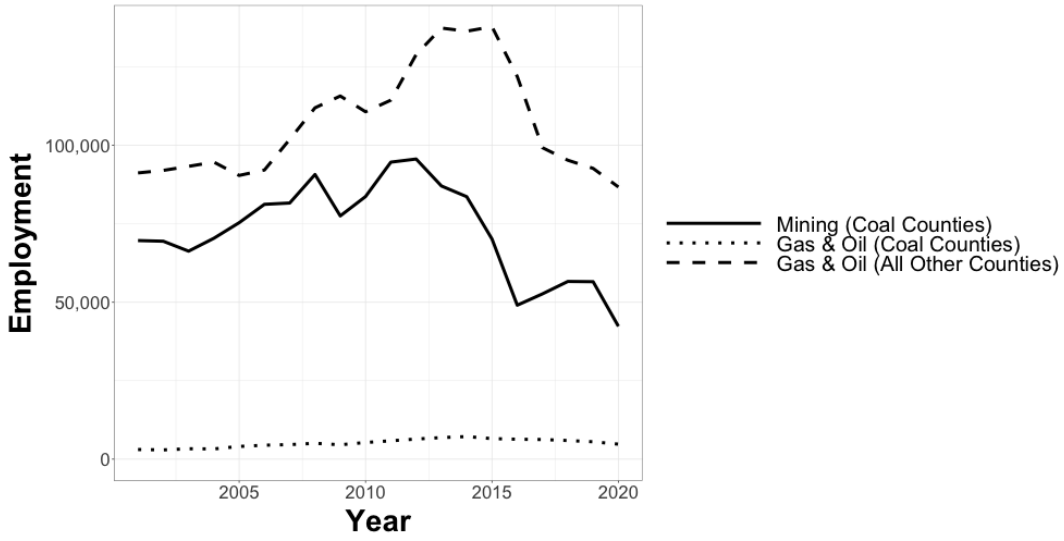


Figure B.3: Mining and Gas/Oil Extraction Employment

Notes: Data source: Quarterly Census of Employment and Wages, U.S. Bureau of Labor Statistics.

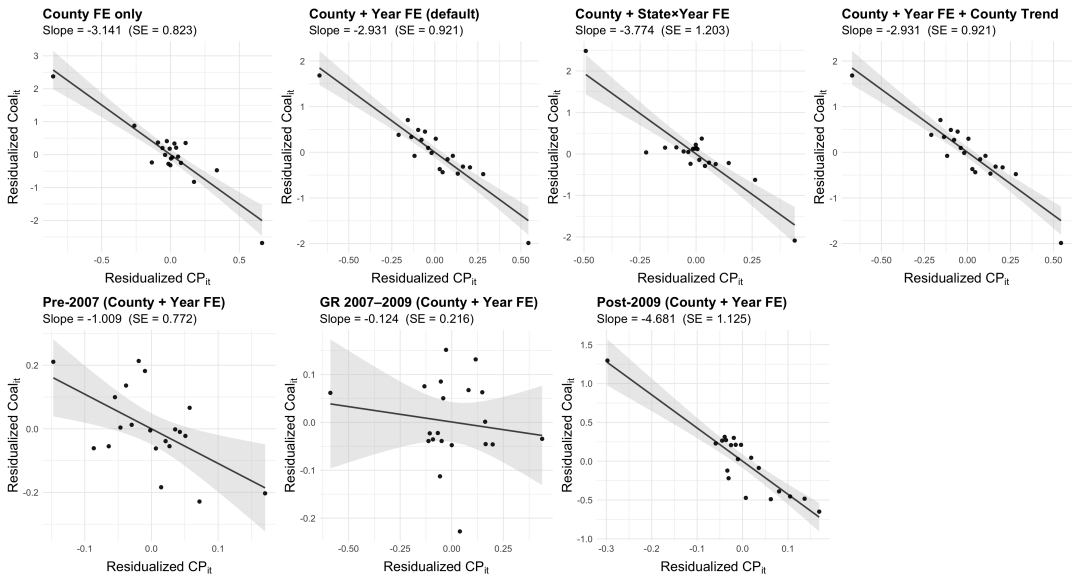


Figure B.4: Within-County Association of Coal Production and Coal-Bust Instrument

Notes: Data source: Quarterly Census of Employment and Wages, U.S. Bureau of Labor Statistics.

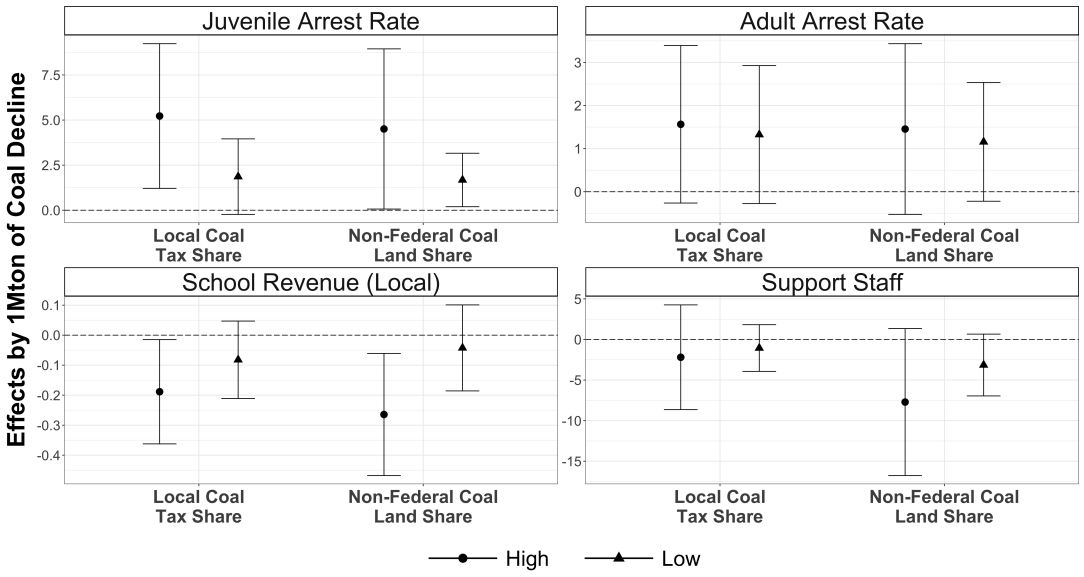


Figure B.5: Impacts of Coal Declines by Local Coal Tax and Non-Federal Coal Land Shares

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable. Each dot is an estimated coefficient; its error bar is the 95% confidence interval.

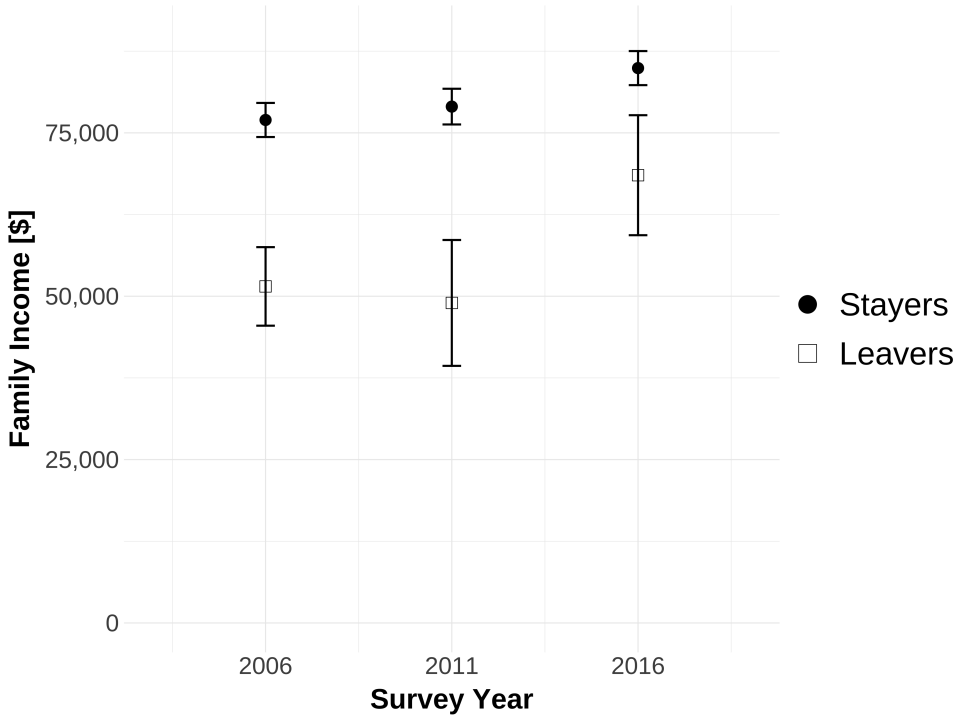


Figure B.6: Family Income of Stayers and Leavers from Coal-Rich Counties

Notes: The dots represent the mean, and the error bars indicate the standard errors. Data source: American Community Survey (2006, 2011, and 2016), U.S. Census Bureau.

Appendix C

Appendix to Chapter 3

C.1 SW-Optimal IGT Responsiveness

Proposition. Let $c_i(q_H, \gamma_H) = (1 - \tau^{priv}) y_i(q_H) + n_i(q_H) \rho\, G(q_H)\, s_i(\gamma_H)$, with $y_i(q_H) = \bar{y}_i + m_i q_H$, $n_i(q_H) = \bar{n}_i + \mu_i q_H$, and $G(q_H) = \tau^s q_H + \sigma^s[y_H(q_H) + y_L(q_H)] - E$. Effective service shares satisfy $s'_H(\gamma_H) = 1 - \phi_H$ and $s'_L(\gamma_H) = -(1 - \phi_L)$. With CRRA u and Pareto weights $\lambda_i > 0$, define $\omega_i(c_i) = \lambda_i u'(c_i)$ and $\omega'_i(c_i) = \lambda_i u''(c_i) < 0$. The planner's FOC is

$$(1 - \phi_H)\, n_H\, \omega_H\big(c_H(q_H, \gamma_H)\big) \;=\; (1 - \phi_L)\, n_L\, \omega_L\big(c_L(q_H, \gamma_H)\big), \tag{C.1}$$

which has a unique interior solution $\gamma^*_H(q_H)$ under $\eta > 0$, $G > 0$, $n_i > 0$, $\rho > 0$. Moreover,

$$\frac{d\gamma^*_H}{dq_H} = \frac{(1 - \phi_L)\big[\mu_L\, \omega_L + n_L\, \omega'_L\, \kappa_L\big] \;-\; (1 - \phi_H)\big[\mu_H\, \omega_H + n_H\, \omega'_H\, \kappa_H\big]}{\rho\, G\Big[(1 - \phi_H)^2 n_H^2 (-\omega'_H) + (1 - \phi_L)^2 n_L^2 (-\omega'_L)\Big]}, \tag{C.2}$$

where

$$\kappa_i \;\equiv\; \frac{\partial c_i}{\partial q_H}\Big|_{\gamma} = (1 - \tau^{priv})\, m_i + \rho\Big[n_i\, s_i(\gamma_H)\, \frac{dG}{dq_H} + G\, s_i(\gamma_H)\, \mu_i\Big], \qquad \frac{dG}{dq_H} = \tau^s + \sigma^s(m_H + m_L). \tag{C.3}$$

Proof. Define

$$F(\gamma_H, q_H) \;\equiv\; (1 - \phi_H)\, n_H\, \omega_H\big(c_H(q_H, \gamma_H)\big) - (1 - \phi_L)\, n_L\, \omega_L\big(c_L(q_H, \gamma_H)\big).$$

By (C.1), $F(\gamma^*_H(q_H), q_H) = 0$. The implicit function theorem yields

$$\frac{d\gamma^*_H}{dq_H} \;=\; -\,\frac{\partial F / \partial q_H}{\partial F / \partial \gamma_H}.$$

For the denominator, $s'_H(\gamma_H) = 1 - \phi_H$ and $s'_L(\gamma_H) = -(1 - \phi_L)$ imply

$$\frac{\partial c_H}{\partial \gamma_H} = n_H \, \rho \, G \, (1 - \phi_H), \qquad \frac{\partial c_L}{\partial \gamma_H} = -n_L \, \rho \, G \, (1 - \phi_L).$$

Hence

$$\frac{\partial F}{\partial \gamma_H} = (1-\phi_H) n_H \, \omega'_H \frac{\partial c_H}{\partial \gamma_H} - (1-\phi_L) n_L \, \omega'_L \frac{\partial c_L}{\partial \gamma_H} = \rho \, G \Big[(1-\phi_H)^2 n_H^2 \, \omega'_H + (1-\phi_L)^2 n_L^2 \, \omega'_L \Big].$$

With CRRA, $u'' < 0$ so $\omega'_i = \lambda_i u''(c_i) < 0$, implying $\partial F / \partial \gamma_H < 0$ (strict monotonicity and uniqueness). For the numerator, holding γ_H fixed,

$$\frac{\partial c_i}{\partial q_H} = (1 - \tau^{priv}) \, m_i \; + \; \rho \Big[n_i \, s_i(\gamma_H) \, \frac{dG}{dq_H} \; + \; G \, s_i(\gamma_H) \, \mu_i \Big] \equiv \kappa_i,$$

and $\partial n_i / \partial q_H = \mu_i$. Therefore

$$\frac{\partial F}{\partial q_H} = (1 - \phi_H) \Big[\mu_H \, \omega_H + n_H \, \omega'_H \, \kappa_H \Big] - (1 - \phi_L) \Big[\mu_L \, \omega_L + n_L \, \omega'_L \, \kappa_L \Big],$$

which, combined with the denominator, gives (C.2). □

Lemma (signs under CRRA). For CRRA with $\eta > 0$, $u'(c) = c^{-\eta} > 0$ and $u''(c) = -\eta \, c^{-\eta-1} < 0$. Hence

$$\omega_i(c) = \lambda_i u'(c) = \lambda_i c^{-\eta} > 0, \qquad \omega'_i(c) = \lambda_i u''(c) = -\lambda_i \eta \, c^{-\eta-1} < 0.$$

Thus the denominator in (C.2) is strictly positive (since it is $-\partial F / \partial \gamma_H$), and the slope $d\gamma^*_H / dq_H$ shares the sign of the difference in bracketed "marginal need" terms in the numerator.

C.2 Alternative Fiscal Equalization Rule

Eq. (3.17) can be expressed as:

$$\tau^l_H + \sigma^l_H m_H + X\gamma_H(q_H) + (Xq_H + Y)\frac{d\gamma_H}{dq_H} = \sigma^l_L m_L + X\gamma_L(q_H) + (Xq_H + Y)\frac{d\gamma_L}{dq_H}$$

where $X = \tau^s + \sigma^s(m_H + m_L)$ and $Y = \sigma^s(n_H + n_L) - K$. Since $\gamma_L = 1 - \gamma_H$, it can be expressed as follows:

$$\tau^l_H + \sigma^l_H m_H + X\gamma_H(q_H) + (Xq_H + Y)\frac{d\gamma_H}{dq_H} = \sigma^l_L m_L + X[1 - \gamma_H(q_H)] - (Xq_H + Y)\frac{d\gamma_H}{dq_H} \quad \text{(C.4)}$$

By rearranging eqn. (C.4),

$$\frac{d\gamma_H}{dq_H} = \frac{-2X\gamma_H + X - Z}{2Xq_H + 2Y} \tag{C.5}$$

where $Z = \tau_H^l + \sigma_H^l m_H - \sigma_L^l m_L$. As the eqn. (C.5) takes a form of a separable differential equation, I can obtain an explicit solution with an appropriate initial condition. Applying the initial condition $\gamma_H(q_H = 0) = 0.5$, the explicit solution of eqn. (C.4) is expressed as follows:

$$\gamma_H(q_H) = \Big(0.5 - \frac{X - Z}{2X}\Big)(2Y)(2Xq_H + 2Y)^{-1} + \frac{X - Z}{2X} \tag{C.6}$$

Rearranging eqn. (C.6),

$$\gamma_H(q_H) = \frac{1}{2}\Big[1 - \frac{Zq_H}{Xq_H - Y}\Big] \tag{C.7}$$

Substituting $X = \tau^s + \sigma^s(m_H + m_L)$, $Y = \sigma^s(n_H + n_L) - K$, and $Z = \tau_H^l + \sigma_H^l m_H - \sigma_L^l m_L$ into eqn. (C.7) yields eqn. (3.19).

C.3 Temporal Variation in the First Successful Fracking across the Shale Plays

To define fracking potential (FP_{it}) that would affect coal demand by power plant j which buys coal from county i at year t, I begin with play-specific fracking potential measures using the Rystad prospectivity score (R_m) in county m within play k using the following equation:

$$\bar{R}_k = \frac{1}{N_m} \sum_{m:R_m \in Play_k}^{N_m} R_m \tag{C.8}$$

For the main analyses, I use a product of the inverse of distance ($dist_{jk}^A$) and indicators for fracking initiation for simplicity (that is, $\bar{R}_k$ is one for all shale gas play k). As the Rystad Energy provided the mean and maximum score within each county, I also report the first stage results using both scores to show the robustness of the IV in Table C.7 and Table C.8. Finally, the remote fracking potential instrument, FP_{it}, is defined as follows:

$$FP_{it} = \sum_{j \in (j,i)} \underbrace{\Big[\sum_k \frac{\bar{R}_k}{dist_{jk}^A} \times \mathbb{1}(Play_{kt} \geq \bar{t}_k) \times G_j \times \mathbb{1}(dist_{ik}^B \geq \bar{d})\Big]}_{q_{ijt}} \tag{C.9}$$

where $dist_{jk}^A$ is distance between plant j and play k to account for proximity to the shale gas play. $\mathbb{1}(Play_{kt} \geq \bar{t}_k)$ is a dummy variable that takes one if year t is greater than or equal to the play-specific announcement year, $\bar{t}_k$. G_j is a gas pipeline capacity in a state where plant j is in operation. $\mathbb{1}(dist_{ik}^B \geq \bar{d})$ rules out play k that locates within $\bar{d}$ miles

from the county i. Table C.7 shows the sensitivity of the instruments to different choices to the minimum distance ($\bar{d}$) between county i and play k and the presence of G_j term.

C.4 Parameter Recovery

C.4.1 Recovery of m_H and m_L

From the assumption that local income is linear in coal production,

$$z_H = m_H q_H + n_H$$

By differentiating with respect to q_H,

$$m_H = \frac{\partial z_H}{\partial q_H} = \frac{\partial log(z_H)}{\partial log(q_H)} \times \frac{\bar{z}_H}{\bar{q}_H}$$

By plugging the income effects estimates ($\frac{\partial log(z_H)}{\partial log(q_H)} \approx 0.213$) in Table 3.1,

$$m_H = 0.213 \times \frac{\$1.4025B}{6.97Mton} \approx \$42.9/ton$$

Similarly, m_L is recovered as follows:

$$m_L = 0.138 \times \frac{\$1.4065B}{6.97Mton} \approx \$27.8/ton$$

C.4.2 Recovery of τ_H^l

To begin by eqn. (3.14),

$$R_{i,Own} = \tau_i^l q_i + \sigma_i^l z_i(q_i)$$

By differentiating with respect to q_H

$$\frac{\partial R_{H,Own}}{\partial q_H} = \tau_H^l + \sigma_H^l \frac{\partial z_H}{\partial q_H}$$
$$\implies \tau_H^l = \frac{\partial R_{H,Own}}{\partial q_H} - \sigma_H^l \frac{\partial z_H}{\partial q_H}$$

Given the assumptions that $m_H = \frac{\partial z_H}{\partial q_H}$ and $\sigma^l = 0.01$, I compute τ_H^l by using the own-source revenue effects estimates ($\frac{\partial log(R_{H,Own})}{\partial log(q_H)} \approx 0.09$) in Table 3.2,

$$\begin{aligned}\tau_H^l &= \frac{\partial log(R_{H,Own})}{\partial log(q_H)} \times \frac{\bar{R}_{H,Own}}{\bar{q}_H} - \sigma_H^l m_H \\ &= \left(0.09 \times \frac{\$44.8M}{6.51Mton}\right) - (0.01 \times \$42.9/ton) \\ &\approx \$0.19/ton\end{aligned}$$

Table C.1: Summary Statistics: Coal and All Counties

	Coal-Producing Counties		All Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
BEA Real GDP [$ million]	2,732	7,297	5,478	23,213
IRS Gross Income [$ million]	1,394	3,628	2,845	10,345
CBP Establishment	1,387	3,132	2,402	8,240
QWI Employment	28,170	73,606	50,248	181,993
Population (Total)	59,625	116,453	99,454	321,052
Age: 0 to 24 [%]	31.0	–	33.9	–
Age: 25 to 64 [%]	52.3	–	52.6	–
Age: 65 to 99 [%]	16.7	–	13.5	–
In-Migration Rate [%]	3.76	1.51	4.99	2.02
Out-Migration Rate [%]	3.84	1.34	4.88	2.07

Notes: All dollar values are adjusted with 2015 CPI.

Table C.2: Cross-Industry Spillover Impact of Coal Declines

	Accomm. & Food (1)	Const-ruction (2)	Education & Health (3)	Mining (4)	Manufac-turing (5)	Transpor-tation (6)	Others (7)
Establishments							
log(Coal Decline)	-0.039*	-0.182***	0.038	-0.676***	-0.191***	-0.218***	-0.157***
	(0.023)	(0.034)	(0.026)	(0.089)	(0.041)	(0.026)	(0.022)
F-statistic	49.6	50.0	50.0	47.3	38.3	50.0	50.0
Observations	2,382	2,384	2,385	2,339	2,353	2,385	2,385
Employment							
log(Coal Decline)	-0.074***	-0.519***	-0.024	-1.078***	-0.397***	-0.244***	-0.382***
	(0.024)	(0.090)	(0.027)	(0.151)	(0.106)	(0.039)	(0.066)
F-statistic	48.2	41.3	50.9	37.1	23.9	45.4	50.1
Observations	2,295	2,218	2,277	1,604	1,973	2,364	2,370
Wage							
log(Coal Decline)	-0.023*	-0.112***	-0.008	-0.122***	-0.085***	-0.090***	-0.008
	(0.012)	(0.022)	(0.008)	(0.020)	(0.022)	(0.015)	(0.028)
F-statistic	49.7	50.4	39.1	45.4	37.2	46.9	10.1
Observations	2,378	2,381	2,219	2,261	2,308	2,335	1,366

Notes: Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.3: Impact of Coal Declines on Local Government Revenue and Expenditure Items (in dollars per capita)

Panel A: Revenue		*Local (Own-Source)*			*Intergovernmental Transfer*		
	Rents & Royalties (1)	Sales Tax (2)	Property Tax (3)	Charges & Fees (4)	Matching Grant (5)	General Purpose (6)	Other Locals (7)
log(Coal Decline)	-31.317	-2.101	19.434	-16.277	2.467	-31.311***	-3.986
	(22.331)	(4.981)	(12.269)	(17.662)	(5.256)	(10.278)	(2.763)
Mean of DV [$]	34	164	383	229	198	133	46
F-statistic	30.2	36.9	36.9	36.9	36.9	36.9	36.9
Observations	107	128	128	128	128	128	128

Panel B: Expenditure		*Specific Purpose*			*General Purpose*		
	Housing & Enviro. (8)	Local Safety (9)	Public Transit (10)	Health & Welfare (11)	General Service (12)	Central Staff (13)	Public Building (14)
log(Coal Decline)	-23.243	0.968	-11.181	-11.272*	-37.967**	-0.829	-0.593
	(14.357)	(10.169)	(6.902)	(6.681)	(17.746)	(8.321)	(5.030)
Mean of DV [$]	202	248	226	109	165	159	35
F-statistic	36.9	36.9	36.9	36.9	36.9	36.9	32.8
Observations	128	128	128	128	128	128	120

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.4). Heteroskedasticity-robust standard errors are reported in parentheses, and the Kleibergen Paap F-statistic is included to assess instrument relevance. All dependent variables are measured as *dollars per capita*. The mean of the dependent variable (DV) is calculated based on each item's value in 2012. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.4: Spillover Effects of Coal Declines on Local Economy

Distance	Local Real GDP (BEA) (1)	Total Firms (CBP) (2)	Total Employment (QWI) (3)	Gross Income (IRS) (4)	Per-Capita Earnings (BEA) (5)	Per-Capita Royalty Inc. (IRS) (6)
70	-0.077**	-0.094***	-0.094***	-0.138***	-0.043*	-0.042
	(0.031)	(0.020)	(0.024)	(0.035)	(0.024)	(0.046)
80	-0.071**	-0.092***	-0.083***	-0.144***	-0.038	-0.039
	(0.032)	(0.022)	(0.023)	(0.039)	(0.022)	(0.042)
90	-0.076**	-0.084***	-0.078***	-0.144***	-0.035	-0.040
	(0.032)	(0.022)	(0.021)	(0.039)	(0.022)	(0.041)
100	-0.068*	-0.079***	-0.065***	-0.138***	-0.032	-0.037
	(0.032)	(0.024)	(0.020)	(0.038)	(0.021)	(0.041)
110	-0.078**	-0.074***	-0.061***	-0.135***	-0.030	-0.030
	(0.035)	(0.024)	(0.020)	(0.038)	(0.023)	(0.040)
120	-0.074**	-0.072***	-0.057**	-0.126***	-0.031	-0.023
	(0.034)	(0.024)	(0.020)	(0.037)	(0.023)	(0.039)
130	-0.071**	-0.074***	-0.058**	-0.127***	-0.032	-0.018
	(0.033)	(0.024)	(0.021)	(0.037)	(0.023)	(0.038)
140	-0.081**	-0.076***	-0.060**	-0.122***	-0.038	-0.015
	(0.035)	(0.024)	(0.021)	(0.038)	(0.023)	(0.036)
150	-0.076**	-0.076***	-0.056**	-0.120***	-0.035	-0.018
	(0.033)	(0.024)	(0.021)	(0.037)	(0.023)	(0.035)

Notes: Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. 'Distance' is measured in miles. All dependent variables are measured as the logarithm of dollars per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.5: Spillover Effects of Coal Declines on Local Government Revenue and Expenditure Items

Panel A: Revenue							
		Local (Own-Source)			*Intergovernmental Transfer*		
	Rents & Royalties	Sales Tax	Property Tax	Charges & Fees	Matching Grant	General Purpose	Other Locals
Distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)
70	-0.025	0.065***	0.017	-0.044	-0.213***	-0.468***	-0.323**
	(0.088)	(0.019)	(0.022)	(0.042)	(0.054)	(0.077)	(0.152)
80	0.051	0.074***	0.028	-0.052	-0.176***	-0.434***	-0.380***
	(0.081)	(0.018)	(0.018)	(0.040)	(0.042)	(0.073)	(0.130)
90	0.058	0.119***	0.039**	-0.043	-0.129***	-0.430***	-0.344***
	(0.070)	(0.023)	(0.016)	(0.037)	(0.035)	(0.069)	(0.125)
100	-0.036	0.155***	0.054***	-0.011	-0.142***	-0.429***	-0.382***
	(0.068)	(0.030)	(0.014)	(0.028)	(0.033)	(0.070)	(0.123)
110	-0.064	0.160***	0.059***	-0.008	-0.124***	-0.419***	-0.376***
	(0.068)	(0.026)	(0.013)	(0.026)	(0.030)	(0.069)	(0.116)
120	-0.066	0.184***	0.066***	0.004	-0.131***	-0.414***	-0.405***
	(0.067)	(0.029)	(0.012)	(0.019)	(0.031)	(0.067)	(0.119)
130	-0.071	0.171***	0.068***	0.002	-0.120***	-0.403***	-0.419***
	(0.066)	(0.027)	(0.012)	(0.020)	(0.033)	(0.065)	(0.119)
140	-0.078	0.169***	0.073***	0.004	-0.122***	-0.405***	-0.410***
	(0.066)	(0.026)	(0.012)	(0.020)	(0.036)	(0.063)	(0.118)
150	-0.079	0.168***	0.077***	0.002	-0.128***	-0.400***	-0.388***
	(0.066)	(0.024)	(0.012)	(0.018)	(0.035)	(0.061)	(0.118)

Panel B: Expenditure							
		Specific Purpose			*General Purpose*		
	Housing & Enviro.	Local Safety	Public Transit	Health & Welfare	General Service	Central Staff	Public Building
Distance	(8)	(9)	(10)	(11)	(12)	(13)	(14)
70	0.043*	-0.043*	-0.003	-0.131**	-0.117***	-0.020	-0.337***
	(0.024)	(0.022)	(0.015)	(0.052)	(0.042)	(0.025)	(0.053)
80	0.049**	-0.021	-0.007	-0.163***	-0.100***	-0.023	-0.270***
	(0.023)	(0.020)	(0.013)	(0.046)	(0.032)	(0.021)	(0.047)
90	0.063**	-0.003	-0.017	-0.154***	-0.097***	-0.015	-0.252***
	(0.026)	(0.017)	(0.013)	(0.047)	(0.029)	(0.018)	(0.045)
100	0.103***	0.015	-0.014	-0.173***	-0.090***	-0.051***	-0.201***
	(0.033)	(0.016)	(0.013)	(0.047)	(0.028)	(0.019)	(0.050)
110	0.116***	0.021*	-0.022	-0.182***	-0.097***	-0.049**	-0.174***
	(0.031)	(0.012)	(0.013)	(0.042)	(0.027)	(0.019)	(0.042)
120	0.046	0.025***	-0.006	-0.169***	-0.077***	-0.061***	-0.171***
	(0.036)	(0.009)	(0.011)	(0.040)	(0.026)	(0.017)	(0.040)
130	0.044	0.022***	-0.016	-0.168***	-0.071***	-0.055***	-0.118***
	(0.034)	(0.007)	(0.013)	(0.044)	(0.024)	(0.017)	(0.042)
140	-0.033	0.018***	-0.008	-0.155***	-0.053**	-0.047***	-0.084*
	(0.035)	(0.007)	(0.013)	(0.047)	(0.022)	(0.016)	(0.050)
150	-0.032	0.013**	-0.015	-0.135***	-0.034*	-0.033**	-0.016
	(0.034)	(0.006)	(0.014)	(0.047)	(0.020)	(0.015)	(0.058)

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable, based on equation (3.4). Heteroskedasticity-robust standard errors are reported in parentheses, and the Kleibergen Paap F-statistic is included to assess instrument relevance. 'Distance' is measured in miles. All dependent variables are measured as the logarithm of dollars per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.6: Covariate Balance between Treatment and Control Groups (Propensity Score)

Covariate	Mean (Treatment)	Mean (Control)	Mean Difference
Propensity score (1:1)			
Log population	10.421	10.349	0.072 (0.126)
Median income per capita	1.288	1.492	-0.204 (0.157)
Log housing value	11.119	11.181	-0.062 (0.041)
Log housing rent	5.939	5.970	-0.031 (0.024)
Unmployment rate	0.073	0.067	0.006 (0.004)
Log marriage	5.597	5.514	0.084 (0.126)
Share of college or over	0.368	0.402	-0.033 (0.015)
Share of over 65	0.145	0.145	0.001 (0.004)
Share of White	0.933	0.915	0.019 (0.011)
N	126	126	
Propensity score (1:2)			
Log population	10.421	10.408	0.013 (0.107)
Median income per capita	1.288	1.538	-0.25 (0.142)
Log housing value	11.119	11.221	-0.103 (0.035)
Log housing rent	5.939	6.018	-0.079 (0.019)
Unmployment rate	0.073	0.059	0.014 (0.003)
Log marriage	5.597	5.545	0.052 (0.109)
Share of college or over	0.368	0.408	-0.04 (0.012)
Share of over 65	0.145	0.142	0.003 (0.003)
Share of White	0.933	0.913	0.021 (0.01)
N	126	252	
Propensity score (1:3)			
Log population	10.421	10.435	-0.014 (0.101)
Median income per capita	1.288	1.569	-0.28 (0.13)
Log housing value	11.119	11.236	-0.118 (0.033)
Log housing rent	5.939	6.044	-0.105 (0.018)
Unmployment rate	0.073	0.056	0.017 (0.003)
Log marriage	5.597	5.583	0.014 (0.101)
Share of college or over	0.368	0.414	-0.045 (0.011)
Share of over 65	0.145	0.142	0.003 (0.003)
Share of White	0.933	0.905	0.029 (0.009)
N	126	378	

Notes: Standard errors from t-test for mean differences are displayed in parentheses.

Table C.7: Instrument Relevance: Coal Supply Response to Coal-Bust Potential

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coal-Bust Potential	-4.01*** (1.12)	-3.99*** (1.08)	-4.39*** (1.06)	-5.01*** (1.22)	-4.31*** (1.07)	-4.12*** (1.03)	-1.07*** (0.26)	-1.31*** (0.34)	-1.67*** (0.48)
Distance [miles]	100	110	120	130	140	150	130	130	130
Fracking Score	one	one	one	one	one	one	one	max	mean
Pipeline (2000)	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Fixed-effects									
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
F-statistic	33.1	32.3	39.1	50.0	36.0	30.8	48.2	44.1	35.1
Observations	2,385	2,385	2,385	2,385	2,384	2,384	2,385	2,385	2,385
R^2	0.802	0.802	0.802	0.803	0.802	0.803	0.803	0.803	0.802

Notes: The estimates, denoted as γ_1 in equation (3.3), are derived from an OLS estimation. "Distance" is the shortest distance ($\bar{d}$) between county i and shale gas play k, assuming a spherical earth. Clustered (county & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.8: Instrument Relevance: Coal Demand Response to Coal-Bust Potential

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Coal-Bust Potential	-7.08*** (1.74)	-7.30*** (1.63)	-7.29*** (1.61)	-8.46*** (1.51)	-8.62*** (1.54)	-9.44*** (1.58)	-1.91*** (0.33)	-2.27*** (0.45)	-3.05*** (0.66)
Distance [miles]	100	110	120	130	140	150	130	130	130
Fracking Score	one	one	one	one	one	one	one	max	mean
Pipeline (2000)	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Fixed-effects									
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
F-statistic	67.6	71.9	71.8	95.8	98.5	111.7	103.8	89.2	78.6
Observations	1,936	1,936	1,936	1,936	1,936	1,936	1,936	1,936	1,936
R^2	0.776	0.776	0.776	0.779	0.780	0.781	0.780	0.779	0.777

Notes: The estimates, denoted as γ_1 in equation (3.3), are derived from an OLS estimation where $log(Coal_{it})$ is replaced with $log(Q_{it})$. "Distance" is the shortest distance ($\bar{d}$) between county i and shale gas play k, assuming a spherical earth. Clustered (county & year) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.9: Robustness of Local Labor Market Results: Rolling Average of Coal Production

	Local Real GDP (BEA)	Total Firms (CBP)	Total Employment (QWI)	Gross Income (IRS)	Per-Capita Net Earnings (BEA)	Per-Capita Royalty Inc. (IRS)
log(Coal Decline)	-0.3770***	-0.1717***	-0.2643***	-0.2264***	-0.1011**	-0.1130*
(2-yr moving avg.)	(0.0794)	(0.0385)	(0.0586)	(0.0461)	(0.0412)	(0.0559)
F-statistic	61.4	62.5	62.5	62.5	61.4	62.5
log(Coal Decline)	-0.4145***	-0.1887***	-0.2908***	-0.2488***	-0.1111**	-0.1242*
(3-yr moving avg.)	(0.0865)	(0.0443)	(0.0661)	(0.0513)	(0.0442)	(0.0609)
F-statistic	62.2	63.3	63.3	63.3	62.2	63.3
Mean of DV	2,767 [$M]	1,390	21,272	1,403 [$M]	20,200 [$]	12,973 [$]
Observations	2,367	2,385	2,369	2,385	2,367	2,385

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable. Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.10: Robustness of Local Labor Market Results: Exclusion of Extreme Coal Counties

	Local Real GDP (BEA)	Total Firms (CBP)	Total Employment (QWI)	Gross Income (IRS)	Per-Capita Net Earnings (BEA)	Per-Capita Royalty Inc. (IRS)
log(Coal Decline)	-0.3680***	-0.1658***	-0.2536***	-0.2202***	-0.0996**	-0.1111*
(> 1Mst of coal)	(0.0711)	(0.0376)	(0.0545)	(0.0442)	(0.0389)	(0.0568)
F-statistic	51.7	52.6	52.9	52.6	51.7	52.6
Mean of DV	2,176 [$M]	1,139	16,228	1,117 [$M]	20,165 [$]	12,983 [$]
Observations	2,288	2,306	2,292	2,306	2,288	2,306
log(Coal Decline)	-0.3564***	-0.1611***	-0.2488***	-0.2127***	-0.0958**	-0.1064*
(< 1,000Mst of coal)	(0.0715)	(0.0342)	(0.0519)	(0.0414)	(0.0397)	(0.0538)
F-statistic	48.8	49.7	49.8	49.7	48.8	49.7
Mean of DV	2,741 [$M]	1,389	21,275	1,402 [$M]	20,059 [$]	12,933 [$]
Observations	2,349	2,367	2,351	2,367	2,349	2,367

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable. Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.11: Robustness of Local Labor Market Results: Different Clustering Choices

	Local Real GDP (BEA)	Total Firms (CBP)	Total Employment (QWI)	Gross Income (IRS)	Per-Capita Net Earnings (BEA)	Per-Capita Royalty Inc. (IRS)
Clustering choice: county						
log(Coal Decline)	-0.3551***	-0.1617***	-0.2489***	-0.2133***	-0.0952***	-0.1065*
	(0.0889)	(0.0531)	(0.0898)	(0.0628)	(0.0359)	(0.0557)
F-statistic	52.2	53.2	53.3	53.2	52.2	53.2
Clustering choice: county and year						
log(Coal Decline)	-0.3551***	-0.1617***	-0.2489**	-0.2133***	-0.0952**	-0.1065
	(0.0879)	(0.0523)	(0.0881)	(0.0615)	(0.0418)	(0.0629)
F-statistic	52.5	53.6	53.7	53.6	52.5	53.6
Clustering choice: commuting zone by year						
log(Coal Decline)	-0.3551***	-0.1617***	-0.2489***	-0.2133***	-0.0952***	-0.1065***
F-statistic	(0.0277)	(0.0190)	(0.0304)			
F-statistic	49.0	50.0	50.1	50.0	49.0	50.0
Clustering choice: state by year						
log(Coal Decline)	-0.3551***	-0.1617***	-0.2489***	-0.2133***	-0.0952***	-0.1065***
	(0.0450)	(0.0230)	(0.0319)	(0.0273)	(0.0215)	(0.0318)
F-statistic	49.0	50.0	50.1	50.0	49.0	50.0
Mean of DV	2,767 [$M]	1,390	21,272	1,403 [$M]	20,200 [$]	12,973 [$]
Observations	2,367	2,385	2,369	2,385	2,367	2,385

Notes: The estimates are derived from the 2SLS estimation using the coal-bust potential as an instrumental variable. Clustered (commuting zone & year) standard errors in parentheses, and the Cragg-Donald F-statistic is reported for instrument relevance. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.12: Placebo Test: Coal Decline 10 Years Ahead

	Revenue			*Expenditure*		
	Local	IGT	All	Specific	General	All
	(1)	(2)	(3)	(4)	(5)	(6)
OLS						
log(Coal Decline)	0.0181	0.0403	0.0226	-0.0131	0.0367	0.0093
(10-year-lagged)	(0.0213)	(0.0375)	(0.0184)	(0.0210)	(0.0330)	(0.0116)
IV (10-year-lagged)						
log(Coal Decline)	0.0560	-0.0292	0.0707	0.0364	0.1009	0.0630
(10-year-lagged)	(0.1338)	(0.2930)	(0.1424)	(0.1426)	(0.1322)	(0.1378)
Observations	122	122	122	122	122	122

Notes: Heteroskedasticity-robust standard errors are shown in parentheses. All dependent variables are measured as the logarithm of dollars per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.13: Falsification Test: Matched Counties in Non-Coal-Producing States

	Revenue			*Expenditure*		
	Local	IGT	All	Specific	General	All
	(1)	(2)	(3)	(4)	(5)	(6)
First Match						
log(Coal Decline)	0.0043	-0.0028	0.0342	-0.0112	-0.0514	-0.0160
	(0.0427)	(0.0759)	(0.0526)	(0.0770)	(0.0581)	(0.0543)
Second Match						
log(Coal Decline)	0.0667	-0.1848	0.0056	-0.1138	-0.1236	-0.1178
	(0.0504)	(0.1256)	(0.0427)	(0.1188)	(0.0826)	(0.1116)
Third Match						
log(Coal Decline)	0.0162	-0.0688	0.0062	-0.0392	0.0068	-0.0314
	(0.0434)	(0.0707)	(0.0348)	(0.0378)	(0.0513)	(0.0289)
Observations	128	128	128	128	128	128

Notes: Heteroskedasticity-robust standard errors are shown in parentheses. All dependent variables are measured as the logarithm of dollars per capita. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table C.14: Average Income and Population in Coal and Non-Coal Counties

	Coal County (H)		*Non-Coal County (L)*	
Year	Income	Population	Income	Population
2012	$35,665	60,104	$39,099	82,232
2017	$36,871	59,314	$41,418	85,845

Table C.15: List of 143 Sample Counties

	County Name	State		County Name	State
1	Bell County	Kentucky	73	Greenbrier County	West Virginia
2	Breathitt County	Kentucky	74	Harrison County	West Virginia
3	Clay County	Kentucky	75	Kanawha County	West Virginia
4	Daviess County	Kentucky	76	Lincoln County	West Virginia
5	Floyd County	Kentucky	77	Logan County	West Virginia
6	Harlan County	Kentucky	78	McDowell County	West Virginia
7	Henderson County	Kentucky	79	Marion County	West Virginia
8	Hopkins County	Kentucky	80	Marshall County	West Virginia
9	Johnson County	Kentucky	81	Mineral County	West Virginia
10	Knott County	Kentucky	82	Mingo County	West Virginia
11	Knox County	Kentucky	83	Monongalia County	West Virginia
12	Laurel County	Kentucky	84	Nicholas County	West Virginia
13	Lawrence County	Kentucky	85	Preston County	West Virginia
14	Leslie County	Kentucky	86	Raleigh County	West Virginia
15	Letcher County	Kentucky	87	Tucker County	West Virginia
16	Magoffin County	Kentucky	88	Upshur County	West Virginia
17	Martin County	Kentucky	89	Wayne County	West Virginia
18	Muhlenberg County	Kentucky	90	Webster County	West Virginia
19	Ohio County	Kentucky	91	Wyoming County	West Virginia
20	Owsley County	Kentucky	92	Delta County	Colorado
21	Perry County	Kentucky	93	Gunnison County	Colorado
22	Pike County	Kentucky	94	La Plata County	Colorado
23	Union County	Kentucky	95	Moffat County	Colorado
24	Webster County	Kentucky	96	Montrose County	Colorado
25	Whitley County	Kentucky	97	Rio Blanco County	Colorado
26	Belmont County	Ohio	98	Routt County	Colorado
27	Carroll County	Ohio	99	Gallatin County	Illinois
28	Columbiana County	Ohio	100	Jackson County	Illinois
29	Harrison County	Ohio	101	Macoupin County	Illinois
30	Jackson County	Ohio	102	Perry County	Illinois
31	Jefferson County	Ohio	103	Randolph County	Illinois
32	Mahoning County	Ohio	104	Saline County	Illinois
33	Monroe County	Ohio	105	Sangamon County	Illinois
34	Muskingum County	Ohio	106	Wabash County	Illinois
35	Noble County	Ohio	107	White County	Illinois
36	Perry County	Ohio	108	Williamson County	Illinois
37	Stark County	Ohio	109	Clay County	Indiana
38	Tuscarawas County	Ohio	110	Daviess County	Indiana
39	Vinton County	Ohio	111	Dubois County	Indiana
40	Allegheny County	Pennsylvania	112	Gibson County	Indiana
41	Armstrong County	Pennsylvania	113	Knox County	Indiana
42	Beaver County	Pennsylvania	114	Pike County	Indiana
43	Butler County	Pennsylvania	115	Sullivan County	Indiana
44	Cambria County	Pennsylvania	116	Vigo County	Indiana
45	Clarion County	Pennsylvania	117	Warrick County	Indiana
46	Clearfield County	Pennsylvania	118	Big Horn County	Montana
47	Elk County	Pennsylvania	119	Musselshell County	Montana
48	Fayette County	Pennsylvania	120	Richland County	Montana
49	Greene County	Pennsylvania	121	Rosebud County	Montana
50	Indiana County	Pennsylvania	122	McKinley County	New Mexico
51	Jefferson County	Pennsylvania	123	San Juan County	New Mexico
52	Luzerne County	Pennsylvania	124	McLean County	North Dakota
53	Lycoming County	Pennsylvania	125	Mercer County	North Dakota
54	Schuylkill County	Pennsylvania	126	Oliver County	North Dakota
55	Somerset County	Pennsylvania	127	Craig County	Oklahoma
56	Venango County	Pennsylvania	128	Haskell County	Oklahoma
57	Washington County	Pennsylvania	129	Le Flore County	Oklahoma
58	Westmoreland County	Pennsylvania	130	Atascosa County	Texas
59	Anderson County	Tennessee	131	Freestone County	Texas
60	Campbell County	Tennessee	132	Harrison County	Texas
61	Claiborne County	Tennessee	133	Leon County	Texas
62	Buchanan County	Virginia	134	Robertson County	Texas
63	Dickenson County	Virginia	135	Rusk County	Texas
64	Lee County	Virginia	136	Titus County	Texas
65	Russell County	Virginia	137	Carbon County	Utah
66	Tazewell County	Virginia	138	Emery County	Utah
67	Wise County	Virginia	139	Sevier County	Utah
68	Barbour County	West Virginia	140	Campbell County	Wyoming
69	Boone County	West Virginia	141	Converse County	Wyoming
70	Clay County	West Virginia	142	Lincoln County	Wyoming
71	Fayette County	West Virginia	143	Sweetwater County	Wyoming
72	Grant County	West Virginia			

Table C.16: Item Description: Local Government Finance

Item Category	Description
Revenue	
Rents and royalties	Revenues from (1) allowing temporary possession of government-owned buildings, land, or other fixed properties; (2) leases (or lease bonus payments) of land relating to natural resource exploration and production; and (3) compensation or portion of proceeds received by a state or local government for granting the privilege of using or developing property or operating under a right, primarily those related to natural resources, such as oil, gas, and mineral rights
Sales tax	Tax revenues from sales of all types of goods and services (including alcoholic beverages, tobacco, and motor fuels) or to all gross receipts, whether at a single rate or at classified rates; and sales use taxes
Property tax	Revenues from taxes imposed on ownership of property and measured by its value
Charges and utilities	Revenues from charges related to air and water transportation, highways, parking facilities, public recreational facilities, education services, housing and community developemnt, sewerage, agricultural products from public lands, and public water, electric power, and gas systems
IG transfer (matching grant)	Revenues from State (or Federal) aid for public roads (e.g., streets and highways), public health, housing and community development, and sewerage
IG transfer (general purpose)	Revenues from State (or Federal) aid for general local government support
IG transfer (from other local governments)	Revenues from interlocal (other county or city governments) support
Expenditure	
Housing and Environment	Expenditures related to (1) housing and redevelopment projects and other activities to promote or aid public and private housing and community development; (2) water resources, mineral resources, agriculture, and the regulation of related industries and agricultural products; (3) recreational and cultural-scientific facilities; (4) garbage, refuse, hazardous, and other solid wastes and the cleaning of public roads
Public Safety	Expenditures related to (1) residential institutions or facilities for convicted adults, or juveniles adjudicated, delinquent or in need of supervision; (2) correctional activities other than residential institutions or facilities; (3) fire protection agencies; (4) police, sheriff, and other governmental departments that preserve law and order, protect persons and property from illegal acts; (5) regulation and inspection of private establishments for the protection of the public
Public Transit	Expenditures related to (1) provision, operation, construction, and support of airport facilities serving the public at-large on a scheduled or unscheduled basis; (2) maintenance, operation, repair, and construction of highways, streets, roads, alleys, sidewalks, bridges, tunnels, ferry boats, viaducts, and related non-toll structures; (3) provision, construction, maintenance, and operation of public parking facilities operated on a commercial basis; (4) provision, construction, operation, maintenance, and support of public waterways and harbors, docks, wharves, and related marine terminal facilities
Public Welfare	Expenditures related to (1) services for the conservation and improvement of public health (e.g., community health care programs); (2) payments under public welfare programs made directly to private vendors; (3) nursing homes and welfare institutions owned and operated by a government for the benefit of needy persons and veterans; (4) cash payments made directly to individuals contingent upon their need or under three Federal assistance programs: Supplemental Security Income; Temporary Assistance for Needy Families, and Medical Assistance Program

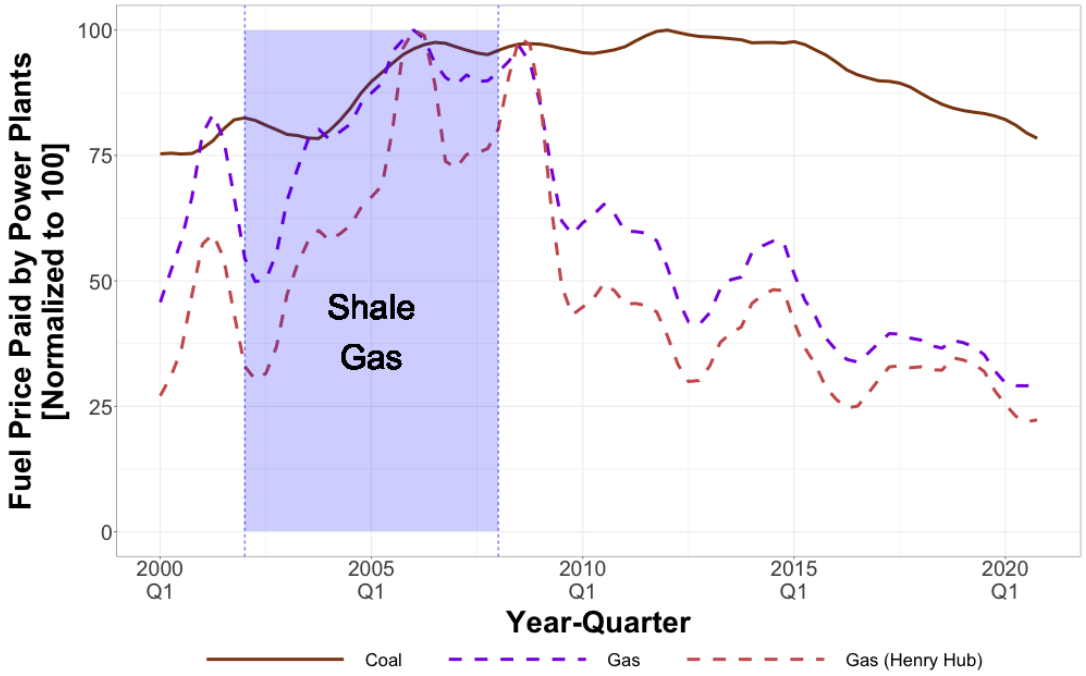


Figure C.1: Average Fuel Costs Paid by Individual Power Plants

Notes: Observations below the 1th percentile and above the 99th percentile of coal and natural gas costs paid by the power plants are truncated.

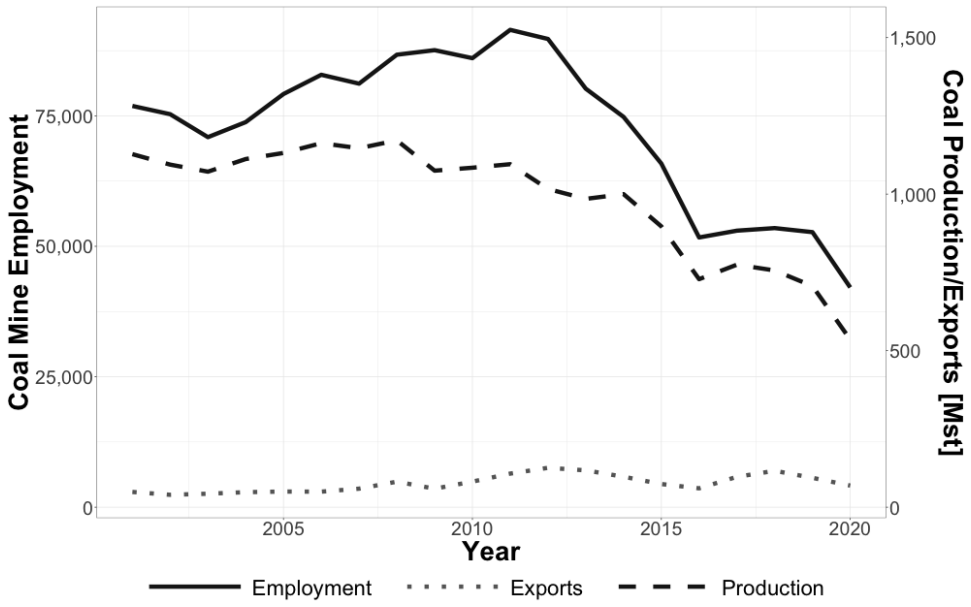


Figure C.2: Employment and Production in Coal Mines

Notes: The unit 'Mst' denotes million short tons. Data source: U.S. Energy Information Administration.

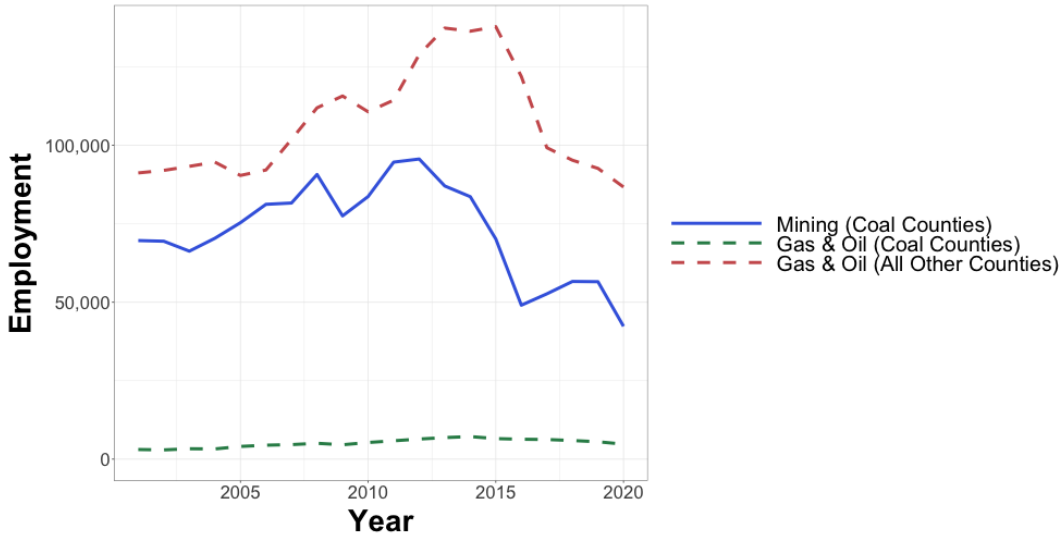


Figure C.3: Mining and Oil/Gas Extraction Employment

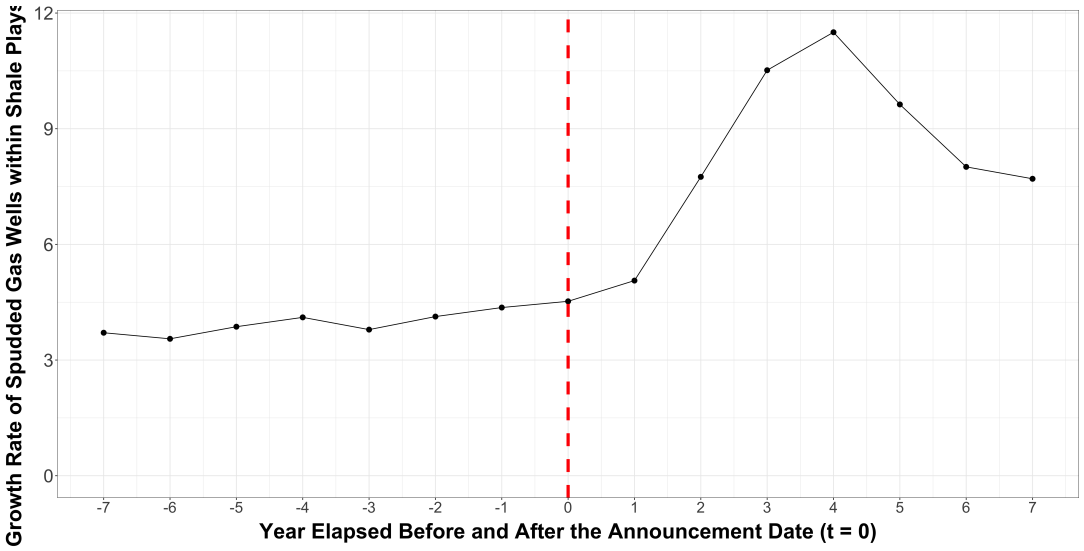


Figure C.4: An Upsurge in Gas Production since the First Announcements of Success on Fracking

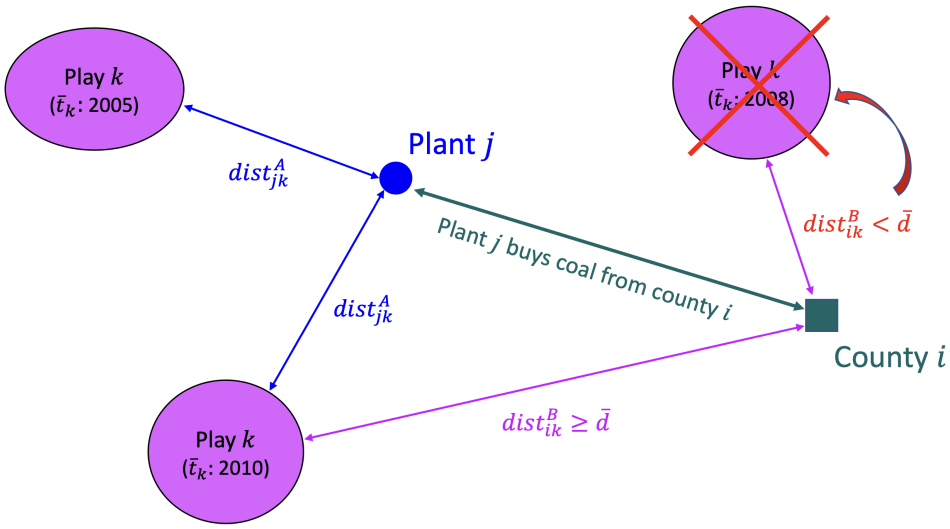


Figure C.5: Illustration of Identification Strategy

Notes: The notations correspond to the equation (C.9) in Appendix.

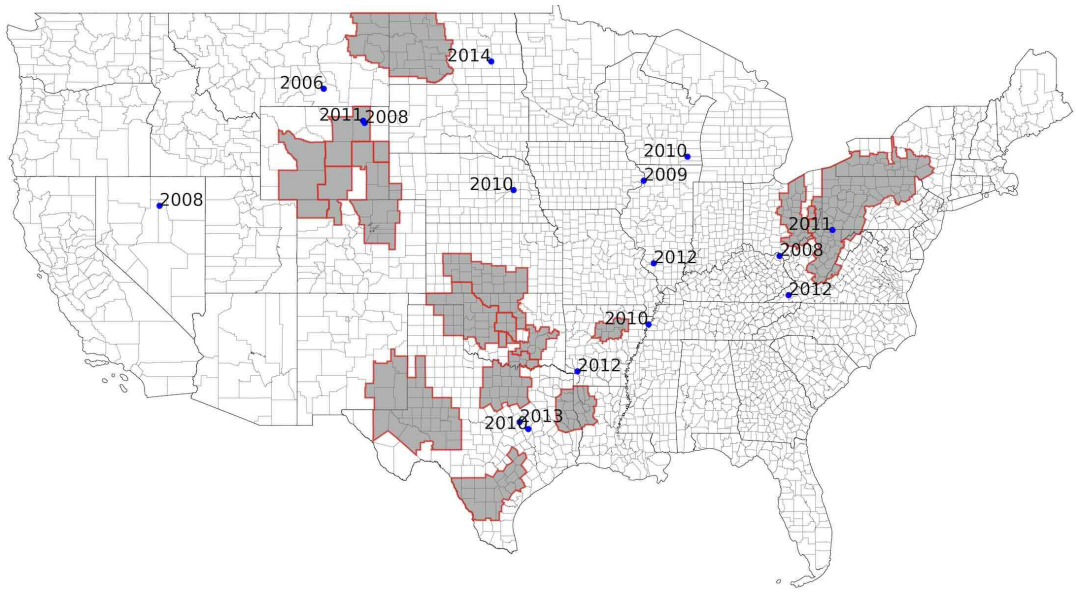


Figure C.6: Coal Power Plants and Shale Gas Plays

Notes: Blue dots represent the coal power plants that were built after 2005, and shaded areas are the shale gas plays. The initial operating years of each coal power plant are displayed.

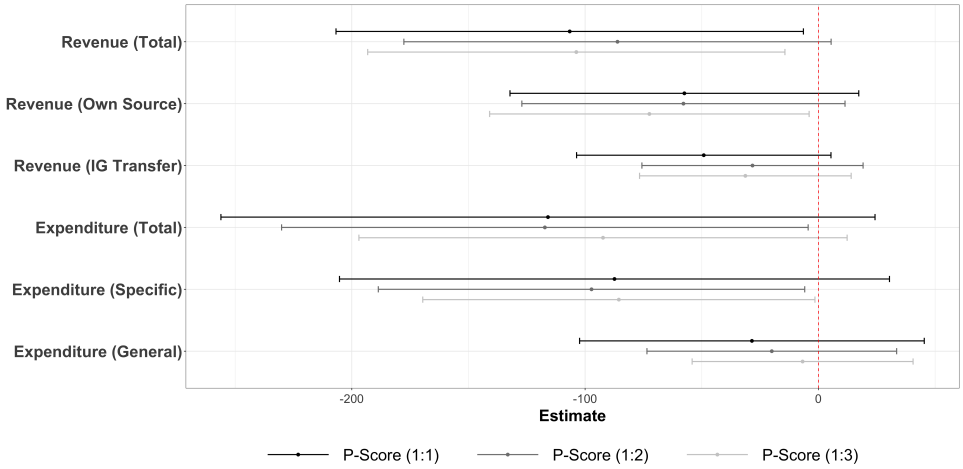


Figure C.7: Results: Local Government Finance (DiD with Matching)

Notes: It illustrates the estimated coefficients (represented by dots) along with their corresponding 95% confidence intervals (depicted as error bars). A detailed summary of all estimates can be found in Appendix Table [TBD].

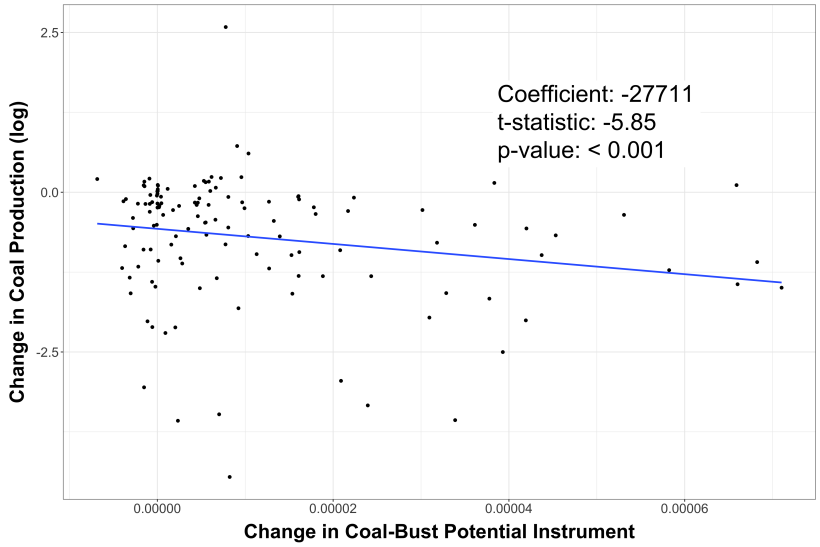


Figure C.8: First-Stage in Long-Difference Specification

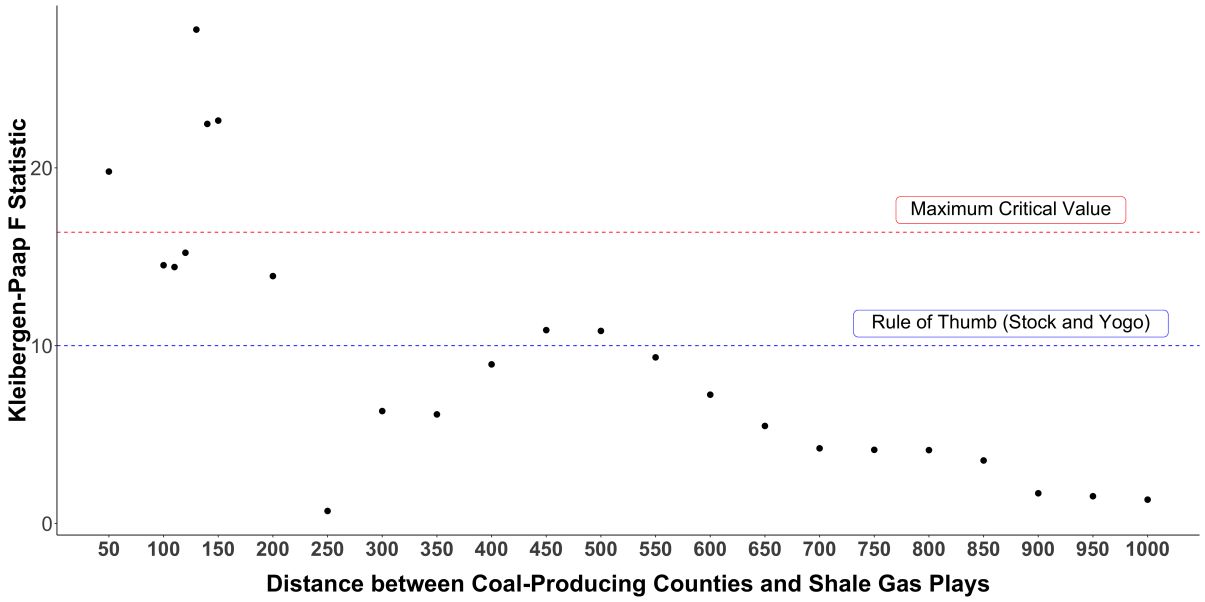


Figure C.9: Weak Instrument Tests

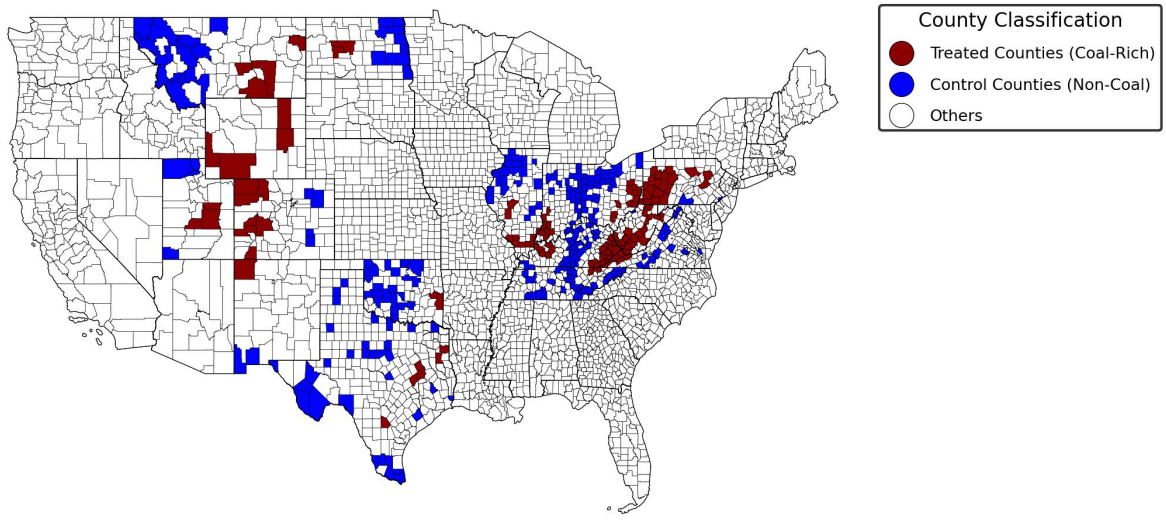


Figure C.10: Treatment and Control Counties by Matching Procedure

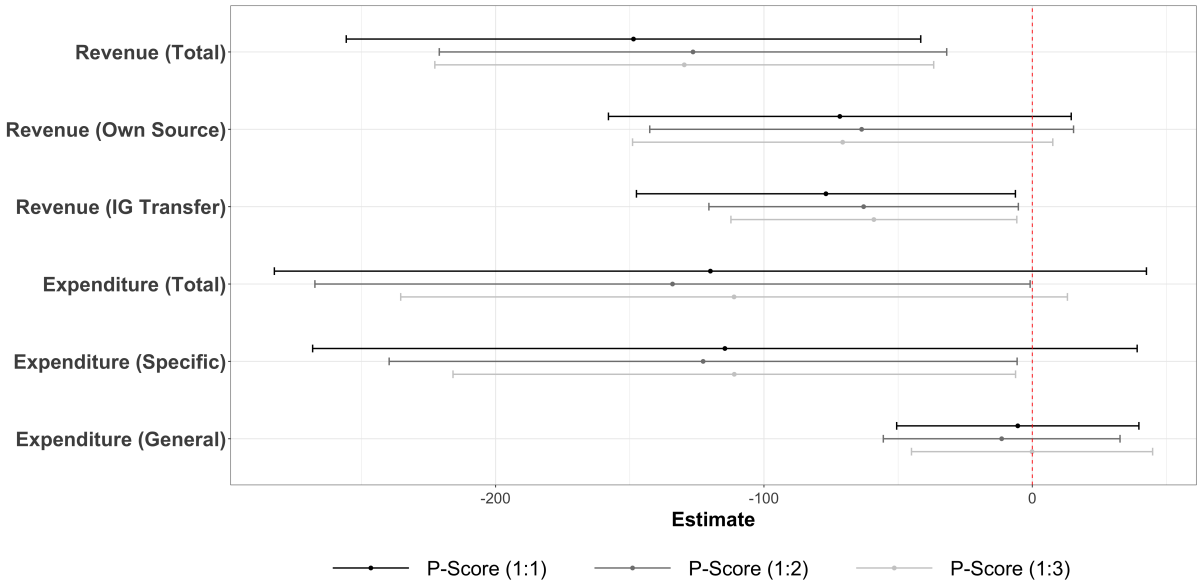


Figure C.11: Local Public Finance Results with All Matching Ratios (with Replacement)

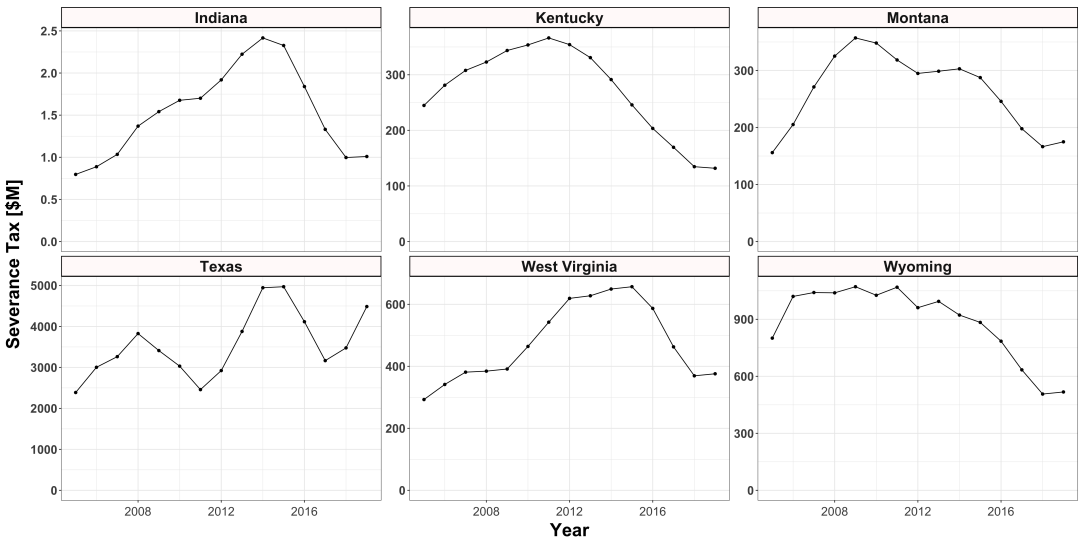


Figure C.12: Severance Tax in Coal-Rich States

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

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