Quantifying the Distortions of Labor Market Power: U.S. Coal Mines 2001-2019

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Abstract

I quantify how labor market power distorts the broader production process, combining evidence from merger event studies and a structural oligopsony model in which wages, employment, capital, and output are jointly determined in equilibrium. Using administrative data from the U.S. coal industry, I show that rent extraction from the labor market not only lowers wages and employment, but also creates a scale effect that reduces the firm's demand for capital, suppresses output, and diminishes aggregate productivity. These "knock-on" distortions of labor market power are four times larger, by value, than the direct welfare loss to workers. My results suggest that labor market outcomes can significantly underestimate the welfare costs of oligopsony, especially in capital-intensive industries like mining.

JEL Codes: J42, L13, D24, L71

Keywords: Monopsony, Labor Market Power, Capital-Labor Complementarity, Welfare Analysis, Mergers and Acquisitions, Coal

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1 Introduction

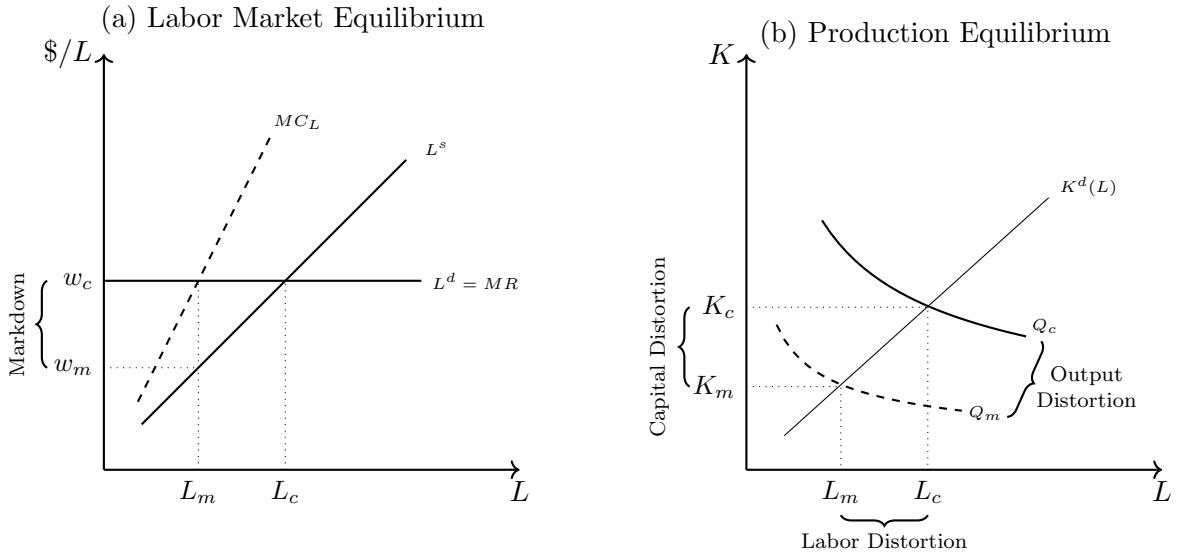
A growing body of evidence documents the consequences of imperfect competition in labor markets. This literature has naturally focused on labor market outcomes: wage markdowns below the product of labor can be significant, suppressing employment and causing deadweight loss in important industries (Card, 2022; Lamadon et al., 2022; Yeh et al., 2022; Prager and Schmitt, 2021; Arnold, 2021; Berger et al., 2022). Yet monopsony can also cause distortions that extend beyond wages and employment to affect outcomes in the broader economy. Incentives to extract rents from the labor market have been shown to affect technological investment (Rubens, 2025) and interact with product market competition (Kroft et al., 2025), for example. Despite increasing interest from researchers and policy markers, the extent of such "knock-on" distortions for other resources, like capital, remains largely an open and empirical question.

This paper quantifies the knock-on distortions of labor market power in an empirical study of the U.S. coal mining industry, leveraging rich administrative microdata on both labor and the production process. I first extend an established causal empirical design to directly test whether increased labor market concentration affects capital and output in addition to wages and employment. Then I develop and estimate an equilibrium oligopsony model that ascribes value to the distortions and decomposes their driving mechanisms.

Both methodologies reveal that the knock-on distortions of labor market power can be even greater than the wage and employment forces behind them. Although coal mine workers are significantly harmed, labor outcomes only account for 20% of the more encompassing distortion of oligopsony in the model. The input complementarity and capital-intensity of coal production generates scale effects (versus substitution effects) that spur the reductions in capital, lowering output in turn and diminishing aggregate productivity. Relative to the oligopsony market structure observed in the data, even a small amount of buyer power leveraged by monopsonistically competitive employers causes significant knock-on distortions. Moreover, the allocative efficiencies from consolidation do not offset the harms of reduced labor market competition, as full blown monopsony would be significantly worse for workers, capital suppliers, and consumers alike.

Figure 1 provides a conceptual framework that motivates the empirical analysis. The left panel shows a labor market with an upward-sloping supply curve, so that a monopsonist's effective marginal cost of labor is above the prevailing wage. Profit maximization equates marginal revenue (labor demand l^d) with marginal cost, creating a wedge or markdown between wages and the product of labor. Rent seeking thus lowers equilibrium employment and suppresses wages relative to a competitive equilibrium, $w_m < w_c$ and $l_m < l_c$.

Figure 1: Direct and Knock-on Effects of Labor Market Power



Labor derives its value from the production process, and the right panel of the figure illustrates the monopsonist's production problem. Assuming that inputs are gross complements, the demands for labor and capital resolve scale and substitution effects in the production decision. Moving with employment, demand for capital falls $k_m < k_c$ relative to a competitive equilibrium. With less of both inputs, the monopsonist's isoquant is lower and output declines $q_m < q_c$.

The coal mining industry is a good empirical laboratory to test this intuition. Regulators maintain decades of rich microdata covering the nearly every coal mine in the U.S., including firm identifiers and granular measures of annual coal output, labor inputs, and a capacity-denominated measure of capital. The geographic distribution of coal deposits also leads to a cross-section of local labor markets with a wide range of concentration and outside employment alternatives from which to gauge market power in the lens of a model. Mining mergers and acquisition events provide additional within-variation in labor market structure for identifying empirical effects that complements the natural between-variation.

I begin by providing direct causal empirical evidence on how labor market concentration affects capital and output in addition to wages and employment. Based on the identification strategies of Prager and Schmitt (2021) and Arnold (2021), I use a difference-in-differences (DID) design that leverages variation induced by mergers and acquisitions (M&A). Specifically, I compare outcomes in "overlap" labor markets (treatment) where merging parties had competing mining operations to "non-overlap" areas (control) where labor market structure remained unchanged. If labor market power is a driving mechanism, the effects of consolidation that significantly increased labor market concentration should be economically larger

and statistically different from the effects of M&A that had smaller impacts on concentration.

I find that mine acquisitions that significantly increased labor market concentration caused wages to fall by an additional 8% and employment to drop an additional 26% relative to smaller acquisitions. Moreover, these labor market outcomes lead to significant knock-on effects: mine capacity and output decline an additional 40% after acquisitions that significantly increased labor market concentration. These results are robust to controlling for product market consolidation and a variety of alternative control group specifications. However, the causal empirical design cannot fully explore the driving mechanisms or quantify welfare and efficiency outcomes.

Toward that end, I offer an oligopsony model of the labor market in which capital and production are resolved in equilibrium with wages and employment. I assume that workers have preferences for differentiated jobs (Bhaskar et al., 2002), and that firms produce coal using a constant elasticity of substitution (CES) technology. I identify and estimate the model by adapting standard techniques from the empirical IO literature on demand and production functions. A methodological contribution is the introduction of a "latent wage" technique which allows for the identification of labor supply parameters even when job-level wages are unobserved, facilitated by the equilibrium relationship between markdowns and marginal products.

Estimates of the structural model suggest that coal mines have significant market power over workers. The firm-level labor supply elasticity is about 2, in the lower range of estimates from other industries (Azar et al., 2022). The inelastic labor supply is driven by relatively strong attachment to mining jobs over non-mining alternatives, in a nesting parameter of 0.55, in combination with the relative concentration of local labor markets for coal. I thus estimate equilibrium markdowns worth 40-50% of the marginal product of labor, on average.

In the production model the estimated elasticity of substitution between capital and labor is 0.71, in the range of recent estimates for other manufacturing industries (Oberfield and Raval, 2021). This input complementarity implies that any movements in labor will likely be transmitted to demand for capital by a significant degree.

I use the estimated model to quantify the aggregate distortions of labor market power via equilibrium counterfactuals. Comparing the observed oligopsony to a counterfactual perfectly competitive labor market, I find that the distortions are economically and statistically significant. In a competitive labor market, wages would be 74% higher and employment 36% higher than in the observed oligopsony. The knock-on distortions are also significant: demand for capital would increase by 32% (+ \$126 billion) and total output would rise by 35% (+ \$188 billion) if labor markets for coal mines were competition. By value, the distortion to capital is nearly double the distortion to worker surplus.

I then decompose the total distortions into their driving forces. I find that scale effects, the contraction in production incentivized by a higher effective marginal cost of labor, play the dominant role. Scale effects of labor market power account for 72% of the reduction in wages, 67% of the distortion to labor, 76% of the reduction in worker surplus, 65% of the knock-on capital distortion, and 62% of the output effect. The substitution effects of labor market power, which incentivize a shift away from labor to more capital intensive production, are present but secondary.

I finally illustrate how the distortions trace with the hypothetical range of labor market power. At the lower bound, I show that monopsonistically competitive behavior can account for half of the distortion to labor market outcomes and about 60% of the distortions to capital and output, suggesting that even a labor market with atomistic but imperfectly competitive firms can lead to significant knock-on distortions. At the upper bound, I find that distortions in a counterfactual monopsony equilibrium are significantly worse than the observed oligopsony, suggesting that the benefits of consolidation do not offset the harms of labor market power for workers, capital suppliers, and consumers. Together, the results highlight that the economic costs of labor market power extend beyond the labor market, with knock-on distortions that may be particularly significant in capital intensive industries.

This paper relates to a broader empirical literature documenting labor market power, reviewed extensively by Card (2022); Manning (2021); Azar and Marinescu (2024). The most closely related papers use models to quantify buyer power and/or its production distortions. Notably, Rubens (2023, 2025) shows that materials oligopsony diminished aggregate productivity in the Chinese tobacco industry, and that labor monopsony affected investment in labor-augmenting technology in the 19th century coal industry. Kroft et al. (2025) identify labor markdowns and product markups in the construction industry, and then infer the oligopsony distortion across the production process. Berger et al. (2022, 2025) provide welfare and deadweight loss analysis from a macro perspective. Finally, my identification of markdowns via the latent wage technique can be viewed as a wedding of Azar et al. (2022), Lamadon et al. (2022), and Yeh et al. (2022). To this structural literature my contributions include (i) a causal empirical test of the knock-on distortions that complements the model-based evidence, linked to (Prager and Schmitt, 2021; Arnold, 2021); (ii) a structural identification strategy based on standard inversion methods in empirical IO; (iii) value-denominated measures of the knock-on distortions that are informed directly by data on capital services and output; and (iv) mechanism analysis that suggests the scale effects of labor market power are dominant drivers of deadweight loss in industries with strong input complementarity (Oberfield and Raval, 2021).

2 Coal Mining Industry and Data

The U.S. coal mining industry is an ideal laboratory for studying labor market power and its distortions. The industry is characterized by geographically distinct local labor markets, high capital intensity, and significant variation in labor market concentration. This section provides a summary of the available data, production technologies used in coal, and the evolution of market structure during the study period.

2.1 Data Sources

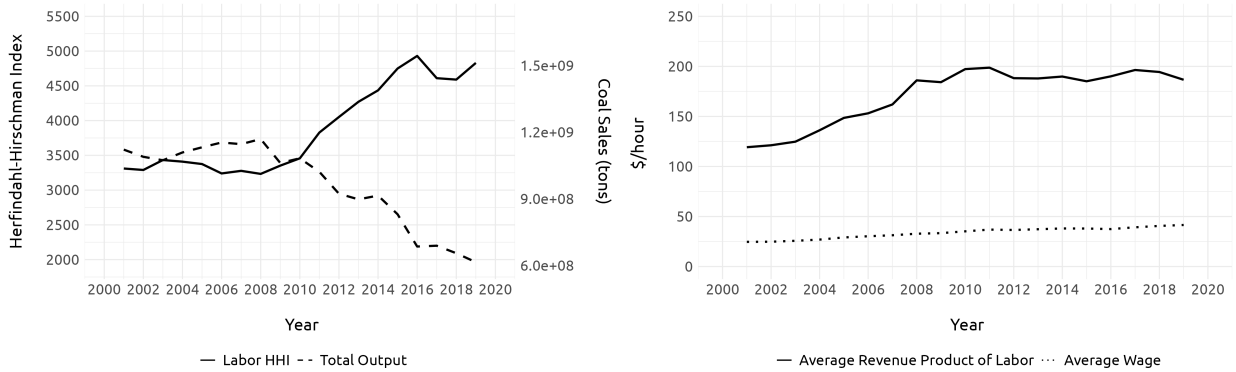
I construct a comprehensive panel of U.S. coal mines from 2001 to 2019 by combining public and confidential administrative data. I observe the universe of coal mines using public data from the **Mine Safety and Health Administration (MSHA)**, which provides annual mine-level employment, hours worked, coal extraction, and job characteristics. I merge this with confidential data from the **Energy Information Administration (EIA) Form 7-A**, which contains mine-level financial information including coal sales (in tons), revenue, additional job characteristics, types of coal, production methods, recoverable reserves (mineral rights), and production capacity. The capacity variable is a measure of operating capital, denominated in tons of potential coal output per year. Finally, I take county-level wages for the mining sector and the size of the total labor force from the **Bureau of Labor Statistics (BLS)**, including the Quarterly Census of Employment and Wages (QCEW).

2.2 Labor Outcomes in a Concentrating Market

The study period covers a significant consolidation in local labor markets for mining and a significant contraction in the U.S. coal industry. Figure 2 illustrates these trends. Panel (a) shows that labor market concentration among coal mines in the average county (solid line) steadily increased after 2010 as total coal output (dashed line) dropped. The average local labor market HHI rose from approximately 3,200 to almost 5,000, effectively shifting the typical market structure from three dominant employers to two.

Panel (b) motivates the labor market power hypothesis. Although the industry contracts, the national average revenue product of labor (ARPL) for coal almost doubles across the study horizon. Over the same period, average wages of coal miners increased much less, roughly in step with aggregate inflation. This widening gap between the wage and the product of labor tracks with the trend in labor market concentration, consistent with the exercise of market power.

Figure 2: Industry Trends in Concentration, Productivity, and Wages



(a) Concentration vs. Output

(b) ARPL vs. Wages

Notes: Panel (a) plots the employment-weighted average Herfindahl-Hirschman Index (HHI) for county labor markets (solid) and total national coal production (dashed). Panel (b) plots the national average revenue product of labor (solid) and the average hourly wage in the coal industry (dashed). Author's calculations based on public MSHA, EIA, and BLS data.

2.3 Capital Intensive Production Technologies

The role of physical capital in the production process motivates the potential for production distortions following these movements in the labor market. Coal production is capital intensive, regardless of the particular extraction method. For example, the most common production technology is continuous underground mining, where workers operate mobile "continuous" cutting vehicles. Longwall mining is a newer underground method using automated shearers and hydraulic shields. Surface mining extracts coal from shallow veins using earth movers, trucks, and other heavy machinery. Depending on geological constraints, several of these processes might be used in parallel at the same mine. Labor complements the machinery and equipment across these technologies (among others, see Appendix Table A.1), and all coal mines are capital intensive operations.

2.4 Panel Setup and Summary Statistics

I define "jobs" and "production units" as an aggregation of mine-year level data to firm-county-year level observations. Firms often report multiple mine identifiers for operations in close geographic proximity (e.g., two access points in the same coal seam). These operations often share operating capital, processing facilities, and labor pools, and typically report capacity, sales, and revenue in the confidential administrative (EIA Form 7-A) data as aggregates across these close-proximity mines. I therefore aggregate the mine-level data to the firm-county level to align the microdata sources and carve out the relevant scope

of production and employment decisions. The final estimation sample consists of 20,870 firm-county-year observations.

Table 1 presents descriptive statistics for the microdata (job-level) and labor market aggregates (county-level), the later presented to highlight between-market variation. The average coal mine job is in a local labor market where the HHI is above the definition for "highly concentrated" markets in antitrust merger guidelines. Moreover, there is a wide range of concentration across markets. This suggests that the coal industry is a good laboratory for studying oligopsony. The industry is also highly capitalized. Reflecting the production technologies discussed above, the average job has a capital-labor ratio of about 15 tons of annual capacity per labor hour. The average job also produces significant output, worth about $160 per hour of work. This suggests that if there is a distortion to employment, then complementary reductions in capital and output are likely to be significant in terms of value.

Table 1: Summary Statistics

	Micro Data (Job-County-Year)		Market Aggregates (County-Year)	
	Mean	St. Dev.	Mean	St. Dev.
Labor (1000 hours)	132.84	284.02	960.27	1308.9
Capacity-Capital (1000 tons)	1441.38	4756.34	10419.71	29879.78
Sales (1000 tons)	790.21	3630.97	5712.42	22779.32
Wage ($/hour)	29.1	8.09	29.38	9.95
Revenue per Labor ($/hour)	160.47	194.29	169.92	89.04
Revenue per Capital ($/ton)	27.82	25.84	28.19	18.7
Coal Price ($/ton)	52.17	30.61	47.2	28.02
Capital/Labor Ratio (tons/hour)	14.9	84.61	10.23	18.09
Number of Mining Jobs	23.04	23.11	7.23	10.69
Labor Market Share	0.06	0.11	0.18	0.17
Outside Option Share	0.54	0.15	0.57	0.17
HHI	2596.79	2144.01	5153.57	3152.3

Notes: Empirical mean and standard deviation of key variables from the EIA-MSHA-BLS data (2001-2019). The micro data (left) aggregate mine-level information to the job-county-year level (N = 20,870). Market aggregates (right) report county-year level totals (N = 2,887).

3 Empirical Effects of Labor Market Consolidation

A strategy to test the empirical effects of labor market power must address endogeneity between market structure, which gives rise to monopsony power, and the economic outcomes determined by that structure. Closely following Prager and Schmitt (2021), I construct a difference-in-differences (DID) estimator that exploits variation in labor market structure due to mergers and acquisitions (M&A). The empirical design of Prager and Schmitt (2021) has two throngs: first identify the causal effect of consolidation, and then test the labor market power hypothesis using variation in treatment intensity across consolidation events.

$$y_{mct} = \sum_{\tau \in [-3,3]} \text{DD}_\tau \cdot 1[\Delta\text{HHI}_{mc} > 0] \cdot 1[t = t_m^* + \tau] + \gamma_{mc} + \gamma_{mt} + e_{mct} \tag{1a}$$

$$y_{mct} = \text{DD} \cdot 1[\Delta\text{HHI}_{mc} > 0] \cdot 1[t \geq t_m^*] + \gamma_{mc} + \gamma_{mt} + e_{mct} \tag{1b}$$

$$\begin{aligned} y_{mct} = \; & \text{DD} \cdot 1[\Delta\text{HHI}_{mc} > 0] \cdot 1[t \geq t_m^*] \\ & + \text{DD}_{\text{big}} \cdot 1[\Delta\text{HHI}_{mc} \geq 500] \cdot 1[t \geq t_m^*] + \gamma_{mc} + \gamma_{mt} + e_{mct} \end{aligned} \tag{1c}$$

Formally, the design is a series of DID regression specifications (1) using a stacked-event panel. Outcome measures y_{mct} vary by M&A event m, county c, and year t. Event m occurs in year t_m^*. Each regression includes event-county fixed effects γ_{mc} to absorb persistent heterogeneity across labor markets and events, as well as event-year fixed effects γ_{mt} to control for secular trends specific to each treatment. Together, these fixed effects also specify event-specific control groups.

3.1 Identification Strategy

Identification relies on two sources of variation. First is the discrete change in market structure caused by labor market overlap at the time of consolidation. In equations (1a) and (1b), treatment is defined by an indicator $1[\Delta\text{HHI}_{mc} > 0]$ for "overlap" counties where the merging firms had competing mining operations prior to M&A. The control group consists of "non-overlap" counties where only one or neither of the parties operated, and thus market structure remained unchanged. The coefficients DD measure the treatment effects of consolidation, identified under the standard DID assumption that outcomes in overlap and non-overlap markets would have evolved in parallel absent M&A.[1]

[1]It is easy to verify that $\text{DD} = \frac{1}{M}\sum_{m \in M} DD_m$: the event-stacked regression estimate is an unweighted average of event-specific DIDs. This is numerically equivalent to alternative DID estimators with event-specific control groups (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020), as long as control groups mirror those used in the respective estimator. Standard errors may differ.

The causal effect of consolidation likely conflates a variety of mechanisms associated with M&A. To distinguish labor market power from other drivers, a second source of identification is needed: variation in treatment intensity. If monopsony drives the result, DIDs should be more pronounced for mergers that significantly increase market concentration. Regression (1c) therefore compares the causal effects of "big" M&A against the effects of other M&A that had smaller impacts on labor market structure, defining "big" as an increase in the labor HHI by 500 points or more. The estimate and standard error to test for labor market power is the interaction term DD_{big}, which measures the marginal effect of a substantial increase in concentration.

3.2 Estimation and Sample Selection

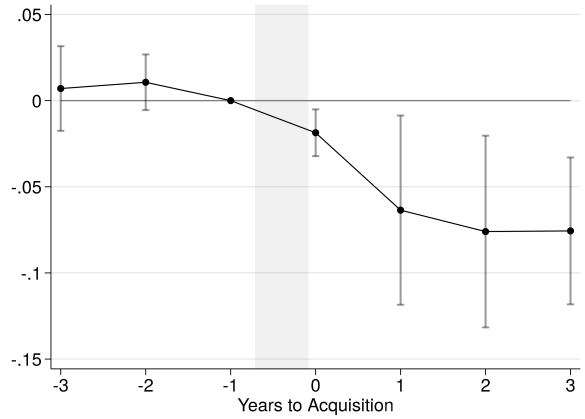
To implement this strategy, I construct an stacked-panel dataset of county outcomes across coal mine M&A events. The raw data contain 72 distinct M&A transactions with 67 overlap labor market events. The main estimation sample is further selected on three criteria. (i) Counties must continually produce coal from 2001-2019. (ii) Included M&A events must have a ±3-year study window. (iii) Counties may not be exposed to any other M&A treatments within a ±2-year window of the acquisition year. After applying these filters there are 46 M&A events in the regression sample.

For each of the 46 treatment events, I create a 7-year panel ($t^*_m \pm 3$ years) containing the treated county and all valid non-overlap control counties, and then append ("stack") the event-specific datasets. The stacked design and sample filters ensure that each treatment event is compared to its own appropriate control group and avoids bias from repeated or staggered cross-event exposures that arises mechanically in a traditional panel regression.

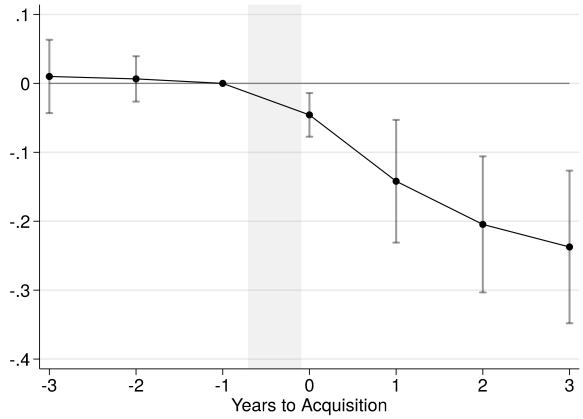
3.3 DID Results

The results from equation (1a) show that labor market consolidation significantly reduces wages and employment, and has significant knock-on effects for capital and output. Figure 3 plots the event study coefficients DD_τ. Prior to the acquisition ($\tau < 0$), estimates support the parallel trends assumption. Following M&A, all outcomes are negatively and sharply affected in overlap labor markets. Effects for capacity and output are at least as large as effects on wages and employment.

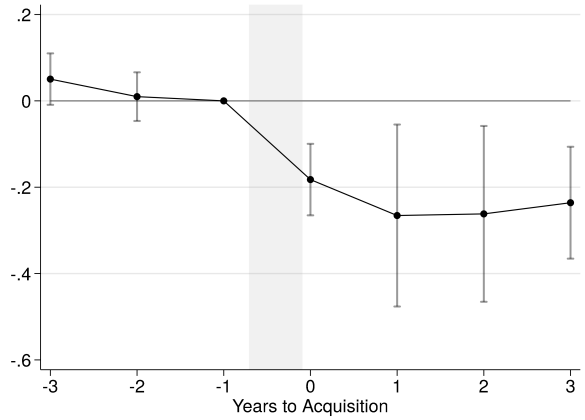
Figure 3: Effects of Labor Market Consolidation following Coal Mine Acquisitions



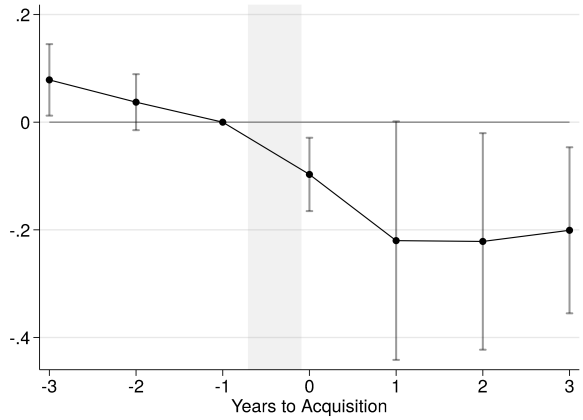
(a) log(Average Mining Wage)



(b) log(Total Mine Employment)



(c) log(Total Mine Capacity)



(d) log(Total Coal Sales)

Notes: Difference-in-differences estimates and 95% confidence intervals for $\hat{DD}_\tau$ from event study equation (1a). Treatment is defined by counties where merging parties had overlapping operations (ΔHHI > 0). Standard errors are clustered at the M&A event $\times$ county level.

Average treatment effects across the post-period closely resemble the event study estimates, but have increased precision. Table 2 presents the post-period pooled DIDs, where the effects of labor market consolidation from equation (1b) are shown in columns (1), (3), (5), and (7). Labor market consolidation causes average mining wages to fall by 6.4% and total mine employment to drop by 16.3%. Coal mine capacity declines by 25.6% and coal sales fall by 22.3%. Each effect is statistically significant beyond the 1% threshold. However, although the point estimates for capital and output are larger than employment, the results do not statistically reject the hypothesis that knock-on effects of labor market consolidation

are equal to the effect on labor itself.

Turning to the formal test of the labor market power hypothesis, Table 2 columns (2), (4), (6), and (8) present results from equation (1c) to isolate the marginal effect of a substantial increases in labor market concentration. All results support the market power mechanism. M&A that increased the labor HHI by more than 500 points caused wages to fall an additional 8.2% more than the effect of smaller M&A. "Big" acquisitions also drive significantly larger reductions in employment (Column 4), capacity (Column 6), and sales (Column 8). This evidence again suggests that the knock-on distortions of labor market power might be even larger than the employment distortions that drive them. However, as before, the regression results do not statistically reject the hypothesis that the marginal effects of big acquisitions are equal for capital, output, and labor.

Table 2: Empirical Effects of Labor Market Consolidation in Coal Mining

	log(Wage)		log(Employment)		log(Capacity)		log(Sales)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Acquisition $\times 1[\Delta HHI > 0]$	-0.064***	-0.025**	-0.163***	-0.038	-0.256***	-0.055	-0.223***	-0.024
	(0.017)	(0.012)	(0.043)	(0.042)	(0.068)	(0.053)	(0.066)	(0.056)
Post-Acquisition $\times 1[\Delta HHI \geq 500]$		-0.082**		-0.262***		-0.421***		-0.417***
		(0.033)		(0.079)		(0.124)		(0.119)
M&A Event × County FE	Y	Y	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.94	0.94	0.95	0.95	0.95	0.95
N Observations	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518

Notes: Estimates from DID specification (1) testing the effects of labor market consolidation on county-level outcomes (2001-2019). The sample includes 46 total overlap events ($\Delta HHI > 0$), 22 of which are "big" concentration events ($\Delta HHI \geq 500$). Standard errors are clustered at the M&A event × county level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

3.3.1 Product market consolidation

Product market forces could theoretically drive the reductions in output and capacity observed in the main results, as recent literature suggests that labor market power and product market power can have distinct and sometimes opposing effects on wages and output (Deb et al., 2022). Even though coal mines typically supply to geographically broad markets and source labor from geographically narrow markets, my test of labor market power could be confounded if product market consolidation correlates with local labor market overlap.

To rule this out, I exploit the distinction between local labor markets (taken as counties) and plausible regional product markets (geological coal basins). Because the geographic boundaries of labor and product markets differ, one can construct DIDs for the effects of product and labor market consolidation that are separately identified. I therefore estimate

a robustness specification that conditions the DID estimator on product market overlap, described in Appendix B.1. The results (Appendix Table A.2) confirm that the main estimates are robust: reductions in wages, employment, capacity, and sales remain economically large and statistically significant even after controlling for product market consolidation. Product market consolidation does independently reduce capacity, but labor market consolidation is a distinct and statistically larger driver.

3.3.2 Robustness

Appendix B.2 examines several threats to identification and robustness to alternative measurement strategies. I examine whether the capacity effects are driven by decreased capital utilization vs outright divestment of mine equipment and assets. I rule out confounding regional economic trends by introducing event-region-time specific fixed effects, forcing within region treatment/control group comparisons. I address transaction-level and firm-level selection bias associated with endogenous M&A by refining control groups to consist of markets where at least one of the parties operated before the acquisition. I correct for treatment-control imbalances by matching the event-specific treatment/control groups based on labor market concentration and coal output. I examine whether results are sensitive to overlapping M&A events. And I replicate the main analysis using alternative data sources to measure employment, output, and capital. Across all of these exercises, the robustness results are similar to the main findings, with economic and statistical significance that suggests that labor market power not only distorts wages and employment but also capital and output.

3.4 Discussion

The causal evidence suggests that labor market consolidation in the coal industry caused reductions in employment, wages, capacity-denominated capital, and output. That the effects of labor market consolidation are larger when M&A significantly increases labor market concentration suggests that market power is a driving mechanism. This corroborates the findings of Prager and Schmitt (2021) in a different industry, and extends their empirical strategy to non-labor outcomes that complement labor in the production process.

Nevertheless, like any causal empirical design, there are questions about mechanisms and welfare that cannot be addressed without bringing additional structure. The next section develops an equilibrium oligopsony model toward this end.

4 Oligopsony Model

4.1 Labor Supply

I model labor supply using a discrete choice framework. Workers i choose between mining jobs $j \in \mathcal{J}_{ct}$ or an outside option $j = 0$ to maximize utility. The mean utility of job j is

$$\delta_{jct} = \alpha w_{jct} + \beta x_{jct} + +\xi_{jc} + \xi_{B(c)t} + \Delta\xi_{jct}$$

The parameter α represents the marginal utility of labor income, determining the sensitivity of labor supply to wages. The remaining terms capture preferences for non-wage amenities (job safety, convenience, etc), where βx_{jct} is observable and $\xi_{jct} = \xi_{jc} + \xi_{B(c)t} + \Delta\xi_{jct}$ are unobserved job characteristics. Fixed effects ξ_{jc} allow preferences to vary arbitrarily at the job-county level, and fixed effects $\xi_{B(c)t}$ allow preferences to vary arbitrarily across time with regional coal basin specific trends. The structural residual of labor supply is $\Delta\xi_{jct}$.

Assuming a nested logit structure to allow for correlated preference shocks (Berry, 1994), the labor supply curve facing firm j is $l^s_{jct}(w) = s_{jct}(\mathbf{w})L_{ct}$. The market share s_{jct} is:

$$s_{jct}(\mathbf{w}) = \frac{\exp(\delta_{jct}/(1-\sigma))}{I_{ct}} \cdot \frac{I_{ct}^{1-\sigma}}{1 + I_{ct}^{1-\sigma}} \tag{2}$$

where $I_{ct} = \sum_{k \in \mathcal{J}_{ct}} \exp(\delta_{kct}/(1-\sigma))$ is the inclusive value of the coal mining nest. The outside option is in a separate nest and has the usual normalized mean utility $\delta_{0ct} = 0$. The nesting parameter $\sigma \in [0, 1)$ governs the substitution between mining jobs relative to the outside option. Details and derivations on the labor utility specification and market size definition L_{ct} are provided in Appendix C.

4.2 Production Functions

Firms produce coal output q_{jct} using labor l_{jct} and capital (measured as capacity) k_{jct} according to a constant returns to scale CES technology:

$$q_{jct} = \exp(\eta_{jct}) \left(b_{ct} l_{jct}^{\frac{c-1}{c}} + (1 - b_{ct}) k_{jct}^{\frac{c-1}{c}} \right)^{\frac{c}{c-1}} \tag{3}$$

The parameter c is the elasticity of substitution between labor and capital. The term b_{ct} captures time-varying and market-specific labor augmenting technology. Total factor productivity (TFP) η_{jct} evolves according to an AR(1) process,

$$\eta_{jct} = a\eta_{jct-1} + \eta_{jc} + \eta_{B(c)t} + \Delta\eta_{jct}$$

where the parameter a governs the persistence of TFP. Fixed effects η_{jc} absorb all cross-sectional variation in TFP at the job-county level, and fixed effects $\eta_{B(c)t}$ allow TFP to trend arbitrarily at the regional coal basin-year level. $\Delta\eta_{jct}$ is the structural residual of the production model, the productivity innovation or "shock."

4.3 Equilibrium

Firms compete in a static Nash-Bertrand game, setting wages and capital to maximize profits

$$\pi_{jct} = p_{jct}q_{jct} - w_{jct}l_{jct} - r_{jct}k_{jct}$$

taking output prices p, capital costs r, and rival wages as given. The equilibrium is characterized by the first-order conditions for capital and wages along with market clearing:

$$r_{jct} = p_{jct}\frac{\partial q_{jct}}{\partial k_{jct}} \tag{4a}$$

$$w_{jct} = p_{jct}\frac{\partial q_{jct}}{\partial l_{jct}} - \mu_{jct}(\mathbf{w}, \mathbf{s}) \tag{4b}$$

$$1 = s_{0ct}(\mathbf{w}) + \sum_{j \in \mathcal{J}_{ct}} s_{jct}(\mathbf{w}) \tag{4c}$$

Equation (4a) equates the marginal cost of capital to its marginal revenue product: mines are price takers in the capital market. Equation (4b) defines the equilibrium wage as the marginal revenue product of labor minus a markdown μ_{jct}. The markdown depends on the own- and cross-price elasticities of labor supply derived from the nested logit structure, see Appendix C for the derivation. Equation (4c) requires that labor market shares, including the outside option, clear the labor market.

4.4 Identification and Estimation

Standard methods for estimating production functions and differentiated product demand rely on "inversion" arguments (Berry, 1994; Gandhi et al., 2020): conditional on parameters, there exists a unique mapping from observed data to the structural residuals. I adapt this framework to address a limitation in the available data. While I observe production inputs and output at the job level, along with labor market shares and rich set of job characteristics, wage information is only observed as county-level averages. To overcome this, I offer an identification strategy that exploits the model's equilibrium conditions to recover latent wages and jointly estimate the labor supply and production parameters.

4.4.1 Structural Residuals and Latent Wage Identification

Let θ be parameters and y be the data for the production and labor supply models. Identification requires a mapping from (θ, y) to the structural residuals $(\Delta\eta, \Delta\xi)$.

Latent wages. The standard inversion for the labor supply residual $\Delta\xi_{jct}$ would treat w_{jct} as data. In the coal data, job-specific wages are unobserved. To address this, I use the equilibrium relationship (4b) between wages, marginal products of labor, and markdowns. Analogous equilibrium relationships are often exploited in empirical IO to recover latent marginal costs, given prices and markups. By the same logic one can recover latent wages, given markdowns and marginal products. The production function provides the additional information that makes this possible: the marginal product of labor as a function of parameters and data. Formally, I define the latent wage mapping $w_{jct}(\cdot)$ as a function of data, parameters to be estimated, and the labor-augmenting technology b_{ct}:

$$\hat{w}_{jct}(\theta, y, b_{ct}; \theta, y) = p_{jct}\frac{\partial q_{jct}}{\partial l_{jct}}(\theta, y, b_{ct}) - \mu_{jct}(\theta, y, b_{ct}) \tag{5}$$

With the additional assumption of Nash equilibrium wages, $\hat{w}_{jct}$ replaces the information requirement for data on w_{jct} in the standard inversion technique for the structural residual of labor supply.

Labor-augmenting technology (b_{ct}). Production and derived marginal products depend on the unobserved labor-augmenting technology b_{ct}. The literature has used first order conditions and input price data to identify such factor-augmenting technology (Demirer, 2025). Naturally, this approach constrains b to the same level of variation in the available data on input prices. I thus identify a county-year level labor-augmenting technology b_{ct}, aggregating the model's equilibrium wage (5) to the market level and requiring that b_{ct} match the predicted average wage to the observed average wage $\bar{w}_{ct}$:

$$\bar{w}_{ct} = \sum_{j \in \mathcal{J}_{ct}} \frac{s_{jct}}{1 - s_{0ct}} \hat{w}_{jct}(b_{ct}; \theta, y) \tag{6}$$

The marginal revenue product of labor in $\hat{w}(\cdot)$ is monotonic in b_{ct}, and the markdown does not depend on b_{ct} provided that market shares are observed. Therefore, the aggregate wage condition is a function $\bar{w} = \mathcal{W}(b, \theta, y)$ that can be inverted to uniquely identify the labor-augmenting technology given candidate parameters and data: $b_{ct}(\theta, y) = \mathcal{W}^{-1}(\bar{w}_{ct}, \theta, y)$.

Recovering the residuals. Having identified $b_{ct}(\theta, y)$ given county-average wage data, the latent job-level wage $\hat{w}_{jct}(\theta, y)$ is recovered via (5). Provided $(b_{ct}(\theta, y), \hat{w}_{jct}(\theta, y))$, the mappings for the structural residuals of labor supply and the production function are the

standard inversions used in empirical IO (Berry, 1994; Berry et al., 1995; Ackerberg et al., 2015; Gandhi et al., 2020; Raval, 2023). The production residual $\Delta\eta_{jct}(\theta)$ is identified as the productivity shock from the AR(1) process of TFP via (3). The labor supply residual $\Delta\xi_{jct}(\theta)$ is identified as the job preference shock after inverting market shares and the mean utility specification (2).

4.4.2 Estimation and Instruments

I estimate the parameters of labor supply and production models jointly using the Generalized Method of Moments (GMM). Identification rests on the moment conditions using instrumental variables (IVs): $\mathbb{E}[\Delta\eta \cdot Z^q] = 0$ and $\mathbb{E}[\Delta\xi \cdot Z^l] = 0$. I construct instruments $Z = (Z^q, Z^l)$ based on three sets of exclusion restrictions, detailed in Appendix C:

> **Timing Assumptions:** Productivity innovations $\Delta\eta_{jct}$ are unknown to firms when the previous period's equilibrium is resolved. Thus, lagged inputs and their interactions serve as valid instruments for the production function.
>
> **BLP and Differentiation IVs:** Following Berry et al. (1995) and Gandhi and Houde (2019), I use the job characteristics of rival firms as instruments for latent wages (markdowns) and market shares. In particular, I assume that observed shocks to rivals' job safety are exogenous to a job's own unobserved quality.
>
> **Waldfogel IVs:** I assume that between-market variation in lagged output prices $\bar{p}_{ct-1}$ and non-mining goods-producing wages w_{0ct} shift labor demand and relative input costs independently of job-level preference shocks.

I estimate the model using a two-step GMM procedure with a weight matrix clustered at the county-year (labor market) level to allow for within-market correlation of residuals.

4.5 Model Estimation Results

Table 3 reports the GMM estimates. The nesting parameter $\sigma = 0.55$ is statistically significant and in the middle of the feasible range, indicating that workers' idiosycratic preferences for mining jobs are highly correlated and that substitution within the mining nest is much stronger than to the outside option. The estimated marginal utility of income is $\alpha = 0.036$, statistically significant but difficult to interpret without translating to elasticities.

Table 3: Labor Supply and Production Function Estimates

Labor Supply – Nested Logit		Estimate (Std. Error)	Identification
Preference nesting parameter	σ	0.5482 (0.1306)	(i) Market-level labor demand & supply shifters: $\Delta\xi_{jct}\|(\bar{p}_{ct-1}, \bar{z}_{ct})$.
Marginal utility of income	α	0.0358 (0.0075)	(ii) Rivals' job characteristic IVs, mean & differentiation: $\Delta\xi_{jct}\|x_{-jct}$.
Time without injuries	$x_{jct}\beta$	-0.4565 (0.0971)	(iii) Strict exogeneity of non-wage job characteristics: $\Delta\xi_{jct}\|x_{jct}$.
Fines for safety violations	$x_{jct}\beta$	0.1625 (0.0228)	
Production Function – CES			
Productivity AR(1) persistence	a	0.3273 (0.0168)	(i) Information set for production lags: $\Delta\omega_{jct}\|(q_{jct-1}, l_{jct-1}, k_{jct-1})$.
Labor-augmenting technology	$\mathbb{E}(b_{ct})$	0.2063 (0.059)	(ii) Market aggregated first-order conditions for equilibrium wages.
Elasticity of substitution (CES)	c	0.7142 (0.0787)	(iii) Exclusion restriction on price shifters: $\Delta\omega_{jct}\|(\bar{p}_{ct-1}, \bar{z}_{ct}, x_{-jct})$.

Notes: Two-stage GMM estimates of labor supply parameters and production function parameters. The value for b_{ct} reports the mean estimate of labor market specific technology parameters (n=2,887). Standard errors in parentheses, clustered at the county-year level.

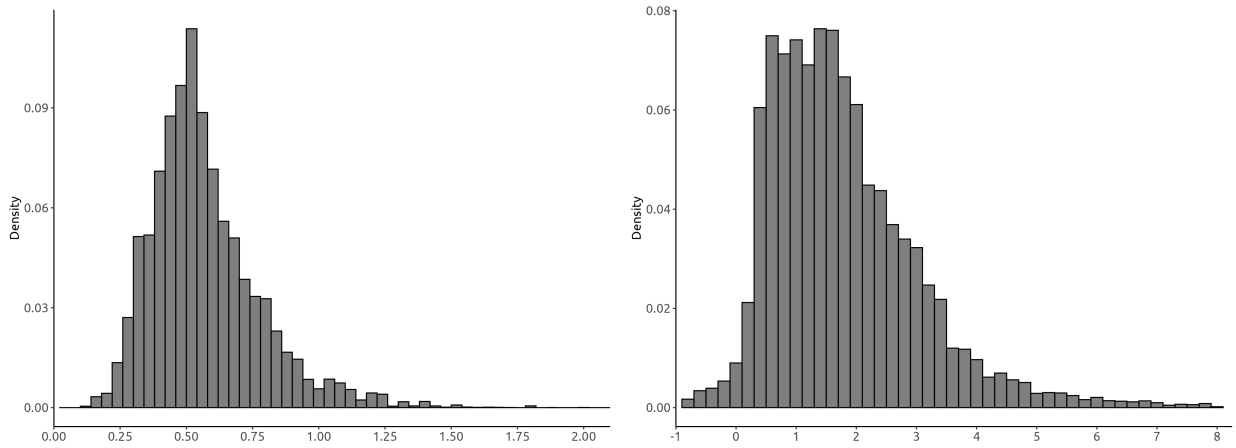
4.5.1 Labor supply elasticities and markdowns

These structural parameters generate the labor supply elasticities shown in Figure 4. Market-level labor supply is relatively inelastic, with a mean around 0.6. This suggests that coal miners have a particular attachment to mining jobs, consistent with their specialized skills and the geographic isolation of coal basins.

Job-level labor supply curves are more elastic than the market-level margin, with a mean own-wage elasticity of approximately 2.0. This estimate is lower relative to findings in other industries. Azar et al. (2022) find firm-level elasticities around 4-5 using job vacancy data and a similar nested logit model. Broader surveys of the literature place the own-wage elasticity between 3 and 4 (Sokolova and Sorensen, 2021). An own-wage labor supply elasticity of 2 either implies substantial job differentiation or persistent preferences for particular mining jobs, granting coal operators significant market power.

These elasticities translate to large equilibrium wage markdowns. Figure 5(b) plots the distribution of markdowns, defined as $(mrpl - w)/mrpl$. The average markdown is about

Figure 4: Distributions of Labor Supply Elasticities

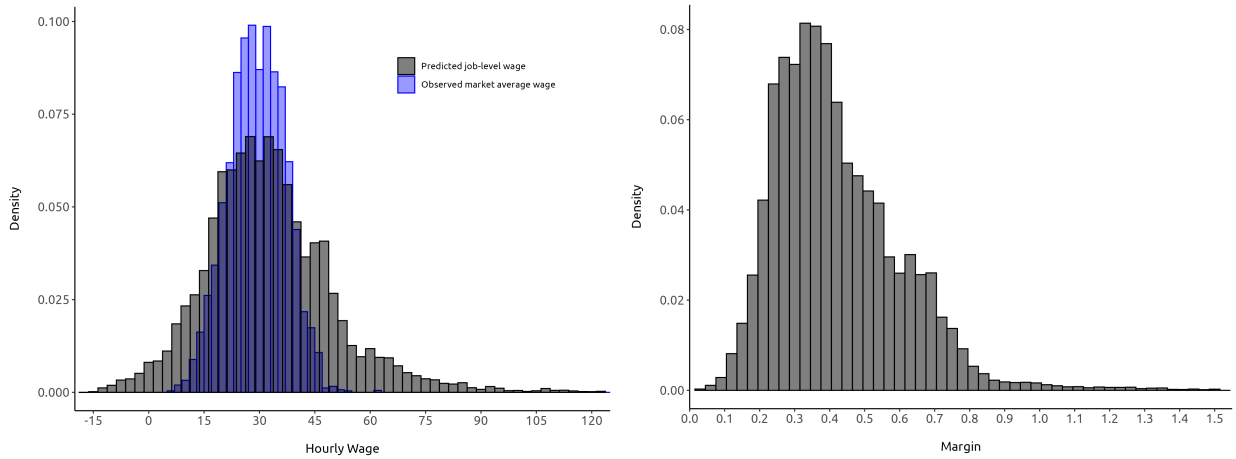


(a) Market elasticity

(b) Job own-wage elasticity

Notes: Panel (a) shows the distribution of estimated market elasticities. Panel (b) shows the distribution of estimated job-specific own-wage elasticities. Author's calculations based on the EIA-MSHA-BLS data (N=20,870).

Figure 5: Distributions of Wages and Markdowns



(a) Job-level and market average wages

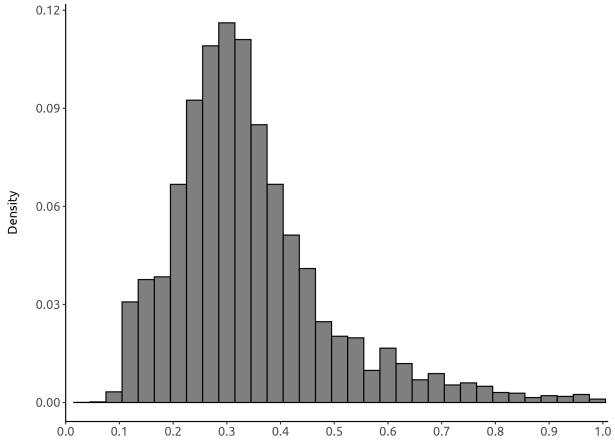
(b) Job-level markdowns (%) $\frac{mrpl-w}{mrpl}$

Notes: Panel (a) plots the distribution of job-level Nash-Bertrand equilibrium wages estimated from the model (black) and the empirical distribution of labor market average wages (blue). Panel (b) shows the distribution of estimated markdowns. Author's calculations based on the EIA-MSHA-BLS data (N=20,870).

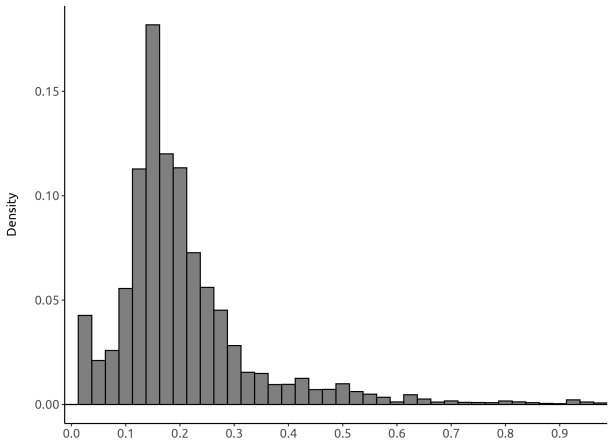
40%, meaning workers are paid a little less than half of their marginal revenue product. These markdowns are higher than averages found in the broader economy (Berger et al., 2022), but are consistent with the relative concentration of local labor markets for coal mines.

4.5.2 Production technology

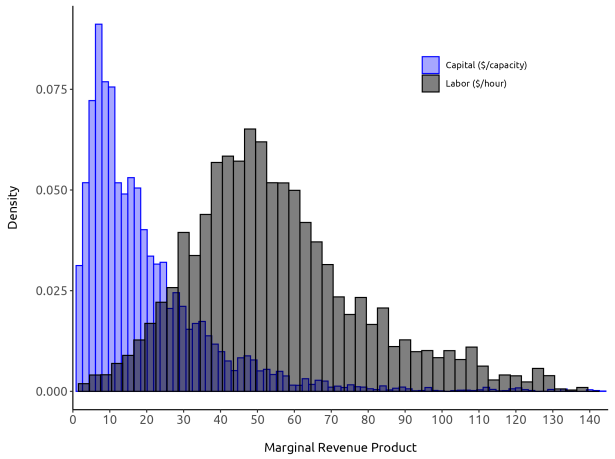
Figure 6: Distributions of Heterogeneity in the Production Model



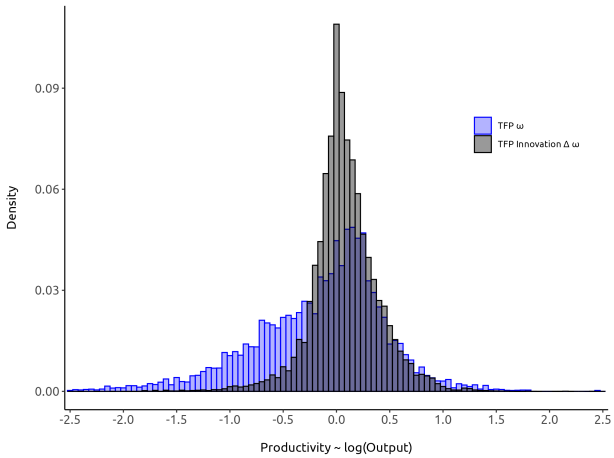
(a) Production elasticity of labor $\frac{\partial q}{\partial l}\frac{l}{q}$



(b) Production labor-augmenting technology $\hat{b}_{ct}$



(c) Marginal revenue products of capital and labor



(d) TFP and productivity innovations $(\eta, \Delta\eta)$

Notes: Author's calculations based on the EIA-MSHA-BLS data (N=20,870).

The estimated elasticity of substitution between capital and labor is $c = 0.71$, shown in Table 3. This estimate rejects both the Cobb-Douglas specification ($c = 1$) and the Leontief model ($c = 0$), and implies that capital and labor are productive complements. This degree of substitution between labor and capital is similar to recent estimates from the broader manufacturing sector, which range from 0.5 to 0.7 (Oberfield and Raval, 2021). Figure 6 illustrates heterogeneity in the estimated production function. Panel (a) shows the output elasticity of labor, which averages 0.3, and confirms that coal mining is a capital-intensive industry.

5 Equilibrium Counterfactuals

I use the estimated structural model to quantify the distortions of labor market power by simulating counterfactual equilibria. This analysis proceeds in four steps. First, I measure the total distortion by comparing the observed oligopsony to a perfectly competitive benchmark. Second, I decompose the total distortion into scale and substitution effects of labor market power. Third, I consider alternative benchmarks to trace out the range of labor market power: monopsonistic competition and full blown monopsony. Finally I examine allocative efficiency and quantify the deadweight loss of imperfect competition, accounting for knock-on distortions. The full set of results is offered in Appendix D, with bootstrapped standard errors based on draws from the asymptotic distribution of model parameter estimates.

Wages, employment, capital, and output are jointly determined outcomes in each simulation. But in order to focus on labor market forces, across all counterfactuals I hold the output price of coal and the marginal cost of capital $(\mathbf{p}, \mathbf{r})$ fixed at their values in the observed oligopsony equilibrium. I examine robustness to finite-elasticity output demand and capital supply curves in the Appendix (TBD).

5.1 Total Distortions: Labor and Knock-on Effects

I define a Perfectly Competitive equilibrium as a set of wages $\mathbf{w}$ and allocations $(\mathbf{l}, \mathbf{k}, \mathbf{q})$ where workers earn their full marginal revenue product $(w_{jct} = p_{jct}\frac{\partial q_{jct}}{\partial l_{jct}}(\mathbf{w}) = MRPL_{jct})$. This serves as the constrained-best benchmark for evaluating the distortions of oligopsony.[2] Table 4 summarizes the industry aggregate results.

Consistent with the causal empirical evidence in Section 3, oligopsony significantly affects worker outcomes. In a competitive market, wages would be 74% higher and employment 36% higher, increasing producers' aggregate labor bill by $124 billion. Worker surplus would be 38% higher in a competitive equilibrium, worth an additional $79 billion in value.

The knock-on distortions to non-labor outcomes are proportionally similar but comparatively larger by value. In a competitive equilibrium, the industry's demand for capital (capacity) would increase by 32%, representing $126 billion in foregone capital services. Total coal output would rise by 35% if labor markets were perfectly competitive, adding $188 billion in revenue.

The results for producer surplus, coal mine profit, highlight the rent transfer due to labor market power. In the perfectly competitive benchmark, producer surplus is eliminated (-100%) by construction, as rents are transferred to workers and capital suppliers. The value

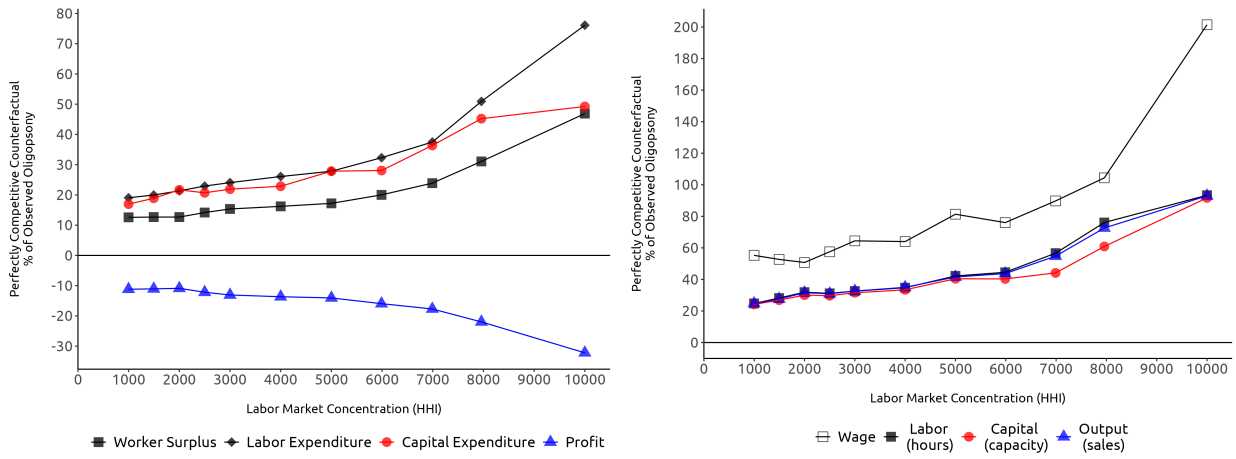
[2] A competitive "law of one price" equilibrium is ruled out by differentiation in the model across jobs, production technologies, output prices, and capital costs.

Table 4: Total Distortions of Labor Market Power (Competitive Benchmark)

	% Change	$ Billions
Wage	73.96	—
	(21.45)	
Employment	35.67	—
	(6.09)	
Capital (Capacity)	32.15	126.40
	(6.18)	(3.33)
Output (Sales)	35.33	187.61
	(5.46)	(5.78)
Worker Surplus	37.97	78.99
	(6.46)	(4.98)
Producer Surplus (Profit)	-100.00	-62.93
	(0.00)	(3.92)
Total Welfare	5.93	16.06
	(0.87)	(1.06)

Notes: Difference between the counterfactual Perfectly Competitive equilibrium and the observed oligopsony. Bootstrapped standard errors in parentheses.

Figure 7: Distortions of Labor Market Power in the Cross-section of Market Structure



(a) Value and Welfare

(b) Wages and Quantities

Notes: Average percent differences between perfectly competitive equilibrium outcomes and the observed oligopsony outcome, by HHI bins.

of the oligopsony distortion to capital and output exceeds the transfer of rents from workers to firms by a factor of four (= (126+188)/79).

Figure 7 illustrates how these distortions vary with concentration in the cross-section of labor markets. Panel (a) presents value-denominated and welfare distortions. Panel (b)

presents the distortions to wages and quantities. For each outcome the gap between the competitive benchmark and the observed oligopsony widens as labor market concentration increases, and in an increasing-convex way. This suggests that local labor market concentration correlates strongly with firms' market power over workers, even accounting for between-market variation in other primitives.

5.2 Scale vs. Substitution Effects

Producer theory predicts two channels for these distortions. Substitution effects suggests that firms facing high effective marginal costs of labor will substitute toward capital. Scale effects suggests that high marginal costs will incentivize firms to produce less overall, reducing demand for all inputs. The model's estimated elasticity of substitution ($c = 0.71$) indicates that capital and labor are gross (but imperfect) complements, implying that scale effects should be the dominant mechanism.

To quantify this, I estimate a Fixed Capital oligopsony counterfactual. I hold capital fixed at its perfectly competitive equilibrium allocation, and then allow firms to re-optimize wages and labor under the observed oligopsony market structure. This isolates the scale effect of labor market power by prohibiting any substitution to capital. Table 5 summarizes the results.

Table 5: Decomposition of Scale vs. Substitution Effects

	Fixed Capital Counterfactual	**Total Distortion**	**Scale Effects**
Wage	20.88	73.96	71.8%
	(5.18)	(21.45)	
Labor	11.93	35.67	66.6%
	(2.23)	(6.09)	
Capital	32.15	32.15	65.0%
	(6.18)	(6.18)	
Output	27.02	35.33	62.0%
	(3.94)	(5.46)	
Worker Surplus	9.08	37.97	76.1%
	(1.80)	(6.46)	
Producer Surplus	-24.55	-100.00	75.5%
	(2.73)	(0.00)	

Notes: Column 3 "Scale Effects" are measured by the residual gap between the Competitive benchmark and oligopsony with Fixed Capital counterfactual. For most outcomes this is 1 - (column 1)/(column 2). For capital (which is fixed in the counterfactual) and output (elevated by fixed capital) I compute off-equilibrium demand for capital and production levels to measure the scale effect. Bootstrapped standard errors in parentheses.

The Fixed Capital equilibrium captures the majority of the total distortion, roughly 2/3 to 3/4 across outcomes. The results indicate that scale effects account for 72% of the total wage distortion (1 - 20.88/73.96); 67% of the employment distortion (1 - 11.9/35.7); and 76% of the effect of oligopsony on worker surplus (1 - 9.08/37.97).

Scale effects likewise play a dominant role in knock-on distortions. To quantify this, I calculate off-equilibrium demand for capital and off-equilibrium output levels given the Fixed Capital equilibrium allocation of labor, i.e. as if capital were unconstrained.[3] By quantities, 65% of the distortion to capital demand and 62% of the output distortion can be attributed to scale effects of labor market power. By value, scale effects account for 80% of the capital distortion (126-25 =$101 billion) and for 85% of the total revenue distortion (188-29 = $159 billion): each larger in value than the total distortion to worker surplus ($79 billion).

If capital is fixed at competitive equilibrium levels, producer surplus is only about $3 billion lower or 5% below the observed oligopsony (= 1 - 3/63). Setting capital and output to off-equilibrium levels given this counterfactual's equilibrium labor allocation, I find that the scale effect of labor market power is the primary mechanism for rent extraction in the coal industry, explaining about 75% of the transfer from workers to firms.

5.3 The Range of Labor Market Power

The perfectly competitive benchmark assumes away all labor market frictions except for differentiation between labor supply curves and differentiation between the non-wage determinants of labor demand curves (e.g. capital costs). I consider two alternative market structures that establish the range of possible labor market power in the model: Monopsonistic Competition and Local Monopsony.

The Monopsonistically Competitive counterfactual isolates the effects of job differentiation, and shuts down the role of market shares and market concentration. Firms face upward-sloping labor supply curves due to worker preferences, but behave atomistically and not strategically. Table 6 shows that this lower bound on labor market power can explain 48% of the total wage distortion (= 1 - 38/74), 57% of the total employment distortion, and 56% of the reduction in worker surplus under oligopsony.

The monopsonistically competitive counterfactual can also account for a large share of the oligopsony distortion to capital and output. In quantities, 74% of the reduction in demand for capital and 54% of the reduction in output materializes at the lower bound of labor market power. By value, monopsonistic competition can explain 57% of foregone capital

[3]These additional calculations are necessary because capital is fixed at a sub-optimal allocation but still utilized by firms in the counterfactual, and counterfactual equilibrium output is elevated by the generous perfectly competitive allocation of capital.

services and 54% of foregone revenue under oligopsony. This implies that while strategic behavior in concentrated markets is important, a significant portion of labor markdowns and knock-on effects arise purely from differentiation and workers' relative attachments to jobs.

The Local Monopsony counterfactual illustrates the worst-case bound for labor market power, assuming one firm controls all mines in a county. This regime lowers wages by 58% relative to the observed equilibrium, reduces employment by 33%, and lowers worker surplus by 22%. Demand for capital is likewise 36% lower under full blown monopsony compared to the observed oligopsony, and output is 33% lower. Nevertheless, producer surplus rises by 32%, illustrating the incentives for consolidation.

Table 6: Alternative Market Structure Benchmarks

	Monopsonistic Competition		**Local Monopsony**	
	% Change	**$ Billions**	**% Change**	**$ Billions**
Wage	38.21	—	-57.85	—
	(6.63)		(12.26)	
Employment	15.16	—	-33.48	—
	(0.57)		(3.88)	
Capital	11.72	11.01	-35.69	-23.01
	(0.56)	(0.77)	(3.89)	(3.77)
Output	16.09	17.27	-32.72	-32.10
	(0.40)	(0.46)	(3.60)	(3.76)
Worker Surplus	16.86	6.99	-22.22	-9.22
	(0.56)	(1.22)	(2.09)	(1.86)
Producer Surplus	-35.96	-4.51	31.94	4.01
	(9.28)	(0.73)	(15.58)	(0.98)
Total Welfare	4.59	2.48	-9.64	-5.21
	(0.21)	(0.56)	(0.48)	(1.09)

Notes: Percent difference from the observed oligopsony equilibrium. Standard errors in parentheses.

5.4 Deadweight Loss and Allocative Efficiency

Labor market power distorts not only the level of resources but also the allocation across firms, affecting aggregate productivity and generating economic deadweight loss. Across the counterfactuals a tension between the benefits of competition and the efficiencies of consolidation is evident.

Aggregate productivity (TFP) and the marginal product of labor are higher in each counterfactual equilibrium, and highest under full monopsony (Table 7). Likewise, the marginal

costs of capital are lower across the counterfactuals, and lowest under monopsony. A single, consolidated decision-maker internalizes all cross-job substitution patterns of workers as well as all variation in productivity across mines, and therefore allocates labor and capital without competitive considerations. As a consequence, the observed oligopsony equilibrium is inefficiently capital-intensive: Capital/Labor ratios drop 2.6% and 3.3% relative to perfect competition and monopsony, respectively. Imperfect competition and incomplete consolidation in oligopsony also leads to a higher aggregate marginal cost of capital: increasing 0.7% and 1.1% compared perfect competition and monopsony, respectively.

Finally I examine the deadweight loss of labor market power: the difference in total welfare between the counterfactual perfectly competitive equilibrium and an equilibrium with imperfect competition. Deadweight loss is greatest under full blown monopsony (15.6% = 5.93 + 9.64), showing that the welfare losses from imperfect competition outweigh the allocative efficiencies from consolidation. Monopsonistic competition has the smallest deadweight loss (1.34% = 5.93 - 4.59), at the lower bound of labor market power. Deadweight loss in the observed oligopsony lies between these extremes (5.9%), accounting for about 38% of the potential deadweight loss of monopsony.

Table 7: Deadweight Loss and Allocative Efficiency

	Competitive Benchmark	**Monopsonistic Competition**	**Local Monopsony**
Total Welfare	5.93	4.59	-9.64
	(0.87)	(0.21)	(0.48)
Total Factor Productivity	3.56	5.72	7.55
	(0.92)	(0.66)	(1.42)
MRP of Labor	2.97	4.50	5.90
	(1.09)	(0.92)	(1.75)
MRP of Capital	-0.66	-0.73	-1.10
	(0.25)	(0.32)	(0.48)
Capital/Labor Ratio	-2.59	-2.99	-3.32
	(0.20)	(0.13)	(0.24)
Output Price	-1.28	-1.79	-2.15
	(0.26)	(0.18)	(0.40)

Notes: Percent difference from the observed oligopsony. Total Welfare represents the inverse of deadweight loss. Standard errors in parentheses.

6 Conclusion

This paper quantifies the broader economic consequences of labor market power. Using rich microdata from the U.S. coal mining industry, I document that buyer power over labor not only transfers rents from workers to firms, diminishing wages and worker surplus; it also distorts the production process itself. Causal empirical evidence from mergers and acquisitions shows that labor market power causes reductions in capital and output alongside the expected effects of lower wages and employment. Through the lens of a structural oligopsony model, these "knock-on" distortions are large and driven by scale effects, reflecting the complementarity of labor and capital in the production process. In the coal industry, the value of foregone output and capital services is four times as large as the direct welfare loss to workers. Imperfect competition distorts allocative efficiency to offset any benefits of consolidation, on net, leading to significant deadweight loss in aggregate. My findings thus suggest that debates focusing solely on worker welfare may significantly underestimate the distortions of labor market power, particularly in capital-intensive sectors.

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A Data Appendix

Table A.1: Labor and Capital Across Coal Production Methods

Method	Description	Skill Level	Skill Set	Worker Safety	Capital Intensity	Material Intensity	Geological Considerations
Surface Mining	Removal of overburden (soil/rock) to expose shallow seams via strip, open-pit, or mountaintop removal.	Medium / General	Operation of draglines, bulldozers, and haul trucks; equipment maintenance.	Low/Mod Risk: Heavy machinery accidents; noise; silica dust.	High: Large fleets of mobile earthmoving machinery.	High: Diesel fuel, ANFO explosives, tires, lubricants.	Shallow: Economically viable only for seams near surface (<200 ft).
Underground Conventional	Cyclical "cut, drill, blast, load" process. Older, discontinuous extraction method.	Medium	Manual drilling; handling explosives; loading. Task-based rather than continuous.	High Risk: Blasting hazards; roof instability; high face exposure.	Low: Basic cutters/loaders; lower barrier to entry.	High: Explosives, blasting caps, drill bits.	Marginal: Often used in older mines or irregular seams.
Underground Continuous	Mechanized extraction using a "Continuous Miner" vehicle to cut and load coal without blasting.	Med-High	Agility in vehicle operation; synchronized shuttle driving; roof bolting.	High Risk: Proximity to cutting face; confined space crushing; roof falls.	Moderate: Scalable investment in mobile miners and haulage.	Medium: Roof bolts, electricity, water (dust suppression), cutting bits.	Variable: Flexible; handles irregular seams and faults well.
Underground Longwall	Automated shearer moves across a wide face (panel); hydraulic shields support roof then allow controlled collapse.	High / Specialized	System monitoring; automation troubleshooting; hydraulic support management.	Moderate Risk: Methane/dust accumulation; high pressure bursts; system failure.	Very High: Massive sunk cost in specialized shields and armored conveyors.	Low: Electricity, hydraulic fluids, emulsions.	Uniform: Requires deep, large, flat coal blocks to justify fixed costs.
Underground Shortwall	Hybrid method using Continuous Miner on a shorter face with self-advancing hydraulic supports.	High / Specialized	Hybrid of mobile machine operation and hydraulic support management.	Mod-High Risk: Proximity to face with less automated protection than Longwall.	Moderate: High support costs but avoids full shearer system expense.	Medium: Electricity, hydraulic fluids.	Niche: Extracts pillars or small blocks where Longwall won't fit.

B Difference-in-differences Appendix

B.1 Product market overlap

A threat to identification is that the observed decline in outcomes may stem from product market consolidation rather than labor market power. To distinguish these mechanisms, I exploit the geographic distinction between local labor markets (counties) and plausible regional product markets (geological coal basins). I define product market treatment based on the EIA's eight major coal basin regions $B(c)$ where the M&A parties had overlapping sales the year before the acquisition. Within these basins, mines often have similar commodity benchmark prices and transportation infrastructure. Because regional product market overlap does not imply local labor market overlap, the effects of each mechanism can be separately identified. I estimate the following regression specification to test whether the main results are robust to conditioning on product market consolidation:

$$\begin{aligned} y_{mct} = {} & \text{DD} \cdot 1[\text{Labor } \Delta\text{HHI}_{mc} > 0] \cdot 1[t \geq t_m^*] \\ & + \gamma_{mc} + \gamma_{mt} + e_{mct} \end{aligned} \tag{7a}$$

$$\begin{aligned} y_{mct} = {} & \text{DD} \cdot 1[\text{Labor } \Delta\text{HHI}_{mc} > 0] \cdot 1[t \geq t_m^*] \\ & + \text{DD}_{\text{big}} \cdot 1[\text{Labor } \Delta\text{HHI}_{mc} \geq 500] \cdot 1[t \geq t_m^*] \\ & + \gamma_{mc} + \gamma_{mt} + e_{mct} \end{aligned} \tag{7b}$$

$$\begin{aligned} y_{mct} = {} & \text{DD}_{\text{L}} \cdot 1[\text{Labor } \Delta\text{HHI}_{mc} > 0] \cdot 1[t \geq t_m^*] \\ & + \text{DD}_{\text{bigL}} \cdot 1[\text{Labor } \Delta\text{HHI}_{mc} \geq 500] \cdot 1[t \geq t_m^*] \\ & + \text{DD}_{\text{Q}} \cdot 1[\text{Output } \Delta\text{HHI}_{mB(c)} > 0] \cdot 1[t \geq t_m^*] \\ & + \text{DD}_{\text{bigQ}} \cdot 1[\text{Output } \Delta\text{HHI}_{mB(c)} \geq 500] \cdot 1[t \geq t_m^*] \\ & + \gamma_{mc} + \gamma_{mt} + e_{mct} \end{aligned} \tag{7c}$$

Table A.2 presents the robustness results alongside the main results from the text. Across all outcomes, the estimated effects of labor market consolidation remain negative, statistically significant, and economically stable after conditioning on product market overlap. For example, the estimated effect of substantial increases in labor market concentration on wages (column 3), employment (column 6), and capital (column 9) are not statistically different from the baseline estimates that ignore product market structure. This robustness suggests that the main results are indeed driven by labor market power rather than latent product market consolidation.

This robustness exercise also suggests that product market consolidation has distinct eco-

nomic effects, as might be expected. Coal basin overlap is associated with higher wages on average (column 3), consistent with merger efficiencies or synergies, whereas labor market overlap itself drives wages down. While product market consolidation does lead to statistically significant reductions in capacity and sales (columns 9 and 12), these effects are economically smaller than those driven by labor market consolidation. Hypothesis tests confirm that the effects of substantial labor market consolidation are statistically distinct from and larger than the effects of substantial product market consolidation for wages ($p = 0.001$), employment ($p = 0.001$), capacity ($p = 0.04$), and sales ($p = 0.006$).

Table A.2: Effects of Labor Market Consolidation vs Product Market Consolidation

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.064***	-0.025**	-0.032***	-0.163***	-0.038	-0.027
	(0.017)	(0.012)	(0.012)	(0.043)	(0.042)	(0.042)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.082**	-0.075**		-0.262***	-0.260***
		(0.033)	(0.032)		(0.079)	(0.078)
Post-Acquisition ×1[Output ΔHHI > 0]			0.014***			-0.018
			(0.005)			(0.013)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.017*			-0.029
			(0.009)			(0.025)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.94	0.94	0.94
	log(Total Mine Capacity)			log(Total Coal Sales)		
	(7)	(8)	(9)	(10)	(11)	(12)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.256***	-0.055	-0.030	-0.223***	-0.024	0.023
	(0.068)	(0.053)	(0.052)	(0.066)	(0.056)	(0.057)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.421***	-0.398***		-0.417***	-0.436***
		(0.124)	(0.118)		(0.119)	(0.120)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.036**			-0.088***
			(0.017)			(0.017)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.153***			-0.014
			(0.032)			(0.028)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.95	0.95	0.95
N. Obs (M&A Event × County × Year)	21,518	21,518	21,518	21,518	21,518	21,518
N. Event × Counties	3,074	3,074	3,074	3,074	3,074	3,074
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,809			1,809
Event × Counties w/ Output Δ HHI ≥ 500			409			409

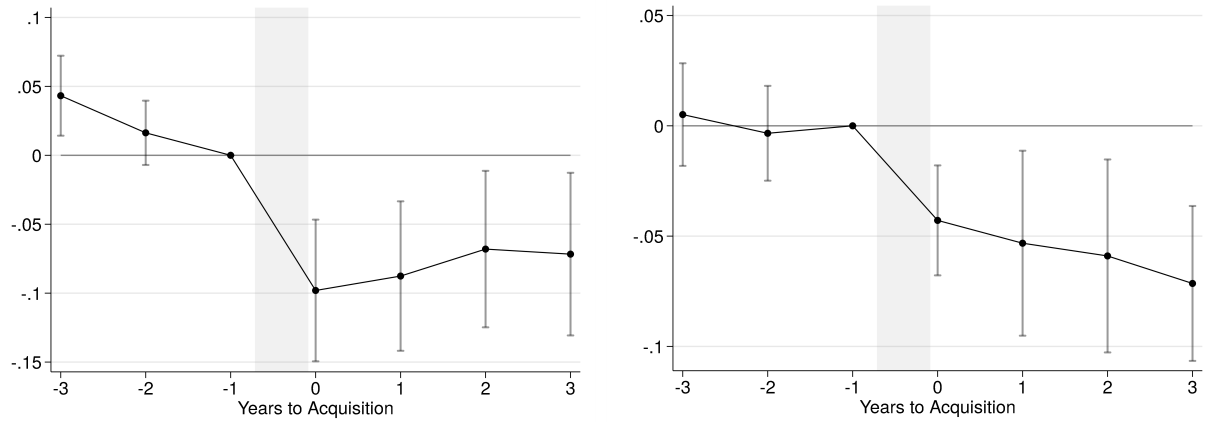
Notes: Estimates and standard errors from DID specification (7) for capital outcome measures in the available data. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

B.2 Robustness

B.2.1 Alternative Outcome Measures

Capacity Utilization vs. Stock. The knock-on effects of labor market power could reflect long-run capital divestment or a temporary dip in utilization commensurate with the decline in employment. Because the main capacity results (Figure 3c and Table 2) conflate these margins, Appendix Figure A.1 decomposes the effect using different EIA data on total capacity stock and utilized capacity. Panel (a) shows that the aggregate capital stock (utilized + idle capacity) falls by approximately 10% in treated counties. Panel (b) shows that the utilization rate of the remaining capital falls by roughly 5%. I also examine the stock of recoverable coal reserves (Appendix Table A.3). While the *utilization* of reserves falls similar to physical capacity, the *stock* of reserves remains largely unchanged. This suggests that the capacity distortions of labor market power are driven by the divestment of equipment and operating capital rather than the abandonment of mineral rights. And labor oligopsonists respond to increased market power not only by idling existing operating capital but also by actively divesting.

Figure A.1: Effects of Labor Market Consolidation on Capital Stock vs Utilization



(a) log(Utilized + Idle Capacity)

(b) $\frac{\text{Utilized Capacity}}{\text{Utilized + Idle Capacity}}$

Notes: Difference-in-differences estimates for $\hat{DD}_\tau$ from Equation (1a). Panel (a) measures the extensive margin (total stock), while Panel (b) measures the intensive margin (utilization rate).

Employment and Output. To ensure results are not artifacts of specific measures, I replicate the analysis using alternative data. The main analysis relies on BLS county-level mine employment and EIA coal sales data. Appendix Tables A.4 and A.5 present results using mine-level employment and hours from MSHA, as well as revenue (EIA) and new

coal extraction (MSHA) as alternative output measures. The estimates are statistically and economically similar to the main results.

Table A.3: Effects of Labor Market Consolidation on Alternative Capital Measures

	log(Total Mine Capacity)			log(Utilized + Idle Capacity)			Fraction Utilized Capacity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.256***	-0.055	-0.027	-0.101***	-0.030	-0.042	-0.057***	-0.009	0.006
	(0.068)	(0.053)	(0.051)	(0.026)	(0.029)	(0.028)	(0.017)	(0.015)	(0.015)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.421***	-0.393***		-0.148***	-0.116**		-0.100***	-0.099***
		(0.124)	(0.117)		(0.048)	(0.045)		(0.031)	(0.030)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.039**			0.030***			-0.025***
			(0.018)			(0.008)			(0.005)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.181***			-0.118***			-0.037***
			(0.035)			(0.016)			(0.009)
M&A Event × County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.99	0.99	0.99	0.89	0.89	0.89
	log(Recoverable Reserves)			log(Utilized + Idle Reserves)			Fraction Utilized Reserves		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Post-Acquisition ×1[Labor ΔHHI > 0]	0.078	0.126	0.039	0.042	0.040	-0.085	-0.024	0.013	0.022
	(0.067)	(0.096)	(0.098)	(0.034)	(0.059)	(0.063)	(0.021)	(0.025)	(0.026)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.100	-0.063		0.006	0.039		-0.079**	-0.080**
		(0.132)	(0.132)		(0.067)	(0.070)		(0.040)	(0.040)
Post-Acquisition ×1[Output ΔHHI > 0]			0.160***			0.224***			-0.015**
			(0.028)			(0.019)			(0.006)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			0.025			0.122***			-0.014
			(0.036)			(0.025)			(0.010)
M&A Event × County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.91	0.91	0.91	0.96	0.96	0.96	0.82	0.82	0.82
N. Obs (M&A Event × County × Year)	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518
N. Event × Counties	3,073	3,073	3,073	3,073	3,073	3,073	3,073	3,073	3,073
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,809			1,809			1,809
Event × Counties w/ Output Δ HHI ≥ 500			409			409			409

Notes: Estimates and standard errors from DID specification (7) for capital outcome measures in the available data. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

B.2.2 Confounding Regional Economic Trends

Regional economic shocks correlated with treatment status threaten identification. For example, if coal production declined more sharply in regions where merging parties happened to overlap, the DID estimator might conflate secular trends with the effects of consolidation. To address this, I augment the DID specification with event-region-specific time trends ($\gamma_{mR(c)t}$), defined by the three major coal-producing regions (Appalachia, Midwest/Central, West). This effectively restricts control groups to non-overlap counties within the same geographic region as the treated county. The results (Appendix Table A.6) remain statistically significant and similar in magnitude to the main estimates, suggesting that broad regional decline does not drive the observed effects of labor market consolidation.

Table A.4: Effects of Labor Market Consolidation on Alternative Employment Measures

	log(Total Mine Employment BLS)			log(Total Mine Employment MSHA)			log(Total Mine Hours MSHA)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.163***	-0.038	-0.027	-0.115**	-0.003	0.035	-0.128**	0.002	0.038
	(0.043)	(0.042)	(0.042)	(0.049)	(0.046)	(0.047)	(0.054)	(0.047)	(0.048)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.262***	-0.260***		-0.235**	-0.251***		-0.271***	-0.291***
		(0.079)	(0.078)		(0.094)	(0.095)		(0.103)	(0.105)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.018			-0.069***			-0.069***
			(0.014)			(0.015)			(0.015)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.034			-0.010			0.009
			(0.028)			(0.025)			(0.025)
M&A Event × County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.94	0.94	0.94	0.95	0.95	0.95	0.95	0.95	0.95
N. Obs (M&A Event × County × Year)	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518
N. Event × Counties	3,074	3,074	3,074	3,074	3,074	3,074	3,074	3,074	3,074
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,809						1,809
Event × Counties w/ Output Δ HHI ≥ 500			409			409			409

Notes: Estimates and standard errors from DID specification (7) for employment outcome measures in the available data. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Table A.5: Effects of Labor Market Consolidation on Alternative Output Measures

	log(Total Coal Sales EIA)			log(Total Coal Extraction MSHA)			log(Total Revenue EIA)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.223***	-0.024	0.026	-0.197***	0.001	0.047	-0.213***	0.025	0.059
	(0.066)	(0.056)	(0.057)	(0.067)	(0.058)	(0.058)	(0.075)	(0.064)	(0.065)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.417***	-0.437***		-0.415***	-0.433***		-0.497***	-0.505***
		(0.119)	(0.120)		(0.122)	(0.123)		(0.135)	(0.134)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.093***			-0.085***			-0.060***
			(0.018)			(0.017)			(0.020)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.021			-0.019			-0.039
			(0.031)			(0.030)			(0.033)
M&A Event × County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.96	0.96	0.96	0.96	0.94	0.94	0.94
N. Obs (M&A Event × County × Year)	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518	21,518
N. Event × Counties	3,074	3,074	3,074	3,074	3,074	3,074	3,074	3,074	3,074
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,809						
Event × Counties w/ Output Δ HHI ≥ 500			409			409			409

Notes: Estimates and standard errors from DID specification (7) for output outcome measures in the available data. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

B.2.3 Selection Bias from Endogenous M&A

The endogenous decision to merge poses a threat if unobservable determinents of M&A are correlated with outcome trends. While a DID design cannot eliminate selection bias from time-varying county-specific unobservables, it can address bias from firm-level or transaction-level shocks. To test this, I restrict the control group to non-overlap counties where one of

Table A.6: Results using within-region based control groups

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.069***	-0.032***	-0.032***	-0.142***	-0.012	-0.023
	(0.016)	(0.012)	(0.012)	(0.044)	(0.039)	(0.039)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.078**	-0.077**		-0.272***	-0.268***
		(0.031)	(0.031)		(0.080)	(0.081)
Post-Acquisition ×1[Output ΔHHI > 0]			0.003			0.035**
			(0.006)			(0.017)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.013			0.058**
			(0.009)			(0.025)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Region × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.94	0.94	0.94
	log(Total Mine Capacity)			log(Total Coal Sales)		
	(7)	(8)	(9)	(10)	(11)	(12)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.188***	-0.009	0.005	-0.187***	0.019	0.036
	(0.062)	(0.047)	(0.049)	(0.065)	(0.050)	(0.051)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.376***	-0.383***		-0.431***	-0.439***
		(0.116)	(0.117)		(0.118)	(0.119)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.051**			-0.058***
			(0.021)			(0.022)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			0.075**			0.015
			(0.032)			(0.031)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Region × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.96	0.96	0.96
N. Obs (M&A Event × County × Year)	21,518	21,518	21,518	21,518	21,518	21,518
N. Event × Counties	3,074	3,074	3,074	3,074	3,074	3,074
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,791			1,791
Event × Counties w/ Output Δ HHI ≥ 500			409			409

Notes: Estimates and standard errors from DID specification (7), including M&A event - region - year specific fixed effects to control for regional economic trends. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

the parties operated mines prior to the merger. This refinement ensures that control counties share the same transaction-level and firm-level exposure to M&A as the treatment county. Despite reducing the overall sample size and removing 2 treatment events that lacked within-M&A control counties, the results (Appendix Table A.7) are similar to the main estimates. This suggests that the findings are robust to selection bias arising from transaction- and firm-level unobservables that determine acquisitions.

Table A.7: Results with M&A party nonoverlap counties as control groups

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.066***	-0.022	-0.030**	-0.175***	-0.044	-0.044
	(0.018)	(0.014)	(0.013)	(0.045)	(0.043)	(0.043)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.086***	-0.080**		-0.253***	-0.253***
		(0.033)	(0.032)		(0.079)	(0.080)
Post-Acquisition ×1[Output ΔHHI > 0]			0.041***			-0.001
			(0.011)			(0.024)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.021**			-0.004
			(0.009)			(0.032)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.94	0.94	0.94
	log(Total Mine Capacity)			log(Total Coal Sales)		
	(7)	(8)	(9)	(10)	(11)	(12)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.239***	-0.007	0.002	-0.208***	0.031	0.051
	(0.075)	(0.065)	(0.064)	(0.071)	(0.063)	(0.063)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.452***	-0.410***		-0.466***	-0.448***
		(0.131)	(0.123)		(0.123)	(0.119)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.018			-0.076***
			(0.027)			(0.026)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.244***			-0.129***
			(0.033)			(0.027)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.97	0.97	0.97
N. Obs (M&A Event × County × Year)	8,274	8,274	8,274	8,274	8,274	8,274
N. Event × Counties	1,182	1,182	1,182	1,182	1,182	1,182
Event × Counties w/ Labor Δ HHI > 0	44	44	44	44	44	44
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			1,022			1,022
Event × Counties w/ Output Δ HHI ≥ 500			311			311

Notes: Estimates and standard errors from DID specification (7), with control groups defined as counties where one of the parties to the acquisition had mining operations, but no overlap with other parties, the year before M&A. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

B.2.4 Treatment-Control Imbalance

Systematic differences between treatment and control counties could indicate violations of the parallel trends assumption. Overlap counties tend to have larger mining sectors and less concentrated labor markets than the average non-overlap county. To ensure results are not driven by these imbalances, I construct a "matched" control group consisting of the 30 non-overlap counties most similar to the treated county in terms of pre-merger labor HHI and total coal revenue. This matching procedure significantly improves balance on observable

characteristics, but reduces the sample size by more than 90%. Despite the loss of power, the results are qualtatively and statistically similar to the main estimates (Appendix Table A.8), suggesting the main results are not driven by selection of dissimilar control markets.

Table A.8: Results with matched treatment/control groups

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.067***	-0.019	-0.018	-0.134***	-0.010	0.048
	(0.018)	(0.014)	(0.014)	(0.046)	(0.045)	(0.046)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.100***	-0.088***		-0.260***	-0.272***
		(0.033)	(0.030)		(0.087)	(0.082)
Post-Acquisition ×1[Output ΔHHI > 0]			0.003			-0.112**
			(0.016)			(0.045)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.070**			-0.128*
			(0.034)			(0.077)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.94	0.94	0.94
	log(Total Mine Capacity)			log(Total Coal Sales)		
	(7)	(8)	(9)	(10)	(11)	(12)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.158**	0.036	0.072	-0.176**	0.044	0.097
	(0.075)	(0.059)	(0.060)	(0.074)	(0.061)	(0.060)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.406***	-0.352***		-0.460***	-0.463***
		(0.141)	(0.124)		(0.136)	(0.129)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.041			-0.098**
			(0.044)			(0.041)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.420***			-0.164**
			(0.079)			(0.064)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.93	0.94	0.94	0.94	0.94	0.94
N. Obs (M&A Event × County × Year)	2,975	2,975	2,975	2,975	2,975	2,975
N. Event × Counties	425	425	425	425	425	425
Event × Counties w/ Labor Δ HHI > 0	46	46	46	46	46	46
Event × Counties w/ Labor Δ HHI ≥ 500		22	22		22	22
Event × Counties w/ Output Δ HHI > 0			294			294
Event × Counties w/ Output Δ HHI ≥ 500			70			70

Notes: Estimates and standard errors from DID specification (7), with event-specific control groups restricted to the 30 most similar nonoverlap counties by HHI and by total revenue, respectively, the year before the acquisition. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

B.2.5 Exposure to Other M&A Events

In a traditional panel regression, repeated exposure to multiple M&A events creates mechanical "weighting" issues that would bias estimates. The stacked-event design rules out

this type of mechanical bias. However, repeated exposure to other M&A might bias the DID estimator through attenuation or SUTVA violations. The main specification excludes counties exposed to other M&A within a ±2-year window. I test the sensitivity of this filter with two alternative criteria. First, a stricter ±3-year exclusion window (dropping 8 events and over 20% of the sample) yields similar results (Appendix Table A.9), suggesting the main estimates are not driven by exposure bias. Second, a more permissive ±1-year exclusion window increases the sample size but also introduces noise, leading to slightly attenuated estimates and reduced precision (Appendix Table A.10), albeit with similar economic conclusions. This suggests that the main sample's ±2-year filter balances sample size with the need for clean identification.

Table A.9: Results without allowing any other M&A exposure (±3 years)

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.067***	-0.013	-0.021*	-0.148***	0.009	0.026
	(0.020)	(0.012)	(0.012)	(0.051)	(0.041)	(0.041)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.113***	-0.106***		-0.333***	-0.334***
		(0.038)	(0.037)		(0.089)	(0.087)
Post-Acquisition ×1[Output ΔHHI > 0]			0.015**			-0.027*
			(0.006)			(0.014)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.014			-0.033
			(0.011)			(0.031)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.94	0.94	0.94
	log(Total Mine Capacity)			log(Total Coal Sales)		
	(7)	(8)	(9)	(10)	(11)	(12)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.210***	0.001	0.035	-0.220***	0.004	0.063
	(0.078)	(0.054)	(0.051)	(0.079)	(0.064)	(0.062)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.445***	-0.413***		-0.473***	-0.485***
		(0.145)	(0.134)		(0.144)	(0.141)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.045**			-0.096***
			(0.019)			(0.020)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.231***			-0.082***
			(0.032)			(0.027)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.96	0.96	0.96
N. Obs (M&A Event × County × Year)	16,856	16,856	16,856	16,856	16,856	16,856
N. Event × Counties	2,408	2,408	2,408	2,408	2,408	2,408
Event × Counties w/ Labor Δ HHI > 0	38	38	38	38	38	38
Event × Counties w/ Labor Δ HHI ≥ 500		18	18		18	18
Event × Counties w/ Output Δ HHI > 0			1,343			1,343
Event × Counties w/ Output Δ HHI ≥ 500			263			263

Notes: Estimates and standard errors from DID specification (7), filtered to counties that had no other exposure to acquisitions in the study window (±3 years). Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

Table A.10: Results allowing other M&A exposure except ±1 year of the treatment event

	log(Average Mining Wage)			log(Total Mine Employment)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.062***	-0.030**	-0.037***	-0.141***	-0.049	-0.034
	(0.016)	(0.013)	(0.013)	(0.041)	(0.042)	(0.042)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.062**	-0.058*		-0.181**	-0.187**
		(0.031)	(0.031)		(0.078)	(0.078)
Post-Acquisition ×1[Output ΔHHI > 0]			0.013***			-0.026**
			(0.005)			(0.013)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.003			-0.009
			(0.009)			(0.025)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.90	0.90	0.90	0.93	0.93	0.93
Post-Acquisition ×1[Labor ΔHHI > 0]	-0.246***	-0.078	-0.041	-0.214***	-0.044	0.016
	(0.062)	(0.055)	(0.053)	(0.059)	(0.057)	(0.056)
Post-Acquisition ×1[Labor ΔHHI ≥ 500]		-0.330***	-0.305***		-0.333***	-0.357***
		(0.114)	(0.107)		(0.107)	(0.107)
Post-Acquisition ×1[Output ΔHHI > 0]			-0.052***			-0.106***
			(0.016)			(0.017)
Post-Acquisition ×1[Output ΔHHI ≥ 500]			-0.203***			-0.030
			(0.030)			(0.026)
M&A Event × County FE	Y	Y	Y	Y	Y	Y
M&A Event × Year FE	Y	Y	Y	Y	Y	Y
Adjusted R^2	0.95	0.95	0.95	0.96	0.96	0.96
N. Obs (M&A Event × County × Year)	26,446	26,446	26,446	26,446	26,446	26,446
N. Event × Counties	3,778	3,778	3,778	3,778	3,778	3,778
Event × Counties w/ Labor Δ HHI > 0	53	53	53	53	53	53
Event × Counties w/ Labor Δ HHI ≥ 500		27	27		27	27
Event × Counties w/ Output Δ HHI > 0			2,231			2,231
Event × Counties w/ Output Δ HHI ≥ 500			526			526

Notes: Estimates and standard errors from DID specification (7), with no exposure to other acquisitions in a 1-year window of the focal treatment event. Standard errors are clustered at the M&A event × county level, the unit of treatment exposure. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

C Structural Model Appendix

C.1 Labor Supply Derivation

Worker i obtains utility from job j in market t according to:

$$u_{ijct} = \delta_{jct} + \epsilon_{ijct} = \alpha w_{jct} + \beta x_{jct} + \xi_{jct} + \epsilon_{ijct} \tag{8}$$

The random utility term follows a generalized extreme value (GEV) distribution consistent with the nested logit model:

$$\epsilon_{ijct} = \zeta_{i\mathcal{J}ct} + (1-\sigma)\tilde{\epsilon}_{ijct}$$

, where ζ is common to all mining jobs and $\tilde{\epsilon}$ is idiosyncratic with a type 1 extreme value distribution.

Total worker surplus (in utility units) is given by the log-sum formula:

$$U_{ct} = \log(1 + I_{ct}^{1-\sigma}) \tag{9}$$

Dividing by the marginal utility of income $W_{ct} = U_{ct}/\alpha$ provides the monetary ($/hour) units presented in the counterfactual welfare analysis.

C.2 Markdown Derivation

The first-order condition with respect to wages implies a markdown μ_{jct} defined by the inverse semi-elasticity of supply:

$$\mu_{jct} = \left(\frac{\partial s_{jct}}{\partial w_{jct}} \frac{1}{s_{jct}}\right)^{-1} = \frac{1-\sigma}{\alpha}\left(1 - \sigma\frac{s_{jct}}{1-s_{0ct}} - (1-\sigma)s_{jct}\right)^{-1} \tag{10}$$

where $s_{0ct} = 1 - \sum_{k\in\mathcal{J}_{ct}} s_{kct}$ is the labor market share of the outside option. The markdown is positive and increasing in the firm's labor market share.

C.3 Labor Market Size

The market size L_{ct} is constructed by scaling the observed labor force in the local area. Specifically, I assume the potential labor market for coal mining is proportional to the county's total labor force $\mathbb{L}_{ct}$. The proportionality factor is calculated as $\tilde{L}_c = 1.5 \times \max_t(\sum_{j\in J}(l_{jct}/\mathbb{L}_{ct}))$, which ensures that there is always a positive outside option to mining employment. Thus, $L_{ct} = \tilde{L}_c \times \mathbb{L}_{ct}$. While this definition of market size seems like it is making strong assumptions about the degree of substitution between mining and non-mining jobs, in the model

the nesting parameter σ disciplines the value of outside alternatives to match substitution patterns in and out of coal mining in the data.

C.4 Structural residuals

Beginning with the production function residual, the productivity process (**??**) implies

$$\begin{aligned}\Delta\omega_{jct}(\theta,y) =& \log(q_{jct}) - (\frac{c}{c-1})\log(b_{ct}(\theta,y)l_{jct}^{\frac{c-1}{c}} + (1-b_{ct}(\theta,y))k_{jct}^{\frac{c-1}{c}}) \\ & - a\big(\log(q_{jct-1}) - (\frac{c}{c-1})\log(b_{ct-1}(\theta,y)l_{jct-1}^{\frac{c-1}{c}} + (1-b_{ct-1}(\theta,y))k_{jct-1}^{\frac{c-1}{c}})\big) \\ & - \omega_{jc} - \omega_{B(c)t}\end{aligned} \tag{11}$$

By this equation and given a candidate set of parameters, the productivity shock is identified by data on production, production lags, and knowledge of the labor-augmenting technology $b_{ct}(\theta,y)$.

Next, the labor supply residual is identified by the usual nested logit inversion from (Berry, 1994).

$$\Delta\xi_{jct}(\theta,y) = \log(s_{cjt}/s_{0ct}) - \sigma\log(s_{jct}/(1-s_{0ct})) - \alpha w_{jct}(\theta,y) - \beta x_{jct} - \xi_{jc} - \xi_{B(c)t} \tag{12}$$

Given a set of candidate parameters and this inversion, the labor supply shock is pinned down by data on market shares and job characteristics, as well as knowledge of the job-specific wage $w_{jct}(\theta,y)$.

C.5 Instrumental Variables

Production Instruments (Z^q): To address the endogeneity of flexible inputs (l,k) in the gross output production function, I rely on a restriction to the firm's information set. Specifically, after conditioning on linear persistence in TFP and any trends in TFP at job-county and coal-basin-year level, the remaining innovations to TFP ($\Delta\eta_{jct}$) are unpredictable at time $t-1$. Therefore, lagged inputs (l_{t-1}, k_{t-1}) and lagged output (q_{t-1}) are independent of the current TFP shock. In addition to using these as IVs, I also interact these production lags with the "Waldfogel" IVs – the average non-mining wage w_{0ct} and lagged market average coal prices $\bar{p}_{ct-1}$ – to improve power by isolating variation in input demand driven by between-market forces.

Labor Supply Instruments (Z^l): Wages and market shares are endogenous to unobserved job quality $\Delta\xi_{jct}$. I use standard BLP and Gandhi-Houde style instruments based on the characteristics of rival firms (specifically, rival mine safety records). The logic is that

unanticipated accidents and safety violations at one mine should affect the market share and the overall competitiveness of other mines in the same labor market. A rival's safety shock should shift a firm's residual supply curve without affecting its unobserved utility directly. I also include the Waldfogel IVs ($w_{0ct}, \bar{p}_{ct-1}$) as an outside option shifter and labor demand shifter, along with interactions with the BLP and differentiation IVs.

D Detailed Counterfactual Results

This appendix provides details for the equilibrium counterfactuals presented in Section 5. The full set of industry aggregate results is shown in Table A.11, organized into three panels:

1. **Prices, Quantities, & Productivity:** Reports the percent changes in equilibrium wages, input demands (labor and capital), output, and productivity metrics (TFP, MRP) relative to the observed oligopsony in the data.

2. **Value & Welfare Outcomes (%):** Reports the percent changes in aggregate welfare measures, including Worker Surplus, Producer Surplus (Profit), and Total Welfare.

3. **Industry Total Value:** Denominates the value and welfare outcomes in dollar values ($ billions) summed over the 2001–2019 sample period, providing a measure of the economic magnitude of the distortions. To anchor the total value measures, note that industry total revenue in the observed oligopsony is about $500 billion.

D.1 Equilibrium Definitions

1. Perfectly Competitive Equilibrium. Firms optimize inputs and output behaving as price takers in the labor market, holding capital costs and output prices fixed. This eliminates the markdown ($\mu_{jct}^{PC} = 0$), implying $w_{jct} = MRPL_{jct}$.

2. Monopsonistically Competitive Equilibrium. Firms face the estimated upward-sloping labor supply curve but ignore their influence on market aggregate labor (the inclusive value, I_{ct}). Markdowns are no longer a function of market shares: $\mu_{jct}^{MC} = \frac{1-\sigma}{\alpha}$. The remaining markdown isolates the distortion arising from job differentiation.

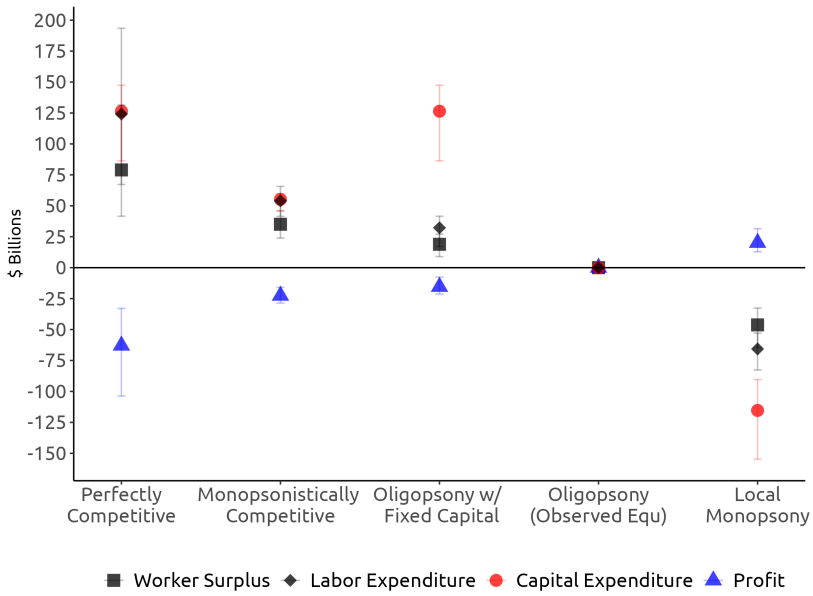
3. Oligopsony with Fixed Capital. Capital is fixed at the level estimated in the Perfectly Competitive equilibrium ($k_{jct} = k_{jct}^{PC}$). Firms then compete in a Nash-Bertrand game setting wages given this fixed capacity, isolating the scale effect.

4. Local Monopsony. All mining jobs in a county c are assigned to a single profit-maximizing entity that sets a vector of wages and chooses a vector of capital to maximize joint profit.

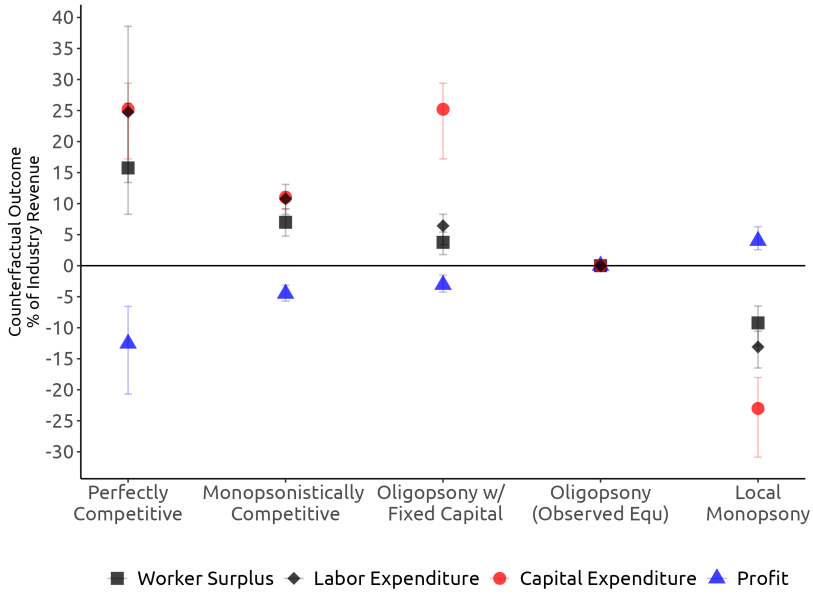
D.2 Supplemental CF Figures

Figure A.2: Equilibrium outcomes relative to observed oligopsony

(a) Total Value in $ Billions over 2001-2019



(b) Normalized as % of Observed Industry Revenue



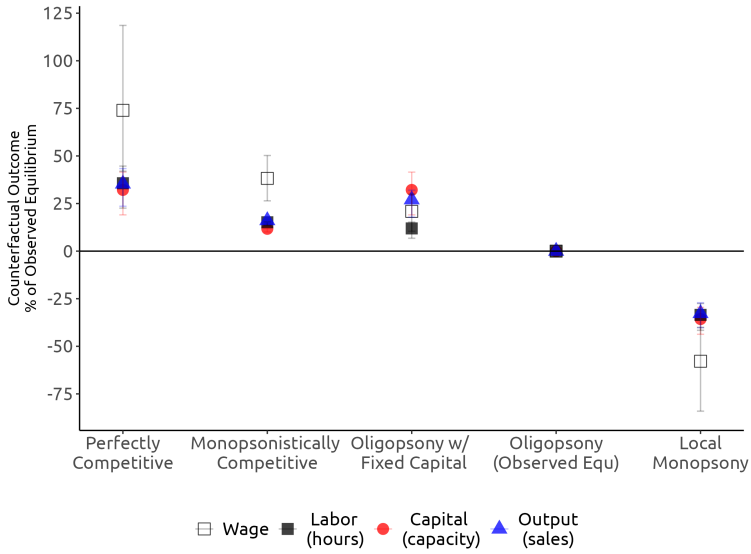
Notes: Percent differences between counterfactual equilibrium outcomes and the oligopsony outcome in the data. 95% confidence intervals based on 100 draws from the asymptotic joint distribution of parameter estimates. Author's calculations based on the EIA-MSHA-BLS data (N=20,870).

Table A.11: Counterfactual Results (2001–2019)

	Perfectly Competitive	Monopsonistically Competitive	Oligopsony with Fixed Capital	Local Monopsony
Prices, Quantities, & Productivity (%)				
Wage	73.96	38.21	20.88	-57.85
	(21.45)	(6.63)	(5.18)	(12.26)
Labor	35.67	15.16	11.93	-33.48
	(6.09)	(0.57)	(2.23)	(3.88)
Capacity-Capital	32.15	11.72	32.15	-35.69
	(6.18)	(0.56)	(6.18)	(3.89)
Coal Output	35.33	16.09	27.02	-32.72
	(5.46)	(0.4)	(3.94)	(3.6)
Coal Price	-1.28	-1.79	-0.08	-2.15
	(0.26)	(0.18)	(0.2)	(0.4)
Total Factor Productivity	3.56	5.72	0.63	7.55
	(0.92)	(0.66)	(0.4)	(1.42)
Marginal Revenue Product of Labor	2.97	4.5	1.51	5.9
	(1.09)	(0.92)	(0.31)	(1.75)
Marginal Revenue Product of Capital	-0.66	-0.73	-6.42	-1.1
	(0.25)	(0.32)	(7.35)	(0.48)
Production Elasticity of Labor	2.07	2.89	4.26	3.88
	(0.81)	(0.8)	(17.64)	(1.42)
Capital/Labor Ratio	-2.59	-2.99	18.07	-3.32
	(0.2)	(0.13)	(3.83)	(0.24)
Value & Welfare Outcomes (%)				
Worker Surplus	37.97	16.86	9.08	-22.22
	(6.46)	(0.56)	(1.8)	(2.09)
Labor Expenditure	136.02	59.17	35.3	-71.96
	(37.66)	(7.53)	(7.67)	(8.57)
Capital Expenditure	36.4	15.9	36.4	-33.22
	(6)	(0.66)	(6)	(3.91)
Revenue	37.42	17.27	28.55	-32.1
	(5.78)	(0.46)	(4.03)	(3.76)
Profit	-100	-35.96	-24.55	31.94
	(0)	(9.28)	(2.73)	(15.58)
Total Welfare	5.93	4.59	1.27	-9.64
	(0.87)	(0.21)	(0.33)	(0.48)
Industry Total 2001-2019 ($ Billions)				
Worker Surplus	78.99	6.99	3.77	-9.22
	(4.98)	(1.22)	(0.96)	(1.86)
Labor Expenditure	124.15	10.77	6.43	-13.1
	(6.77)	(1.34)	(1.38)	(1.54)
Capital Expenditure	126.4	11.01	25.21	-23.01
	(3.33)	(0.77)	(3.33)	(3.77)
Revenue	187.61	17.27	28.55	-32.1
	(5.78)	(0.46)	(4.03)	(3.76)
Profit	-62.93	-4.51	-3.08	4.01
	(3.92)	(0.73)	(0.72)	(0.98)
Total Welfare	16.06	2.48	0.68	-5.21
	(1.06)	(0.56)	(0.25)	(1.09)

Notes: Comprehensive results corresponding to the summaries in Section 5. Bootstrapped standard errors in parentheses are calculated using 100 draws from the asymptotic joint distribution of the parameter estimates.

Figure A.3: Wages and inputs-output quantities relative to observed oligopsony



Notes: Percent differences between counterfactual equilibrium outcomes and the oligopsony outcome in the data. 95% confidence intervals based on 100 draws from the asymptotic joint distribution of parameter estimates. Author's calculations based on the EIA-MSHA-BLS data (N=20,870).