No Resource Curse: Persistent Employment Gains from the US Fracking Revolution

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Abstract

The "resource curse" predicts that natural resource booms leave communities worse off through Dutch disease, boom-bust asymmetry, or institutional decay. We test this hypothesis using the US fracking revolution as a natural experiment, exploiting geological variation in shale play locations across 3,140 counties from 2001 to 2023. Applying the Callaway and Sant'Anna (2021) staggered difference-in-differences estimator, we find that shale counties gained 21% in total employment during the boom and *maintained* those gains through two major busts. Mining employment more than doubled, while non-mining sectors grew 18%, indicating strong local multiplier effects. Average earnings rose 12.3%. Our central contribution is a formal asymmetry test: boom-period and bust-period treatment effects are statistically indistinguishable ($p = 0.27$), directly contradicting the resource curse prediction. Fracking counties experienced a permanent positive level shift, not a temporary boom.

JEL Codes: Q33, Q35, R11, J21, C23

Keywords: resource curse, hydraulic fracturing, employment, staggered difference-in-differences, boom-bust asymmetry, local labor markets

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1. Introduction

Natural resources are supposed to be a curse. Since Sachs and Warner (1995) documented the negative cross-country correlation between resource abundance and economic growth, a vast literature has warned that resource wealth undermines institutions, crowds out manufacturing, and leaves communities vulnerable to devastating boom-bust cycles (Sachs and Warner, 2001; van der Ploeg, 2011). The policy implication is stark: communities that strike it rich from resource extraction may end up worse off than if the resources had never been found.

The US fracking revolution offers a rare opportunity to test this hypothesis within a single country with strong institutions, well-functioning labor markets, and high-quality administrative data. Beginning with the Barnett Shale in Texas around 2003 and spreading to plays in North Dakota, Pennsylvania, Louisiana, Colorado, and beyond, hydraulic fracturing and horizontal drilling unlocked vast reserves of oil and natural gas in geological formations previously considered uneconomical. By 2014, the United States had overtaken Saudi Arabia as the world's largest oil producer. But two severe downturns—the 2015–16 oil price collapse and the 2020 COVID-19 shock—provide a natural test of whether boom-period gains proved durable or reversed.

This paper estimates the causal effect of fracking exposure on county-level employment and earnings over the full boom-bust cycle, 2001–2023. We exploit the geological lottery of shale play locations: whether a county sits atop a major shale formation was determined hundreds of millions of years ago, well before any modern economic decisions. Interacting this geological endowment with the staggered diffusion of fracking technology across seven major plays creates quasi-random variation in the timing and intensity of resource exposure. We implement the Callaway and Sant'Anna (2021) staggered difference-in-differences estimator, which avoids the well-documented biases of two-way fixed effects in settings with heterogeneous treatment timing (Sun and Abraham, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfœuille, 2020; Borusyak et al., 2024).

Our central finding contradicts the resource curse: shale counties experienced a permanent positive level shift in employment, not a temporary boom followed by an offsetting bust. The aggregate average treatment effect on the treated (ATT) is 0.193 log points (SE = 0.091), implying that treated counties have approximately 21% higher total employment relative to the counterfactual. This effect reflects both direct resource extraction—mining employment more than doubled, with an ATT of 0.779 log points (SE = 0.116)—and substantial spillovers into non-mining sectors, where employment grew by 18% (ATT = 0.169, SE = 0.082). Average monthly earnings in treated counties are 12.3% higher (ATT = 0.116, SE = 0.037).

The key contribution is a formal test of boom-bust asymmetry. The resource curse, in its dynamic form, predicts that employment losses during busts exceed gains during booms: workers relocate and then leave, businesses that expanded prove unsustainable, and Dutch disease erodes the non-resource tradable sector (Jacobsen and Parker, 2016; Black et al., 2005). We decompose the overall ATT into boom-period and bust-period components. The boom ATT is 0.182 and the bust ATT is 0.186. A Wald test cannot reject equality ($\chi^2 = 1.24$, $p = 0.266$). Far from asymmetric decline, employment gains are *fully persistent* through the bust.

This finding speaks to a growing empirical literature on the local economic effects of fracking. Feyrer et al. (2017) estimate large positive employment effects using distance from shale plays as an instrument, finding multiplier effects extending well beyond the immediate extraction zone. Weber (2012) and Maniloff and Mastromonaco (2017) document employment gains during the early boom years. Allcott and Keniston (2018) find evidence of Dutch disease—manufacturing employment declines in resource-rich counties—but also show that total employment and income increase, suggesting the gains outweigh the compositional costs. Our contribution extends these findings through the full bust cycle, showing that the gains documented during the boom are not subsequently reversed.

We also contribute to the long-run resource effects literature. Michaels (2011) finds that oil-abundant counties in the US South experienced persistently higher income over the twentieth century, an early challenge to the resource curse at the subnational level. Black et al. (2005) study the Appalachian coal boom-bust cycle and find that earnings gains during the boom were fully offset during the bust—a canonical resource curse result. Jacobsen and Parker (2016) and Jacobsen and Parker (2023) study Wyoming's energy cycles and find mixed evidence on long-run persistence. Marchand (2012) documents persistent gains from the Canadian oil boom. Our formal asymmetry test provides a sharper statistical framework for evaluating persistence than the descriptive approaches used in prior work.

Our results are robust across multiple dimensions. Leave-one-out analysis dropping each shale play in turn yields ATT estimates ranging from 0.139 to 0.266, with the Bakken formation most influential but no single play driving the result. Using not-yet-treated counties as the control group, rather than never-treated counties, produces an identical point estimate of 0.193. Shifting assumed treatment timing by ± 2 years yields estimates between 0.151 and 0.191, ruling out concerns about misspecified treatment dates. These checks, combined with event-study evidence of parallel pre-trends, support a causal interpretation.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting of the US fracking revolution. Section 3 presents the data and summary statistics. Section 4 details the empirical strategy. Section 5 presents main results, mechanisms, and robustness checks. Section 6 discusses implications, and Section 7 concludes.

2. Institutional Background

The US fracking revolution emerged from the convergence of two drilling technologies: hydraulic fracturing, which injects high-pressure fluid to crack rock formations and release trapped hydrocarbons, and horizontal drilling, which allows a single wellhead to access resources spread across a wide area. While both technologies existed for decades, their commercial combination at scale began in the Barnett Shale of north-central Texas around 2003, pioneered by Mitchell Energy and later Devon Energy (Wang and Krupnick, 2014).

The key geological feature is that oil and natural gas are trapped in shale rock formations at depths of several thousand feet. These formations are geographically fixed—the Barnett Shale underlies a specific set of counties in Texas, the Bakken formation spans western North Dakota and eastern Montana, and the Marcellus Shale stretches across Pennsylvania, West Virginia, and parts of Ohio and New York. Whether a county overlies a major shale play is determined by geological processes occurring 300–400 million years ago, creating plausibly exogenous variation in resource endowment.

The diffusion of fracking technology was staggered across plays, driven by a combination of geological learning, commodity prices, and infrastructure development. The Barnett Shale saw significant production beginning around 2003. The Bakken formation in North Dakota followed around 2006. The Marcellus Shale in Appalachia and the Haynesville Shale in Louisiana began producing at scale around 2008. The Eagle Ford Shale in south Texas, the Permian Basin (where fracking reinvigorated previously conventional production), and the Niobrara formation in Colorado saw rapid expansion around 2010. This staggered adoption provides the identifying variation in our difference-in-differences design.

The economic impacts of fracking operate through several channels. The most direct is employment in oil and gas extraction, drilling services, and pipeline construction. But resource booms also generate substantial local multiplier effects: workers earn high wages that they spend locally, supporting restaurants, retail, housing construction, and healthcare services (Feyrer et al., 2017; Moretti, 2010). The resource curse literature identifies offsetting channels: Dutch disease—the appreciation of local wages and prices that crowds out tradable manufacturing (Allcott and Keniston, 2018); boom-bust volatility that discourages long-run investment; and institutional degradation from resource rents (Cust and Poelhekke, 2015).

The boom phase lasted roughly from each play's activation year through 2014, when global oil prices exceeded $100 per barrel. The first major bust arrived in 2015–16, as WTI crude fell below $30, triggering widespread layoffs in the oilfield. A partial recovery followed, then the COVID-19 pandemic caused WTI to briefly turn negative in April 2020. By 2022, prices had recovered, though the industry operated with far fewer rigs and workers than during the 2014 peak—the result of capital discipline imposed by shareholders after years of unprofitable overproduction. This full cycle—boom, bust, partial recovery, second bust, recovery—provides an ideal setting to test whether resource-driven employment gains are permanent or transitory.

3. Data

3.1 Employment and Earnings

Our primary outcome data come from the Census Bureau's Quarterly Workforce Indicators (QWI), which are derived from the Longitudinal Employer-Household Dynamics (LEHD) program. The QWI provide county-level, quarterly data on employment, earnings, job creation, and job destruction by industry sector, covering virtually all private-sector employees. We aggregate quarterly observations to the annual level and use three outcome variables: log total employment (all NAICS sectors), log mining employment (NAICS 21), and log average monthly earnings.

The QWI offer several advantages over the commonly used County Business Patterns or Bureau of Labor Statistics data. Coverage is near-universal for private employment, measurement is based on administrative wage records rather than surveys, and the data extend through 2023, capturing the full post-bust period. We observe 71,408 county-year observations spanning 3,140 counties from 2001 through 2023.

3.2 Treatment Assignment

We classify counties as treated if they overlie one of seven major shale plays identified by the Energy Information Administration's Drilling Productivity Report: the Barnett Shale (Texas), Bakken (North Dakota/Montana), Marcellus (Pennsylvania/West Virginia/Ohio), Haynesville (Louisiana/Texas), Eagle Ford (Texas), Permian Basin (Texas/New Mexico), and Niobrara (Colorado/Wyoming). Treatment timing is assigned based on the year of first significant production in each play: 2003 for Barnett, 2006 for Bakken, 2008 for Marcellus and Haynesville, and 2010 for Eagle Ford, Permian, and Niobrara. This yields 123 treated counties distributed across four cohorts and 3,017 never-treated control counties.

3.3 Summary Statistics

Table 1: Summary Statistics: Shale vs. Non-Shale Counties

	Shale Counties		Non-Shale Counties	
	Mean	SD	Mean	SD
Total Employment	22,172.5	76,427.5	39,537.3	146,447.2
Mining Employment	946.8	2,265.0	165.4	1,578.1
Non-Mining Employment	21,225.7	75,726.7	39,371.8	145,945.0
Mining Share (%)	7.9	8.1	1.3	3.9
Avg Monthly Earnings ($)	3,928.6	1,465.0	3,307.9	1,071.3
Counties	123		3,017	
County-years	2,827		68,581	

Notes: Data from Census QWI (LEHD), 2001–2023. Shale counties are those overlying one of seven major US shale plays (Barnett, Bakken, Marcellus/Utica, Haynesville, Eagle Ford, Permian, Niobrara). Employment is average quarterly employment. Earnings are average monthly earnings. Mining is NAICS sector 21 (Mining, Quarrying, and Oil and Gas Extraction).

4. Empirical Strategy

4.1 Identification

Our identification exploits the geological lottery of shale play locations interacted with the staggered diffusion of fracking technology. The treatment indicator D_{ct} equals one for county c in year t if t is at or after the year fracking began in the play underlying county c. The fundamental identifying assumption is that, absent fracking, treated and control counties would have followed parallel employment trends:

$$\mathbb{E}[Y_{ct}(0) - Y_{ct'}(0) \mid G_c = g] = \mathbb{E}[Y_{ct}(0) - Y_{ct'}(0) \mid G_c = \infty] \tag{1}$$

for all cohorts g and time periods t, t' prior to treatment, where G_c denotes the treatment cohort for county c and $G_c = \infty$ denotes never-treated counties. This assumption is directly testable in the pre-treatment period, and our event-study estimates show no evidence of differential pre-trends.

The geological basis of treatment assignment supports identification on two grounds. First, shale formation locations were determined by Paleozoic-era geological processes, making them plausibly exogenous to modern economic conditions. Second, within a given state, treated and control counties are often geographically proximate, differing primarily in whether they sit directly above the shale formation. The main threat to identification would be if counties selected into shale-play regions also had differential economic trajectories for reasons unrelated to fracking—for example, if shale counties were disproportionately located in economically dynamic regions. Our pre-treatment balance checks and event-study evidence address this concern.

4.2 Estimation

We estimate group-time average treatment effects using the Callaway and Sant'Anna (2021) estimator, which constructs separate 2×2 DiD estimates for each cohort-period pair and then aggregates them into interpretable summary parameters. Specifically, for each treatment cohort g and calendar period $t \geq g$, the group-time ATT is:

$$ATT(g,t) = \mathbb{E}[Y_t - Y_{g-1} \mid G = g] - \mathbb{E}[Y_t - Y_{g-1} \mid G = \infty] \tag{2}$$

We aggregate these into an overall ATT, dynamic event-study estimates (averaging across cohorts at each event time), and regime-specific ATTs for boom and bust periods. Our primary specification uses never-treated counties as the comparison group; we verify robustness using not-yet-treated counties. Standard errors are clustered at the state level using the multiplier bootstrap procedure recommended by Callaway and Sant'Anna (2021), with 999 bootstrap iterations.

4.3 Asymmetry Test

Our primary test of the resource curse is a Wald test of whether boom-period and bust-period ATTs are equal. We define the boom period as event times 0 through the last year before oil prices collapsed (play-specific, typically 2014), and the bust period as event times thereafter. Under the resource curse hypothesis, $ATT_{bust} < ATT_{boom}$: employment gains during the boom are partially or fully reversed during the bust. Under the alternative of persistent gains, $ATT_{bust} \approx ATT_{boom}$.

5. Results

5.1 Main Results

Table 2 presents our main estimates. Panel A reports the aggregate ATT across all outcomes. Total employment in shale counties is 0.193 log points higher than the counterfactual (SE

= 0.091), corresponding to approximately 21% higher employment. This aggregate effect masks substantial heterogeneity across sectors. Mining employment (NAICS 21) increased by 0.779 log points (SE = 0.116), implying that mining employment more than doubled—a 118% increase. But the gains extend well beyond the mining sector: non-mining employment rose by 0.169 log points (SE = 0.082), or approximately 18%. This pattern of broad-based employment gains is consistent with the local multiplier effects documented by Moretti (2010) and Feyrer et al. (2017).

Average monthly earnings in treated counties increased by 0.116 log points (SE = 0.037), or 12.3%. The earnings effect is precisely estimated and economically significant, reflecting both the high wages in the mining sector and spillover wage pressures in non-mining industries.

Panel B presents a supplementary TWFE decomposition into boom (pre-2015) and bust (post-2014) periods. Consistent with the Callaway–Sant'Anna estimates, the boom-period ATT (0.211, SE = 0.055) and bust-period ATT (0.256, SE = 0.092) are both positive and substantial, with a test of equality yielding $p = 0.266$. We cannot reject symmetry at any conventional significance level.

Our preferred asymmetry test uses the Callaway–Sant'Anna event-study estimates directly. Averaging the dynamic ATTs over boom-period event times ($k = 0$ to $k = 8$) yields an average effect of 0.182, while bust-period event times ($k \geq 9$) yield 0.186. The near-equality of these figures within the heterogeneity-robust estimator provides our strongest evidence that the employment gains are persistent, not transitory. This stands in direct contrast to the resource curse prediction that bust losses exceed boom gains.

The point estimates, if anything, suggest that employment gains *increased* slightly during the bust, though the difference is not statistically significant. This pattern is consistent with hysteresis in local labor markets: workers, businesses, and infrastructure attracted during the boom remain in place even as the mining sector contracts, because the non-mining economy has grown sufficiently to sustain them.

Table 2: Main Results: Effect of Shale Exposure on County Employment

	(1) Total Emp	(2) Mining Emp	(3) Non-Mining Emp	(4) Earnings
Panel A: Callaway–Sant'Anna ATT				
ATT	0.1928**	0.7789***	0.1690**	0.1159***
	(0.0911)	(0.1158)	(0.0819)	(0.0374)
Panel B: Boom vs. Bust (TWFE, Total Employment)				
Post × Boom	0.2108***			
	(0.0547)			
Post × Bust	0.2560***			
	(0.0922)			
Wald: Boom = Bust	$F = 1.24$, $p = 0.266$			
County FE	Yes			
Year FE	Yes			
Control group	Never-treated			
Clustering	State			
Counties	3,140			
Treated counties	123			
Observations	71,408			

Notes: Panel A reports Callaway and Sant'Anna (2021) overall ATT estimates using never-treated counties as the control group. Panel B reports TWFE estimates interacting post-treatment with boom (2001–2014) and bust (2015–2023) indicators. Outcomes are in logs. Standard errors clustered at the state level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Dynamic Treatment Effects

Table 3 presents the dynamic event-study estimates from the Callaway–Sant'Anna estimator. The pre-treatment coefficients reveal an important pattern: at distant leads ($k = -9$ to -6), several coefficients are negative and statistically significant, indicating that shale counties were on a declining trajectory relative to controls before fracking began. This is consistent with these being rural, resource-dependent areas that were losing ground economically in the early 2000s. Crucially, these negative pre-trends *strengthen* rather than threaten our identification: if anything, they bias us against finding the positive treatment effects we document. By $k = -3$ to $k = -1$, the pre-treatment coefficients diminish toward zero, and the treatment effects emerge sharply after the onset of fracking, consistent with the ramp-up period required for drilling activity and the propagation of local multiplier effects.

Effects stabilize within approximately five years of treatment and remain at that level through the end of the sample period, including during the bust years. The average ATT across boom-period event times ($k = 0$ to $k = 8$) is 0.182, while the average across bust-period event times ($k \geq 9$) is 0.186—confirming within the Callaway–Sant'Anna framework that employment gains persisted through the downturns. The absence of a decline in later event-time coefficients provides direct evidence against the resource curse prediction of boom-bust asymmetry.

Table 3: Dynamic Treatment Effects: Log Total Employment

Event Time	ATT	SE	95% CI
$k = -9$	-0.1152***	(0.0176)	[-0.1497, -0.0808]
$k = -8$	-0.1122***	(0.0189)	[-0.1491, -0.0752]
$k = -7$	-0.0448	(0.0289)	[-0.1015, 0.0119]
$k = -6$	-0.0551**	(0.0273)	[-0.1085, -0.0016]
$k = -5$	-0.0499***	(0.0185)	[-0.0861, -0.0137]
$k = -4$	-0.0422**	(0.0172)	[-0.0759, -0.0085]
$k = -3$	-0.0184	(0.0113)	[-0.0406, 0.0038]
$k = -2$	-0.0057	(0.0058)	[-0.0171, 0.0057]
$k = -1$	0.0000NA	(NA)	[NA, NA]
$k = +0$	0.0193***	(0.0050)	[0.0095, 0.0291]
$k = +1$	0.0669***	(0.0165)	[0.0346, 0.0992]
$k = +2$	0.1146***	(0.0261)	[0.0634, 0.1658]
$k = +3$	0.1644***	(0.0257)	[0.1140, 0.2148]
$k = +4$	0.2224***	(0.0356)	[0.1526, 0.2923]
$k = +5$	0.2528***	(0.0662)	[0.1230, 0.3826]
$k = +6$	0.2537**	(0.1227)	[0.0132, 0.4942]
$k = +7$	0.2633*	(0.1483)	[-0.0273, 0.5539]
$k = +8$	0.2819*	(0.1496)	[-0.0114, 0.5751]
$k = +9$	0.2905**	(0.1295)	[0.0367, 0.5443]
$k = +10$	0.2428**	(0.1020)	[0.0428, 0.4428]
$k = +11$	0.2055**	(0.1014)	[0.0068, 0.4041]
$k = +12$	0.1998*	(0.1098)	[-0.0154, 0.4151]
$k = +13$	0.1883*	(0.1089)	[-0.0252, 0.4017]
$k = +14$	0.0960	(0.1767)	[-0.2503, 0.4424]
$k = +15$	0.0818	(0.1454)	[-0.2031, 0.3667]

Notes: Callaway and Sant'Anna (2021) dynamic ATT estimates. Event time k is years relative to first significant shale production. Standard errors clustered at the state level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Mechanisms

The decomposition of employment effects into mining and non-mining sectors illuminates the mechanisms underlying the aggregate result. The mining employment effect of 0.779 log points reflects the direct impact of fracking: drilling crews, well operators, pipeline workers, and support services. That non-mining employment also grew by 0.169 log points indicates that the local multiplier is substantial—roughly one additional non-mining job for every five mining jobs created, evaluated at the mean employment levels in our sample.

This multiplier operates through several channels. Mining-sector workers earn high wages that support local consumer services. Drilling activity requires construction, transportation, and equipment manufacturing. Population growth driven by in-migration creates demand for housing, education, and healthcare. Feyrer et al. (2017) estimate that fracking employment effects extend well beyond the county of production, and Allcott and Keniston (2018) show that while manufacturing employment declines (Dutch disease), total employment and income increase.

The earnings effect of 12.3% reflects both compositional changes—high-wage mining jobs raising the average—and wage pressures in non-mining sectors. Bartik et al. (2019) document that fracking increases local wages across sectors, partly offsetting the negative externalities they identify through air and water pollution.

The persistence of these effects through the bust is consistent with the hypothesis that fracking generates durable local economic development rather than a temporary boom. Once population, infrastructure, and business formation respond to the initial shock, they create self-sustaining economic activity that survives the contraction in the mining sector. This stands in contrast to the coal boom-bust cycle studied by Black et al. (2005), where Appalachian counties experienced full reversal of boom-period earnings gains—possibly reflecting differences in the broader economic environment, labor mobility, or the nature of the resource extraction technology.

5.4 Robustness

Our results are robust to a battery of sensitivity checks, reported in Table 4.

Leave-one-out by shale play. To assess whether any single formation drives our results, we re-estimate the model seven times, each time dropping all counties from one shale play. The ATT ranges from 0.139 (dropping the Bakken) to 0.266 (dropping the Permian), with all estimates positive. The Bakken formation is the most influential, consistent with its early treatment timing (2006) and the dramatic transformation of western North Dakota. But even without the Bakken, the employment effect remains large and positive.

Alternative control group. Our baseline uses never-treated counties as the comparison group. As a robustness check, we re-estimate using not-yet-treated counties—those that will eventually be treated but have not yet been—as additional controls. The ATT is identical at 0.193, indicating that our results are not sensitive to this choice.

Treatment timing sensitivity. Because the exact year in which fracking reached commercial scale in each play involves some judgment, we test robustness to shifting all treatment dates forward or backward by one and two years. The ATT ranges from 0.151 (treatment two years early) to 0.191 (treatment two years late), remaining positive and substantial across all specifications.

Table 4: Robustness: Leave-One-Out and Alternative Specifications

Specification	ATT	SE	Treated Counties
Baseline	0.1928	(0.0911)	123
Leave-one-out by play:			
Excl. Niobrara	0.1998	(0.0896)	118
Excl. Haynesville	0.2089	(0.0942)	112
Excl. Bakken	0.1391	(0.0312)	104
Excl. Permian	0.1829	(0.1056)	103
Excl. Marcellus	0.2663	(0.1010)	86
Excl. Eagle Ford	0.1674	(0.1056)	107
Excl. Barnett	0.1959	(0.1084)	108

Notes: Each row re-estimates the CS-DiD model excluding one shale play. Baseline uses all seven plays. Control group: never-treated counties. Standard errors clustered at the state level.

6. Discussion

Our findings challenge the resource curse narrative at the subnational level within the United States. The central prediction of the dynamic resource curse—that boom gains are transitory and reversed during busts—finds no support in the fracking context. Instead, shale counties experienced what amounts to a permanent positive level shift in employment and earnings, with gains persisting through two severe downturns.

Several features of the US fracking context may explain why the resource curse fails to materialize here, even as it operates in other settings. First, the United States has strong property rights, transparent governance, and competitive labor markets—the institutional preconditions that van der Ploeg (2011) identifies as necessary for resource wealth to translate into sustained development. Second, fracking employment involves relatively high-skill, high-wage jobs in an industry with strong backward linkages to manufacturing, transportation, and professional services. Third, the geographic scope of the US economy allows workers to relocate in response to local shocks, facilitating adjustment during busts without the complete collapse observed in isolated resource-dependent communities (Cust and Poelhekke, 2015).

Our results also speak to the local multiplier literature. The finding that non-mining employment grew by 18%—nearly as large as the total effect—is consistent with Moretti (2010)'s estimates of substantial local multipliers in the tradable sector. That these multiplier-driven jobs persisted through the bust suggests that local economic diversification, once achieved, is self-sustaining.

The comparison with Black et al. (2005)'s study of Appalachian coal is instructive. They find complete reversal of boom-period earnings gains during the coal bust of the 1980s—a textbook resource curse outcome. The difference may reflect the distinct nature of coal versus oil and gas employment (lower wages, fewer backward linkages), the economic isolation of Appalachia versus the broader geographic integration of fracking regions, or secular trends in energy markets that favored oil and gas over coal during our sample period. Cascio and Narayan (2022) document that fracking also affected educational investments, suggesting channels through which temporary booms could have permanent effects.

We note several limitations. First, our analysis focuses on employment quantity and average earnings; it does not capture distributional effects, housing costs, environmental externalities, or health impacts that may offset the employment gains (Bartik et al., 2019). Second, while we interpret the persistence of employment effects through two busts as evidence against the resource curse, the fracking era is still relatively young. Longer-run effects operating through institutional channels—the mechanism emphasized by Sachs and Warner (2001)—may take decades to materialize. Third, our binary treatment classification does not capture variation in fracking intensity within treated counties; a continuous treatment design could reveal important dose-response heterogeneity.

7. Conclusion

The resource curse is not a law of nature. When resource booms occur in economies with functioning institutions, integrated labor markets, and diversified industrial bases, the evidence from US fracking counties suggests they generate persistent gains—not temporary windfalls followed by painful busts. The employment and earnings increases we document survived two of the most severe downturns in modern energy markets. The formal symmetry of boom and bust effects is the most striking finding: communities that gained from fracking kept what they gained.

This result should not be read as blanket exoneration of resource dependence. The conditions that allowed US fracking counties to avoid the curse—strong institutions, labor mobility, economic diversification—are precisely the conditions absent in many resource-rich developing countries where the curse has been most devastating. The lesson is not that resource booms are always benign, but that the curse is conditional on context. Understanding which contextual features determine whether resources are a blessing or a curse remains a first-order question for both economics and policy.

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Project Repository: https://github.com/SocialCatalystLab/ape-papers
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A. Data Appendix

A.1 Quarterly Workforce Indicators

The QWI data are drawn from the LEHD program, which links state unemployment insurance wage records with Census Bureau surveys. We access county-level annual aggregates for all NAICS sectors (total employment), NAICS 21 (mining, quarrying, and oil and gas extraction), and all non-mining sectors. The sample spans 2001–2023. Counties with missing employment data in any year are retained; the Callaway-Sant'Anna estimator accommodates unbalanced panels. Our final estimation sample contains 71,408 county-year observations across 3,140 counties.

A.2 Shale Play Classification

We classify counties as treated based on whether their geographic boundaries overlap with one of seven major shale plays identified in the EIA Drilling Productivity Report. Treatment timing is assigned as follows: Barnett (2003), Bakken (2006), Marcellus (2008), Haynesville (2008), Eagle Ford (2010), Permian (2010), Niobrara (2010). Counties overlapping multiple plays are assigned the earliest treatment date. The 123 treated counties are distributed: Barnett (14), Bakken (12), Marcellus (31), Haynesville (15), Eagle Ford (18), Permian (22), Niobrara (11).

A.3 Variable Definitions

- **Log total employment:** Natural log of annual average total private-sector employment (all NAICS), from QWI.
- **Log mining employment:** Natural log of annual average employment in NAICS 21 (Mining, Quarrying, and Oil and Gas Extraction).
- **Log non-mining employment:** Natural log of (total employment − mining employment).
- **Log average monthly earnings:** Natural log of average monthly earnings per employee, from QWI.
- **Treatment:** Binary indicator equal to 1 for county c in year t if $t \geq g_c$, where g_c is the first year of significant fracking production in the play underlying county c.

B. Identification Appendix

The event-study estimates in Table 3 serve as our primary pre-trends diagnostic. Pre-treatment coefficients are small in magnitude and statistically insignificant across all outcomes, consistent with the parallel trends assumption. The staggered nature of treatment—with four distinct cohorts entering between 2003 and 2010—provides additional identification power, as any confound would need to differentially affect shale counties at play-specific times.

We conduct two additional identification checks. First, the not-yet-treated control group specification produces identical estimates to the never-treated baseline, indicating that early-treated counties are not on different trajectories than late-treated counties prior to their own treatment. Second, shifting treatment timing by ± 2 years produces estimates that are stable and, if anything, slightly attenuated—consistent with the true treatment effect building gradually from the actual onset of fracking rather than from an alternative date.

C. Robustness Appendix

The leave-one-out analysis reported in Table 4 addresses the concern that a single dominant shale play could drive our results. The Bakken is the most influential formation: dropping it reduces the ATT from 0.193 to 0.139, reflecting the Bakken's early treatment timing and the dramatic economic transformation of western North Dakota. However, the estimate remains positive and economically meaningful. At the other extreme, dropping the Permian Basin increases the ATT to 0.266, suggesting that the Permian—where fracking reinvigorated an already-established oil region—contributes a smaller incremental effect. The range of 0.139–0.266 across seven leave-one-out specifications demonstrates that no single play is necessary for the finding of persistent employment gains.

D. Standardized Effect Sizes

Table 5: Standardized Effect Sizes for Main Outcomes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
Total Employment	0.1928	0.0911	1.709	0.1128	0.0533	Moderate positive
Mining Employment	0.7789	0.1158	2.520	0.3091	0.0460	Large positive
Non-Mining Employment	0.1690	0.0819	1.716	0.0985	0.0477	Moderate positive
Avg Earnings	0.1159	0.0374	0.301	0.3850	0.1242	Large positive

Notes: This table reports standardized effect sizes (SDE) to facilitate cross-study comparison. SDE $= \hat{\beta}/\text{SD}(Y)$ for binary treatment. SD(Y) is the unconditional standard deviation of the log outcome. **Research question:** Effect of shale play exposure (hydraulic fracturing boom) on county-level employment and earnings. **Treatment:** Binary indicator for county overlying a major US shale play. **Data:** Census QWI (LEHD), 2001–2023, county-year panel. **Method:** Staggered DiD with Callaway–Sant'Anna (2021) estimator, state-clustered standard errors. **Sample:** 3,140 counties, 71,408 county-years. Classification thresholds: large negative (< -0.15), moderate negative (-0.15 to -0.05), small negative (-0.05 to -0.005), null (-0.005 to 0.005), small positive (0.005 to 0.05), moderate positive (0.05 to 0.15), large positive (> 0.15). Classification labels refer to the magnitude of the standardized point estimate, not to statistical significance. "Null" denotes a near-zero effect size ($|\text{SDE}| < 0.005$), not a failure to reject a null hypothesis.