Received: 8 July 2021 | Accepted: 22 June 2022

DOI: 10.1002/soej.12595

RESEARCH ARTICLE

Southern Economic Journal WILEY

The impact of oil and gas job opportunities during youth on human capital

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Abstract

Leaving school to work trades off schooling with on-the-job human capital acquisition. How do industry shocks impact how youth make this trade-off? Exploiting the geography of natural resources, I estimate the effect of oil and gas job prospects on college and work outcomes. Using CPS data, I find that these job opportunities decrease college-going for men but not women. I next assess the importance of this schooling loss for later outcomes using longitudinal geocoded NLSY79 data. I find permanent declines in college attainment but gains in employment and earnings at ages 25–30, driven by cohorts who reach college age during industry booms. The results suggest that informal human capital can compensate for schooling loss for the men who leave school for oil and gas work. They speak to the need for further research on non-college work as a form of human capital investment outside of the traditional college pathway.

KEYWORDS

college enrollment, gender, human capital, oil and gas production

JEL CLASSIFICATION

J21, J24, I26, Q33

1 | INTRODUCTION

We have much to learn about how transitory employment shocks affect permanent outcomes. My paper explores how oil and gas job opportunities during youth impact educational attainment and work outcomes later on. Since most occupations in the industry pay well but require only a high school diploma or equivalent, greater job availability should theoretically decrease college enrollment. Empirically, however, the impact may be negligible, since the oil and gas industry follows boom and bust cycles. During booms, newspapers report thousands of new high-paying jobs; during busts, many jobs vanish, potentially leaving thousands unemployed (Hargreaves, 2012; Hays LLC, 2013; Janneman, 2017). Given these risks, forward-looking agents may stay in school despite the availability of high-paying oil and gas jobs, making it unclear whether these jobs will affect schooling at all. Indeed, prior literature has reported mixed results, with some finding declines in college enrollment (Kumar, 2017; Mosquera, 2022; Rickman et al., 2017), some finding declines in high school progression (Cascio & Narayan, 2022), and others finding no change in schooling (Marchand & Weber, 2020; Weber, 2014).

If oil and gas jobs do decrease college enrollment, how damaging is this schooling loss for the future? There is currently limited work on later life implications. As Jacobsen (2019a) points out, most related work relies on fracking booms for identification, which hinders assessment of long-term effects since fracking booms occurred after the 2000s. A second limitation, discussed in Jacobsen (2019a) and Jacobsen et al. (2021), is that most analyses occur at the level of places, as opposed to people, making it difficult to track impacts as people move. Almost all prior papers compare aggregate measures across different labor markets, whereas individual-level analysis is necessary to determine how shocks during youth affect the evolution of education and employment over the lifecycle.[1]

My paper addresses the open questions and limitations identified above. To examine effects during youth and midlife, I use an instrumental variable strategy that exploits geographic variation in the natural resources for oil and gas production. The instrument leverages the fact that natural resources take millions of years to form, and would predate unobserved characteristics correlated with both employment and education. Cross-sectional variation stems from the fact that areas with rich resources should have greater labor demand than areas with poor resources. Time-series variation stems from the boom-bust nature of the industry, which generates large changes in labor demand over time (Amadeo, 2018; Cai et al., 2019; Marchand & Weber, 2020; McNally, 2017, 2018; Sam et al., 2018). The identifying assumption is that oil and gas resources only influence college enrollment rates through affecting oil, gas, and related job prospects. I apply this approach at the state level to establish baseline results on short-term college enrollment using the Current Population Survey. After using the baseline results to assess the validity of the identification method, I examine individual-level outcomes in adulthood using the geocoded National Longitudinal Survey of Youth (1979a). Although the two approaches cover different boom and bust periods, use different types of data, and conduct analyses at different levels of geography, they produce quantitatively similar results.

I find that in the short term, a rise in oil and gas job opportunities significantly decreases enrollment for men but not women. The results are consistent with the fact that men comprise over 90% of workers in the oil and gas industry, and would be disproportionately impacted relative to women. The effects are concentrated among part-time enrollees, who are most likely to

[1]The exception is Jacobsen et al. (2021), which focuses on the impact of energy booms on residents' general wealth.

be marginal students.[2] Growth in employment opportunities is concentrated in the oil, gas, and mining industries, all shown by prior work to be susceptible to oil and gas production (see Allcott & Keniston, 2017; Fetzer, 2014; Feyrer et al., 2017; Jacobsen, 2019b). I check that the results are unlikely to be driven by alternative explanations such as the migration of low-skilled workers into resource-rich states, marriage market concerns, and serial correlation in the error terms.

To assess the importance of the short term results, I then investigate (1) whether the enrollment decline reflects temporary pauses or permanent losses in schooling and (2) the ramifications for work when older. My second set of results focuses on effects by midlife using National Longitudinal Survey of Youth (1979b) data. Using the same identification approach, I find that exposure to oil and gas job opportunities leads to permanent schooling loss. Men are more likely to leave school to work, less likely to graduate with a bachelor's degree, and have significantly lower educational attainment by their 30s.

Leaving school early trades off education with work experience, so the effects on work outcomes are ambiguous. Regression results demonstrate that greater exposure when young predicts higher employment, higher earnings, and lower welfare receipts, but these effects do not persist beyond the early 30s. The estimates are strongest for cohorts that reach college age during industry booms. For cohorts that reach college age during busts, exposure to oil and gas opportunities does not decrease schooling, but decreases earnings at ages 30–35. These differential impacts suggest that employment conditions during youth influence earnings during midlife, even after industry shocks fade.

Thus, the first contribution of this paper is assessing the effects of leaving school to work early on outcomes decades later. In contrast to prior work on education effects (Black et al., 2005; Cascio & Narayan, 2022; Emery et al., 2012; Kovalenko, 2020; Kumar, 2017; Marchand & Weber, 2020; Mosquera, 2022; Rickman et al., 2017; Weber, 2014), I use panel data on individuals from youth until midlife to examine how schooling loss affects outcomes at ages 25–44. Oil and gas job opportunities appear to lower educational attainment but *improve* employment and earnings. This challenges the canonical trade-off story between education and work. Leaving school means individuals avoid paying schooling costs but sacrifice formal human capital. Starting work early gives individuals more time to accumulate specific human capital on the job. I find no trade-off between leaving school and starting work early, as those who are likely to leave school experience better work outcomes later on. This is perhaps because oil and gas job opportunities induced dropout for part-time college enrollees, who were marginally attached to school and who may not have gained much from finishing college.

These results inform the existing literature on long-term wealth impacts (Jacobsen et al., 2021; Mosquera, 2022). Jacobsen et al. (2021) find declines in wealth following industry busts, which were especially severe among older residents who delayed retirement. Mosquera (2022) finds no aggregate impacts on long-term wealth, as measured by home and vehicle ownership in Ecuador. My results differ from those in Jacobsen et al. (2021) and Mosquera (2022) for two reasons. First, rather than wealth effects, I focus on the earnings impacts of trading off formal schooling for on-the-job training. Earnings effects could differ markedly from wealth effects during industry busts, since an industry bust would decrease residents' property values

[2]Other papers have also found that better outside options decrease the college enrollment of marginal students. In Charles et al. (2018), housing booms decrease enrollment in 2-year and community colleges, where marginal students are more likely to enroll. Kovalenko (2020) reports that energy booms decrease enrollment in community colleges but not 4-year colleges.

and royalty payments but not necessarily their human capital. Second, rather than the entire population, I focus on marginal students exposed to employment opportunities during youth to better understand how early exposure impacts later career outcomes. Evaluating my results against those of Jacobsen et al. (2021) and Mosquera (2022) suggests that focusing on aggregate wealth impacts masks potential positive human capital impacts of oil and gas work for marginal groups.[3]

In terms of approach, my instrumental variable approach has two distinct advantages. Because I do not rely on fracking booms for identification, I can investigate the impacts of oil and gas employment with a greater number of states than the few affected by fracking activity.[4] Second, my short-term results do not rely on one particular boom period, but on the entirety of oil and gas employment over a long time horizon, 1968–2013. These two features enable me to provide a holistic picture regarding how skill investments respond to oil and gas industry changes, as opposed to the impact of fracking alone (see Cascio & Narayan, 2022; Kovalenko, 2020) or the impact of energy booms in a few select states (see Marchand & Weber, 2020; Rickman et al., 2017; Weber, 2012).

In demonstrating the gender asymmetric effects of industrial change, I also contribute to the literature on the gender gap in educational attainment. Much of the literature argues that men lag behind women academically because they face greater barriers to human capital investment (see Becker et al., 2010; Bertrand & Pan, 2013; Goldin et al., 2006), leading to concerns that men will fall behind in their careers (Rosin, 2010). My paper takes a novel approach by focusing on a key margin of the college-going decision: the trade-off between schooling and work experience. It shows that men may actually gain by leaving school early, if they compensate for it through greater work experience. The gender gap in schooling may therefore be less problematic for men's work outcomes than currently feared, if informal human capital gained on the job can compensate for schooling loss.

The paper proceeds as follows. Section 2 provides background on oil and gas employment and describes the data. Section 3 outlines the general approach. Section 4 discusses the short term regression specifications and results. In flushing out the mechanisms behind my baseline findings, Section 4 further justifies the empirical approach for the specifications and results presented in Section 5, which explores effects by midlife. Section 6 discusses implications for policy and future research.

2 | BACKGROUND AND DATA

2.1 | Background

The majority of oil and gas jobs require only a high school diploma (Chao & Utgoff, 2005; Cornfield, 2013; Hargreaves, 2012; Janneman, 2017; Nussbaum, 2018). To illustrate, Table 1 displays the top 10 oil and gas occupations by labor share, which account for 62.35% of all jobs in the industry. For each occupation, the table lists education requirements, proportion of college graduates, and proportion female. Common occupations include truck driver, construction

[3]The caveat is that for some cohorts, mid-career earnings declined as the industry busted, which is consistent with Jacobsen et al. (2021)'s finding of negative income effects during industry busts.

[4]The impact of fracking may not represent the impact of oil and gas employment as a whole. Fracking only accounts for 11% of crude oil and natural gas extracted in the United States since 1900, and has only occurred in 18 of the contiguous 48 states (see Appendix A for details). It has an unconventional extraction process, and may employ particular types of workers that differ from those who work in conventional oil and gas production.

TABLE 1 Top 10 occupations in oil, gas, & related industries by labor share

1990 occupation code	Labor share	% Female	% College	Entry-level education
Truck, delivery, and tractor drivers	22.61	4.64	30.12	HS Diploma
Carpenters	7.84	1.13	34.05	HS Diploma
Managers and administrators, n.e.c.	7.57	10.22	59.63	Bachelor's degree
Construction laborers	7.24	3.35	28.80	HS Diploma
Supervisors of construction work	3.22	2.09	44.55	HS Diploma
Electrical engineer	3.18	7.34	91.94	Bachelor's degree
Electricians	3.03	1.43	45.41	HS Diploma
Painters, construction and maintenance	2.99	5.25	35.02	No formal education
Plumbers, pipe fitters, and steamfitters	2.52	0.85	35.16	HS Diploma
Masons, tilers, and carpet installers	2.15	1.10	26.60	No formal education

Note: Top 10 occupations in oil, gas, and related industries by labor share. Among the listed occupations, 82.76% require a high school diploma or less. Data on education requirement from Bureau of Labor Statistics and O*NET. All other data from Current Population Survey, 1962–2012.

laborer, or pipe fitter. Among listed occupations, 82.76% require a high school diploma or less, yet pay highly since they demand high physical skill and the willingness to work in hazardous conditions (Chao & Utgoff, 2005).[5] Growth in oil and gas job prospects should therefore raise the expected earnings of high school graduates. An absolute increase would raise the opportunity cost of attending college, while an increase relative to college earnings would decrease the returns to a college degree. I expect both channels to operate in decreasing college enrollment.[6]

I also anticipate job opportunities to primarily affect men, since the industry is over 90% male. Table 1 column (3) shows that the female share falls below 10% for all occupations except manager, which typically requires a college degree. The gender disparity is consistent with prior research on men's greater propensity to work in riskier jobs (Bureau of Labor Statistics, 2018; DeVore, 2018). Figure 1 plots the average fraction employed in oil and gas work by gender and resource level. The male labor share hovers at 11%–13% in high (median or above) resource states and 9%–12% in low (below median) resource states, while the female labor share falls below 2% in all states. Substantial gaps in labor share between high- and low-resource states persist for men but are much smaller for women. The descriptive evidence here suggests that oil and gas resource wealth would have a greater effect on non-college job prospects for men than women.[7] I confirm this in the first stage results in Section 4.2.

[5]Some occupations require further schooling or training, but these requirements are typically less intensive than associate's or bachelor's degree programs.
[6]To illustrate why, Appendix Figure S1 plots "expected earnings" against oil and gas production. I construct a rough measure of expected earnings by following Charles et al. (2018) and interacting the labor share in oil, gas, and related work with median earnings in a state-year. As production increases, high school graduates' expected earnings rise, both absolutely and relative to college graduates.
[7]Female college-going decisions may nevertheless be affected, if oil and gas production affect occupations that employ large fractions of women or if their marriage market prospects change due to changing economic conditions (Maurer & Potlogea, 2021).

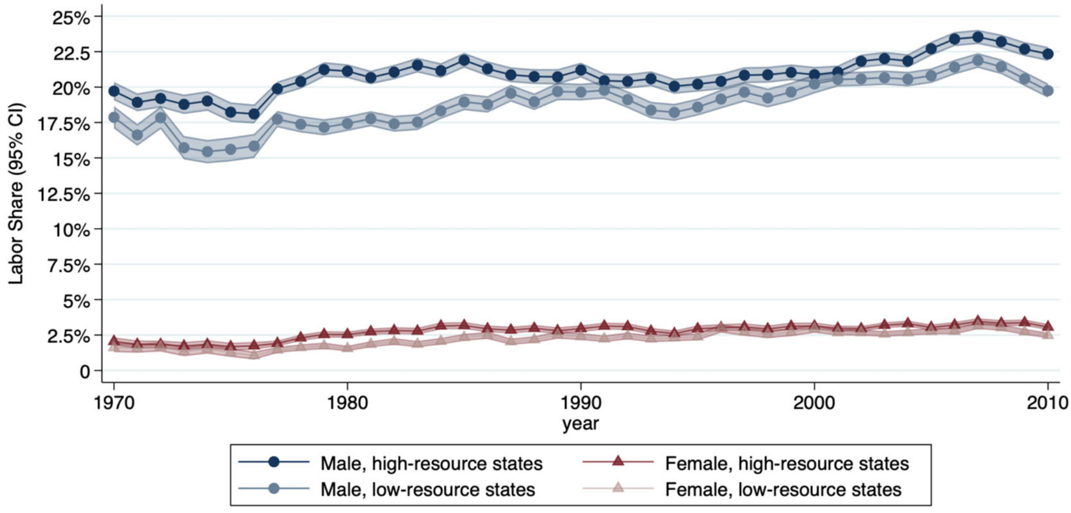

FIGURE 1 Labor share in oil, gas, and related industries by high- and low-resource states. Proportion employed in oil, gas, and related industries as a share of total employment. Dark markers represent states with median or above oil and gas resources. Light markers represent states with below-median resources. Gray bands represent 95% confidence interval. Data from CPS and Allcott and Keniston (2017). [Color figure can be viewed at wileyonlinelibrary.com]

2.2 | Data

This paper uses a variety of data sources. I construct my instrument using natural resource data from Allcott and Keniston (2017) and employment data from the Annual Social and Economic Supplements of the Current Population Survey (CPS-ASEC). Baseline results on college enrollment are established using the CPS. To explore later life ramifications, I turn to geocoded data from the National Longitudinal Survey of Youth (NLSY79). In robustness checks, I use data from Autor and Dorn (2013) and Autor et al. (2013) to account for occupational structure, automation, and competition from trade.

2.2.1 | Natural resource data

My instrumental variable approach follows Allcott and Keniston (2017). Allcott and Keniston (2017) compile a data set of resources for the contiguous United States in 1960–2012 using information from state geological surveys and DrillingInfo, a market research company. Key to the identification strategy is the density of natural resources for oil and gas production:

$$r_a = \frac{\sum_{t=1960}^{T} Production_{a,t} + ProvenReserves_{a,T} + UndiscoveredReserves_{a,T}}{Area_a}.$$

Natural resource density in an area a is measured as the per-area sum of (1) oil and gas that has been extracted from area a from 1960 to year T, (2) the total amount of unextracted reserves known to exist within area a in year T, and (3) the total amount of undiscovered reserves believed to exist within area a in year T based on estimates from the United States Geological Survey. My preferred measure of natural resources only includes information up to $T = 1995$, which intentionally excludes new information about natural resources that may be influenced by oil and gas exploration, labor market conditions, and educational decisions.[8] Robustness checks in Appendix Table S5 panels A and B confirm that results do not change when using information up to $T = 2013$, suggesting that information is unlikely to be endogenous to extraction activity (a concern raised by Cassidy, 2019).

Appendix Figure S2 shows maps of resource density by state (panel A) and county (panel B). Due to data characteristics described below, I use state-level variation for the baseline analysis using CPS data and county-level variation for the later life analysis using NLSY79 data. To ease interpretability, Allcott and Keniston (2017) transformed resource wealth into the USD equivalent based on average prices of oil and natural gas in 1960–2011. Resource densities range from \$0 per square mile to \$18 million per square mile at the state level and \$190.31 million per square mile at the county level. Although aggregating resource density to the state and county levels generates large differences in resource variation, the regressions produce similar results across the two approaches.

2.2.2 | Current Population Survey

To establish baseline results, I use the Annual Social and Economic Supplements of the Current Population Survey (CPS-ASEC), which surveys 150,000–200,000 households each year from 1962 to present day (Flood et al., 2018). The main analysis focuses on 1986–2012, since 1986 is the first year in which respondents were asked about their current school enrollment status and 2012 is the last year in which the resource data are available. The dependent variable is current enrollment status among 18–24 year olds. The main independent variables are the 22–65 year old population share working in the oil and gas industry *or* in the oil, gas, and "related" industries, where "related" industries are construction and mining, based on prior work which shows that oil and gas production substantially affected employment in construction and mining (see Fetzer, 2014; Feyrer et al., 2017).[9] Appendix Table S1 lists the 1990 industry and occupation codes used to classify workers into the "oil & gas" industry or the "oil, gas, & related" industries.

There are four advantages to the CPS-ASEC data. First, it reasonably trades off frequency with sample size. My analysis requires annual data with large cross-sections in order to explore industry-specific trends on 18–24 year olds, a small slice of the overall population. The surveys allow for analysis of oil and gas jobs as early as 1986, facilitating analysis across a long time horizon and capturing variation in job opportunities other than those created by fracking alone. Each cross-section is large enough to permit examination of state-level changes by industry, but the sample size and sampling procedure cannot accommodate statistical inference for smaller units of geography, such as the county or commuting zone (U.S. Census Bureau, 2006). My main regression specifications therefore occur at the state-year level.

[8]Using information up to 1995 intentionally excludes new information about oil and gas reserves that could have been discovered after the advent of fracking in 2006. If states that engaged in fracking systematically differed from states that did not, and fracking led to the discovery of new information about natural resources, constructing r_a to include information on resources after 2006 would compromise instrument exogeneity.

[9]As discussed in Section 3, I use the 22–65 year old population share as the independent variable to avoid potential simultaneity problems associated with 18–24 year olds leaving college.

Second, the CPS-ASEC asks respondents about *current* college enrollment status, which updates based on contemporaneous economic conditions. Using other education measures, such as highest educational attainment or years of education, would include individuals who have already left school, making it more difficult to detect small changes in enrollment rates. The highest educational attainment variable also cannot distinguish students who choose to leave school from students who fail to progress and must repeat coursework.

Third, the current college enrollment status variable distinguishes between full- or part-time student status, enabling me to explore heterogeneity across types and identify the marginal student. Fourth, the CPS-ASEC possesses rich data on migration. Oil and gas work attracts migrant workers, many of whom do not hold college degrees. In robustness checks, I show that my results do not change when the analysis sample excludes workers who did not migrate in the past year. This suggests that my main results are driven by the treatment effect of oil and gas opportunities on residents, as opposed to composition effects of workers due to migration.

2.2.3 | National Longitudinal Survey of Youth (1979)

The National Longitudinal Survey of Youth 1979 (NLSY79) repeatedly interviews 12,686 individuals born between 1957 and 1965. It complements the CPS data in three ways. First, the NLSY79 tracks respondents from age 14–22 in 1979 until present day, allowing me to investigate whether the schooling loss in the short-term translates into persistent effects on human capital and work by midlife. Second, the geocoded data track migration patterns. In Appendix Table S6, I show that greater predicted exposure to oil and gas job opportunities has no significant effect on the likelihood of moving across counties, making it unlikely for migration to drive the results for the NLSY79 sample. This is consistent with my short term CPS analysis, where estimates are unchanged when the sample is modified to account for migration. Third, it permits analysis at the county-by-age level, which leverages finer variation than possible with the CPS data alone.

One drawback of the NLSY79 is its small sample size, which makes it difficult to pin down the industries that youth would enter once exposed to job opportunities. I therefore present reduced form regression results. The small sample size, combined with the fact that sample attrition is more severe in later years (see Appendix A), presents a trade-off between examining outcomes later, to measure persistent effects, and earlier, when there is sufficient power to detect significant changes. I examine educational attainment in 2000, when individuals are 35–44 years old. Since work outcomes are sampled every survey year and change over the lifecycle, I explore employment and earnings for each year between the ages of 25 and 35.

If transitory industry shocks influence permanent outcomes, the NLSY79 sample presents the best chance of finding effects out of all data sources I am aware of. NLSY79 respondents reached ages 16–18 in 1972–1981, precisely when oil and gas employment saw its greatest growth in the past 50 years. The largest decline in oil and gas employment happened to occur just as respondents would have entered the labor force. Appendix Figure S3 shows that oil and gas employment grew sharply in 1976–1982 from about 140,000 to almost 260,000 workers, precisely during the youth of the NLSY79 sample. It then plummeted after 1982 and bottomed out in 2000–2005 to about 120,000 workers. The effects of subsequent booms and busts are likely weaker, since they were less volatile. Since the CPS sample reached ages 16–18 during 1986–2012, we would expect more muted long-term employment outcomes for the CPS sample than the NLSY79 sample.

The fluctuations in oil and gas employment suggest that different cohorts in the NLSY79 may experience different effects, based on employment conditions during youth. I split the NLSY79 sample into three cohorts and define these cohorts based on when they reach ages 16–18, when most youth start making college enrollment decisions. The *1973–75 cohort* reached ages 16–18 in 1973–75, when oil and gas employment began to grow from its trough of 140,000 (see Appendix Figure S3). The *1976–78 cohort* reached ages 16–18 in 1976–1978, when oil and gas employment grew at accelerating pace from 150,000 to 200,000 workers. Finally, the *1979–81 cohort* reached ages 16–18 in 1979–1981, when employment grew at its highest pace before topping out at 260,000 workers in 1981.

2.3 | Summary statistics

Table 2 displays summary statistics for the resource data (panel A), the CPS data (panel B), and the NLSY79 data (panel C). The first column displays summary statistics for all observations, while the last two columns report summary statistics by regions where the resource level is low (below median) or high (at or above median). Panel A shows that while the average resource density is 1.83 millions of dollars per square mile for all 3050 counties in the data set, there is a great deal of heterogeneity across counties. The resource density for low-resource counties is $2424 per square mile on average and ranges from $0–$13,482 per square mile. The resource density for high-resource counties is $3.66 million per square mile on average and ranges from $13,606 to $190.31 million per square mile.

Panel B shows the CPS data, used to establish baseline results. Full-time college enrollment hovers at 30.1%–32.0% for men and 32.5%–35.1% for women, while part-time college enrollment hovers at 6.0%–7.2% for men and 7.9%–8.6% for women. Oil and gas work, as a share of the 22–65 year old population, is around 1.7%–2.7% for men but one sixth of that for women. When related industries, namely mining and construction, are added, the share increases to 19.2%–21.5% for men and 2.3%–2.9% for women. Panel C summarizes the NLSY79 data, used to explore later life outcomes. Educational outcomes appear comparable between high- and low-resource areas: men and women both have around 13 years of schooling on average, 10.1%–11.9% of men and 6.7%–8.4% of women reported ever leaving school to work, and the proportion with bachelor's degrees are 18.3%–19.8% for men and 22.5%–22.7% for women (comparable to the CPS sample).

3 | METHODOLOGY

Ordinary least squares regressions may not necessarily isolate the causal effect of oil and gas employment opportunities on college enrollment. One major concern is reverse causation, since the supply of non-college workers affects equilibrium employment in oil, gas, and related work. Time-varying omitted variables could also confound regression estimates. For example, declining labor demand in the technology industry could decrease the college enrollment rate and raise the supply of workers for oil and gas occupations, creating a negative correlation between college-going and oil and gas labor share.

To overcome these challenges, my two-stage least squares approach exploits variation from natural resources to predict oil and gas job opportunities. Following the methodology of Allcott and Keniston (2017), I construct my preferred instrument by interacting the measure of natural

TABLE 2 Summary statistics

	All	Resource level Low	High
Panel A: Resource data			
Oil & gas reserves (1960–1995)	1.829	0.00242	3.655
	(7.815)	(0.00405)	(10.75)
Observations	3050	1525	1525
Panel B: CPS data			
Allcott-Keniston instrument (1960–1995)	0.0425	0.000708	0.0732
	(0.0808)	(0.000937)	(0.0953)
Male full-time college enrollment	0.309	0.320	0.301
	(0.462)	(0.467)	(0.459)
Male part-time college enrollment	0.0671	0.0603	0.0720
	(0.250)	(0.238)	(0.258)
Female full-time college enrollment	0.336	0.351	0.325
	(0.473)	(0.477)	(0.469)
Female part-time college enrollment	0.0830	0.0791	0.0856
	(0.276)	(0.270)	(0.280)
Oil & gas share	0.0130	0.00974	0.0155
	(0.113)	(0.0982)	(0.123)
Oil & gas share (men)	0.0230	0.0172	0.0272
	(0.150)	(0.130)	(0.163)
Oil & gas share (women)	0.00372	0.00278	0.00440
	(0.0608)	(0.0527)	(0.0662)
Oil, gas, & related share	0.124	0.114	0.131
	(0.329)	(0.318)	(0.338)
Oil, gas, & related share (men)	0.205	0.192	0.215
	(0.404)	(0.394)	(0.411)
Oil, gas, & related share (women)	0.0263	0.0234	0.0286
	(0.160)	(0.151)	(0.167)
Observations	6,176,048	2,614,120	3,561,928
Panel C: NLSY79 data			
Allcott-Keniston instrument (1960–1995)	0.0439	0.0000582	0.0878
	(0.194)	(0.000101)	(0.267)
Ever left school to work, men	0.109	0.101	0.119
	(0.311)	(0.301)	(0.324)
Ever left school to work, women	0.0743	0.0667	0.0837
	(0.262)	(0.249)	(0.277)
Ever attended college, men	0.507	0.501	0.515
	(0.500)	(0.500)	(0.500)

(Continues)

TABLE 2 (Continued)

	All	Resource level Low	High
Ever attended college, women	0.603	0.590	0.612
	(0.489)	(0.492)	(0.487)
Bachelor's degree, men	0.184	0.198	0.183
	(0.387)	(0.399)	(0.387)
Bachelor's degree, women	0.220	0.227	0.225
	(0.415)	(0.419)	(0.418)
Some college no bachelor's, men	0.637	0.605	0.644
	(0.481)	(0.489)	(0.479)
Some college no bachelor's, women	0.634	0.615	0.632
	(0.482)	(0.487)	(0.482)
Years of schooling, men	12.92	12.97	12.92
	(2.529)	(2.539)	(2.589)
Years of schooling, women	13.27	13.26	13.33
	(2.521)	(2.516)	(2.568)
Observations	12,686	5770	6483

Note: High-resource areas are those with median or higher resource densities. Low-resource areas have below median resource densities. In the resource data and NLSY79 data, observations are at the county level. In the CPS data, observations are at the state level. The resource data measure oil and gas density in millions of dollars per square mile (in 2010 dollars). In the CPS data, oil and gas work is calculated as a share of the 22–65 year old population. The college enrollment rate is the share of 18–24 year olds currently enrolled in college. In the NLSY79 data, education measures are collected in 2000, when individuals are 35–44 years old. Standard deviations in parentheses.

reserves in an area a, r_a, with time-series variation in national oil and gas employment share, E_t. The instrument takes the form r_aE_t. It predicts actual oil, gas, and related employment through scaling the resource density with the national oil and gas labor share. Within the same year (holding E_t constant), areas with richer resources are predicted to exhibit greater labor demand than areas with poorer resources. Within a geographic area (holding r_a constant), the labor share is predicted to be high when national oil and gas employment is high.

It is important to clarify the story that the two-stage specification is intended to capture. I argue that a student might forego attending college after observing others taking oil, gas, and related jobs around him. Therefore, the first stage dependent variable must measure the job take-up of *others*, not the student himself. The second stage regression is designed to then measure how the change in perceived job opportunities influences the student's own enrollment. The two-stage regression is *not* intended to measure the student's own employment decision on his own enrollment, since the decision to leave school and the decision to work are presumably simultaneous. If students left school for other reasons, those in areas with greater oil and gas opportunities would be more likely to take up oil and gas work, confounding the instrumental variable estimates. The independent variable is therefore the industry share of individuals past college age (22–65 year olds) to ensure that college enrollment declines are driven by job growth among others, rather than the students themselves.

Second, I use the population share rather than the labor share. Oil, gas, and related job opportunities may shift students from school to work in other industries, which would change both the size and composition of the labor force. A labor share variable would change in non-monotonic ways due to growth in both the numerator (oil and gas workers) and denominator (all workers), whereas the population share variable is cleaner since its denominator would remain fixed. The results are robust when 18–22 year olds are included in the worker share and when labor share is used in place of the population share, indicating that simultaneity concerns and changes in worker composition are not driving the primary effects.[10]

The identification strategy is a modified Bartik-style instrument, which is numerically equivalent to using natural resources r_a as the instrument and national employment E_t as the weights to a two-step generalized method of moments procedure (Goldsmith-Pinkham et al., 2020). The exclusion restriction is that natural resources for oil and gas production only influence college enrollment through influencing labor demand in non-college jobs, either in absolute terms or relative to college jobs. One advantage of the instrument is that reverse causation is impossible: current educational and labor market characteristics cannot affect oil and gas deposits formed millions of years ago. Furthermore, omitted variable bias is unlikely. The instrumental variable specification nets out confounding variation generated by labor market changes, which do not depend on the level of oil and gas resources beneath the earth, such as technology or service sector growth.

Indeed, the exclusion restriction would only be violated if omitted variables correlated with both oil and gas resources and education (1) vary with national oil and gas labor share and (2) generate differential impacts by gender. It is difficult to think of alternative explanations that would fulfill both criteria.[11] Nevertheless, I assess instrument validity by following the recommendation in Goldsmith-Pinkham et al. (2020) to correlate resource density with potential demographic confounders. The estimates, reported in Appendix Table S2, show that workers' observed characteristics do not significantly differ by resource density in the CPS data (column 1) or the NLSY79 data (columns 2 and 3). Further justifications for instrument validity are discussed in the short-term results in Section 4.2 and the robustness checks in Appendix B.

4 | COLLEGE ENROLLMENT DURING YOUTH

4.1 | Specification

I use CPS data to establish baseline results on college enrollment. All regressions occur at the state-year level unless otherwise stated. Standard errors are clustered at the state level. The first-stage regression is specified as follows:

$$x_{st}^{g} = \alpha_0 + \alpha_1 r_s E_t + \alpha_2 W_{st} + \theta_s + \psi_{dt} + u_{st}^{g}, \tag{1}$$

where, the instrument $r_s E_t$ interacts natural oil and gas resources in a state s with the national oil and gas share in year t. The error term differs by gender g, since men and women sort into

[10]Results are available upon request.

[11]Prior work shows that oil and gas production directly impacts non-wage income, local government finances, and school resources (Bartik et al., 2019; Feyrer et al., 2017; Jacobsen, 2019b; Marchand & Weber, 2020; Weber, 2012, 2014), but it is unlikely for these alternative channels to generate differential impacts by gender.

oil and gas work at different rates. The control matrix W_{st} includes the proportion female, proportion black, and proportion by 10-year age bin. Following Allcott and Keniston (2017), I also control for resource density, state fixed effects, and region-by-year fixed effects. Region-by-year fixed effects account for potential differences in how time shocks impact employment across four regions (northeast, south, west, and midwest).[12] On the other hand, state fixed effects absorb time-invariant unobserved differences across states that influence employment. By controlling for state and region-by-year dummies, Equation (1) captures changes in employment across states over time net of time-invariant state-level features and year-level shocks that could differ by region.

The variable x_{st}^{g} is oil and gas workers of gender g as a share of the 22–65 year old population in state s and year t. By using oil and gas share as the dependent variable, the first stage regression assumes that oil and gas labor demand raises the expected earnings of high school graduates through creating new job opportunities in a high-paying industry, as opposed to raising the wages of existing jobs. This would occur if supply is elastic, and workers fill new vacancies without requiring much wage growth. Most occupations in oil, gas, and related industries do not require special skills or impose other barriers to entry (e.g., roustabouts and truck drivers), suggesting that employers could easily fill vacancies as long as pay was already high. Consistent with this notion, the instrument exhibits a strong relationship with employment but no significant relationship with wages (as shown in Tables 4 and 6 in Section 4.2).

The second stage regression takes the form

$$y_{st}^{g} = \beta_0 + \beta_1 \widehat{x}_{st}^{g} + \beta_2 W_{st} + \theta_s + \psi_{dt} + \varepsilon_{st}^{g}, \tag{2}$$

where, $\widehat{x}_{st}^{g}$ is the share of gender g in oil and gas employment predicted from variation in $r_s E_t$ conditional on the controls in the first stage. The dependent variable y_{st}^{g} is the share of 18–24 year olds of gender g currently enrolled in college in state s and year t. The independent variable $\widehat{x}_{st}^{g}$ is the predicted variation in oil and gas share based on geological resources for oil and gas extraction. The control matrix W_{st} is the same as in Equation (1).

4.2 | Results

The reduced form and second stage coefficients are interpreted based on a \$1 million per square mile increase in resource density at the average oil and gas share of 1.3% (see Table 2). With the exception of the OLS coefficients, I convert regression estimates by multiplying by 0.013 when reporting magnitudes in text. To provide a concrete sense of this variation, a \$1 million dollar per square mile rise in resource density is equivalent to moving from Minnesota (no resources) to Illinois (\$0.94 million per square mile of resources). Oil and gas shares are reported in standard deviations unless otherwise stated.

Table 3 compares the OLS and reduced form results. The reduced form estimates in panel C differ substantially from the OLS results in panels A and B. They reduced form coefficients show that a rise in resource density of \$1 million per square mile corresponds to a 0.79 percentage point decline in part-time male enrollment ($p < .01$) and a 0.42 percentage point decline in part-time female enrollment ($p < .05$). The point estimates for male and female part-time enrollment significantly differ at the 10% level, which is consistent with the hypothesis that

[12]Panels E and F of Appendix Table S4 demonstrate that results do not change when year fixed effects are used.

TABLE 3 OLS & reduced form regressions

	Male enrollment		Female enrollment	
	Full-time (1)	**Part-time (2)**	**Full-time (3)**	**Part-time (4)**
Panel A: OLS regression of college enrollment on oil & gas share				
Labor share	−0.090*	−0.018	−0.041	0.008
	(0.053)	(0.022)	(0.051)	(0.025)
Observations	1344	1344	1344	1344
Panel B: OLS regression of college enrollment on oil, gas, & related share				
Labor share	−0.212***	−0.045*	−0.037	0.043*
	(0.061)	(0.023)	(0.060)	(0.023)
Observations	1344	1344	1344	1344
Panel C: Reduced form regression of college enrollment on instrument				
Instrument	−0.341	−0.611***	−0.236	−0.321**
	(0.281)	(0.184)	(0.219)	(0.128)
Observations	1344	1344	1344	1344
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes

Note: Panel A shows the OLS regression results of college enrollment on oil & gas share. Panel B adds related industries. Panel C displays the reduced form regression results of college enrollment on the instrument. Regressions control for proportion by gender, race, and 10-year age bin, as well as resource density, state dummies, and region-by-year dummies. Dummies for missing variables suppressed. Standard errors clustered at state level. *$p < .10$, **$p < .05$, ***$p < .01$.

men's job opportunities were more affected than women's. I find no significant effect on full-time enrollment for men or women.

In contrast, the OLS results in panel A display insignificant correlations between college enrollment rates and oil and gas share. Panel B includes "related" industries and occupations established by prior work to be affected by oil and gas production, namely mining and construction (see Allcott & Keniston, 2017; Fetzer, 2014; Feyrer et al., 2017; Jacobsen, 2019b). The inclusion of "related" jobs yields significant relationships between employment and male full-time, male part-time, and female part-time enrollment. The estimates indicate that a one standard deviation rise in oil, gas, and related labor share, corresponding to about 33 percentage points, is associated with a 21.2 percentage point decline in full-time male enrollment ($p < .01$), a 4.5 percentage point decline in part-time male enrollment ($p < .10$), and a 4.3 percentage point rise in part-time female enrollment ($p < .10$).

The reduced form estimates highlight the value of the instrumental variable strategy in this context, where confounding variation between labor market conditions and educational outcomes compromise causal inference using the OLS results. The significant negative OLS coefficient for male full-time enrollment in panel B becomes insignificant in the reduced form specification, suggesting that the OLS estimate could be driven by the simultaneity or omitted variable problems discussed in Section 3. For example, oil and gas companies may choose to drill in states with greater shares of non-college men, where it is easy to find people willing to

TABLE 4 First stage regression of employment on instruments (baseline results)

	Labor share		
	All **(1)**	**Men** **(2)**	**Women** **(3)**
Panel A: oil & gas share			
Instrument	1.323**	2.057*	0.561*
	(0.601)	(1.083)	(0.131)
F-statistic	7.830	10.811	0.519
Observations	1878	1878	1878
Panel B: oil, gas, & related share			
Instrument	1.544***	2.513***	0.547***
	(0.405)	(0.715)	(0.116)
F-statistic	13.824	12.097	5.726
Observations	1878	1878	1878
Demographic controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes

Note: First stage regression of labor share on instruments. Panel A uses oil & gas labor share as the dependent variable, while panel B includes related industries. Column (1) examines the share for all workers, column (2) examines the share for men only, and column (3) examines the share for women only. Regressions control for proportion by gender, race, and 10-year age bin, as well as all resource density, state dummies, and region-by-year dummies. Dummies for missing variables suppressed. Standard errors clustered at state level. Kleibergen-Paap first stage *F*-statistic reported. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

work as manual laborers. In equilibrium, this would lead to the negative correlation on male enrollment in panel B.

To further explore how the instrument impacts enrollment through job prospects, Table 4 reports the first stage regressions of employment on the instrument. Panel A focuses on employment in only the oil and gas industries, while panel B includes "related" industries. Across both panels, the large positive coefficients indicate that the instrument is effective in predicting employment in the relevant industries. Column (1) shows that a $1 million per square mile rise in resource density at the national average oil and gas share of 1.3% corresponds to a 0.017–0.020 standard deviation rise in labor share. The next two columns break down the first stage effect by gender, using the proportion of men in the industry among 22–65 year old men (column 2) or the proportion of women in the industry among 22–65 year old women (column 3). They reveal that the estimates are three to five times larger for men than for women, which is unsurprising given that the oil and gas industry is over 90% male. Comparing column (2) with (3), the estimates are 0.027–0.033 standard deviations for men and 0.007 for women. The greater first stage point estimate for men is consistent with the patterns shown in Figure 1, which indicate that oil and gas employment has a stronger effect on the job prospects of men than women.

In all specifications, there is sufficient power to predict oil and gas employment share for men but not women, as the first stage Kleibergen-Paap *F* statistics exceed 10 for male share but not for female share (Kleibergen & Paap, 2006; Sanderson & Windmeijer, 2016; Staiger &

Stock, 1997). The second stage standard errors on female enrollment will be imprecise, since fewer than 1% of women work in the industry. The low covariance between the instrument and female labor share in the oil and gas industry inflate the standard errors in the two stage least squares specification, leading to imprecise estimates. Since the instrument is weak for women, it is difficult to compare effects across gender in the two stage least squares regressions. I therefore use the second stage results for women as a placebo test for men's outcomes based on the premise that very few women would take up oil and gas jobs. To directly compare across genders, I use the reduced form regressions in Table 3.

I then turn to the main two stage least squares results presented in Table 5. Across all specifications, the coefficient estimates show that rising oil and gas employment leads to a significant decline in male part-time enrollment ($p < .01$). To make sense of the magnitudes, it is useful to compare these estimates to the reduced form estimates in Table 3 panel C. Based on the first stage regression estimates in Table 4, a rise in resource density of $1 million per square mile at average oil and gas share corresponds to a 0.027–0.033 standard deviation increase in oil and gas work for men. Multiplying these values by the coefficients in Table 5 panels A and B indicates that a $1 million per square mile rise in resource density would decrease part-time male enrollment by 0.66–0.94 percentage points, a tight interval which includes the 0.79 percentage point reduced form estimate.

Next, I explore potential channels behind these results. The paper argues that oil and gas job opportunities induce men to leave school through increasing their expected earnings without a college degree. The mechanism is that new job openings in oil, gas, and related industries

TABLE 5 Second stage regression results

	Male enrollment		**Female enrollment**	
	Full-time (1)	**Part-time (2)**	**Full-time (3)**	**Part-time (4)**
Panel A: Oil & gas share				
Oil & gas share	−0.137	−0.245***	−1.690	−2.301
	(0.087)	(0.085)	(2.443)	(3.385)
First stage F-statistic	10.811		0.519	
Observations	1344	1344	1344	1344
Panel B: Oil, gas, & related share				
Oil, gas, & related share	−0.159	−0.285***	−0.821	−1.118
	(0.105)	(0.103)	(0.777)	(0.572)
First stage F-statistic	12.097		5.726	
Observations	1344	1344	1344	1344
Demographic controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes	Yes

Note: Two stage least squares results. Panel A uses oil & gas share as the instrumented variable, while panel B uses oil, gas, & related share as the instrumented variable. All regressions control for proportion by gender, race, and 10-year age bin, as well as resource density, state dummies, and region by year dummies. Dummies for missing variables suppressed. Standard errors clustered at state level. Kleibergen-Paap first stage F-statistic reported. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

TABLE 6 Regression of earnings and hours worked on instruments (individual-level regressions)

	All (1)	Men (2)	Women (3)
Panel A: Log wages in oil, gas, & related industries			
Instrument	0.434	0.608	−1.298
	(0.415)	(0.495)	(1.180)
Observations	330,693	296,737	33,956
Panel B: Any hours worked in oil, gas, & related industries			
Instrument	0.035**	0.060**	0.011***
	(0.016)	(0.028)	(0.004)
Observations	7,363,769	3,552,713	3,811,056
Panel C: Hours worked per week in oil, gas, & related industries			
Instrument	−17.749***	−18.821***	3.309
	(6.306)	(6.466)	(7.796)
Observations	404,276	365,685	38,591
Demographic controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Region by year FE	Yes	Yes	Yes

Note: Individual-level regressions of work outcomes on the instrument. Regressions control for gender, race, and age, as well as resource density, state dummies, and region by year dummies. Dummies for missing variables suppressed. Standard errors clustered at state level. Kleibergen-Paap first stage *F*-statistic reported. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

increase men's perceived likelihood of finding a high-paying job with only a high school diploma. However, expected earnings could also rise through growth in the wages of existing jobs.

To test whether this alternative channel contributes to the rise in expected earnings, I use individual-level regressions of log wages and work hours in oil, gas, and related industries.[13] Based on the results, shown in Table 6, I conclude that the bulk of the rise in expected earnings comes from the creation of new jobs, as opposed to growth in the wages of existing jobs. Panel A shows no significant effects on the wages of existing jobs. Panel B, on the other hand, shows a rise in the population share who work any hours in oil, gas, and related industries, indicating that the instrument predicts the creation of new jobs. Panel C demonstrates a significant decline in average hours worked each week in these industries. The results are consistent with the entry of new workers into these industries, where the marginal new worker clocks in fewer hours than the average existing worker. Taken together, panels A–C of Table 6 suggests that oil and gas booms raise men's expected earnings by creating new vacancies in high-paying jobs, as opposed to raising the wages of existing jobs.

[13]When examining whether the instrument influences the earnings of existing jobs, individual level regressions are preferable over regressions conducted at the state-year level, which may fall prey to the ecological fallacy (Faraway, 2002). In addition, individual level regressions facilitate examination of the effect of the instrument on the full distribution of earnings, rather than selected moments aggregated to the state-year level.

Why does Table 6 show no growth in wages, even though prior work reported growth in local wages (Allcott & Keniston, 2017; Bartik et al., 2019; Cai et al., 2019; Cascio & Narayan, 2022; Feyrer et al., 2017; Jacobsen, 2019b; Keane & Prasad, 1996; Kumar, 2017; Marchand & Weber, 2020; Weber, 2012, 2014)? Prior studies focused on average wage growth across many industries at the labor market level. This approach cannot determine whether average wages rose because existing jobs increased pay or because of new job creation in high-paying positions. In contrast, I focus on wages at the individual level, which enables me to show that wages among existing oil, gas, and related workers did not rise. My findings suggest that the rise in expected earnings documented by prior work occurred through more people taking new jobs in the industry.

I then explore which industries experienced the largest impacts on employment. Figure 2 demonstrates that the estimated effect is highest for oil and gas work and mining work, which corroborates the findings of related research (see Allcott & Keniston, 2017; Fetzer, 2014; Feyrer et al., 2017; Jacobsen, 2019b; Michaels, 2011). Unlike Table 4, coefficients are reported in percentage points rather than standard deviations to facilitate comparison of the effects across industries. A \$1 million increase in resource density at the average employment share of 1.3% leads to a 1.30 and 1.35 percentage point increase in the oil and gas industry and mining industry labor shares, respectively. The estimated effect is six times as large for men as for women, with estimates of 2.24 and 2.15 percentage points for men and 0.33 and 0.26 percentage points for women. I include construction under oil, gas, and related work, since prior literature finds significant impacts on construction (see Allcott & Keniston, 2017; Fetzer, 2014; Feyrer et al., 2017; Jacobsen, 2019b). However, I find that for all industries other than the oil and gas industry and the mining industry, estimated effects are small and insignificant. Overall, Figure 2 rounds out the story behind the 2SLS results by showing that the instrument raises employment in precisely the industries most sensitive to oil and gas production.

4.2.1 | Robustness of short term results

The results presented in Tables 3–6 and Figure 2 rule out alternative explanations like changes in family income, school resources, or aggregate economic activity, since they cannot generate gender differences in college-going. Below, I summarize a few important robustness checks regarding explanations that could generate gender differences in college-going. All robustness checks are discussed in greater detail in Appendix B.

I begin by accounting for alternative explanations behind the gender difference in enrollment. By using natural resource density as the instrument, I attempt to isolate the variation in labor demand traceable back to a state's capacity to offer oil and gas opportunities, netting out omitted variables correlated with both energy production and college returns. Column (2) of Appendix Table S3 checks this assumption by controlling for actual oil and gas production. The results do not appreciably change compared to the main two stage least squares estimates, reproduced in column (1) to facilitate comparison. Second, oil and gas opportunities could raise the marriage market prospects of male high school graduates, in which case we would observe differences in college-going based on the local sex ratio. Column (3) reproduces the main results while controlling for the sex ratio of youth close to the age of first marriage. Finally, gender differences in enrollment could arise from gender-specific impacts of occupational structure, automation, or trade, which could also influence employment in oil, gas, and related industries

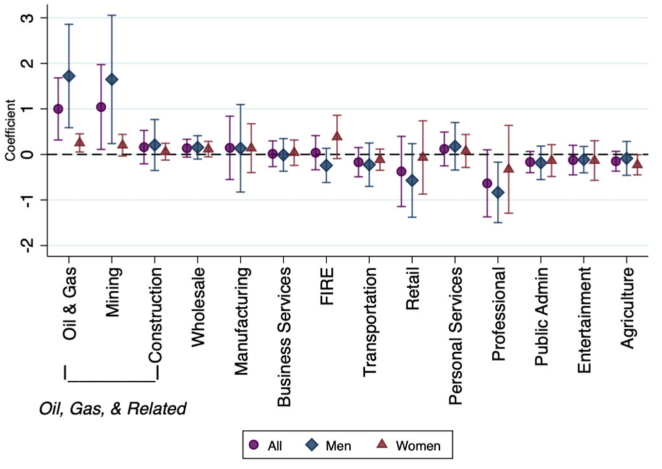

FIGURE 2 Short term effect on employment by industry. Regression of employment by industry on instrument. Coefficients reported in percentage points. Circles denote coefficient when dependent variable is share of all workers; diamonds denote coefficient when dependent variable is male share; triangles denote coefficient when dependent variable is female share. "Oil, gas, and related" industries include oil & gas, construction, and mining. Instrument levels above 95th percentile censored at 95th percentile. Data from the CPS (1986–2012) [Color figure can be viewed at wileyonlinelibrary.com]

(see Autor & Wasserman, 2013; Autor et al., 2013). Columns (4)–(6) show that controlling for these alternative explanations barely changes the regression estimates.

Next, I test alternative specifications of the first and second stage regression equations. Appendix Table S4 panels A and B use only workers who did not move in the past year. The results are nearly identical to those in Table 5, indicating that changes in worker composition are not the primary driver of the main results. Panels C and D show that the results replicate when pooling male and female oil and gas worker shares together, as opposed to using only the male share to examine male enrollment and only the female share to examine female enrollment. Panels E and F substitute region-by-year fixed effects with year fixed effects. Appendix Table S4 panels G and H demonstrate that serial correlation is not a primary driver of the results by controlling for the lag of oil and gas employment.

Other major robustness checks include assessing instrument validity, shown in Appendix Table S5. I modify the instrument to include knowledge of oil and gas resource wealth from 1995 to 2013 to incorporate information gained from fracking activity. Additionally, I switch to a leave-one-out construction of the instrument to account for local shocks that could influence both education and employment patterns. Finally, I construct an alternate instrument that replaces resource level with a dummy for being a top resource state to account for skewness in the instrument distribution.

5 | EDUCATION AND EARNINGS BY MIDDLE AGE

The decline in part-time enrollment highlights the importance of answering two questions. First, does the enrollment decline reflect a temporary pause or a permanent exit from school? Second, if people permanently leave school, are oil and gas jobs "traps"? Lucrative jobs might entice youth to forego college only to disappear when the industry busts, leaving workers with lower schooling and worse long term employability.

In this section, I describe the econometric approach and report the results for human capital and work outcomes by middle age. I find that for men, exposure to oil and gas jobs decreases permanent educational attainment. Trading off formal schooling for on-the-job experience appears to *increase* employment and earnings for most workers, but there is some evidence of earnings declines for others. These heterogeneous effects appear to arise from oil and gas employment conditions when workers are 16–18 years old. In contrast, results are almost always insignificant for women.

5.1 | Specification

To examine impacts by middle age, I use the same identifying variation as the baseline approach. As with any analysis of longer term effects, it is difficult to isolate the specific channels through which exposure to job opportunities during youth impacts outcomes decades later. This section therefore reports reduced form results. By tracking the same individuals from youth in 1979 until midlife in 2012, the NLSY79 enables the following specification:

$$y_i = \alpha_0 + \alpha_1 r_c E_0 + \alpha_2 W_{it} + \theta_{0,s} + \varepsilon_i. \tag{3}$$

The outcome variable y_i represents educational attainment of individual i at midlife. The matrix W_{it} includes time-invariant individual characteristics: race, gender, whether born in the United States, whether a U.S. citizen, mother's highest education, and Armed Forces Qualification Test (AFQT) scores to measure IQ.[14] The matrix W_{it} also contains age and age squared in the year in which the outcome variable is measured, as well as county-level labor shares in manufacturing, trade, services, and government.

The instrument $r_c E_0$ is modified from Equation (1) to capture predicted oil and gas employment opportunities based on the county of residence c when "young." The variable r_c exploits cross-county variation in resource levels, while the variable E_0 represents national oil and gas employment when young. Exposure to oil and gas job opportunities may have different effects for youth not yet enrolled in college compared to those already enrolled. Learning about lucrative non-college job opportunities will increase dropout rates among those already in college, but decrease the share who have ever enrolled in college among those not yet college age. However, it is impossible to determine whether or when this "exposure" to oil and gas jobs occurs for each individual, making it difficult to distinguish these margins.

I therefore construct the instrument based on *hypothetical exposure age*. Leveraging the granularity of the geocoded NLSY79 data, I construct a county-level measure of exposure to oil and gas jobs during each age from 16 to 20, when youth are forming beliefs about college-going. I then run separate regressions to estimate the effect in hypothetical scenarios where individuals are all exposed to oil and gas jobs at the same age. For example, the results when hypothetical exposure age is 16 reflect the effects if all individuals in the sample first had the opportunity to learn about oil and gas jobs at age 16. This approach is a generalized version of an approach taken by prior papers which cannot identify the exact time at which an individual would be exposed to job opportunities. For example, Rickman et al. (2017) set the hypothetical exposure age at 18 years old throughout their analysis, while Kumar (2017) assumes that hypothetical exposure age would have occurred during high school.

[14]The literature on returns to education commonly uses AFQT scores to measure IQ (see Neal & Johnson, 1996).

Education outcomes are time-invariant (e.g., ever obtain bachelor's degree), making cross-county differences in oil and gas resource density the key source of instrumental variation. Using county dummies would exclude individuals who are the sole observation in their county from the estimation of α_1, since the effect of interest would be absorbed in the county fixed effect. The remaining variation would occur from comparing across the individuals who reside in the same county but reach a given age in a different year. Only 70–80 counties have more than 10 respondents per gender-county-year cell, making it difficult to derive meaningful results from within-county cross-cohort variation. Instead, I control for state of residence when young, meaning that Equation (3) relies on cross-county variation within a state and age cohort. This approach assumes that state-level characteristics, such as legislation or industrial composition, are the most relevant for determining employment and education (see Autor & Dorn, 2013). The identifying assumption is that conditional on invariant factors at the state level, natural resources at the county level only influence education through their impact on employment. This is in keeping with the random shares framework of Goldsmith-Pinkham et al. (2020), where the "shares" are equivalent to resource density.

For work and employment outcomes, which vary over time, I modify Equation (3) and examine outcomes based on age when older:

$$y_{ij} = \alpha_0 + \alpha_1 r_c E_0 + \alpha_2 W_i + \theta_{0,s} + \psi_j + \varepsilon_{ij}, \tag{4}$$

where, j indexes age at which the outcome is measured, from 25 to 35 years old. To smooth over noise given the small sample, I compute y_{ij} as the rolling average of outcome y for individual i in the 5 years around age j. To measure average exposure over youth, I compute the instrument $r_c E_0$ as the average of the instruments across the hypothetical exposure ages of 16–20. The vector ψ represents year dummies corresponding to age j. The matrix W_i includes all controls listed above in Equation (3) except age controls. As with the analysis on education, the primary source of variation is across counties within a state.

There are many reasons why the results from this approach would differ from the short term results using CPS data, presented in Section 4.2. First, educational attainment measures differ. While the CPS analysis focuses on current enrollment for a cross-section of individuals, the NLSY79 results pertain to whether an individual has ever reached certain educational milestones by midlife. Second, the NLSY79 sample experienced different oil and gas employment fluctuations than the CPS sample, as discussed in Section 2.2.3. Third, the CPS sample distinguishes between full- and part-time enrollees, but the small sample size in the NLSY79 would make it difficult to estimate reliable effects after splitting by enrollee type. Fourth, although I explore the mechanisms behind the short term findings, it is difficult to pin down specific channels in exploring how impacts evolve decades later. Leaving school early affects the timing of labor force entry, occupational choice, and career decisions, which could all contribute to differences between short and longer term outcomes. Despite these differences, I find similar results on educational attainment between the two samples.

5.2 | Results

5.2.1 | Educational attainment by midlife

Figure 3 reports estimated regression coefficients on educational outcomes by 2000, when respondents are 35–44 years old. The point estimates in Figure 3 are reported in Appendix Table S7. The upper left panel of Figure 3 examines the likelihood that individuals will ever

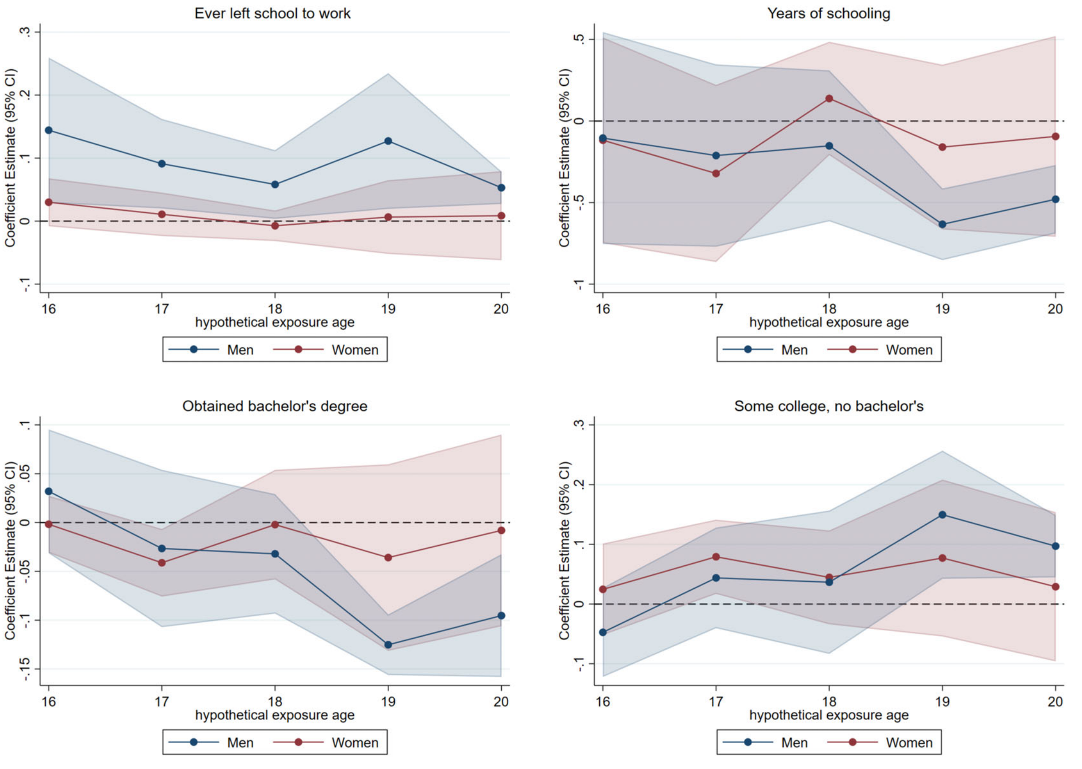

FIGURE 3 Long term effects on schooling. Confidence intervals for reduced form coefficients on schooling. Coefficients reported in percentage points. The *x*-axis uses the instrument based on the respondent's county of residence and year at a given hypothetical exposure age (see text). All regressions control for age, square of age, black, Hispanic, whether born in the United States, U.S. citizenship status, AFQT score (standardized), mother's highest grade completed, and father's highest grade completed. County level controls include labor shares in manufacturing, trade, services, and the government. All regressions include state dummies and dummies for missing variables. Standard errors clustered at state level. Data from NLSY79. Instruments constructed using data from CPS and Allcott and Keniston (2017) [Color figure can be viewed at wileyonlinelibrary.com]

leave school for work opportunities. For each hypothetical exposure age from 16 to 20, greater predicted oil and gas opportunities significantly predict leaving school to work for men but not women. Coefficient estimates range from 0.53 to 1.44 ($p < .05$ in all cases). The interpretation is that at the average oil and gas labor share of 1.3%, a \$1 million per square mile increase in resource density is associated with a 0.07–0.19 percentage point rise in the likelihood of leaving school to work. In other words, living in a county with \$1 million in oil and gas resource density (e.g., Iosco County, Michigan) relative to an area with no resources (e.g., Luce County, Michigan) appears to increase men's likelihood of exiting school by a tenth to a fifth of a percentage point on average.

The upper right panel investigates whether this translates into lower schooling years by midlife. The coefficient estimates indicate that exposure at ages 19–20 decreases the highest grade completed for men but not women. As one may expect, the effects are most pronounced after age 18, when students graduate high school and qualify for most oil and gas jobs. At these ages, a \$1 million dollar square mile increase in resource density leads to a 0.006–0.008 decline in total years of schooling ($p < .01$). Again, for women the point estimates do not significantly differ from 0, as one would expect if oil, gas, and related industries have negligible impacts on women's labor market prospects.

Parallel results hold for the likelihood of ever graduating from college (middle left panel) and entering college but failing to earn a bachelor's degree (middle right panel). The effect is sharpest at hypothetical exposure ages of 19–20, when respondents would have enrolled in college. A resource density increase of $1 million per square mile at the average oil and gas share corresponds to a 0.12–0.16 percentage point decrease in the likelihood of obtaining a bachelor's degree ($p < .01$) and a 0.12–0.20 percentage point increase in the likelihood of attending college but failing to earn a bachelor's degree ($p < .01$). The point estimates across the two measures are statistically indistinguishable, suggesting that the decline in bachelor's degree attainment is driven by men who already enrolled in college.

These estimates are close to the estimated effects on leaving school to work, but are far smaller than the 0.79 percentage point decline in part-time male enrollment from the reduced form short term results shown in Table 3 panel C. This is because the short term results apply to only part-time enrollment, while the midlife results examine bachelor's degree attainment for all respondents with at least a high school diploma. When the 0.79 percentage point estimate is weighted by the fraction of all male students enrolled part-time in the CPS (see Table 2 panel B), I obtain an estimate of $0.79 \times 0.067/(0.067 + 0.309) = 0.14$. The 0.14 percentage point decline in overall enrollment from the short-term results falls within the 0.12–0.16 percentage point range of the NLSY79 results on bachelor's degree attainment. Thus, the CPS and NLSY79 results yield similar estimates, despite using different boom-and-bust cycles, sources of geographic variation, and schooling measures.

For women, estimates are largely insignificant. The exceptions are that women are significantly less likely to obtain a bachelor's at the hypothetical exposure age of 17. It is possible that the expansion of oil and gas production indirectly impacted women's education through changing local economic conditions or marriage market returns. However, the regression results show that these effects largely do not hold for other hypothetical exposure ages. Taken together, this set of results suggests that the impacts of oil and gas opportunities were concentrated in men, while impacts for women were weaker and less systematic.

Related work finds that fracking booms raise male high school dropout rates, which could change the composition of high school graduates in my analysis sample (see Cascio & Narayan, 2022). The impacts I find on educational attainment and work could therefore be driven by men leaving high school, rather than college. I rule out this possibility in Appendix Table S8, which includes high school dropouts and replicates almost all of the prior results in Figure 3. The exception is that estimates on ever leaving school to work change from being significant at the 5% level to being marginally significant or insignificant for men, which suggests that oil and gas opportunities induce men in my sample to leave college but *not* high school. These findings are consistent with Table 1, which shows that eight of the 10 most common oil and gas jobs require at least a high school diploma.

Cohort effects

If more job opportunities lead men to leave college, cohorts that experience industry upticks during youth should exhibit greater schooling loss. To test this hypothesis, I re-estimate the regressions in Figure 3 while interacting the instrument with dummies for each of the three cohorts described in Section 2. Table 7 presents the regression estimates that distinguish by cohort, with a separate column for each outcome measure. In all regressions, the 1973–75 cohort is the omitted category. I only estimate the impact of hypothetical exposure ages from

TABLE 7 Reduced form regression of educational attainment on instrument, by cohort

	Men				Women			
	Ever left school to work (1)	Years of schooling (2)	Bachelor's (3)	Some college no bachelor's (4)	Ever left school to work (5)	Years of schooling (6)	Bachelor's (7)	Some college no bachelor's (8)
Hypothetical exposure age: 18								
Instrument × 1976–78 cohort	−0.012	−0.105	−0.055***	0.026	0.017	0.198	−0.014	0.056*
	(0.025)	(0.147)	(0.017)	(0.063)	(0.025)	(0.177)	(0.026)	(0.031)
1979–81 cohort	−0.051	0.164	0.023	−0.028	0.041*	0.032	−0.024	0.042
	(0.037)	(0.175)	(0.035)	(0.052)	(0.024)	(0.163)	(0.031)	(0.047)
Instrument × 1979–81 cohort	0.130**	−0.226	−0.016	0.055	0.016	0.031	0.017	0.016
	(0.058)	(0.374)	(0.046)	(0.073)	(0.029)	(0.241)	(0.044)	(0.097)
Observations	1285	1285	1285	805	1420	1420	1420	992
Hypothetical exposure age: 19								
Instrument × 1973–75 cohort	−0.227	−1.271	−0.235	0.142	0.041	−0.137	0.060	−0.641*
	(0.284)	(1.830)	(0.282)	(0.428)	(0.094)	(0.364)	(0.077)	(0.349)
1976–78 cohort	−0.071*	0.501*	0.095**	−0.133**	−0.031	−0.130	0.031	−0.050
	(0.040)	(0.259)	(0.043)	(0.059)	(0.032)	(0.264)	(0.061)	(0.079)
Instrument × 1976–78 cohort	0.099**	−0.703***	−0.169***	0.157**	−0.001	−0.148	−0.049	0.087**
	(0.048)	(0.087)	(0.018)	(0.077)	(0.036)	(0.231)	(0.036)	(0.043)
1979–81 cohort	−0.117**	0.721**	0.117**	−0.173**	0.032	0.038	0.027	−0.018
	0.051)	(0.309)	(0.054)	(0.078)	(0.039)	(0.320)	(0.057)	(0.074)
Instrument × 1979–81 cohort	0.173***	−0.527**	−0.065**	0.135***	0.014	−0.109	−0.015	0.053
	(0.067)	(0.225)	(0.027)	(0.035)	(0.015)	(0.312)	(0.062)	(0.097)
Observations	1494	1494	1494	928	1682	1682	1682	1173
Hypothetical exposure age: 20								
Instrument × 1973–75 cohort	−0.026	−0.247	−0.085	0.089	0.110	−0.523	−0.057	0.042

(Continues)

TABLE 7 (Continued)

	Men				Women			
	Ever left school to work (1)	Years of schooling (2)	Bachelor's (3)	Some college no bachelor's (4)	Ever left school to work (5)	Years of schooling (6)	Bachelor's (7)	Some college no bachelor's (8)
	(0.063)	(0.285)	(0.101)	(0.111)	(0.095)	(0.501)	(0.083)	(0.189)
1976–78 cohort	−0.035	0.433*	0.106***	−0.152***	−0.012	−0.022	0.034	−0.032
	(0.038)	(0.243)	(0.038)	(0.053)	(0.028)	(0.219)	(0.047)	(0.061)
Instrument × 1976–78 cohort	0.020	−0.674***	−0.126***	0.110**	−0.012	0.006	0.003	0.025
	(0.057)	(0.130)	(0.041)	(0.046)	(0.042)	(0.329)	(0.048)	(0.060)
1979–81 cohort	−0.075	0.522*	0.108**	−0.164**	0.032	0.038	0.027	−0.018
	(0.058)	(0.304)	(0.050)	(0.076)	(0.039)	(0.320)	(0.057)	(0.074)
Instrument × 1979–81 cohort	0.186***	−0.329	−0.050	0.068	0.014	−0.109	−0.015	0.053
	(0.056)	(0.206)	(0.032)	(0.087)	(0.015)	(0.312)	(0.062)	(0.097)
Observations	1694	1694	1694	1059	1903	1903	1903	1325
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family & IQ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Reduced form regressions of educational attainment measures on instrument. The 1973–75 cohort reached age 16 in 1973–75, the 1976–78 cohort reached age 16 in 1976–78, and the 1979–81 cohort reached age 16 in 1979–81. During this period, oil and gas employment was highest during 1979–1981, second highest in 1976–78, and lowest in 1973–75. Demographic controls include age, square of age, black, Hispanic, whether born in the United States, U.S. citizenship status. Family & IQ controls include respondent's Armed Services Qualifying Test (AFQT) score, mother's highest grade completed, and father's highest grade completed. Standard errors (clustered at state level) in parentheses. *$p < .10$, **$p < .05$, ***$p < .01$.

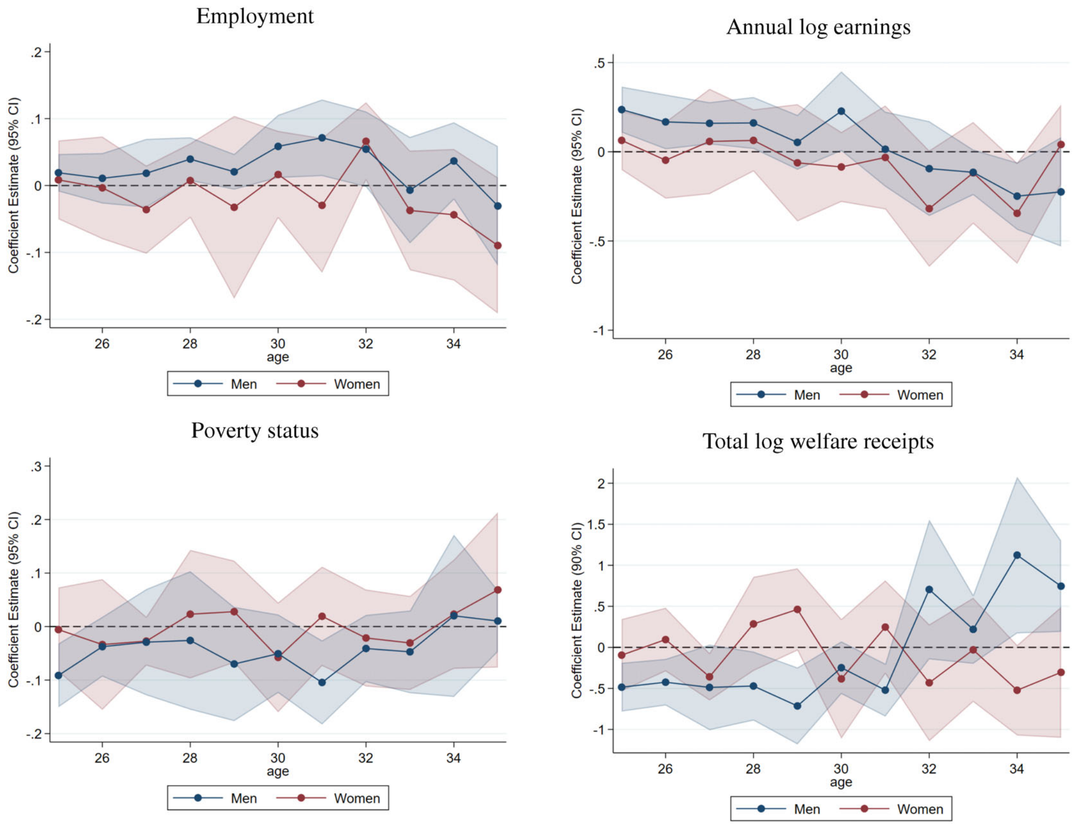

FIGURE 4 Long term effect on work outcomes. Estimated effect of exposure to oil & gas job opportunities on work outcomes by age. Coefficients reported in percentage points. The exposure variable is the average predicted exposure (as measured by the instrument) from age 16 to 20. The *x*-axis represents the age at which the work outcome is measured. To smooth over noise from misreporting and nonresponse, outcomes are calculated as the average measure within a 5 year window. All regressions control for age, square of age, black, Hispanic, whether born in the United States, U.S. citizenship status, AFQT score (standardized), mother's highest grade completed, and father's highest grade completed. County level controls include labor shares in manufacturing, trade, services, and the government. All regressions include state dummies and dummies for missing variables. Standard errors clustered at state level. Data from NLSY79. Instruments constructed using data from CPS and Allcott and Keniston (2017) [Color figure can be viewed at wileyonlinelibrary.com]

18 to 20, since the 1973–75 and 1976–78 cohorts would have already passed ages 16–17 when the NLSY79 surveys began.

Columns (1)–(4) display the results for men, while columns (5)–(8) display the results for women. As with the full sample results in Figure 3, impacts are concentrated at the hypothetical exposure ages of 19–20 for men but almost always insignificant for women. Consistent with expectations, the effects are strongest for the 1976–78 and 1979–81 cohorts, who would have been 16–18 years old during a period of enormous growth in oil and gas employment. In contrast, effects are insignificant for the 1973–75 cohort, which experienced an industry bust when they were 16–18 years old.

For men in the 1976–78 and 1979–81 cohorts, effects mirror those reported in Figure 3. Relative to the 1973–75 cohort, greater predicted oil and gas job opportunities increase the

TABLE 8 Reduced form regression of work outcomes on instrument, by cohort

	Men				Women			
	Employment (1)	Log salary (2)	Poverty status (3)	Log welfare (4)	Employment (5)	Log salary (6)	Poverty status (7)	Log welfare (8)
Panel A: Age = 25								
Instrument × 1973–75 cohort	−0.015	0.098	−0.126	−1.050***	0.131***	0.212*	−0.097	−1.286*
	(0.028)	(0.223)	(0.093)	(0.242)	(0.037)	(0.116)	(0.111)	(0.705)
1976–78 cohort	−0.001	−0.292***	0.104	0.155	0.004	0.066	0.037	0.051
	(0.040)	(0.090)	(0.071)	(0.326)	(0.025)	(0.155)	(0.065)	(0.322)
Instrument × 1976–78 cohort	0.012	0.337***	−0.101	−0.811***	0.032	0.057	−0.018	−0.317
	(0.026)	(0.117)	(0.088)	(0.235)	(0.026)	(0.083)	(0.045)	(0.425)
1979–81 cohort	−0.005	−0.141	0.099	−0.174	0.061	0.240	−0.024	−0.307
	(0.045)	(0.125)	(0.084)	(0.366)	(0.044)	(0.203)	(0.065)	(0.453)
Instrument × 1979–81 cohort	0.046*	0.233**	−0.064	0.133	−0.101	−0.055	0.059	0.949*
	(0.027)	(0.095)	(0.066)	(0.265)	(0.076)	(0.275)	(0.087)	(0.571)
Observations	2007	1957	2007	2007	2172	2044	2172	2172
Panel B: Age = 30								
Instrument × 1973–75 cohort	0.035	−0.393***	0.060	−0.202	0.012	0.189	−0.175	−2.630***
	(0.066)	(0.085)	(0.087)	(0.389)	(0.121)	(0.239)	(0.106)	(0.567)
1976–78 cohort	0.025	0.112	−0.010	−0.028	−0.024	−0.121	0.013	−0.252
	(0.050)	(0.140)	(0.052)	(0.222)	(0.034)	(0.076)	(0.035)	(0.276)
Instrument × 1976–78 cohort	0.095***	0.357**	−0.076	−0.517*	0.040	−0.035	−0.071	−0.088
	(0.018)	(0.166)	(0.082)	(0.304)	(0.033)	(0.120)	(0.064)	(0.446)
1979–81 cohort	0.028	0.103	−0.033	0.137	−0.008	−0.002	−0.042	−0.388
	(0.059)	(0.152)	(0.062)	(0.348)	(0.056)	(0.134)	(0.057)	(0.443)
Instrument × 1979–81 cohort	0.029	0.491**	−0.096**	0.067	−0.070	−0.458*	0.090	0.457
	(0.034)	(0.202)	(0.043)	(0.259)	(0.065)	(0.249)	(0.081)	(0.775)
Observations	1986	1915	1986	1986	2194	2009	2194	2194
Panel C: Age = 35								
Instrument × 1973–75 cohort	0.008	−0.591***	−0.001	1.915***	0.183***	−0.069	0.226	−1.322***
	(0.029)	(0.089)	(0.079)	(0.518)	(0.035)	(0.240)	(0.170)	(0.401)
1976–78 cohort	−0.034	0.022	−0.444***	0.010	0.120***	0.919***	−0.171	−1.135**

TABLE 8 (Continued)

	Men				Women			
	Employment (1)	**Log salary (2)**	**Poverty status (3)**	**Log welfare (4)**	**Employment (5)**	**Log salary (6)**	**Poverty status (7)**	**Log welfare (8)**
	(0.028)	(0.106)	(0.048)	(0.213)	(0.036)	(0.143)	(0.120)	(0.577)
Instrument × 1976–78 cohort	−0.045	−0.195	0.003	0.187	−0.065	−0.101	0.011	0.161
	(0.069)	(0.365)	(0.088)	(0.899)	(0.049)	(0.140)	(0.077)	(0.606)
1979–81 cohort	0.007	−0.056	−0.353***	−0.088	0.188***	0.933***	−0.177	−1.361**
	(0.027)	(0.067)	(0.036)	(0.164)	(0.051)	(0.214)	(0.135)	(0.681)
Instrument × 1979–81 cohort	−0.066	0.272*	0.027	−0.020	−0.234*	0.600***	0.108	−0.822
	(0.080)	(0.142)	(0.078)	(0.555)	(0.137)	(0.187)	(0.164)	(0.682)
Observations	1196	1145	1196	1196	1339	1197	1339	1339
State of birth FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Family & IQ controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Reduced form regression of work outcomes at ages 25–35 on instrument. The 1973–75 cohort reached age 16 in 1973–75, the 1976–78 cohort reached age 16 in 1976–78, and the 1979–81 cohort reached age 16 in 1979–81. During this period, oil and gas employment was highest during 1979–1981, second highest in 1976–78, and lowest in 1973–75. Demographic controls include gender, black, Hispanic, whether born in the United States, U.S. citizenship status. Family & IQ controls include respondent's Armed Services Qualifying Test (AFQT) score, mother's highest grade completed, and father's highest grade completed. Dummies for state of birth and missing variables suppressed. Standard errors (clustered at state of birth) in parentheses. *$p < .10$, **$p < .05$, ***$p < .01$.

likelihood of leaving school to work and decrease average years of schooling by age 35–44. Again, they decrease the likelihood of obtaining a Bachelor's degree but increase the likelihood of having some college without a Bachelor's. The growth in the likelihood of entering college but not obtaining a Bachelor's roughly equals the decline in the likelihood of obtaining a Bachelor's, suggesting that the decline in educational attainment is driven by men already enrolled in college.

5.2.2 | Work and earnings

I next turn to the effects on work outcomes at ages 25–35. Surprisingly, I find that oil and gas employment opportunities *improve* employment and earnings. Figure 4 plots the estimated impacts on employment, earnings, poverty status, and welfare receipt by age. The upper left panel shows that exposure to more opportunities increases employment by 0.08 percentage points when men reach 30–31 years of age. The upper right panel shows a rise in earnings by 0.31% at around the same time, ages 25–28. Consistent with the increase in employment, the bottom right panel shows that greater exposure decreased total welfare receipts by 0.63% during ages 25–31.[15] There is also some evidence of a decline in the likelihood of entering poverty at these ages, but the standard errors are imprecise given the small sample. The results are consistent with Black et al. (2002), who find greater employment and lower disability program participation following coal booms. Appendix Figure S6 replicates these results while including high school dropouts, indicating again that my results are not driven by any impact of oil and gas opportunities on high school dropout rates.

These findings inform concerns in the prior literature and popular media regarding the detrimental impact of oil and gas work on long-term worker outcomes (see Rickman et al., 2017). My estimates suggest that men more exposed to oil and gas opportunities experienced *better* outcomes from leaving school to work early, potentially because they had more time to accumulate industry-specific human capital on the job. For these men, there appears to be *no* tradeoff between leaving school, which sacrifices formal human capital, and working early, which increases informal human capital. Instead, they avoided the cost of attending college while landing jobs that increased their likelihood of employment, raised their earnings, and decreased welfare receipts in their late 20s and early 30s. Rather than "traps" which deprive youth of valuable schooling, these results suggest that oil and gas jobs can present promising alternatives to college for these particular men.

One caveat is that I do not find persistent impacts beyond age 35, which is consistent with the lack of long-term wealth effects reported in Mosquera (2022) for Ecuador. In my case, this likely stems from low power in the NLSY79, given that standard errors grow with age. Since low power inhibits the ability to detect long-term effects, the conclusions from the above results only apply to outcomes up to midlife.

Cohort effects

To assess the validity of the above results, I explore whether effects vary based on oil and gas employment levels during ages 16–18, when youth make the college enrollment decision. Above, I reported declines in schooling in the 1976–78 and 1979–1981 cohorts (Table 7).

[15]Since the amount of welfare individuals receive is non-linear in earnings, it is unsurprising that the effect on welfare receipts could exceed the effect on earnings.

Leaving school early could give these cohorts more time to build industry-specific human capital on the job. If on-the-job human capital compensated for schooling loss, we would expect oil and gas opportunities to increase employment and earnings for these cohorts compared to the 1973–75 cohort, who did not exhibit declines in schooling.

Table 8 examines cohort effects by interacting the specification in Figure 4 with dummies for the three cohort groups. Exposure to more oil and gas opportunities increases earnings by 0.3%–0.6% at ages 25–30 for the 1976–78 and 1979–1981 cohorts, matching the results that pool cohort in Figure 4. In contrast, earnings decline by 0.5%–0.8% at ages 30–35 for 1973–75 cohort, who during youth would have witnessed oil and gas employment levels that were among the lowest in the past 50 years. The decline in earnings at age 35 accompanies a 2.5% increase in welfare receipts for the 1973–75 cohort.[16]

These results are surprising since all three cohorts reached ages 30–35 in 1983–1996, a period of steady decline in oil and gas employment. We may have expected earnings declines across the board, especially given Jacobsen et al. (2021)'s finding that long-run wealth declined during industry busts. Why then did oil and gas opportunities only decrease earnings for the 1973–75 cohort? First, exposure did not make the 1973–75 cohort more likely to leave college, which makes sense since they reached college-going age during an industry bust. The industry bust likely presented fewer opportunities to develop on-the-job human capital outside of college. By comparison, the other two cohorts may have developed on-the-job skills that provided them with better job prospects despite the industry downturn during ages 30–35. Second, there may be differential selection across cohorts. Those in the 1973–75 cohort who select into oil, gas, and related work when opportunities were scarce may have lower earnings potential than those in the 1976–78 and 1979–81 cohorts, who would have entered the industry when opportunities were at their peak.

Again, given the small sample size of the NLSY79 data, it is difficult to assess the validity of these conjectures. My findings so far highlight the need for future work that uses a greater sample of oil and gas workers to explore (1) the differential effects of entering the oil and gas industry in boom versus bust times and (2) differential selection into oil and gas work in boom versus bust times.

6 | CONCLUSION

Theory predicts that raising the value of outside options would shift marginal individuals out of attending college (see Becker, 1975). Empirically, however, it is not obvious that oil and gas employment would lower college enrollment rates, even if most jobs only require a high school diploma. Future job prospects are uncertain, given the industry's boom-and-bust nature. Oil and gas work may therefore not induce high school graduates to forego college, since it is uncertain whether they can sustain a lifelong career in the industry.

This paper finds that the truth is in the middle. Oil and gas employment primarily affects college enrollment for men, who comprise almost the entirety of this workforce. The effect is concentrated among part-time enrollees, who are the most likely to be marginal students. My identification strategy exploits geographic variation in the resources for oil and gas production, with the premise that resource-rich states will provide more job opportunities during industry

[16]This is despite the fact that exposure decreased welfare receipts by 1.4% at age 25 for this cohort in 1982–1984, when oil and gas employment hit its peak.

booms than resource-poor states. I find that a $1 million per square area rise in resource density (at the average oil and gas population share of 1.3%) corresponds to a 0.66–0.94 percentage point decline in the proportion of 18–24 year old men enrolled part-time. The impacts on full-time male, full-time female, and part-time female enrollment are insignificant.

After establishing these baseline results, I apply this strategy to explore education and work outcomes at ages 25–44 using longitudinal geocoded data from the NLSY79. I find that exposure to oil and gas opportunities makes men more likely to leave school to work and less likely to obtain a bachelor's degree. Surprisingly, this corresponds to higher employment, greater earnings, and lower welfare receipts during the early 30s, possibly because those who leave school acquire informal human capital by starting their careers early. The positive early career benefits appear to be concentrated among cohorts who experience plentiful employment opportunities during their youth. For cohorts that entered the industry when employment was low, there is evidence of mid-career earnings declines.

This paper speaks to the human capital consequences of industrial growth. Oil and gas booms appear to lower educational attainment among men marginally attached to school. However, for these men, experience in oil and gas work can compensate for the loss in formal schooling, leading to growth in employment and earnings decades after the booms fade. These results invite a reconsideration of concerns regarding the long-term harms of oil and gas jobs on workers (see Jacobsen et al., 2021; Rickman et al., 2017). They suggest that non-college jobs could *improve* the future work outcomes of youth, by expanding the choice set of ways to develop human capital outside of the traditional college pathway. The other side of this coin is that youths' human capital development and lifetime career outcomes could be harmed by policies which limit non-college jobs. For example, environmental regulations that limit oil and gas production could cut off valuable career paths for young men. Similarly, social stigma casting blue collar work as inferior to cognitive work may turn youth away from career paths that match their skills, inhibiting them from reaching their full potential. My results suggest that finishing college may not be beneficial for everyone. They highlight the need for further research exploring the merits of noncollege work.

ACKNOWLEDGMENTS

I am grateful to Hunt Allcott and Daniel Keniston for providing the data on oil and gas resources. I thank Charles Courtemanche and two anonymous referees for excellent feedback on the paper. I thank Soren Anderson, Eduardo Azevedo, Iwan Barankay, Dale Belman, Kerwin Charles, Matthew Davis, Emma Dean, Gilles Duranton, Ryan Fackler, Clayton Featherstone, Fernando Ferreira, Joseph Gyourko, Steven Haider, Scott Imberman, Robert Jensen, Judd Kessler, Ben Keys, Ilyana Kuziemko, Corinne Low, Katherine Milkman, Olivia Mitchell, Karthik Nagarajan, Muriel Niederle, Alex Rees-Jones, Anya Samek, Paul Sangrey, David Schindler, Katja Seim, Todd Sinai, Jeremy Tobacman, Petra Todd, Maisy Wong, Doug Webber, Karen Ye, Hanzhe Zhang, Weilong Zhang, H2D2 Research workshop participants, WSAWBA conference participants, and Applied Economics student seminar participants at Wharton for helpful comments.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Chuan, A. (2022). The impact of oil and gas job opportunities during youth on human capital. *Southern Economic Journal*, *89*(2), 406–439. https://doi.org/10.1002/soej.12595