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The relationship between oil production and infant health outcomes: Evidence from fracking boom[☆]

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ABSTRACT

This paper examines the effects of oil and gas production on infant health using birth records from 1990 to 2020. We focus on the rise of unconventional extraction methods—particularly hydraulic fracturing ("fracking")—as a quasi-exogenous shock to local production. Exploiting the staggered discovery of fracking potential across shale counties, coupled with measures of production potential as identifying variation, we implement a difference-in-differences design to estimate the impact of drilling exposure on birth outcomes. We find that exposure to drilling activity significantly reduces birth weight, increases the incidence of low birth weight and preterm birth, and impairs fetal growth. Linking drilling to changes in local ambient pollution, we show that exposure significantly increases concentrations of ozone, $PM_{2.5}$, PM_{10}, and SO_2—pollutants known to affect fetal development. These environmental changes likely contribute to the observed negative effects on infant health. Our findings offer insights into the broader costs and benefits of oil and gas extraction for local communities.

1. Introduction

The recent boom in unconventional oil and gas development, especially shale gas extraction via hydraulic fracturing ("fracking"), has profoundly transformed the U.S. energy sector. While fracking has generated significant economic benefits, including lower energy costs, job creation, and reduction in conventional pollution), it has also raised serious environmental and public health concerns. Research shows that drilling activity leads to sizable local economic gains, including higher income, employment, housing prices, and public revenues in producing counties (Apergis, 2019; Feyrer et al., 2017; Wilson, 2022). However, fracking operations have also been linked to increased local air and water pollution, noise, and other environment externalities, prompting widespread public debate and policy efforts to balance economic gains against potential health risks (Apergis et al., 2019; Black et al., 2021; Hill, 2018; Hill and Ma, 2022).

Infants are particularly vulnerable to environmental stressors, as fetal development is highly sensitive to pollution exposure. A substantial body of literature has documented the adverse effects of prenatal exposure to ambient pollutants—such as those from traffic and industry—on infant health outcomes (Chay and Greenstone, 2003; Currie et al., 2009, 2023; Currie and Walker, 2011, 2019; Hill, 2018; Hill and Ma, 2022). Yet, despite growing evidence, our understanding of the human health impacts of the fracking boom remains insufficiently understood at a broader geographic scale.

In this paper, we investigate the effects of oil and gas production induced by fracking boom on infant health a broad sample of states. Using U.S. birth certificate data from 1990 to 2020, we leverage the staggered timing and geographic rollout of fracking operations as a quasi-experimental shock. Important to our design, shale drilling decisions during the boom were largely driven by geology and resource productivity, not local demographic change, making them plausibly exogenous shocks to local pollution. Consistent with prior studies, we find that fracking activity is associated with significant increases in air pollutants, including SO_2, ozone, PM_{10}, and $PM_{2.5}$ (Black et al., 2021; Hill, 2018). In response to this exposure, we document significant

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declines in average birth weight of approximately 10 g. We also find that fracking exposure increases the likelihood of low birth weight, preterm birth, and small for gestational age by approximately 2–3 %.

These estimates should be interpreted with appropriate caution. Our empirical strategy exploits variation in geological suitability for hydraulic fracturing, which affects local conditions through multiple channels. In addition to increasing environmental exposures such as pollution, greater drilling productivity also generates local economic benefits—such as higher employment, wages, and income—that may themselves affect infant health. As a result, our estimates capture the overall net effect of these opposing forces rather than isolating a single mechanism. If local economic gains tend to improve infant health, the negative effects we document likely represent a lower bound on the negative impacts operating through environmental exposures alone.

Our paper contributions to the literature in two main ways. First, while prior studies have largely focused on individual states like Pennsylvania (Currie et al., 2017; Hill, 2018) or Colorado (Hill, 2024), our study extends this literature to a sample of 19 states. By leveraging a comprehensive dataset covering multiple shale plays across diverse geographic, regulatory, and geological contexts, we substantially expand the scope of existing evidence. This broader setting allows us to exploit variation in the staggered timing of fracking adoption across counties, an identification strategy not employed in prior work, to assess its causal impact on infant health. Additionally, we examine a wider range of birth outcomes, including fetal growth, gestational age, preterm birth, and small-for-gestational-age, offering a more nuanced view of how early-life health responds to local drilling exposure.

We should note one limitation of using county level exposure data as well as oil/gas production data. Our analysis relies on the county of birth to measure exposure, which may introduce measurement error if pollution varies substantially within counties or if residential mobility during pregnancy is non-random. While this approach is common in large-scale studies using national data, it lacks the geographic precision of studies using finer spatial data (Currie et al., 2017; Hill, 2018). We acknowledge this tradeoff and interpret our results as capturing average exposure effects (i.e., intent to treat effects) at the county level rather than precise individual-level exposures (i.e., treatment untreated effects).

2. Background

U.S. oil production peaked around 1970 at 9.6 million barrels per day before entering a prolonged decline, primarily due to the depletion of conventional reservoirs—geologic formations like sandstones or carbonates where oil and gas flow freely and can be extracted using vertical wells with minimal stimulation. By 2008, production had fallen to a low of approximately 5 million barrels per day. This trajectory shifted dramatically in the late 2000s with the widespread adoption of horizontal drilling and hydraulic fracturing, two technologies that enabled the commercial development of unconventional resources—oil and gas trapped in formations with low natural permeability, such as shale, tight sandstones, and coalbeds. These formations, often referred to as tight oil or shale gas, require artificial stimulation to release hydrocarbons, since they do not flow easily on their own. As these techniques scaled up, they unlocked vast new reserves, particularly in regions known as shale plays—geographic zones targeting specific shale formations with high hydrocarbon potential, such as the Bakken, Eagle Ford, and Marcellus. Between 2008 and 2019, U.S. oil production more than doubled, surpassing 12 million barrels per day and making the United States the world's largest oil producer (Nakhle, 2024). Natural gas output surged as well, with the U.S. overtaking Russia as the top producer by 2009. This shale-driven boom fundamentally altered global energy dynamics, driving down prices and reducing U.S. dependence on imports.

Hydraulic fracturing (or "fracking")—a well stimulation method that involves injecting a high-pressure mixture of water, sand (known as proppant), and chemicals into the rock—has existed in various forms since the 1950s (Hubbert and Willis, 1957; Montgomery and Smith, 2010). In conventional oil and gas extraction, vertical wells are drilled directly into permeable rock layers, allowing hydrocarbons to flow naturally or be pumped to the surface. In contrast, unconventional production relies on a more complex process. Wells are first drilled vertically to reach the target shale formation, then gradually curved to continue horizontally for thousands of feet within the hydrocarbon-bearing layer. This horizontal section greatly increases contact with the reservoir, maximizing recovery potential. Once drilling is complete, the well must be completed—a term that encompasses all post-drilling operations required to bring the well into production. In the case of shale wells, multi-stage hydraulic fracturing is a key part of the completion process. The wellbore is lined with steel casing, which is perforated at targeted intervals along the horizontal segment. Pressurized fluid is then injected to fracture the dense rock, and proppant is pumped in to keep the fractures open. This process allows oil or gas to flow into the wellbore, making commercial extraction possible from formations that would otherwise yield little or no output using traditional methods.

2.1. *Geographic and Temporal Variation in Oil and Gas Production*

Oil and gas production in the United States exhibits substantial variation across both geography and time, shaped by differences in subsurface geology, the diffusion of extraction technologies, local policy adoption, and market conditions.

Geographic variation is primarily driven by the distribution of geologically viable shale formations. Only a subset of U.S. counties overlay formations with the depth, thickness, and thermal maturity necessary for economically viable hydraulic fracturing (Raimi et al., 2025). These geological characteristics were formed millions of years ago and remained unknown to local populations until relatively recently, making them plausibly orthogonal to the economic, demographic, and health characteristics of those regions.

Consequently, the shale boom has produced highly uneven local effects. Some counties—particularly those located within prolific shale plays such as the Permian, Bakken, and Marcellus—experienced rapid and substantial increases in drilling and output (Black et al., 2021; Gold, 2014). Others, even within the same basin, remained inactive either due to poor geology, limited infrastructure, or policy restrictions (e.g., New York State's fracking moratorium). Within active plays, firms initially target "core" areas with the highest shale quality, and only later expand into marginal zones as prices rise or technology improves (Bartik et al., 2019). These features create fine-grained variation in exposure to the shale boom across adjacent counties, enabling within-basin comparisons that mitigate broader regional confounding factors.

Temporal variation in production is driven by oil and gas price cycles and continued technological advancement. During periods of high oil and gas prices, drilling activity expands, often reaching marginal areas. On the other hand, price downturns—such as the 2014 oil price crash—lead to reduced investment and production. This cyclical response coupled with gradual technological diffusion contribute to staggered production trajectories across counties.

An important aspect of temporal variation (used by Bartik et al. 2019 and implemented in this study) relates to the timing of shale production. Specifically, the staggered year in which each shale formation becomes economically viable for horizontal drilling serves as a temporal source of variation. This temporal variation combined with pre-existing geological suitability introduces quasi-exogenous shocks that help isolate the causal effects of fracking oil/gas production.

3. Literature review

Oil and gas drilling has been shown to significantly degrade local environmental quality, with implications for infant health. For example, Bonetti et al. (2021) use a large US dataset to show that new hydraulic fracturing wells cause measurable increases in salts and metallic elements in nearby surface waters. They find small but significant post-fracking spikes in ions such as barium, chloride, and strontium. Similarly, Hill and Ma (2022) document that shale gas drilling increases contaminants in public water supplies, reducing drinking water quality in fracking regions. Other studies report analogous findings in air pollution: for instance, Gonzalez et al. (2022) find that counties with new oil wells see higher ambient air pollutant concentrations, including ozone, $PM_{2.5}$, and CO. Xu et al. (2018) show that conventional gas oil and gas extraction raises heavy metal leaching toxicity. Xu et al. (2016) provide evidence that offshore drilling increases atmospheric metallic and arsenic pollution.

A growing number of studies link drilling activity to adverse birth outcomes via these pollution channels (Calderon et al., 2016; Oduyemi et al., 2021; Sun et al., 2021; Sun and Wang, 2021). For instance, Hill (2018) exploits the timing of shale gas well development and finds that mothers living within 2.5 km of new fracked wells faced higher risks of low birth weight and preterm birth. An additional fracking well raised the probability of a low-birth-weight baby by about 7 %. Likewise, Currie et al. (2017) use cross-sibling comparisons and find that in utero exposure to fracking (<1–3 km) in Pennsylvania causes statistically significant declines in birth weight and increases in low birth weight incidence. Gonzalez et al. (2020) examine the reduced-form impacts of natural oil and gas production in California on birth outcomes. They find that higher levels of production is associated with a higher likelihood of preterm delivery. Tran et al. (2020) employ a similar approach and geographic region and find increases in low birth weight. Cushing et al. (2020) examine the impacts of flaring from unconventional oil-gas production on pollution and birth outcomes. They find that flaring increases pollution and adversely affects infants' health outcomes. These drilling–health studies typically emphasize environmental mechanisms. For instance, Hill and Ma, (2022)) explicitly link shale drilling to contaminated water exposures: each additional well drilled within 1 km of a water source reduces gestation length by roughly 0.15 weeks and lowers infant birth weight by approximately 25 g.

4. Data sources

The primary data source for our analysis is the restricted-access Vital Statistics birth records, which we restrict the sample to mothers aged 19–40. We exclude teenage mothers (i.e., those younger than 19) because their adverse birth outcomes may be influenced by factors unrelated to intrauterine shocks, potentially confounding the estimated effects of pollution (Chen et al., 2007; Shaw et al., 2006; Weng et al., 2014). Similarly, we exclude mothers over the age of 40, as advanced maternal age is also linked to adverse birth outcomes that may stem from factors unrelated to prenatal development (Liou et al., 2010; Weng et al., 2014).

These birth records provide detailed information on birth outcomes and maternal characteristics. We collapse the birth records data at the county of birth, birth-year, child's gender, mother's education (0–8 years of schooling, 9–12 years of schooling, some college education, bachelor-and-above education), mother's age (19–24, 25–29, 30–34, and 35–40.), and mother's race/ethnicity (white, black, and Hispanic) level.

Temporal and geographic variation in shale county oil and gas production, as well as county-level oil and gas production values, are obtained from Bartik et al. (2019). Bartik et al. (2019) purchased the Rystad prospectivity data through Rystad Energy, which includes GIS shapefiles of shale suitability across North American plays. The prospectivity score of Rystad Energy measures the geological suitability of different locations within a shale play for hydraulic fracturing. It combines several geological attributes (e.g., shale depth, thickness, thermal maturity, porosity, permeability, clay content, and total organic carbon) using a nonlinear algorithm specific to each shale formation. Bartik et al. (2019) map the resulting scores from GIS shapefiles of shales and then aggregate them to the county level. They compute the maximum score within a county as their preferred measure, arguing that the highest-quality resource likely drives drilling decisions and production potential. Counties are then ranked by these scores and divided into quartiles, with the top quartile considered as having high fracking potential. We employ this High Prospectivity (*HP*) indicator (i.e., top-quartile of prospectivity score within the national distribution of the score) serves as a pre-treatment indicator of exposure to fracking.

We further employ data from multiple sources to construct county-level control variables.[1] Per capita measures of income are obtained from the Bureau of Economic Analysis. Per capita unemployment insurance payments come from the Bureau of Labor Statistics. Data on average weekly wages, as well as the percentage of employment in different industries, are drawn from the Quarterly Census of Employment and Wages. Demographic variables (including the percentage of different race, gender, and age groups) are sourced from the Surveillance, Epidemiology, and End Results Program (SEER, 2019).

We utilize air pollution data from the Daily Summary Data files available in the EPA's Pre-Generated Data Files, extracted from United States Environmental Protection Agency (USEPA) (USEPA) (2024). These files, part of the EPA's Air Quality System (AQS), report daily pollutant concentrations at the monitor-pollutant level across the United States. Our analysis of the effects of drilling on pollution focuses on four major pollutants—ozone (O_3), sulfur dioxide (SO_2), particulate matter less than 10 micrometers (PM_{10}), and particulate matter less than 2.5 micrometers ($PM_{2.5}$)—for which data coverage is more comprehensive and whose adverse health impacts are well-documented in the literature (Amjad et al., 2021; Clay et al., 2019; Ha et al., 2014; Jones, 2020; Lee et al., 2013). The Daily Summary Data provide aggregated daily measures for criteria pollutants, with records extending back to 1980. We aggregate these data to the county-year level and merge them with our county-level covariates dataset.[2]

The outcomes we study in this paper are several birth outcomes reported by Natality files in addition to several derivatives of these outcomes. Birth weight is the weight of an infant at birth and is measured in grams. Low birth weight is a binary outcome that turns on if birth weight is less than 2500 g. Full-term birth weight is the weight of an infant at maturity, i.e., for infants with gestational age between 37 and 42 weeks. Fetal growth is birth weight divided by gestational age and is measured in grams/week. It shows the weekly intrauterine growth of the infant. Small for gestational age is a binary variable that turns on if the birth weight is at the bottom-decile of birth weight distribution specific to each gestational week. Gestational age is the period between the last menstrual and the birth and is measured in weeks. Finally, preterm birth is a binary variable that equals one if gestational age is less than 37 weeks.

We merge natality data with shale oil and gas production data based on the mother's county of residence and the child's year of birth. The

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[1] One limitation of our analysis is the reliance on county-level exposure and production data, which may introduce measurement error if pollution varies within counties or if families move during pregnancy. While common in large-scale studies, this approach lacks the spatial precision of finer-grained data (Currie et al., 2017; Hill, 2018, 2024; Hill and Ma, 2022). We therefore interpret our estimates as capturing average intent-to-treat effects at the county level rather than individual-level treatment effects.

[2] We recognize that pollution measurements obtained from monitoring stations may be subject to measurement error. Prior research indicates that the placement of these monitors is not always random; local authorities might avoid locating them in areas with high pollution levels, and socioeconomic factors such as income and race can influence where monitors are installed (Grainger and Schreiber, 2019). Consequently, the EPA's Daily Summary Data may not fully capture pollution exposure in certain communities, particularly those that are underserved or strategically overlooked, which could introduce bias into our estimates.

Table 1
Summary Statistics.

	Top Quartile Prospectivity Score Counties		Bottom-Three Quartile Prospectivity Score Counties	
Variable	Mean	STD. Dev.	Min	Max
Birth Weight	3192.63	437.35	3214.02	448.78
Full-Term Birth Weight	3297.29	345.69	3323.16	352.89
Low Birth Weight	.1	.21	.09	.22
Very Low Birth Weight	.02	.1	.02	.1
Gestational Age	38.76	2.01	38.77	2.05
Preterm Birth	.12	.24	.13	.24
Fetal Growth	82.06	10.18	82.58	10.43
Small for Gestational Age	.14	.25	.13	.24
Child Female	.49	.5	.5	.5
Mother White	.69	.46	.69	.46
Mother Black	.14	.35	.17	.38
Mother Age 10–19	.22	.42	.24	.42
Mother Age 20–24	.26	.44	.27	.44
Mother Age 25–29	.21	.41	.22	.41
Mother Age 30–34	.16	.36	.15	.36
Mother Age 35–39	.1	.3	.09	.29
Mother Age 40–54	.04	.2	.03	.18
Mother education 0–8	.09	.28	.08	.28
Mother education 9–11	.16	.37	.17	.37
Mother education 12	.26	.44	.27	.44
Mother education 13–15	.23	.42	.24	.43
Mother education 16-Above	.21	.4	.2	.4
Born after Shale First Year	.29	.45	.3	.46
Observations	102,038		359,880	

Notes. Number of pre-collapse observations is 4769,800. The data covers the years 1990 – 2020.

primary analysis is restricted to shale counties, though we later demonstrate robustness to including all counties within the broader shale basins. Given that the sharp boom in oil and gas production occurred during the 2000s and 2010s, we limit the sample to birth years 1990–2020 in order to capture multiple cohorts both before and after the onset of fracking activity.

Table 1 provides summary statistics of the final sample for high exposure and low exposure counties in the left and right panels, respectively.[3] The average birth weight is about 3192 and 3214 g in high and low exposure counties, respectively. Approximately 10 %, 12 %, and 14 % of infants in high-exposure counties are classified as low birth weight, preterm, and small for gestational age, respectively, compared to 9 %, 13 %, and 13 % in low-exposure counties.

Fig. 1 presents several descriptive maps of the counties in our final sample. The top left panel shows the geographic distribution of shale counties across major basins. The top right panel displays the first year in which shale production began in each county. The bottom left panel illustrates the distribution of counties based on realized oil and gas production. Finally, the bottom right panel depicts the geographic variation in average birth weight across the counties in the final sample.

Fig. 2 plots annual oil-equivalent production (in billion BOE) separately for counties in shale plays with the highest production (top quartile), counties in shale plays with lower production (bottom three quartiles), and counties outside shale plays. Production in top-quartile shale counties remained flat through the 1990s but rose steeply after 2005, reflecting the onset of the shale boom. In contrast, bottom-quartile shale counties saw only modest gains, and counties outside shale plays exhibited no discernible change over the entire period.

5. Empirical methodology

Using individual birth records, we first aggregate outcomes to county–year–demographic cells and then employ an event-study difference-in-differences design to these aggregated data to estimate fracking's impact on infant health. Our analysis focus on counties that sit on top of shale formations—areas where fracking is possible. By doing this, we compare similar counties that could all potentially start fracking. Thus, identification exploits plausibly exogenous variation in the timing of fracking adoption across geologically similar counties. Following Bartik et al. (2019), we assume that—conditional on fixed effects and trends—fracking timing is uncorrelated with unobserved determinants of infant health. The design compares changes in birth outcomes before and after fracking onset in early-treated counties to those in later-treated counties. This approach isolates causal effects under a staggered treatment framework using interaction weighted estimator of Sun and Abraham (2021), which is especially useful in settings in which all units are treated and the treatment may exhibit heterogenous effects. Specifically, we estimate regressions of the following form:

$$y_{gearcdt} = \alpha_0 + HP_c \times \sum_{j \neq -1} \omega_j I(t - t_c^*) + \gamma_g + \lambda_e + \theta_a + \phi_r + \xi_t + \zeta_c \times T + \varepsilon_{gearct} \tag{1}$$

Where y is the average birth outcome for a group defined by gender g, mother's education e, mother's age a, mother's race r, county c, and year t. The parameters γ, λ, θ, ϕ, ξ, and ζ represent gender, maternal education, maternal age, maternal race, year, and county fixed effects, respectively. We further control for secular changes in counties' characteristics that evolve linearly over the years by including a county-specific linear time trend ($\zeta \times T$).[4] Standard errors are clustered at the county level to account for serial correlations in the error terms. We weight all regressions by the total number of birth counts in each cell.

HP is a binary indicator equal to 1 if a county falls in the top quartile of fracking suitability, based on an index developed by Bartik et al. (2019) using data from Rystad Energy. Rystad Energy, an global oil and gas consulting firm, constructs this index based on factors such as the thickness, depth, and thermal maturity of shale formations. The parameter t^* refers to the fracking start year (i.e., the initial year of horizontal drilling) in the shale in which the county is located. The coefficients ω_j represent differences between higher- and lower-fracking-suitability counties, in the years before and after the first year of production. The negative event time coefficients (ω_j for $j < 0$) provide an empirical test of pre-existing trends in birth outcomes while positive event time coefficients (ω_j for $j > 0$) provide dynamic and transparent evolution of effects after the fracking boom.

Additionally, we summarize all post-event coefficients into an exposure measure which measures the average effects in years after productions starts in high production intensity counties as measures by prospectivity score, as follows:

$$y_{gearcdt} = \alpha_0 + \Omega HP_c \times Post_t + \gamma_g + \lambda_e + \theta_a + \phi_r + \xi_t + \zeta_c \times T + \varepsilon_{gearct} \tag{2}$$

This specification compares birth outcomes among infants born before and after the onset of local oil and gas production, across shale counties that vary in their geological prospectivity. The variable *Post* is an indicator equal to one if the infant's birth year occurs after the county's first year of horizontal drilling. All other parameters and controls are similar to the Eq. (1).

This design exploits staggered treatment timing across counties located within shale basins that differ in their geological suitability for

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[3] Throughout the paper, we use the terms "high exposure county" and "top-quartile prospectivity score county" interchangeably.

[4] A key limitation of including county-specific linear trends is that it assumes unobserved confounders evolve linearly over time, which may not hold in practice. To address this concern, we estimate an alternative specification that includes county fixed effects interacted with a quadratic function of birth year, allowing for more flexible within-county time dynamics; results remain robust and consistent with our main findings (Appendix Table A-1).

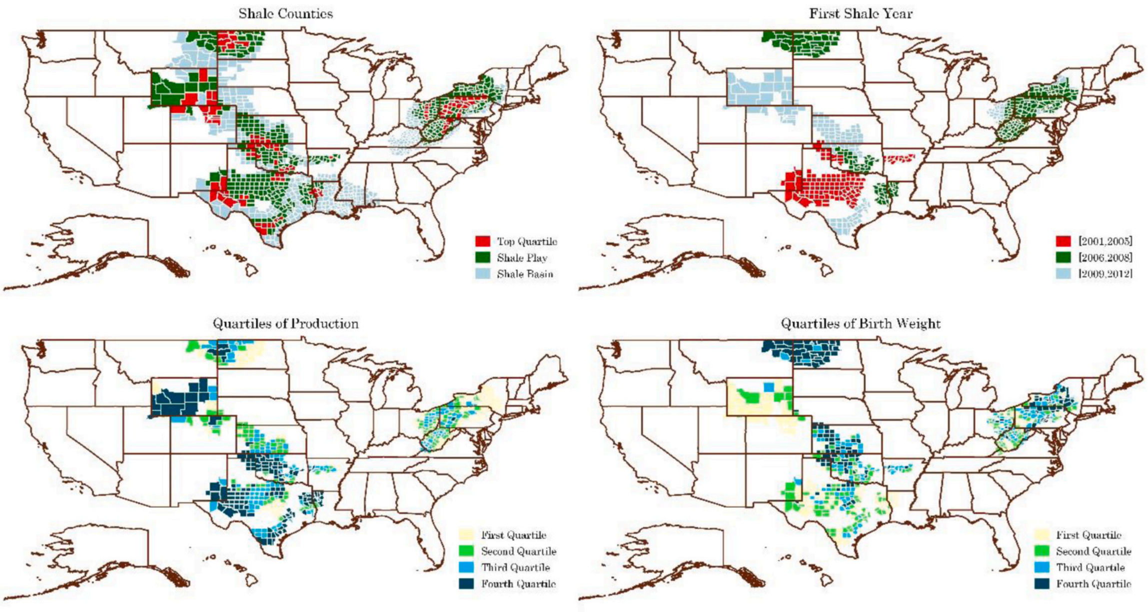

Fig. 1. Geographic Distribution of Counties, Production, and Birth Weight.

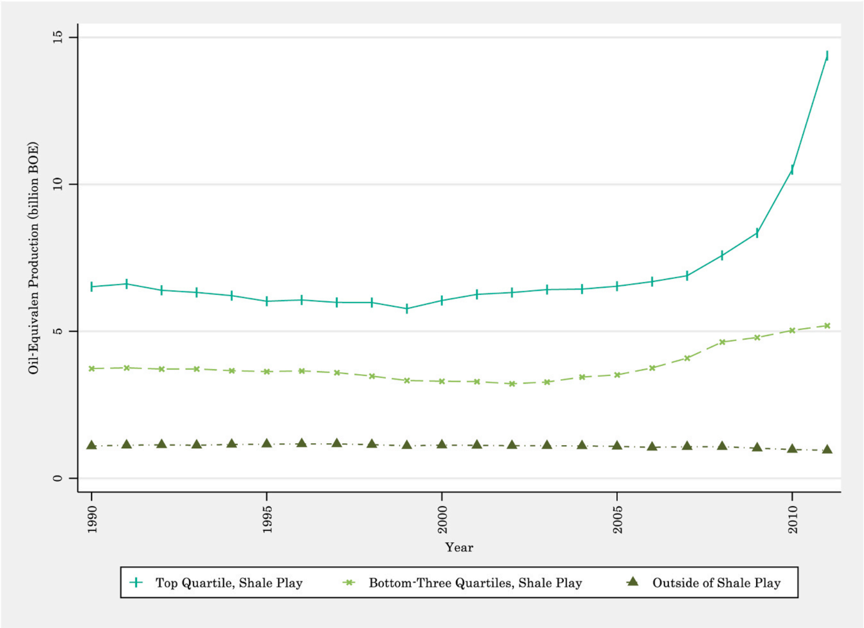

Fig. 2. Evolution of Oil-Equivalent Production across the Top-Producing States. Notes. This figure shows the temporal evolution of total oil-equivalent production. *Top Quartile* group represents counties that fall in the top quartile of fracking suitability, based on an index developed by Bartik et al. (2019) using data from Rystad Energy. *Shale Plays* are defined based on geological boundaries of major shale formations identified by the U.S. Energy Information Administration. While production remains relatively flat for Shale Plays and non-Shale Plays, Top Quartile counties see a sharp rise starting around 2005, reflecting the impact of the shale boom. BOE = barrel of oil equivalent.

hydraulic fracturing and assumes that, conditional on fixed effects and county-specific trends, the timing of fracking adoption is as good as random. Thus, our estimate of Ω capture the average effect of fracking-induced production in high-prospectivity counties versus low-prospectivity counties on infant health in treated counties over time. To ease the flow of interpretation, we refer to the interaction term of *HP* × *Post* as exposure.

6. Results

6.1. *Endogenous fertility*

Changes in oil-gas production can be translated into changes in county characteristics, migration, and a general shift in sociodemographic features of the county (Kearney and Wilson, 2018; Mayer et al., 2018). These changes can generate endogeneity in our regressions of birth outcomes if there is selective fertility, i.e., certain characteristics

Table 2
Exploring for Endogenous Fertility.

	Mother White	Mother Black	Mother Age 10–19	Mother Age 20 – 24	Mother Age 25 – 29	Mother Age 30 – 34	Mother Age 35 – 39	Mother Age 40 – 54	Mother Education 0–8	Mother Education 9 – 11
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HP×Post	.00031	-.00268	-.00032	-.00022	-.00042	.00294	-.0012	-.00077	.00128	.0144**
(Exposure)	(.00433)	(.0037)	(.0051)	(.00554)	(.00529)	(.00432)	(.0026)	(.0011)	(.00222)	(.0059)
Observations	461918	461918	461918	461918	461918	461918	461918	461918	461918	461918
R-squared	.09061	.0902	.04387	.01885	.01318	.03665	.0137	.00307	.03258	.06222
Mean DV	0.737	0.148	0.244	0.274	0.215	0.151	0.088	0.029	0.086	0.439
	Mother Education Some College	Mother Education 16-Above	Mother Education Missing	Mother Smoking	Number Of Prenatal Visit	Month Prenatal Care Began	Child Female	Father White	Father Black	Father Age > 34
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
HP×Post	-.0006	-.00054	-.01454***	.00738***	.23911***	-.06711***	-.00026	-.02856***	-.00165	-.00045
(Exposure)	(.00504)	(.00524)	(.00154)	(.00148)	(.0195)	(.00819)	(.00612)	(.00363)	(.00216)	(.00238)
Observations	461918	461918	461918	461918	455926	452460	461918	461918	461918	461918
R-squared	.01443	.08012	.13323	.24871	.24544	.24784	.00024	.1225	.0901	.05695
Mean DV	0.234	0.197	0.044	0.113	11.214	2.702	0.496	0.659	0.090	0.164

Notes. The table presents regression on a series of parental characteristics on oil-gas production, conditional on county fixed effects, year fixed effects, and county-specific time-trend. Standard errors, clustered at the county level, are in parentheses. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions are weighted using the total number of births in each cell. HP indicates counties in the top quartile of fracking suitability.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

lead mothers to select themselves into the maternity ward and those characteristics are correlated with their pregnancy outcomes. We explore this source of endogeneity by regressing a series of parental characteristics on oil-gas production, conditional on county fixed effects, year fixed effects, and county-specific time-trend.

The results are reported in Table 2. We find no significant changes in several observable maternal characteristics—including race, age, and education—associated with exposure to fracking. The point estimates are generally small in magnitude relative to the mean of each outcome and are statistically insignificant in most cases (columns 1–13). One exception is a modest increase in the share of smoking mothers, corresponding to roughly a 6 % change from the mean. In contrast, we observe an increase in the number of prenatal visits (column 15) and earlier initiation of prenatal care (column 16), suggesting improvements in healthcare utilization. These patterns may reflect enhanced employment opportunities and improved access to private health insurance. We find no evidence of changes in child gender (column 17). While the share of births to white fathers declines slightly, the estimate is small and not mirrored by a corresponding change in the share of black fathers (columns 18–19). Overall, the results do not suggest systematic shifts in the sociodemographic composition of births that would confound the estimated effects of fracking exposure on infant health.

6.2. *Drilling and county characteristics*

Before evaluating the associations between oil and gas production and the birth outcomes of exposed children, we begin by presenting "first-stage" estimates that examine the relationship between fossil fuel production and county characteristics. Similar to regressions of Eq. 2, we include county fixed effects, year fixed effects, and a linear county specific trend. These regressions are implemented using Sun and Abraham (2021)'s weighted estimator. The results are reported in Table 3. We document significant and sizable increases in oil and gas production following exposure, confirming that our exposure measure effectively captures variation in extraction activity. These effects are particularly pronounced for horizontal drilling (hydraulic fracturing), with exposure associated with approximately a 0.36 standard deviation increase in both oil and gas production (columns 2 and 4). Consistent with prior literature, we also observe significant increases in multiple air pollutants: exposure is linked to 0.27, 0.26, 0.44, and 0.36 standard deviation increases in SO_2, ozone, PM_{10}, and $PM_{2.5}$, respectively (Black et al., 2021; Hill, 2018).[5,6]

In parallel, we find that exposure leads to increases in per capita income, wages, and overall employment (columns 10–12). Looking across industry sectors, the results indicate small but statistically significant reductions in agricultural employment, while mining, construction, and a broad category of "all other industries" see gains; we do not detect meaningful effects in utilities or manufacturing (columns 13–18). These findings are consistent with prior work documenting local economic spillovers from oil and gas development (Bjørnland and Skretting, 2024; Feyrer et al., 2017; Gittings and Roach, 2020). By contrast, we observe a significant decline in the housing price index, suggesting that increases in industrial activity may generate local disamenities that offset demand pressures (column 19). Finally, we find no statistically significant change in per capita tax revenues (column 20) although the positive and fairly sizable coefficient may imply higher public revenue.

These economic changes may influence infant health through several pathways. Higher wages and employment opportunities can improve access to healthcare and nutrition, thereby supporting healthier birth outcomes (De Cao et al., 2022; Lindo, 2011; Lindo et al., 2018; Olafsson, 2016). At the same time, rising housing prices may increase wealth for homeowners but impose financial strain on renters, both of which can shape maternal stress and housing stability—factors known to affect infant health (Daysal et al., 2021; Leifheit et al., 2020). On the other hand, increased production may also elevate pollution exposure, which can harm fetal development (Currie et al., 2014; Currie and Neidell,

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[5] While our results document significant increases in ambient air pollutants following drilling activity, our county-level empirical design does not allow us to separately identify the relative contributions of different environmental exposure pathways. In addition to air pollution, other mechanisms, such as water contamination, noise, or increased traffic, may also contribute to the observed adverse birth outcomes. Due to these data limitations, we interpret our estimates as capturing the overall health impact of drilling-induced environmental changes, rather than isolating a specific causal pathway.

[6] Appendix Figure A-1. reports event study results for several pollutants as well as income and employment outcomes. We should note that for pollution outcomes (columns 5–9), we include county and year fixed effects but exclude county-specific trends, as monitoring data are available for only a limited set of counties and years, and adding trends would absorb much of the identifying variation.

Table 3
The Association between Oil and Gas Production and County Characteristics.

	Outcomes:				
	Total Oil Production (STD)	Total Horizontal Oil Production (STD)	Total Gas Production (STD)	Total Horizontal Gas Production (STD)	SO2 (STD)
	(1)	(2)	(3)	(4)	(5)
HP×Post	.20998***	.35763***	.20029***	.35502***	.26717***
(Exposure)	(.02495)	(.03518)	(.03898)	(.05551)	(.04894)
Observations	13572	13572	13572	13572	2149
R-squared	.88557	.77245	.72053	.43341	.78831
Mean DV	1.127	0.332	16.213	3.416	4.326
	NO2 (STD)	Ozone (STD)	PM10 (STD)	PM2.5 (STD)	Per Capita Income ($1000)
	(6)	(7)	(8)	(9)	(10)
HP×Post	.00707	.25677***	.43683***	.36359***	1.15257***
(Exposure)	(.03979)	(.04265)	(.06812)	(.04321)	(.268)
Observations	1227	3373	1899	1597	16108
R-squared	.92738	.73478	.73882	.89256	.9102
Mean DV	9.250	31.970	21.875	10.044	38.909
	Per Capita Weekly Wage ($100)	Per Capita Employment	Per Capita Employment in Agriculture	Per Capita Employment in Mining	Per Capita Employment in Utility
	(11)	(12)	(13)	(14)	(15)
HP×Post	.20613***	.0068***	-.00059***	.00369***	.00034
(Exposure)	(.03251)	(.00198)	(.00008)	(.00063)	(.00022)
Observations	14603	15047	15047	15047	15047
R-squared	.92087	.94541	.72904	.85405	.89399
Mean DV	7.482	0.255	0.001	0.011	0.004
	Per Capita Employment in Construction	Per Capita Employment in Manufacturing	Per Capita Employment in All Other Industries	Housing Price Index	Per Capita Tax
	(16)	(17)	(18)	(19)	(20)
HP×Post	.00096*	-.00072	.00158	-10.48861***	40.06133
(Exposure)	(.00051)	(.00078)	(.00118)	(1.78507)	(50.34738)
Observations	15047	15047	15047	11138	9903
R-squared	.78182	.92391	.95552	.97125	.78886
Mean DV	0.015	0.037	0.135	219.955	557.292

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions of columns 1–4 and 10–20 include county fixed effects, year fixed effects, and county-specific linear trend. The regressions of columns 5–9 include county fixed effects and year fixed effects. STD stands for standardized variables (with respect to the mean and standard deviation of the sample). HP indicates counties in the top quartile of fracking suitability. The Mean DV in columns 1–9 are based on the raw variables before standardizing. Oil production is measured in billions of barrels per year, gas production in trillion cubic feet per year, and pollution in parts per billion.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

2005; Currie and Walker, 2011). Thus, the net effect of fracking-induced production on infant health is theoretically ambiguous and must be assessed empirically, which we turn to in the next section.

6.3. *Main results*

The main event study results from Eq. (1) are presented across the panels of Fig. 3 and Fig. 4. Most of the point estimates for negative event-time indicators are small and statistically insignificant, alleviating concerns about pre-existing trends in birth outcomes prior to drilling. In contrast, the post-treatment coefficients reveal deteriorations in infant health following the onset of oil and gas production. These adverse effects are particularly evident for birth weight, full-term birth weight, fetal growth, and preterm birth.

The difference-in-differences estimates from Eq. (2), reported in Table 4, confirm these findings. The initiation of fracking led to a reduction of approximately 10.2 g in birth weight and 9.2 g in full-term birth weight (columns 1–2). We also observe increases in the incidence of low birth weight (25 basis points), preterm birth (36 basis points), and small for gestational age (30 basis points), corresponding to relative increases of 2.7 %, 2.9 %, and 2.3 % from their respective means (columns 3, 6, and 8).

These estimates should be interpreted with appropriate caution. Our empirical strategy exploits plausibly exogenous variation in geological suitability for hydraulic fracturing to identify the effects of oil and gas production on infant health outcomes. While geological productivity provides a powerful source of identifying variation, it affects local conditions through multiple channels. In addition to increasing environmental exposures, greater drilling productivity also generates local economic benefits, including higher employment, wages, and income, which may themselves influence infant health. As a result, our estimates capture reduced-form net effects that combine potentially offsetting environmental and economic channels, rather than isolating a single causal pathway. To the extent that local economic gains tend to improve infant health, the adverse effects documented here may therefore represent a lower bound on the negative health impacts operating through environmental exposures alone.

6.4. *Sensitivity analysis*

In Table 5, we show the robustness of the results across alternative specifications and subsamples. Panel A presents results from the most parsimonious specification, which includes only county and year fixed effects. In Panel B, we augment the model with a comprehensive set of parental controls, including indicators for father's age, father's race, and missing values for paternal characteristics, as well as maternal characteristics such as number of prenatal visits, initiation of prenatal care in the first trimester, and smoking during pregnancy. Panel C further adds county-level covariates, including per capita income, per capita dividend income, average weekly wage, per capita employment, unemployment rate, per capita income maintenance benefits, and per capita transfer receipts—all expressed in 2017 constant dollars. The persistence of negative health effects after including county economic controls indicates that the adverse impacts on infant health are not mainly driven by concurrent economic gains from drilling activity. The modest attenuation of the estimates suggests that local economic conditions play a limited, partially offsetting role, while the adverse infant health effects remain robust.

In Panel D, we allow the effect of county fixed effects to vary by observable characteristics by interacting them with child gender,

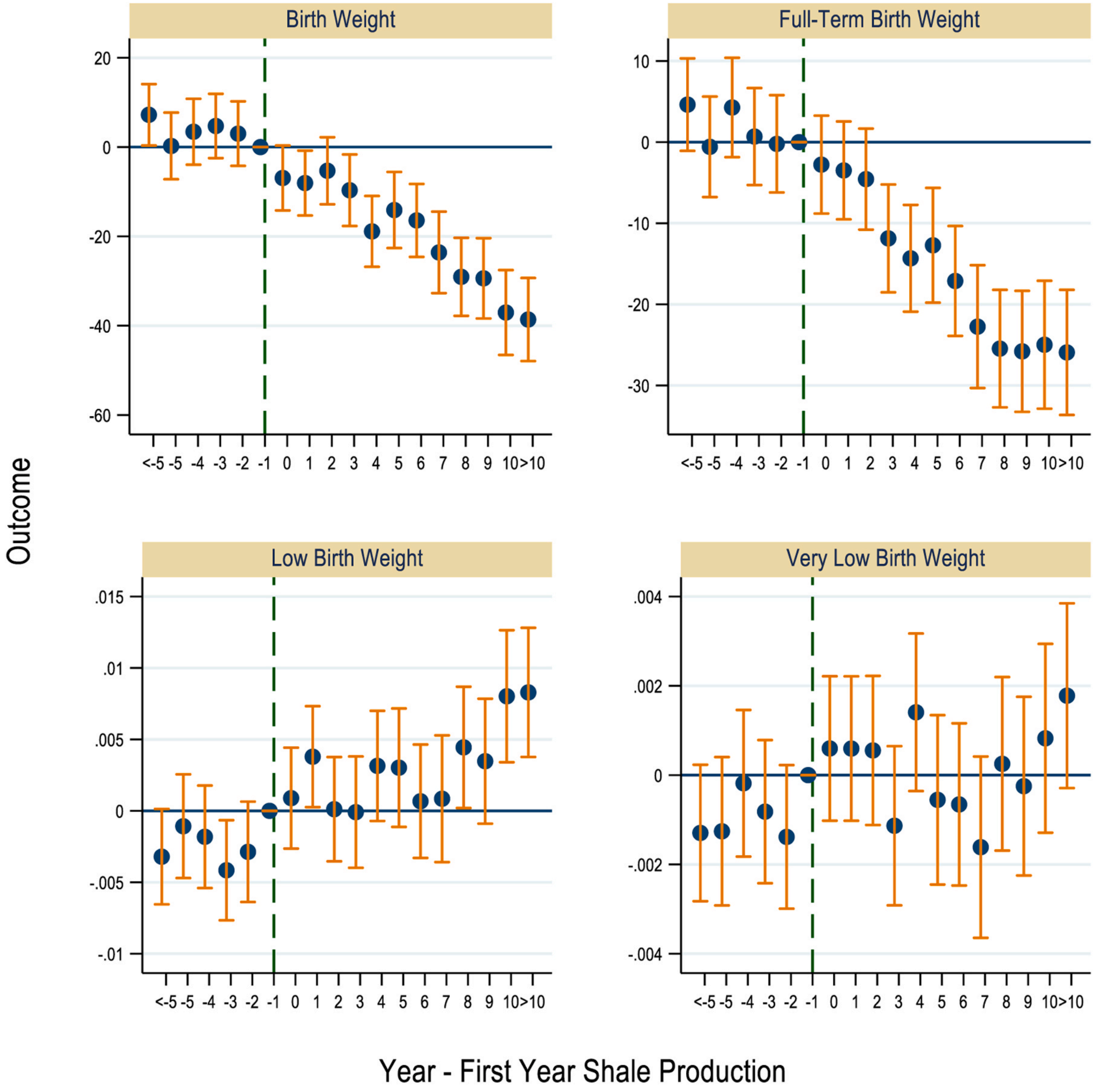

Fig. 3. Event Study Analyses to Examine the Effects of Oil/Gas Production on Infant Health Outcomes. Notes. Point estimates and 95 % confidence intervals are reported. Standard errors, clustered at the county level, are in parentheses. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell.

maternal race, and maternal education indicators. Finally, Panel E expands the sample to include non-shale counties located within the same basin, providing an additional set of control counties. Across all model specifications, we observe consistent and comparable point estimates, suggesting that our findings are robust to a range of alternative control strategies and sample definitions.

6.5. Heterogeneity across subsamples

Table 6 presents heterogeneity analyses by maternal age, maternal education, and child gender to examine whether the effects of drilling on infant health vary across subpopulations. In Panel A, we restrict the sample on mothers under the age of 20. Exposure is associated with a 10.9-gram reduction in birth weight and a 9.1-gram decline in full-term birth weight, both statistically significant at the 5 % level. While we do not find significant changes in gestational age or preterm birth for this group, we observe a 0.25-gram per week decline in fetal growth and nearly a 1 %age point increase in the likelihood of being small for gestational age—an increase of about 7 % relative to the sample mean of 0.13. These results suggest that while young mothers may not experience meaningful changes in gestational duration, fetal development and outcomes related to physical development are more adversely affected.

Panel B reports the results for the subsample of mothers aged 20 or older. The results are similar in direction but slightly smaller in magnitude. Exposure is associated with a 9.5-gram decline in birth weight and an 8.4-gram decline in full-term birth weight. We observe

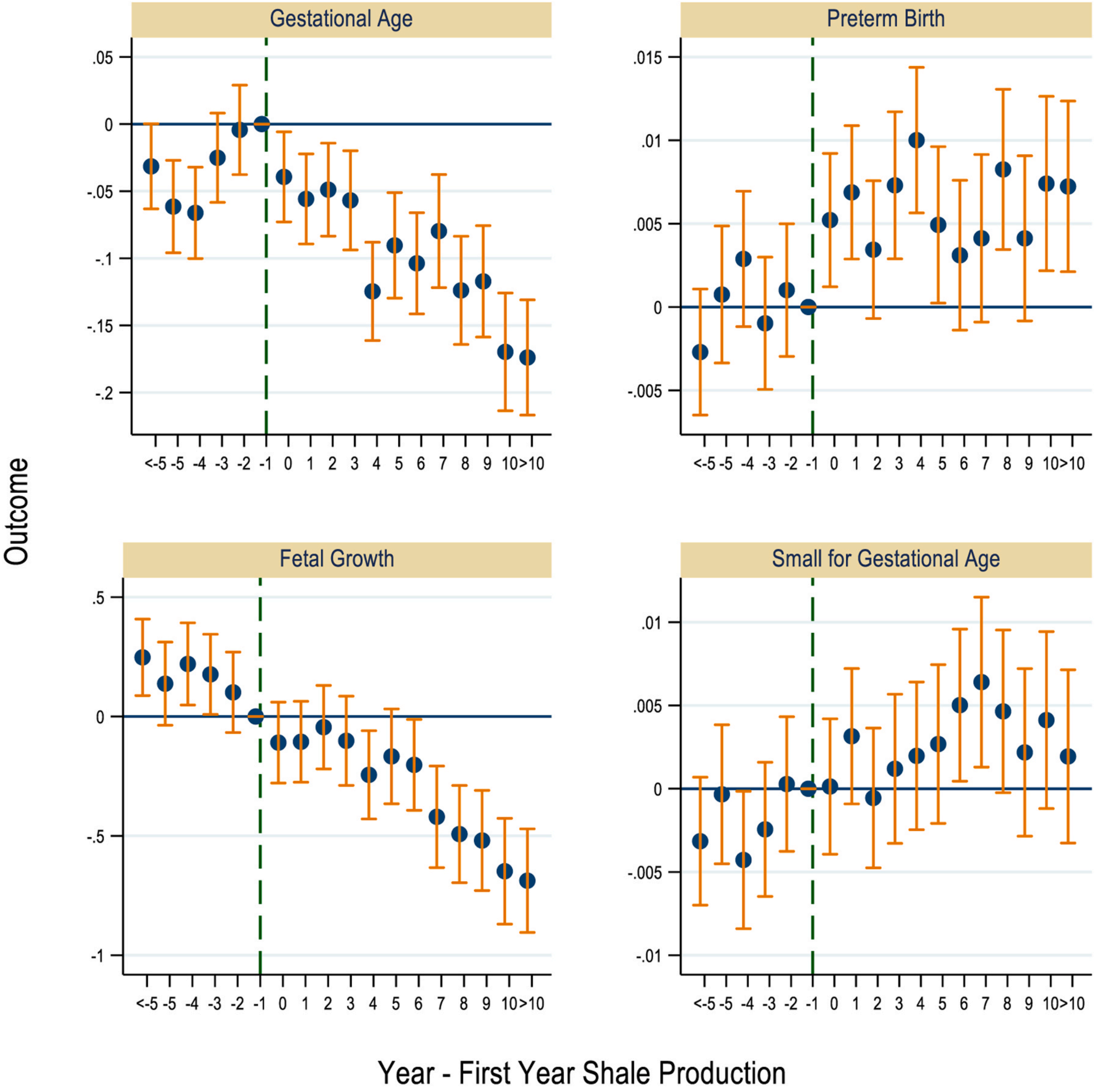

Fig. 4. Event Study Analyses to Examine the Effects of Oil/Gas Production on Infant Health Outcomes. Notes. Point estimates and 95 % confidence intervals are reported. Standard errors, clustered at the county level, are in parentheses. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell.

larger declines in gestational age (0.05 weeks) and a 0.44 %age point increase in the probability of preterm birth, compared to the younger cohort. Fetal growth falls by 0.13 g per week, substantially smaller than the effects of younger mothers in panel A. These patterns suggest that while both age groups experience adverse effects from drilling activity, younger mothers are more affected in terms of fetal growth, whereas older mothers are more impacted on gestational length and prematurity.

Panel C examines effects for mothers with less than a high school education. This group exhibits the strongest and most consistent negative effects. Birth weight declines by 17.7 g and full-term birth weight by 12.3 g—more than double the magnitude observed among more educated mothers. Fetal growth falls by 0.42 g per week, and the likelihood of being small for gestational age increases by 0.93 %age points, or about 6 % relative to the sample mean. We also observe a significant increase in low birth weight of 0.65 %age points (approximately a 6.4 % rise). These results indicate that mothers with lower educational attainment are disproportionately affected by environmental stressors stemming from oil and gas production, consistent with past research (Currie et al., 2009; Gonzalez et al., 2020; Hill, 2018).[7]

Panel D presents results for mothers with at least a high school degree. While exposure is still associated with significant declines in birth weight (7.8 g) and full-term birth weight (7.3 g), the estimated effects

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[7] A natural question is whether the larger adverse health effects observed for mothers with lower educational attainment might be offset by local economic benefits from drilling activity, such as increased employment, wages, or income. To explore this possibility, Appendix Table ↱A-2 examines this comparing counties with higher versus lower shares of low-educated mothers. The table shows that drilling exposure increases income and wages in both types of counties. However, employment gains and production intensity are larger in counties with *lower* shares of low-educated mothers (Panel B). In contrast, counties with *higher* shares of low-educated mothers (Panel A) experience weaker employment responses, even though these are the counties where adverse infant health effects are more pronounced. Taken together, the results indicate that the largest infant harms occur in places that do not experience the strongest local economic benefits from drilling.

Table 4

The Associations between Prenatal Exposure to Oil-Gas Production and Birth Outcomes.

	Outcomes:							
	Birth Weight (1)	Full-Term Birth Weight (2)	Low Birth Weight (3)	Very Low Birth Weight (4)	Gestational Age (5)	Premature Birth (6)	Fetal Growth (7)	Small for Gestational Age (8)
HP×Post	-10.15449***	-9.21115***	.00252**	.00023	-.04117***	.00361***	-.17355***	.00301**
(Exposure)	(2.30087)	(1.90918)	(.00112)	(.00051)	(.01062)	(.00127)	(.05364)	(.00129)
Observations	461,918	438,686	461,918	461,918	461,918	461,918	461,918	461,918
R-squared	.26142	.32639	.07189	.02458	.13166	.06529	.25412	.13624
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128

Notes. Standard errors, clustered at the county level, are in parentheses. HP indicates counties in the top quartile of fracking suitability. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell. The definition of the outcomes are as follows. *Birth Weight* is the weight of infant at birth and measured in grams. *Low birth weight* is a binary outcome that turns on if birth weight is less than 2500 g. *Very Low birth weight* is a binary outcome that turns on if birth weight is less than 1500 g. *Full-term birth weight* is the weight of infant at maturity, i.e., for infants with gestational age between 37 and 42 weeks. A preterm birth dummy variable is a binary indicator that captures whether a birth was preterm, defined as being born before 37th week of gestation. *Fetal growth* is birth weight divided by gestational age and is measured in grams/week. It shows the weekly intrauterine growth of the infant. *Small for gestational age* is a binary variable that turns on if the birth weight is at the bottom-decile of birth weight distribution specific to each gestational week. *Gestational age* is the period between the last menstrual and the birth and is measured in weeks.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5

Robustness of the Main Results to Alternative Specifications and Subsamples.

	Outcomes							
	Birth Weight (1)	Full-Term Birth Weight (2)	Low Birth Weight (3)	Very Low Birth Weight (4)	Gestational Age (5)	Premature Birth (6)	Fetal Growth (7)	Small for Gestational Age (8)
Panel A. Only Fixed Effects								
HP×Post	-9.3049***	-8.91269***	.00219*	.00004	-.03649***	.00326**	-.1573***	.00291**
(Exposure)	(2.59434)	(2.2341)	(.00115)	(.00052)	(.01098)	(.0013)	(.06076)	(.00137)
Observations	461918	438686	461918	461918	461918	461918	461918	461918
R-squared	.06077	.07736	.01297	.00488	.07154	.01714	.04257	.02128
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128
Panel B. Adding More Parental Controls								
HP×Post	-10.15756***	-7.55859***	.00287***	.00059	-.05529***	.00499***	-.15116***	.00177
(Exposure)	(2.2469)	(1.90271)	(.0011)	(.00049)	(.01028)	(.00125)	(.05274)	(.00128)
Observations	449581	428738	449581	449581	449581	449581	449581	449581
R-squared	.29598	.34197	.09249	.04651	.17536	.0897	.28079	.14648
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128
Panel C. Adding County Controls								
HP×Post	-7.94229***	-7.07244***	.00218*	.00028	-.04428***	.00392***	-.11209**	.00173
(Exposure)	(2.41548)	(2.00507)	(.00117)	(.00054)	(.01114)	(.00133)	(.0563)	(.00135)
Observations	441533	419203	441533	441533	441533	441533	441533	441533
R-squared	.25822	.32189	.07064	.02423	.13116	.06478	.25028	.1336
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128
Panel D. Adding County-Gender, County-Race, and County-Mother-Education Dummies								
HP×Post	-9.34119***	-8.5678***	.00243**	.00016	-.04056***	.00355***	-.1525***	.00283**
(Exposure)	(2.30818)	(1.9108)	(.00113)	(.00052)	(.01068)	(.00128)	(.05375)	(.00129)
Observations	461893	438658	461893	461893	461893	461893	461893	461893
R-squared	.2702	.33778	.07611	.02821	.13698	.06959	.26448	.14475
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128
Panel E. Including All Counties in the Basin								
HP×Post	-12.50795***	-12.6956***	.00298***	.00019	-.02892***	.00292**	-.25627***	.00516***
(Exposure)	(2.23881)	(1.85765)	(.00109)	(.0005)	(.0104)	(.00124)	(.05227)	(.00125)
Observations	859092	813748	859092	859092	859092	859092	859092	859092
R-squared	.26515	.32544	.07605	.02551	.14078	.07448	.24974	.13253
Mean DV	3211.604	3321.423	0.095	0.018	38.773	0.128	82.521	0.131

Notes. Standard errors, clustered at the county level, are in parentheses. HP indicates counties in the top quartile of fracking suitability. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell. The definition of the outcomes are as follows. *Birth Weight* is the weight of infant at birth and measured in grams. *Low birth weight* is a binary outcome that turns on if birth weight is less than 2500 g. *Very Low birth weight* is a binary outcome that turns on if birth weight is less than 1500 g. *Full-term birth weight* is the weight of infant at maturity, i.e., for infants with gestational age between 37 and 42 weeks. A preterm birth dummy variable is a binary indicator that captures whether a birth was preterm, defined as being born before 37th week of gestation. *Fetal growth* is birth weight divided by gestational age and is measured in grams/week. It shows the weekly intrauterine growth of the infant. *Small for gestational age* is a binary variable that turns on if the birth weight is at the bottom-decile of birth weight distribution specific to each gestational week. *Gestational age* is the period between the last menstrual and the birth and is measured in weeks.

County controls include per capita income, per capita dividend income, average weekly wage, per capita employment, unemployment rate, per capita income maintenance benefit, and per capita current transfer receipts. All dollar values are converted into 2017 constant dollars to reflect real values.

Additional parental controls include measures of prenatal visits, prenatal care timing, and dummies for father’s race and age.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6
Heterogeneity Across Subsamples.

	Outcomes							
	Birth Weight	Full-Term Birth Weight	Low Birth Weight	Very Low Birth Weight	Gestational Age	Premature Birth	Fetal Growth	Small for Gestational Age
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Mother Age < 20								
HP×Post	-10.86095**	-9.07357**	.00317	.0002	-.02072	.0021	-.25338**	.00957***
(Exposure)	(4.93889)	(4.14203)	(.00248)	(.00112)	(.02502)	(.00292)	(.1163)	(.00293)
Observations	107513	102577	107513	107513	107513	107513	107513	107513
R-squared	.24726	.30181	.06814	.02514	.1317	.06553	.22449	.12687
Mean DV	3192.918	3293.668	0.092	0.017	38.835	0.135	81.978	0.137
Panel B. Mother Age ≥ 20								
HP×Post	-9.49179***	-8.41262***	.00237*	.00034	-.0511***	.00437***	-.13078**	.00112
(Exposure)	(2.60438)	(2.15224)	(.00126)	(.00058)	(.01168)	(.00141)	(.06052)	(.00143)
Observations	354405	336108	354405	354405	354405	354405	354405	354405
R-squared	.24515	.30902	.07246	.02729	.13478	.05709	.24436	.13171
Mean DV	3239.934	3347.406	0.090	0.017	38.874	0.118	83.031	0.125
Panel C. Mother Education < 12 Years								
HP×Post	-17.65135***	-12.34837***	.00647**	.0006	-.03941	.00036	-.42486***	.00928***
(Exposure)	(5.47241)	(4.62376)	(.00282)	(.00124)	(.02701)	(.00318)	(.12896)	(.00335)
Observations	115386	108424	115386	115386	115386	115386	115386	115386
R-squared	.16637	.20707	.04971	.02153	.10708	.05622	.15256	.08568
Mean DV	3167.489	3269.135	0.101	0.018	38.856	0.137	81.288	0.156
Panel D. Mother Education ≥ 12 Years								
HP×Post	-7.84135***	-7.25551***	.00177	.00025	-.04638***	.00485***	-.09214	.00131
(Exposure)	(2.54139)	(2.09533)	(.00121)	(.00056)	(.01147)	(.00138)	(.05899)	(.00138)
Observations	346532	330261	346532	346532	346532	346532	346532	346532
R-squared	.26593	.33167	.07731	.02784	.14448	.06039	.26246	.14109
Mean DV	3248.858	3355.717	0.087	0.017	38.867	0.118	83.271	0.118
Panel E. Child Female								
HP×Post	-6.71258**	-3.59614	.00212	.00114	-.0548***	.00506***	-.07179	.00292
(Exposure)	(3.20916)	(2.67023)	(.00164)	(.00073)	(.01505)	(.00178)	(.07503)	(.00198)
Observations	229134	218165	229134	229134	229134	229134	229134	229134
R-squared	.21898	.24581	.07981	.02688	.13563	.06703	.18633	.11068
Mean DV	3180.575	3277.363	0.095	0.017	38.948	0.116	81.394	0.151
Panel F. Child Male								
HP×Post	-13.32079***	-14.44604***	.00289*	-.00064	-.02786*	.00219	-.26805***	.00311*
(Exposure)	(3.2927)	(2.7248)	(.00152)	(.00072)	(.01498)	(.0018)	(.07655)	(.00165)
Observations	232783	220521	232783	232783	232783	232783	232783	232783
R-squared	.2279	.26763	.06463	.0258	.1217	.06213	.20192	.09514
Mean DV	3275.555	3390.514	0.086	0.017	38.782	0.129	84.132	0.105

Notes. Standard errors, clustered at the county level, are in parentheses. HP indicates counties in the top quartile of fracking suitability. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell. The definition of the outcomes are as follows. *Birth Weight* is the weight of infant at birth and measured in grams. *Low birth weight* is a binary outcome that turns on if birth weight is less than 2500 g. *Very Low birth weight* is a binary outcome that turns on if birth weight is less than 1500 g. *Full-term birth weight* is the weight of infant at maturity, i.e., for infants with gestational age between 37 and 42 weeks. A preterm birth dummy variable is a binary indicator that captures whether a birth was preterm, defined as being born before 37th week of gestation. *Fetal growth* is birth weight divided by gestational age and is measured in grams/week. It shows the weekly intrauterine growth of the infant. *Small for gestational age* is a binary variable that turns on if the birth weight is at the bottom-decile of birth weight distribution specific to each gestational week. *Gestational age* is the period between the last menstrual and the birth and is measured in weeks.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

on binary outcomes such as low birth weight, small for gestational age, and very low birth weight are smaller and statistically insignificant. These comparisons suggest that socioeconomic status, proxied by educational attainment, moderates the vulnerability to pollution exposure.

In Panel E and F, we examine heterogeneity by child gender. For male infants, we observe large and statistically significant declines in both birth weight (13.3 g) and full-term birth weight (14.4 g). Fetal growth declines by 0.27 g per week, and the likelihood of being small for gestational age rises by 0.31 %age points. By contrast, the corresponding estimates for female infants are smaller in magnitude and less consistently significant. These results are consistent with a broader biological literature showing that male fetuses tend to be more vulnerable to in utero stressors than females (Clark et al., 2021; Currie and Schwandt, 2016; Kraemer, 2000).

6.6. *Discussion on magnitudes*

To contextualize the magnitude of drilling-related health impacts, we compare our estimates to prior research on anti-smoking policies and income support programs. For example, Evans and Ringel (1999), using U.S. natality data from 1989 to 1992 and state-level cigarette excise tax changes during the late 1980s and early 1990s, find that a $1 increase in cigarette taxes is associated with an approximately 21-gram increase in birth weight (Table 3 Model 3). By comparison, our estimate in Table 4 indicates that exposure to drilling activity is associated with a 10.2-gram reduction in birth weight, nearly half the gain linked to a $1 increase in cigarette taxes. While these estimates are not directly comparable (given differences in policy context, timing, and underlying behavioral responses) they provide a benchmark suggesting that the magnitude of the health effects we document is economically meaningful.

Additionally, our findings are align with those of Hill (2018), who examines the impact of shale gas extraction in Pennsylvania and reports that, at the intensive margin, each additional gas well near a mother's residence is associated with about a 5-gram reduction in term birth weight. By contrast, our estimates in Table 4 indicate a 10-gram decrease in birth weight per unit of drilling exposure—roughly double Hill's effect size. Several factors may account for this difference. First, while Hill's analysis focuses on the number of wells as the exposure measure, our approach used plausibly exogenous variation in the timing of fracking adoption across geologically suitable counties where fracking could feasibly occur. Second, we examine a larger and more heterogeneous population across 14 states, which could amplify average effects if some of these states experience more intensive drilling operations or have weaker environmental regulations.

7. Conclusion

Recent expansions in oil and gas production—driven largely by the widespread adoption of horizontal drilling and hydraulic fracturing—have reshaped local economies and environments across U.S. counties. While the economic benefits of these developments are well recognized, growing attention has turned to their broader implications for public health (Bartik et al., 2019; Black et al., 2021; Gourley and Madonia, 2018). This study contributes to that conversation by providing national evidence on the causal effects of fracking-driven production on infant health outcomes. Using the universe of birth records in shale counties from 1990 to 2020 and implementing a difference-in-differences strategy, we exploit quasi-experimental variation in the staggered timing of fracking adoption across geologically similar counties—defined by pre-determined shale prospectivity—to estimate the causal impact of oil and gas production on infant health outcomes. We document that increased oil and gas activity leads to significant declines in birth weight, fetal growth, and gestational age, along with increased rates of low birth weight, preterm birth, and small-for-gestational-age infants. We further show that these health effects are plausibly driven by fracking-induced increases in harmful air pollutants—including ozone, $PM_{2.5}$, and SO_2—highlighting the environmental and human costs of resource extraction that may not be fully captured in standard economic assessments.

Ethical Approval

Not applicable.

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Consent to Participate

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Consent to Publish

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Research involving Human Participants and/or Animals

Not Applicable

CRediT authorship contribution statement

Hamid Noghanibehambari: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Mahmoud Salari:** Writing – review & editing, Resources. **Nahid Tavassoli:** Writing – review & editing. **Hoa Vu:** Writing – review & editing.

Declaration of Competing Interest

The authors claim that they have no conflict of interest to report.

Appendix A

Appendix Table ↱A-1
Robustness Check: Including County Fixed Effects with Quadratic Trends in Birth Year

	Outcomes:							
	Birth Weight (1)	Full-Term Birth Weight (2)	Low Birth Weight (3)	Very Low Birth Weight (4)	Gestational Age (5)	Premature Birth (6)	Fetal Growth (7)	Small for Gestational Age (8)
HP×Post	-10.16432***	-9.22922***	.00252**	.00023	-.04124***	.00362***	-.1736***	.00301**
(Exposure)	(2.3045)	(1.91225)	(.00112)	(.00051)	(.01063)	(.00127)	(.05372)	(.00129)
Observations	461918	438686	461918	461918	461918	461918	461918	461918
R-squared	.26142	.32639	.07189	.02458	.13166	.06529	.25412	.13624
Mean DV	3228.442	3334.220	0.090	0.017	38.864	0.122	82.773	0.128

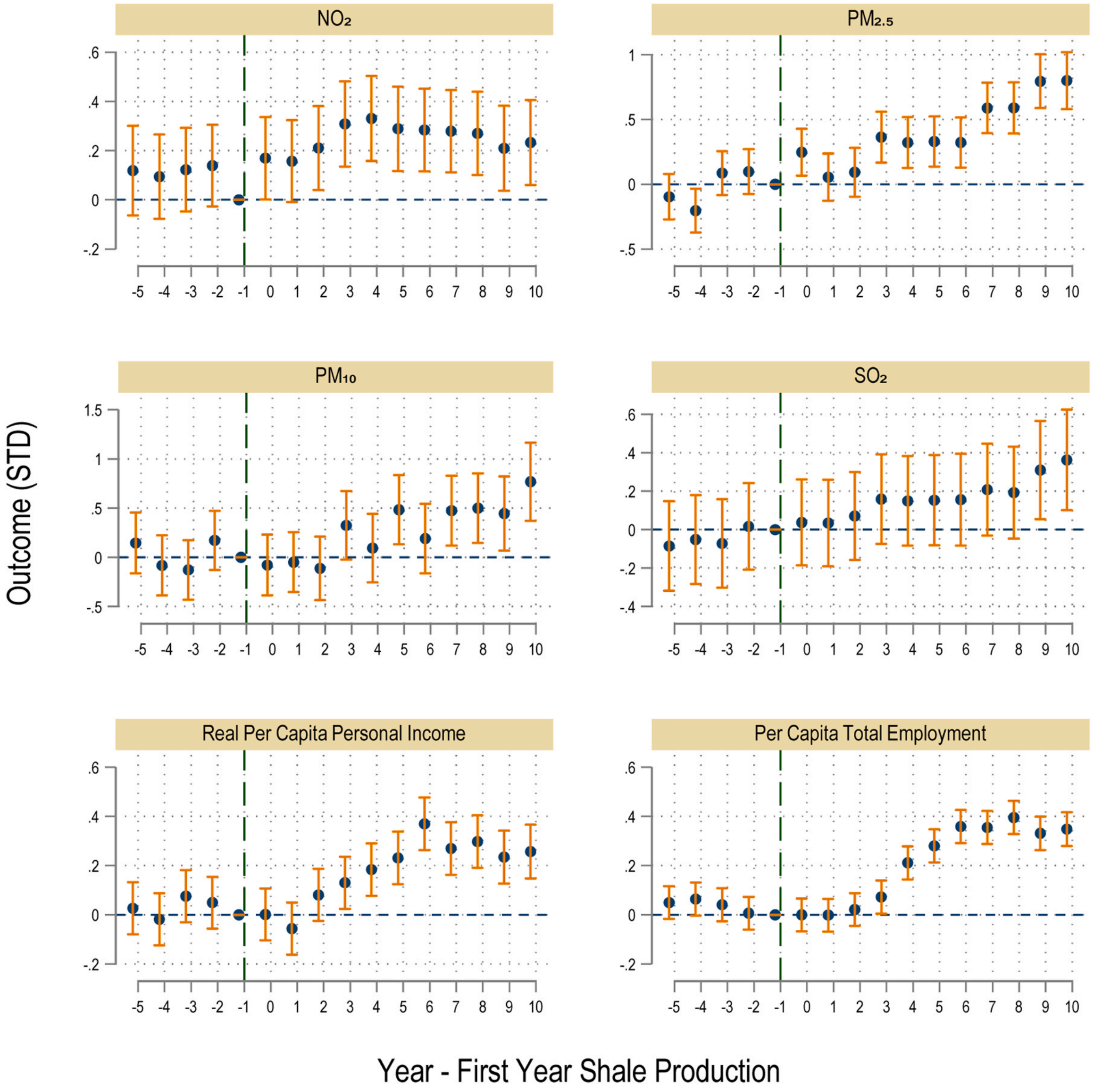
Notes. Standard errors, clustered at the county level, are in parentheses. HP indicates counties in the top quartile of fracking suitability. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions include dummies for maternal education, maternal age, mother race, and child gender. The regressions are weighted using the total number of births in each cell. The definition of the outcomes are as follows. *Birth Weight* is the weight of infant at birth and measured in grams. *Low birth weight* is a binary outcome that turns on if birth weight is less than 2500 g. *Very Low birth weight* is a binary outcome that turns on if birth weight is less than 1500 g. *Full-term birth weight* is the weight of infant at maturity, i.e., for infants with gestational age between 37 and 42 weeks. A preterm birth dummy variable is a binary indicator that captures whether a birth was preterm, defined as being born before 37th week of gestation. *Fetal growth* is birth weight divided by gestational age and is measured in grams/week. It shows the weekly intrauterine growth of the infant. *Small for gestational age* is a binary variable that turns on if the birth weight is at the bottom-decile of birth weight distribution specific to each gestational week. *Gestational age* is the period between the last menstrual and the birth and is measured in weeks.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table ↱A-2
Heterogeneity in First-Stage Production and Economic Outcomes by Share of Low Educated Mothers

	Outcomes:						
	Total Oil Production (STD) (1)	Total Horizontal Oil Production (STD) (2)	Total Gas Production (STD) (3)	Total Horizontal Gas Production (STD) (4)	Per Capita Income ($1000) (5)	Per Capita Weekly Wage ($100) (6)	Per Capita Employment (7)
Panel A. Counties with Higher Share of Low Educated Mothers							
HP×Post	.0359	.17705***	.01875	.10129	.66126**	.1758***	.00301
(Exposure)	(.03151)	(.03841)	(.05776)	(.12442)	(.30221)	(.04022)	(.0023)
Observations	5594	5594	5594	5594	5793	5688	5698
R-squared	.97028	.95747	.82895	.55685	.95512	.9592	.97894
Mean DV	1.734	0.522	21.276	4.199	35.022	7.398	0.269
Panel B. Counties with Lower Share of Low Educated Mothers							
HP×Post	.1484***	.23506***	.11931**	.12802***	.3882	.23272***	.00647**
(Exposure)	(.02083)	(.03019)	(.05039)	(.03337)	(.40708)	(.0514)	(.00271)
Observations	5624	5624	5624	5624	5817	5701	5720
R-squared	.87672	.65458	.83924	.60499	.90872	.9344	.9657
Mean DV	0.620	0.100	11.637	1.138	37.655	7.217	0.257

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. HP indicates counties in the top quartile of fracking suitability. STD stands for standardized variables (with respect to the mean and standard deviation of the sample). Oil production is measured in billions of barrels per year, gas production in trillion cubic feet per year, and pollution in parts per billion.
High (low) share of low-educated mother counties are those above (below) the median share of mothers with less than 12 years of schooling.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$



Appendix Figure ↱A-1. Event Study Analyses to Examine the Effects of Drilling Activity on County Characteristics. Notes. Point estimates and 95 % confidence intervals are reported. Standard errors, clustered at the county level, are in parentheses. The regressions include county fixed effects, year fixed effects, and county-specific linear trend. The regressions are weighted using county population

Data availability

The data that has been used is confidential.

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