# Dutch Disease or Dutch Blessing?

## Shale Gas Shock in the United States and its Impact on Education

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GitHub Repo: `https://github.com/wooyongp/shale-gas-education`

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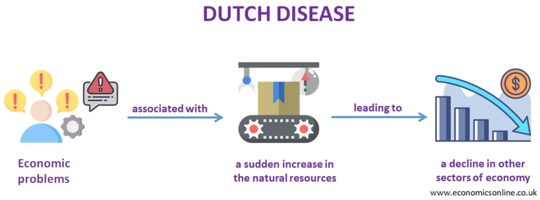
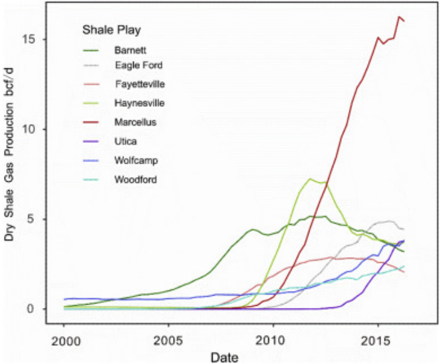
# Is the Shale Gas Boom a Blessing or a Curse?




- **Dutch Disease** refers to negative economic effects that can follow a resource boom or discovery
- When resource industries grow quickly, they create many well-paying jobs that don't require much education
- As a result, young people may choose to work instead of staying in school leading to lower educational attainment

# Distributional Effects: Dutch Blessing?

**Research Questions**

- Did the Shale boom really undermine local educational attainment?
- Was the effect uniform across different income groups?

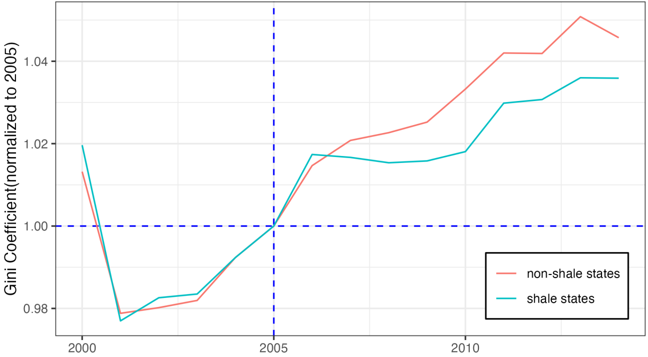
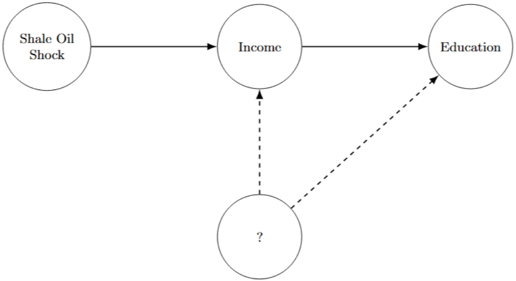



Figure: Gini Index Before and After the Shale Gas Shock

# Causal Identification via DAG

**Causal Relations**

- Shale Gas Boom $\rightarrow$ Income
- Shale Gas Boom $\rightarrow$ Education
- HTE by Income Quartiles




**Policy Implications**

- How can we ensure that the benefits / burdens of resource booms are equitably distributed?
- Should the government intervene to mitigate the negative effects of resource booms?

# Literature Review

- Positive Effects of Shale Gas Shock **on Income**
  - Higher per capita income in shale counties(Weinstein and Partridge 2011)
- Negative Effects of Shale Gas Shock **on Education**
  - Decline in high school and college attainment in West Virginia, Montana, and North Dakota(Rickman, Wang, and Winters 2017)
  - Increased dropout rates among immigrants in Texas(Carpenter, Anderson, and Dudensing 2019)
- Limitations in Prior Studies and our Contribution
  - No discussions of **heterogeneous treatment effects**
  - Identified positive education effects among **low-income households**.

# IPUMS ACS Data

- IPUMS ACS - 1yr from 2002 to 2010
- Variables of Interest : Household Income, Education Attainment, School Attendance, etc.
- Covariates are mostly balanced, excluded five states (Hawaii, Alaska, Puerto Rico, Colorado, and Wyoming)

| | Age | Observations | Weighted Population | Personal Income | | | Family Income | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Mean | Std. Dev. | Count | Mean | Std. Dev. | Count |
| Non-shale | [5, 10] | 1,308,465.00 | 170,364,982.00 | NaN | -0.00 | 0.00 | 72,838.58 | 75,229.40 | 1,298,525.00 |
| | [16, 18] | 716,276.00 | 89,493,317.00 | 2,152.02 | 5,346.15 | 716,139.00 | 76,209.93 | 75,288.26 | 684,920.00 |
| | [18, 24] | 1,396,758.00 | 201,384,880.00 | 10,645.98 | 13,378.58 | 1,396,368.00 | 59,542.08 | 63,236.34 | 1,287,939.00 |
| | total | 17,029,516.00 | 2,116,225,634.00 | 32,089.57 | 45,426.91 | 13,756,814.00 | 71,707.67 | 72,064.18 | 16,680,293.00 |
| Shale | [5, 10] | 301,477.00 | 40,178,779.00 | NaN | -0.00 | 0.00 | 62,547.86 | 64,017.72 | 299,038.00 |
| | [16, 18] | 162,607.00 | 20,788,610.00 | 2,107.18 | 5,266.69 | 162,587.00 | 67,489.58 | 66,903.25 | 155,650.00 |
| | [18, 24] | 315,031.00 | 47,152,003.00 | 10,024.05 | 12,636.98 | 314,959.00 | 52,141.72 | 55,290.96 | 291,304.00 |
| | total | 3,794,579.00 | 478,463,294.00 | 28,501.66 | 40,124.54 | 3,043,685.00 | 63,292.86 | 62,940.60 | 3,709,749.00 |
| | Age | | | Education (Years) | | | College Enrollment | | |
| | | | | Mean | Std. Dev. | Count | Mean | Std. Dev. | Count |
| Non-shale | [5, 10] | | | 0.63 | 1.31 | 1,308,465.00 | 0.00 | 0.00 | 1,308,465.00 |
| | [16, 18] | | | 10.60 | 1.32 | 716,276.00 | 0.23 | 0.42 | 716,276.00 |
| | [18, 24] | | | 12.37 | 2.02 | 1,396,758.00 | 0.82 | 0.39 | 1,396,758.00 |
| | total | | | 11.14 | 5.28 | 16,429,863.00 | 0.64 | 0.48 | 17,029,516.00 |
| Shale | [5, 10] | | | 0.60 | 1.25 | 301,477.00 | 0.00 | 0.00 | 301,477.00 |
| | [16, 18] | | | 10.48 | 1.40 | 162,607.00 | 0.21 | 0.41 | 162,607.00 |
| | [18, 24] | | | 12.22 | 2.00 | 315,031.00 | 0.80 | 0.40 | 315,031.00 |
| | total | | | 10.74 | 5.21 | 3,656,064.00 | 0.61 | 0.49 | 3,794,579.00 |

Table: Summary Statistics

# Methodology - (1) Sun and Abraham (2021) DiD

Staggered treatment is a policy design where different groups have different implementation/dropout dates.

| | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ |
|---|---|---|---|---|---|
| $g_1$ | X | X | X | X | X |
| $g_2$ | X | X | X | X | X |
| $g_3$ | X | X | X | X | X |
| $g_4$ | X | X | O | O | O |
| $g_5$ | X | X | O | O | O |

Table: Cannonical DiD

| | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ |
|---|---|---|---|---|---|
| $g_1$ | O | O | O | O | O |
| $g_2$ | X | O | O | O | O |
| $g_3$ | X | X | O | O | O |
| $g_4$ | X | X | X | O | O |
| $g_5$ | X | X | X | X | O |
| $g_\infty$ | X | X | X | X | X |

Table: Staggered Adoption

# Methodology - (1) Sun and Abraham (2021) DiD

In our case of shale gas boom, the treatment assignment is staggered across states.

| Year | State |
|---|---|
| 2005 | Texas |
| 2006 | Arkansas |
| 2006 | Oklahoma |
| 2008 | Alabama |
| 2008 | Louisiana |
| 2008 | Pennsylvania |
| 2008 | West Virginia |

Table: Shale Gas Extraction Beginnings by State

$=$

| | $t_1$ | $t_2$ | $t_3$ | $t_4$ | $t_5$ |
|---|---|---|---|---|---|
| $g_1$ | O | O | O | O | O |
| $g_2$ | X | O | O | O | O |
| $g_3$ | X | X | O | O | O |
| $g_4$ | X | X | X | O | O |
| $g_5$ | X | X | X | X | O |
| $g_\infty$ | X | X | X | X | X |

Table: Staggered Adoption

# Methodology - (1) Sun and Abraham (2021) DiD

- In canoncial DiD, we often employ two-way fixed effects (TWFE) where $\beta$ captures the ATT:
  - $Y_{i,g,t} = \beta \cdot D_{i,g,t} + \delta_t + \delta_g + \varepsilon_{i,g,t}$
  - $\delta_t, \delta_g$: time and group fixed effects
  - $D_{i,g,t}$: the treatment indicator for individual $i$ in group $g$ at time $t$

- Multiple studies have shown that TWFE can be a biased estimator of ATT in staggered designs(Goodman-Bacon 2021, De Chaisemartin and d'Haultfoeuille 2020)

- Alternative approaches: Sun and Abraham (2021), Callaway and Sant'Anna (2021), Borusyak, Jaravel, and Spiess (2024), Athey et al. (2021)

# Methodology - (2) Synthetic Controls

- Constructions of SCM
  - Treatment Group: Texas
  - Donor Pool: Every other state in the US mainland except shale gas boom states(á la Cunningham and Kang 2019)
- Why did we use both DiD and SCM?
  - Athey et al. (2021) shows that DiD and SCM can be interpreted as different matrix factorization methods.
  - DiD is more flexible in modeling the counterfactuals($Y_{treated}(0)$).
  - SCM is less flexible but less vulnerable to spurious extrapolation of the counterfactuals.

# Assumptions for Causal identification

- Sun and Abraham (2021) DiD
  - **Parallel Trends**: The treated and control groups would have followed the same trend in the absence of treatment
  - **No Compositional Changes**: The composition of the treated and control groups remains constant over time
- Synthetic Control Method
  - The treated group (Texas) is a linear interpolation of the control group (donor pool)

# Main Result: Income

- Household income increased by 2.5% overall in the third year after the shale boom.
- In 1Q, the increase was 18%; in 2Q, it was 5%; in 3-4Q, it was not statistically significant.

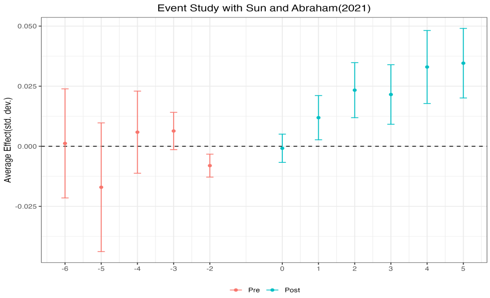



Figure: Overall Income

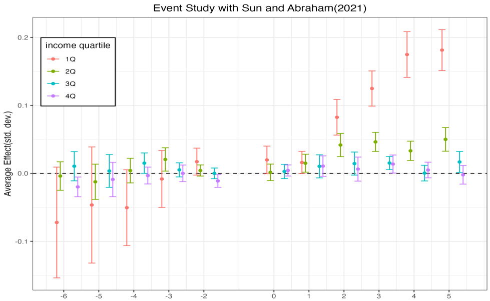



Figure: Income by Quartile

# Main Result: Education

- College enrollment increased by 7.5%p overall in the third year after the shale boom.
- The increase was mainly driven by the 1Q households.
- Drawback: Violation in the parallel trend assumptions in the left figure

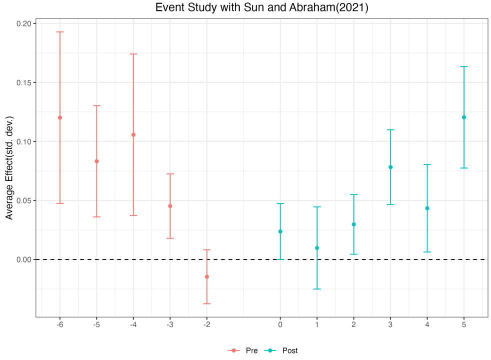



Figure: College Enrollment

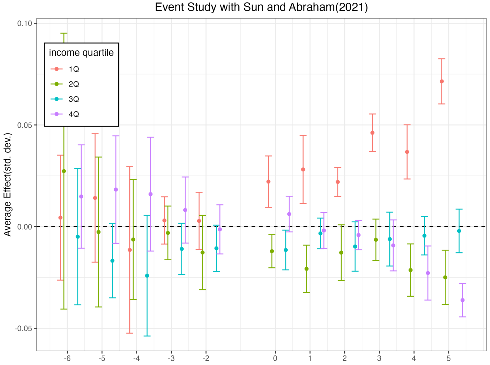



Figure: College Share by Income Quartile

# SCM College Shares (Age 18-24)

- included 2000 and 2001 to increase the pre-treatment fit
- Separate analysis for male and female college shares
- A slight drop in college shares in 2006-2008 for males

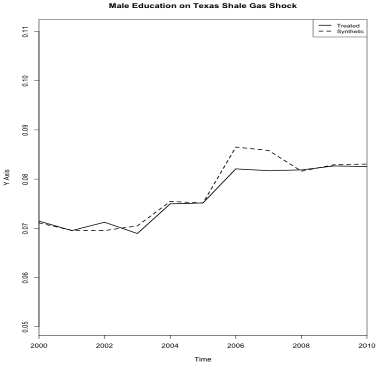



Figure: SCM Male Education

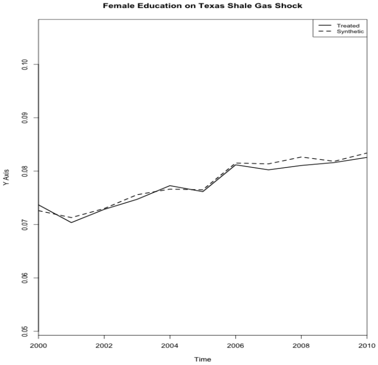



Figure: SCM Female Education

# Robustness Check for SCM

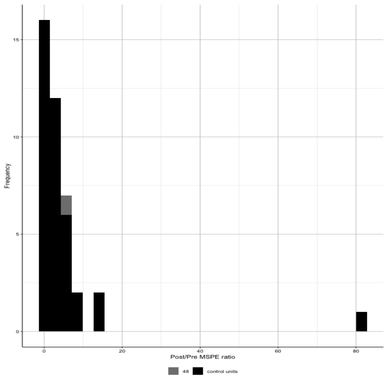



Figure: SCM Male Education

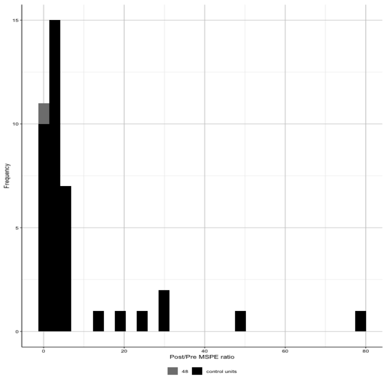



Figure: SCM Female Education

- As supported by the MSPE placebo test results, the slight drops in previous results cannot be attributed to the shale gas boom.

# Extensions: Other Educational Outcomes

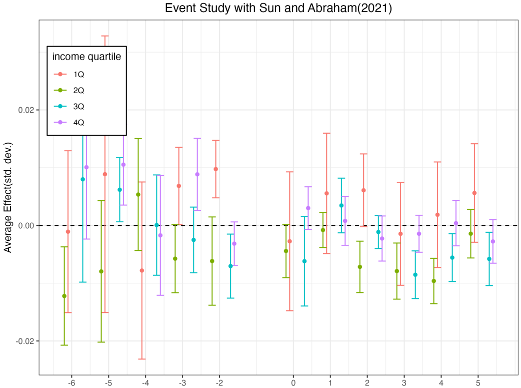



Figure: Elementary School Attendance by Income Quartile

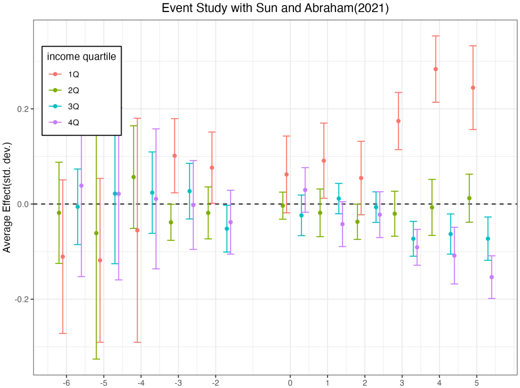



Figure: High School Attendance by Income Quartile

# Validity of the Identification Assumptions

**Parallel Trends**

- Most outcomes show no significant pre-trends $\Rightarrow$ supports parallel trends assumption.
- Some evidence of pre-trends:
  - Household income (1Q): slight upward pre-trend, but post-treatment increase is larger and steeper.
  - College enrollment: significant pre-trend, but disappears when controlling for income $\Rightarrow$ supports *conditional* parallel trends.
- Anticipatory behavior unlikely: treatment not anticipated by households.

**Compositional Changes**

- Concern: selective migration from non-shale to shale states may bias estimates upward.
- Evidence: slight increase in migration rate post-treatment, but unclear if this causes bias. Details

**Dynamic Treatment Effect Homogeneity**

- Important assumption for SADiD; discussed further in the analysis.

# Conclusion

- Shale gas boom increased income and college enrollment especially for low-income households
- Our analysis challenge conventional "Dutch Disease" rather suggesting a "Dutch Blessing" of resource-driven shock
- Limitations
  - Focused on short- to medium-run effects
  - Did not capture spillovers across states

# Future Work

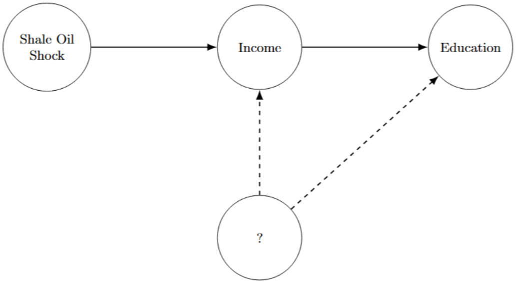



Figure: DAG

- Explore long-term effects of the shale gas boom on education and income
- IV-regression using the shale shock as an instrument for income.
  - we were not able to use SADiD as the first stage because F-test was not satisfied.
  - possible to use the shale gas production volumne as an instrument that is more relevant to income.

# Appendix

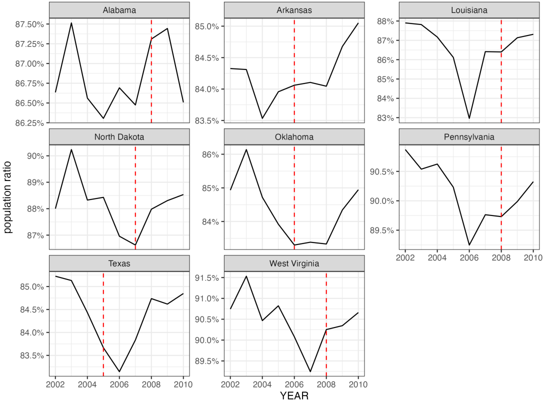



Figure: Migration Rate Before and After the Shale Gas Shock

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