Dutch Disease or Dutch Blessing?
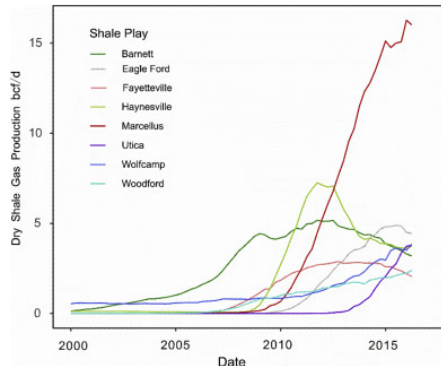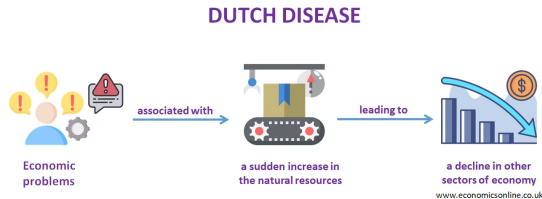## Shale Gas Shock in the United States and its Impact on Education

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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

Economic problems → associated with → a sudden increase in the natural resources → leading to → a decline in other sectors of economy

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- **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
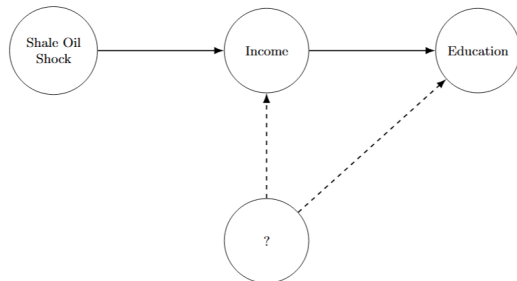
Causal Relations

- 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

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_∞	x	x	x	x	x

Table: Staggered Adoption

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

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	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_∞	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 β captures the ATT:
    - $Y_{i,g,t} = \beta \cdot D_{i,g,t} + \delta_t + \delta_g + \varepsilon_{i,g,t}$
    - δ_t, δ_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.
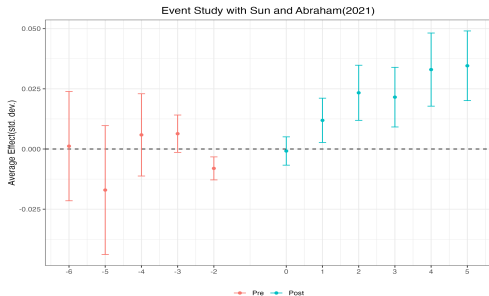
Figure: Overall Income
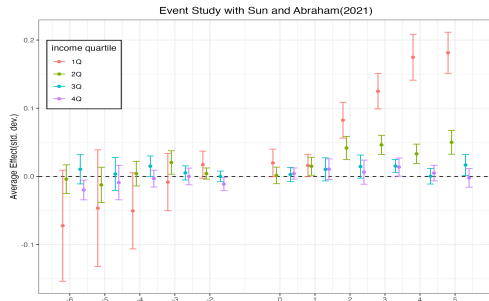
Figure: Income by Quartile

- 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.
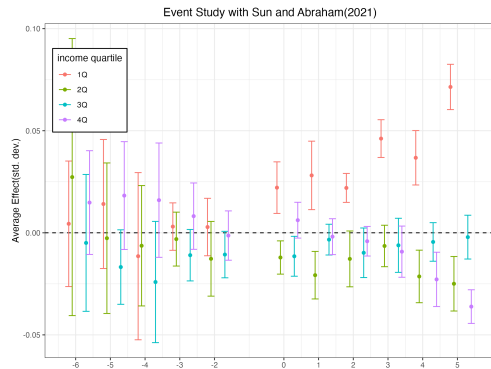- Drawback: Violation in the parallel trend assumptions in the left figure
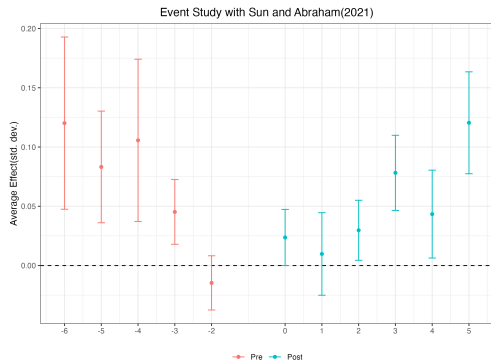
Figure: College Enrollment

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
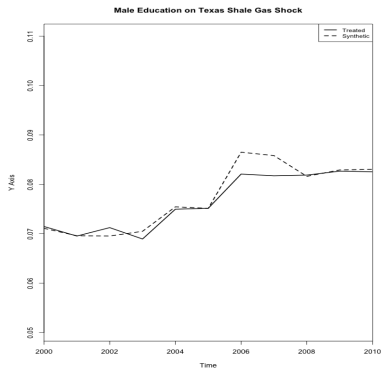- A slight drop in college shares in 2006-2008 for males
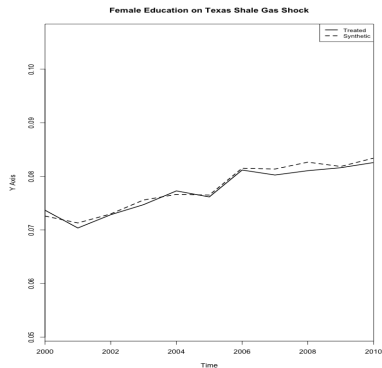

Figure: SCM Male Education

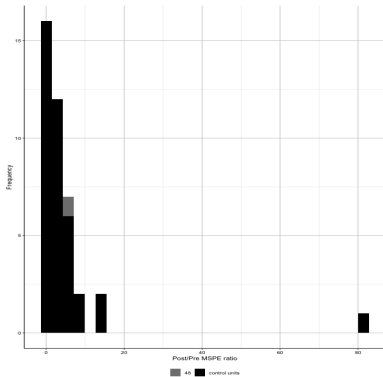Figure: SCM Female Education
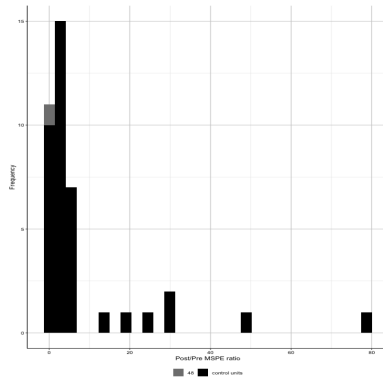
Figure: SCM Male Education

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.

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.

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
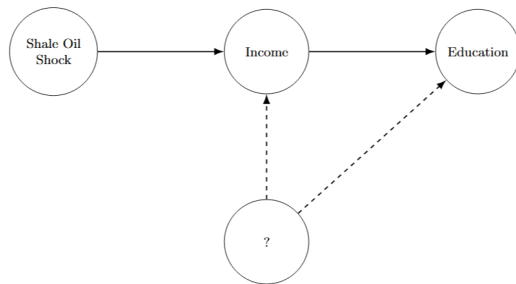 - Did not capture spillovers across states

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.

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