Distributional Equity in the Employment and Wage Impacts of Energy Transitions

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Please Note:

- All participants will be muted during the webinar
- Please submit questions via the Q&A window
- The webinar is being recorded, and both that recording and the slides will be shared on our website and via email after today

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Source: David de la Iglesia Villar

Acknowledgement & Disclaimer, Citation, & Contact Information

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Report Link*: https://emp.lbl.gov/publications/distributional-equity-employment-and

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*Article is *open access*. It is freely available at the hyperlink above.

Meet the authors

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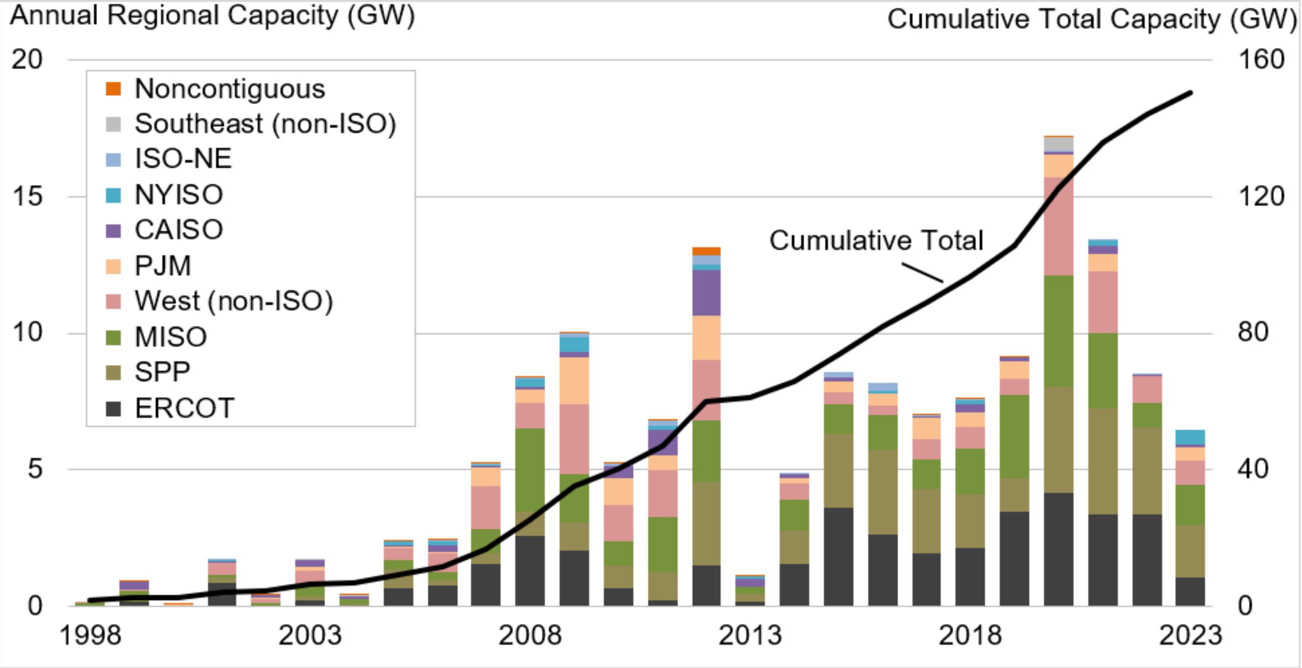
Background

Motivation

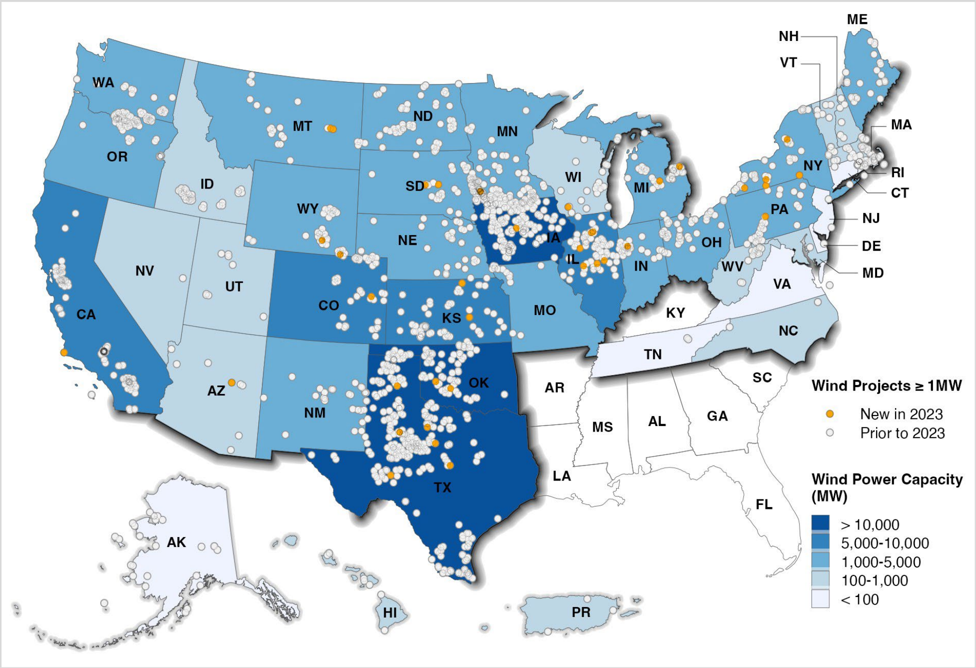
- Large growth in quantity and locations of wind energy in the US could result in a potential shift in local labor markets
- Significant long-term impacts from wind energy on public services (e.g., hospitals, roads, schools) have been found previously, but few related long-term examinations of income and employment exist

Annual and cumulative growth in U.S. wind power capacity thru 2023



Source: American Clean Power Association, LBNL

U.S. wind power installations by state thru 2023



Source: American Clean Power Association, LBNL

Wind projects as a local economic shock

- Wind development, tied to the location of wind resources, can provide a local economic shock

- **One view on the magnitude of impact:**
  - Wind projects do not require many workers once operating. So, most employment impacts occur during construction

- **Another view:**
  - Local tax payments to schools and counties, and
  - Rents to landowners,
  - Can create <u>permanent</u> compositional changes in demand and supply for skills, tasks, and services

Wind development as a means to address inequality

- The local economic shock of wind development is not dissimilar to shocks from other previous energy developments – both provide opportunities to provide local benefits

- **How <u>might</u> those benefits be distributed?**
  - Current federal and some state policies incentivize renewable energy development to address historical energy development inequities

- **How <u>are</u> they distributed?**
  - Very little has been done to measure past impacts to better understand where incentives might be most valuable to address policy goals

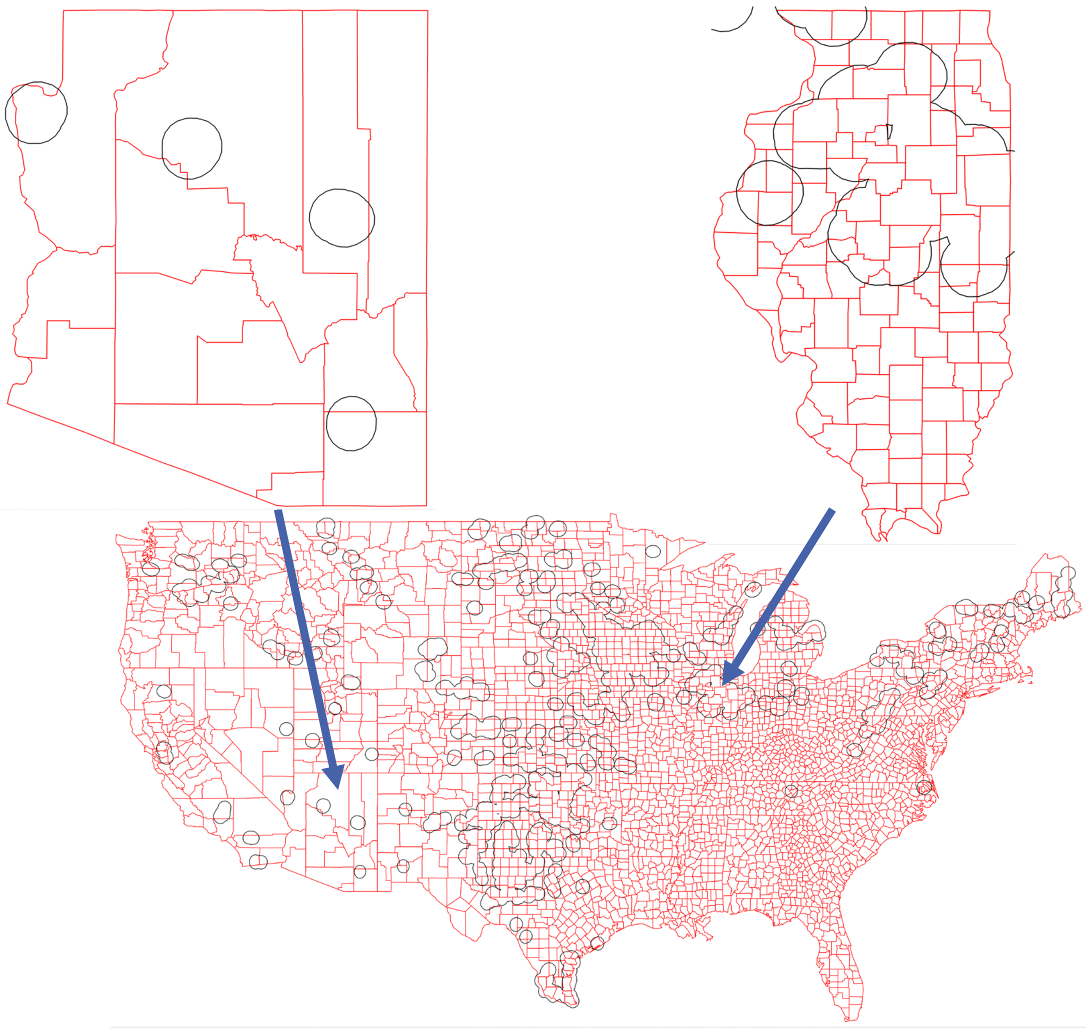
Study overview

Research questions

- Who has benefited, locally, from wind energy development and by how much?
  - Focusing on employment and income

- How do conventional county-level measurements differ from high-resolution worker-level measurements?
  - Most existing evidence from county-level data
  - Counties are irregularly sized and shaped, raising issues of:
    - **Measurement error in treatment** – might vary across space and be correlated with both economic outcomes <u>and</u> where wind energy is installed
    - **Modifiable Areal Unit Problem (MAUP)** – county borders are arbitrarily related to locations of wind development
    - **Ecological fallacy** – inferences about individuals made from groups (i.e., county averages)

20-mile wind project radii vs US county shapes & sizes



Methods and data summary

- Use the near-population of geocoded workers in 23 states to:
  - Estimate the impact of wind projects on employment and earnings;
  - Examine differences by race, ethnicity, gender, and education;
  - Quantify how different our estimates are from county-level data.

- Implement a new causal inference methodology on a unique restricted-access U.S. Census dataset*
  - Local projections difference-in-differences (LPDID) using
  - Longitudinal Employer-Household Dynamics (LEHD) dataset

** This is thoroughly discussed in the paper; we will not discuss in detail today*

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Summary of findings

- **Employment:** Average increase of 231 jobs within 20 miles of a wind project
  - This equates to 0.51 local jobs per million dollars of wind capacity investment
- **Income:** Average increase of $1,270 (4%) in annual earnings within 20 miles of a wind project
  - This equates to 0.16 dollars of local worker earnings per dollar of wind capacity investment
- **Who benefits?** Highest impacts among black workers, men, and those either with a college degree or without a high school diploma
  - Differences are economically meaningful but not statistically significant
- **County- vs. worker-level estimates:** estimates using county-level data mimic previous findings, and are considerably lower than our worker-level results

Our worker-level estimates differ from, and are larger than, our and previous county-level results

- Employment:
  - county-level estimates:
    - Others: ~0 to 90 jobs
      - e.g., Gilbert et al, 2023; Brunner and Schwegman, 2022; Brown et al, 2012
    - Ours: ~80 jobs, non-significant
  - our worker-level estimates: ~230 jobs
- Income:
  - county-level estimates:
    - Others: 0 to 3 percent
      - e.g., De Silva et al, 2016; Mauritzen, 2020; Shoeib et al, 2022; Brunner and Schwegman, 2022
    - Ours: non-significant (i.e., close to 0%)
  - our worker-level estimates: ~4.0 percent

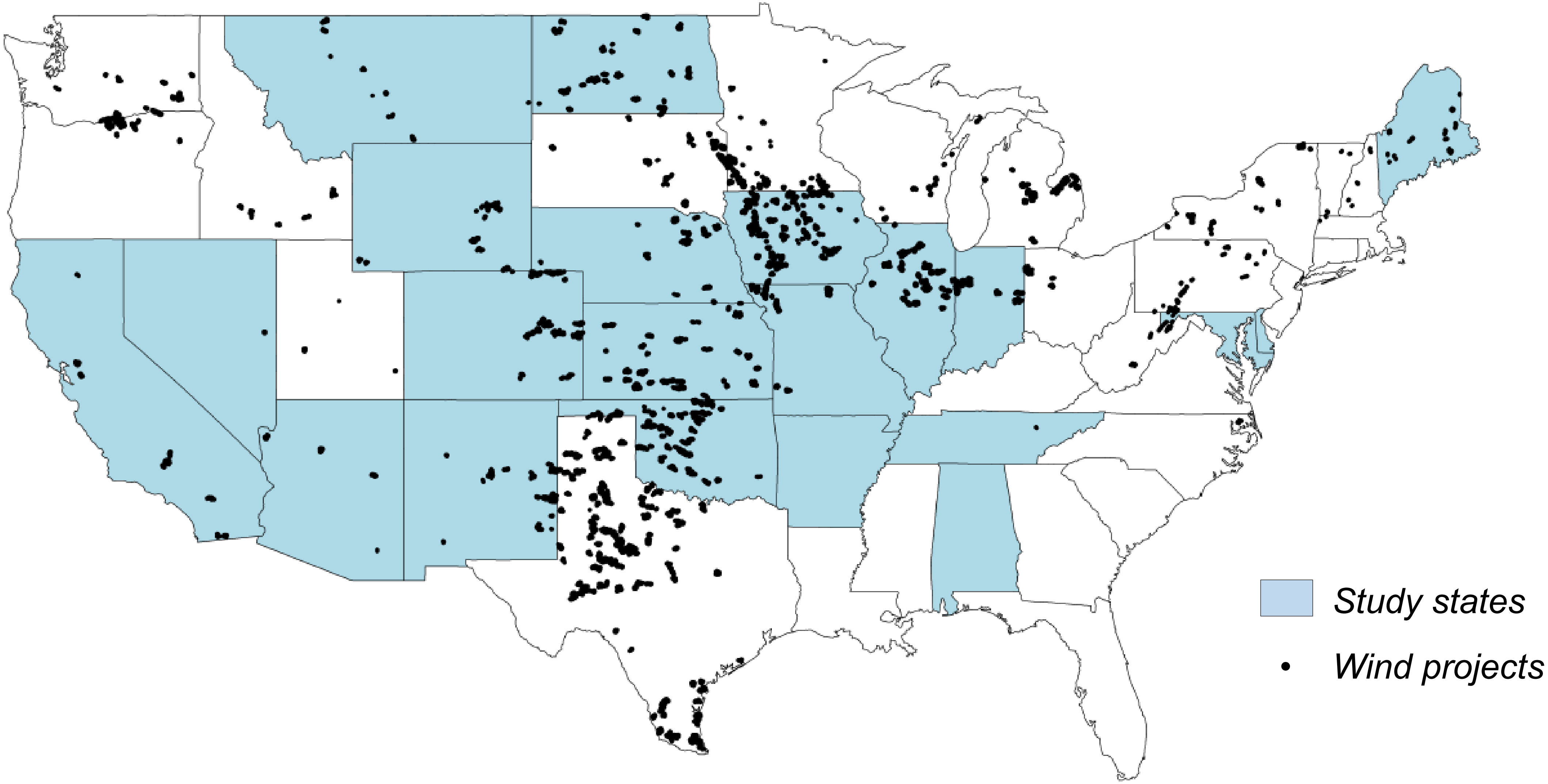
Source: Bureau of Labor Statistics

Data

Data

- U.S. Census Bureau’s Longitudinal Employer-Household Dynamics (LEHD) dataset
  - Restricted access, geocoded residence information accessed from within a U.S Census Federal Statistical Research Data Center
  - Workers’ quarterly earnings and employment status from 2000 to 2020
    - Anyone who participated in state unemployment insurance program at any time
    - ~96 percent of workers, does not include non-wage/salary income
    - Race, ethnicity, education, sex, age
  - 23 states agreed to share
- US Wind Turbine Database:
  - Geocoded wind turbines by capacity, year operational, and plant/project
  - Used thru 2020 data
- For each worker residence, we aggregate wind capacity within 20 miles each year

Study states and wind project locations (thru 2020)

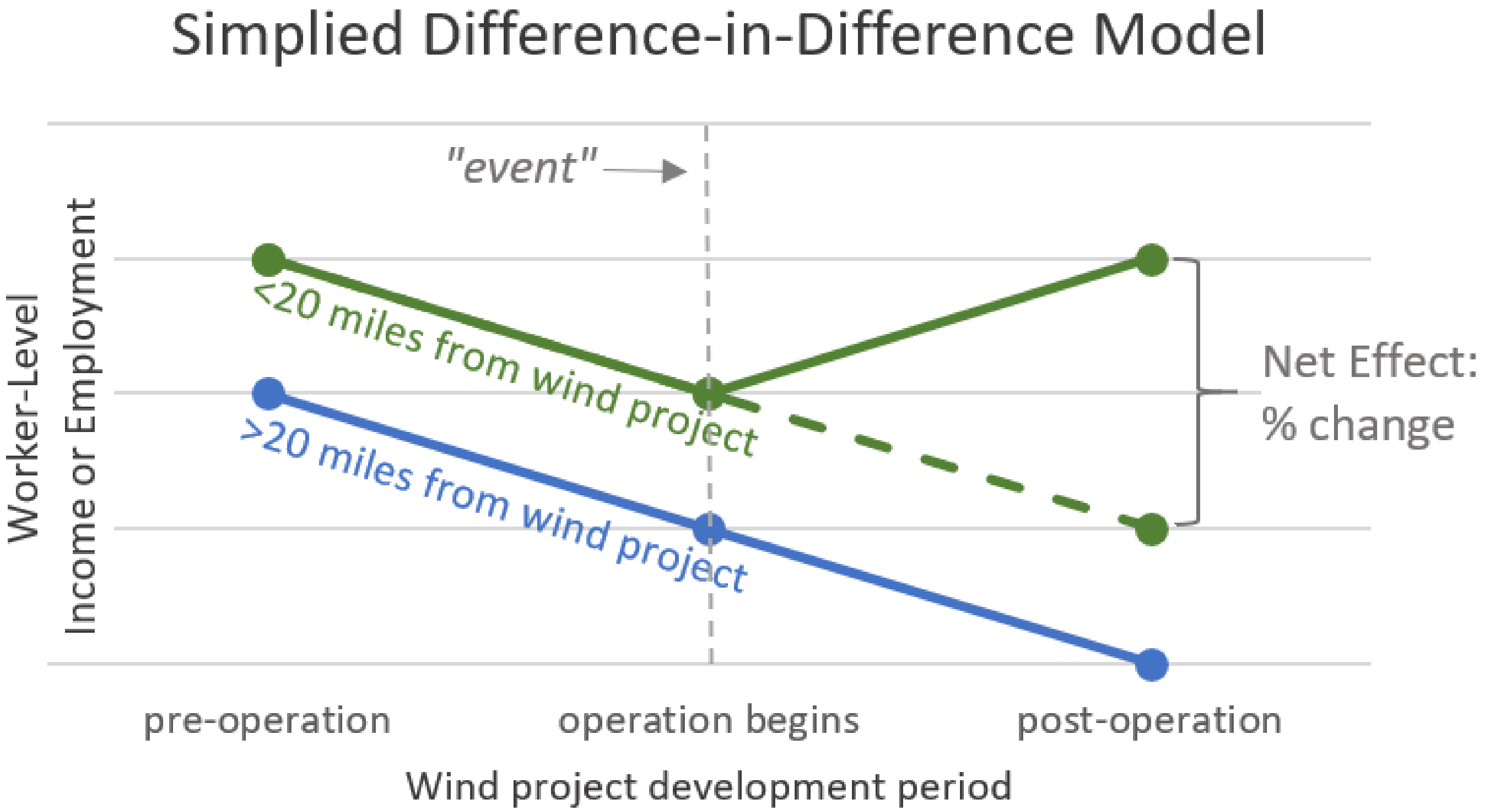


Methods

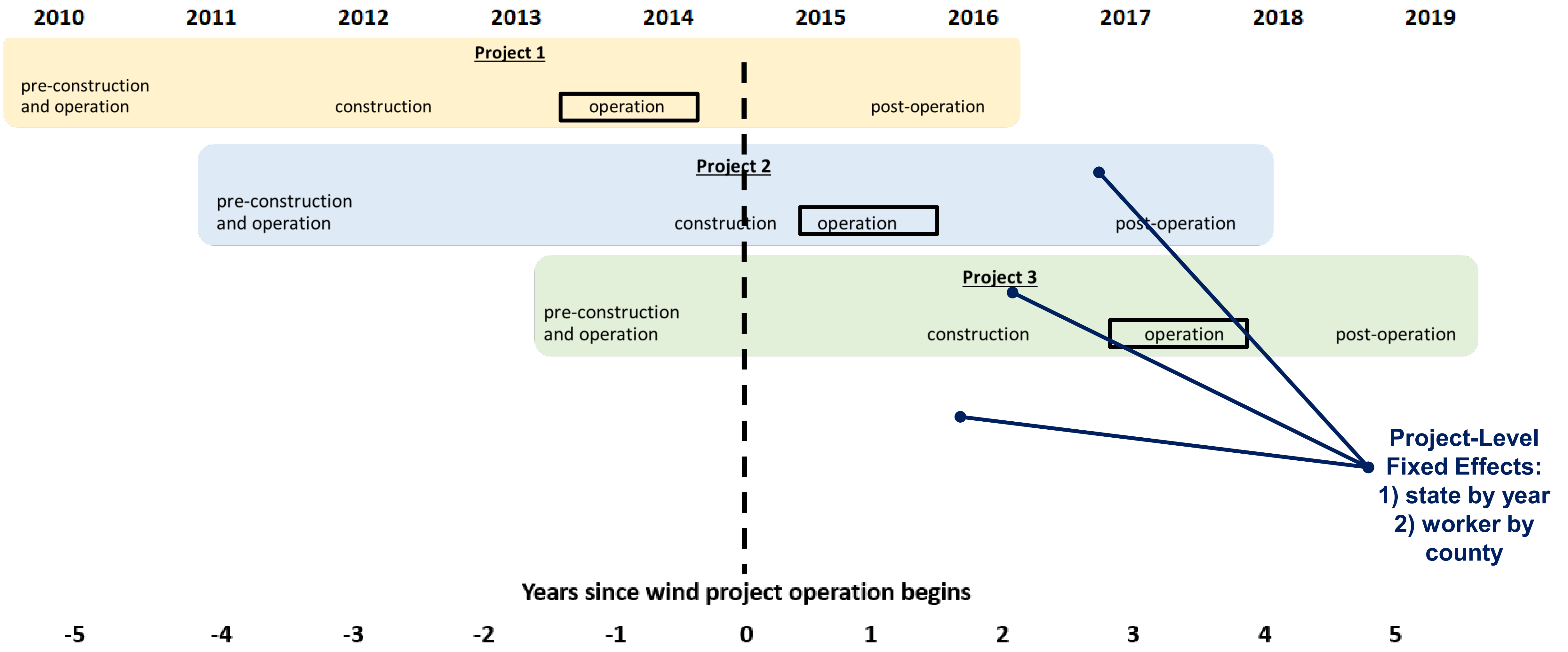
Empirical Approach

- Local Projections Difference-in-Differences (LPDID) *(Dube, Girardi, Jorda, & Taylor;2023)*
- Method can handle:
  - binary or continuous treatment
    - i.e., wind project presence/absence (i.e, binary) and capacity of wind project (i.e., continuous)
  - time-varying pre-treatment control variables including lags of time & space
    - e.g., installed wind capacity at distances beyond 20 miles
- Computationally efficient for large datasets
- Event study estimates can be considered Impulse-Response Functions
  - Average worker's employment/wage response in "year t+h" to new capacity arriving in "year t"

The difference-in-difference (DiD) model is the standard for measuring “event” impacts with high precision and minimal bias

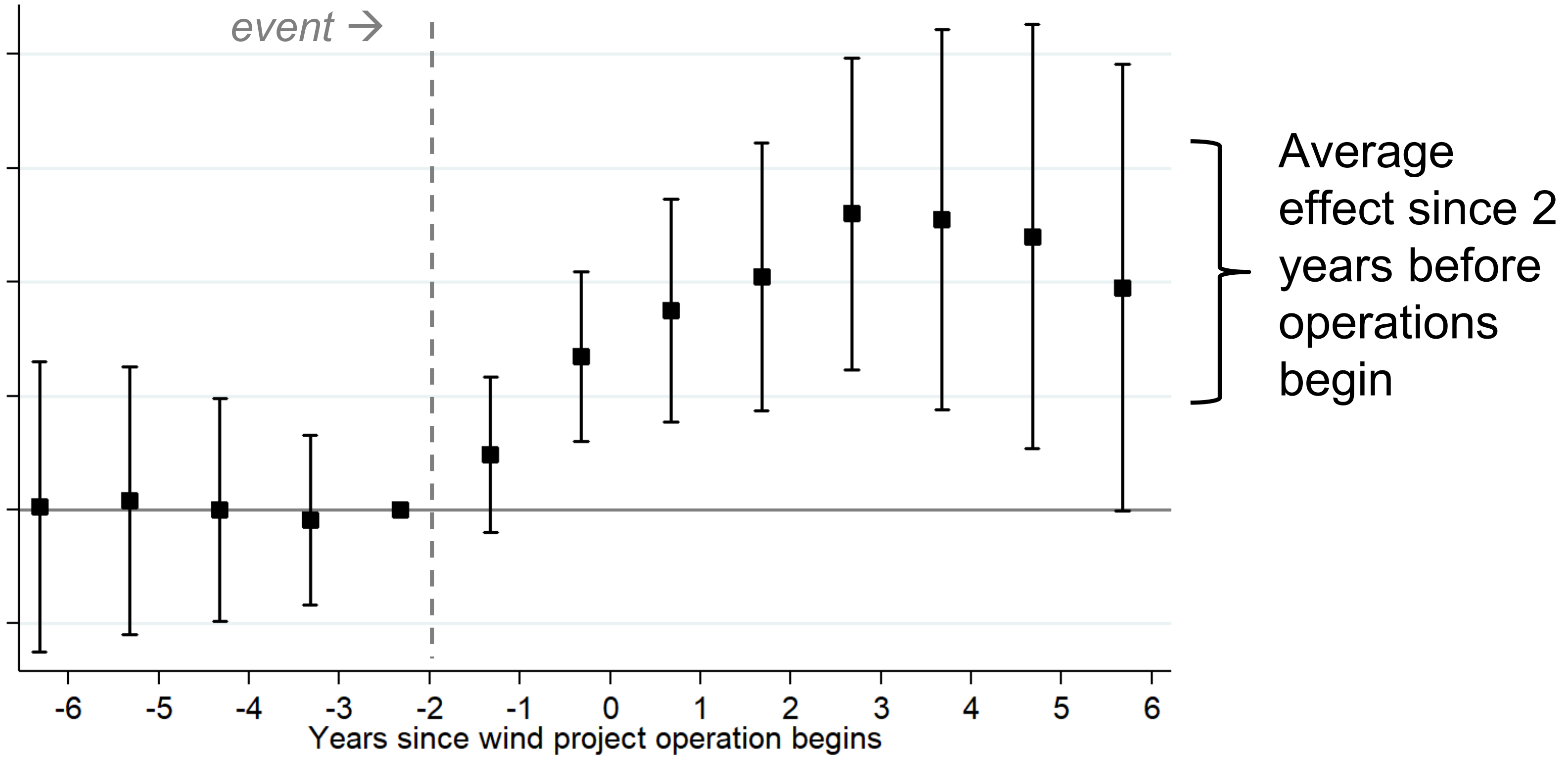


Our Empirical Strategy Uses A “Stacked” Difference-in-Difference Model with Fixed Effects



Event study results example

- The "event" is project construction but we continue to examine effects well after operations have begun
- We assume construction begins ~ 2 years before operations
- Results show effects on workers living within 20 miles of a wind project compared to all others
- Pre-trends before the "event" should be non-significant, indicating effects within 20 miles are statistically indistinguishable from others



Model

$$y_{ict} = \gamma D_{ict} + X'_{ict}\beta + \alpha_{ic} + \mu_{st} + \epsilon_{ict}$$

- D_{ict} = *binary (>10MW in 20 miles) or continuous (GW in 20 miles)*
- X_{ict} *includes spatial lags of GW at 20-40, 40-60, etc.*
  - *Control for spillovers, no causal interpretation*
- *Worker-by-county, state-by-year fixed effects* α_{ic}, μ_{st}
  - α_{ic} *control for unobserved characteristics of worker "i" while living in county "c".*
  - μ_{st} *control for unobserved state-level macroeconomic trends or state policy changes*
- *Not computationally feasible to estimate this on the full dataset or even slices/subsets of it*

Estimation of model parameters

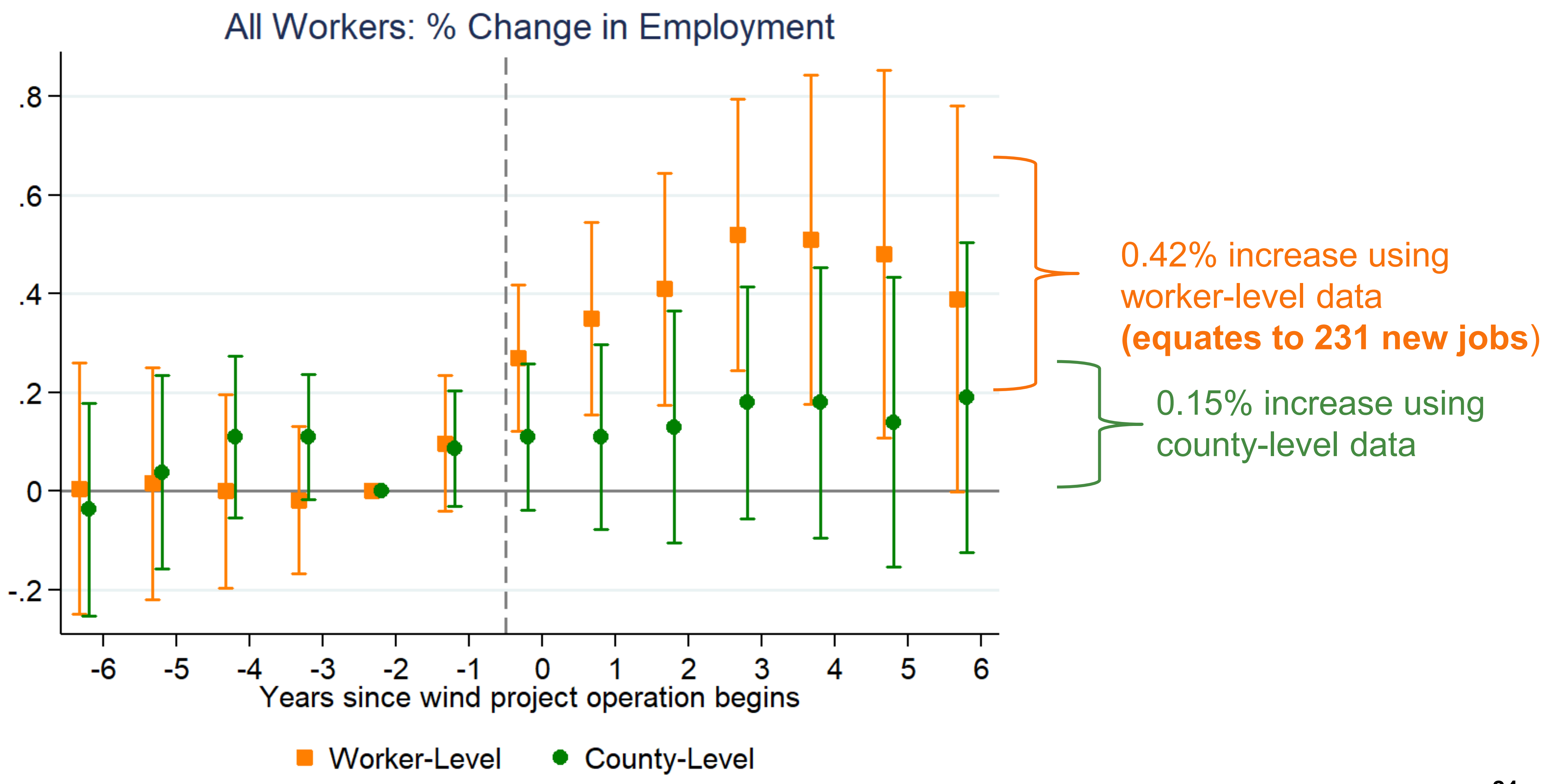
- LPDID involves running regressions with increasing long difference "h":

$$y_{ic,t+h} - y_{ict} = \delta_h \Delta D_{ict} + \Delta X'_{ict}\beta^h + \Delta\mu^h_{st} + \epsilon^h_{it}$$

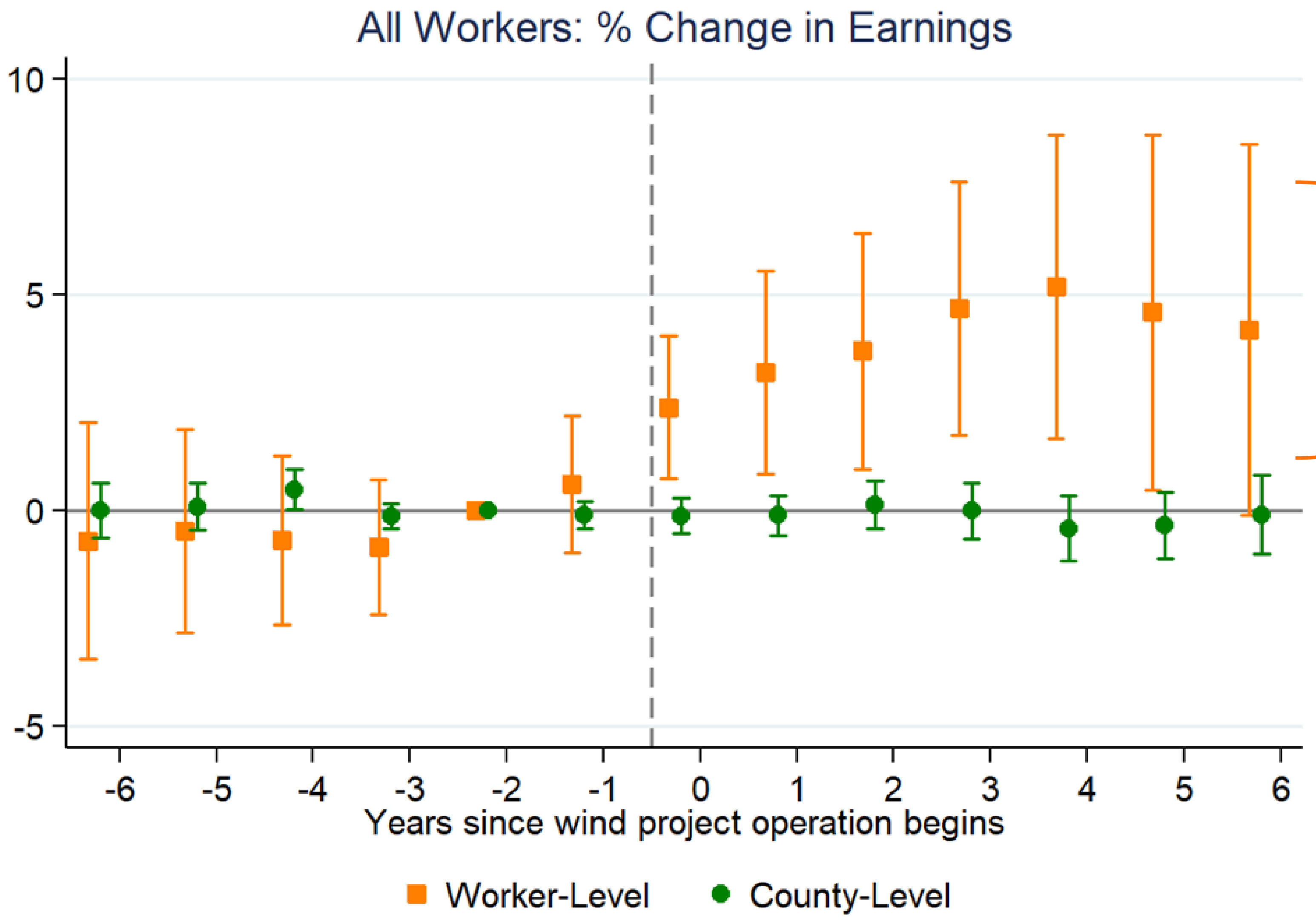
- Each regression sample includes only treated $\Delta D_{it} > 0$ and clean controls $D_{i,t+h} = 0$.
- Unit α_{ic} fixed effects are differenced out
- δ_h are event study coefficients of interest
  - averaging them gives γ, the "average treatment effect"
- Dataset still too big, so we:
  - Resample 1 million worker IDs, rerun this LPDID routine 100 times
  - Report mean/std. dev of coefficients across draws

Results

Worker- and county-level average impact on employment within 20 miles



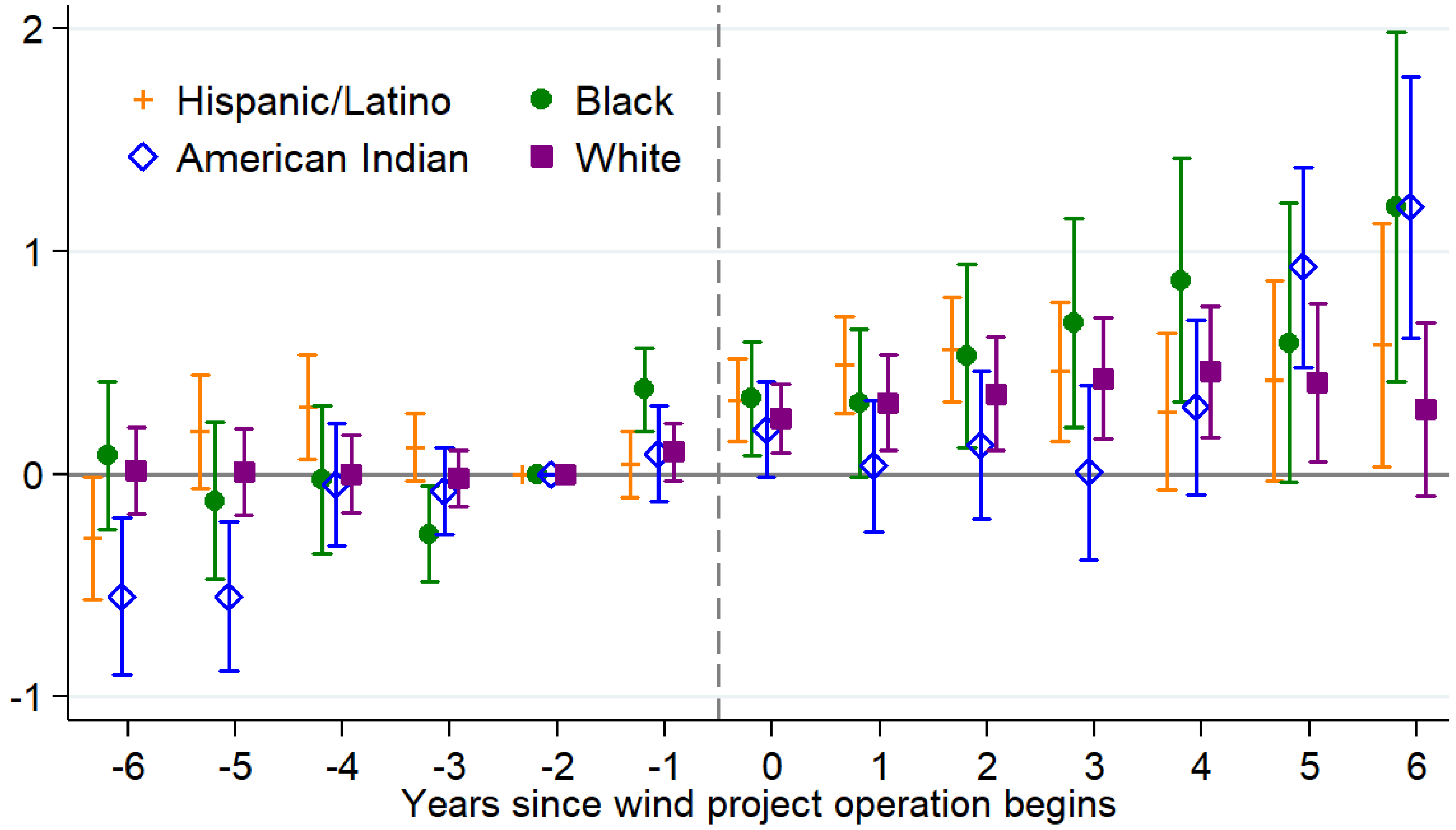
Worker- and county-level average impact on earnings within 20 miles



4% increase using worker-level data
equates to $1,270 additional annual income

non-significant change using county-level data

Worker-level % change in employment (and implied new jobs): by race and ethnicity



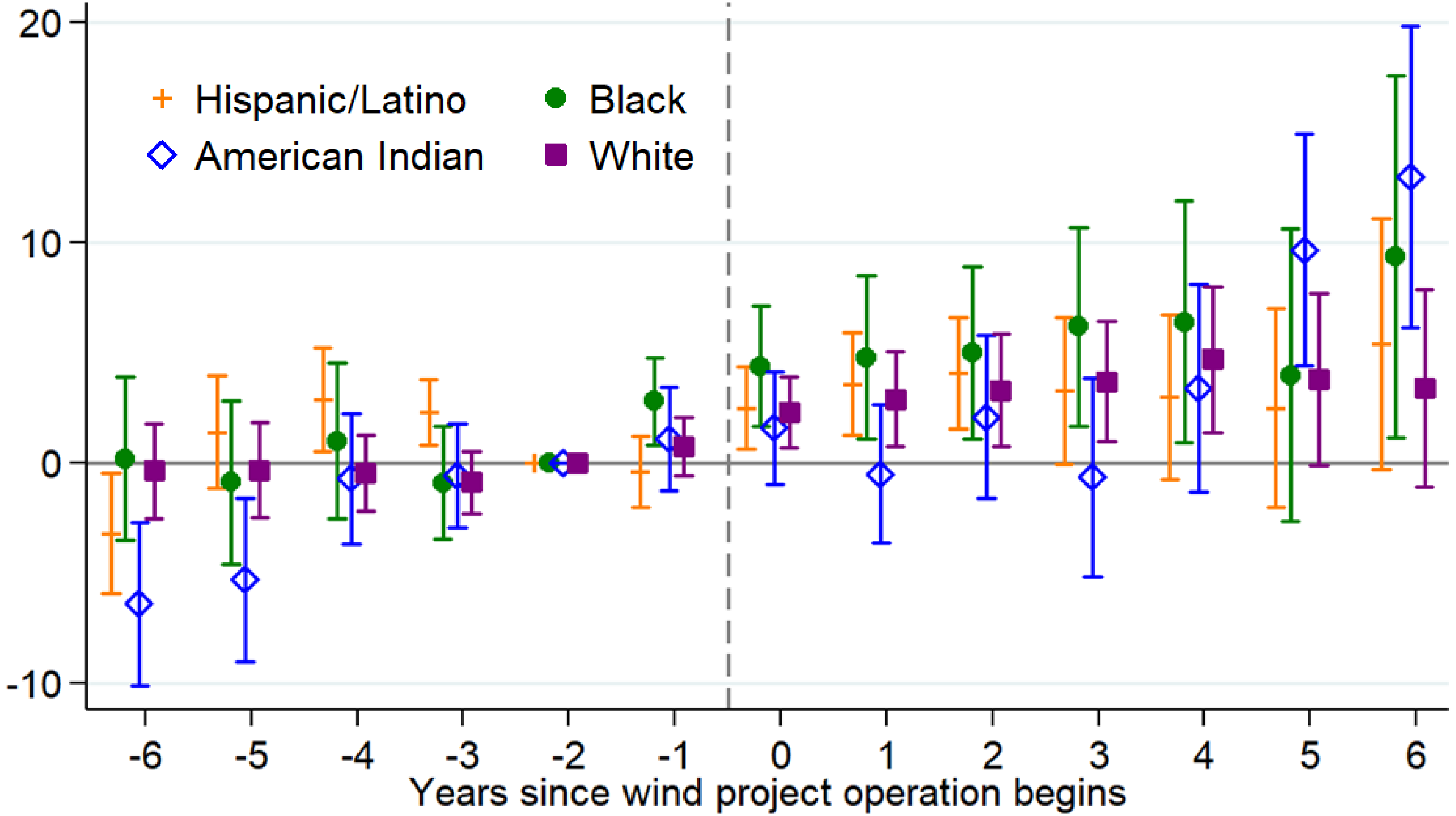
Black: 0.64% (25 jobs)

Hispanic: 0.45% (34 jobs)

A. Indian: 0.40% (4 jobs)

White: 0.36% (160 jobs)

Worker-level % change in income (and implied new earnings): by race and ethnicity



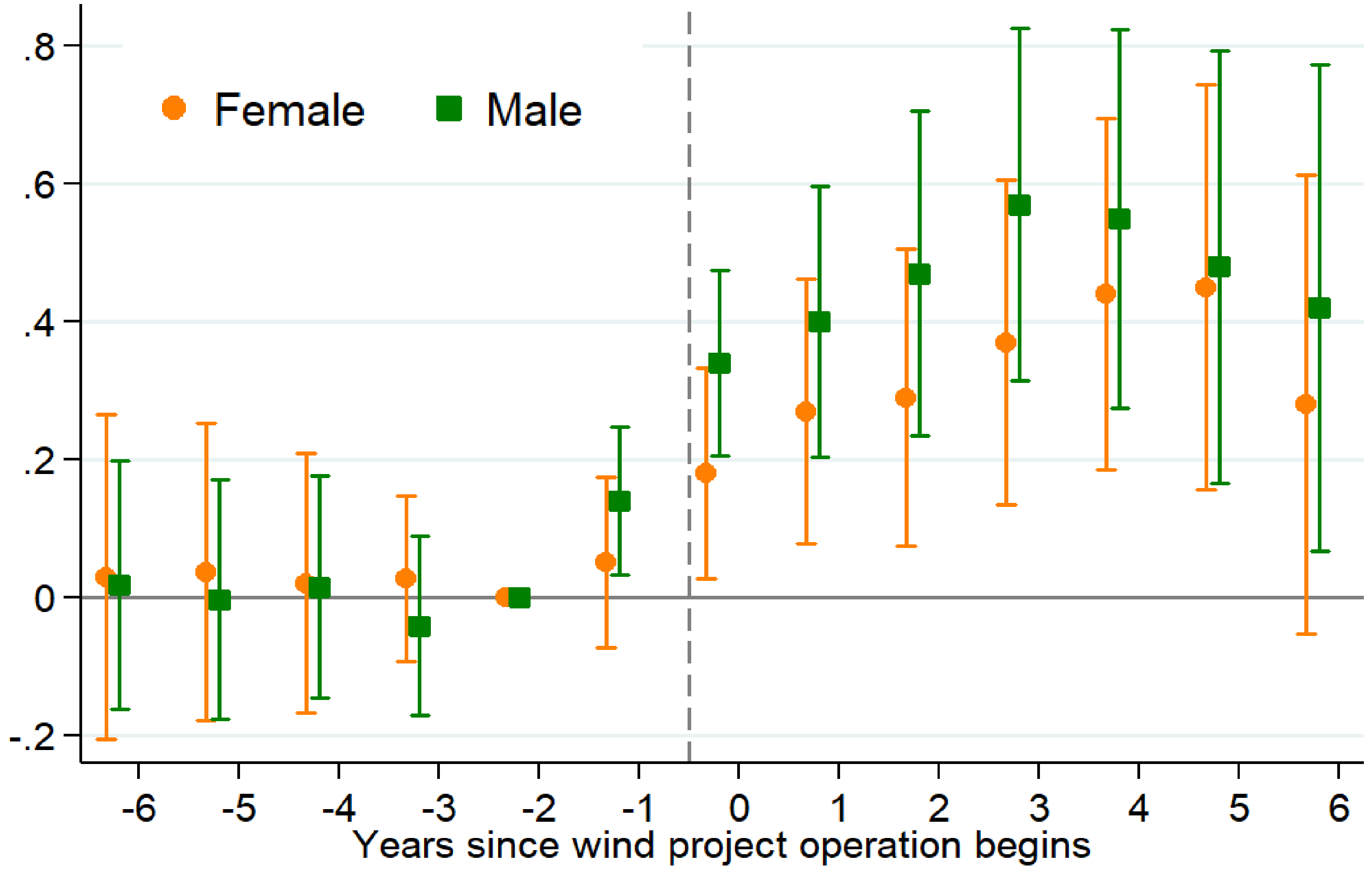
Black: 5.7% ($1,330)

A. Indian: 4.1% ($768)

Hispanic: 3.5% ($883)

White: 3.5% ($1,110)

Worker-level % change in employment (and implied new jobs): by sex



Male: 0.46% (131 jobs)

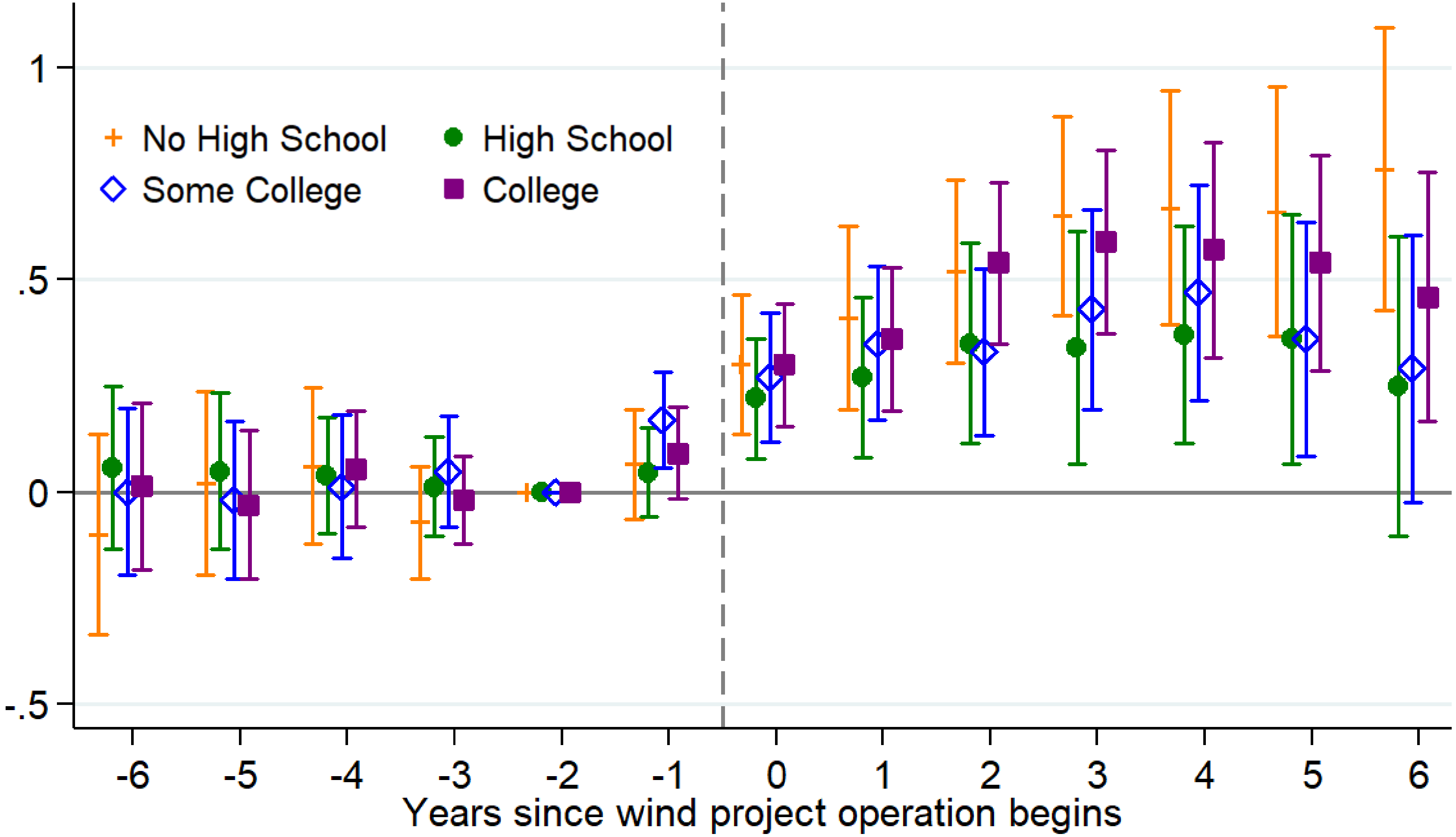
Female: 0.33% (88 jobs)

Worker-level % change in income (and implied new earnings): by sex

Male: 4.9% ($1,900)

Female: 2.9% ($710)

Worker-level % change in employment (and implied new jobs): by education



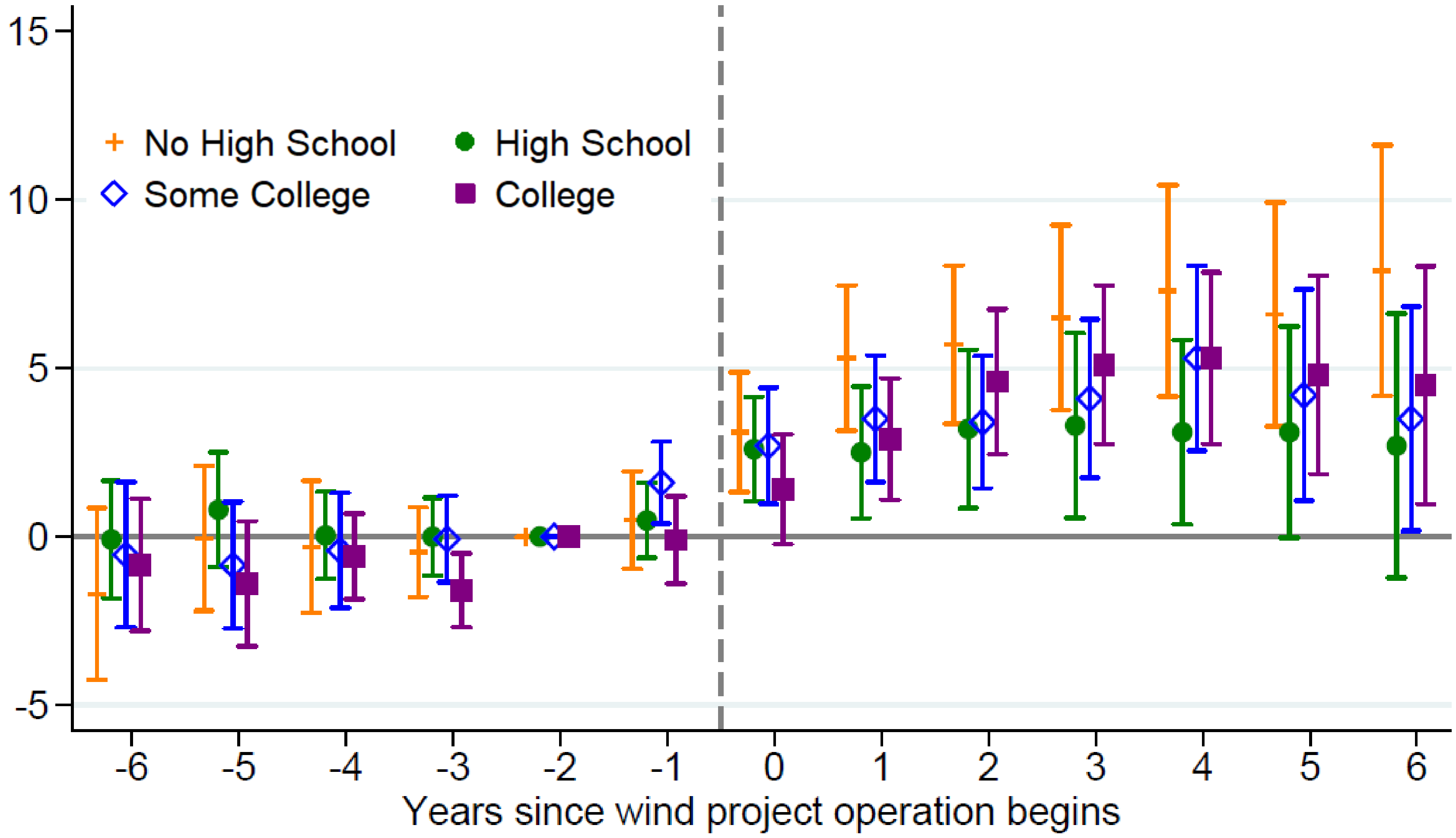
No H. School: 0.57% (45 jobs)

College: 0.48% (67 jobs)

Some College: 0.36% (65 jobs)

High School: 0.31% (47 jobs)

Worker-level % change in income (and implied new earnings): by education



No H. School: 6.0% ($1,170)

College: 4.1% ($2,020)

Some College: 3.8% ($1,130)

High School: 2.9% ($706)

Conclusion

Conclusion

- Wind installations have non-trivial employment and earnings impacts.
  - Impacts are not limited to the construction phase!
  - ~231 jobs per plant, $1,270 per person in earnings
  - This equates to 0.51 jobs per million dollars of wind investment, and
  - 0.16 dollars in local worker earnings per dollar of wind investment

- There are meaningful distortions in the magnitudes of impact estimates using county-level data as compared to worker-level estimates

- Earnings and employment is larger among
  - Male workers
  - College-educated or those without a high-school diploma
  - Black workers

Questions?

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References

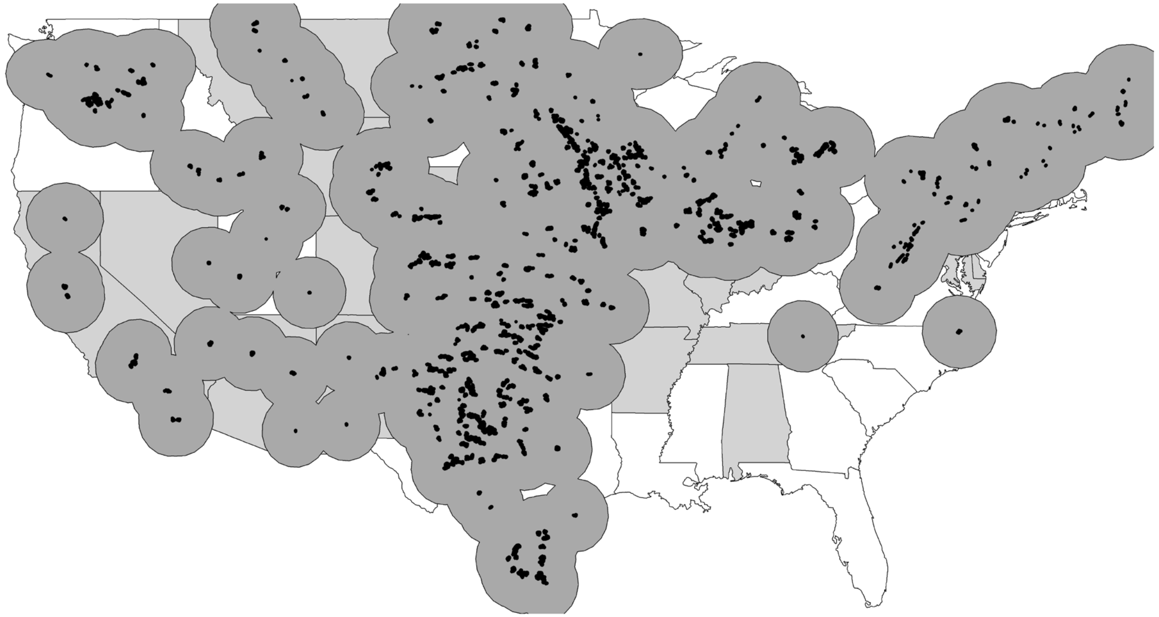
- Brown, J. P., Pender, J., Wiser, R., Lantz, E., & Hoen, B. (2012). Ex post analysis of economic impacts from wind power development in US counties. *Energy Economics*, *34*(6), 1743-1754.
- Brunner, E. J., & Schwegman, D. J. (2022). Commercial wind energy installations and local economic development: Evidence from US counties. *Energy Policy*, *165*, 112993.
- De Silva, D. G., McComb, R. P., & Schiller, A. R. (2016). What Blows in with the Wind?. *Southern Economic Journal*, *82*(3), 826-858.
- Dube, A., Girardi, D., Jorda, O., & Taylor, A. M. (2023). *A local projections approach to difference-in-differences event studies* (No. w31184). National Bureau of Economic Research.
- Feyrer, J., Mansur, E., & Sacerdote, B. (2020). Geographic dispersion of economic shocks: Evidence from the fracking revolution: Reply. *American Economic Review*, *110*(6), 1914-1920.
- Gilbert, B., Gagarin, H., & Hoen, B. (2023). *Geographic Spillovers of Wind Energy Development on Wages and Employment* (No. 2023-01).
- James, A. G., & Smith, B. (2020). Geographic dispersion of economic shocks: Evidence from the fracking revolution: Comment. *American Economic Review*, *110*(6), 1905-1913.
- Mauritzen, J. (2020). Will the locals benefit?: The effect of wind power investments on rural wages. *Energy policy*, *142*, 111489.
- Shoeib, E. A. H., Renski, H. C., & Infield, E. H. (2022). Who benefits from Renewable Electricity? The differential effect of wind power development on rural counties in the United States. *Energy Research & Social Science*, *85*, 102398.

Appendix 1: Choosing Methods

Who is "treated"? Why focus on the 20-mile radius?

- How should we measure spillovers?
- Propagation Model
  - Aggregate outcomes in rings around helicopter drop of capacity
  - Impacts significant out to 100 miles, but impacts may be overstated
    - Oil & gas: Feyrer, Mansur, Sacerdote (2017)
    - Wind: Gilbert, Gagarin, Hoen (2023)
  - Impacts may be overstated – at 100 miles, nearly everyone is treated!

100-mile radii around wind projects cover most of the sample



- Spatial Lag Model
  - Aggregate treatment (wind capacity) in rings around impacted unit (person/county)
  - Dominant approach in the literature
  - More conservative estimates of magnitudes AND spillovers
    - Oil & gas: (James & Smith, 2020) – 60 miles, smaller impacts

Spatial lag model

$$Y_{icst} = \sum_{d} \beta_d Energy_{idt} + \gamma X_{it} + \alpha_i + \mu_c + \delta_{st} + \epsilon_{i,t}$$

- Y_{icst}: *outcome for worker i in county c, state s, year t.*
- $Energy_{idt}$: *sum of wind capacity within "d" mile donut of i*
  - *"d" = 0 to 20 miles, 20 to 40 miles, 40 to 60, 60 to 80, 80 to 100*
  - *Likely endogenous – use instrumental variable for each donut ring:*
    - *(average wind speed in the ring) * (national/global trends in commodity prices and wind expansion)*
- X_{it}: *control variables*
- $\alpha_i, \mu_c, \delta_{st}$: *individual, county, state-by-year fixed effects*

Detailed instrumental variables strategy

- Energy development near an individual may be correlated with:
  - Location preferences, local economic shocks, policy affecting local labor market
- Need an instrumental variable that:
  - Varies by individual, time, and distance, and captures exogenous shocks to project development
- Intuition: when there are national/global market shocks favorable to wind development, turbines will likely be built in places with favorable wind speeds
- Strategy:
  - Divide U.S. into 200,000 hexagons ~ size of a Census block group
  - Poisson regression of wind capacity in each hexagon-year on:
    - Cubic function of average wind speed X National trend in wind capacity expansion
    - Hexagon and state-by-year fixed effects
  - Predict capacity in each hexagon-year
  - Sum predicted capacities at distance “d” from each worker “I” in each year “t”
  - This would be our instrument for each $\mathrm{Energy}_{\mathrm{idt}}$

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Spatial lag model results

- 0.1 percent random sample, data from 2000 to 2014
- Effect sizes drop off beyond the 0- to 20-mile ring
- This approach is too computationally demanding for the full sample: Main results use LPDID method and focus on impacts within 20 miles, control for capacity at greater distances

Employment

	0 to 20 m.	20 to 40 m.	40 to 60 m.	60 to 80 m.	80 to 100 m.
Panel A: Worker-Level					
Installed Capacity (GW)	2.6 (2.1)	-0.66 (0.37))	-0.33 (0.15)	-0.14 (0.086)	-0.05 (0.052)
R^2	0.20				
K-P Wald F-stat	265				
$N \cdot T$	1438000				
Panel B: County-Level					
Installed Capacity (GW)	3.8 (3.3)	1.8 (1.7))	2.1 (1.0)	1.4 (0.71)	1.0 (0.53)
R^2	0.22				
K-P Wald F-stat	2110				
$N \cdot T$	29750				

Log Earnings

	0 to 20 m.	20 to 40 m.	40 to 60 m.	60 to 80 m.	80 to 100 m.
Panel A: Worker-Level					
Installed Capacity (GW)	20 (12)	1.7 (2.4))	0.12 (0.96)	-0.27 (0.57)	-0.075 (0.34)
R^2	0.18				
K-P Wald F-stat	265				
$N \cdot T$	1438000				
Panel B: County-Level					
Installed Capacity (GW)	4.1 (2.3)	2.2 (0.84))	1.2 (0.45)	0.75 (0.31)	0.51 (0.22)
R^2	0.90				
K-P Wald F-stat	2110				
$N \cdot T$	29750				

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Appendix 2: Continuous Treatment (GW)

LPDID average treatment effects on employment for continuous treatment (GW within 20 miles)

	All	Black	Am. Ind	White	Hispanic	Female	Male	No High	High Sch.	Some Coll	College
Panel A: Worker-Level											
ATE	1.3	2.4	0.28	1.1	0.98	0.85	1.6	1.5	0.92	1.3	1.2
	(0.73)	(1.2)	(1.9)	(0.72)	(0.79)	(0.69)	(0.66)	(0.74)	(0.72)	(0.62)	(0.68)
cumulative	-0.99	-2.6	-6.0	-1.3	-0.30	-0.47	-0.99	-1.1	-0.87	-0.056	-2.2
pretrend	(1.3)	(1.7)	(1.8)	(1.1)	(1.2)	(1.2)	(1.1)	(1.2)	(1.1)	(1.3)	(0.97)
Panel B: County-Level											
ATE	0.65	-2.7	-1.9	0.71	-1.5	0.31	0.93	1.4	0.55	0.20	0.62
	(0.59)	(3.8)	(3.5)	(0.57)	(1.6)	(0.52)	(0.80)	(1.3)	(0.75)	(0.58)	(0.83)
	[-0.51,1.8]	[-10,4.7]	[-8.7,4.9]	[-0.41,1.8]	[-4.6,1.6]	[-0.71,1.3]	[-0.63,2.5]	[-1.2,4.0]	[-0.92,2.0]	[-0.93,1.33]	[-1.0,2.3]
cumulative	1.43	-10	2.7	0.83	3.2	2.2	0.72	4.4	0.57	1.0	2.4
pretrend	(1.2)	(10)	(12)	(1.1)	(4.3)	(1.4)	(1.4)	(2.7)	(1.5)	(1.5)	(1.8)

Notes: This table reports the average of event study coefficients (δ_h) in the post-treatment period as "Average Treatment Effects", for both worker-level and county-level regressions. These are estimates of γ from equation (2) in the paper. The dependent variable is the percentage of the year in which a worker had non-zero earnings. The treatment is a continuous measure of the gigawatts (GW) of capacity within 20 miles of a worker's residence, or within the county in county-level regressions. Aggregating to 20 miles around county centroids produced similar results which are omitted here. Worker level estimates are parameter averages and standard deviations across 100 model estimates from repeated random draws from the near-population. County-level estimates use the full dataset aggregated to the county level, with standard errors clustered at the county level. The cumulative pre-trends test reports the sum of event study coefficients over the pre-treatment period, and its standard deviation across draws (worker level) or analytical standard error (county level).

LPDID average treatment effects on earnings for continuous treatment (GW within 20 miles)

	All	Black	Am. Ind	White	Hispanic	Female	Male	No High	High Sch.	Some Coll	College
					Panel A: Worker-Level						
ATE	12	25	3.7	10	3.3	7.0	17	16	9.0	13	11
	(7.8)	(12)	(21)	(7.7)	(8.1)	(7.1)	(7.2)	(7.9)	(7.7)	(6.8)	(7.4)
cumulative	-19	-6.5	-71	-21	-9.6	-18	-15	-15	-8.1	-15	-37
pretrend	(14)	(18)	(21)	(12)	(12)	(12)	(11)	(13)	(12)	(13)	(10)
					Panel B: County-Level						
ATE	-1.5	1.1	-4.9	-1.7	-5.9	-1.0	-1.8	-4.9	-0.78	-1.3	-3.0
	(2.4)	(12.1)	(8.6)	(2.5)	(4.1)	(1.8)	(2.9)	(4.1)	(2.2)	(2.4)	(3.1)
	[-6.2,3.1]	[-23,25]	[-22,12]	[-6.6,3.2]	[-14,2.0]	[-4.5,2.5]	[-7.4,3.8]	[-13,3.2]	[-5.1,3.6]	[-6.0,3.3]	[-9.1,3.1]
cumulative	1.1	17	-3.1	0.88	-9.7	3.6	0.38	-9.7	1.9	0.17	5.4
pretrend	(3.6)	(37)	(24)	(3.6)	(11)	(3.7)	(4.2)	(7.1)	(4.5)	(4.9)	(4.8)

Notes: This table reports the average of event study coefficients (δ_h) in the post-treatment period as "Average Treatment Effects", for both worker-level and county-level regressions. These are estimates of γ from equation (2) in the paper. The dependent variable is the log of earnings, with the sample limited to employed workers (those with at least two quarters of non-zero earnings in a year). The treatment is a continuous measure of the gigawatts (GW) of capacity within 20 miles of a worker's residence, or within the county in county-level regressions. Aggregating to 20 miles around county centroids produced similar results which are omitted here. Worker level estimates are parameter averages and standard deviations across 100 model estimates from repeated random draws from the near-population. County-level estimates use the full dataset aggregated to the county level, with standard errors clustered at the county level. The cumulative pre-trends test reports the sum of event study coefficients over the pre-treatment period, and its standard deviation across draws (worker level) or analytical standard error (county level).