Local Economic Benefits of Wind Component Manufacturing

Maxwell Fleming[a,b,*] and Ben Gilbert[b]

[a]Critical Materials Institute, Golden, CO
[b]Colorado School of Mines, Department of Economics and Business, Golden, CO

December 22, 2023

Abstract

We estimate the causal effect of domestic wind component manufacturing activity on local household income. We combine panel data from a variety of sources in order to quantify these effects using several identification strategies, including an inverse-propensity-weighted shift-share instrumental variables framework. We find statistically and economically significant positive impacts of wind component manufacturing on local median household incomes. The size of these impacts are several times larger than the largest local earnings impacts of wind power generation facilities estimated in recent literature. We also find that the impacts are significantly smaller in counties containing disadvantaged communities, rural counties, and counties with facilities that manufacture specific component types. These heterogeneous impacts suggest that specific targeting is required for policies to achieve the current administration's Justice40 initiative goals.

Keywords: Energy transition, manufacturing, economic impacts, energy justice

*Corresponding author. Colorado School of Mines, Department of Economics and Business.
Email address: mfleming@mines.edu

1 Introduction

Understanding the labor market impacts of a transition to renewable energy sources, including how these impacts are distributed among different communities, is crucial for stakeholders who may be guiding the location and type of renewable energy investments. In particular, the Biden administration has focused significant resources on expanding both renewable energy generation and domestic renewable energy component manufacturing.[1] Another stated goal of the administration through its Justice40 Initiative is to steer the economic benefits of energy transition investments towards so-called "historically disadvantaged communities" or DACs. Manufacturing and generation are likely to have very different local economic impacts, however. Even some of the larger estimates of the local economic impacts of renewable energy generation are fairly modest in comparison to other types of economic activity [Gilbert et al., 2023a, Chan and Zhou, 2023], despite rent and royalty payments to landowners and tax payments to local jurisdictions creating potential indirect economic multipliers [Brunner and Schwegman, 2022, Castleberry and Scott Greene, 2017, Shoeib et al., 2021]. While manufacturing in general is thought to have some of the largest local economic multipliers among different industries, less is known specifically about renewable energy component manufacturing impacts, including potential heterogeneous impacts in different types of communities.

In this paper, we estimate the the causal effect of domestic wind component manufacturing activity on county-level household median income. We further evaluate whether this component manufacturing effect differs in counties that contain DACs, rural counties, or counties with specific types of manufacturing facilities. A key question is whether DACs have the local human capital, infrastructure, or networks to fully support and benefit from the specialized manufacturing facilities required for green technology industries. A related issue is whether the location of DACs is confounded with other local economic features that determine their suitability for manufacturing activity but are not determined by their status

[1] For example, the Inflation Reduction Act includes $10 billion in tax credits for domestic manufacturing facilities that produce renewable energy components, batteries, and other inputs for energy transition technologies, as well as bonus tax credits for renewable energy generation facilities using domestically-sourced inputs.

as "historically disadvantaged". Previous research on the locational decisions of domestic wind component manufacturers has suggested that wind component manufacturing (WCM) facilities are more likely to be located in counties with greater wind resources, i.e., closer to the location of development of generation facilities, and where general manufacturing is a larger share of the local economy [Kim, 2019]. However, data limitations have historically prevented more in-depth investigations of either wind component manufacturers' location decisions or their local economic impacts because most publicly available manufacturing datasets do not specifically differentiate wind component facilities.

We combine panel data from several sources in order to quantify these effects using an inverse-propensity-weighted shift-share instrumental variables framework. Data on the presence/absence, number, and type of WCM facilities per county are available from American Clean Power [2022], an industry association, in annual snapshots which we have obtained from 2018 and 2022.[2] We combine this with a state-level panel of aggregate annual revenues at WCM facilities gathered by Petridis [2022], a private industry data aggregator. We use these two sources to construct estimates of county-level annual WCM revenue, our main treatment variable. We combine this data with county-level data on household earnings from the American Community Survey. We estimate a "long difference" regression from 2018 to 2022, instrumenting for changes in county-level WCM revenue with functions of county average wind speeds and lagged shares of county GDP attributable to general manufacturing activity. We further use the Biden Administration's designation of "disadvantaged communities" under the Justice40 Initiative Council on Environmental Quality [2022] to code counties as either containing a disadvantaged community or not.

We find a strong positive relationship between WCM activity and median income in counties that have manufacturing facilities. This general finding is robust across instrumental variables approaches and robust to specifications with and without several inverse propensity weighting strategies. This relationship is significantly dampened in counties that contain DACs as defined by the Biden administration's Justice40 Initiative. Our preferred estimates indicate that for each additional 17 million dollars in WCM revenues attributable

[2]These data are unfortunately not available in an annual panel.

to a given county, the median annual income in that county rises by $1,962.95 and $6,283.61. These effects are several times larger than some of the largest earnings estimates from wind generation found in the literature; for example, Gilbert et al. [2023a] find an average earnings impact from wind generation facilities of $1,100. Our estimated WCM impacts are reduced by 27.9%-81.0% in component manufacturing counties that also contain DACs. Upon further investigating these results, we find that counties with DACs are more likely to be rural and are more likely to contain facilities that manufacture specific types of components such as electrical equipment or transmission equipment. We then re-estimate our heterogeneous treatment effects along these dimensions. We find that the dampened manufacturing earnings impacts in DACs persists even when controlling for these factors. Although earnings impacts are also smaller in rural counties and in counties with electrical and transmission equipment manufacturing facilities, estimated impacts in DAC counties also remain lower when controlling for these effects.

Our research is most closely related to the emerging literature on the quality of "green jobs" [Curtis and Marinescu, 2022, 2023, Colmer et al.] as well as the more mature literature on the local economic impacts of energy development [Gilbert et al., 2023a,b, Chan and Zhou, 2023, Brunner and Schwegman, 2022, James and Smith, 2020]. We differ from the green jobs literature in that we don't focus specifically on direct effects on employment at component manufacturing facilities, but rather on the overall local economic impact on median incomes. In that sense our work is closer to the larger 'economic multiplier' literature for manufacturing, which focuses on the spillover effects of additional jobs created from traded and non-traded jobs (Moretti [2010], Nguyen and Soh [2017]).

Osman and Kemeny [2022] identifies five general weaknesses in the economic multiplier literature; this work improves on three of them. First, sweeping definitions of manufacturing, generally relying on 2-digit NAICS codes; we focus specifically on the WCM industry, which is more granular than 6-digit NAICS codes[3]. Second, the multiplier literature suffers from location-specific ommitted variables; we begin an investigation into the location-specific characteristics such as rurality and manufacturing facility types that prevent DACs

[3]NAICS code 333611 (Turbine and Turbine Generator Set Units Manufacturing) includes both wind and gas turbines.

from achieving the same level of benefits from WCM as non-DAC counties. Third, the multiplier literature focuses primarily on the largest cities, while we disaggregate the data to the county level and specifically investigate rural communities.

The paper proceeds as follows: section 2 describes the empirical model, section 3 describes our data sources, section 4 presents empirical results, and section 5 concludes.

2 Methods

2.1 Empirical Model

Our empirical model for the heterogeneous relationship between WCM revenues in county c in year t (Rev_{ct}) and median household incomes (Inc_{ct}), depending on DAC status, is

$$Inc_{ct} = \beta_1 Rev_{ct} + \beta_2 Rev_{ct} \times DAC_c + \alpha_c + \eta_{st} + \epsilon_{ct} \tag{1}$$

where DAC_c is a binary indicator for whether or not county c contains DAC communities,[4] α_c is a time-invariant county fixed effect, and η_{st} are state-by-year fixed effects to account for state-level macroeconomic trends that might be correlated with local WCM activity.

The estimation of equation (1) is hampered by data limitations and the endogeneity of changes in local WCM activity over time, however. We discuss the data in more detail in section 3, but briefly stated, a county-level annual panel of WCM activity such as revenues is not publicly available, to our knowledge. We were able to obtain aggregate state-level annual revenues at WCM facilities (Rev_{st}), as well as two snapshots of counts of the number of WCM facilities in each county in 2018 and 2022. We use these facility counts to construct the binary variable $Ever_c$ to indicate whether county c ever has a WCM facility, as well as $Share_c$ which is the fraction of the state's WCM facilities located in county c. The interaction between Rev_{st} and $Ever_c$ capture the effects of variation in state-level WCM revenues on income in counties that have WCM facilities. The interaction between Rev_{st} and $Share_c$ captures the effect of state-level revenues attributable to county c, under the

[4]We also estimate specifications using a continuous variable for the share of the county's population residing in DACs.

assumption that county-level revenues are roughly proportional to the fraction of the state's facilities in that county. Although both of these interactions are imperfect measures of county-level annual WCM revenues, both improve upon the current state of knowledge. To the extent that measurement error from these proxies is approximately classical, our instrumental variables approach described below will help remove some of the associated bias.

As we also do not have annual county-level data on WCM facility counts, we will focus on the long difference:

$$\Delta Inc_c = \beta_0 + \beta_1 \Delta Rev_s + \beta_2 \Delta Rev_s * Ever_c + \beta_3 \Delta Rev_s * Ever_c * DAC_c + \epsilon_c \qquad (2)$$

where in some specifications we include state fixed effects to capture the long difference in state-by-year fixed effects. The difference is taken between 2018 and 2021. Interacting the Rev_s and $Ever_c$ measures how the presence of manufacturing in a county allows households to capture benefits from WCM revenues generated in their state. Interacting the three variables measures how household incomes in WCM counties with DACs differ from those in a non-DAC county with WCM.

Because the DAC screening tool was created in 2022, it's not possible to identify DACs prior to the sample period for WCM facilities and household income, leading to potential endogeneity. Although populations may fluctuate over time, we think it is reasonable to assume that for most counties the binary presence of DACs varies much less over time than the percent of the population living in the DAC because of the stability of place-based characteristics through time. For this reason, we restrict our models to D_c, binary presence of DAC in county c, rather than a continuous variable for percent living in DACs which would vary more over time. However, we have estimated models using the continuous measure of percent of the county population living in DACs and our results are generally robust to either specification.

There is still likely endogeneity in our other right-hand side variables. Greater state level WCM revenues could be linked to more robust state commerce which households capture unrelated to wind components. WCM facilities are concentrated in the rust belt (see fig. 3) where the decline of other manufacturing could lead to lower median household income. WCM firms could also select communities in which to expand their facilities that are already experiencing local economic booms unobserved to the econometrician.

For these reasons, we IV for the endogenous treatment variables using first stage regressions of the form:

$$X^i_{sc} = \alpha_{i0} + \alpha_{i1} wspeed_c * DAC_c + \alpha_{i2} wspeed^2_c * DAC_c + \\ \alpha_{i3} wspeed^3_c * DAC_c + \alpha_{i4} Mfrac_c + \mu_s + \epsilon_i \quad (3)$$

where $X^i_{s,c}$ includes the endogenous variables ΔRev_s, $\Delta Rev_s * Ever_c$, and $\Delta Rev_s * Ever_c * DAC_c$.

We construct the IV using a quadratic function of average windspeed in county c ($wspeed_c$) interacted with DAC status DAC_c. We also include the 2012 share of county GDP in $Mfrac_c$. The intuition behind these instruments is that $wspeed_c$ measures the amount of wind resource available in county c, which does not directly impact income but leads to more local wind power development and more potential WCM. The lag in $Mfrac_c$ is long enough that it shouldn't directly impact current income, but a stronger existing manufacturing base in a county makes it more plausible for WCM to be cited there. DAC_c is not an instrument itself, but since it is not endogenous for the resons cited above, it is interacted with the instruments. An alternate specification could interact DAC_c and $Mfrac_c$.

2.2 SSIV

We augment the above IV approach using the anticipated phaseout date of the production tax credit at the end of 2020, which caused a sharp increase as investors pushed to start projects before the end of the year Petridis [2022] (see fig. 1). This resulted in a sharp increase in aggregate nationwide WCM revenues. We expand the model to exploit this shock with a shift-share instrument. We follow Autor et al. [2013], who use the increase in Chinese

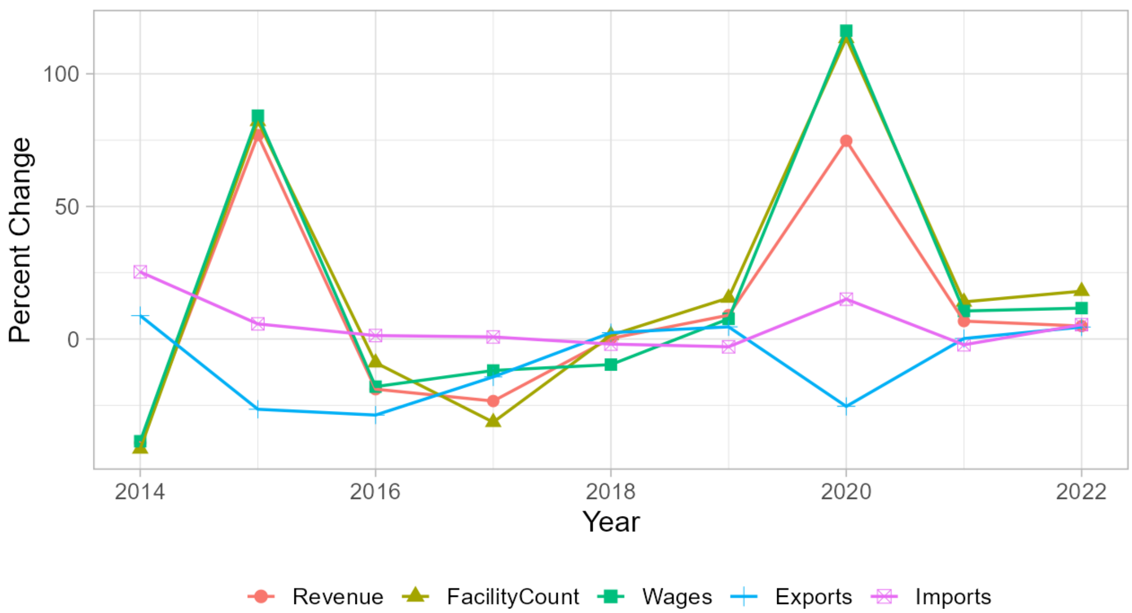

Figure 1: Percent change in revenue, facility count, wages, exports, and imports 2014-2022. We exploit the large increase between 2018 and 2021 for the shift-share IV. Source: IBISWorld

imports to other countries as an exogenous source of variation to measure the impact of competition with China on US manufacturing. In our case, measuring the shock at the national level is a useful source of variation as it impacted state manufacturing revenues, but is unlikely to have influenced median household income at the county level except through local WCM activity. We add the following shift-share instrument to equation (3):

$$z_c = \Delta g_{US} * Mfrac_c * Ever_c \tag{4}$$

where z_c is predicted growth of WCM in county c, Δg_{US} is the change in nationwide WCM revenues in the US between 2018-2021, $Mfrac_c$ is the lagged general manufacturing share of county GDP in 2012, and $Ever_c$ is the binary presence of manufacturing in county c at any point in the sample period. This creates an instrument exploiting the aggregate shock which is sensitive to the presence of general manufacturing at the local level, and specifically targets counties with WCM.

2.3 Inverse Probability of Treatment Weighting

In addition to our IV approach, we further introduce inverse probability of treatment weighting (IPTW) in order to address the fact that counties with and without WCM may be systematically different, leading to selection bias between the treatment (WCM) and control (non WCM) counties. We use county average wind speed and the lagged (2012) presence of overall manufacturing in the county as factors that would make certain counties more or less likely to be chosen for WCM facilities. As Kim [2019] finds, WCM facilities are more likely to be located in counties nearby development of wind generation projects, so the local wind resource is relevant for WCM siting. Further, counties with more general manufacturing are more likely to have labor supply and infrastructure required for WCM. The IPTW approach weights each county so that we make comparisons between counties that are most similar, aside from the presence of WCM.

We implement IPTW with two steps. First, we calculate propensity scores using logit function:

$$Pr(Ever_c = 1|x_c) = \frac{e^{x_c\beta}}{1 + e^{x_c\beta}} \tag{5}$$

where x_c includes 2012 manufacturing revenues as a percent of GDP, 2012 counts of general manufacturing facilities, and county average wind speed. We then re-weight counties with the estimated propensity score prior to estimating our IV models:

$$p_c = \frac{Rev_s * Ever_c}{Pr(Ever_c = 1|x_c)} \tag{6}$$

Figure 2 shows the propensity score assigned to treated and untreated units for a series of specifications for x_c. Positivity and overlap of scores of treated and untreated counties ($Ever_c = 1$ or 0) is achieved in all cases. The four plots in the middle and right columns of this figure are used in our model specifications.

3 Data

We combine several datasets to construct the panel for our empirical model. Our outcome variable ΔInc_c in all models is the long difference in median household income in dollars

Figure 2: Histogram of propensity scores for 6 logistic regressions. The title indicates where the following variables are used for x_c in eq. (5) & (6): Manufacturing 1 indicates general manufacturing counts, Manufacturing 2 indicates the fraction of manufacturing revenues as a percent of county GDP, Windspeed indicates a quadratic function of county windspeed, commas indicate these variables are added in the logistic regression, asterisks indicate they are interacted. These plots are all trimmed to remove units with a score of less than 0.1 or greater than 0.9. The four plots in the middle and right columns of this figure are used in our model specifications.

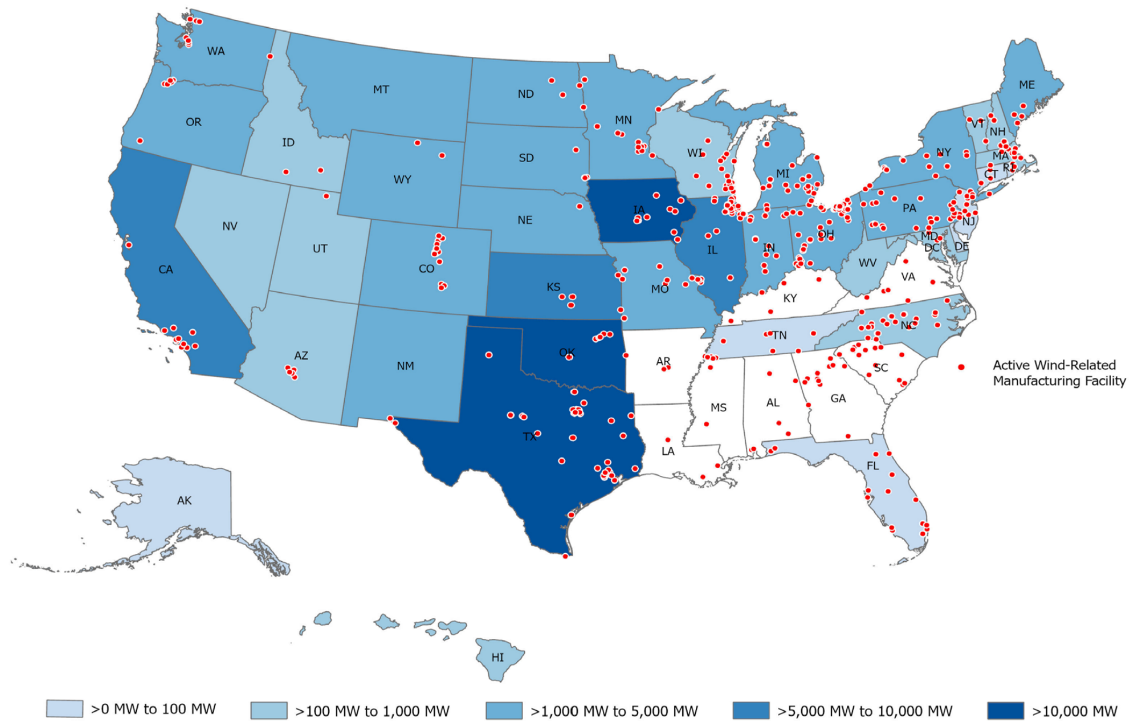

Figure 3: Manufacturing facilities and installed wind power capacity.
Source: American Clean Power

between 2018 and 2021, retrieved from US Census Bureau [2016-2022]. We obtain facility locations, counts, and types from American Clean Power [2022] which we used to construct the $Ever_c$ variable for the binary presence of manufacturing in county c (see fig. 3). The current 2022 database provided the counts for 2022, and we obtained a previous copy from 2018. Unfortunately American Clean Power does not maintain an annual historical database, nor does any other organization maintain exhaustive historical databases with this information, to our knowledge. This provided data on either side of the 2020 shock necessary to construct the shift-share instrument and long difference. We combine this with state-level aggregate annual revenues at WCM facilities gathered by Petridis [2022], which also includes county-level facility counts which were used to verify the information in American Clean Power [2022]. We used these annual revenues for the Rev_s variable.

The variables constructed using the American Clean Power [2022] and Petridis [2022] datasets are the basis for the two types of specifications we use to specify our model. In the levels specification, the variable ΔRev_s is the difference in state WCM revenues for state s

in millions of dollars between 2021 and 2018. The coefficients on this variable for dependent variable ΔInc_c should be interpreted as the change in median household income resulting from a \$1 million change in state-level WCM revenues. We interact ΔRev_s with $Ever_c$, the presence of WCM in county c at any point in our sample period. The interpretation of this coefficient is the *additional* impact of a \$1 million change state-level manufacturing revenues in counties with WCM, relative to counties with no WCM. This allows us to isolate the direct impact of within-county manufacturing.

In the shares specification, we approximate the share of state revenues attributable to county c:

$$RevShare_{c,t} = \frac{FC_{c,t}}{\sum_{c \in s} FC_{cs,t}} * Rev_{st} \tag{7}$$

Where FC_c is the facility count in county c at time t, and $FC_{cs,t}$ are the facility counts for all counties in the same state. We calculate $\Delta RevShare_c$ as the long difference between 2021 and 2018. The coefficients on $\Delta RevShare_c$ should be interpreted as the change in median household income resulting from a \$1 million change in county c's share of state s's WCM revenues. Changes in this variable occur from either a change in state-level WCM revenue, or changes in WCM facilities in the county.

We further use the Biden administration's designation of "disadvantaged communities" under the Justice40 Initiative [Council on Environmental Quality, 2022] to code counties as either containing a disadvantaged community or not. The mapping of these counties is shown in fig. 4. In both types of specifications, we add an interaction term with binary variable DAC_c, the presence of DACs in county c. The interpretation of these interaction terms is the increase (or decrease) median household income that counties with WCM *and DACs in them* derive from a \$1 million change in state (or county share of state) WCM revenues, relative to counties with WCM but no DACs. We construct a similar interaction term with binary variable $Rural_c$ to identify rural counties as defined by US Census Bureau [2010] in later specifications of the SSIV.

We retrieved county-level GDP from Bureau of Economic Analysis [2021] and county-level general manufacturing revenues from US Census Bureau [2021], both from 2012, to

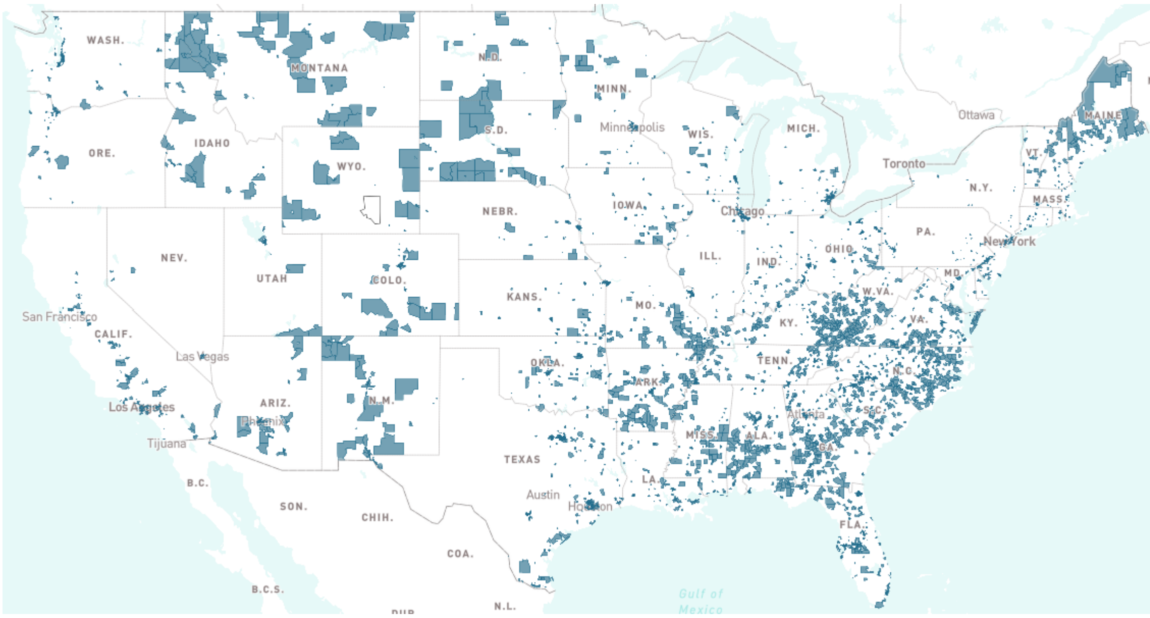

Figure 4: 255 of 339 wind manufacturing counties have DACs within them.
Source: Argonne National Labs - Energy Justice Mapping Tool

construct the lagged general manufacturing share of county GDP, variable $Mfrac_c$. We used this variable to construct our IV, SSIV, and in some specifications of the logit function to calculate propensity scores. We obtained county-level average wind speed data from the Wind Integration National Dataset Toolkit [Draxl et al., 2015], which we used in the IVs and propensity scores. This gives us a useful reference for the wind resource potential in a county.

The standard deviations (sd dev.) of the variables in table 1 help provide a reference point for the financial interpretation of our coefficients on median household incomes:

Table 1: Summary Statistics

Variable	sd dev.	Mean
DeltaInc_c	3954.419	6878.755
Revenue_s	219.6677	207.3755
DeltaRev_s	302.4375	248.6649
RevShare_c	4.5484	1.0071
DeltaRevShare_c	17.1252	2.6275
DACPop	0.1974	0.111

4 Empirical Results

4.1 IV Results

Table 2 presents the result for our basic long-difference IV specification. The standard deviations in table 1 will be helpful in interpreting these results. The results in columns 1 and 2 use the share specifications for county-level WCM revenue, and columns 3 through 5 use the levels specifications. Multiplying the coefficients by the standard deviation for the relevant variable helps understand relative effects. The results in column 1 indicate a \$1,383.84 increase in median household income from a one standard deviation increase in $\Delta RevShare_c$ of \$17.125 million. Adding the DAC_c interaction term increases benefits to \$3,599.16 for non-DAC counties and decreases the benefit to \$685.19 for counties with DACs, a reduction of 81.0%. For the specification in column 3, the impact of a one standard deviation increase in statewide ΔRev_s of \$302.44 million on median household income is \$2,945.46. Adding the $Ever_c$ interaction in column 4 shows that households in counties with WCM in them derive an additional \$1,873.92 per standard deviation increase in statewide WCM revenues, relative to those without. Adding the DAC_c interaction term increases the benefit to WCM counties to \$4,501.52, and shows that households in counties with DACs derive only \$2,528.10 from WCM, a reduction of 43.8%.

4.2 Comparison with and without IPTW

Table 3 shows the difference in models 2 and 5 from Table 2 when calculated without IPTW. For the shares specifications in columns 1 and 2, we use the propensity score based on interacting general manufacturing counts with the quadratic windspeed function. This increases the magnitude of the coefficient on $\Delta RevShare_c$, leading to statistical significance given a similar standard error. It also slightly decreases the magnitude of the DAC_c interaction term. This suggests that the benefits to WCM counties are larger when compared with non-WCM counties with similarly robust local manufacturing sector and wind resource potential.

For the levels specifications in columns 3 and 4, we use IPTW calculated with lagged

	Dependent variable:				
	DeltaInc				
	(1)	(2)	(3)	(4)	(5)
$\Delta RevShare_c$	80.808**	210.170***			
	(34.456)	(67.300)			
$\Delta RevShare_c * DAC_c$		−170.159***			
		(63.528)			
ΔRev_s			9.739***	7.275***	6.209***
			(0.521)	(1.326)	(1.460)
$\Delta Rev_s * Ever_c$				6.196**	14.884***
				(3.050)	(4.041)
$\Delta Rev_s * Ever_c * DAC_c$					−6.525***
					(1.760)
Constant			4,435.473***	4,245.322***	3,857.180***
			(31.869)	(99.166)	(149.741)
Pscore					
Trimmed Manufacturing 1, Wspeed	Yes	Yes	No	No	No
Manufacturing 2*Windspeed	No	No	Yes	Yes	Yes
Fixed Effects					
State	Yes	Yes	No	No	No
Observations	620	620	2,539	2,539	2,539
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 2: IV Results. Models 1-2 are constructed using the shares specification, and models 3-5 are constructed using the levels specification. The median households in counties with manufacturing derive between \$3,599.16 (model 2) and \$4,501.47 (model 5) from a one standard-deviation in state WCM manufacturing revenues. Households in in DAC manufacturing counties derive between 43.8%-81.0% less in median household income.

	Dependent variable:			
	DeltaInc			
	(1)	(2)	(3)	(4)
$\Delta RevShare_c$	92.578	210.170***		
	(67.892)	(67.300)		
$\Delta RevShare_c * DAC_c$	−181.022**	−170.159***		
	(91.438)	(63.528)		
ΔRev_s			−6.181***	6.209***
			(2.204)	(1.460)
$\Delta Rev_s * Ever_c$			43.874***	14.884***
			(8.016)	(4.041)
$\Delta Rev_s * Ever_c * DAC_c$			−28.272***	−6.525***
			(6.359)	(1.760)
Constant			7,249.048***	3,857.180***
			(409.619)	(149.741)
Pscore				
Manufacturing 2*Wspeed	No	No	No	Yes
Trimmed Manufacturing 1, Wspeed	No	Yes	No	No
Fixed Effects				
State	Yes	Yes	No	No
Observations	2,539	620	2,539	2,539
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 3: Inverse propensity score weighting results for models 2 and 4 in table 2. The shares and levels specifications result in contrasting coefficients without IPTW. With two different IPTW strategies, the interpretation of the two specifications as discussed above roughly converge, demonstrating that our IV and IPTW strategies are robust to multiple specifications.

manufacturing share of GDP and local windspeed. The differences between these are more pronounced, with the sign of ΔRev_s flipping, and the magnitudes on the interaction terms varying more. In the levels specifications, WCM counties would have an overstated advantage when selection bias results in control counties with less comparable levels of local manufacturing and WRP. However, models 2 and 4 roughly converge when interpreted with their respective standard errors, given contrasting regressors and IPTW strategies. This shows that our IV and propensity score strategies are robust to multiple specifications.

4.3 Comparison with and without SSIV

	Dependent variable:			
	DeltaInc			
	(1)	(2)	(3)	(4)
$\Delta RevShare_c$	210.170***	114.625***		
	(67.300)	(41.927)		
$\Delta RevShare_c * DAC_c$	−170.159***	−130.850***		
	(63.528)	(45.298)		
ΔRev_s			6.209***	7.862***
			(1.460)	(0.909)
$\Delta Rev_s * Ever_c$			14.884***	10.081***
			(4.041)	(2.343)
$\Delta Rev_s * Ever_c * DAC_c$			−6.525***	−5.682***
			(1.760)	(1.582)
Constant			3,857.180***	4,017.390***
			(149.741)	(99.652)
SSIV	No	Yes	No	Yes
Pscore				
Trimmed Wind	Yes	Yes	No	No
Manufacturing 2*Windspeed	No	No	Yes	Yes
Fixed Effects				
State	Yes	Yes	No	No
Observations	620	620	2,539	2,539
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4: SSIV results.

Table 4 presents results incorporating the shift-share instrument into the model. Columns 1 and 3 include only the instruments specified in (3), while columns 2 and 4 add the shift-share instrument specified in (4). In the models with SSIV, the magnitude of all coefficients for counties with manufacturing and/or DACs is diminished relative to the models without SSIV in table 2. This suggests that the basic IV model may be overstating the effects.

Using the standard deviations from table 1, the coefficients for $\Delta RevShare_c$ in column 2 result in an increase in median household income of \$1,962.95 which is completely counteracted by the DAC interaction term. The coefficients in column 4 imply that a one standard deviation increase in $\Delta Rev_s * Ever_c$ result in a \$3,048.87 increase in median household income, but these benefits are 56.36% lower for DACs. The range in benefits between the levels and shares specifications are smaller in the SSIV results in Table 4 than in the basic IV results in Table 2. The reduction in benefits for DACs in the SSIV results in column 4 of Table 4 is similar to table 2. Column 2 of Table 4 is our only specification that displays a complete elimination of benefits for DACs, which could be overstated.

4.4 DACs, Facility Types, and Rural Counties

This section explores potential mechanisms by which the economic impact of WCM revenues may be lower in DACs. Figure 5 shows the facility counts for specific product classifications, grouped by the percent of the county population residing in a DAC (i.e., grouped by the DACPop variable from Table 1). There are two key takeaways from Figure 5. First, WCM facilities are generally located in counties with less than 25% of their populations living in DACs. Second, the facility types that are located in counties with a high share of their population living in DACs are mainly producing electrical and transmission equipment (which are also the most abundant facility types in general). Figure 6 presents the same counts, divided by million county residents. Here again we see that the population-normalized facility counts for electrical and transmission equipment, and to a lesser extent raw materials, are much higher in counties with the majority of their residents living in DACs. This figure uncovers a stylized fact that there are a higher concentration of electrical, raw materials, and transmission facilities in DACs relative to the size of their populations. This stylized fact suggests that these high DAC counties with specific types of WCM facilities also have low population density. Inspection of the map of DAC communities in Figure 4 also suggests that DACs are often in rural counties.

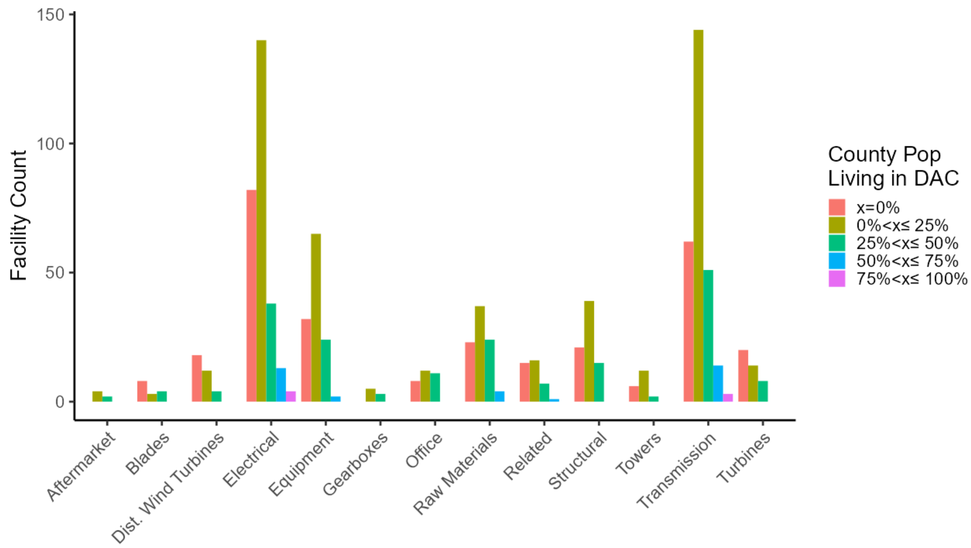

Figure 5: Counts of manufacturing facility categories by DAC population. In absolute terms, manufacturing facilities for most categories are located primarily in counties with less than 25% of their populations living in DACs. Counties with 0% DAC population are separated as they are the largest category. See B for what components are included in each category.

These observations raise two questions about whether our DAC findings could be explained by other features of the local economy. First, do certain WCM facility types that happen to be located in DACs simply generate smaller economic impacts because of the type of manufacturing rather than their location in a DAC? Second, are rural counties less able to capture manufacturing benefits than their more urban counterparts, again regardless of their DAC status?

In order to investigate these questions, we add two more binary variables to the SSIV specification. Table 5 includes interaction terms with $Facility_c$, which indicates the presence of electrical, raw materials, or transmission manufacturing in a county, and $Rural_c$, which indicates that more than 50% of the county population lives in rural areas as defined by US Census Bureau [2010].

By comparing columns 2 and 4 to column 3 in Table 5, we can see that the point estimates of the interactions with $Facility_c$ and $Rural_c$ are negative and larger in magnitude than the interaction with DAC_c. This finding is maintained in the specification in column 5 which includes all three interactions. This finding indicates that local economic impacts

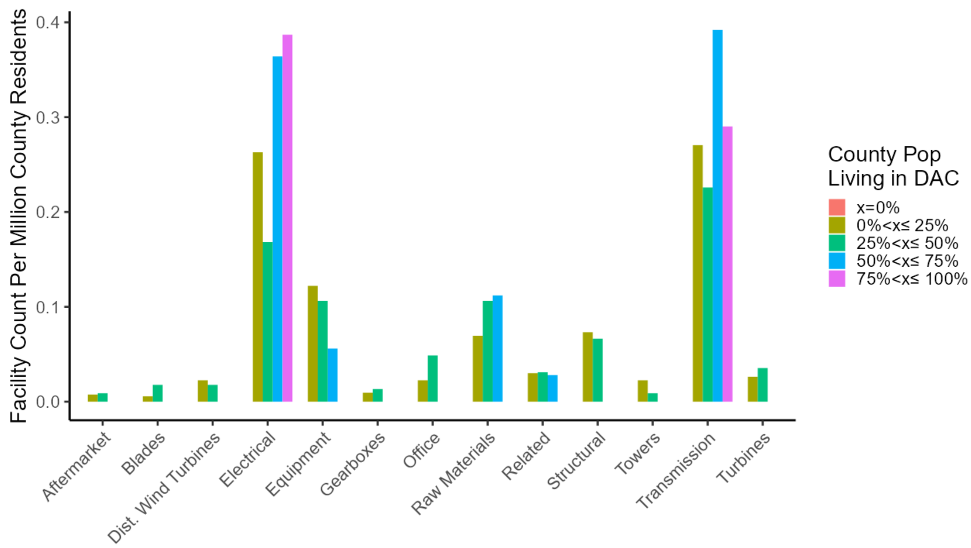

Figure 6: Manufacturing facility categories per million county residents, by DAC population. Electrical, Transmission, and Raw Materials are more heavily concentrated in counties with more than 25% of their population living in DACs than figure 5. This also highlights the rural nature of DACs with manufacturing. We add variables $\Delta RevShare_c * Facility$ and $\Delta RevShare_c * Rural$ in table 5 to investigate manufacturing in counties with these characteristics.

are smaller for WCM facilities that produce electrical and transmission equipment and raw materials, and are smaller in rural counties. Nevertheless, the DAC_c interaction coefficient remains negative and statistically and economically significant which suggests that even conditional on facility type and rural status, counties with DACs experience smaller local economic impacts. However, the DAC interaction coefficient is not large enough to entirely negate all local economic benefits from WCM, whereas rurality and facility type come close. This suggests that while DAC status remains an important factor in diminishing WCM benefits, facility type and rurality play a dominant role in reducing benefits for those counties.

5 Conclusion

This paper explores the local labor market impacts of a transition to renewable, manufacturing-intensive energy sources. We estimate the causal effect of wind component manufacturing (WCM) on median household incomes at the county level, using a inverse propensity

	Dependent variable:				
	DeltaInc				
	(1)	(2)	(3)	(4)	(5)
$\Delta RevShare_c$	45.476***	183.241**	79.972***	47.816***	366.926***
	(6.154)	(84.188)	(9.717)	(6.268)	(133.488)
$\Delta RevShare_c * Facility_c$		−160.686			−325.775**
		(97.631)			(149.368)
$\Delta RevShare_c * DAC_c$			−89.534***		−102.408**
			(19.283)		(41.413)
$\Delta RevShare_c * Rural_c$				−197.952***	−227.509**
				(49.159)	(105.998)
Constant	7,280.332***	6,962.407***	7,478.186***	7,414.457***	7,016.228***
	(105.875)	(247.734)	(115.867)	(112.414)	(358.481)
Pscore					
Trimmed Manufacturing 2, Windspeed	Yes	Yes	Yes	Yes	Yes
Observations	1,462	1,462	1,462	1,462	1,462
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5: Rural, facility, DAC decomposition results. A one sd dev. increase in DeltaRevShare_c yields a $6,283.61 increase in median household income, with a reduction of 28.0% for DACs, a reduction of 62.0% for rural counties, and a reduction of 88.8% for counties with electrical, raw material, or transmission facilities.

weighted shift-share instrumental variables framework. We investigate mechanisms that might reduce the benefits to Justice40 disadvantaged communities (DACs) through rurality and manufacturing facility type.

We find evidence that the presence of WCM in a county increases median household income by between $1,962.95 and $6,283.61. We differentiate between counties with and without DACs, finding that counties with WCM and DACs achieve only 19.0% - 72.1% of the income benefit of non-DAC counties, with one model showing all benefits are eliminated in DAC counties. Rural counties achieve 38.0% of the income benefit, and those with electrical, raw material, and transmission manufacturing facilities achieve only 11.2%. This provides evidence that investments in the current structure of manufacturing are unlikely to accrue benefits to DACs, rural communities, and specific manufacturing sectors at the same rate that they do elsewhere: policies and projects must specifically target these communities to ensure a just energy transition. We might be tempted to conclude that if policy makers have a distributional or energy justice objective, they should invest in higher-value manufacturing facilities in rural and/or DAC counties. However, we are not yet able to draw this strong of a conclusion without exogenous changes in a higher variety of WCM facility types in DAC counties. Policy makers could invest in experimental or exploratory programs to test this hypothesis, and researchers could investigate impacts on DACs from high tech manufacturing across a wider array of industries in order to gain insight into this question.

Our current results are not directly comparable to the economic multiplier literature, which focuses on how many additional jobs are created following the addition of one manufacturing job, or on the increases in local GDP from an additional dollar in manufacturing earnings. Our results are centered on median household income, which does not translate into changes in job counts, or spending or earnings multipliers. In ongoing research, we will incorporate the impact on jobs and local GDP to yield results that are more universally comparable with works such as Batini et al. [2022], Franklin et al. [2019], Osman and Kemeny [2022].

Acknowledgements

This work was supported by the Critical Materials Innovation Hub, funded by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Advanced Materials and Manufacturing Technologies Office.

References

American Clean Power. Cleanpoweriq database. Technical report, 2022. url https://cleanpoweriq.cleanpower.org/app/ .

David H Autor, David Dorn, and Gordon H Hanson. The china syndrome: Local labor market effects of import competition in the united states. *American economic review*, 103(6):2121–2168, 2013.

Nicoletta Batini, Mario Di Serio, Matteo Fragetta, Giovanni Melina, and Anthony Waldron. Building back better: How big are green spending multipliers? *Ecological Economics*, 193:107305, 2022.

Eric J Brunner and David J Schwegman. Commercial wind energy installations and local economic development: Evidence from us counties. *Energy Policy*, 165:112993, 2022.

Bureau of Economic Analysis. Regional economic accounts CAGDP1: GDP summary by county and MSA. Technical report, US Department of Commerce Washington, DC, 2021. url https://apps.bea.gov/regional.

Becca Castleberry and J Scott Greene. Impacts of wind power development on Oklahoma's public schools. *Energy, Sustainability and Society*, 7(1), 2017. ISSN 21920567. doi: 10.1186/s13705-017-0138-8.

H Ron Chan and Christy Zhou. Charged up? distributional impacts of green energy on local labor markets. *Distributional Impacts of Green Energy on Local Labor Markets (August 3, 2023)*, 2023.

Jonathan Colmer, Eva Lyubich, and John Voorheis. Nice work if you can get it? the distribution of employment and earnings during the early years of the clean energy transition.

Council on Environmental Quality. Climate and economic justice screening tool. Technical report, Executive Office of the President, 2022. url https://www2.census.gov/geo/docs/reference/ua/County$_{R}ural_{L}ookup.xlsx$.

E Mark Curtis and Ioana Marinescu. Green energy jobs in the us: What are they, and where are they? Technical report, National Bureau of Economic Research, 2022.

E Mark Curtis and Ioana Marinescu. Green energy jobs in the united states: What are they, and where are they? *Environmental and Energy Policy and the Economy*, 4(1): 202–237, 2023.

Caroline Draxl, Andrew Clifton, Bri-Mathias Hodge, and Jim McCaa. The wind integration national dataset (wind) toolkit. *Applied Energy*, 151:355–366, 2015.

Hope Franklin, Thomas McComb, and Stanislaw J Rzeznik. Benchmark update of the regional input-output modeling system. *Survey of Current Business*, 99(11):1–7, 2019.

Ben Gilbert, Hannah Gagarin, and Ben Hoen. Distributional equity in the employment and wage impacts of energy transitions. Technical report, National Bureau of Economic Research, 2023a.

Ben Gilbert, Hannah Gagarin, and Ben Hoen. Geographic spillovers of wind energy development on wages and employment. Technical report, 2023b.

Alexander G James and Brock Smith. Geographic dispersion of economic shocks: Evidence from the fracking revolution: Comment. *American Economic Review*, 110(6):1905–1913, 2020.

Haeyeon Kim. Three essays on mineral economics and economic geography. 2019.

Enrico Moretti. Local multipliers. *American Economic Review*, 100(2):373–377, 2010.

Ha Nguyen and Jiaming Soh. Employment multipliers over the business cycle. *World Bank Policy Research Working Paper*, (8105), 2017.

Taner Osman and Tom Kemeny. Local job multipliers revisited. *Journal of Regional Science*, 62(1):150–170, 2022.

Alex Petridis. Wind turbine manufacturing in the us. Technical report, IBISWorld, 2022. url https://www2.census.gov/geo/docs/reference/ua/County_Rural_Lookup.xlsx .

Eman Ahmed Hamed Shoeib, Elisabeth Hamin Infield, and Henry C. Renski. Measuring the impacts of wind energy projects on u.s. rural counties' community services and cost of living. *Energy Policy*, 153, 6 2021. ISSN 03014215. doi: 10.1016/J.ENPOL.2021.112279.

US Census Bureau. County rurality level: 2010. Technical report, US Department of Commerce Washington, DC, 2010. url https://www2.census.gov/geo/docs/reference/ua/County_Rural_Lookup.xlsx .

US Census Bureau. 5-year american community surveys. Technical report, US Department of Commerce Washington, DC, 2016-2022. url https://www2.census.gov/geo/docs/reference/ua/County_Rural_Lookup.xlsx .

US Census Bureau. Manufacturing: Geographic area series: Industry statistics for the states, metropolitan and micropolitan statistical areas, counties, and places: 2012, economic census, ecn core statistics summary statistics for the u.s., states, and selected geographies: 2017. Technical report, US Department of Commerce Washington, DC, 2021. url https://data.census.gov/table/ECNBASIC2012.EC1231A1?g=010XX00US0500000&$n = 31 - 33$.

A Supplemental: State Fixed Effects and Rural Decomposition

	Dependent variable:				
	DeltaInc				
	(1)	(2)	(3)	(4)	(5)
$\Delta RevShare_c$	30.976***	−46.766	34.182***	32.450***	50.210
	(5.695)	(74.526)	(10.333)	(5.773)	(138.889)
$\Delta RevShare_c * Facility_c$		88.571			−14.365
		(84.606)			(143.091)
$\Delta RevShare_c * DAC_c$			−7.460		−11.904
			(20.079)		(35.778)
$\Delta RevShare_c * Rural_c$				−127.188***	−130.302**
				(44.367)	(51.863)
Pscore					
Trimmed Manufacturing 2, Windspeed	Yes	Yes	Yes	Yes	Yes
Fixed effects					
State	Yes	Yes	Yes	Yes	Yes
Observations	1,462	1,462	1,462	1,462	1,462
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6: State fixed effects results. These present the same models as in table 5, but include state fixed effects. Statistical significance declines and reduces magnitude. All five models include interaction terms which have high levels of collinearity built in. State fixed effects reduce the amount of remaining variation, which reduces the ability to precisely estimate coefficients. While the magnitude of $DeltaRevShare_c$ on is reduced relative to 5, it is still in the same ballpark for all models 1, 3 and 4. Model 5 suffers the worst from collinearity issues with all the interaction terms.

B Facility Categories

Aftermarket
- Gearboxes

Blades
- Utility scale blades

Blades — Turbines
- Nacelle assembly — Utility scale blades

Distributed Wind Turbines
- Towers
- Turbines

Electrical
- Cable
- Control systems
- Electronic components

- Enclosures
- Encoders
- Generator components
- Power converter
- Power converter — Power Transmission
- Power Transmission
- Sensors
- Switches
- Utility poles
- Wire & Cable

Electrical — Generators

- Generators — Power converter

Equipment

- Blade fabrication
- Construction
- Covers
- Fall protection
- Lighting
- Manufacturing machinery
- Met towers
- Other equipment
- Test systems

Gearboxes

- Gearboxes

Non-manufacturing office

- Office

Power transmission

- Bearings
- Bolting systems
- Brakes
- Couplings
- Drive train components
- Gears
- Hydraulics
- Lubricants
- Machining/fabrication
- Sensors
- Sliprings

Power transmission — Raw Materials

- Composite coatings — Lubricants
- Composites — Machining/fabrication

Raw Materials

- Coatings
- Composite coatings
- Composites
- GeoTubes and fabrication

- Plastics
- Steel

Related

- Distribution Center
- Parts
- Service
- Software

Structural

- Castings
- Fasteners
- Offshore wind foundations

Towers

- Concrete hybrid towers
- Towers

Turbines

- Nacelle assembly