THREE ESSAYS ON RENEWABLE ENERGY AND SUSTAINABILITY

by

Nhu Nguyen

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STATEMENT OF COMMITTEE APPROVAL

Dr. Russell Hillberry, Chair
Department of Agricultural Economics

Dr. Carson Reeling
Department of Agricultural Economics

Dr. David Johnson
Department of Industrial Engineering

Dr. Michael Wilcox
Department of Agricultural Economics

Approved by:
Dr. Nicole Widmar

To my late father in Heaven

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ABSTRACT

This study investigates the economic rents of the wind energy industry in the U.S. and their economic impacts on local economies, using Benton and White counties in Indiana as study regions. By calibrating a partial equilibrium model using 2007-2010 data of the industry, we find a resource rent of $9.72/MWh. We then use a general equilibrium model with Dutch Disease features to study the optimal tax levied on this rent, and the economic impacts of redistributing the tax revenues back to the county residents. An exhaustive rent tax increases real county personal income by as high as 9.1% and as low as 2%, depending on the county's features. Applying an incentive compatible resource rent tax rate and redistributing the revenues to the county's laborers leads to an increase of 3.5% and 16% in their income in White and Benton counties, respectively. We also perform robustness checks by allowing labor mobility between counties to examine the impacts of resource rents on the county economy under endogenous labor growth. All data acquired comes from the U.S. Census Bureau, county Quarterly Census of Employment and Wages, the National Renewable Energy Laboratory reports, the Lawrence Berkeley Laboratory, Indeed.com, news articles, and wind developers websites.

Using the Regional Energy Deployment System (ReEDS) model, we estimate the deadweight loss imposed by county-level wind power development restrictions in the form of increased electricity costs due to suboptimal siting. This is accomplished by optimizing the power system of the United States' Midcontinent Independent System Operator (MISO) from 2020 to 2050. We perform the optimization with and without land-use constraints arising from simulated potential local ordinances restricting wind power development, and under multiple scenarios reflecting different renewable portfolio standards (RPS). We find that local restrictions on wind power increase the total system cost by 0.15%-0.3% and the wholesale electricity price by 1.8%-

2.7%, depending on the RPS scenario. Changes in the generation and installed capacity mixes are more substantial and depend on both the level of county restrictions on wind power, and RPS requirements, thus indicating an interaction between RPS requirements and local wind power restrictions. We also find that plausible restrictions on wind development do not pose major barriers to meeting renewable energy targets in a cost-effective manner. All data is embedded inside the Regional Energy Deployment System (ReEDS) model of the National Renewable Energy Laboratory.

The USDA promotes adoption of conservation practices beneficial for soil health and environment through agricultural cost-share payment programs such as EQIP or CSP. Although the efficiency of these programs has been evaluated through additionality estimates, which represent the percentage of farmers who would adopt a practice only with payments, the potential complementarities between certain combinations of practices have often been overlooked. Unaccounted for, these complementarities may impact additionality estimates. This paper provides a thorough investigation of additionality estimates of common practices, including no-till, nutrient management and cover crops, accounting for potential complementarities between them. We find no significant differences between traditional additionality estimates and estimates accounted for potential complementarities between the three practices. The results thus indicate that despite agronomic evidence of synergies in co-adopting these three practices, we find no solid indication of adoption complementarity between them in reality. Data is acquired from the U.S. Department of Agriculture and Esri maps.

1. TAXATION OF ECONOMIC RENTS IN THE WIND POWER SECTOR AND THEIR EFFECTS ON RURAL ECONOMIES

*This essay contains portions of the paper "Renewable resource rents, taxation and the effects of wind power on rural economies" by Russell Hillberry and Nhu Nguyen.

Abstract

This study investigates the economic rents of the wind energy industry in the U.S. and their economic impacts on local economies, using Benton and White counties in Indiana as study regions. By calibrating a partial equilibrium model using 2007-2010 data of the industry, we find a resource rent of $9.72/MWh. We then use a general equilibrium model with Dutch Disease features to study the optimal tax levied on this rent, and the economic impacts of redistributing the tax revenues back to the county residents. An exhaustive rent tax increases real county personal income by as high as 9.1% and as low as 2%, depending on the county's features. Applying an incentive compatible resource rent tax rate and redistributing the revenues to the county's laborers leads to an increase of 3.5% and 16% in their income in White and Benton counties, respectively. We also perform robustness checks by allowing labor mobility between counties to examine the impacts of resource rents on the county economy under endogenous labor growth.

1.1 Introduction and motivation

In 2020, 337.5 million megawatt hours (MWh) of electricity were generated by wind power in the United States, up from only 5.6 million MWh in the year 2000 (Table 7.2b, EIA 2021a). The *utility-scale* generation assets that produce the vast majority of this electricity are typically located in rural areas, and their presence is seen as a potential boon to the local economies in which they are located (Ailworth 2017).[1] The presumed positive effects of the industry on rural economic development have been a key political rationale for federal subsidies to the sector (Grassley 2020). But the industry is capital intensive, and financed almost exclusively by capital that is external to the communities that host it. The sector buys few intermediate inputs, and most of its capital goods are purchased from outside the counties where generation assets are installed. These features of the sector can act to limit the local economic impact of wind energy generation.

Empirical literature finds mixed results of local benefits from the arrival of utility-scale wind power.[2] Relatedly, many local governments have restricted investments in utility-scale wind generating capacity through moratoria, outright bans, or by imposing restrictive provisions that make utility-scale investments uneconomical.[3] These facts raise the question: *Are there policies that can magnify the local economic benefits of hosting wind powered electricity generation, thus making community acceptance of wind-powered turbines more likely?* This paper investigates the possibility that state and local tax policy can increase the local benefits the sector generates. The paper also investigates a related set of questions concerning the likely effects of the arrival of wind power on the distribution of incomes in local economies, and the scope for local tax policy to affect distributional outcomes. A maintained hypothesis in our analysis is that a more even distribution

[1] DOE (2012) defines "utility-scale" turbines as those with nameplate capacity of 1 megawatt (MW) or more. The utility-scale projects we consider consist of many large turbines located in proximity to one another on "wind farms." Utility-scale turbines are subject to local oversight, especially through limits the planning commission imposes on the siting of large structures.

[2] See Brown, *et al.* (2012), De Silva, *et al.* (2016), Mauritzen (2020), Brunner & Schwegman, (2022a), Brunner & Schwegman (2022b), and Shoeib *et al.* (2022). We review this literature later in the paper.

[3] See Bednarikova, *et al.* (2020) for further discussions of local policies used to restrict wind power generation in Indiana. Bessette and Mills (2021) study the phenomenon in the broader context of the US Midwest.

of the benefits generated by the sector would improve its chances of broader acceptance in rural America.[4]

To address these issues we build and calibrate a small open economy model with endogenous investment in a rural county's wind sector. The general equilibrium model is a multi-sector adaptation of Corden and Neary (1982), with the wind energy sector as the booming sector.[5] The model is static, but external providers of capital must earn a return that is at least as high as their opportunity cost in order to provide factor services to the wind energy sector.

The arrival of the wind energy sector generates economic rents, which are attributable to a) the presence of an important unpaid factor of production (the wind), and/or b) generous federal subsidies. We use data from two counties in Indiana to quantify the size of these rents, and to identify the factor owners who receive those rents. A resource rent tax allows the rents to be redistributed without limiting investment. In the calibrated model we redistribute rents to the local citizenry, subject to the constraint that the construction of utility-scale wind farms remains incentive compatible, both for external capital and for local landowners who must accept the presence of turbines on their land. The rents that the tax extracts from external capital provide additional income to residents of the county, income that increases demand for locally supplied

[4] A key rationale given for restricting investments in generation capacity is typically the negative externality that the turbines impose on the local viewscape. We do not model this externality or attempt to quantify it. We presume that only a small minority of the local population - those residing in the immediate vicinity of the turbines - are materially affected by changes in the viewscape. Our view of the problem is that the venue for local political contests around the matter (the local planning commission) is one that gives outsized influence to this vocal minority. The relatively small number of direct local beneficiaries of the industry (i.e., the landowners hosting the turbines and a small number of not-yet-present well-paid workers who service them) may lose this political contest. More broadly distributed material benefits (including payments to those who live and work in the local towns) would presumably broaden the coalition of county residents that would support acceptance of the turbines. See Bednarikova *et al.* (2020), Rand & Hoen (2017), Olson-Hazboun, Krannich & Robertson (2016), Petrova (2013).

[5] Our choice of a Dutch Disease model is intended to highlight the possibility of negative economic consequences of the sector's arrival on some local agents, especially employers in the other tradeable industries. The model also captures a potentially important positive channel, local spending of new income generated by the sector, which we view as an important aspect of the problem.

retail services. The consequences of this increase in demand follow the standard intuition of Corden and Neary, but their magnitude is weakened by our assumption that consumers can imperfectly substitute retail services from outside the county for domestic retail services with a rising relative price.

Our case study focuses on data from the initial wave of utility-scale wind turbines constructed in the U.S. state of Indiana. Most of these investments were supported by incentives from the American Recovery and Reinvestment Act of 2009 (ARRA). We calculate that production from these investments generated approximately $9.72 of economic rent per MWh of electricity produced in the counties we study.[6] These rents accrue primarily to external capital owners, but also to landowners who lease their land for use by the wind farms. In a general equilibrium in which we assume that all locally supplied factors are owned by a single representative agent, we calculate that the *arrival* of the wind powered electricity generation industry raises real incomes by 1.1 percent in the smaller of the two counties and by 0.2 percent in the larger county. We estimate that an incentive compatible resource rent tax that captures a larger share of the rents for local communities could increase local incomes by as much as 9.1 percent and 2 percent, respectively. These benefits are the result of increased tax payments by the sector to local governments, which rise by a factor of seven in each county when rent taxes are imposed. In order to highlight the distributional consequences - of the sector's arrival and of the rent tax - we extend the model, assigning income from locally supplied factors to distinct agents and allowing the redistribution of tax revenues to be targeted solely to local suppliers of labor. The

[6] The size of these rents vary over time. Changes in the rents are driven by changes in turbine technology, the prices of electricity and changes in the scale of federal subsidies to the sector. Technology has improved since the period we study, even as prices in long-term electricity contacts and federal subsidies have fallen. We consider the implications of such changes for our analysis in section 6.

redistribution of all economic rents to labor via taxation raises real labor income by 16 percent in the smaller county and by 3.5 percent in the other.

Our paper is a contribution to the literature on the efficient taxation of natural resource rents. Garnaut and Clunies-Ross (1975) argue that a) the capital intensity of mining projects and b) limited scope for local sourcing of inputs means that the primary economic benefits of mining projects for developing countries must come mainly through taxation. In the context of mining, highly volatile commodity prices are a potential source of resource rents, and the authors propose a time-consistent approach to taxing such rents. The circumstances of wind energy – in terms of capital intensity and limited local sourcing – are similar to the developing country mining context, but the sources of economic rent are different. We argue that the presence of an unpaid - but critical - factor of production (the wind) is an important source of rents, as are generous federal subsidies paid to facilitate investment in the sector. Our identification of resource rents in a renewable energy sector appears to be novel, relative to the resource rent literature, which has focused on non-renewable resources, especially petroleum.[7]

We also contribute to the literature on economic impacts of wind energy. A large number of studies - generally conducted outside the discipline of Economics - employ input-output models in an effort to quantify *ex ante* economic impacts of wind power in national and/or state contexts.[8] A more recent literature has used *ex post* econometric methods to measure the effect of investments

[7] See Lund (2009) and Smith (2013) for reviews of the resource rent tax literature.

[8] The JEDI model (NREL 2004) is an input-output framework that has been developed specifically for this purpose. The use of an input-output model is intended to highlight the economic contribution of demand spillovers to upstream sectors that provide inputs (both intermediates and inputs in capital goods used in the sector). NREL (2014) use the JEDI model to study the impacts of the first 1000 MW of capacity in Indiana. Such estimates suffer from the standard weaknesses of the input-output framework for economic analysis (see Gretton 2013). Input-output models are also poorly suited for analysis of tax policy, which is a primary focus of our analysis.

in wind energy or other renewables on economic outcomes at the county level.[9,10] While the econometric studies offer some evidence on distributional outcomes, it is difficult to draw robust inferences on distributional consequences from the literature.[11,12] Our approach, a calibrated general equilibrium model, is better suited to tax policy analysis than is either econometrics or input-output modelling.[13]

Our work is tangentially related to the recent literature on the economic impact of place-based policies. Federal subsidies to the wind sector, which were made especially generous in response to the global financial crisis, indirectly subsidize investment in a subset of rural areas with adequate wind resources and relatively easy access to the electric grid. In our work these federal policies are exogenous, but their existence creates room for local governments to respond optimally, taxing excess profits earned through investments subsidized by federal policy. Federal subsidies are one source of economic rents in the sector, rents that state and local governments can

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[9] Several papers find a statistically significant positive effect of wind power development on local personal income of varying magnitudes (Brown et al., 2012; De Silva et al., 2016; Brunner & Schwegman, 2022a). However, a study on USDA defined rural counties from 1990-2015 shows little to no effects on per capita income (Shoeib et al., 2022). Exploring other parameters, some research also find positive impacts of wind development on local wages (Mauritzen, 2020) and local tax revenues and county spending (Brunner & Schwegman, 2022b). The effects of wind development on local employment is mixed, when one paper found significant positive impacts (Brown et al., 2012), but several others showed no significant effects (Brunner & Schwegman, 2022a; Shoeib et al., 2022).

[10] Perhaps more interestingly, some studies suggest that although the overall employment effects are insignificant or small, some sectors such as construction and retail expand, while most other sectors either contract or have insignificant changes (De Silva et al., 2016; Brunner & Schwegman, 2022a).

[11] De Silva, *et al.* (2016), Brunner & Schewegnan (2022a) and Brunner & Schewegnan (2022b) are studies known to us that have addressed distributional outcomes. De Silva, *et al*. OLS regressions using data from Texas find a smaller impact of wind capacity on median incomes than on mean incomes. Using a diff-in-diff model, Brunner & Schwegman (2022a) and Brunner & Schwegman (2022b) examine the differences in the effects by capacity per capita in rural and non-rural settings, where counties at the 75th percentile of installed capacity and beyond sees a much larger increase in GDP per capita and total local tax revenue per capita and other outcomes.

[12] Both De Silva *et al*. (2016) and Brunner & Schewegnan (2022a) results suggest industry heterogeneity in the effects of wind on employment. Specifically, although the overall employment effects are insignificant or small, some sectors such as construction and retail expand, at the expense of agriculture and a few others.

[13] Connolly (2020) uses a computable general equilibrium model to study the effect on Scotland of offshore wind energy developments. Like his, our paper studies the likely consequences of the sector's arrival on a local economy. We also isolate resource rents and consider the implications of taxing those rents.

capture through efficient taxation. We demonstrate that economic rents in the sector can be sizable and show that the taxation of these rents can raise local incomes and ameliorate distributional consequences of the arrival of utility scale wind generation on a local economy.

These lessons have an important policy context. The growth of renewable energy in the United States is subject to substantially more local control than is the case in other countries (Bessette and Mills, 2021). In the context that we study (Indiana), local restrictions on the construction of utility-scale turbines are thought to have reduced investments in wind energy production by as much as $5 billion.[14] Foregone investments in other states would expand that number considerably. Larger and more evenly distributed economic benefits from wind energy generation would presumably make hosting the sector more attractive to rural communities, whose consent is critical to meeting national and international renewable energy goals.

The organization of the paper is as follows. Section 0 provides technological, policy and geographical background. Section 0 describes the partial equilibrium model and calibrates the model to quantify economic rents. Section 0 outlines the general equilibrium model and an extension. In section 0 we calibrate the general equilibrium model and use it to quantify the potential implications of a resource rent tax. Section 0 offers a brief discussion of the administrative viability of local resource rent taxes. Section 0 concludes.

1.2 Background and setting

The qualitative insights of the models we develop are quite general, but in order to provide quantitative insights we calibrate them to a specific context. Because wind generation technology changes rapidly over time, model calibration depends on the choice of a specific time period. We

[14] This estimate is from the Indiana Conservative Energy Alliance, a lobby group supporting more wind energy development that is quoted in Bednarikova (2020).

believe the period surrounding the global financial crisis is of interest because a) federal subsidies to the sector were large and transparent, and b) this period saw rapid growth in utility-scale wind power generation capacity, including the introduction of the sector into many rural communities. In this period, the predominant technology consisted of turbines with approximately 1.5 MW of nameplate capacity, and "hub heights" of approximately 80 meters. Our calibration depends on the technical and cost parameters of this generation of turbines.

The development of the utility-scale wind power sector has been generously supported by the United States federal government. The longest-lived subsidy has been the production tax credit (PTC), which is per unit production subsidy for electricity produced by renewable fuels.[15] Since 2008, wind energy developers have had the choice to receive an up-front investment tax credit (ITC) instead of the production-dependent PTC (CRS, 2020). As part of the federal government's response to the global financial crisis, Section 1603 of the ARRA authorized federal grants to subsidize investments in projects beginning in 2009 or 2010 (CRS, 2020). The high cost of acquiring external capital during the global financial crisis made these grants a preferred alternative to the ITC and PTC during the latter half of the time period we study. Information on the size of Section 1603 grants made to individual projects is publicly available, which is another reason that our calibration considers the impact of projects constructed during this time period.

Although our insights are, for the most part, general to other locations, we focus our attention on two neighboring counties in West-Central Indiana: Benton County and White County. These were the first two counties in Indiana to host utility-scale wind farms, and those counties received their initial investments during our period of interest.[16] The wind conditions in both

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[15] Wind facilities that begin construction prior to January 1, 2022 receive \$0.018/kWh of production during the first ten years of operation (EIA 2021b). The PTC was first authorized in 1992 (CRS, 2020).

[16] The entire first round of investments in White County were subsidized through the 1603 program. Some investments in Benton County preceded the program, and so received different forms of subsidy.

counties are similar, and the initial investments in wind energy production were at large and similar scales. The counties have similar economic structures, though White County has a larger population and agriculture plays a smaller role there. We use data from the two counties because the comparative approach offers insight into the effects of the industry on counties where the size of the wind sector, relative to the population, is substantially different.

Table 1.1 presents some context about the two counties, reporting economic and demographic statistics in 2007 (a period roughly coincident with the installation of the first turbines). BEA (2020) estimates of the counties' total personal income - which we take to be good indicators of the counties' economic size - put White County near the median US county in 2007, while Benton County is near the 25th percentile. Using population rather than income as a measure of county size, these two counties are somewhat smaller, relative to the distribution of US counties. Both counties' per capita incomes are above the US median, with Benton County having somewhat higher value of per capita income than White County. White County is at the 55th percentile of US counties in population density, and Benton County is at the 32nd percentile.

Table 1.1. Demographic and economic characteristics of case study counties.

	Benton County, IN		White County, IN	
	Level	Percentile in US	Level	Percentile in US
Personal income (2007)	$292 million	0.233	$778 million	0.512
Population (2007)	8,805	0.190	24,762	0.485
Per capita income (2007)	$33,190	0.665	$27,802	0.566
Population density (2000)	23.13 persons / sq mile	0.320	49.92 persons / sq mile	0.550
Net cash farm income (2007)	$52.3 million	0.869	$72.9 million	0.928
Corn sales (2007)	$84.9 million	0.963	$103.4 million	0.979
Soybean sales (2007)	$44.3 million	0.967	$36.7 million	0.932
Nameplate capacity of generating assets (2011)	840.55 MW	0.989	500.85 MW	0.960
Estimated value of electricity (2011)	$178.8 million	n/a	$106.8 million	n/a

Table notes: Personal income, population and per capita income data from BEA (2020). Net cash farm income, corn sales and soybean sales from 2007 US Census of Agriculture. Generating capacity data are taken from Hoen*, et al.* (2018). The estimated value of generated electricity are author calculations that incorporate the capacity figures, a capacity factor of 0.38**,** and a $63.86 per MWh price of electricity. $63.86 was the median levelized price in PPA contracts concluded during the years 2007-2010 for projects that operate in the territory of the Midwest Independent System Operator.

In order to understand the dependence of the two counties on agriculture, we report statistics from the 2007 U.S. Census of Agriculture. Total net farm income in the two counties is quite high by U.S. standards; in 2007, both counties were in the top 15 percent of U.S. counties. The ratio of net farm income to total personal income was approximately 0.18/1 in Benton County, and 0.09/1 in White County. Agriculture in both counties is dominated by corn and soybean production. Both counties were in the top 5 percent of U.S. corn-producing counties, and the top 10 percent of soybean-producing counties.

Finally, we turn to the size of the wind sector in the two counties. Because we wish to focus our analysis on the first wave of investments in the counties, we report values of generating capacity that began operating prior to 2011. At the end of 2010, the two counties had 840.55 MW (Benton) and 500.85 MW (White) of installed capacity that was operational. At that time, both counties' installed capacity measures put them in the top four percent of the 349 US counties with installed capacity. Put another way, Benton County was ranked 5th among US counties in wind generating capacity at the close of 2010, and White County 15th. There were no operational utility-scale turbines in either county as late as 2007, so the initial wave of investments in these two counties is clearly large, even in the context of a much larger U.S. market.

In order to put the size of the sector in further context, relative to the local economies, we estimate the market value of wind generated electricity produced in each county in 2011. Assuming wholesale electricity prices of $63.86 per MWh and a capacity factor of 0.38 (two values we use throughout our subsequent calculations and justify later in the paper) the installed capacity in Benton County produced electricity worth approximately $178.8 million in Benton County and $106.8 million in White County. These estimates suggest that the value of the electricity generated in the two counties is of the same order of magnitude as corn and soybean sales combined.

In our view the figures in Table 1.1 support a claim that these two counties are a useful laboratory for studying local implications of wind power. Both counties host a large wind sector, which allows for sizable impacts of wind energy generation on the local economy. The two counties have similar wind conditions, and, during the period we study, installed turbines with similar technological capabilities. The counties differ somewhat in the scale of the wind sector, and in the population, so the size of the wind sector on a per capita basis is larger in Benton than in White County. The consequences of this difference are visible in our results.

1.3 A partial equilibrium model of renewable resource rents

1.3.1 Resource rents in the wind power sector

We begin the description of our modeling framework by outlining a static partial equilibrium model of production in the utility-scale wind energy sector. Although the time profile of costs and revenues in the sector would seem to be quite different, the structure of the industry is such that the use of a static model is reasonable.[17] In the model firms make an annualized output decision taking output and input prices, subsidies and taxes as given. Output quantities are constrained by limits the local government has set on the amount of generating capacity allowed. Economic rents emerge as the gap between revenues (gross of subsidies) and costs (gross of taxes). Rents in the model can be understood as supernormal profits earned by the industry because the counties' good wind conditions allow the factor bundle to produce at an average cost that lies below the contracted price of electricity. One can also conceive of these rents as payments that would go to a hypothetical supplier of local wind services, if there were one. Federal subsidies also contribute to the size of these rents.

We first describe an important constraint on production: at any given time the number of installed turbines depends upon the decisions of a local government (i.e. the local planning commission). Aggregate capacity in a county is calculated as the sum of the 'nameplate' capacities

[17] The sector is capital intensive, and the vast majority of these costs are paid up front. Most of the ongoing costs are also predictable at the time of investment. Leases for the land used to host the turbines are contracted through the length of the project. Payments to a local government are either negotiated up front or are largely predictable tax liabilities. Labor costs linked to ongoing maintenance are also largely predictable. Electricity prices are known at the beginning of the project (and fixed through the life of the project) via Power Purchase Agreements (PPAs), in which a counterparty commits to purchasing the future stream of electricity at a known, fixed price. Federal subsidies are also known (and sometimes paid entirely) at the beginning of the project.

of each of the installed turbines. We represent the quantity of nameplate capacity installed in a county as V.[18]

Another key factor in the supply of wind energy services is the quality of the local wind resource. The engineering literature on wind-generated electricity defines the "capacity factor" of a wind turbine or wind farm as a parameter that translates nameplate capacity into expected electricity output.[19] The capacity factor takes into account both the technological features of the turbines and the quality of the wind resource in which they are located. The capacity factor enters as a parameter in our model, and we denote it a.

Firms in the model maximize profits by choosing the quantity of electricity output, E. The choice of E is constrained by the number of turbines allowed by the county government and by the capacity factor a. In order to represent production in units of MWh, we also represent the number of hours in a year as h. Formally, we represent the physical constraint on production as

$$E \ \leq aVh. \tag{1}$$

The industry maximizes profits, subject to (1). A Lagrange multiplier representation of the problem is as follows:

$$\max_{E,\lambda} \mathcal{L} = (P_E + S - rent\ tax - C(\overline{IP}, 1))E + P_V(aVh - E) \tag{2}$$

where P_E is the price of electricity per MWh (set outside the county), S a per unit production subsidy from the federal government, $C(\overline{IP}, 1)$ a unit cost function given a vector of prices for market-supplied inputs $\overline{IP}$, and $(P_E + S - C(\overline{IP}, 1))E$ are the profits available to this price-taking but output-constrained industry. $rent\ tax$ is the resource rent tax per unit production (\$/MWh).

[18] The Latin term for wind is *ventum*, so we use V to indicate variables relating to the wind. This follows from a similar convention that indicates land with the letter T, following the Latin for land, *terra*.

[19] Variable wind conditions and the need for occasional repairs mean that the turbines are not always in operation, and sometimes operate at less than full speed. The capacity factor is a productivity measure that links nameplate capacity (which measures capacity of the turbines at full speed) to the actual output of electricity.

P_V is the Lagrange multiplier on the supply constraint and represents the implicit factor price of wind services.

The first order Kuhn-Tucker conditions associated with the optimization of (2) are as follows:

$$P_E + S - rent\ tax - C(\overline{IP}, 1) - P_V \leq 0 \quad \perp \quad E \geq 0 \tag{3}$$

and

$$aVh \geq E \quad \perp \quad P_V \geq 0 \tag{4}$$

where $\perp$ indicates a complementary slackness condition. Using (3), note that $E > 0$ implies that P_V measures the gap between revenues and costs per unit of energy. This is the resource rent.

To facilitate transparent calibration to available data, we define the unit cost function $C(\overline{IP}, 1)$ as a Cobb-Douglas function that uses the prices of capital, labor, land and intermediate inputs. Denoting these, respectively as P_K, P_L, P_T and P_M, the unit cost function in the model is written as

$$\mathrm{C}(\overline{IP}, 1) = (P_K(1 + ptax))^{\alpha_K} P_L^{\alpha_L} P_T^{\alpha_T} P_M^{\alpha_M}$$

where the α terms are cost shares that sum to 1. This formulation also includes an annualized measure of local taxes paid by the wind industry (*ptax*), which would include property taxes as well as other payments.[20]

Factor incomes are attributable to two sources: standard payments for factor services, and (potentially) a share of the economic rents. Normal factor payments are calculated by applying Shephard's Lemma to the cost function and multiplying by the factor price and the scale of output. Income from economic rents is allocated to the factors in a manner that is determined outside the

[20] The normal return on capital in the model, P_K, is taken to represent the return that capital holders earn after corporate and other federal and state taxes have been assessed. This is consistent with its treatment in the study we use to detail annualized production costs. The taxes we consider in this paper are only local taxes on the wind industry: property taxes and our proposed resource rent tax.

model.[21] We denote the share of total rent payments that accrue to factor *f* with the parameter γ_f, with $\sum_f \gamma_f = 1$. The income paid to factor *f*, Y_f is the sum of the normal factor returns and the rent payments:

$$Y_f = \alpha_f C(\overline{IP}, 1)E + \gamma_f P_V V.^{22} \tag{5}$$

The partial equilibrium model consists of equations 3-5. The model solves for variables P_V, E, and Y_f given values of the parameters P_E, S, P_f, α_f, a, V and γ_f. Calibration of the partial equilibrium model requires data-driven choices of its input parameters, given observed values of the equilibrium.[23]

1.3.2 Calibration of the Partial Equilibrium Model

We calibrate the model by choosing parameters that are consistent with publicly available information on the expected revenues, cost components, subsidies received, and taxes paid by the developers who constructed the 80-meter turbines in Benton and White Counties during the years 2007 to 2010. Our data come from a mix of sources. Estimates of output at the county level rely on data for *V*, which we take from Bednarikova *et al.,* (2020). The capacity factor *a* is a representative value for this generation of turbines, 0.38 (see Tegen, *et al.*, 2012). Available information on county-level estimates suggest this figure is reasonable for Benton and White

[21] In practice the allocation of rents is determined by contracts that outside capital negotiates with the landowners. Some of the rents also appear to be shared with local governments through "economic development" payments.

[22] Note that for Cobb-Douglas functions, simple manipulation following Shephard's lemma returns $\alpha_f \frac{C(\overline{IP},1)}{P_f}$ as the unit demand for factor f. Multiplying by P_f turns quantities into values, so unit factor payments become $\alpha_f C(\overline{IP}, 1)$.

[23] When we move to calibration of the GE model we will also make appropriate price normalizations.

Counties.[24] The number of hours in a year is h = 8670. Tegen, *et al.* (2012) detail components of annualized costs of construction and operation for turbines that use the technology we consider. We take these figures to be inclusive of rents and use available data on factor quantities employed and on factor prices to determine the portion of the industry's payments to factors that compensate the factors' opportunity costs. The remaining payments to individual factors are taken to be rents. Project level estimates of federal investment subsidies under the 1603 program help us to pin down an estimate of S. Translation of all information into common units (MWh of electricity) allows an estimate of the economic rent per unit of output, P_V. This information is reported in Table 1.2.

A critical component of the calibration is our estimate of the price of electricity. Normally this price is volatile, but a useful feature of the industry for our calibration is that wind turbine investments are typically funded through long-lived Power Purchase Agreements (PPAs) that see an electricity buyer commit to paying a fixed price for all the electricity produced throughout the life of the project.[25,26] Wiser, *et al.* (2021) provide a database of PPA prices, over time and geography. This database provides data on contract prices but does not link the reported prices to specific projects. The data are comprehensive however, and we are able to collect PPA price data for projects located with the area administered by the Midcontinent Independent System Operator

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[24] The information available on capacity factors in the two counties is not precise but suggests that the local capacity factors may be slightly higher than the figure we use. NREL calculations of capacity factors for 60,000 square kilometers in Indiana shows that approximately 5000 square km in Indiana have capacity factors for 80M turbines that exceed 0.35. The best locations in the state have capacity factors as high as 0.42. The figure does not show the location of the most productive acres within Indiana, but other NREL data show that a region including these two counties hosts the best wind conditions in the state. See figures 3 and 1 in Bednarikova, *et al.* (2020). We believe 0.38 to be a conservative estimate of the capacity factor for these turbines in these locations.

[25] These contracts are critical for the wind farm developers because they can be used as leverage to obtain lower cost financing. Contract buyers benefit from the ability to lock in a fixed price of electricity for a long duration, typically 20-30 years. The risk of subsequent fluctuations in the price of electricity are borne by the electricity buyer, who does not appear in our model.

[26] By the definition of the Department of Energy, Power Purchase Agreement (PPA) is "an arrangement in which a third-party developer installs, owns, and operates an energy system on a customer's property. The customer then purchases the system's electric output for a predetermined period" (DOE, n.d.)

(MISO) for the years 2007-2010. PPA prices in this region during this time period have a mean of $65.56/MWh and a median of $63.86/MWh.[27] We use the median price as the price relevant to our calibrations.

Table 1.2. Calculation of per unit costs and economic rents, turbines installed 2007-2010

Item	Citations	Per 1.5MW turbine (1 acre)	Per MW	Per MWh
PPA price	Wiser et al., (2021)			$63.86
Gross capital cost	Tegen et al. (2012)	*$3,232,500*	$2,155,000	$61
Section 1603 grants	U.S. Dept of Treasury (2011)	*$828,028*	*$552,018*	*$15.86**
Net capital cost				*$45.14**
O&M (with land lease and labor)	Tegen et al. (2012)	*$51,000*	$34,000	$10
O&M (without land lease and labor)	Tegen et al. (2012); Bednarikova et al. (2020)			*$6.96 (Benton)** *$7.13 (White)**
Labor cost	Bednarikova et al. (2020)	*$9,183 (Benton)* *$5,028 (White)*	*$6,122 (Benton)* *$5586.15 (White)*	*$1.84 (Benton)* *$1.67 (White)**
Land lease payment	Bednarikova et al. (2020)	*$6,000*	$4,000	*$1.2*
Cash rent for land	Dobbins et al. (2007)	$157/acre		
Assumed opportunity cost of land		$1,000/turbine		*$0.2**
Implied landowner economic rent	Own calculation			*$1**
Capital economic rent	Own calculation	*$42,252*	*$28,168*	*$8.72**

Table notes: This table provides source information and figures used to calibrate the partial equilibrium model and calculate economic rents. * Indicates own estimation.

[27] The range is quite large, from $40.69 to $124.93/MWh. However, the gap between the contracts at the 25th and 75th percentile is much smaller: $54.53/MWh to $73.77/MWh. The wide range of prices is likely due to the fact that the PPA data include the prices of renewable energy certificates (RECs), which are marketable certificates that capture the additional market value linked with the production of renewable energy. Our conversations with market participants indicate that the value of RECs typically depend on the degree to which state's imposed renewable portfolio standards. Strict portfolio standards for utilities located in a state generates sizable demands for RECs in that state. Indiana's portfolio standards are not linked solely to the production of renewable energy and are therefore not binding during this period.

Tegen, *et al.* (2012) provide detailed information on the elements of costs associated with the construction, operation, and maintenance of a 1.5 MW turbine of the generation we consider. Their levelized cost of energy (LCOE) calculations imply that capital costs were \$61/MWh for the projects we study. These estimates assume a real, after-tax "fixed charge rate" of 9.5 percent and a 20-year project life.[28] The calculations also assume a mix of debt and equity financing at interest rates observed in projects constructed during our period of interest. Our rent calculations presume that the rate of return assumed in Tegen *et al*. (2012) fully compensates outside capital for its opportunity costs.

The capital costs of all of the White County projects we study (as well as one of the Benton County projects) were offset to a degree by the grants from section 1603 of the ARRA. US Dept of Treasury (2018) offers project-level detail on section 1603 grants awarded. Since all of the White County projects used this funding mechanism, we use payments to White County projects to estimate the scale of the subsidy *S*. Those payments totaled \$276,478,428, which corresponds to \$912,470 per 1.5 MW turbine, or approximately \$15.86/MWh of energy produced (Department of Treasury, 2018). Our estimate of the net capital cost paid by developers is thus \$45.14/MWh.

Most of the other costs of production are paid by the developers over the life of the project. These are largely predictable, and their approximate scale is published in the literature. Tegen, *et al.* (2012) put operating and maintenance (O&M) costs of this generation of turbines at \$10/MWh. O&M costs include payments to landowners, labor, and suppliers of intermediates.

To estimate labor costs, we extrapolate backward local estimates of direct labor employed by the industry in Benton and White counties (from Bednarikova, *et al.*, 2020), and of estimated

[28] Tegen et al, citing Short et al (1995), define the fixed charge rate as "the amount of revenue per dollar of investment that must be collected annually from customers to pay the carrying charges on that investment. Carrying charges include return on debt and equity, income and property tax, book depreciation, and insurance."

compensation costs in the industry.[29] These calculations imply labor costs of \$1.84/MWh in Benton County and \$1.67/MWh in White County. We assume that these are normal factor payments, without any embedded rents.[30]

Landowners in the region who had turbines installed on their land in 2007-2010 receive payments of approximately \$6,000-\$7,000 per turbine annually.[31] We consider these to include both payments for factor services and a share of the economic rents. Landowners are in a position to extract rents because they control the industry's access to the wind. But accepting the turbines also generates an opportunity cost - the market value of factor services that the land would otherwise provide. One estimate of the opportunity cost would be the cash rental rate for farmland. One local official interviewed for Bednarikova, *et al.* (2020) suggests a working assumption that one acre of land is required for each turbine. In a survey of cash rental rates for west central Indiana, Dobbins, *et al*. (2007) report the average cash rental rate for agricultural land in this region was \$157/acre in 2007. In order to be conservative in our rent calculation, we instead assume an opportunity cost of \$1,000/turbine.[32]

Assuming a \$6,000 annual payment, and a \$1,000/turbine opportunity cost of the associated land, landowners earn economic rents of \$5,000 per turbine. Our standard adjustments

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[29] We collected the annual salary for wind technicians from Indeed.com, approximately \$60,000/year. Bednarikova (2020) reports locally sourced data on 2020 employment for our two counties. We require employment data for 2007-2010, which we lack. We assume that employment is proportional to total nameplate capacity. Total capacity during the period of interest was approximately 75% of the value in 2020. As such, we assume that wind employment from 2007-2010 was 75% of the reported employment figures in Bednarikova (2020). We multiply by \$60,000 to estimate the approximate wage bill.

[30] Workers in the sector earn high wages, relative to local counterparts. In our view, these reflect additional skill, joint production with high levels of capital, and hedonic wages linked to irregular schedules and the possible dangers of turbine maintenance activities.

[31] These prices are contracted and subject to non-disclosure clauses, so there is no formal data available. Several different sources in the counties have nonetheless provided estimates the attribute to "coffee shop talk." It appears that the contracted prices are in fact quite similar, and in the range of \$4000/MW of capacity per turbine per year. We therefore use \$6000/ turbine in our estimates for 1.5 MW turbines.

[32] This would account for either higher rates of land use (because of access roads, for example), or additional costs of allowing turbines that put the opportunity cost of land above the cash rental rate.

for the capacity factor and for annual hours of operation put the value of landowners economic rent at \$1/MWh. The implied market value of land factor services is \$0.20/MWh.

Of the \$10/MWh of O&M costs, the calculations so far imply that approximately \$3/MWh in Benton County and \$2.87/MWh in White County are paid to suppliers of land and labor. We attribute the remaining O&M costs to intermediates.[33]

We calculate the economic rents accruing to capital as the revenue (\$63.86/MWh) less operating and maintenance costs (\$10/MWh) and the cost of private capital (\$45.14). Economic rents to capital owners, presumably resident outside the county, thus amount to \$8.72/MWh.[34] As noted above, landowner rents are (conservatively) \$1/MWh. Together these imply total rents in the sector of \$9.72/MWh. Together, these estimates imply model parameters of $\gamma_K = 0.897$, and $\gamma_T = 0.103$.

In order to move to quantitative exercises, we also need to calibrate the electricity generation sector's cost function, $C(\overline{IP}, 1)$. This entails calculation of factor and input cost shares. Were there no rent embedded in the Tegen. *et al.* estimates, the denominator for calculating cost shares would be \$71 (total gross cost per MWh). Since that figure does include rents, and taxes, we adjust the denominator in the share calculation. \$71 less \$9.72 of rent on the turbines generates a denominator of \$61.28/MWh. The numerator in the calculation of the capital share α_K is the total cost of capital less the capital providers' economic rent, or \$52.28/MWh. This implies $\alpha_K = 0.86$.

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[33] Tegen, *et al.* also include payments to governments in the O&M costs. These payments turn out to be somewhat large, relative to the county economies, but small relative to the cost of building and maintaining the turbines. In our model, we include a role for the industries' existing payments to local governments. We treat these payments as an *ad valorem* tax imposed on wind industry capital, since property taxes are the primary source of such payments.

[34] In their estimates of capital costs, Tegen, *et al.* assume straight line depreciation of capital costs. The Modified Accelerated Cost Recovery System (MACRS) offers a more generous tax treatment by allowing more rapid depreciation schedule. If we recalculate, assuming that the developers applied MACRS, we estimate that these projects earned rents of \$12.36/MWh. We use the smaller figure as it offers a more conservative estimate of the benefits of resource rent taxation.

The factor share of land in the cost function is calculated with the opportunity cost ($0.2/MWh) over $61.28 ($\alpha_T = 0.003$). The implied labor share is $\alpha_L = 0.028$ in Benton County and $\alpha_L = 0.015$ in White County. The remainder of the non-tax cost is attributed to intermediates ($\alpha_M = 0.11$ in Benton County and 0.12 in White County).

1.4 General equilibrium model

Our calibration of the partial equilibrium model of the wind industry completed, we turn to the general equilibrium model. We formulate the model as a mixed complementarity problem, following closely James Markusen's teaching notes and Markusen (2020) on the construction and calibration of simple general equilibrium models with trade.[35] We employ a small open economy model, adapting it to include an endogenous supply of external capital to the wind sector, imported intermediates, a trade imbalance, and an imported final consumption good that is an imperfect substitute for local retail. All of these features are presumably important in the context we study. Our model also contains a role for tax policy and redistribution. Other than the features we describe above, ours is a textbook model. Since the vast majority of intermediate goods are imported into these counties, a simple model structure seems appropriate. We view the simplicity of the model as a reasonable expression of the economic structure of these small economies.[36] The simplified model structure facilitates straightforward calibration of the model and allows us to see model mechanisms operating clearly.

[35] See Markusen (n.d.)., Markusen (2020), and Mathiessen (1985), which first described the representation of general equilibrium as a mixed complementarity problem and discusses computational algorithms for solving a model of this kind. Rutherford (1995) offers mixed complementarity representations of three additional models and discusses two algorithms for solving models of this type. Markusen synthesizes these insights, along with subsequent developments, for the purpose of pedagogy.

[36] One assumption of standard international trade models that may not be well-suited to the analysis of US county economies are the assumptions regarding factor mobility, especially as they relate to labor. We conduct a robustness check where we assume that all employment in the wind sector is done by labor that immigrates to the county when the wind sector arrives.

The model structure follows Corden and Neary (1982). This "Dutch Disease" model was developed to help understand likely short- to medium-term effects, on a small open economy, of a "boom" in a single tradeable sector. Dutch Disease effects traditionally are examined at the national level. However, multiple recent papers have shown evidence of a Dutch Disease at the local economy scale[37]. Studying the Silicon Valley, Kwon & Sorenson (2021) present the clearest case of a local Dutch Disease[38]. However, other papers show relatively mixed results. Studies on coal, oil & gas, and military sectors show positive impacts of a boom on local output, wages and employment, especially of non-tradeable sectors, the first indicator of a possible Dutch Disease at the local level[39]. However, the empirical findings on the boom effects on highly tradable sectors are mixed[40]. The textbook model has three sectors – a non-tradeable sector, a "booming" tradeable sector, and a "lagging" tradeable sector. Each sector employs a sector-specific factor and an intersectorally mobile factor. In the model, a "boom" in one of the tradeable sectors has two effects.

[37] Literature on the local manifestation of the Dutch Disease spans across multiple industries, from military (Nakamura & Steinsson (2014) to coal (Black et al., 2005) to oil & gas (Maniloff & Mastromonaco, 2014; Allcott & Keniston 2017), and recently, technology (Kwon & Sorenson, 2021).

[38] Kwon & Sorenson (2021) Examining venture capital investments effects on the economy of the Silicon Valley using a fixed-effect model, They found that on average, doubling venture capital investments will increase tradable tech establishments by 0.8%, while non-tech tradable establishments decrease by 1.6%, suggesting a crowd out of non-boom tradable sectors. Their results also suggest a positive impact on non-tradable sectors establishment and employment. Wages show heterogeneity however, as high-skilled workers gain higher wages, and low-skilled workers see their wages decrease.

[39] Studying the effects of the 1970s coal boom in the local economies of 4 U.S. states, Black, McKinnish & Sanders (2005) results suggest that a coal boom increases local wages by 27.3% for mining sector and 5.8% on average for all non-mining sectors. Nakamura & Steinsson (2014) examine the impacts of military spending on state output and employment and found a positive effects on both state output and overall employment. Research in oil and gas boom also show an increase in overall employment and wages at the local level, including non-tradable sectors and sectors related to oil and gas (Maniloff & Mastromonaco, 2014; Allcott & Keniston, 2017). These results of increase in wages and employment indicate that complete migration may not take place at the local economy level, and thus does not offset all impacts created by economic shocks on the local labor market, which enable possible Dutch Disease effects at the local level.

[40] Kwon & Sorenson (2021) show that non-boom tradable sectors would shrink, but Maniloff & Mastromonaco results indicate that the boom does not cause any significant impacts on the tradable (manufacturing) sector. Similarly, Allcott & Keniston (2017) study the impacts of oil and gas boom during the 1970s and 1980s on U.S. counties economy and found that the boom causes no significant effects on manufacturing productivity, indicating no evidence of a Dutch Disease. Black, McKinnish & Sanders (2005) suggest no evidence of significant spillover either way of a coal boom onto the tradable sectors, although the authors also show that manufacturing employment in counties with a coal boom decreases during the peak of the boom.

In the *resource movement effect,* the expansion of the booming sector draws some portion of the mobile factor out of the other two sectors. In the *spending effect*, spending of new income from the boom leads the non-tradeable sector to expand at the expense of the tradeable sectors. An appreciation of the real exchange rate follows from an increase in the relative price of the non-tradeable. The size of each of the two effects depends on model parameters. Net impacts - on the economy and on most factors of production - depend on the relative sizes of the two effects.

The booming sector in our model is the wind energy sector. Reflecting local realities, we use two lagging tradeable sectors (manufacturing and agriculture) rather than one. We split these sectors in our model because they differ so substantially in their factor demands (especially for land), and because we wish to track (and tax) the rents that landowners receive from the wind sector. We aggregate a variety of non-tradeable services, including private sector retail as well as local government employment (which includes schools and public administration). Labor in the model is intersectorally mobile. Land is quasi-specific; it can be used in either the wind or agriculture sectors. With the exception of the wind energy sector (which imports its capital services from outside the county), each sector has its own locally owned sector-specific capital. All sectors use imported intermediates purchased at prices that are fixed throughout the experiments.

1.4.1 Model equations

We model the sectors other than the wind energy sector as competitive industries that take both output and input prices as given. Each sector s has a zero-profit condition, which we represent as a variational inequality:

$$c^s(\overline{IP}, 1) \geq P^s \quad \perp \quad Q^s \geq 0 \qquad (6)$$

The left-hand side of the variational inequality compares unit costs and prices. The right-hand side indicates that sector output Q^s is positive when the zero-profit condition holds with equality, as is the case throughout our exercises.[41]

Each sector's cost function is assumed to be Cobb-Douglas with cost share parameters for labor, land, sector-specific capital and imported intermediate good. The demand (D) for input $i \in I$ by sector s is derived by applying Shephard's Lemma to $c^s(\overline{IP}, 1)$ and scaling by Q^s:

$$D_i^s = \alpha_i^s \frac{c^s(\overline{IP},1)}{P_i} Q^s \, . \tag{7}$$

Inputs are either sourced locally or externally. Intermediate inputs for all sectors are assumed to be imported into the county. Wind industry capital services are also imported. All other factors - land, labor, and sector-specific capital in the non-wind industries - are locally supplied. In the case of imported inputs, input prices are fixed, and (7) determines the quantity of inputs used. In the case of locally supplied factors, a factor market clearance condition relates factor supplies and demands and determines the factor's price. The variational inequality associated with market clearance for locally supplied factors is:

$$S_f \geq D_f^E + \textstyle\sum_s D_f^s \qquad \perp \quad P_f \geq 0 \tag{8}$$

where S_f is the local supply of the factor input f, D_f^E and D_f^s are factor input demands from the electricity and conventional sectors, respectively. P_f is the (endogenous) price of the factor input.[42]

Arbitrage conditions link local prices to prices in the broader US market. These apply both to the county's imports and exports, to intermediates and to final goods. For exports, the arbitrage condition is:

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[41] The variational inequality in (6) can be derived from profit maximization that chooses Q, given P^s and $\overline{IP}$.

[42] Factors *f* are a subset of inputs *I*. We use separate notation for *f* and *I* when it facilitates exposition, as it does in the factor market clearance equation. Intermediates, the inputs that are not factors of production, are all assumed to purchased outside of the county economy at fixed prices.

$$P^s \geq P^s_{US} * PFX \quad \perp \quad X^s \geq 0, \tag{9}$$

where P^s_{US} is the price in the broader US market (which is taken as given), PFX is the "price of foreign exchange" variable, and X^s the quantity of exports of good s.[43] An equivalent condition applies to sales of electricity when the industry is allowed to operate. The arbitrage that determines quantities of imported intermediates is similar:

$$P^s_{i,US} * PFX \geq P^s_i \quad \perp \quad M^s_i \geq 0 \tag{10}$$

with $P^s_{i,US}$ again the price of the input on the broader US market, P^s_i the local input price, and M^s_i the quantity of sector s inputs purchased outside the county.[44] Conditions analogous to (10) determine the quantity of intermediates (M^E) and capital services (K^E) imported by the electricity sector.[45] Imports of final retail (Q^r_{US}, to be derived shortly) are also determined by an arbitrage condition like (10). We assume no imports of agricultural or manufacturing products for final consumption, treating final goods produced downstream of these sectors as part of retail consumption.

Income and welfare

In our benchmark model, a local representative agent receives factor income and a share of the economic rents from the wind sector, as well as factor income from the other sectors, transfers, and tax revenue.

[43] The variational inequality in (9) relates to profit maximization of perfectly firms engaged in arbitrage. PFX can be understood as a measure of the nominal exchange rate between local and US currencies. In this context the value should, of course, be 1. We choose PFX as the model numeraire and set it to 1 throughout all exercises.

[44] As with (9), equation (10) are the via Kuhn-Tucker conditions associated with profit-maximizing arbitrageurs.

[45] This is the condition that disciplines participation in the wind energy sector by outside actors, most notably capital. In the model, capital's return on participation includes the normal factor return and the rents that it receives. Any local taxation of capital that would cause the after-tax return to capital to fall below the US after tax price of capital would shut down participation by capital, shutting down the sector.

$$Y = \sum_f \left(\alpha_f \ \frac{C(\overline{FP},1)}{P_f} P_f E \right) + (1 - tax)\gamma_T P_V aVh + \ \sum_s \sum_f \alpha_f \ \frac{C(\overline{FP},1)}{P_f} P_f \ Q^s + T + TR \qquad (11)$$

where T is transfer income from outside the county and TR is tax revenue. Our focus is on new taxes that arrive with the wind sector, which have two sources: property taxes (TR_{Prop}) and resource rent taxes (TR_{RR});

$$TR = \underbrace{ptax(\alpha_K P_E E) P_K^E K^E}_{TR_{Prop}} + \underbrace{tax P_V aVh}_{TR_{RR}}. \qquad (12)$$

Consumer behavior is summarized by a unit expenditure function. Consumers have constant elasticity of substitution (CES) preferences over the output of a locally supplied retail sector ($r \in s$), and an imported final retail good. In the mixed complementarity framework, this is modeled as a zero-profit condition relating the cost of a single unit of utility to its price, *PU,* (on the left-hand side of the variational inequality) determining the quantity of utility achieved, *U*, (on the right-hand side).

$$(\theta^r * P^{r\,1-\sigma} + (1 - \theta^r) * P_{US}^{r\ \ 1-\sigma})^{\frac{1}{1-\sigma}} \geq PU \qquad \perp \quad U \geq 0, \qquad (13)$$

where θ^r is a distributional parameter governing the importance of domestic retail in consumer preferences and P_{US}^r is the price of final retail goods and services that are imported by the county. Goods market clearance conditions are as follows: The market for the locally supplied final retail clears with local supply equal to local demand.

$$Q^r \ \geq \ \frac{\theta^r (P^r)^{-\sigma}}{PU^{1-\sigma}} U \qquad \perp \quad P^r \ \geq 0, \qquad (14)$$

with demand determined by an application of Shephard's Lemma and scaled by U. Prices for the imported final retail good are fixed for market participants in the county. Imported quantities demanded of the imported final retail good Q_{US}^r are:

$$Q_{US}^r = \ \frac{(1-\theta^r) * \left(P_{US}^r\right)^{-\sigma}}{PU^{1-\sigma}} U. \qquad (15)$$

The trade balance equation is as follows:

$$(PE + S)E + \sum_s PX^s X^s + T \geq \sum_s IP^s M^s + IP^E M^E + PK^E K^E + \gamma_K (1 - tax) P_V aVh + P_{US}^r Q_{US}^r$$

$$\perp \quad PFX \geq 0 \tag{16}$$

(PE+S)E is the value of electricity exports, gross of the federal subsidy *S*. When the wind sector arrives in the county, these new revenues appear in the balance of payments, and must be balanced either by reductions in exports of other goods ($\sum_s PX^s X^s$), or by corresponding increases in payments to the outside world (on the right-hand side of 16). *T* captures net payments to the county from other sources and is held fixed throughout our exercises. $\sum_s IP^s M^s$ and $IP^E M^E$ represent purchases of inputs by the preexisting and the wind energy sectors, respectively. $PK^E K^E$ represents payments for the factor services of wind energy capital. The economic rents, net of taxes, that are paid to external capital are captured by $\gamma_K (1 - tax) P_V aVh$. $P_{US}^r Q_{US}^r$ represents local consumer's purchases of final retail services from outside the county. The variable that is determined by the balance of payments condition is PFX, the model's numeraire.

The primary mechanisms driving the model's response to rent taxes operate through equations (11), (12) and (16). Setting *tax*>0 increases local tax revenues (in 12), increasing local incomes in turn (11). A positive tax also reduces the county's rent payments to external capital (16). This can be balanced by increased purchases of outside retail ($P_{US}^r Q_{US}^r$) or of intermediates for the preexisting sectors ($\sum_s IP^s M^s$). There will also tend to be a reallocation of output among the pre-existing sectors $\sum_s PX^s X^s$, with higher local incomes generating growth in the non-tradeable retail sector, which attracts labor and land from the agriculture and manufacturing sectors. Since the tax is an efficient tax on rents in the electricity sector, it does not affect the sector's output decisions, nor does it directly affect factor prices. Changes in the relative size of the preexisting sectors affect factor prices, which in turn affect factor input demands by each of the sectors.

1.4.2 Extension to multiple local agents

So far, the model assumes a representative local agent that receives all the income earned in the county. In reality, households are likely to differ substantially in their sources of income. If so, the arrival of the wind sector is likely to have significant distributional consequences across households. In order to study this possibility, we construct five local households, each of which is an owner of one of the five locally supplied factors.[46] This allows our analysis of the distributional consequences of the wind energy boom to go beyond simple movements in relative factor prices (as is done in Corden and Neary). This is important because the allocation of economic rents is central to the distributional questions we raise.

In terms of model equations, the shift from a representative agent to a multiple agent version of the model is simple. Each of the five locally supplied factors - land, labor, and the sector-specific capitals for agriculture, manufacturing, and retail - is given their own income equation. That equation appears as

$$Y_f = \sum_s \alpha_f \, c^s(\overline{FP}, 1) \, Q^s + \left(\alpha_f \, c(\overline{FP}, 1) \, E + (1 - tax)\gamma_f P_V V\right) +$$

$$\delta_f(T * PFX + TR_{Prop}) + \theta_f TR_{RR} \tag{17}$$

This term is a disaggregation of (11), and most of the notation follows from there. δ_f is calibration parameter that defines the share of county wide transfer income and property tax revenue that

[46] One could also specify different θ^r parameters for each household in the expenditure function. Since we lack data that would inform these choices, we refrain from doing so. We assume that households' allocation of retail spending across local and outside retail services is unaffected by their factor ownership.

accrues to each factor f ($\sum_f \delta_f = 1$). θ_f is a policy parameter; it defines the share of resource rent tax revenues that are allocated to the household holding factor f, with $\sum_f \theta_f = 1$.

1.4.3 Calibration of the GE model.

As in Markusen (n.d.) and Markusen (2020), we calibrate the model by construction of a social accounting matrix (SAM), which is a matrix representation of flows of income/expenditure between households and firms, and between the county of interest and the broader US economy. Our small rural counties lack a fully developed input-output table that would support the construction of a detailed SAM, but our simple structure and the ready availability of other data allow us to complete the task. Calibration of the model requires a reconciliation of the data that produces a measure of a) the scale of output for each sector, b) the share of sector revenues that go to each input, c) measures of total factor incomes of local factors, d) data on economywide income, which allows inferences about the size of net transfers into the county, and e) shares of final expenditures on domestic and external retail services. We use data from various sources to construct these SAMs.

In our model, the domestic economy is made up of three sectors: agriculture, manufacturing and retail services. Our first goal in calibration is to define the make-up of these sectors, and to calculate total county wages in each sector. The Quarterly Census of Employment and Wages (QCEW) offers county-level information each quarter on employment and wages by North American Industry Classification (NAICS) sector. We aggregate the NAICS codes up to our three sectors. This accomplished, it is straightforward to calculate the wage bill for each sector in each county.

Our next exercise is to calculate input cost shares for the manufacturing and services sectors. To do this, we aggregate the "use" tables of the 2007 U.S. input-output table to match our aggregate sectors. Since we have specific knowledge of agriculture in the two counties, we take the local agriculture sector to be a weighted average of only two of the agricultural sectors in the BEA table (Grains and Oilseeds). We weight these by 70% grain and 30% oilseeds to calculate input shares for local agriculture.[47] From the tables, we collect each aggregate sector's measure of output, and subtract tax payments. For each sector, the labor share is calculated as payments to labor over this value. Likewise, the intermediate share is the share of intermediate purchases in gross output net of taxes. For the manufacturing and retail services sectors, each sector's capital share is its operating surplus over the same denominator. The land share in these latter two sectors is taken to be zero.

In the agriculture sector, we assume that payments to both capital and land are captured in the input-output table's operating surplus measure. The question is, how should these payments be divided between the two factors? We turn to the 2007 Census of Agriculture, which reports both the total value of agricultural land and structures and the total value of agricultural machinery for each county. The sector-specific capital share is calculated by applying the share of machinery in this sum to the share of operating surpluses in gross output net of taxes. The "land" factor share in agriculture is proportional to the share of land and buildings in the census of agriculture data.[48] The work so far produces calibrated cost functions for all three of the conventional sectors s. All sectors have relatively large intermediate input shares. Retail and manufacturing are relatively labor intensive. Agriculture does not use labor intensively; it is the land intensive sector.

The next step in calibration is to determine gross output by sector, and the magnitude of each sector's input payments. For agriculture, our gross output measure comes from the 2007

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[47] This weighting reflects the weighting of corn and soybeans respectively in the 2007 Census of Agriculture's value of crops sold for the two counties.

[48] Since buildings are better thought of as capital, our treatment may overstate the cost share of land in agriculture and understate the cost share of ag-specific capital.

Census of Agriculture, which reports the value of sales of soybeans and of corn for each county. We treat this sum as gross output in the sector and calculate payments to each input using the Cobb-Douglas shares calculated from the BEA table. For the manufacturing and retail sectors, we lack good county-level data on sector gross output, but the QCEW provides good information on employment and wages. This information allows a direct calculation of each sector's payments to labor. Dividing this value by each sector's factor share produces an estimate of sector gross output; applying the remaining input shares to gross output generates sector payments to capital and for intermediates.

These estimates in turn allow an estimate of the Gross Domestic Product (GDP) of each county prior to the arrival of the wind energy sector. GDP is simply the sum of payments received by the local factors in the non-wind sectors. This value can be compared against data on county-wide household income. Our imputed GDP is lower than reported county-wide income figures, which we find to be intuitive. Many county residents would have sources of income from outside the county (Social Security payments, external investment, or labor income, etc.).[49] In the model we treat the gap between implied local factor incomes and measured county incomes as a net transfer from the outside world, *T*. We calibrate *T* and assume it is unchanged throughout the exercises.

The last calibration challenge we face is how to account for local residents' consumption purchases from outside the county. These are small rural counties, so residents would frequently travel to larger nearby counties for consumption and entertainment. They might also be expected to purchase retail goods and services on-line. Since there would be no available data that could inform this, we simply treat this as a calibration residual. The gap between county-wide personal

[49] Imputed GDP in Benton County is $157.5 million, compared with a BEA estimate of household income of $271 million. Imputed GDP in White County is $476.7 million against a household income estimate of $730 million.

income and the gross output of the local retail sector is assumed to represent consumption of goods purchased outside the county. The share of domestic consumption in total county income is the model parameter θ^r. For both counties in the model, domestic retail accounts for approximately half of total spending. The calculations here are sufficient to produce the SAM for each county. Table 1.8 and Table 1.9 in the appendix report the SAMs for Benton and White Counties respectively. Table 1.10 provides similar figures for the wind sector in each county; these govern the economic impact of the wind sector's arrival in our counterfactual exercises.

Calibration also requires a choice of the elasticity of substitution, σ. In international trade and the economic geography literatures, authors typically assume a value of σ=5. Estimates of this magnitude come from studies of trade in goods. It is not immediately clear what the most appropriate assumption is when we are considering a rural county's retail services aggregate. One might suspect that the retail purchases from outside the county are a relatively poor substitute for locally produced retail services. However, in these rural counties people often travel to more densely populated counties nearby, so substitution of many retail services may not be so difficult. In our preferred estimates, we use σ=5. But we also estimate with σ=1, a Cobb-Douglas parameterization, and show that the size of σ affects the strength of the Dutch Disease. The main policy lessons are, however, robust to the choice of σ.

When we move to the multiple agent model, there is another set of parameters that must be calibrated. The δ_f parameters govern the allocation across households of transfer payments and property tax revenues. This is another situation where we lack good data. What we do in this instance is to calculate each factor's share of the county's GDP, and award the same share of transfer income and of property tax revenue to that factor. This share is δ_f.

1.4.4 Equilibrium in the calibrated model.

The calibration and simulation methods used in the standard GAMS framework are straightforward, but too lengthy to explain in detail here. Briefly, each of the model equations is scaled by value data taken from the SAM. Quantity units are chosen such that $X of value is equal to X quantity units; an assumption that sets all benchmark prices to 1. The scaling of the model equations in calibration means that the quantity variables can also be treated as index values that are benchmarked at 1. Well-established model consistency checks – an application of Walras' Law and a homogeneity test – ensure that the calibrated model solves correctly for a general equilibrium. The counterfactual exercises - both the arrival of the wind sector and the equilibrium with taxes - produce changes in the price and quantity indexes whose solutions are represented in terms of $\pm\%\Delta$. The model is solved in levels, but the results are reported in a manner that is consistent with the hat calculus methods of Dekle, Eaton and Kortum (2007). A consistency check at the new equilibrium (another application of Walras' Law), ensures that the model is fully consistent even after we move away from the benchmark. For details about these procedures, see Markusen's teaching notes and Marukusen (2020).

1.4.5 Counterfactual analysis

Our counterfactual analysis includes two thought experiments. First, we consider the impact of the arrival of the wind sector on the local economy. This shock is calibrated to data on the scale of the initial wave of investments (2007-2010) and illustrates our estimate of the wind energy sector's arrival on local outcomes. In our second exercise, we consider the effects of applying an optimal resource rent tax (calculated jointly with the effects of the arrival of the wind sector). We conduct counterfactual analysis for both the representative agent model and the multiple household model and do so for both counties.

Counterfactual 1. Arrival of the wind sector.

The policy variable that we change to capture the effects of the sector's arrival is the wind capacity variable V. In the initial calibration, V = 0, which implies the $E = aVh$ term in equation 1 is zero in the benchmark. In each county's counterfactual exercise, we model the arrival of the wind sector by setting aVh to be the dollar value of electricity generated by each county. This treatment normalizes P_E to 1, implicitly changing units of electricity from MWh in the partial equilibrium model to dollar-equivalent units of electricity in the general equilibrium model.[50]

The arrival of the wind sector requires an inflow of foreign capital services and intermediate goods to support the boom in the wind sector. The resource movement effect occurs as a shift of labor and land away from the other local sectors and into the production of wind energy. Higher incomes in the county lead to increased purchases of local retail. Relative to the standard Dutch Disease model the real exchange rate appreciation is muted because locals purchase retail services outside the county. The reliance of all sectors on intermediate inputs that are purchased outside the county at fixed prices also dampens Dutch Disease effects.

The arrival of the wind generating electricity sector generated increased revenues to these counties' governments, in the form of property taxes and in the sector's other payments to local governments. We capture these flows in the model with *ptax*. We calibrate this rate so that the wind sector's arrival generates tax revenues that are broadly consistent with what has been observed in the two counties. Table 4 in Bednarikova, et al. (2020) reports the sector's payments of property taxes to the two counties for the years 2010-2019. These grew steadily over the period reaching \$4.3 million and \$2.3 million in 2019 for Benton and White Counties, respectively (both counties had offered generous abatements in the early years, which sharply reduced revenues in

[50] The price is fixed on external markets throughout all exercises. Defining units such that $P_E = 1$ simply allows all initial relative prices to be set to 1.

the earliest years). We calibrate *ptax* to 0.002, which causes our model to produce annualized property tax payments that are somewhat lower than the 2019 annual figures, but much higher than in an average year.[51]

Counterfactual 2. Taxing resource rents

The key policy variable that we change in our second exercise is *tax,* a proportional tax on the resource rents. We consider tax rates from 0-100. Conceptually, a 100% tax on the rents is optimal, but two practical considerations intervene. First, because we use a single policy instrument to tax rents accruing to two different agents, an exhaustive rent tax is not incentive compatible for at least one of the two agents. This issue is compounded by changes in factor prices induced by the wind's arrival. Notably, the market return to land (net of the rents) falls with the sector's arrival (the spending effect dominates the resource movement effect in this regard). A rent tax that extracts the entirety of landowners' rent is thus not incentive compatible, and landowners' consent is critical for wind energy production.

We wish to only consider rent taxes that are fully incentive compatible. In the representative agent model, a 99 percent rent tax is incentive compatible because the recycled tax revenue offsets losses that accrue to land.[52] In the multiple agent model, we must choose lower rent tax rates to insure participation in the sector by landowners. For each parameterization we

[51] We calibrate the model to relatively high annualized tax payments in order to be conservative. The industry made other payments to the counties that were outside the property tax system. White County, for example, received $7.5 million dollars of economic development payments during the early years of these projects' life, when the abatement limited property tax payments by the industry. Our calibrated rate is below the actual property tax rates in the counties, because the large tax abatements the two counties awarded reduced the revenues they would otherwise have collected.

[52] In all exercises we consider outside capital continues to the participate in the wind sector. The price of capital determined in markets outside the county is P_K^E, which remains fixed across all scenarios. The rents that accrue to capital in the wind electricity sector are excess returns to outside capital. In our model, capital services are endogenously provided to the wind sector at that rate so long as we set the rent tax rate below 100%.

consider, we search for the largest possible rent tax that maintains the utility of landowners at the levels of utility they achieved prior to the arrival of the wind sector.[53]

Robustness exercises

The rent tax creates a sizable pool of funds that can be used to favor any one of the local factors. We hypothesize that the allocation that would generate the greatest political support for wind energy is one that targets the factor that is the primary source of income for the largest number of voters, labor. In order to estimate the maximal gains for labor, we allocate all the rent tax revenue that accrues from an incentive compatible rent tax to labor. Our policy variables for this exercise are θ_f. We set $\theta_f = 1$ for labor, and $\theta_f = 0$ for all other factors.

Factor price changes in the Dutch Disease model mean that some factors are worse off after the "boom," especially specific capital in the lagging tradeable sectors. We also conduct a thought experiment where we allocate revenue from the resource rent tax across the factors to ensure a Pareto efficient outcome; that is, one in which no *local* factor is made worse off by the arrival of the sector and the imposition of the tax. In this exercise we calculate the values of θ_f that are required to maintain the utility of all factors at their benchmark levels. These allocations do not exhaust available rent tax revenues, and we allocate the remainder to labor by choice of θ_L.

Next, we note that a model assumption that labor is intersectorally (but not geographically) mobile may not be fully appropriate in the context we study. In particular, it seems likely that the skilled workers employed in the wind sector are notably different than those employed in the other

[53] Prudence would suggest that actual rent tax rates be set somewhat lower than the maximum estimated incentive compatible tax rate, in order to ensure that critical factors of production choose to participate. For example, Australia's short-lived 2012 Mineral Resource Rent Tax was set at only 30% of the estimated supernormal profits earned by the sector. We report results for the maximum incentive compatible tax rate in order to illustrate an upper bound on the local benefits that accrue from taxation.

sectors and may be drawn into the county from outside.[54] If the sector were to import all of its workers, the resource movement effect would be largely neutralized (the sector still draws a small amount of land away from agriculture). In order to consider this possibility, we simulate a counterfactual analysis that includes an endogenous expansion of the local labor force.

1.5 Results

1.5.1 Representative household model

Wind power sector's initial arrival

We first report the results for the model with the representative household. In our GE model, the representative household is the aggregated consumer, representing the combined household types of landowners, laborers, and capital services of the three sectors agriculture, manufacturing and domestic retail services[55]. The representative household thus receives income from all sources that each of the five household types receives. The results are reported as percentage changes relative to the benchmark level. In the benchmark model solution, all variables at equilibrium have a value of 1. Any shock to the economy, such as the arrival of the wind sector and/or economic rent tax associated with it changes the level of the variables by a percentage compared to the benchmark level in the form of $\pm\Delta\%$. Besides modelling the arrival of the wind sector, we also perform a counter-factual scenario of a near complete rent tax of 99% on the sector for each county to examine the effects of a virtually exhaustive rent tax on the economy. Table 1.3 shows the results of the model with a representative household. Columns (1) and (3) contain the

[54] Ours is a steady state model. One might expect that over time, local labor could be trained to do the turbine maintenance jobs that dominate the sector's steady state labor demands. Qualification for turbine maintenance jobs requires only two years of specialized training, followed by one year of on-the-job training (DOE 2021).

[55] This is done by summing over factor f in equation (17).

results of the arrival of the wind sector in Benton and White counties. Columns (2) and (4) show the results of a near complete wind rent tax of 99%. We report the results with an elasticity of substitution between domestic and imported retail services of $\sigma = 5$. The results with $\sigma = 1$ can be found in Appendix 0, Table 1.13.

Table 1.3. GE model calibration results – representative consumer

	Benton County		White County	
	(1)	(2)	(3)	(4)
Variable	Wind sector arrival (%Δ)	Wind sector plus 99% tax (%Δ)	Wind sector arrival (%Δ)	Wind sector plus 99% tax (%Δ)
P^{ag}	0	0	0	0
P^{mfg}	0	0	0	0
P^{rtl}	+ 1.5	+ 3.2	+ 0.2	+ 0.7
Q^{ag}	- 1.9	- 2.1	- 0.8	- 0.8
Q^{mfg}	- 5.2	- 7.2	- 0.6	- 1.2
Q^{rtl}	- 3.1	- 0.5	- 0.2	+ 0.6
FP_L	+ 5.2	+ 7.4	+ 0.5	+ 1.2%
FP_T	- 0.4	- 0.6	0	0
FP_{K-ag}	- 1.9	- 2.1	- 0.8	- 0.8
FP_{K-mfg}	- 5.2	- 7.2	- 0.6	- 1.2
FP_{K-rtl}	- 1.6	+ 2.7	0	+ 1.3
Q^{r}_{US}	+ 4.2	+ 16.5	+ 0.9	+ 4.3
U_{rep}	+ 1.1	+ 9.1	+ 0.2	+ 2.0
Tax revenue form wind energy	\$3.64 million	\$26.94 million	\$2.17 million	\$16.09 million

*P is price of the sector/good, Q is domestically produced quantity of the good/sector, FP is the factor price, M_retail is the quantity of imported retail and services, U is the utility level, and $U_{representative}$ *is the utility level of the representative consumer.* The first counter-factual represents wind arrival in two counties (column 1 and 3). In the second counter-factual (column 2 and 4), we calibrate wind arrival plus a near complete rent tax (99%). The elasticity of substitution between domestic and imported retail & services (R&S) $\sigma = 5$. All results are compared to benchmark level of 1.

Columns (1) and (3) show the results of the arrival of the wind sector in Benton and White counties. When the sector arrives, it competes for factors of production from other traditional sectors, including land and labor. As such, traditional sectors reduce production. This is the resource movement of the Dutch Disease. From column (1) and (3), the agriculture sector of

Benton and White counties decrease by 1.9% and 0.8%, and the manufacturing sector of the two counties decrease by 5.2% and 0.6%, respectively. These are the outcomes of both the resource movement and effect and spending effect, as an increase in consumers' income will also expand the domestic retail services sector at the expense of the manufacturing and agriculture sectors.

The magnitude of the decrease in the traditional sectors depends on which factor of production they rely more heavily on, and the endowment of those factors in the local economy. In our analysis, manufacturing is more labor intensive than agriculture, and agriculture is more land intensive than manufacturing (see sectors' cost shares in Appendix 0). The wind power sector uses more labor than land, thus its arrival draws more resources from the manufacturing sector than from the agriculture sector. The labor endowment in White County is larger than in Benton County, thus the impact on White County manufacturing is smaller. The domestic retail services sector also shrinks, as its labor force is drawn to the wind sector[56]. The increased income also causes the price of domestic retail services P^{rtl} to rise by 1.5% and 0.2% in Benton and White counties, respectively (due to an increase in the sector's demand), even though the shift in resources reduces the outputs of the sector Q^{rtl}. This increase in price drives consumers to purchase more of imported retail services Q_{US}^{r}, as the import sector's price is fixed in the broader U.S. market.

Factor prices FP_f may increase or decrease, depending on how intensive the new sector is in each factor of production it competes against other sectors, and how much the traditional sectors shrink. The wind energy sector's arrival pushes up the price of labor, as the spending effect expands the domestic retail services sector, which is labor extensive. Columns (1) and (3) show

[56] The sector is influenced by both the resource movement effect and the spending effect, and the net effect demonstrates which effect prevails.

that FP_L increases by 5.2% and 0.5% in Benton and White counties, respectively. The wind energy and agriculture sectors are the only sectors to use land, however at different magnitudes. As the wind energy sector uses little land, while the agriculture sector uses most of the land, land price does not increase. Instead, it decreases by 0.4% in Benton County and stays the same in White County, due to the shrinking of the agriculture sector.

The entrance of the wind power sector also brings local residents economic benefits from two sources. The first source comes from the share of the economic rents enjoyed by the landowners who lease their land for wind turbines. Of the $9.72/MWh economic rent, landowners receive $1/MWh, or around 10% of the total rent. The second source comes from the property tax collected from the sector. Property tax revenues amount to $3.64 million in Benton County and $2.17 million in White County, assuming the tax rate of 0.002 (0.2%). The additional income is added into the income of local residents, as shown in equation (17). The residents will in turn use the income to purchase more domestic and imported retail services, thereby increasing residents' welfare/utility as a whole, and expands both domestic and imported retail services. In specific, Benton County residents' utility increases by 1.1%, and White residents' utility increases by 0.2%. Columns (1) and (3) show that the quantity of domestic retail services decreases by 3.1% in Benton (more than $23 million and 0.2% in White counties, respectively. This is because local residents can substitute domestic retail services for imported goods, as the quantity of imported retail services rise by 4.2% in Benton and 0.9% in White counties.

Wind power sector arrival and resource rent tax

Columns (2) and (4) show the results of an exhaustive tax on the resource rents generated by the wind power sector (99% tax rate). The extra tax generates higher total tax revenues, raising it to nearly $27 million in Benton County and more than $16 million in White County. The agriculture and manufacturing sectors further decline, as the domestic retail services sector expands due to the spending effect, and thus attracts labor from the other two sectors. The extra tax income is enjoyed by the local residents (the representative household).

The results show that a near complete rent tax increases the welfare of Benton County residents by 9.1%, and of White County by 2%. The extra tax income induces county residents' consumption of both domestic and imported retail services, but the majority of income is spent on imported retail services, as imported goods increase by 16.5% and 4.3% in Benton and White counties. The results indicate that imported retail services capture most of the income growth in the counties. This is attributable to the high level of substitutability between the two bundles, and the fixed market price of imported retail services. However, the domestic retail services sector performs much better compared to the initial arrival of the wind power sector without a tax (columns (1) and (3)), shown via the increase in Q^{rtl} in column (2) compared to column (1), and column (4) compared to column (3).

1.5.2 Factor-specific households

In this section, we calculate the factor-specific incomes and utilities for each factor owning representative household, or household type, and apply the optimal economic rent tax, or incentive compatible tax. The factor-specific model is the expansion of the original GE model, where each factor of production household receives income from specific sources. This treatment helps inform the distributional consequences of the policy choices. Landowners' approval of turbines located on their land is a crucial element of the wind industry. In our scenarios, we need to ensure that landowners are not worse off compared to before the arrival of the wind industry. To do so, we set the incentive compatible economic rent tax rate so that landowners' utility, or welfare, is at least as high as the benchmark level of 1. We perform the exercise with both retail & services elasticity of substitution $\sigma = 1$ and $\sigma = 5$, to observe how different substitutability in consumption changes the effects of a tax on the local economy. Table 1.4 contains the results of the incentive compatible rent tax in both Benton and White counties with two elasticity of substitution choices.

Table 1.4. GE model calibration results – factor-specific utility model with incentive compatible economic rent tax

	Benton County		White County	
	(1)	(2)	(3)	(4)
Variable	Wind sector plus 35% tax, $\sigma \approx 1$ (%Δ)	Wind sector plus 63% tax, $\sigma = 5$ (%Δ)	Wind sector plus 68% tax, $\sigma \approx 1$ (%Δ)	Wind sector plus 82% tax $\sigma = 5$ (%Δ)
P^{ag}	0	0	0	0
P^{mfg}	0	0	0	0
P^{rtl}	+ 4.5	+ 2.6	+ 1.0	+ 0.6
Q^{ag}	- 2.2	- 2.0	- 0.9	- 0.8
Q^{mfg}	- 8.6	- 6.5	- 1.6	- 1.1
Q^{rtl}	+ 1.3	- 1.4	+ 1.1	+ 0.5
FP_L	+ 8.9	+ 6.6	+ 1.5	+ 1.1
FP_T	- 0.8	- 0.5	- 0.1	0
FP_{K-ag}	- 2.2	- 2.0	- 0.9	- 0.8
FP_{K-mfg}	- 8.6	- 6.5	- 1.6	- 1.1
FP_{K-rtl}	+ 5.9	+ 1.1	+ 2.1	+ 1.1
Q_{US}^{r}	+ 5.9	+ 12	+ 2.1	+ 3.7
U_L	+ 10.6	+ 16.1	+ 3.0	+ 3.5
U_T	0	0	0	0
U_{K-ag}	- 3.0	- 2.1	- 1.2	- 0.9
U_{K-mfg}	- 6.7	- 4.7	- 1.6	- 1.1
U_{K-rtl}	+ 1.6	- 0.3	+ 1.0	+ 0.4
U_{rep}	+ 3.9	+ 6.2	+ 1.5	+ 1.7
Tax revenue from wind energy	$9.52 million	$17.15 million	$11.05 million	$13.33 million

*P is price of the sector/good, Q is domestically produced quantity of the good/sector, FP is the factor price, M_retail is the quantity of imported retail and services, U is the utility level, and U_{rep} is the utility level of the representative consumer. Column (1) and (3) contain the incentive compatibility tax rate results for Benton and White counties at $\sigma \approx 1$, or a Cobb-Douglas demand. Column (2) and (4) represent the results for Benton and White counties at $\sigma \approx 5$, or a CES demand. All results are compared to benchmark level of 1.

Columns (1) and (3) contain the result of an incentive compatible economic rent tax in Benton and White counties under $\sigma \approx 1$, while columns (2) and (4) show the results of a tax under

$\sigma = 5$. The $\sigma \approx 1$ scenario assumes a Cobb-Douglas demand for retail services, so domestic and imported retail services are not very substitutable. This means that more of the increase in income that accompanies the growth in the wind power sector flows into increased demand for local retail services, and the spending effect of the Dutch Disease becomes larger. When the county residents receive more income from the arrival of the wind sector, they spend a larger portion of the extra income on domestic retail services than they would under the scenario when they can substitute domestic retail services more conveniently with imported goods. This is shown via the increase in the quantity of domestic retail services Q^{rtl} by 1.3% and 1.1% in Benton and White counties in columns (1) and (3), compared to a much lower Q^{rtl} in columns (2) and (4), where the elasticity of substitution is higher, and domestic and imported retail services are much more substitutable. Similarly, Q_{US}^{r}, the quantity of imported retail services increase by 5.9% and 2.1% in Benton and White counties in the Cobb-Douglas scenario. The figures are much lower than the increase of 12% and 3.7% in the two counties under $\sigma = 5$, where domestic and imported retail services are highly substitutable.

Under the $\sigma \approx 1$ scenario, the domestic retail services sector grows more as a result of the shock, because consumers do not substitute as easily toward imported retail services. When domestic retail services expands, it attracts more labor at the expense of agriculture and manufacturing. Landowners have two different sources of income: one from the value of factor price of land, and the other comes from the portion of resource rents arising from hosting wind turbines. As agriculture contracts, land demand decreases, leading to reduced land price FP_T, which decreases landowners' utility. Therefore, landowners have less excess rent that we can collect through taxation, and thus the lower rent tax rate. Conversely, when $\sigma = 5$, much of the extra income is spent on imported retail services. Thus, the domestic retail services sector does not expand as much. As agriculture retains more labor and does not shrink as much as under the Cobb-Douglas scenario, land value/price decreases less than the Cobb-Douglas scenario, and landowners have a larger excess revenues base upon which the larger rent tax rate.

The different rent tax rates between the columns determine the effects on each factor owner's utility, the representative utility, and the tax revenues. In each column, the tax revenue shows the total tax revenues from property tax and rent tax collected from the wind sector in Benton and White counties. Since the tax revenues are distributed back to the laborers, the higher the tax rate, the higher the laborers' welfare U_L becomes. For Benton County, a 35% tax rate boosts laborers' utility by 10.6%, and an 63% tax rate results in an increase of 16% in laborers' utility, or income. In White County, a 68% tax rate increases U_L by 3%, and the increasing rate is 3.5% under an 82% tax rate. The utility of manufacturing, agriculture and domestic retail services capital owners is determined more by the expansion/contraction of the domestic retail services sector, induced in turn by the spending effects and the elasticity of substitution σ. When the spending effects are stronger, as in the Cobb-Douglas setting, the domestic retail services sector expands more at the expense of agriculture and manufacturing, thus reducing the welfare of agriculture and manufacturing capital owners' welfare and increasing domestic retail services capital owner welfare.

1.5.3 Pareto improvement scenario

In section 0, we examined the optimal rent tax rate, or the incentive compatible tax rate for each county. This tax rate ensures that landowners are at least as well off as before the wind sector entered the county, thus giving them the incentive to accept turbines on their land. However, as Table 1.3 has demonstrated, the arrival of the wind power sector triggers the Dutch Disease, and the associated resource movement and spending effects reduce the utility of manufacturing and domestic retail services sectors. Manufacturing is affected the most, as they are more labor intensive than agriculture, and lose labor both to the wind power sector and, in the case of White County, the domestic retail services sectors. In this section, we examine the possibility of a Pareto improving outcome. Such an outcome is clearly possible under a scenario where the rent tax revenues are differently. We consider one such scenario, distributing tax revenues to the owners of manufacturing and agriculture capital up to the point where their utility levels reach their benchmark utility level. The remainder of the revenues are given to labor, as a thought exercise[57]. We still set the tax distribution to ensure that landowners are not worse off than before wind arrives. In this scenario, we choose the elasticity of substitution $\sigma = 5$. The results are presented in Table 1.5.

Table 1.5.Wind rent tax distribution under a Pareto improvement equilibrium.

	Benton County		White County	
Rent tax rate	63%		80%	
	Share of tax revenues	Utility (%Δ)	Share of tax revenues	Utility (%Δ)
U_L	0.880	+ 14.5	0.938	+ 3.3
U_T	-0.001	0	-0.0001	0
U_{K-ag}	0.009	0	0.005	0
U_{K-mfg}	0.102	0	0.105	0
U_{K-rtl}	0.009	0	-0.048	0
Rent tax revenue	$17.15 million		$13.33 million	

Table notes: Share of rent tax revenue paid to each factor (δ_f) and levels of utility achieved in an equilibrium that is a Pareto improvement over the benchmark scenario. Other model outcomes (e.g. prices and quantities) are consistent with those reported in Table 1.3.

In Table 1.5, the columns "share of tax revenues" show the percentage of total tax revenues distributed to each of the household type, and "utility" represents the subsequent welfare/utility resulted from the distribution. In Benton County, domestic retail services capital receives 0.9% of

[57] There is room for further redistribution in other Pareto efficient outcomes.

the tax revenues, while in White County, they have to give back 4.8% of the extra income, as they expand thanks to the spending effects (refer to Table 1.3). Agriculture receives 0.9% of the revenues in Benton County, and 0.5% in White County. As manufacturing is the most negatively affected, the owners of manufacturing capital must receive a sizable portion of the tax revenues to be as well off as before the wind energy sector enters, approximately 10% of tax revenues should flow to these households in both Benton and White counties. As the tax rate is already incentive compatible for landowners, they keep a portion of the resource rent, and thus essentially do not need to receive any of the tax revenues. Laborers receive the rest of the tax revenues, after the distribution to other household types. They receive 88% of the tax revenues in Benton County, and nearly 94% in White County. Only 6-12% of the tax revenues needs to be reallocated to reach the Pareto efficient equilibrium. After the distribution, laborers' utility increase by 14.5% in Benton County, and 3.3% in White County, a decrease of 1.6% and 0.2% compared to the scenario when they receive the whole tax revenues (refer to Table 1.4).

1.5.4 Labor migration and the resource movement effect

So far, we have performed the analysis with the assumption that the wind sector uses only domestic labor to service the turbines, thus activating the resource movement effect and harming the traditional sectors. However, we need to consider the possibility that workers inside the county are unwilling to, or unable to switch their occupation, say for example, from agriculture or manufacturing sectors to wind technicians. As the wind technician occupation requires specific skills and time to gain those skills, the wind sector may not be able to secure all its workers within a county.[58] Plus, Benton and White counties are rather small, and residents from neighboring counties can travel there to work and spend their income there. In order to consider a robustness check in which some labor is drawn into the county with the arrival of the wind energy sector, we assume an alternative scenario in which the wind energy sector employment is satisfied completely by labor from outside the county. Though the scenario appears extreme, we wish to study and present the effects of the wind sector on the local economy in the absence of the resource movement effect, as we "import" wind labor from outside the county.

We calibrate this scenario in several steps. First, we simulate the arrival of the wind sector as in other scenarios. When the wind power sector arrives, the labor price FP_L increases, in part due to the resource movement effect, and in part due to the spending effect, when the retail services sector expands. The resource movement effect will vanish if wind power sector labor is comprised solely of immigrant workers from neighboring counties. Thus, in our scenarios where the wind energy sector enters the economy, we supplement the labor endowment (labor supply) of the county until the ratio of total wage bill in the traditional sectors before and after the arrival of wind energy sector equals FP_L after wind energy sector's arrival. This implies that the quantity of labor in all non-wind sectors is fixed, but labor could still be re-allocated via the spending effects. While we consider the income spent on the local economy of immigrant workers part of the spending effect, we separate their welfare from domestic workers' welfare, and exclude them as a recipient of the economic rent tax revenues. We calculate the utility of domestic workers by dividing their income by the cost-of-living index PU and distribute the rent tax revenues associated with the

[58] Ivy Tech college requires 34 credits for the industrial wind technology certificate, which takes approximately 1 year. See https://catalog.ivytech.edu/preview_program.php?catoid=5&poid=4125&returnto=519 (Ivy Tech Community College, n.d.)

incentive compatibility tax rate to them as other scenarios. Table 1.6 represents the results of this scenario for an elasticity of substitution $\sigma = 5$ for Benton and White counties.

Table 1.6. Simulation results under the scenario of labor migration for the wind industry, and the exclusion of resource movement effect

	Benton county		White county	
	(1)	(2)	(3)	(4)
Variable	Wind imported labor (%Δ)	Wind imported labor plus 78% tax (%Δ)	Wind imported labor (%Δ)	Wind imported labor plus 85% tax (%Δ)
P^{ag}	0	0	0	0
P^{mfg}	0	0	0	0
P^{rtl}	+ 0.6	+ 2.0	+ 0.1	+ 0.6
Q^{ag}	- 1.4	- 1.5	- 0.7	- 0.8
Q^{mfg}	- 0.5	- 2.1	0	- 0.7
Q^{rtl}	+ 1.3	+ 3.5	+ 0.3	+ 1.0
FP_L	+ 0.5	+ 2.1	+ 0.1	+ 0.6
FP_T	+ 0.1	- 0.1	+ 0.1	0
FP_{K-ag}	- 1.4	- 1.5	- 0.7	- 0.8
FP_{K-mfg}	- 0.5	- 2.1	- 0.1	- 0.7
FP_{K-rtl}	+ 1.9	+ 5.5	+ 0.4	+ 1.5
Q^r_{US}	+ 4.5	+ 14.2	+ 1.0	+ 3.9
U_L	+ 0.2	+17.2	0	+ 3.4
U_T	+ 3.5	0	+ 2.2	0
U_{K-ag}	- 0.9	- 1.6	- 0.5	- 0.8
U_{K-mfg}	- 0.4	- 2.0	- 0.1	- 0.8
U_{K-rtl}	+ 1.0	+ 2.5	+ 0.2	+ 0.7
Tax revenue from wind energy	\$3.64 million	\$21.23 million	\$2.17 million	\$13.82 million

P_s is price of the pre-existing sector/good s, Q_s is locally produced quantity of the good/sector, FP is the factor price, M_retail is the quantity of imported retail and services purchased, and U_f is the utility level of the representative household holding factor f. The wind sector's arrival generates property tax revenue, which appears in all scenarios. Tax revenues in columns 2 and 4 also include revenues from rent taxes.

Columns (1) and (3) show that, without the resource movement effect, the endogenous growth in the labor supply mitigates the losses for agriculture and manufacturing sectors from the Dutch Disease. This is especially visible for manufacturing, as their produced quantity Q_s becomes much higher than when the wind sector uses domestic labor (refer to Table 1.3 andTable 1.4).

However, since the wind sector imports all labor now, the factor price of domestic labor does not rise as much, only 0.5% in Benton and 0.1% in White counties, compared to 5.2% in Benton and 0.5% in White counties as when the sector draws domestic labor away from other sectors. As the traditional sectors do not shrink significantly, and labor price does not hike as much, the county residents can afford a little more consumption, as implied in the increase in imported retail services Q_{US}^{r} compared to the scenario of domestic labor alone.

Columns (2) and (4) indicate a higher incentive compatible tax rate in both Benton and White counties, compared to the domestic-only labor scenario. These two columns show similar patterns as in columns (1) and (3), where the Dutch Disease effects weaken from the immigrant workers. Agriculture and especially manufacturing and retail services shrink much less (as they are more labor intensive than agriculture), compared to the domestic labor scenario. Wages still increase thanks to the expansion of those sectors (in relative to the domestic labor scenario), but not as much as in the domestic labor scenario, where both resource movement and spending effects are present. A higher tax rate grants the counties more tax revenues, and in Benton County it enables domestic laborers a higher utility/welfare, which can be seen as a "compensation" to the lower wage FP_L. In particular, when compared to the domestic labor scenario, Benton County laborers' utility increases by 1.1%. However, the increase in the tax rate in White County is not sufficient to counter the effect of a lower wage, and White County laborers' utility decreases by 0.1% compared to the domestic-only labor scenario.

1.5.5 Wind power industry profitability and economic rents in recent years

The dynamics of the wind power purchase agreement (PPA) prices and the technological features of the wind electricity industry mean that the economic rent of the sector fluctuates over time. Therefore, we examine the capital economic rent in the 2018-2020 period, as this is the most recent period in which we can gather data. We use the capital and O&M cost, project design life, net annual energy production and capacity factor data from NREL 2020 Cost of Wind Energy Review (Stehly & Duffy, 2022). Stehly & Duffy reported a nominal discount rate of 5.23% for a representative wind project. The capital expenditures for a 2.8 MW land-based turbine, the model that is used in the report is $22.8/MWh, or $1.462 million per MW. The O&M cost is $11.5/MWh, or $43,000/MW; the net annual energy production is 3,703 MWh/MW/year; the capacity factor is 0.423, and the project life is 25 years (Stehly & Duffy, 2022). However, the report of NREL uses a 2.8 MW wind turbine model, while the turbines built in Indiana in 2018-2020 are an assortment of 2.5 MW, 2.8 MW, 3.6 MW and 4.2 MW, with the majority being 3.6 MW (Hoen et al., 2021). Thus, the costs in the report may be underestimated (as installed turbines are larger than reported turbines), and the capital factor and production may also be underestimated for the economic rent analysis.

The 2018-2020 wind PPA price of the MISO area comes from the 2021 wind market report of Lawrence Berkeley National Laboratory, with a value averaged among all projects of $20.1/MWh (Wiser et al., 2020). In this time period, the PTC replaced Section 1603 grants. The PTC value from 2018 to the end of 2021 is $0.015/kWh, or $15/MWh, which can be applied for the first 10 years of the project (NC Clean Energy Technology Center, 2021; DOE, n.d.)[59].. The average rental rate per acre in West Central Indiana in 2018-2020 was on average $246/acre (Dobbins, 2019; Kuethe & Dobbins, 2020). We assume the same land lease payment and opportunity cost for landowners as in 2007-2010.

We calculate the labor cost in Benton and White counties in 2018-2020 using the same method as in the 2007-2008 period. In 2018-2019, Benton County has around 95 people employed

[59] Source information https://programs.dsireusa.org/system/program/detail/734 and https://windexchange.energy.gov/projects/tax-credits.

long-term in the wind industry (Benton County Economic Development), while White County has 63 people (EDP Renewables, 2021). In 2020, both Benton and White counties host a new commercial wind farm (Hoen et al., 2021). The Benton County project has a rated capacity of 402 MW, while White County new wind farm boasts a rated capacity of 102 MW (Hoen et al., 2021). Still assuming that the number of turbines is proportional to the number of wind technicians, we estimated the additional permanent employment to be approximately 23 workers for Benton County, and 4 for White County[60]. The assumed salary remains at around $61,000/year. Hence, total labor cost per year is $7,198,000 for Benton County, and $4,087,000 for White County. Total installed capacity up to 2020 is 986.3 MW for Benton County, and 801.25 MW for White County. As such, labor cost per MW is $7,298 for Benton County and $5,102 for White County. In MWh, the values are $1.97/MWh for Benton County and $1.4 for White County.

While the PTC has a value of $15/MWh, project developers can only apply them for the first 10 years of the project (NC Clean Energy Technology Center, 2021; DOE, n.d.). Meanwhile, projects from 2020 on average operate about 25 years (Stehly & Duffy, 2022). Thus, we annualize the PTC using NREL discount rate and retrieve a value of $8.51/MWh. Using the annualized PTC, the PPA price, and the costs, we calculate capital economic rent to be ($20.1 + $8.51) – ($22.8 + $11.5) = -$5.7/MWh. This indicates that wind developers incur a loss in this period. The summarized information regarding economic rent, cost and price in 2018-2020 can be found in Table 1.7.

[60] Up until 2019, Benton has around 622 turbines in commercial wind farms (Hoen et al., 2021). Benton County Economic Development estimates that 95 permanent jobs are associated with the number of turbines available before 2020. Thus, each turbine supports around 0.15 jobs in Benton approximately. The new project in Benton has 150 turbines, which implies that around 23 new permanent jobs are added in the county now. I perform a similar calculation for White and estimate that the county has around 4 new permanent jobs in the wind sector.

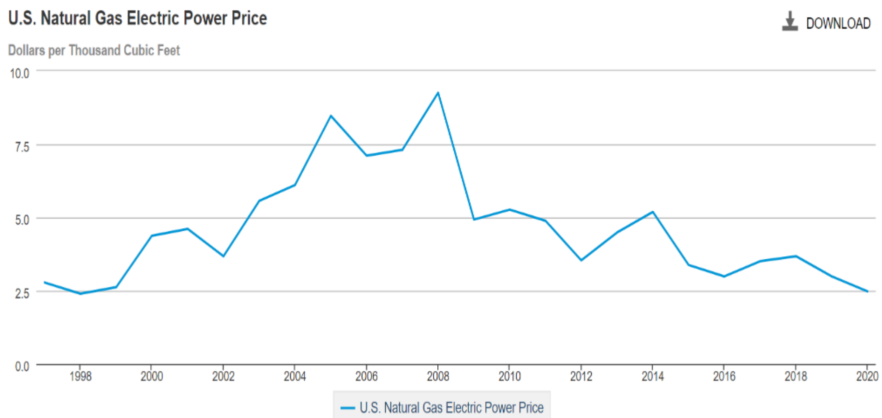
Table 1.7. Wind power sector cost, profits and economic rents from 2018-2020

Items	Citations	Per 2.8 MW turbine (1 acre)	Per MW	Per MWh
PPA price	Wiser et al., (2020)			$20.1
Capital cost	(Stehly & Duffy, 2022)	*$4,093,600*	$1,462,000	$22.8
Production tax credit (PTC)	(NC Clean Energy Technology Center, 2021; DOE, n.d.)			$15 (annualized $8.51)
O&M (with land lease and labor)	(Stehly & Duffy, 2022)	*$120,400*	$43,000	$11.5
O&M (without land lease and labor)	(Stehly & Duffy, 2022); Bednarikova et al. (2020)			*$9.55 (Benton)** *$10.1 (White)**
Labor cost	(Stehly & Duffy, 2022)		*$7,298 (Benton)* *$5,102 (White)*	*$1.95 (Benton)** *$1.4 (White)**
Land lease payment	Bednarikova et al. (2020)	*$10,400*	$4,000	*$1.1**
Cash rent for land	Dobbins (2019); Kuethe & Dobbins (2020)	$246		
Assumed opportunity cost for land		$1,000		*$0.1**
Implied landowner economic rent	Own estimation			*$1**
Capital economic rent (without MACRS)	Own estimation			*$-5.7**
Capital economic rent (with MACRS)	Own estimation			*-$3.92 - $-3.6**

* Indicates own estimation. We assume opportunity cost to landowners when hosting turbines to be $1,000/acre/turbine to account for rental rate and all other hidden costs. Capital economic rent is calculated by subtracting the revenue per MWh by the total cost per MWh. Revenue per MWh is sum of PPA price and PTC, and total cost is sum of capital cost and O&M cost per MWh. I approximate labor cost per MW by dividing total labor cost by the total rated capacity in each county. Assumed opportunity cost for land is around 1/10 total land lease payment, and implied landowner economic rent is around 9/10 total land lease payment. To convert from MW to MWh for all figures except for gross capital cost and net capital cost, divide the figures by the annual net production of 3,703 MWh. To convert gross capital cost and net capital cost from MW to MWh, follow the LCOE calculation formula from Stehly & Duffy (2022).

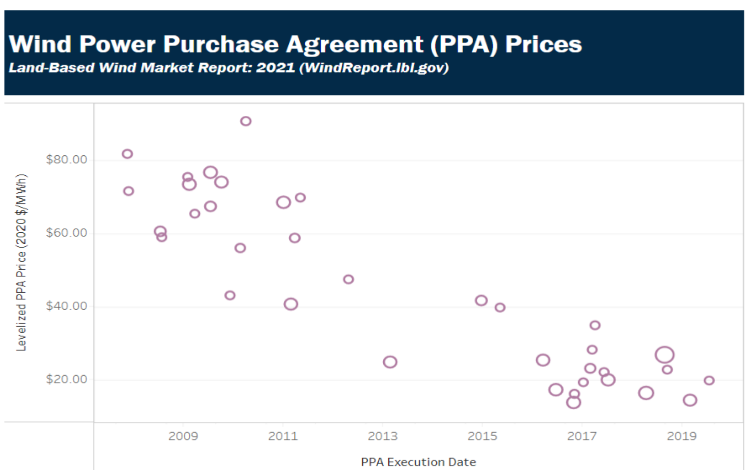
The low PPA price in the 2018-2020 period is due in part to the connection between electricity price and natural gas price (Alvarez & Molnar, 2021; Indiana Energy Association, 2018; U.S. Energy Information Administration, 2021). The pattern is even clearer in Indiana, where natural gas increasingly contributes to the generation mix (Indiana Energy Association, 2018).

Figure 1.1 contains the historical price movement of natural gas electric power price in the U.S., and Figure 1.2 presents the PPA prices secured by wind projects in the MISO area from 2008 to 2020.



Source: U.S. Energy Information Administration (2020)

Figure 1.1. U.S. Natural gas electric power price



Source: Wiser et al. (2020)

Figure 1.2. PPA price of land-based wind power projects in MISO from 2008-2020

Figure 1.1 shows that before 2008, the price of natural gas used in electricity generation increased continuously and reached its highest value in 2008. At the same time, MISO PPA prices shown in Figure 1.2 hovered around \$60-\$80/MWh from 2008-2010. After the fracking boom took place, the natural gas price began to decrease continuously until 2020. From 2011-2019, the PPA price in MISO has plummeted for all projects, reaching around $20-$30, or even lower in 2018-2020. Thus, the recent low price of natural gas has reduced economic rents by reducing the market price of electricity. However, this trend may not be permanent. In 2021, natural gas price has increased substantially in Europe, leading to higher demand of coal, and ultimately creates a surge in electricity price in Europe (Alvarez & Molnar, 2021). The International Monetary Fund has predicted the persistence of the increase in energy price for at least a year, due to an inadequate supply of natural gas (Pescatori et al., 2021). The 2022 Ukraine war has furthered driven up natural gas price in Europe and elsewhere (Boehm, 2022). Thus, a similar rise or strong volatility in natural gas price can push up electricity price, and potential profits and economic rents for the wind power industry.

1.6 Discussion

It is useful to distinguish the form of our proposed tax from other taxes that have been applied to the sector. The most common form of local taxation of the industry is via property taxes. Revenues from property taxes vary substantially over the length of the project, as the turbines owners depreciate out the capital. The counties we study gave large property tax abatements that substantially reduced their tax revenues from these projects in the beginning of the project lifetimes. Resource rent taxes offer the possibility of higher revenues, and of steadier revenue streams for county governments throughout the life of industrial scale wind projects. However, it is important to note that counties currently do not have the legal authority to impose this tax, a situation that would need to be addressed by state legislature. They also normally do not possess the sufficient analytical tools and resources to accurately identify the rents.

In recent years, the state of Texas recently imposed an output tax on wind generated electricity (Sixel, 2020; Baltz, 2021). Taxes on the quantity of electricity produced discourage production, and are therefore not economically efficient. A well-structured resource rent tax would not reduce investments in wind energy. In our view, such a tax could potentially increase wind energy production by making the industry more palatable to local communities, thereby limiting the degree to which land use restrictions preclude wind energy production altogether.

Resource rent taxes are typically operationalized as a proportional tax on supernormal profits. In the case of wind energy, taxes would be assessed at the level of individual projects or farms. Inframarginal projects, which earn excess returns, would be the ones whose profits would be taxed. Marginal projects earning only a normal return would not pay resource rent taxes, and therefore not be deterred from production. This is the manner in which resource rent taxes can be efficient.

One practical difficulty that arises in the assessment and calculation of resource rent taxes is defining what constitutes "normal" profits. Taxation of rents linked to petroleum and other mineral taxes has proven difficult in real-world settings. It is our view that the US electricity sector is already well-structured for the calculation of project-specific supernormal profits. A long history (and well-developed body of case law) has resolved most issues regarding the calculation of normal returns to capital on investments undertaken by regulated utilities. Similar metrics could be applied to the independent power projects that are most relevant to the setting we consider. These calculations can be carried out by the public utility commissions (PUCs), organizations that are responsible for overseeing electricity rates of regulated utilities, and make sure that they are fair, just and reasonable (National Conference of State Legislatures, 2019). Some of the examples include PPAs approval by the PUCs in Ohio and Connecticut (Center for Strategic & International Studies, 2016; Connecticut Department of Energy & Environmental Protection, 2020). Despite this, the PUCs, which typically regulate monopoly providers, would need explicit authority to acquire information from independent power providers for such analyses. This explicit authority would have to be established by the state legislature. The setting of rent tax rates could be done at either the county or the state level, but that decision ultimately lies with state legislatures.

In the settings where implementing a resource rent tax proves challenging, second-best options would include using existing county-level tax authorities to extract more revenue, often through property tax. Given the large rents our study has uncovered, it's plausible that past tax abatements have been more than sufficient to induce investments. Counties may ideally consider current economic conditions when determining the appropriateness of an abatement, taking into account factors such as current PPAs pricing and the size of federal subsidies. These projects in our studies were installed at a time when prices were high, and the subsidies were generous, indicating that the projects would likely have proceeded even without the abatements. In summary, at the very least, if the process of implementing a resource rent tax proves challenging, county governments can reduce or eliminate property tax rebates. These rebates may be unnecessary to attract investment given the presence of resource rents, depending on the situation.

1.7 Conclusion

In this paper we develop a partial equilibrium model of the wind-generated electricity sector and integrate it into a general equilibrium model that allows us to study the local economic impact the sector has on a rural community. Factor services supplied by the wind itself and generous federal subsidies are sources of economic rent, which is divided between external suppliers of capital and local landowners. The existence of resource rents opens up the possibility that state or local tax policy could improve aggregate local welfare and mitigate the distributional consequences of the sector's arrival in a rural community. The general equilibrium model allows us to investigate the consequences of the sector's arrival on a small open economy, and the way in which tax policy interacts with it.

In order to put the magnitude of these possible gains in context we consider the effects of wind energy investments undertaken in 2007-2010 and do so in the specific context of two Indiana counties that saw especially large growth in wind energy generation during that period. The gross output of the wind sector in these counties is quite large relative to the scale of the county economies, but the sector value added that is produced by locally owned factors is rather small in comparison. The existence of resource rents allows a role for taxation in the sector, taxation that need not, in principle, limit the sector's growth. We build and calibrate a general equilibrium model that allows endogenous outside investment in the wind sector and demonstrate that the taxation of economic rents can magnify substantially the local economic benefits of the wind sector's arrival. The substantial funds that can be raised via rent taxes can also be used to compensate losses associated with the sector's arrival. These insights may offer an answer to the problem that has limited expansion of the industry, particularly in the Great Lakes region - local opposition to the presence of the industry has blocked a large number of economically viable projects.

We report results for exhaustive rent taxes and for smaller - but still quite large – rent taxes in several robustness checks. These should be considered exploratory efforts, rather than explicit policy recommendations. Rent taxes that are beyond their efficient levels would preclude investment in the sector. Our estimates suggest that rent taxes well below the exhaustive level would still generate substantial improvements in local welfare.

We view our paper as a contribution to the larger literature on the local economic impact of wind energy investments. Much of the literature to date consists of input-output modeling and econometric studies. Our general equilibrium approach allows us to investigate distributional issues and local tax policy analysis. The data requirements for such models is normally quite burdensome, but our assumption that the small rural economies we study contain few relevant input-output linkages allows us to complete the task.

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1.9 Appendix

This Appendix contains detailed information described in the main text. In part A, we present the Modified Accelerated Cost Recovery Program (MACRS) potential effects on the estimation of wind power sector resource rents. Part B contains the Social Accounting Matrix (SAM) for Benton and White counties, and explanations of the SAM's mechanism. In part C, we discuss robustness check calibration scenarios for the GE model under the assumption of elasticity of substitution between domestic and imported retail services $\sigma = 1$ (Cobb-Douglas). Finally, we show all calculations of cost share for each factor of production in each sector in our PE and GE models.

1.9.1 Social accounting matrix benchmark values

In order to construct the SAM tables that contain the benchmark values for the variables in the GE model, we estimate the cost share of each of the factor of production for each sector: agriculture, manufacturing, retail services, and wind energy. We then apply the Shephard's lemma on the land and labor cost to estimate the demand for each factor of production in each sector in dollar value, normalizing all factor prices to 1. The next paragraphs describe the process in detail.

Cost shares and SAM benchmark values of the wind power sector

In this section, we describe in detail the imputation for cost shares, SAM benchmark values and economic rent in the wind sector. As in the calculations of cost shares and SAM benchmark values for other sectors, we start with collecting cost and revenue data. We then dissect the cost items and apply the Federal subsidy onto the capital cost base to find the economic rent. We impute the cost share of each factor of production by dividing the cost of each factor by the levelized cost of energy (LCOE), which is the total cost per MWh of a wind turbine. The process is described below.

We collect the capital cost, O&M expenses, discount rate, capacity factor, and net annual energy production from the 2010 wind energy cost report of NREL (Tegen et al., 2012). The capital cost is $2,155/kW. The O&M expenses amount to around $34/kW. Note that NREL considers land lease to be a part of O&M expenses. Hence, if we remove the land lease from the O&M cost, the expenses become $34 – $6 = $28/kW. Of $28/kW, $15 is labor, equipment, facilities per kW; and $12 is levelized replacement cost per kW. The capacity factor of a 2007-2010 turbine is 38%. Finally, the net annual energy production is 3,345 MW. We convert all costs in terms of $/MWh.

We collect land lease payment information from Bendnarikova et al. (2020) and use the figure $6,000/acre/turbine in our paper. We collect employment data in the wind sector in Indiana from several sources. We retrieve Benton County employment data in the wind industry sector from the website of the Benton County Economic Development Corporation. Employment in 2020 was 95 people[61]. White County wind power industry employment data comes from the website of Meadow Lake Wind Farm, and in 2020 White County had 63 people having a permanent job in the wind industry[62] (EDP Renewables, 2021). However, for the analysis purpose of the study, we only consider wind industry employment in Benton and White counties from 2007 to 2010. We assume that employment is proportional to rated capacity and the number of turbines in a county. The proportion of turbines in Benton and White counties in the period 2007-2010 is 88% and 73%,

[61] Source information https://benton4business.com/benefits. Downloaded October 15, 2020.

[62] Source information https://meadowlakewindfarm.com/wp-content/uploads/sites/15/2014/03/IN-Meadow-Lake-Wind-Farm-Fact-Sheet-June-2020.pdf. Downloaded October 15, 2020

respectively. Hence, the estimated employment in the wind sector in Benton and White counties in the period 2007-2010 is 84 people and 46 people, respectively. As wind technicians charged with turbines maintenance represent the bulk of the permanent workforce of the industry in each county, we assume that labor in the wind power sector is comprised fully of wind technicians. Annual salary for wind technician is around $53,000, with an estimated $8,000 in annual overtime pay, which is a total of around $61,000/year (BLS, 2023)[63]. Using these figures, total labor cost in a year is $5,124,000 for Benton County, and $2,806,000 for White County. Total installed capacity in Benton and White counties in the period 2007-2010 are around 837 MW and 501 MW, respectively. As such, labor cost per MW is $6,122/MW for Benton County, and $5,600/MW for White County. In MWh, the labor cost is $1.84/MWh for Benton County, and $1.67/MWh for White County. Hence, O&M cost excluding land lease and labor is $6.36/MWh for Benton County and $7.2/MWh for White County.

In order to determine the profits of the wind power sector, besides costs we also need to determine the revenues and government incentives. While the production tax credit allows tax credit for every MWh of output, the investment tax credit grants renewable energy projects a credit of 12-30% of investment costs at the beginning of the project (WINDExchange, n.d.)[64]. Wind projects in Benton and White counties in 2007-2010 received a type of investment tax credit called the Section 1603 grant.

In 2009 President Obama signed the American Recovery and Reinvestment Act of 2009 (ARRA). Section 1603 was created as a part of the ARRA. Section 1603 allows RE projects to receive one-time payments from the Department of Treasury in place of the PTC (U.S. Department

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[63] See several sources: https://www.bls.gov/ooh/installation-maintenance-and-repair/wind-turbine-technicians.htm; https://www.indeed.com/career/wind-turbine-technician/salaries; https://www.glassdoor.com/Salaries/wind-technician-salary-SRCH_KO0,15.htm

[64] Sources information https://windexchange.energy.gov/projects/tax-credits. Downloaded October 1,2020.

of Treasury, 2009). The payments amount to 26%-30% of the investment costs for large wind projects that are constructed within the period from 2009 to 2012, with the credits terminated on January 1, 2013.[65] From Section 1603 awardees list, we collect the data for 5 wind projects in Indiana that received the grant from 2009 to 2012. These include Hoosier Wind Farm, Meadow Lake Wind Farm I, II, III, and IV (U.S. Department of Treasury, 2018)[66]. The 5 wind farms received in total $346,033,633. The 2007-2010 total capacity of the 5 wind farms combining are 606.85 MW (Bednarikova et al., 2020). Assuming the capital cost of $2,155/kW from NREL, the total capital cost of the four wind farms combining is around $1,307,761,750. From these figures, we can compute the proportion of the grants in the total cost to be around 26%. As such, total capital investment cost is reduced to 61*(1-0.26) = $45.14/MWh. Thus, total cost per MWh is the capital cost per MWh with Section 1603 grant plus the O&M cost per MWh, which is $45.14 + $10 = $55.14/MWh.

We use data from the Power Purchasing Agreement (PPA) prices of the Midcontinent Independent System Operator area from 2007-2012 to calculate the fixed electricity price in the model. The average PPA of the Great Lakes region in this period was $63.86/MWh (Wiser et al., 2020). Using this value, the supernormal profit, or economics rent of capital (wind developers) is $63.86 - $55.14 = $8.72/MWh. The remaining $1 of landowners economic rent comes from the assumed opportunity cost of $1,000 and the land lease payment of $6,000 per turbine.

[65] Sources information https://home.treasury.gov/system/files/216/GUIDANCE.pdf. Downloaded October 5, 2020.

[66] The grants awarded to Hoosier, Meadow Lake I, II, III and IV are $69,555,205, $55,212,505, $59,303,557, $48,780,848, and $113,181,518, respectively.

Cost shares and SAM benchmark values of agriculture, manufacturing and retail services sectors

Sectors definition and labor cost imputations

In this section, we first define and classify the three traditional sectors used in our paper: agriculture, manufacturing and retail services, and the labor costs used to compute values in the SAM of Benton and White counties. To estimate the labor cost for manufacturing and retail services later used , we collect the data for employment, number of establishments, and wages for these sectors from the Quarterly Census of Employment and Wages (QCEW) database for Indiana, which is available on the Indiana's Public Data Utility (Indiana's Public Data Utility, n.d.)[67]. The database consists of four quarters, with employment, number of establishments, and wages for each quarter in a year. We collect Benton and White counties data for the year 2006. In calculating employment, we sum the number of workers of all sub-sectors in a main sector for each quarter[68]. The main sectors are agriculture, manufacturing, and retail services. We categorize the sub-sectors using the North American Industry Classification System (NAICS) codes as follow:

- Agriculture: agriculture, forestry, fishing and hunting (NAICS code 11----)
- Manufacturing: mining (NAICS code 21----), manufacturing (NAICS code 31----), transportation and warehousing (NAICS code 48----)
- Retail services: utilities (NAICS code 22----), construction (NAICS code 23----), wholesale trade (NAICS code 42----), retail trade (NAICS code 44----), information (NAICS code 51----), finance and insurance (NAICS code 52----), real estate and rental and leasing (NAICS code 53----), professional, scientific, and technical services (NAICS code 54----), management of companies and enterprises (NAICS code 55----), administration and

[67] Sources information https://www.stats.indiana.edu/about/qcew.asp. Downloaded September 1, 2020.
[68] Our main sectors are agriculture, manufacturing, and retail services.

support and waste management and remediation services (NAICS code 56----), educational services (NAICS code 61----), health care and social assistance (NAICS code 62----), arts entertainment recreation (NAICS code 71----), accommodation and food services (NAICS code 72----), public administration (NAICS code 92----) , and other services (NAICS code 81----).

We then average the number of workers of four quarters to find the average total employment of a main sector in 2006. We perform the same procedure with the number of establishments. We sum up the wages of all sub-sectors within a main sector for all four quarters to find the total wages paid in a year.

A number of sub-sectors within the services sectors experience non-disclosure issue, especially for employment and wages[69]. In order to incorporate this, we assume that the sub-sectors with non-disclosure information have the number of workers per establishment equals to the average number of workers per establishment of all other sub-sectors. We take the average number of workers in an establishment of a sub-sector by dividing the number of workers in that sub-sector by the number of establishments for quarter 2. We then average the average number of workers of all sub-sectors without non-disclosure information and find the number to be 10.04 workers per establishment for Benton and 11.3 for White. This number is then multiplied with the number of establishments of sub-sector with non-disclosure information to find their number of workers. We then take the average of four quarters for total employment of all sub-sectors, with and without non-disclosure information. We perform a similar procedure for wages of the services sector, but instead of taking the average of all four quarters, we sum up all four quarters to find the total wages in a year.

[69] There are a limited number of establishments in those sub-sectors. In order not to produce information that would allow someone to infer the employment level of individual firms, these data are suppressed.

Cost shares of factor of production in agriculture, manufacturing, and retail services sectors

For the imputation of cost shares in each sector, we collect and combine data from several sources. We first use the 2007 input-output use tables of the Bureau of Economic Analysis (BEA input-output use tables) (U.S. Bureau of Economic Analysis, 2007)[70]. However, the data is only available nationally. Thus, we assume national patterns for Benton and White counties. The BEA tables provide us the total values of intermediate goods, total compensation of employees, other taxes on production, gross operating surplus, and total industry output values. To find the share of intermediate goods in total output before taxes, we divide the values of intermediate goods by the total industry output less taxes for each three main sectors defined above. We perform similar procedure for compensation of workers and consider this the labor cost share. The share of intermediate goods values, or intermediates cost share in total output before taxes for agriculture, manufacturing and retail services sectors are 0.58, 0.63, and 0.41, respectively. The share of labor values, or labor cost share in total output before taxes for agriculture, manufacturing and services sectors are 0.12, 0.19, and 0.36 respectively.

Since Benton and White counties' agricultural output is concentrated in a smaller subset of crops (corn and soybeans), we wish to use only those sectors of agricultural production that are relevant to those settings. Agricultural outputs from the BEA input-output table include all agricultural products. We collect agricultural data for Benton and White counties in 2007 from the United States Department of Agriculture (USDA), National Agricultural Statistics Services (NASS) 2007 census (U.S. Department of Agriculture, n.d.)[71]. The data includes corn and soybean sales, measured in dollar; corn (grain) and soybean acres harvested; corn (grain) and soybean

[70] Sources information https://apps.bea.gov/iTable/iTable.cfm?reqid=52&step=102&isuri=1&table_list=4&aggregation=sec. Downloaded August 20, 2020.

[71] Source information https://quickstats.nass.usda.gov/. Downloaded September 10, 2020.

production, measured in bushels; asset values of agricultural land (including buildings), measured in dollar; and asset values of total machinery, measured in dollar. We collect and use data of corn and soybean because the combined sales of corn and soybean for each county is approximately 90% of total sales of commodity for each county. Therefore, we opted to collect the BEA input-output data for oilseed and grain, which represent soybean and corn. Using this data, we estimate the national share of intermediate goods, wages, and operating surplus for aggregate of soybeans and corn[72]. Next, we calculate the share of soybeans and corn in total sales of the two crops for Benton and White counties. The share of soybean in both counties are similar and close to 70%, and as such we use the soybean : corn ratio of 0.3 : 0.7. Finally, we estimate the average share of intermediate goods, wages and operating surplus for Benton and White counties agriculture sector by taking the weighted average of national share of intermediate goods, wages and operating surplus of oilseed and grain, using the 0.3 : 0.7 ratio. The estimated weighted average shares of intermediate goods, wages and operating surplus are 0.69, 0.03 and 0.28, respectively. These shares are used for both Benton and White counties' agriculture sector, as they share similar trends in corn and soybean sales.

In the case of agriculture, we need to allocate gross operating surplus to capital and to land. To split gross operating surplus, we first sum asset values of agricultural land (including buildings) and the values of machinery assets that come from USDA 2007 census to retrieve the total values of assets[73]. In order to find the share of land and machinery, we divide each by the total values of assets. Using this calculation, the share of land in the total value of assets for Benton and White

[72] Shares of intermediate goods for soybean and corn are 0.57 and 0.744, respectively. Shares of wages for soybean and corn are 0.01 and 0.04, respectively; and shares of operating surplus for soybean and corn are 0.42 and 0.22, respectively.

[73] The asset values of agricultural land, including buildings of Benton and White counties are $916,550,000 and $1,219,857,000, respectively. Machinery assets values of Benton and White counties are $92,745,000 and $122,461,000, respectively.

counties is both 0.91 (91%). The share of capital in the total value of assets is therefore 0.09 (9%). This calculation lumps agricultural land and buildings together, while buildings may fit better in the category of capital, alongside machinery. While this is an imperfect estimation of the cost shares, we have no better alternative. We then match the shares with "share of operating surplus in total output" in BEA input output. The weighted average share of operating surplus in total industry output for the agriculture sector is 0.28 (28%). Hence, the share of land in total industry output for the agriculture sector is 0.255 (0.91*0.28% = 0.255) and share of capital is 0.025 (0.09*0.28 = 0.025). These values act as parameters for the cost function of the sector.

We assume the share of land in manufacturing and retail services to be minimal. As such, share of capital is share of operating surplus in the total industry output for these two sectors. The share of *capital* for the manufacturing sector is 0.18, and for retail sector is 0.23. In summary, the cost function for each sector is expressed as below:

$$\text{Agriculture}: C_{Ag} = P_T^{0.255} * P_L^{0.03} * P_{K-ag}^{0.025} * P_{M-ag}^{0.69}$$

$$\text{Manufacturing}: C_{Man} = P_T^{0} * P_L^{0.19} * P_{K-man}^{0.18} * P_{M-man}^{0.63}$$

$$Retail: C_{Ret} = P_T^{0} * P_L^{0.36} * P_{K-ret}^{0.23} * P_{M-ret}^{0.41}$$

where C_{Ag}, C_{Man}, C_{Ret} are the per unit cost of production for agriculture, manufacturing, and retail, respectively. $P_T, P_L, P_{K-ag}, P_{K-man}, P_{K-ret}, P_{M-ag}, P_{M-man}, P_{M-ret}$ are price of land, labor, capital for agriculture, manufacturing, and retail, and intermediate goods for the three sectors, respectively. We normalize all factor prices to 1.

We next impute the endowments, or demand of each factor of production for each sector using the Shephard's lemma. As the Shephard's lemma can only be applied on a cost function whose value is known, we must either collect or estimate the total cost of one factor production in each sector. For agriculture, we choose the benchmark factor of production to be land. The Shephard's lemma of the cost function for agriculture for land is:

$$\frac{dC_{ag}}{dP_T} * P_T * Y_{ag} = \text{acres harvested(corn + soybean)} * \text{land } rent\ per\ acre$$
$$= total\ cost\ of\ land\ in\ agriculture$$

The values for Benton and White counties are:

$$\text{Benton County: } \frac{dC_{ag}}{dP_T} * P_T * Y_{ag} = \$40{,}061{,}847$$

$$\text{White County: } \frac{dC_{ag}}{dP_T} * P_T * Y_{ag} = \$44{,}318{,}117$$

Thus:

$$\text{Benton County: } 0.255 * (P_T^{-0.727} * P_L^{0.12} * P_{K-ag}^{0.027} * P_M^{0.58}) * P_T * Y_{ag} = \$40{,}061{,}847$$

$$\text{White County: } 0.255 * (P_T^{-0.727} * P_L^{0.12} * P_{K-ag}^{0.027} * P_M^{0.58}) * P_T * Y_{ag} = \$44{,}318{,}117$$

Then, the value of total output in the agriculture sector Y_{ag} for Benton and White counties are:

$$Y_{Ag}^{Benton} = \$157{,}105{,}282$$

$$Y_{Ag}^{White} = \$173{,}796{,}537$$

Then, we apply the Shephard's lemma to the agriculture sector with respect to the price of capital used in agriculture:

$$\frac{dC_{ag}}{dP_{K-ag}} * Y_{ag} = K_{ag}$$

where K_{ag} is the demand for capital for the agriculture sector. In equilibrium, it equals the supply, or endowment of capital of the agriculture sector. As such:

$$0.025 * (P_T^{0.273} * P_L^{0.12} * P_{K-ag}^{-0.973} * P_{M-ag}^{0.58}) * Y_{ag} = K_{ag}$$

$$\Rightarrow \begin{cases} K_{Ag}^{Benton} = \$3{,}927{,}632 = P_{ag} * K_{ag} \\ K_{Ag}^{White} = \$4{,}344{,}913 = P_{ag} * K_{ag} \end{cases}$$ Where K_{ag} is the value of capital services[74]

Similarly, the demand for intermediate goods in the agriculture sector can be found by using Y_{ag}.

$$\frac{dC_{ag}}{dP_{M-ag}} * Y_{ag} = M_{ag}$$

where M_{ag} is the value of the demand for intermediate goods for the agriculture sector. In equilibrium, it equals total supply. We assume that all intermediate goods are imported. As such, the demand values for intermediate goods for Benton and White counties are:

$$0.69 * (P_T^{0.273} * P_L^{0.12} * P_{K-ag}^{0.027} * P_{M-ag}^{-0.42}) * Y_{ag} = M_{ag}$$

$$\Rightarrow \begin{cases} M_{Ag}^{Benton} = \$108{,}402{,}645 \\ M_{Ag}^{White} = \$119{,}919{,}610 \end{cases}$$

The demand for labor in the agriculture sector can be found using:

$$\frac{dC_{ag}}{dP_L} * Y_{ag} = L_{ag}$$

where L_{ag} is the value of the demand for labor for the agriculture sector.

$$\Rightarrow \; 0.03 * (P_T^{0.273} * P_L^{-0.88} * P_{K-ag}^{0.027} * P_{M-ag}^{0.58}) * Y_{ag} = L_{ag}$$

$$\Rightarrow \begin{cases} L_{Ag}^{Benton} = \$4{,}713{,}158 \\ L_{Ag}^{White} = \$5{,}213{,}896 \end{cases}$$

For the manufacturing and retail services sector, we do not have the total cost of land, and we also assume the cost share of land in the sectors to be negligible. Hence, we choose labor to be the factor of production in the Shephard's lemma to find the value of total output of manufacture and retail services.

[74] This is not the stock of capital but rather the flow of capital over a period of time.

Now that we have the total labor cost for the manufacturing and retail services sectors, we can apply the Shephard's lemma on the total labor cost function to find the total output values in each of the two sectors. For manufacturing, the process is as follows:

$$\frac{dC_{man}}{dP_L} * P_L * Y_{man} = \text{total wages for manufacturing sector in a county}$$
$$= total\ cost\ of\ labor\ in\ manufacturing$$

The values for Benton and White counties are:

Benton County: $\frac{dC_{man}}{dP_L} * P_L * Y_{man} = \$20{,}348{,}242$

White County: $\frac{dC_{man}}{dP_L} * P_L * Y_{man} = \$81{,}250{,}322$

where P_L is the average wage of all industries in 2006 in Benton and White counties. Y_{man} is the value of total output of manufacturing.

$$\Rightarrow\ 0.19 * (P_T^0 * P_L^{-0.81} * P_{K-man}^{0.18} * P_{M-man}^{0.63}) * P_L * Y_{man} =$$
$$total\ cost\ of\ labor\ in\ manufacturing$$

Assuming $P_T, P_L, P_{K-man}, P_{M-man}$ to be 1, Y_{man}^{Benton} and Y_{man}^{White} would be:

$$Y_{man}^{Benton} = \$107{,}096{,}011$$

$$Y_{man}^{White} = \$427{,}633{,}274$$

The value of the demand for labor in the manufacturing sector is also therefore $20,348,242 for Benton County, and $20,122,847 for White County.

The demand for capital in the manufacturing sector can be found via:

$$\frac{dC_{man}}{dP_{K-man}} * Y_{man} = K_{man}$$

where K_{man} is the value of the demand for capital in the manufacturing sector.

$$\Rightarrow\ 0.18 * (P_T^0 * P_L^{0.19} * P_{K-man}^{-0.82} * P_{M-man}^{0.63}) * Y_{man} = K_{man}$$

$$\Rightarrow \begin{cases} K_{man}^{Benton} = \$19{,}277{,}282 \\ K_{man}^{White} = \$76{,}973{,}990 \end{cases}$$

Similarly, we compute the value of the demand for intermediate goods in the manufacturing using the Shephard's lemma:

$$\frac{dC_{man}}{dP_{M-man}} * Y_{man} = M_{man}$$

where M_{man} is the value of the demand for intermediate goods in the manufacturing sector.

$$\Rightarrow \; 0.63 * (P_T^0 * P_L^{0.19} * P_{K-man}^{0.18} * P_{M-man}^{-0.37}) * Y_{man} = M_{man}$$

$$\Rightarrow \begin{cases} M_{man}^{Benton} = \$67{,}470{,}487 \\ M_{man}^{White} = \$269{,}408{,}963 \end{cases}$$

All demand for intermediate goods in the manufacturing sector are assumed to be imported.

Similar to the manufacturing sector, we use labor as the factor of production in the Shephard's lemma to compute the total output of the retail sector.

$$\frac{dC_{ret}}{dP_L} * P_L * Y_{ret} = \text{total wages for retail services sector in a county}$$
$$= total\ cost\ of\ labor\ in\ retail\ services$$

where Y_{ret} is the value of the total output of the retail sector in Benton and White counties

Benton County: $0.36 * (P_T^0 * P_L^{-0.67} * P_{K-ret}^{0.25} * P_{M-ret}^{0.42}) * P_L * Y_{ret} = \$42{,}181{,}513$

White County: $0.36 * (P_T^0 * P_L^{-0.67} * P_{K-ret}^{0.25} * P_{M-ret}^{0.42}) * P_L * Y_{ret} = \$161{,}460{,}594$

$$\Rightarrow \begin{cases} Y_{ret}^{Benton} = \$117{,}170{,}870 \\ Y_{ret}^{White} = \$448{,}501{,}658 \end{cases}$$

Now that we compute the total value of the demand for labor in the three sectors agriculture, manufacturing, and retail, we can compute the total demand for labor. At equilibrium, total demand equals total supply and thus the endowment. Therefore, the endowment for labor in Benton and White combining for the non-wind sectors is:

$17,609,603 + $20,348,242 + $42,181,513 = $80,139,358 for Benton County and $19,480,491 + $20,122,847 + $161,460,594 = $201,063,932 for White County.

We compute the demand for capital in the retail sector as below:

$$\frac{dC_{man}}{dP_{K-ret}} * Y_{ret} = K_{ret}$$

$$\Rightarrow \quad 0.23 * (P_T^0 * P_L^{0.33} * P_{K-ret}^{-0.75} * P_{M-ret}^{0.42}) * Y_{ret} = K_{ret}$$

$$\Rightarrow \quad \begin{cases} K_{ret}^{Benton} = \$26{,}949{,}300 \\ K_{ret}^{White} = \$103{,}155{,}381 \end{cases}$$

Similarly, the demand for intermediate goods in the retail sector can be found via:

$$\frac{dC_{ret}}{dP_{M-ret}} * Y_{ret} = M_{ret}$$

where M_{ret} is the value of the demand for intermediate goods in the retail sector.

$$\Rightarrow \quad 0.41 * (P_T^0 * P_L^{0.33} * P_{K-ret}^{0.25} * P_{M-ret}^{-0.58}) * Y_{ret} = M_{ret}$$

$$\Rightarrow \quad \begin{cases} M_{ret}^{Benton} = \$48{,}040{,}057 \\ M_{ret}^{White} = \$183{,}885{,}683 \end{cases}$$

Just as the demand for intermediate goods in the agriculture and manufacturing sectors, all demand for intermediate goods in the retail sector is met by imports from outside the county.

1.9.2 Social accounting matrix (SAM)

A social accounting matrix (SAM) is a data system that records the transactions and interdependence between sectors in an economy at a defined period of time. It represents the production process, income distribution and redistribution between sectors, factors of productions, and the rest of the world. Each cell contains the value of receipt from one actor in the economy to another. The SAMs used to represent economic payments in Benton and White counties are presented in Table 1.8 and Table 1.9.

Table 1.8. Social accounting matrix for Benton County

	Agriculture	Manufacturing	Retail services	Exports	Imports	Welfare	Consumption
Land	-40,061,847	0	0				40,061,847
Labor	-4,713,158*	-20,348,242	-42,181,513				67,242,913*
Ag Capital	-3,927,632*						
Mfg Capital		-19,277,282*					50,154,214*
Retail Capital			-26,949,300*				
Intermediates	-108,402,645*	-67,470,487*	-48,040,057*		223,913,189*		
Gross output	157,105,282*	107,096,011*		-264,201,293*			
Final Retail			117,170,870*		153,908,130*	-271,079,000	
Welfare activity						271,079,000	-271,079,000
Balance of payments				264,201,293*	-377,821,319*		113,620,026*

Data sources: US input-output table (BEA, 2020); Census of Agriculture (USDA, 2007); Quarterly Census of Employment and Wages (BLS, 2007); Dobbins & Cook (2007); Tegen et al. (2012); Wiser et al. (2020). Detailed explanation of the construction of this SAM appears in section 3.3 of the paper. * indicates imputed values. Our calculations imply net transfer payments to residents of the county of $113,620,026, the figure in the lower right corner of the SAM.

Table 1.9. Social accounting matrix for White County

	Agriculture	Manufacturing	Retail services	Exports	Imports	Welfare	Consumption
Land	-44,318,117	0	0				44,318,117
Labor	-5,213,896*	-81,250,322	-161,460,594				247,924,812*
Ag capital	-4,344,913*						
Mfg capital		-76,973,990*					184,474,284*
Retail capital			-103,155,381*				
Intermediates	-119,919,610*	-269,408,963*	-183,885,683*		573,214,256*		
Gross output	173,796,537*	427,633,274*		-601,429,811*			
Final retail			448,501,658*		281,771,342*	-730,273,000	
Welfare activity						730,273,000	-730,273,000
Balance of payments				601,429,811*	-854,985,598*		253,555,787*

Data sources: US input-output table (BEA, 2020); Census of Agriculture (USDA, 2007); Quarterly Census of Employment and Wages (BLS, 2007); Dobbins & Cook (2007); Tegen et al. (2012); Wiser et al. (2020). Detailed explanation of the construction of this SAM appears in Section 4.2 of the paper. * indicates imputed values. Our calculations imply net transfer payments to the economy of $253,555,787, the figure in the lower right corner of the SAM.

Values of rows that are intersection between factors of production and the three sectors show the demand of those factors in each of the sector, and the payments to those factors from each sector. The values in the gross output and final retail rows represent the domestic output of the sectors and the export and import values, in dollars. The welfare activity row demonstrates the welfare, or consumption of the county residents, which comprises of domestically produced and imported retail services. Finally, the balance of payment row shows the balance of receipts with the rest of the world. More specifically, Benton and White counties receive a foreign transfer in the amount of $113,620,026 and $253,555,787[75], respectively, and these funds are included in the balance of payments.

As an illustration, consider Table 1.8, which represents payment flows in Benton County. The matrix captures transactions between various agents in the local economy, including the agriculture, manufacturing, retail services sectors, factor inputs (land, labor, and sector-specific capital), and external accounts (exports, imports, and balance of payments).

In column 1, we observe the payment flows originating from the agriculture sector. The sector pays $40,061,847 to land, $4,713,158 to labor, and $3,927,632 to agricultural capital. It also spends $108,402,645 on intermediate inputs, which are goods and services used as inputs for agricultural production. The gross output for the agriculture sector amounts to $157,105,282. Columns 2 and 3 contain similar activities from manufacturing and retail services sectors. The exports column (column 4) shows the total value of goods and services exported from the county, which equals $264,201,293. The imports column (column 5) indicates the total value of goods and services imported into the county, amounting to $377,821,319.

[75] Foreign transfer can include pensions, social welfare, or salary earned from working in the neighboring county, etc.

The welfare column (column 6) represents payments made to households in the form of wages, rental income, and profits. Households receive $67,242,913 in labor income, $50,154,214 in agricultural capital income, and other income components from land and various capitals. The welfare activity row shows the total welfare payments of $271,079,000 made by households, which are matched by an equal value of consumption expenditures in the consumption column. The balance of payments row indicates the net inflows or outflows of funds to or from the county. In this case, there is a net transfer payment of $113,620,026 to the residents of Benton county, as seen in the lower right corner of the SAM.

Each row in SAM shows the factor income sources, and how they spend the income. The first row in the SAM for Benton County represents the income received by landowners for the use of their land. In this case, the entire income of $40,061,847 for land comes from the agricultural sector, as indicated by the negative value in the agriculture column. This means that land is only utilized as a factor of production in the agricultural sector, and not in the manufacturing or retail services sectors. The positive value of $40,061,847 in the consumption column suggests that landowners spend their entire income on consumption, which includes retail services, both domestic and imported. By analyzing the first row, we can infer the role of land in the Benton County economy and how the income generated from land use is channeled back into the local economy through consumption. Table 1.10 contains the gross output for and input payments by the wind energy sector for both counties.

Table 1.10. Gross output for and input payments by the wind energy sector

	Benton County	White County
Land	504,331	301,274
Land rent	2,799,765	1,672,500
Labor	4,639,853	1,506,367
Wind capital	143,331,129	85,621,940
Intermediate	17,550,750	11,749,668
Gross output	166,026,065	99,179,250

Gross output and payments made by the wind energy sector. These data determine the size of the shock associated with the first counterfactual exercise, the arrival of the wind sector, and the distribution of wind sector revenues when it is operating.

1.9.3 MACRS depreciation

The Modified Accelerated Cost Recovery System (MACRS) is a depreciation method used in the United States for tax purposes. Established by the Internal Revenue Service (IRS), it allows businesses to recover the cost of assets over a specific period of time through annual tax deductions. The MACRS depreciation structure classifies assets into different property classes, each with a predetermined recovery period and a set of applicable depreciation rates. This type of depreciation can be beneficial for renewable energy projects such wind or solar as it can significantly reduce the net cost of investment.

Under MACRS, assets are depreciated using a double-declining balance method, which results in larger deductions in the early years and smaller deductions later on. However, certain property classes also use the straight-line method. The system also incorporates the half-year and mid-quarter conventions, which dictate how depreciation is calculated in the first and last years of an asset's life, depending on when it was placed in service.

The primary goal of the MACRS depreciation structure is to stimulate economic growth by encouraging businesses to invest in new assets, as the accelerated depreciation deductions can reduce their taxable income and, consequently, their tax liability. The MACRS depreciation structure has a significant impact on the wind energy industry, as it reduces the cost by offering accelerated depreciation benefits. Wind energy projects typically fall under the category of "5-year property" within the MACRS classification system. This means that wind energy assets, such as wind turbines and associated equipment, can be depreciated over a 5-year period using the double-declining balance method. The accelerated depreciation provided by MACRS allows wind energy project owners to recover a larger portion of their initial investment costs in the early years of the project. This helps reduce the taxable income and tax liability for these businesses, improving the project's overall economics and making it more attractive for investors.

Renewable energy (RE) projects have been eligible for MACRS depreciation since 1986 (NC Clean Energy Technology Center, 2018). Specifically, wind projects are allowed to depreciate their properties with acceleration in a 5-year schedule[76]. The ARRA grants RE projects, including wind, a bonus 50% first-year depreciation on top of MACRS, which is enacted in 2008 (NC Clean Energy Technology Center, 2018). The detailed depreciation schedule for RE projects, wind included, can be found in Table 1.11.

Table 1.11. MACRS depreciation schedule for renewable projects, wind included

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Year 6**
MACRS	20.00	32.00	19.20	11.52	11.52	5.76
MACRS + 50% bonus depreciation	60.00	16.00	9.60	5.76	5.76	2.88

Source: U.S. Partnership for Renewable Energy Finance, MACRS Depreciation and Renewable Energy Finance (n.d.)

Based on this depreciation schedule, we estimate the extra benefits that wind projects receive by comparing the difference in tax liability a wind project may face when it uses MACRS, versus when it uses normal straight-line depreciation method. First, we make financial assumptions

[76] For a detailed accelerated depreciation schedule, refer to https://www.irs.gov/publications/p946.

for a representative wind project based on a financial report for wind energy of NREL in 2017, including loan term and debt/equity ratio (Schwabe et al., 2017).

2008-2012 corporate tax rate was 35% (Tax Policy Center, 2015)[77]. We use a rate of return of 10%, and an interest rate of 7%. We use the capital investment cost, O&M cost, capacity factor, and operating life data from 2010 NREL wind energy cost report (Tegen et al., 2012), combining with Section 1603 grants. We use the same revenue data from Wiser et al., (2020). The financial and technical assumptions for a representative wind project is detailed in Table 1.12.

Table 1.12. Financial and technical assumptions of representative wind farm in period 2008-2012

		Unit	**Source**
Debt interest rate	7	%	Moody (2020)
Rate of return	10	%	n/a
Loan term	15	Years	Schwabe et al., (2017)
Debt/equity ratio	35/65	%	Schwabe et al., (2017)
Capacity factor	38	%	Tegen et al., (2012)
Capital investment cost	42.7	$/MWh	Tegen et al., (2012); NC Clean Energy Technology Center (2018)
Project life	20	Years	Tegen et al., (2012)
O&M cost	10	$/MWh	Tegen et al., (2012)
Revenue	60	$/MWh	Wiser et al., (2020)

The depreciation amount based on the capital investment cost per MW after Section 1603, using straight line method, MACRS method, and MACRS + 50% method. Taxable income follows the formula:

Taxable income = revenue – depreciation amount – O&M cost – interest payment

[77] Sources information https://www.taxpolicycenter.org/sites/default/files/legacy/taxfacts/content/pdf/corporate_historical_bracket.pdf. Downloaded October 18, 2020

We compute tax liability by multiplying taxable income by 35%, which is the corporate tax rate. We then find the differences in the tax liabilities between straight-line, MACRS and MARCS + 50% by deducting tax liabilities using MACRS from those using straight-line method, and tax liabilities using MACRS + 50% from those using straight-line method for each operating year. Next, we find the net present value (NPV) of the 20-year stream of differences in tax liabilities between straight-line and MACRS, and between straight-line and MACRS + 50%, using the discount rate of 10%. The NPV for the differences in tax liability between straight-line and MACRS method is $183,464, and between straight-line and MACRS + 50% method is $219,300. Hence, the extra tax saving worth per year, or the extra economic rent for the project is $12,843/MW of capacity if it uses MACRS, and $15,350/MW of capacity if it uses MACRS + 50%, assuming an interest rate of 7%. In MWh, this translates to extra resource rents of $\frac{12,843}{3,345} = \$3.84/MWh$ for MACRS, and $\frac{15,350}{3,345} = \$4.6/MWh$ for MACRS + 50%, where 3,345 is the annual electricity output reported by NREL (Tegen et al., 2012). Thus, the total resource rent with MACRS and MACRS + 50% would be $\$9.72/MWh + \$3.84/MWh = \$13.56/MWh$ and $\$9.72/MWh + \$4.6/MWh = \$14.32/MWh$, respectively. These calculations are likely relevant to the true resource rents estimates enjoyed by the industry. However, we do not include MACRS in our main model and calibration, as we wish to stay conservative about identifying economic rents.

For the calculation of 2018-2020 MACRS value, we update MACRS depreciation calculation with new values of capital cost, O&M cost, project design life and the PPA price. The flat corporate tax rate in 2018-2020 was 21% (Tax Foundation, 2021). We keep all other values and the calculation process the same as in the procedure that we perform for 2007-2010. The lower tax rate decreases the tax liability for straight-line depreciation case, while increasing the tax liability of MACRS and MACRS + 50% cases, especially in the first few years. Thus, the difference between tax liability between using straight-line depreciation and MACRS decreases. The extra tax saving worth per year, or the extra economic rent for a wind project is $6,587/MW of capacity if developers use MACRS, and $7,677/MW of capacity if they use MACRS + 50%. In MWh, the extra economic rent translates to $1.78/MWh with normal MACRS, and $2.1/MWh with MACRS + 50%. Thus, we calculate the economic rents of capital to be $(\$20.1/MWh + \$8.51/MWh) - (\$22.8/MWh + \$11.5/MWh) + \$1.78/MWh = -\$3.92/MWh$ with MACRS, and $(\$20.1/MWh + \$8.51/MWh) - (\$22.8/MWh + \$11.5/MWh) + \$2.1/MWh = -\$3.6/MWh$ with MARCS. It means that in the period of 2018-2020, even with MACRS, the industry had negative rents due to the low energy price.

1.9.3 General equilibrium model – robustness checks

In this section, we present the calibration results of the GE model for Benton and White counties with the arrival of the wind sector, and the arrival plus an exhaustive economic rent tax. The elasticity of substitution between domestic and imported retail services $\sigma = 1$, which presents a Cobb-Douglas preference of county residents. Table 1.13 contains the calibration results for the robustness check.

Table 1.13. GE model calibration results with wind arrival and an exhaustive rent tax - $\sigma = 1$

	Benton County		White County	
	(1)	(2)	(3)	(4)
Variable	Wind sector arrival (%Δ)	Wind sector plus 99% tax (%Δ)	Wind sector arrival (%Δ)	Wind sector plus 99% tax (%Δ)
P_{ag}	0	0	0	0
P_{mfg}	0	0	0	0
P_{rtl}	+ 3.1	+ 7.0	+ 0.4	+ 1.4
Q_{ag}	- 2.1	- 2.5	- 0.8	- 0.9
Q_{mfg}	- 7.1	- 11.3	- 0.8	- 1.9
Q_{rtl}	- 0.7	+ 4.9	+ 0.1	+ 1.5
FP_{labor}	+ 7.2	+ 12.1	+ 0.7	+ 1.9
FP_{land}	- 0.6	- 1.1	- 0.1	- 0.1
$FP_{capital-ag}$	- 2.1	- 2.5	- 0.8	- 0.9
$FP_{capital-mfg}$	- 7.1	- 11.3	- 0.8	- 1.9
$FP_{capital-rtl}$	+ 2.4	+ 12.3	+ 0.5	+ 2.9
M_retail (final)	+ 2.4	+ 12.3	+ 0.5	+ 2.8
U_{Labor}	+ 2.9	+ 24.4	+ 3.0	+ 4.4
U_{Land}	+ 1.9	- 3.4	0	- 1.0
U_{ag}	- 2.4	- 4.2	- 1.2	- 1.5
U_{mfg}	- 5.3	- 0.2	- 1.6	- 2.4
U_{rtl}	+ 0.2	+ 4.1	+ 1.0	+ 1.0
$U_{representative}$	+ 1.1	+ 9.0	+ 0.2	+ 2.0
Tax revenue form wind energy	$9.52 million	$17.15 million	$11.05 million	$13.33 million

* P is price of the sector/good, Q is domestically produced quantity of the good/sector, FP is the factor price, M_retail is the quantity of imported retail and services, U is the utility level, and $U_{representative}$ *is the utility level of the representative consumer*. The first counter-factual represents wind arrival in two counties (column 1 and 3). In the second counter-factual (column 2 and 4), we calibrate wind arrival plus a near complete rent tax (99%). The elasticity of substitution between domestic and imported retail & services (R&S) $\sigma = 1$. All results are compared to benchmark level of 1..

Table 1.13 shows that under a Cobb-Douglas preference assumption, the Dutch Disease is stronger, as county residents cannot substitute domestic retail services with their imported counterparts easily. This is shown via a steep contraction of agriculture and manufacturing when the wind sector arrives, and especially when we apply a rent tax on either county, where the domestic retail services sector expands significantly at the expense of imported retail services. As the domestic retail services sector expands, the competition for domestic labor becomes more fierce, thus pushing up their value and welfare. The positive effect of the wind power sector's arrival on imported retail services also becomes smaller when σ is lower. The elasticity of substitution does not change the total tax revenues collected by the county, as the rent tax revenues depends on the rent per MWh and the electricity output only. Rather, it only affects the distributional outcomes.

2. THE IMPACTS OF LOCAL WIND POWER RESTRICTIONS ON THE POWER SYSTEM OF THE MIDCONTINENT INDEPENDENT SYSTEM OPERATOR AREA

Abstract

Using the Regional Energy Deployment System (ReEDS) model, we estimate the deadweight loss imposed by county-level wind power development restrictions in the form of increased electricity costs due to suboptimal siting. This is accomplished by optimizing the power system of the United States' Midcontinent Independent System Operator (MISO) from 2020 to 2050. We perform the optimization with and without land-use constraints arising from simulated potential local ordinances restricting wind power development, and under multiple scenarios reflecting different renewable portfolio standards (RPS). We find that local restrictions on wind power increase the total system cost by 0.15%-0.3% and the wholesale electricity price by 1.8%-2.7%, depending on the RPS scenario. Changes in the generation and installed capacity mixes are more substantial and depend on both the level of county restrictions on wind power, and RPS requirements, thus indicating an interaction between RPS requirements and local wind power restrictions. We also find that plausible restrictions on wind development do not pose major barriers to meeting renewable energy targets in a cost-effective manner.

2.1 Introduction

2.1.1 Motivation

In 2018, the electricity sector was responsible for around 25% of the United States' (U.S.) greenhouse gas emissions (GHG) (U.S. Environment Protection Agency (EPA), 2020). Within the sector, fossil fuels accounted for nearly 63% of total electricity generation (U.S. Energy

Information Administration (EIA), 2020). Renewable energy sources such as wind and solar power have been promoted as clean alternatives to fossil fuel electricity due to the lower GHG emissions over their life cycle.

Despite their role in combatting climate change, in many U.S. counties, local governments have rejected or restricted economically viable wind projects (Bednarikova et al., 2020; Gearino, 2021; Zuckerman, 2022; Bryce, 2022; Simon, 2022). Some of the reasons for these rejections or restrictions include visual and/or noise concerns (Haac, Kaliski & Landis, 2019; Rand & Hoen, 2017; Mills et al., 2014a; Mills et al., 2014b; Petrova, 2013); potential or perceived impacts on property values (Rand & Hoen, 2017; Mills et al., 2014a; Mills et al., 2014b; Petrova, 2013); unequal distribution of local economic benefits from wind projects (Bednarikova et al., 2020; Rand & Hoen, 2017; Olson-Hazboun, Krannich & Robertson, 2016; Petrova, 2013); or the immobility, immutability, and imposition of wind projects (Pasqualetti, 2011). The rejection of wind power in a county with favorable wind resources could theoretically lead to inefficient buildout of wind farms, as wind developers will have to site projects elsewhere. Alternative locations may have lesser/worse wind resources or be farther away from existing transmission networks, thus potentially increasing the overall system cost. In this paper, we explore the extent to which the adoption of ordinances restricting wind development would impact energy prices and the composition of energy resources used to meet future renewables targets.

Specifically, we study an optimized power system of the Midcontinent Independent System Operator (MISO) region of the U.S. (see Figure 2.1). We employ the Regional Energy Deployment System (ReEDS), a capacity expansion model developed by the U.S. National Renewable Energy Laboratory (NREL) for this purpose. The model possesses multiple features suitable for modeling the integration of variable renewable energy (RE) in the regional power system. It also accounts for comprehensive sets of technical and economic constraints that enables it to simulate and forecast the regional power system with high accuracy. The model objective is total system cost minimization, accounting for multiple types of constraints. In our analysis, we focus on land use constraints that may arise from potential county-level restrictions on wind energy development and their economics implications[78]. On a broad scale, we seek to explore the optimized resource mix, total system cost, and wholesale electricity price in MISO under different wind power supply and Renewable Portfolio Standard (RPS) scenarios.

Source: Khoury (2021)

Figure 2.1. Map of all Independent System Operators (ISO) in the U.S., including MISO

The increasing relevance of RE has spurred a growing literature on power system optimization with integrated RE sources. Depending on the research question, studies have explored a variety of objective functions. An instance of a non-cost minimization objective is the minimization of excess energy produced from RE sources (Tafarte et al., 2014). Some studies seek to fulfill multiple optimization objectives and investigate the overall picture of the power grid of a region or country (Shmelev & van den Bergh, 2016; Lu et al., 2016). Some research attempts to optimize the deployment and transition of a specific technology, such as hydrogen (Yang and

[78] The MISO region includes parts or almost all of 15 states: Alabama, Arkansas, Illinois, Indiana, Iowa, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, North Dakota, South Dakota, Texas, and Wisconsin.

Ogden, 2013). However, the models they use, MARKAL and TIMES, may pose certain limitations. They do not consider detailed geospatial features of some RE sources such as wind and solar that are associated with wind speed and solar irradiance. They also do not incorporate certain electricity system characteristics related to RE sources, including but not limited to the spatial disaggregation of the transmission network, or the existence of restricted land areas unavailable for wind and solar development. The spatial dynamics are thus relatively limited (Loulou et al., 2004; Loulou et al., 2016). Others focus more on microeconomic analyses of RE integration, for example uncertainties in the penetration levels of RE sources into the grid (Fursch et al., 2014). Deng & Lv (2020) provide a summary of 34 optimization studies that incorporate RE technologies from 2013 to 2018, most of which focus on the European continent. They emphasize the importance of accounting for the intermittency feature of RE sources via the modifications of capacity and operating constraints, interregional transmission, energy storage, demand response, flexibility resources, and higher temporal-spatial resolution, noting that future studies can improve on at least some of those aspects[79]. Several articles explore the optimized power system focusing on land use constraints (Mai et al., 2021; Wu et al., 2020; Price et al., 2020; Price et al., 2018). These studies focus on siting regimes that address social, environmental and technical concerns, but the authors impose the regimes uniformly and implementation policies standardized over a region or nation. In this article, we propose a more realistic approach, where different sub-regions (i.e., counties) wield their own siting authority and can act independently from each other.

[79] All of these features are addressed in ReEDS to a high level of detail. The model has a high spatial resolution to better represent variable RE resources and the regional and interregional/interstate grid. Its multi-dimensional parameters and variables allow for a smoother temporal-spatial connection. The model incorporates a comprehensive list of generation technologies, including different types of storages and variable RE technologies. It also allows for the inclusion of demand response and models different types of flexibility resources. The details for these features and others can be found in its user guide (Ho et al., 2021).

Numerous studies also investigate the optimal size and locations of RE projects. The spatial variability of RE resources such as wind speed, combined with land use conflicts, highlight the importance of optimization studies on the placement and size of RE projects that satisfy economic, technical, and geographical constraints (Cetinay et al., 2017). Overall, existing studies either explore aspects of the power system that are fundamentally different from our study, do not focus on wind and solar energy, or pose limitations in incorporating characteristics of the power system that emerge or modify with the arrival of variable RE sources such as wind and solar.

Within the literature that we are aware of, the work of Mai et al. (2021) and Bessette & Mills (2021) bear the most resemblances to our study. To address the potential issue of land use constraints, Mai et al. (2021) uses the Regional Energy Deployment System (ReEDS) model to study the optimized power system of the U.S. The variables of interest in their analysis include cost and generation mix of the U.S. power system under three siting regimes for wind power projects. They consider three main siting regimes with increasing levels of restrictions to land use and analyze their impacts in three scenarios: business-as-usual (BAU), low emissions, and 40% wind by 2050. Their results indicate that stricter siting regimes lead to lower wind deployment growth compared to more relaxed regimes, and also give rise to more solar, coal-fired, and natural gas in all scenarios. For instance, under the 95% CO_2 reduction scenario, 2050 onshore wind capacity with the most restricted regime (limited access) is 37% lower than with the average regime (reference access). Bulk electricity price is also higher with the limited access regime, being 4% higher than the reference access regime under the BAU scenario. Nevertheless, Mai et al. (2021) applied each of their siting regimes to every potential wind site throughout the U.S. study area. Counties that host wind sites have heterogeneous siting ordinances, characteristics, and attitudes towards wind energy (Bessette & Mills, 2021; Mills et al., 2014a; Mills et al., 2014b;

Mills, 2018). In their work, Bessette & Mills (2021) examine the connection between county characteristics and the contention score/level that the residents show towards wind projects. They find that the percentage of farm operators not residing on the farm, natural amenity rank, and the percentage of Republican voters have significant impact on the contention level. Overall, their regression model demonstrates high explanatory power. Nevertheless, Mills' work does not evaluate quantitatively the impacts of these heterogeneities on the system cost, electricity price, or the generation mix and installed capacity.

2.1.2 Contributions

This study builds upon the work of Mai et al. (2021) and Bessette & Mills (2021). We examine the impacts of the uncertainties in land use restrictions on the energy system of the Midwestern Independent System (MISO) area. In particular, using the ReEDS model, we seek to understand the extent to which local ordinances restricting development of wind resources impact regional electricity and power system costs, energy mix and installed capacity, and the ability to meet RPS goals. The analysis addresses this issue by using a combination of the results of Bessette & Mills (2021) and a Monte Carlo simulation on the acceptance or rejection of wind power by U.S. counties within MISO in states that adopt county-level siting authority. In brief, we use the Bessette & Mills model of county characteristics' influence on wind farms to perform a probabilistic forecast of counties that may reject wind development. We estimate the relative probability that a county will reject wind based on its forecasted contention score, and then apply a Monte Carlo simulation using the probability as inputs to give 100 different equiprobable realizations of counties that may reject wind. We then modify the wind supply curve in ReEDS by excluding counties forecasted to reject wind. We set three restriction levels, where the most restricted scenario excludes all counties without a wind project yet, the free-for-all scenario places no restrictions, and the Monte Carlo simulation acts as the moderate scenario. Throughout the U.S., there have been multiple occasions where the county does not ban wind outright, but their characteristics and ordinances may prevent a profitable wind project, thus pushing wind outside the county (Gibson & Bowman, 2021; Gearino, 2021). This withdrawal of wind from unwelcoming counties effectively removes certain potential sites from the supply curve. As such, in our simulations we are agnostic to the actual policy mechanism by which counties prevent wind development within their borders. If the unavailable potential sites have strong wind resources and/or are close to the transmission network, their removal from consideration may increase overall system costs.

Our analysis contributes to the literature in two important ways. First, we account for heterogeneity in counties' characteristics and residents' attitudes toward wind power, thereby advancing the work in Mai et al. (2021). Second, we treat counties' attractiveness to wind developers as an uncertainty and use Monte Carlo simulation to estimate variability in the aggregated impact of many counties acting independently to permit or restrict development. Our results show that county restrictions increase wholesale electricity price only by 1.8%-2.7%, and total system cost by 0.15%-0.3%. However, changes in generation mix and installed capacity are more significant, where the difference between the most restricted and free-for-all scenarios wind installed capacity reaches more than 15%. Intuitively, solar UPV installed capacity rises when we place restrictions on wind, but the magnitude of difference between them magnifies when RPS requirements become more ambitious.

2.2 Methodology

2.2.1 ReEDS model

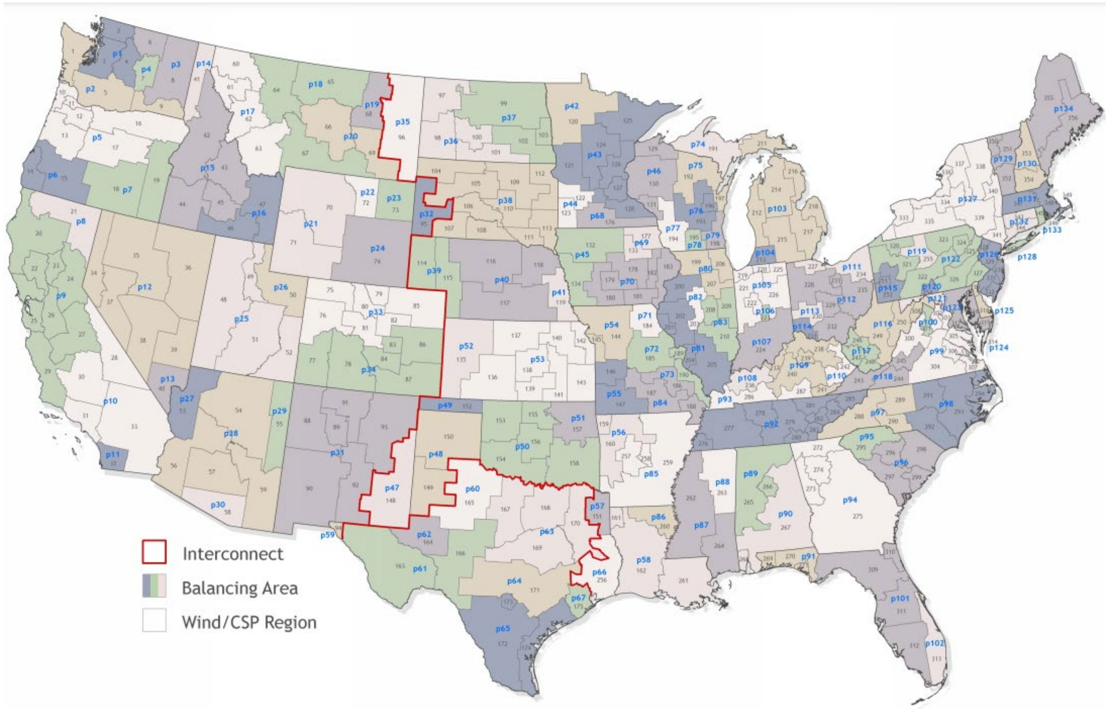
The study employs the Regional Energy Deployment System (ReEDS) model developed by the National Renewable Energy Laboratory (NREL) (Ho et al., 2021). ReEDS is a capacity expansion and dispatch model that seeks to minimize the total cost of the electric power system of a region or the whole country. ReEDS currently covers the contiguous 48 states of the U.S., and parts of Canada and Mexico. In this paper, we configure ReEDS to model the power system of the region managed by the Midcontinent Independent System Operator (MISO). ReEDS outputs the optimized cost and other parameters from 2010 to 2050. Outputs of ReEDS include but are not limited to: generation and installed capacity of each generation technology, operating reserves, curtailment rate over time, bulk system electricity price (wholesale price), and the present value of total electric sector cost (Ho et al., 2021).

The ReEDS model is primarily used by energy planners associated with governmental agencies, such as NREL or the Lawrence Berkeley Lab. It belongs to a family of models that focus on the entire energy system of a region rather than individual utilities. The model is versatile and can be used for multiple purposes, including, but not limited to analyzing the costs, benefits, and challenges of integrating renewable energy into the system at different levels. Researchers who wish to study different spatial related topics such as transmissions availability and locations of renewable energy installed capacity can also utilize ReEDS. Users can alternate different parameters and constraints to study their impacts on the system and energy technologies deployment The model can provide insights into the optimal deployment of different renewable energy technologies, taking into account multiple parameters, including reliability, transmissions, costs, or land use constraints, among others. Many publications related to the ReEDS model can be found on the NREL – ReEDS website[80].

ReEDS employs a high degree of spatial and temporal resolution. Within the U.S., researchers can model capacity expansion for 134 balancing areas (BA), which are geographical regions that contain multiple counties where electricity supply equals demand (i.e., load) (Ho et al., 2021)[81]. The BAs are further sub-divided into 356 resource regions (RR). Each RR consists of one or more counties (often a few adjacent counties) that characterize RE resource quantities and quality, such as wind and solar resources (Ho et al., 2021). Specifically, they contain resource supply curve points spaced regularly in 20×20-km grid cell. Figure 2.2 contains the map that shows all BAs and RRs of ReEDS.

[80] The website of NREL - ReEDS can be found at https://www.nrel.gov/analysis/reeds/publications.html.

[81] Balancing areas do not represent independent system operators (ISOs). Rather, they are county aggregates that respect states' boundaries, and represent nodes where power supply equals load.



Source: Ho et al. (2021)

Figure 2.2. ReEDS 134 balancing areas and 356 resource regions

When a local jurisdiction, commonly a county, rejects wind power, an unknown quantity of wind resources would not be available for new wind farm projects. This essentially creates a constraint on the wind resource supply curve, shifting it upward. In other words, there may be scenarios where new wind projects are not built in the most desirable location, thus increasing cost and inefficiencies. In order to study these scenarios, we remove the possibility of investing in wind power capacity in a number of counties from different states within MISO. This is done by shifting the resource supply curve of wind power upward, which consists of more than 57,000 points of potential sites for wind farms all around the U.S. Each point in the resource supply curve has several features that characterize the quantity and quality of wind resource at a given location, including wind speed, available capacity (MW), capacity factor, distance to the transmission network (in km), among others. In cases where wind power is not welcome in one or more regions, the points that are associated with those regions will not be available for investment. Sections 0 and 0 discuss this process in detail.

In terms of temporal resolution, ReEDS models 17 time slices annually[82], wherein it satisfies demand and operates reliability services for each. The 17 time slices contain 8,760 hours of a year, with each time slice comprising multiple hours within a season, plus summer peak hours. This aids ReEDS in partially taking into consideration the variations in demand and RE generation throughout the year. In order to further account for the uncertainty of wind and solar generation, ReEDS includes a number of parameters, such as capacity value for system adequacy, generation forecast error, and curtailment estimates, among others. The model covers a large range of technologies, including, but not limited to coal, oil, two types of natural gas, geothermal, hydropower, nuclear, wind, and multiple types of solar. Likewise, multiple storage technologies are also represented in the model, such as pumped storage hydropower (PSH), batteries of different capacities and compressed air energy storage (CAES).

ReEDS aims to minimize the total cost of the power system of a region or the whole U.S., which includes capital and operations and maintenance (O&M) cost items. ReEDS also takes into consideration the lengthy time necessary for constructing new projects or for obtaining siting permits for wind and solar projects, as well as long-haul transmission lines. Thus, the model incorporates the penalties for capacity that exhibit features of swift growth[83].

Within the cost function, the investment in technologies that use a resource supply curve is the most noteworthy in this paper, as wind is one of those, as discussed above. Naturally, if an investment is planned to take place in a specific region, it is likely that such region has desirable

[82] Each timeline contains a number of hours of a given year, ranging from 40 hours (summer peak) to 960 hours (overnight winter). For the detail of the time slices, refer to Table 1 in Ho et al. (2021).
[83] Refer to the Appendix in the ReEDS user guide for more details on the calculation of the total cost (Ho et al., 2021).

features for a wind farm. It can have high wind speed and/or is relatively close to the transmission lines, hence incurring a lower investment cost per MW. If a wind farm investment is forced to move to less desirable counties or regions, it will face a higher cost per MW. The changes in the available wind resources and potential alterations in the investments in wind power in a region or state may also give rise to changes in the distribution of investments in RE in the state and in the MISO area power system. For instance, solar power may gain more traction if wind is restricted, or wind development may stall in a state and thrive more in a nearby state that employs less strict ordinances and siting procedures. The magnitude of these changes depends on the number of counties that do not welcome wind, the wind resources available in those counties, and the availability of suitable transmissions.

All data and inputs are included in the ReEDS model. For instance, electricity demand growth projection and fossil fuel prices come from the EIA Annual Energy Outlook 2016. They extend from 2010 to 2050, with data from 2018 up until 2050 being projections taken from multiple outside sources (Ho et al., 2021). Main model inputs and data include technology costs, fuel prices, renewable portfolio standards (RPS) requirements, and electricity demand growth (Mai et al., 2016). ReEDS also incorporates storage as a technology, and thus exogenous storage costs are also inputs of the model. The model includes transmission costs to give more accuracy to the system cost estimation. Alongside RPS requirements, carbon constraints implemented by regulations also appear in the model. Certain types of inputs have low, medium and high value scenarios. These include technology costs (including natural gas price), fuel prices, transmission losses, and electricity demand (load data). Wind and solar resources supply curves, including transmission interconnection cost and capacity are also inputs of the model.

The model contains "switches," which allow users to alter certain input parameters for a solve. For instance, the user can choose to allow interstate transmissions, only intra-state, or no new transmission at all. We choose to allow any necessary transmission to be built without constraints. One of those switches also allows users to choose whether to include electric vehicle (EV) demand or not. In the model, EV demand and its future projection are exogenous, and do not change throughout the solution. In this paper, we include EV demand in the total electricity demand due to the realistic adoption of EV in the US, where EV sales increase continuously (Alliance for Automotive Innovation, 2020; Denny et al., 2019)[84]. ReEDS does not include switches for certain parameters, one of which is RPS requirements at the state level, a crucial component of our analysis. We therefore alter state's RPS manually by modifying the annual RPS requirements for the four states in our experiment (Indiana, Illinois, Missouri, and Michigan), while keeping the RPS requirements for other MISO states the same. Refer to section 0 for the details on RPS requirements modification.

ReEDS parameters and variables are represented using sets. We include the list of major sets that are used in the model in Table 2.1.

[84] Refer to ReEDS guidance for more details on other switches (Ho et al., 2021).

Table 2.1. Major sets in ReEDS and their indicator

Set index	Indicator	Set index	Indicator
I	technology (wind, solar, geothermal etc.)	F	set of demand flexibility types: daily, previous, next, adjacent[85]
V	technology class. For example: on-land wind has 10 classes.	Sc	resource supply curve attributes, where Sc = {cost, capacity}
R	regions (balancing area: 134 of them; resource region: 356 of them)	Tr	transmission type (AC or DC)
Rr	resource region (356 regions)	Sd	storage duration bins
H	hour blocks (17 blocks)	Rt	type of operating reserve constraints
Szn	seasons (4 seasons)	E	emission category
T	all years from 2010-2050	P	renewable standard portfolio constraint categories, including clean energy standards, where P = {RPS_All, RPS_Bundled, CES, CES_Bundled, RPS_Wind, RPS_Solar}
B	resource supply curve bins, determined by spur line costs[86]	St	U.S. states

Due to the complexity of the model, this paper introduces only certain model features and representative variables and constraints, including those that the wind resources supply curve is relevant to. The National Renewable Energy Laboratory (NREL) guidebook on ReEDS provides the detailed description of the model (Ho et al., 2021).

2.2.2 Objective function

ReEDS aims to minimize the total capital investment, operations and maintenance (O&M) costs of a regional or national power system. In general, the total cost is comprised of two main

[85] Flex_type in ReEDS
[86] Rscbin in ReEDS

cost items, capital and operations and maintenance (O&M) costs. These items break down into several categories including: the net present value (NPV) of new generation, storage, and transmission capacity costs, O&M costs, and ancillary services cost. The objective function that minimizes this total cost includes hundreds of parameters and variables, from hourly generation by technology to annual added capacity, among others[87].

The model also accounts for RE investment incentives and policies that ultimately influence the cost of a technology and/or the total system cost. ReEDS also takes into consideration the length of time necessary for constructing new projects or for obtaining siting permits for wind and solar projects, as well as long-haul transmission lines. The model incorporates the penalties for capacity that grows too quickly, or of delays in construction. Each element of the capital and O&M costs consists of multiple terms made up of combinations of variables and parameters that satisfy the spatial and temporal constraints of the model. For an illustration of a few terms in the capital and O&M cost, refer to Appendix 2.6.1.

ReEDS reports the total cost in 5 main cost categories: capital, O&M, fuel, transmission, and production tax credit (PTC). The PTC component has negative value, reflecting its purpose as a subsidy rather than a true cost. The cost of each future year is discounted by the default discount rate of 5%, and the dollar year in our study is 2018[88]. ReEDS gives the total system cost for each year and each balancing area (BA). However, the reduced model output report only produces the total cost in the final modeled year, which is 2050 in our study.

Within the cost function, the investment in technologies that use a resource supply curve is the critical concern in this paper, as wind is one of them. In the ReEDS model, there are 10

[87] Refer to the model access on NREL website for a more detailed inspection of those parameters and variables.
[88] More detailed explanations about the total cost calculations can be found in ReEDS user guide Appendix (Ho et al., 2021).

classes of wind based on wind speed, with class 1 having the highest wind speed and class 10 the lowest. The higher the wind speed is, the lower the cost per MW that the investment incurs. This is because wind turbines that are built in locations with higher wind speed will generate a higher annual energy production, and vice versa. Naturally, if an investment is planned to take place in a specific region, it is likely that such region has desirable features for a wind farm. They can have characteristics such as high wind speed, proximity to the transmission lines, and hence incurring lower investment cost. Thus, if a wind investment is forced to move to less desirable counties or regions, it will face a higher cost per MW, and as such the total investment cost term in the objective function will increase. The changes in the available wind resources and potential alterations in the investments in wind power in a state may also give rise to changes in the distribution of investments in renewable energy in the power system of the state and the MISO area as a whole. For instance, solar power may be prioritized and develop more in the case that wind is restricted, or wind development in a state may stall and thrive more in a nearby state that employs less strict ordinances and siting procedure. The magnitude of these changes depends on the number of counties that do not welcome wind, and the wind resources available in those counties.

2.2.3 Constraints

In order to minimize the total system cost, ReEDS satisfies a wide range of constraints. There are eight main types of constraints: load, planning reserve, operating reserve, generator operating, transmission, resource, emission, and renewable portfolio standards or clean electricity standards. The next paragraphs provide a brief explanation for each type of constraint. An example of each type of constraint can be found in Appendix 2.6.2.

- Load constraints: supply of power must meet the forecasted demand via regional generation or import. They include load constraints to compute marginal value of electricity price, and load flexibility constraints. One constraint of this type is the load constraint for marginal value of electricity.
- Planning reserve constraints: Ensure adequate generation to meet forecasted peak demand, plus an additional safety margin (also called reserve margin).
- Operating reserve constraints: Unexpected changes in generation and load have to be satisfied by reserve capacity.
- Generator operating constraint: technological related constraints regarding the capacity and generation of each technology.
- Transmission constraints: transmission lines between regions have a certain capacity, and thus power travelling across regions are bound to be within this capacity. Capacity accounting for transmission is one of the example constraints for this type of constraint.
- Resource constraints: The resources for variable RE technologies such as wind, solar, or geothermal are heterogeneous in terms of locations. For instance, wind speed or solar irradiance at one location can be different from another. This heterogeneity influences the cost and capacity of such technology at various locations. The constraint that limits generation to available capacity acts as an example of this constraint category.
- Emission constraints: the researcher can place a limit on emissions from non-renewable technologies. The emissions contain SO_2, NOX, mercury, and CO_2. The emissions limit is per hour, and the emissions sources can either be taxed or capped.

Renewable portfolio standards (RPS) or clean electricity standards: The researcher can input custom RPS at state of federal level for any given year. Similarly, clean energy standards can be implemented at choice.

Besides the block constraints, there are certain constraints that are not categorized as constraints on the power system itself, but rather related to investment or capacity. In other words, those are the constraints that omit infeasible investment plans. Certain constraints of this type are also directly related to local objection of wind power, via the wind supply curve. Those constraints belong to the capacity auxiliary category.

2.2.4 Wind resources supply curve

The reference access wind supply curve contains more than 57,000 points for potential construction of wind farms all around the U.S., as described in section 0. Each point contains information on the quality and quantity of the resources, including wind speed, available capacity, location (longitude and latitude), and distance to transmission lines, among others. The supply curve already omits points that cannot be considered for development, such as points in reservation areas, close to residential areas, or close to airports. Using the longitude and latitude of each point, we match all the points in the supply curve to the 356 RRs and the associated counties. While the wind supply curve incorporates the potential capacity for each point, it does not contain the grid connection cost. The formula for grid connection cost, taken from the Wind Vision report of the DOE (DOE, 2015) takes the form:

$$\begin{aligned} &Grid\ connection\ cost \\ &\qquad = grid\ feature\ cost + distance * transmission\ cost * regional\ multiplier \end{aligned}$$

Grid feature cost depends on whether a substation is readily available for a potential wind development site or not, whose details can be found in the Wind Vision report (DOE, 2015). The distance from a point in the supply curve to the nearest substation determines the necessity to construct a new substation. Ho et al. (2021) provides information on the spur line technical requirements and transmission cost. To discover the grid feature of each potential wind point, we match the Geographic Information System (GIS) shapefile of all 230-kV substations around the U.S. into the map of the supply curve points, RRs and the associated counties, as solar and wind plants use 230-kV transmissions lines (Ho et al., 2021; EIPC, 2015)[89]. We then find the distance of each point in the supply curve to the nearest 230-kW substation. If this distance is smaller than the distance to transmission represented in the wind supply curve, the point is assumed to have an existing substation, and needs a new substation otherwise. Taking the distance to transmission of each point, the grid feature and the 230-kV spur line cost per mile for wind, we estimate the base transmission cost for each supply point.

The regional multipliers are collected from the Eastern Interconnection Planning Collaborative (EIPC, 2015). EIPC uses multipliers for new lines in estimating grid connection costs, which comes from Table 5.2 in EIPC study (EIPC, 2015). Wind and solar use lines with voltage < 230 kV, 1 circuit, and 300 MW capability. The multipliers are the average of their lower and upper values. We map supply curve points into the designated regions and subsequently the multiplier of each region into each point. MISO areas have a multiplier of approximately 1. The final grid connection cost is the multiplication of the base transmission cost with the regional multipliers. The connection costs of points within a class and resource region are clustered into

[89] See section 6.2 of Ho et al. (2021) and EIPC report section 5.1 for discussion of 230-kV transmission lines for wind and solar plants.

five groups, each containing similar cost values. We then combine points within a class into five resource bins based on the five grid connection cost groups.

2.2.5 County wind ordinances and objection

Within MISO, certain states grant siting authorities to local governments, the majority of cases at the county level. Those include Indiana, Illinois, Michigan, Missouri, South Dakota, Montana, Arkansas, and Texas[90]. There is no statute directed towards wind power yet in Louisiana and Mississippi (Kahn & Shields, 2020), and as such we exclude those two states from the experiment of county wind power restrictions. Arkansas Statute §23-3-201 and South Dakota codified law §43-13-21—24 state that state government has siting authorities over large, commercial wind projects; the definition of large is not explicit in Arkansas, while in South Dakota, state government has authority over any project that exceeds 100 MW. This paper considers the development of only commercial wind projects with a capacity of at least 100 MW. We thus also exclude South Dakota and Arkansas from the experiment. A large portion of Montana and Texas do not lie within MISO but rather within Northwest and ERCOT (Federal Energy Regulatory Commission, n.d.). We therefore do not include these two states in the experiment either. Kentucky presents an intriguing case, where state government has the authority over projects of 10 MW and above. However, Kentucky state government requires such projects to be positioned at least 2,000 feet away from residential neighborhoods, schools, hospitals or nursing facilities, a condition considered not to be ideal for a commercially viable wind farm, according to multiple wind developers (Crawford, 2022; Eller, 2021; Platsky, 2019; NeuenSchawander, 2018).

[90] Siting authorities in Michigan can be at a level lower than county, such as township.

Hence, we assume that Kentucky rejects wind power in the moderate and conservative cases when performing the experiment.

Overall, we include Indiana, Michigan, Missouri, and Illinois in the experiment of county-level wind power restrictions. In the experiment, we perform a Monte Carlo simulation to forecast the counties in those four states that will reject wind power for the entire period of study (2020 to 2050). We examine three scenarios of county wind restrictions: a conservative scenario, where we assume the highest restriction level of wind development at potential counties; a moderate scenario, where we forecast wind power objection by estimating the wind farm contention scores of potential counties using the regression results of Bessette & Mills (2021); and a "free-for-all" scenario, where the development of new wind projects can take place in any potential counties in the four-state area. In the next paragraphs, we provide the details of each of the scenarios.

- Conservative scenario (most restricted scenario): We assume that all potential counties in the four-state area without a wind project yet will reject wind. That is, all the potential counties in the four states Indiana, Illinois, Michigan, and Missouri will have zero capacity from 2020 until 2050. We also assume no future wind capacity for Kentucky due to their stringent siting requirements.
- Free-for-all scenario (no restriction scenario): We assume no restriction in potential counties in the four-state area and counties in Kentucky. Wind developers can develop projects where it is the most profitable for them[91].
- Moderate case (Monte Carlo iteration scenario): We forecast stochastically the chance that a county without installed capacity yet in the four-state area will reject wind power. This

[91] ReEDS assumes a wind project chooses the "best" wind points available, e.g. points that boast idealistic wind speed, distance to transmission, potential capacity etc. One county can have several wind points of similar characteristics, and the total potential capacity of all wind points within a county limit the investment of wind within that county.

is a multi-step simulation process that is based on the regression results of Bessette & Mills (2021), where the authors study the relationship between the contention level for a wind project in a county and the associated county and residents' characteristics. The following paragraph explains in further detail the steps for the simulation. In this scenario, we still assume no future capacity for Kentucky for the same reason as the conservative scenario.

Bessette & Mills (2021) collected the contention level (scores) for selected wind projects within MISO via a survey to county residents to approximate their degree of acceptance towards the associated wind project(s) in their county. In total, residents impacted by 69 wind farms were surveyed and assigned contention scores ranging from 0 to 10; 0 indicates the county residents being least receptive to the wind project, and 10 shows the complete welcome of the wind farm. They then examined the relationship between the contention scores and selected characteristics of the county or block group. These include the average county farm size, the percentage of principal owners not residing on farm operated, the natural amenity score, the percentage of population with a bachelor's degree or higher, the percentage of population that voted for Mr. Donald Trump in the 2016 presidential election, and the percentage of population that works from home. They found a significant relationship between the contention score and the percentage of principal owners not residing on farm operated, the natural amenity rank, and the percentage of county population that voted for President Trump. See Table 5 in Bessette & Mills (2021) for the detailed regression results.

We first replicate Bessette and Mills' regression, using all county level data from sources indicated in their work[92]. While the R-squared value is lower, the results at the county level are

[92] Bessette & Mills (2021) data includes both county and block group level. Since we wish to perform the experiment at the county level, we replicate their results using data collected at the county level only.

similar to those of Bessette & Mills, and all signs are the same, thus giving us confidence to apply them in our analysis. Refer to Appendix 2.6.3 for the replicated regression results. We then use our regression results to perform an out-of-sample prediction of contention scores for all counties in the four states in the experiment, including those without a wind project yet and those that have project(s) but do not appear in Bessette & Mills (2021)[93,94]. Then, we construct a distribution of contention score using the predicted scores of all counties of the four states, both with wind projects and without. Based on this distribution and a county's predicted contention score, we find a relative probability that a county without a wind project yet will reject a potential one[95].

We next perform a Monte Carlo simulation for the acceptance or rejection of a potential wind project in counties without a project yet. This is done by simulating a series of Bernoulli trials for every county without a wind farm yet, using the relative probability found in the previous step. The simulation is iterated over 100 times, with each replication giving a different predicted set of counties that reject wind farms in the four-state area, and the resulting set of rejections is applied for each year of the analysis from 2020 to 2050. Table 1 contains the summary statistics for the 100 iterations, and Figure 2.3 shows the map with the probability of rejecting wind investment in the four-state area for each county.

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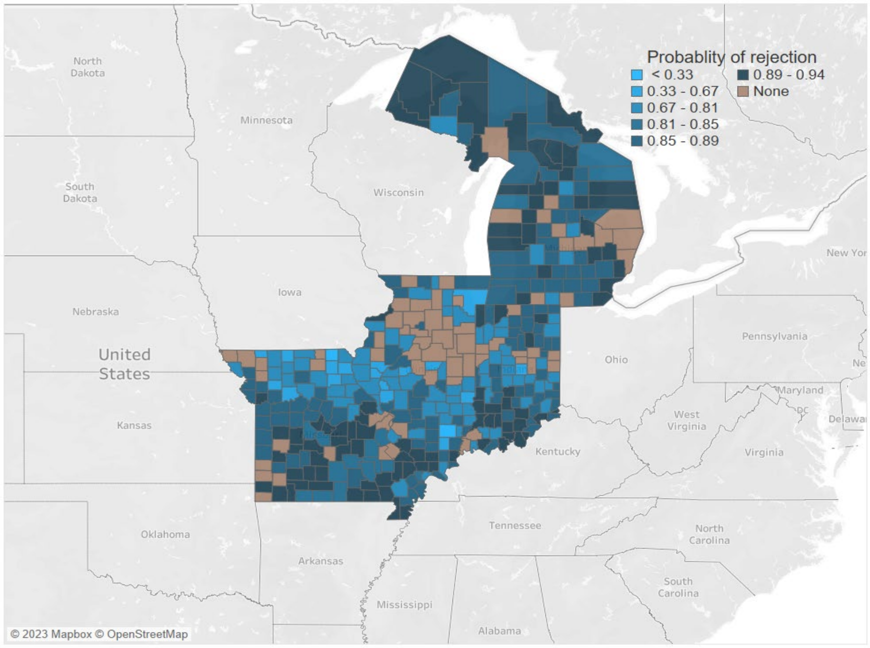
[93] The 69 wind projects included in Bessette & Mills (2021) do not include all wind projects in the four experimental states. We use the replicated regression results to forecast the contention score of both counties without a wind project yet, and counties with at least one commercial wind project in the four experimental states but are not included in Bessette and Mills.

[94] We collect counties and residents' characteristics for counties in the four-state areas for the out of sample regression from sources provided in Bessette & Mills.

[95] We find the discrete distribution of contention scores of counties with existing wind farms and those without a wind project yet for ranges from 0-1 to 8-9, which is a total of 9 bins. After that, we divide the number of counts in each bin of the distribution of the scores of windless counties by the number of total counts in each bin for the scores of both counties without wind and those with existing projects to find the relative probability that a wind farm possessing a score within that bin will reject wind projects. Using this result, we can estimate the relative probability of rejecting wind projects of each county without wind yet. The probability stays the same over the course of the analysis (2020-2050).



Note: The 338 counties without a wind project yet have blue shades of color. 53 counties with a current wind farm have a probability of 1 and are not shown as "none" in brown color.

Figure 2.3. Probability of rejecting wind investment in Indiana, Illinois, Michigan and Missouri for counties without a wind project yet

We study the impacts of county wind power restrictions under two scenarios with varying state Renewable Portfolio Standards (RPS): a standard case, where the analysis uses the current scheduled RPS in each state, which we term the business-as-casual RPS (BAU-RPS) case; and the High RPS case, where state RPS goals are set to a target of 90% renewable energy in the four experimental states by 2050[96]. In order for ReEDS to run as smoothly as possible, changes in state RPS should not be abrupt. We thus set the state RPSs to increase incrementally by 2% each year, starting with 50% in 2030 and 90% in 2050 in each of the four states. Before 2030, the four experimental states follow their current RPS schedules. Each iteration is run through the two RPS cases.

[96] RPS schedule of all other states not in the experiment within MISO remain.

Decarbonization of the grid has been a desired goal in the U.S., bolstered in the recent years by the constant decrease in the cost of RE power (Wiser et al., 2021; Chandler, 2018). However, deep penetration of RE can present multiple challenges, such as resource adequacy and reliability (e.g. Boughan et al., 2022; Ndrio & Gross, 2017; Kwon et al., 2019; MISO, 2021), or transmission infrastructure (Boughan et al., 2022; Howland, 2022; MISO, 2021), among others. These challenges can bring forth adaptive changes in the power system, including but not limited to alterations in the resource mix, increased storage capacity, additional transmission infrastructure construction, changes in the reserve margins, or changes in the system cost (MISO, 2021; Howland, 2022; Bettoli et al., 2021; Cochran et al., 2015). Therefore, by performing our analysis of county wind power restrictions under the BAU-RPS and High RPS cases, keeping all other assumptions constant, we will be able to observe both the effects of county wind restrictions on the power system and the effects of different RPS requirements on the power system separately and together[97]. We simulate the model over a 30-year period, from 2020 to 2050[98].

ReEDS calculates and reports generation and capacity for each technology, new annual capacity, annual retirements, operating reserves, new transmission, bulk electricity price (wholesale electricity price), total system cost, among other metrics. Most of the results are given for each studied year, with some reported only for the final run year. Due to model complexity and run time considerations, we do not model every consecutive year in the period of 2020 to 2050. This practice is consistent with NREL in their work that involves ReEDS. The results from running

[97] We run each of the 100 Monte Carlo simulation iterations on ReEDS that make up the moderate scenario under each of the RPS cases. We also run the conservative (most restrictive) and the free-for-all (least restrictive) scenarios under the two RPS cases. We then compare the results of the three scenarios for selected parameters. By doing this, we can separate the effects of county wind restrictions and of different RPS requirements on the power system, and thus able to discern whether the changes in the results originate from the changes in the RPS requirements, or from county wind restrictions.

[98] The years include 2020, 2022, 2024, 2026, 2030, 2035, 2040, 2045, 2050. We do not run the model in consecutive year as to reduce computer power and memory. The consecutive run results do not differ significantly from a sparser run.

non-consecutive years are not drastically different from those given by a consecutive model run. The years that are modeled for both cases include: 2020, 2022, 2024, 2026, 2030, 2035, 2040, 2045, and 2050.

The outputs of interest include the generation mix, the installed capacity of each technology, the present value of system cost, and the average regional bulk (wholesale) electricity cost, in $/MWh. We expect the local objections to wind power to create variation in the optimized investments in renewable energy in the MISO area. This may change the generation mix and the present value of the system cost, as well as the average electricity cost. The potential changes in these three parameters depend on the counties that are forecasted to object wind in each iteration. If counties that object to wind are among those that boast desirable wind resources and/or transmission network coverage, then it is possible that we will observe larger changes in the generation mix as well as the costs, and vice versa.

Our analysis's main limitation lies in more precise forecasting of counties that will reject wind power development. As counties siting rules vary widely, we do not have a specific method to predict the outcome of wind development based on siting rules. This prompts us to use counties' characteristics instead. Also, we wish to isolate the effects of county restrictions on wind development, and therefore assume constant other controversial parameters, including solar UPV and transmission. It means that our analysis does not consider county restrictions to solar UPV, nor do we assume constraints on transmissions investments and availability.

2.3 Results

In this paper, we focus on the impacts of potential county wind power restrictions on the buildout of renewables on the Midwestern Independent System Operator (MISO) grid. We also examine the resulting total system cost and wholesale electricity price of the region. Thus, we will present and compare the outcomes of interest for three county restriction scenarios-- conservative, free-for-all, and moderate--under two RPS cases: BAU-RPS and High RPS[99]. Most of the results are presented as a time series, but a few are reported only for the final study year (2050). We expect the local objections of wind power to create alternations in the optimized investments in renewable energy in the MISO area. This may change the generation mix and the present value of the system cost, as well as the wholesale electricity cost. The potential changes in these three parameters depend on the counties that are forecasted to object wind in each iteration. Besides incorporating uncertainties in local objection to wind power, we also alternate the default model to include an increasing exogenous EV demand, as mentioned in section 0. Our findings are broadly consistent with Mai et al. (2021), Phadke et al. (2020), and Wu et al. (2020).

We perform the Monte Carlo simulation with 100 iterations for the moderate scenario. There are 391 counties in the four experimental states, 338 of which have not had wind projects yet and enter the simulation. On average, of a total of those 338 counties, 296 are excluded in any given iteration, with a range of 279 to 310 counties[100]. As the majority of counties in the 4-state area do not have a wind project yet, the relative probability of hosting a wind project, explained in section 0 is low. This explains the relatively large number of counties being excluded in a given iteration, thus making the moderate scenario closer to the most restricted scenario than the free-for-all scenario. In order to control for county size, we also track the land area and potential wind capacity lost in each simulation. Refer to Table 2.2 for the related statistics of the 100 iterations.

[99] BAU-RPS: business-as-casual renewable portfolio standard, where all states follow their current RPS scheme. High RPS: assume 90% RE by 2050 in the four experimental states: Indiana, Illinois, Michigan, and Missouri.

[100] The number of counties loss seems to be large because at the time of the experiment, there are many more counties without a wind project yet than those with a project, thus lowering the relative probability of a county without wind yet will host a wind farm.

Table 2.2. County parameters statistics of 100 Monte Carlo simulation iterations for the moderate county wind restriction scenario

Scenario		RE-rejecting		RE-accepting	
	Parameter	Average	Range	Average	Range
Moderate	County (counties)	296	[279 – 310]	42	[59 – 28]
	Land area (sq mile)	161,100	[152,476 – 169,790]	21,930	[13,250 – 30,560]
	Potential wind capacity (MW)	365,400	[320,390 – 390,922]	51,300	[25,800 – 96,300]
Free-for-all	County (counties)	0		391	
	Land area (sq mile)	0		216,560	
	Potential wind capacity (MW)	0		498,005	
Most restricted	County (counties)	338		53	
	Land area (sq mile)	183,040		33,520	
	Potential wind capacity (MW)	416,710		81,295	

* Note that the lost remaining values of each parameter in the moderate scenario represents the values of the 338 counties without a wind project yet. They *do not* include the counties, land area and potential wind capacity of the 53 counties that have wind project(s). Values in the free-for-all scenario represent those of all 391 counties, and values in the most restricted scenario represent only those of the 53 counties with wind project(s).

2.3.1 Wholesale electricity price

In ReEDS, the wholesale electricity price is the marginal value of the load balance constraints. As the load balance constraints are linked to other constraints related to supply/demand, capacity, and operating constraints, among others, its shadow price can be seen as the marginal value, or cost of an additional MWh of load on the system (Ho et al., 2021). In other words, the wholesale electricity price can be understood as the marginal cost of generation and transmission. The wholesale electricity price has five components: energy, capacity, operating reserves, state and national RPS requirements (Ho et al., 2021). Therefore, each feature of the grid (component) plays a part in the total unit cost of wholesale electricity. In this section, we report the impacts of different RPS cases (BAU-RPS and High RPS), and county wind power restriction scenarios (most restrictive and free-for-all) on the system wholesale price.

In both RPS cases, the wholesale prices in both the most restricted and free-for-all scenarios increase gradually from 2022 to 2050. However, most of the increase takes place in the period 2022-2030, while prices from 2030 to 2050 remain relatively stable. These increases come primarily from the capacity component of the wholesale price, while the energy component decreases slightly over time. These results seem to be at odds with Phadke et al. (2020), where the authors suggest a slight and gradual decrease in the wholesale electricity cost from 2020 to 2035. Nevertheless, their work studies the whole U.S., while we focus on the MISO region in this study, and wholesale electricity price movement over time may differ between regions.

The impacts of the highest and lowest county-level wind power restrictions on the wholesale price can be seen on Figure 2.4. We can observe that the two price series under the two restriction levels move very closely to each other and are nearly indistinguishable until 2050, where the price in the most restrictive scenario exceeds that of the least restrictive scenario (free-for-all) by 1.8%-2.7%, depending on the RPS scheme assumptions[101]. This finding is consistent, though smaller in magnitude, with Mai et al. (2021), which found the electricity price under the Limited Access to be 4% higher than the Reference Access. Under a more ambitious RPS scheme (High RPS case), prices of the county most restrictive scenario show a slightly clearer trend of departure from those of the free-for-all (least restrictive) scenario. Starting from 2030 (the year that we impose a 50% RPS in the High RPS case), the differences in the wholesale prices between the two extreme county wind power restriction scenarios widen every modeled year until 2050.

[101] In the BAU-RPS case, the highest county restriction level scenario (most restrictive) price is 2.7% higher than the lowest restriction level scenario (free-for-all), and the figure for the High RPS case is 1.8%.

The moderate county wind power restriction scenario price series lies between the free-for-all and the most restrictive scenarios for either RPS scheme. In particular, the 2050 average wholesale electricity prices of the moderate scenario are 1%-2.1% higher than the price of the free-for-all scenario, and 0.7% lower than the price of the most restrictive scenario for both RPS cases[102]. These results indicate that county restrictions of wind power development in MISO do not have significant impacts on the wholesale electricity price of the region.

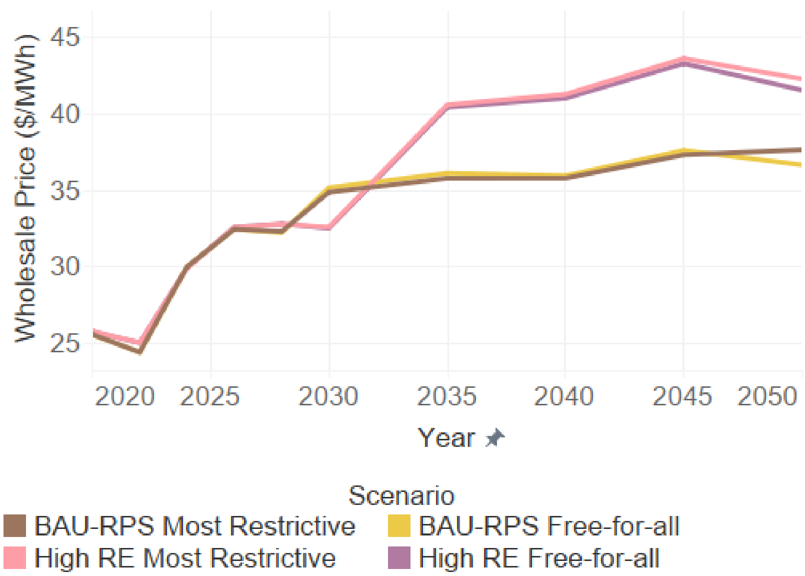


Figure 2.4. Wholesale electricity prices of the most restricted and free-for-all scenarios, under BAU-RPS and High RPS cases

The gaps are more notable when we examine the effects of two different RPS schemes (BAU-RPS versus High RPS) on the system wholesale prices. Overall, the 2022 wholesale price is around $25/MWh, and increases to around $42/MWh in 2050 in the High RPS case. As Figure 2.4 shows, the differences in the wholesale prices between the BAU-RPS and High RPS cases for any county wind power restriction level start to widen in 2022 and peak in 2045, before decreasing

[102] 2050 average wholesale electricity price of 100 iterations of the moderate scenario is $37.5/MWh in the BAU-RPS case, and $42/MWh in the High RPS case.

in 2050. On average, 2050 High RPS wholesale price is around 12.3%-13.3% higher than that of the BAU-RPS case. These results are consistent with Phadke et al. (2020), which forecasts the wholesale price in the 90% clean electricity scenario to be 12% higher than the price in the scenario where there is no new policy (55% clean electricity) by 2035, the final year where all RPS requirements must be realized.

In our analysis, most of the price series differences between two RPS cases come from the capacity and state RPS components of the wholesale price, showing an increase in cost when the system installs additional capacity to satisfy RPS requirements. In contrast, the energy component of the High RPS case is around 20% lower than its BAU-RPS counterpart. This pattern applies for all county wind power restriction levels, including the moderate restriction scenario, whose prices series do not differ drastically from either the free-for-all or the most restrictive scenario[103]. These results indicate that the RPS schemes, rather than county-level restrictions on wind power, drive the large part of the differences in wholesale price within MISO. They also suggest that in MISO, an ambitious RPS scheme will push up planning reserve costs[104]. Nevertheless, in the long run, the capacity and state RPS components will stabilize, and combining with the gradual decrease in the energy component, the differences between the BAU-RPS and High RPS cases shrink.

Across the Monte Carlo simulations, we find no statistically significant relationship between the wholesale electricity price and the number of counties or potential wind capacity excluded from development in the MISO region. This finding is consistent with the above analysis

[103] 2050 average wholesale price of the BAU-RPS moderate scenario is 10-12% lower than that of the High RPS case in free-for-all (10%) and most restricted scenarios (12%). 2050 average wholesale price of the High RPS moderate scenario on average are 11.5%-14.5% higher than BAU-RPS case in free-for-all (14.5%) and most restricted (11.5%) scenarios.

[104] The capacity component of the wholesale price is the marginal value of the planning reserve margin constraint.

that county restriction levels in the four-state area have little impact on wholesale electricity price in the MISO region.

Figure 2.4 shows that the difference in the wholesale prices between the free-for-all and most restrictive scenarios for either RPS scheme become more noticeable only from 2045. Therefore, we perform two experiments as robustness checks to test the sensitivity of the wholesale price results. In the first experiment, we modify the High RPS scheme so that the final year that the system has to meet the 90% renewable energy mandate is 2045 rather than 2050. In addition, we smooth out the temporal dimension of the model by running the model in 2-year interval for the whole studying period, rather than 5-year interval as in the main model. In the second experiment, we keep the original High RPS scheme of the main model, and just smooth out the temporal dimension.

The results of the BAU-RPS case are the same between two experiments, as the high RPS scheme does not apply to them. Both robustness check experiments give similar results, in which the gap between the free-for-all and most restrictive scenarios in the High RPS case shrinks from 1.8% in the main model to around 0.4-0.5% in 2050. In the BAU-RPS case however, the gap slightly reduces, but in the opposite direction with the main model findings. Specifically, the results show that the BAU-RPS most restrictive price is around 1.4% lower than the free-for-all price. Nevertheless, the results of other parameters such as total system cost or installed capacity mix are still similar to the main findings. In addition, in the main model results, approximately 30% of the simulated wholesale prices in the moderate county restrictions scenario are higher than that of the most restrictive scenario in either RPS case. Therefore, there may be uncertainties involving in the findings of the most restrictive and free-for-all scenarios wholesale prices, and the difference between them may not accurately reflect the reality. Moreover, the robustness check results show that the High RPS wholesale price findings may be slightly sensitive more to temporal dimension than to RPS schemes. However, the BAU-RPS results do not show clear sensitivity to any parameter change, and thus the gap between the most restrictive and free-for-all wholesale prices in the BAU-RPS case in 2050 may emerge due to other sources.

2.3.2 Present value of total system cost

The total system costs in 2050 of the BAU-RPS cases range between \$505.16 billion (free-for-all scenario) to \$505.92 billion (most restrictive scenario), and the average total cost of the moderate scenario unsurprisingly lies between them with a value of \$505.77 billion. Thus, the total cost in the most restrictive scenario is only 0.15% higher than that of the free-for-all scenario. The pattern is similar for the High RPS case, where the difference between the free-for-all and most restrictive scenarios is only 0.3%. The increase in cost when restrictions grow is consistent with other studies, despite the smaller magnitude (Mai et al., 2021; Wu et al., 2020; Price et al., 2020; Price et al., 2018). Exclusion of certain counties in certain states is less restrictive than applying a uniform siting regime over the whole region, as it allows for the regional movement flexibility of wind development. This may explain the relatively small rise in the system cost in our analysis compared to other studies. Another explanation lies in the relatively abundant wind resources that many regions in MISO have[105]. Moreover, we only apply restrictions in states that grant siting permission to local authorities within MISO. Wind power is free to develop in states that retain siting permission at the state level, thus reducing the cost.

Nevertheless, similar to the wholesale electricity price, the differences in the total cost under the BAU-RPS cases and the High RPS cases are more profound, though not substantial. We

[105] Refer to the "U.S. wind speed at 80-meter above surface level" map of NREL (Draxl et al., 2015).

find that the High RPS total costs range from \$520.5 billion to \$522.02 billion. High RPS total costs are 3%-3.1% higher than their counterparts in the BAU-RPS case for all three county restriction scenarios. These results corroborate our findings on the impacts of county-level restrictions on the wholesale electricity price and indicate that uncertainties in county policies in these regions do not significantly influence MISO overall system cost or wholesale electricity price. Table 2.3 contains the total cost of all RPS cases and county wind restriction scenarios.

Table 2.3. Present value of system cost (\$ billion US) in each scenario and case.

	BAU-RPS case			High RPS case		
Scenario / Cost category	Free-for-all	Moderate (average)	Most restricted	Free-for-all	Moderate (average)	Most restricted
Capital	141.9	143.5	143.5	176.2	175.8	175.6
PTC	-12.3	-12.2	-12.2	-12.3	-12.2	-12.2
O&M	198.1	197.9	197.8	196.1	195.7	195.6
Fuel	174.0	172.8	173.0	150.4	151.5	151.8
Trans	3.6	3.8	3.8	6.3	6.3	6.3
Other	N/A	N/A	N/A	3.8	4.7	4.8
Total	505.2	505.8	505.9	520.5	521.7	522.0

2.3.3 Generation and installed capacity

In this section, we compare the generation and installed capacity of wind and solar energy for each modeled year in the BAU-RPS case and High RPS case for three county wind power development restriction scenarios. As we wish to investigate the ultimate impacts of county wind power restriction and RPS requirements, we only report the final modeled year, 2050, which is the year that all RPS requirements must be satisfied.

Generation

In both free-for-all and most restrictive scenarios for both BAU-RPS and High RPS cases, the total 2050 generation hovers around 1,163 TWh. Figure 2.5 presents the distribution of 2050 wind and UPV solar generation in the moderate scenario for both the BAU-RPS and High RPS cases. The reference lines in the figure represent the generation of wind and UPV solar for the two extreme scenarios. In the High RPS case, wind generation of the free-for-all and most restrictive scenarios are 341 TWh and 286 TWh, respectively, and solar generation of the two extreme scenarios are 239 TWh and 265 TWh, respectively. As Figure 2.5 shows, the free-for-all scenario boasts the highest wind generation among all scenarios, which is 16% greater than the most restricted scenario, and 13% greater than the moderate scenario's average outcome. In terms of generation shares however, wind deployment in the most restrictive scenario lags behind the free-for-all scenario (24% versus 29%). Within the moderate scenario, wind generation varies from 278 TWh to 323 TWh.

UPV solar distribution in the High RPS case shows the exact opposite pattern to wind distribution. The free-for-all scenario unsurprisingly has the lowest solar generation, being around 9% lower than the moderate scenario on average, and 10% lower than the most restrictive scenario. Intuitively, the moderate scenario has more solar generation than the free-for-all scenario, but less than the most restrictive scenario. In addition, wind generation under the High RPS case exceeds solar UPV by a relatively wide margin, with the moderate scenario wind generation being 12.5% more than solar generation on average. The range between wind and solar generation becomes widest in the free-for-all scenario, and closest in the most restrictive scenario. These results suggest a few points. First, even though total cost and wholesale electricity price do not change drastically, county restrictions on wind development do decrease wind generation and increase solar generation as a substitute for wind. Second, under a High RPS assumption, the MISO power system benefits substantially from wind development compared to solar. Even in the scenario where the majority of counties in the four-state area block wind development, wind generation is still higher than solar.

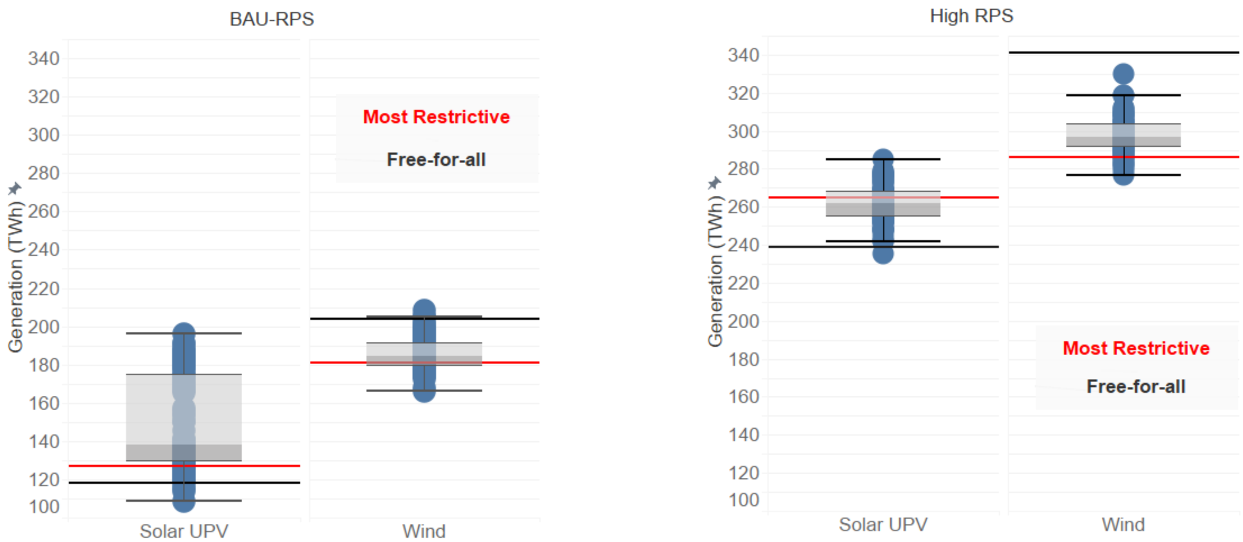


Figure 2.5. BAU-RPS and High RPS moderate scenario wind and solar generation distribution, in comparison with the free-for-all and most restrictive scenarios

Figure 2.5 shows wind and UPV solar distribution of the 3 county restriction scenarios under the BAU-RPS and High RPS cases. Under the BAU-RPS case, the system has much less wind and solar generation compared to the High RPS case in 2050. The free-for-all scenario of the case wind generation reaches 204 TWh, and solar UPV caps at 118 TWh. Thus, taking the BAU-RPS case as the baseline, High RPS free-for-all wind generation is 51% higher, while solar generation is 68% higher. Even without ambitious RPS goals, the general patterns of wind and solar generation still hold, wherein without county restrictions, the system favors wind over solar, and with restrictions, solar generation increases in substitution for wind. The patterns of wind generation in the 3 scenarios of the BAU-RPS case also share similarities with the High RPS case, where the free-for-all scenario deploys around 9.2% and 12% more wind than the moderate and most restrictive scenarios, respectively. Again, the gap shrinks in terms of generation share, when the free-for-all scenario only has around 2% point more wind than the most restrictive scenario.

However, UPV solar distribution patterns of the BAU-RPS case bear certain differences from those in the High RPS case. The solar distribution in the moderate scenario is much wider than that in the High RPS case, with a range of 108 TWh to 196 TWh, a 58% difference between the minimum and maximum values, compared to the 19.2% difference in the range of High RPS moderate scenario solar generation distribution. While the moderate scenario on average has 23% more solar than the free-for-all scenario, it also has 16% more solar than the most restrictive scenario. There are a few explanations for this phenomenon. First, in the BAU-RPS case, the grid does not have to abide to renewable deployment obligations, and thus can switch to other traditional technologies in the face of intense wind power restrictions. Indeed, the most restrictive scenario under BAU-RPS has 23 TWh, or 14% more combined-cycle (cc) natural gas than the moderate scenario on average. Second, the distribution of total installed capacity of the moderate scenario is relatively variable but typically higher than the other scenarios, spanning from 332 GW to 360 GW over the 100 replicates, compared to values of 339 GW in the most restricted scenario and 335 GW in the free-for-all scenario. This may be due to the relatively low capacity factor of UPV solar (around 31% by 2050) compared to land-based wind (around 42% by 2050 on average). Thus, solar generation may be highly unpredictable at a low level of installed capacity. There can be other explanations that are outside the scope of this study. While the High RPS case also experiences this phenomenon of disparity in installed capacity among the iterations, the range is much smaller.

Installed capacity

In this section, we analyze the 2050 installed capacity of wind and solar UPV for all county wind power development restriction scenarios and RPS cases. Figure 2.6 represents the boxplots of wind and solar UPV moderate scenario distribution under the BAU-RPS and High RPS cases.

Under the High RPS case, compared to the average value of the moderate scenario, free-for-all wind capacity is 13% higher, and most restrictive wind capacity is around 4% lower. The patterns are similar, though slightly less significant under the BAU-RPS case. The results are aligned with Wu et al. (2020), though their findings for the Western region have a larger magnitude (around 50% difference between the most relaxed and most restrictive siting regimes). Nevertheless, in terms of absolute values, the differences between the 3 scenarios are much less noticeable, especially in the BAU-RPS case. Recall from Table 2.2 that the average remaining potential wind capacity in the four-state area reaches 52.5 GW, which satisfies nearly 100% of wind installed capacity in the BAU-RPS case under the free-for-all scenario. However, we find no significant relationship between the number of counties or land area excluded in the four-state area and wind installed capacity in the Monte Carlo simulations under either RPS case. This can be due to the low variation in the number of counties and land area excluded in each iteration. From Table 2.2, the range of counties and land area excluded is rather narrow, and closer to the most restrictive scenario than the free-for-all scenario.

Solar UPV distribution differs noticeably between the two RPS cases. Under the High RPS case, free-for-all and most restrictive solar capacity are 8.3% lower and 0.8% higher than average moderate solar capacity. Under the BAU-RPS case, free-for-all and most restrictive solar capacity are 22% lower and 14% lower than average moderate capacity. First, the moderate scenario BAU-RPS solar capacity reflects the pattern of solar generation covered in section 0. Second, the difference between BAU-RPS and High RPS solar capacity is larger than that of wind, thus a small difference in the absolute values translates into large percentage differences.

Under both RPS cases, installed wind capacity lags behind solar UPV in all scenarios, and the gap widens as the county wind restrictions or RPS requirements increase. Under the High RPS case, the differences between solar and wind installed capacity under the 3 scenarios, from the least to the most restrictive, are 25%, 46%, and 50%, respectively. Under the BAU-RPS case, the differences are milder, where the values from the least to the most restrictive scenarios are 7.4%, 41%, and 30.2%, respectively. This pattern is in line with section 0, where solar generation is substituted for wind generation when county restriction level rises, but the magnitude of substitution is larger in the High RPS case. It also indicates that the grid has more wind generation than solar UPV generation despite wind resources having considerably lower installed capacity. This can be due to the higher capacity factor of wind compared to solar UPV, and the favorable environment for wind power in the MISO region.

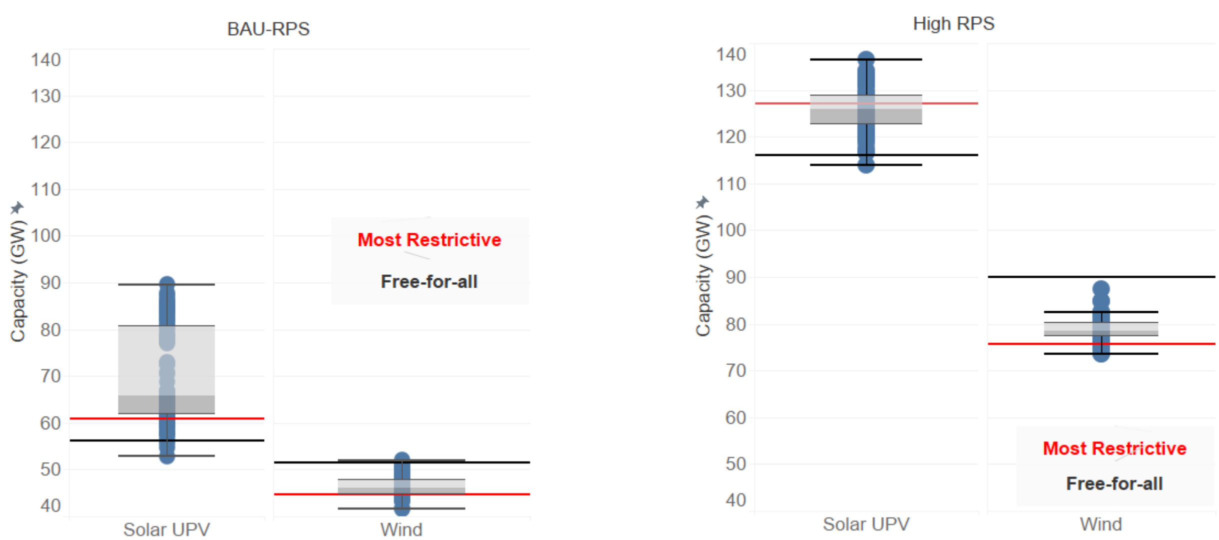


Figure 2.6 BAU-RPS and High RPS moderate scenario wind and solar capacity distribution, in comparison with the free-for-all and most restricted scenarios;

Substitutability between wind and solar UPV

In the previous sections, we have seen that county wind development restrictions can decrease generation from wind and increases generation from solar UPV via alternating their installed capacity. This general pattern applies for both BAU-RPS and High RPS cases. Nevertheless, the results also show that wind and solar installed capacity are much higher in the High RPS case. In addition, the differences between the three scenarios, and between wind and solar installed capacity under the High RPS case exceed those in the BAU-RPS case by a relatively wide margin, especially in terms of absolute values. Therefore, we suspect that county wind development restrictions may create a larger impact on the renewable energy technologies buildout when the system has to satisfy a more ambitious RPS scheme. We evaluate the substitutability between wind and solar UPV as a method to examine this hypothesis. In doing this, we compare the 2050 installed capacity between wind and solar UPV in the moderate county wind power development restriction scenario, as the replicates of this scenario grant us data for the comparison. Figure 2.7 shows the relationship between 2050 wind and solar installed capacity under the BAU-RPS High RPS cases.

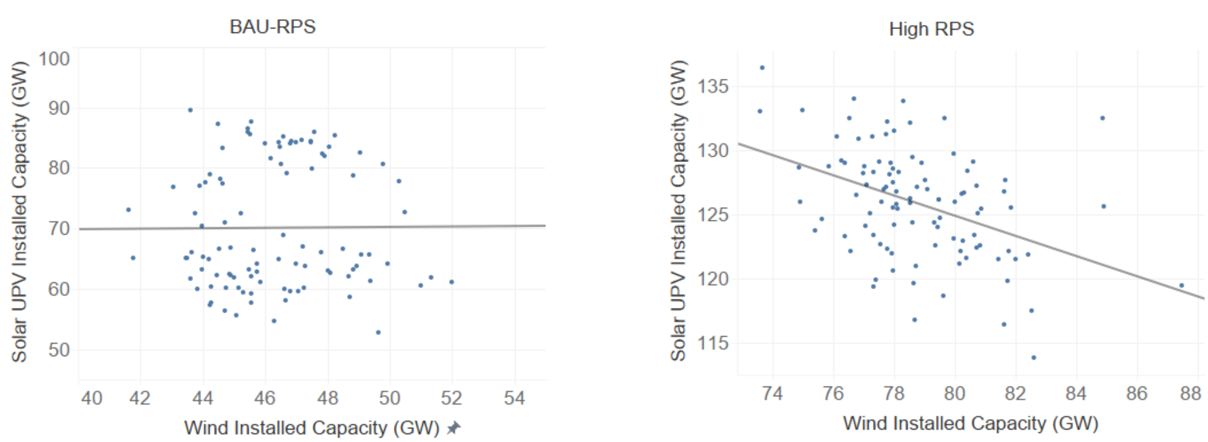


Figure 2.7. Relationship between wind and solar installed capacity under the BAU-RPS and High RPS cases.

Figure 2.7 shows a clear substitute relationship between wind and solar UPV installed capacity under the High RPS case. The linear-linear and log-log relationships between the two are represented by:

$$Solar\ capacity = -0.78 * Wind\ capacity + 187.4$$

$$Log\ solar\ capacity = -0.5 * Log\ wind\ capacity + 7.01$$

The $R^2 = 0.18$, and P-value < 0.001. It indicates that on average, under the High RPS case, each 1% increase in wind power installed capacity is associated with a 0.5% decrease in solar UPV installed capacity in MISO. Although the R^2 is relatively small, indicating the likelihood of other omitted variables, the equations inform us the degree to which wind is substituted by solar UPV. This further indicates that under an ambitious RPS scheme, county wind development restrictions will lead to significant alternations of the regional energy portfolio, especially between variable RE sources.

On the contrary, there is no clear relationship between wind and solar UPV installed capacities in the BAU-RPS. Precisely, the relationship between the two is represented by:

$$Solar\ capacity = 0.037 * wind\ capacity + 68.4$$

The $R^2 = 0.0006$, and P-value = 0.9. Section 0 has demonstrated the much smaller gap between wind and solar installed capacity in the BAU-RPS case compared to the High RPS case for all scenarios. Recall that both RE technologies in the BAU-RPS case have much higher installed capacity than their counterparts in the High RPS case. The results thus indicate that under the BAU-RPS assumption, the power system does not prioritize variable RE as the main sources of energy. Hence, even when many counties reject wind power development, the system does not seek to replace it fully or chiefly with solar, but rather with a combination of other energy sources, as it does not need to meet strict RPS requirements as in the High RPS case. In addition, Table 2.2

shows that the average potential capacity remaining in an iteration reaches around 51.3 GW, while the free-for-all wind installed capacity under the BAU-RPS case is 51.5 GW. Thus, even under a moderate level of restriction, the remaining capacity in the four states in is sufficient to meet all demand for wind power development in MISO under a BAU-RPS case. As such, county wind power development restrictions may have an interaction with RPS requirements in terms of system energy portfolio. Nevertheless, we do not observe such an interaction when it comes to system cost or wholesale electricity price.

2.4 Discussions and conclusions

We perform the analysis of land use uncertainty impacts on wind power development in the MISO region using a complex and high-resolution capacity expansion model which incorporates a wide range of technical assumptions about transmission, storage, renewable energy (RE) resources and other factors. Combined with its detailed modeling of spatiotemporal features via the use of time and region parameters, ReEDS carries improvements in modeling and documenting the trajectory of RE buildout. Our analysis shows that overall, county-level wind restrictions increase system cost and wholesale electricity price, while decreasing installed wind capacity and boosting solar installations as a substitute. Table 2.4 summarizes all key output metrics in our analysis for 2050.

Table 2.4. Summary results of key outputs for 2050 for all RPS cases and county wind power development restriction scenarios

Parameter	BAU-RPS			High RPS		
	Free-for-all	Moderate*	Most restrictive	Free-for-all	Moderate*	Most restrictive
Wholesale electricity price ($/MWh)	36.7	37.5	37.7	41.6	42	42.3
Total system cost (billion $)	505.2	505.8	505.9	520.5	521.7	522
Wind generation (TWh)	204.4	185.5	180.7	341.1	297.2	286
Solar generation (TWh)	117.8	149	127.4	239	262	265
Wind capacity (GW)	51.5	46.3	44.7	89.8	78.8	75.6
Solar capacity (GW)	56.3	70	61	115.8	126	127.2

*All results of the moderate county wind power development restriction scenario represent average values over the 100 Monte Carlo iterations.

In our experiments, county restrictions raise the wholesale price by only 1.8%-2.7%, and the total system cost rises even less, only around 0.15%-0.3% even when all counties without current wind projects are assumed to reject them in the future. The results are directionally aligned with prior literature, though smaller in magnitude. Two possible explanations include the nature of wind restrictions in our analysis, and the relative abundance of wind resources in the MISO region. While the previous literature applies land use restriction regimes uniformly throughout the studied area, our analysis focuses on a more realistic scenario, where different counties can make siting decisions independently from each other. In addition, relevant studies examine different geographic scopes for their restriction regimes, while we only focus on the four states in MISO with county-level siting authority. Therefore, wind farms, facilities whose profits rely on economies of scale, can move to a less restrictive county nearby with relative ease. Interestingly, the differences in wholesale price and system cost instead widen significantly with RPS requirements, but we find little interactions between RPS requirements and county wind restrictions when it comes to wholesale price and system cost.

Installed capacity and generation of wind decrease as county wind restrictions increase, accompanied by a rise in solar installed capacity and generation. In both RPS cases, the moderate scenario on average has around 12-13% more and 3-4% less installed capacity than the free-for-all and most restrictive scenarios. The differences in terms of generation and capacity shares, however, hover only around 2-4% between the most restricted and free-for-all scenarios. The magnitude of the differences and changes in wind and solar development enlarge when the RPS goals become more ambitious. In addition, wind and solar installed capacity exhibits a much clearer substitution relationship when RPS requirements rise. These indicate an interaction between RPS requirements and county wind restrictions regarding the buildout of RE technologies, which is consistent with previous literature. Overall, our findings show that county restrictions on wind power development in the MISO region may alter the composition of technologies mix. However, we find little evidence that they will create major barriers to the cost-efficient development and integration of renewable energy into the regional grid.

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2.6 Appendix

This Appendix includes the illustration of certain terms in the objective function and constraints of the ReEDS model.

2.6.1 Objective function

$$capital\ cost = \left(\sum_{t} pvf_c ap_t\right.$$

$$* \left(\sum_{i,v,r} INV_{i,v,r,t} * (capm_{i,r,t} * oc_{i,t} - ptc_{i,v,r,t}\right.$$

$$\left.\left. * \left(\sum_{h} hr_h * cf_{i,v,r,h,t} * \left(1 - \sum\nolimits_{r} cur_{i,r,h,t} + curm_{i,r,h,t}\right)\right)\right)\right) \tag{1}$$

$$- \left(\sum_{i,v,r,h} ptc_{i,v,r,t} * GEN_{i,v,r,h,t} * hr_h\right)$$

$$+ \left(\sum_{i,v,r} cup_{i,t} * capm_{i,r,t} * UP_{i,v,r,t}\right) + \sum\nolimits_{i,v,r,b} INV_{R\,i,v,r,b,t}$$

$$* rsa_{r,i,b,cost} * km_{i,r,t} + + \sum\nolimits_{r,rr,tr} ((trc_r + trc_{rr})/2)$$

$$* INV_{T\,r,rr,t,tr} * d_{r,rr,tr} + Z$$

$$O\&M\ cost = pom_t * \left(\sum\nolimits_{i,v,r,h} hr_h * vom_{i,v,r,t} * GEN_{i,v,r,h,t}\right) + (\sum\nolimits_{i,v,r} fom_{i,v,r,t} * CAP_{i,v,r,t}) + W \tag{2}$$

pvf_cap_t: present value factor for overnight cost

$INV_{i,v,r,t}$: generation capacity added in year *t*

$capm_{i,r,t}$: final capital cost multiplier for regions and technologies

$oc_{i,t}$: overnight capital cost

$ptc_{i,v,r,t}$: present value of all production tax credit payments for 1 hour of operation at capacity factor = 1

hr_h: hours in each time block

$cf_{i,v,r,h,t}$: modeled capacity factor as a fraction

$cur_{i,r,h,t}$: average curtailment rate of all resources in a given year as a fraction.

$curm_{i,r,h,t}$: marginal curtailment rate for new resources as a fraction.

$GEN_{i,v,r,h,t}$: electricity generation in hour h

$cup_{i,t}$: overnight cost of upgrading to technology i

$UP_{i,v,r,t}$: investments in upgraded capacity from one sub-technology to another (upgrade type of wind turbine for example)

$INV\_R_{i,v,r,b,t}$: investment in technologies that use a resource supply curve

$rsa_{r,i,b,cost}$: resource supply curve $RSA_{r,i,b,sc}$, where sc = cost

$km_{i,r,t}$: capital cost multiplier for resource supply curve technologies that have their capital costs included in the supply curves

trc_r: cost of transmission line capacity for each region per MW/mile

$INV\_T_{r,rr,t,tr}$: investment in transmission capacity

$d_{r,rr,tr}$: distance between balancing area by line type in miles

pom_t: present value factor of operations and maintenance costs (unitless)

$vom_{i,v,r,t}$: variable O&M cost ($/MWh in 2004 dollar)

$fom_{i,v,r,t}$: fixed O&M cost ($/MWh in 2004 dollar)

Z and W represent the rest of the terms in the capital and O&M costs, and they include:

Z: The remaining of the capital cost, including thesum of thecost of water access, the slack variable to update water source type (wst) in the unit database, the costs of refurbishments of resource curve technology - present-value of any production tax credits, the costs of substations, and the cost of back-to-back AC-DC-AC interties.

W: The remaining of the O&M cost, including the sum of - hourly arbitrage value for storage - penalty for retiring a technology (represents friction in retirements) + operating reserve costs + cost of coal and nuclear fuel (except coal used for cofiring) + cofired coal consumption + cost of natural gas (static natural gas price) + cost of natural gas (census division supply curves for natural gas prices) + cost of natural gas (national supply curve for natural gas prices with census division multipliers) + cost of natural gas (national and census division supply curves for natural gas prices) + biofuel consumption + international hurdle costs + any taxes on emissions + ACP purchase costs - revenue from purchases of curtailed VRE (these are the rest of O&M costs).

The term $\sum_{i,v,r,b} INV\_R_{i,v,r,b,t} * RSA_{r,i,b,cost} * KM_{i,r,t}$, $INV\_R_{i,v,r,b,t}$ indicates the investment in MW in technology i, class v, region r, resource bin b, and year t. the term $RSA_{r,i,b,cost}$ represents the cost per MW of technology i, region r, and resource bin b[106]. In this paper, we focus on wind power, thus i = wind. As mentioned in the article, if a wind investment takes place in less desirable counties or regions due to county wind restrictions, it will face a higher cost per MW, which means that the total investment cost $\sum_{i,v,r,b} INV\_R_{i,v,r,b,t} * RSA_{r,i,b,cost} * KM_{i,r,t}$ will increase.

[106] Each ReEDS region and class combination is divided into 5 resource bins that are determined based on grid connection cost. Each bin has similar capacity (in MW).

2.6.2 ReEDS constraint examples

ReEDS has multiple constraints within a constraint type. Refer to the model documentation at Ho et al. (2021) and NREL ReEDS GitHub open source for a full characterization of model constraints. In this section, we only present an example of each type of constraint for illustrative convenience.

- Load constraints: supply of power must meet the forecasted demand via regional generation or import. They include load constraints to compute marginal value of electricity price, and load flexibility constraints. One constraint of this type is the load constraint for marginal value of electricity.

One constraint of this type is the load constraint for marginal value of electricity, which is presented as:

$$L_{r,h,t} = LE_{r,h,t} + CEX_{r,h,t} + LEV_{r,h,t} + \sum\nolimits_{f} F_{f,r,h,t} \tag{3}$$

where

$LE_{r,h,t}$: exogenous and static load

$CEX_{r,h,t}$: exogenously defined exports to Canada

$LEV_{r,h,t}$: load from EV charging

$F_{f,r,h,t}$: flexible load shifted to each of the 17 time slices

- Planning reserve constraints: Ensure adequate generation to meet forecasted peak demand, plus an additional safety margin (also called reserve margin).

$$
\begin{aligned}
\sum_{i,v} CAP_{i,v,r,t} + \sum_{i,rr} cc_{i,rr,szn,t} & \\
& + \sum_{i,v,rr} mcc_{i,rr,szn,t} * (INV_{i,v,rr,t} + INV\_R_{i,v,rr,t}) \\
& + \sum_{i,v,rr,sd} cc\_s_{i,sd} * CAP\_S_{i,v,rr,szn,sd,t} + \sum_{i,v,h} GEN_{i,v,r,h,t} \\
& + \sum_{i,v} CAP_{i,v,r,t} * h\_szn\_cap_{i,szn,r} + \sum_{rr,tr} (1 - trl_{rr,r,tr}) \\
& * RMT_{rr,r,tr,szn,t} - \sum_{rr,tr} RMT_{r,rr,tr,szn,t} \\
& \geq (d\_peak_{r,szn,t} + PEAK\_ADJ_{r,szn,t}) * (1 + prm_{r,t})
\end{aligned}
\tag{4}
$$

where

$CAP_{i,v,r,t}$: total generation capacity

$cc_{i,rr,szn,t}$: capacity credit for existing capacity, in MW.

$mcc_{i,rr,szn,t}$: marginal capacity credit

$INV\_R_{i,v,rr,t}$: investment in refurbishments of technologies that use a resource supply curve

$cc\_s_{i,sd}$: capacity credit of storage by duration

$CAP\_S_{i,v,rr,szn,sd,t}$: generation capacity by storage duration bin for relevant technologies

$h\_szn\_cap_{i,szn,r}$: seasonal max capacity adjustment for dispatchable hydro

$trl_{rr,r,tr}$: fraction of transmission loss between r and rr

$RMT_{rr,r,tr,szn,t}$: planning reserve margin capacity traded from r to rr

$d\_peak_{r,szn,t}$: busbar peak demand by season, in MW

$PEAK\_ADJ_{r,szn,t}$: peak busbar load adjustment based on load flexibility, in MWh

$prm_{r,t}$: planning reserve margin by balancing area

- Operating reserve constraints: One of the constraints of this type is the operating reserve capacity availability constraint, which is expressed as:

$$r\_frac_{i,rt} * \sum_{szn,hh} GEN_{i,v,r,hh,t} \geq OT_{rt,i,v,r,h,t} \quad (5)$$

$r\_frac_{i,rt}$: fraction of a technology's online capacity that can contribute to a reserve type

$OT_{rt,i,v,r,h,t}$: operating reserves by type

- Generator operating constraint: One instance of this type of constraint is the constraint on upper bound on minimum generation level, which can be expressed as:

$$\sum_{i,v} GEN_{i,v,r,h,t} \geq MINGEN_{r,szn,t} \quad (6)$$

where $MINGEN_{r,szn,t}$ is the minimum generation level in each season.

- Transmission constraints: Capacity accounting for transmission is the representative constraint for this type of constraint:

$$CTR_{r,rr,tr,t} = ex\_tr_{r,rr,tr,t} + ex\_tr_{rr,r,tr,t} + \sum_{tt} (INV\_T_{r,rr,tt,tr} + INV\_T_{rr,r,tt,tr}) \quad (7)$$

where:

$CTR_{r,rr,tr,t}$: capacity of transmission

$EX\_TR_{r,rr,tr,t}$: cumulative exogenous transmission capacity of one direction, in MW

- Resource constraints: The constraint that limits generation to available capacity acts as an example of this constraint category, and is represented as:

$$av_{i,v,h} * \sum_{rr} CAP_{i,v,rr,t} + \sum_{rr} cf_{i,v,rr,h,t} * CAP_{i,v,rr,t} \\ \geq GEN_{i,v,r,h,t} + \sum_{rt} OT_{rt,i,v,r,h,t} \tag{8}$$

where

$av_{i,v,h}$: fraction of capacity available for generation by hour

$cf_{i,v,rr,h,t}$: capacity factor

$\sum_{rr} cf_{i,v,rr,h,t} * CAP_{i,v,rr,t}$: sum of non-dispatchable capacity multiplied by rated capacity factor used for technologies with a capacity factor.

- Emission constraints: The annual emissions cap is a representative constraint of this category:

$$\frac{e\_cap_{e,t}}{e\_scale} \geq \sum_{r} EMIT_{e,r,t} \tag{9}$$

where:

$e\_cap_{e,t}$: emissions cap, in metric tons

e_scale: scaling factor for emissions

$EMIT_{e,r,t}$: endogenous CO_2 emissions in a region, in million metric tons CO_2

- Renewable portfolio standards (RPS) or clean electricity standards: An example of this constraint category is the generation of RE credits by state:

$$\sum_{v,r,h} rps\_fr_{p,i,st} * hr_h * GEN_{i,v,r,h,t} \geq \sum_{st} REC_{p,i,st,sst,t} \tag{10}$$

where $REC_{p,i,st,sst,t}$ is the renewable energy credits from state st to state sst

2.6.3 Replicated regressions results of Bessette & Mills (2021)

Table 2.5. Regression replication results

VARIABLES	(1) Bessette & Mills regression replication results
Agricultural	
Farm size	0.00197
	(0.00321)
Principal operators not residing on farm (%)	-0.0709
	(0.0491)
Land use	
Amenity rank	0.972**
	(0.380)
Demographics	
Population with a Bachelor's degree (%)	-0.0230
	(0.0524)
Population voted for Mr. Trump (%)	-0.0192
	(0.0380)
Population work from home (%)	-0.201
	(0.141)
States	
Indiana	-1.344
	(0.865)
Michigan	-0.421
	(0.933)
Minnesota	-1.962**
	(0.778)
Constant	5.330*
	(2.856)
Observations	69
R-squared	0.508

*Table notes: while Bessette & Mills (2021) use certain independent variables at the block group level, we collect all variables at the county level. Thus, the magnitudes of our coefficients are slightly different from Bessette & Mills.

3. ADDITIONALITY IN CONSERVATION PRACTICE ADOPTION UNDER COMPLEMENTARITY

Abstract

The USDA promotes adoption of conservation practices beneficial for soil health and environment through agricultural cost-share payment programs such as EQIP or CSP. Although the efficiency of these programs has been evaluated through additionality estimates, which represent the percentage of farmers who would adopt a practice only with payments, the potential complementarities between certain combinations of practices have often been overlooked. Unaccounted for, these complementarities may impact additionality estimates. This paper provides a thorough investigation of additionality estimates of common practices, including no-till, nutrient management and cover crops, accounting for potential complementarities between them. We find no significant differences between traditional additionality estimates and estimates accounted for potential complementarities between the three practices. The results thus indicate that despite agronomic evidence of synergies in co-adopting these three practices, we find no solid indication of adoption complementarity between them in reality.

3.1 Introduction

3.1.1 Motivation

In the U.S., the agriculture sector contributed around 650 million tons of GHG in 2019 and was among the five economic sectors that pollute the most (US EPA, 2019). In addition, the sector is among the leading sources of water and soil pollution via fertilizers, pesticides, or herbicides, among others, both locally and across states (Zayas, 2016; Bensada, 2020; EPA, 2022; National Geographic, n.d.). This highlights the importance of improvements or alterations in soil and water management in the quest of reducing GHG and pollution in the agriculture sector. Multiple organizations have suggested conservation practices, such as conservation tillage, nutrient management, or cover crops, as among the potential solutions for decreasing soil and water impacts and GHG from the agriculture sector (Russell, 2014; Clark, 2015; Zayas, 2016; Behnke & Villamil, 2019; EPA, 2022). Due to conservation practices' potential for improving environmental quality and the extra costs associated with them, federal and local governments have supported their adoption with cost-share programs such as the Environmental Quality Incentives Program (EQIP) or Conservation Stewardship Program (CSP) (Zayas, 2016; Wallander, 2019; EPA, 2022). From 2016-2020, total payments from the two programs amounted to more than $15 billion (USDA 2021).

Our paper seeks to investigate the additionality of cost share payment programs for common conservation practices, considering the potential correlations between practices. Additionality, or the principle that we should only pay farmers to adopt conservation practices that they would not adopt in the absence of a cost share, is an important criterion for measuring the performance and cost-effectiveness of conservation programs like EQIP and CSP (Claassen & Duquette, 2014; Wang, Pathak & Adusumilli, 2019). Previous work measures additionality using treatment effects estimators (e.g., Wang, Pathak & Adusumilli, 2019; Pathak, Paudel & Adusumilli, 2021; Claassen, Duquette & Smith, 2018). Larger treatment effects from conservation payments—i.e., a larger difference in adoption rates among farmers who receive a conservation payment and those who do not—indicate greater additionality. Claassen, Duquette & Smith (2018) use this approach to measure additionality of conservation payments in the US for several practices, including conservation tillage, nutrient management, and various structural practices like filter strips and riparian buffers. The authors find high additionality for structural practices, indicating that cost-share payments can play a crucial role in encouraging adoption of these practices. Conservation tillage, on the other hand, has the lowest level of additionality. Their results are consistent with Wang, Pathak, and Adusumilli (2019), who find high additionality in structural practices that are associated with improving or conserving water quality in Louisiana.

All this prior work implicitly assumes that the decision to adopt a given practice is independent of the decision to adopt other practices. However, certain conservation practices in combined use may generate complementary benefits. For instance, Zhou et al. (2017) and Marcillo & Miguez (2017) examine the co-effects of no-till and cover crops on crop yield and net returns. Both studies show that, when used in combination, cover crops and conservation tillage generate higher net returns for farmers. Naeem *et al.* (2018) suggest that combined application of biochar and compost improves soil quality more than just biochar or compost alone. Studying adoption time of common conservation practices, Canales *et al.* (2020) show that those who adopt no-till have a much shorter adoption time for cover crops.

Complementarities between conservation practices mean that, conditional on adopting one practice, other related practices may be adopted even without further cost share payments—or, at the very least, the size of the cost-share required to induce adoption of the related practices may be smaller. As a result, estimates of conservation program additionality that ignore complementarities in adoption decisions may be overstated.

A vast literature has been dedicated to studying the effectiveness of multiple incentive program types on conservation practice adoption (e.g. see Engel *et al.*, 2008 and Piñeiro *et al.*, 2020 for a review of 577 relevant articles). Studies on additionality, however, are more limited. Lichtenberg (2021) studies the additionality of conservation practices in Maryland, focusing on the number of practices adopted. His results suggest that additionality increases with the number of practices adopted, but at a diminishing rate. Investigating additionality of cover crops in Iowa, Sawadgo & Plastina (2021) found that cost-share programs increase the area of cover crops planted by 15 percentage point on average.[107] Nevertheless, only one paper examines the possibility of co-adoption of practices via counterfactual analysis (Lichtenberg, 2021). The study shows that while additionality increases with the number of subsidized practices, the growth is uneven and possibly inconsistent. Doubling or tripling the number of subsidized practices leads to adopting only 1.0 to 1.5 extra practices. However, this prior work does not provide estimates of additionality for specific practices whose complementarity may differ across different combinations of practices and hence may affect additionality estimates, nor does it focus on the extent to which additionality estimates are potentially biased if complementarities are not accounted for.

Our work applies a novel regression adjustment approach for estimating additionality that explicitly accounts for possible correlation in adoption decisions driven by complementarities. We focus on conservation tillage, cover crops, and nutrient management. Previous literature shows that their combination tends to produce the best outcomes for both soil health and environmental protection (e.g., Smith *et al.*, 2015; Pittelkow *et al.*, 2015, SARE, 2020). In addition, their popularity is either relatively high among conservation practices, or has been increasing in the recent years (SARE, 2020; Dobberstein, 2019, USDA, 2018), therefore motivating us to focus on them.[108]

Despite prior work suggesting the existence of complementarities between practices, we find no evidence of correlation in practice adoption. Specifically, the additionality estimates of a

[107] They found that farmland share under cover crops will increase from 12% to 27% when farmers receive cost-share payments programs for cover crops.

[108] No-till acres increased from 3 million in 1972 to 104 million in 2017, while cover crops acres increased from 10.2 million in 2012 to 15.3 million in 2017 (Dobberstein, 2019). Nutrient management on the other hand enjoys high popularity; 65% of farmers apply nutrients at the recommended rates (USDA, 2018).

cost share payment for no-till is 23.8% under the unadjusted model. The estimates are 24.8% and 22.9% when we adjust for potential complementarity with cover crops or nutrient management, respectively, showing insignificant differences. Similarly, the unadjusted additionality estimate of cover crops is 44.7%, while the estimate adjusted for potential correlation with no-till is 44.5%. Additionality estimate of nutrient management without adjusted for potential complementarity with no-till is 28.1%, and it is 30.1% under the adjusted model. We also perform a robustness check, employing a treatment effects model using adjusted inverse propensity score weighting (IPSW). The point estimates indicate complementarity between no-till and cover crops and no-till and nutrient management. However, the results are unstable, and the additionality estimates have large confidence intervals. Our findings indicate no reliable evidence of complementarity in practice adoption following conservation payments despite the general consensus in the agronomic literature on the benefits of co-adoption of certain conservation practices. These results suggest the potential for unrealized gains to producers from conservation.

3.1.2 Background

Agricultural conservation practice incentive programs in the U.S. have a long history, dating back to the Soil Conservation Act of 1935 (Coppess, 2014). Today, there are multiple financial and technical support programs, including the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP), the Conservation Reserve Program (CRP), the Agricultural Conservation Easement Program (ACEP), the Regional Conservation Partnership Program (RCPP), and the Conservation Technical Assistance (CTA)s program (Wallander, 2019). Each program has its own set of eligibilities and characteristics, but all aim to support farmers in successfully adopting conservation practices that target soil erosion, watershed contamination, or drought, among others (USDA, 2022; USDA, n.d.). From 2017 to 2020, the three largest programs in terms of budget were EQIP (22% of total spending), CSP (22.4% of total spending), and CRP (43% of total spending). Together, the USDA spent nearly $15 billion on these three programs for the period 2017-2020 (EWG, 2022). Adjusted for inflation, total spending for all major USDA conservation programs amounted to nearly $25 billion from 2017 to 2020 (Wallander, 2019).

Given the significant spending on conservation programs, it is crucial to assess the cost-effectiveness of these investments and identify opportunities for savings. An accurate and unbiased estimate of additionality is key to achieving this goal. Although some studies have investigated additionality, only a limited number have explicitly accounted for the possibility of co-adoption of practices or potential complementarities. In light of this research gap, we will now present our methodology for formally defining additionality and describing our empirical approach for estimating it in the context of payments for potentially complementary practices.

3.2 Data

We collect the data for the analysis of additionality under complementary practices from multiple sources. The main dataset comes from the U.S. Department of Agriculture's Agricultural Resource Management Survey (ARMS). The survey contains information on field-level cropping practices, field features and resource use, and farm-level finance and farmers' personal demographics. The survey is divided into three phases. The first phase determines whether the farmer and farm qualify as a potential participant in phases II and III. In phase II, the respondent answers survey questions related to their production of a specific major commodity on a randomly drawn field that year. The chosen commodity changes from year to year. Questions in phase II ask about conservation practice adoption and related information, application of nutrients, and field features, among other aspects of production. Phase III of the survey collects data at the farm level, which includes, but is not limited to, commodity marketing and income, operating and capital expenditures, farm assets and debts, and farmer characteristics. The three phases are conducted in order starting in early summer (phase I), fall (phase II), and late winter (phase III).

ARMS uses a stratified sampling design, which means that farms are grouped into strata by regions or by states (in cases of states that have a larger sampled population), farm sales category, and commodity specialty. Due to the structured nature of selection, each observation in a stratum has a probability weight that represents their selection probability, which ensures the representativeness of farms in different regions, size, and crop specialty. In this analysis, we use ARMS data from three years: 2016 (corn), 2017 (spring wheat, winter wheat and durum wheat), and 2018 (soybean), as those are among the most common crops throughout the US (combined production is around 53% of total crop production) and are therefore the targets of the majority of conservation assistance programs (NASS, 2017).

From the phase II field-level survey, we collect information on conservation practice adoption, particularly whether the farmer has adopted no-till, nutrient management, or cover crops, whether those practices receive any type of conservation funding (EQIP, CSP, CRP, or other federal funding), the year those practices are applied, and if adoption of the practice is a part of compliance requirements.[109] We also collect data on overall soil quality, which includes wetland and erosion status of the soil (i.e., whether the field is identified as wetland and/or highly erodible). Following Claassen *et al.* (2018), we obtain information on whether manure has been applied to the field, and finally, whether the farmer owns the field or not. The relationship between

[109] Circumstances that necessitate compliance typically include, but are not limited to, participation in federal programs (such as those of the NRCS or FSA), compliance with federal regulations (such as the Clean Water Act), or state and local requirements to preserve soil and water quality (EPA, n.d.; Stubbs, 2012; USDA, n.d). The farmers typically have flexibility in choosing the practices that best suit their farms to meet the compliance. The NCRS provides guidance on conservation practices customized to individual farms, known as the "conservation practice standards" (USDA, n.d.).

conservation practices adoption and land ownership has been studied extensively (see Prokopy *et al*., 2008 and Knowler & Bradshaw, 2007 for a review and summary). In general, landowners have more incentives to invest in conservation practices due to the long-term benefits for their land regarding soil health and productivity. Claassen *et al.* (2018) collect data on manure application due to the practice's relation to nutrient management, which entails identifying the quantity, scheduling, and techniques of fertilizer or manure application.

From the phase III farm-level survey, we obtain data on total acres in operation, farmers' demographics, including age, education (i.e., whether the farmer has a college degree or not), and whether farming is the main source of income for the respondent's household or not. We do not use data on race and gender since most observations (>90%) are white and male. We then merge the data in the field- and farm-level surveys together. We use only observations from farmers that respond to both the field- and farm-level surveys. The retention rate in each of the three years of the surveys we use ranges from 33% to 42%. Overall, we have 1,110 observations for 2016, 1,292 for 2017, and 1,210 for 2018, for a total of 3,612 observations. Due to the nature of wheat as either a grain crop or cover crops, there are concerns that wheat farmers might be less inclined to adopt cover crops than soybean or corn farmers (Frankenfield, 2023; SARE, n.d.). We find that around 17% of all cover crops adopters are wheat farmers. In fact, wheat farmers grow the crop for multiple purposes, depending on their priorities (Klein & McClure, 2020). Therefore, our dataset includes wheat farmers even when we examine cover crop additionality.

Following Claassen *et al.* (2018), we collect external data that ARMS does not cover to account for additional drivers of practice adoption. We use county-level data on 2017 population density from the Census Bureau and ArcGIS hub (Esri, 2022; U.S. Census Bureau, n.d.). We collect state-level information on slope and soil productivity index—particularly for corn, soybean and small grains—from the Soil Geographic Database of the USDA, using the Gridded Soil Survey Geographic (gSSURGO) database. The data is then joined with the counties shapefile from the Census Bureau to obtain county-level information on soil productivity and slope. As federal financial assistance for neighboring farms may affect the decision-making process of the farmers (Claassen *et al*., 2018), we also collect data on CRP and EQIP payments for conservation practices at the county level. In addition, we calculate the average payments for neighboring counties for each county in the main dataset. County-level CRP payments come from the Farm Service Agency of USDA, while we extract the EQIP payments from the Financial Assistance Program Data Dashboard of the NRCS.[110]

In accordance with USDA practice in using the ARMS dataset, we include expansion weight variables to ensure the sample is representative of the population. We also include replicate weights provided in the dataset to better estimate standard errors. The ARMS User Guide suggests using 30 weight variables, which are given in the phase III data. For more details on the expansion and replicate weights, refer to the ARMS User Guide (Katchova, Barton & Jones, 2021). Finally, we incorporate the weights in our models using the jackknife estimation method per the suggestion of USDA, as it allows for the replication of estimation results.

Table 3.1 contain the summary statistics of the variables that are covariates in our treatment models, including continuous and binary ones. Besides those variables, our models also include indicators for crops grown (soybean/corn, or wheat) and indicators for whether the farmer adopts a conservation practice as part of a compliance requirement. As our analysis focuses on the

[110] The data for CRP county payments can be found at https://www.fsa.usda.gov/programs-and-services/conservation-programs/reports-and-statistics/conservation-reserve-program-statistics/index, and the federal total payments for conservation programs comes https://www.farmers.gov/data/financial-assistance/download. We construct data on average payments to neighbor counties by merging the county level CRP and EQIP payments data with the adjacent counties data file from the Census Bureau at https://www.census.gov/programs-surveys/geography/technical-documentation/records-layout/county-adjacency-record-layout.html, then averaging the payments of all neighboring counties for each associated county.

additionality and the potential complementarity between different conservation payments, we are also interested in the statistics of farmers who adopt no-till, cover crops, and nutrient management. Table 3.2 contains the summary statistics on the adoption of these three practices with regard to their financial subsidy status. we examine the adoption decision of no-till, cover crops and nutrient management with and without financial assistance for the practice. In total, approximately 56% of respondents in the dataset adopt no-till, suggesting its high popularity among farmers. In addition, among those who adopt, only around 23% of farmers report receiving some type of financial assistance to adopt no-till. This may be due to the cost-saving advantages of no-till, therefore indicating the low dependency of the practice on financial assistance. Cover crops, in contrast, are much less popular; only 10% of responders adopt the practice. Of those who adopt, nearly 27% rely on federal financial assistance. Nutrient management's popularity lies between no-till and cover crops; around 22% of respondents adopt the practice, with approximately 25% of adopters receiving financial assistance.

Table 3.3 and Table 3.4 present the prevalence of no-till and cover crops, and no-till and nutrient management individual and co-adoption.

Table 3.1. Model variables summary statistics

Continuous variables						
Variable	N	Mean	Std. dev.	Min	Max	Source
Age	3,612	57.85	12.62	—	—	USDA (2016, 2017, 2018)
Soil productivity*	3,612	0.40	0.18	0.01	0.90	USDA (n.d.)
Operation acres	3,612	2,653.73	4,447.17	—	—	USDA (2016, 2017, 2018)
CRP per acre*	3,612	70.90	36.83	0.00	211.97	USDA (2023)
CRP per acre* (neighbor)	3,612	69.54	34.10	0.00	236.44	USDA (2023)
EQIP per acre*	3,612	214.28	454.99	3.96	22,348.27	USDA (2022)
EQIP per acre (neighbor)*	3,612	243.19	392.62	17.67	6,214.32	USDA (2022)
Population density* (2017)	3,612	79.95	173.24	0.28	3,004.94	Census Bureau (n.d.); Esri (2022)
Highly Erodible	3,612	0.14	0.35	0	1	USDA (2016, 2017, 2018)
Wetland	3,612	0.03	0.18	0	1	USDA (2016, 2017, 2018)
Manure	3,612	0.12	0.32	0	1	USDA (2016, 2017, 2018)
College	3,612	0.32	0.47	0	1	USDA (2016, 2017, 2018)
Mostly Farmer	3,612	0.90	0.30	0	1	USDA (2016, 2017, 2018)
Owned Field	3,448	0.50	0.50	0	1	USDA (2016, 2017, 2018)

*Indicates values obtained from the authors' own calculations from original raw data sources. Soil productivity, CRP per acre, EQIP per acre, and population density are county-level variables. The minimum and maximum values of age and operation acres are left unspecified to comply with USDA requirements for using the ARMS dataset. A number of respondents did not respond to the question of whether they owned the field or not, so the number of observations are different from other variables.

Table 3.1 shows large variability among the respondent in terms of field characteristics and farmer demographics. We observe that most fields in the survey are not considered either highly erodible or wetland. The majority of respondents do not apply manure to their field and answer that farming is their principal occupation. The education level is more balanced, where around one third of farmers have a college degree. Approximately half of them own the field based on which they answer the field level survey for a given year.

Table 3.2. Adoption decision of no-till, cover crops and nutrient management with respect to financial assistance

Practice	Adoption decision	Financial payment		Total
		0	1	
No till	0	1,596	0	1,596
	1	1,543	473	2,016
	Total	3,139	473	3,612
Cover crop	0	3,243	0	3,243
	1	269	100	369
	Total	3,512	100	3,612
Nutrient management	0	2,821	0	2,821
	1	591	200	791
	Total	3,412	200	3,612

In Table 3.2, we examine the adoption decision of no-till, cover crops and nutrient management with and without financial assistance for the practice. In total, approximately 56% of respondents in the dataset adopt no-till, suggesting its high popularity among farmers. In addition, among those who adopt, only around 23% of farmers report receiving some type of financial assistance to adopt no-till. This may be due to the cost-saving advantages of no-till, therefore indicating the low dependency of the practice on financial assistance. Cover crops, in contrast, are much less popular; only 10% of responders adopt the practice. Of those who adopt, nearly 27% rely on federal financial assistance. Nutrient management's popularity lies between no-till and cover crops; around 22% of respondents adopt the practice, with approximately 25% of adopters receiving financial assistance.

Table 3.3. Interaction between no-till and cover crops adoption decisions

No till	Cover crop		Total
	0	1	
0	1,518	78	1,596
1	1,725	291	2,016
Total	3,243	369	3,612

Table 3.4. Interaction between no-till and nutrient management adoption decisions

No till	Nutrient management		Total
	0	1	
0	1,375	221	1,596
1	1,446	570	2,016
Total	2,821	791	3,612

Table 3.3 and Table 3.4 present preliminary evidence on complementarities in adoption decisions of no-till and cover crops and no-till and nutrient management, respectively.[111] The tables show how likely it is that producers who adopt no-till, cover crops, or nutrient management will also adopt another practice. For example, the probability a farmer adopts cover crops given that they do not adopt no-till is $78/1596 \approx 4.9\%$, and the probability that a farmer adopts cover crops given that they also adopt no-till is $291/2016 \approx 14\%$. Similarly, the probability of adopting nutrient management given non-adoption of no-till is $221/1596 \approx 14\%$, while the probability of adopting nutrient management while also adopting no-till is $570/2016 \approx 28\%$. Performing a Chi-squared independence test for both pairs, we obtain a P-value of 5^{-21} for no-till – cover crops, and

[111] We do not examine the connection between cover crops and nutrient management because of the low combined popularity of the two practices in the dataset.

2^{-25} for no-till – nutrient management. The test results reject the null hypothesis that the practices are uncorrelated. While this does not yet confirm the presence of complementarity between two given conservation practices, it serves as a justification for our hypothesis of complementarity in conservation practice adoption. Next, we show how the presence of complementarities will generate bias in estimating treatment effects from conservation payments and, hence the additionality of these payments using standard models that do not account for correlation in practice adoption decisions.

3.3 Methodology

3.3.1 Average treatment effect for the treated (ATT) under assumption of complementary practices

Following Claassen, Duquette & Smith (2018) and other previous work (Lichtenberg, 2021; Sawadgo & Plastina, 2021; Claassen & Ribaudo, 2016), we estimate the additionality of potentially complementary conservation practices as the average treatment effect on the treated (ATT). In the context of policy evaluation, the ATT demonstrates the effectiveness of a program on an outcome of interest for entities that receive the treatment. In our work, the binary outcome of interest is whether a farmer adopts each of two different conservation practices following a conservation payment. Denote the farmer's adoption decision for practice $k = 1, 2$ as Y_k, where $Y_k = 1$ if the farmer adopts practice k and zero otherwise. We assume the farmer can potentially receive cost-share payments to support adoption of one or more practices, consistent with existing conservation programs in the US. In the presence of potential complementarities between practice adoption decisions, Y_k should depend on receiving a payment for each practice. Hence, we write the farmer's adoption decision as $Y_k(D_1, D_2)$, where $D_k = 1$ if the farmer receives a cost-share payment to support adoption of practice k and zero otherwise. Let Z be a vector of farm and farmer characteristics. We also assume unconfoundedness holds such that, conditional on Z, adoption and treatment for all practices are uncorrelated. We then write the ATT for practice 1 as

$$ATT_1 = E(Y_1(1, D_2) - Y_1(0, D_2)|D_1 = 1, Z) = 1 - E(Y_1(0, D_2)|D_1 = 1, Z), \qquad (11)$$

with the ATT for practice 2 defined analogously. ATT_1 represents the mean difference in adoption of practice 1 with and without payment for practice 1, conditional on the farmer receiving a cost share payment for practice 1. The second equality stems from the fact that, under a conservation program, adoption of practice 1 is mandatory upon receiving payment, and hence $E(Y_1(1, D_2)|D_1 = 1, Z) = 1$. The second right-hand side (RHS) term in each equality characterizes the adoption decision for practice 1 in a counterfactual world where the farmer—who is treated in reality—does not receive the payment. It is thus unobservable and requires estimation.

An unbiased treatment effects estimator requires:

$$E(Y_1(0, D_2)|D_1 = 0, Z) = E(Y_1(0, D_2)|D_1 = 1, Z). \qquad (2)$$

Intuitively, expected adoption among those who are untreated (left-hand side of (2)) should equal the expected adoption among those who are treated, but in a counterfactual world where they are not treated (RHS of (2)). Ignorance of potential complementarities, and hence correlations between practice adoption decisions, may violate (2) and lead to an upward bias of the ATT estimate. To see this, note that:

$$\begin{aligned} E(Y_1(0, D_2)|D_1 = 0, Z) &= E(Y_1(0,0)|D_1 = 0, D_2 = 0, Z)\,\Pr(D_2 = 0|D_1 = 0, Z) \\ &\quad + E(Y_1(0,1)|D_1 = 0, D_2 = 1, Z)\,\Pr(D_2 = 1|D_1 = 0, Z) \\ &= E(Y_1(0,0)|Z) Pr(D_2 = 0|D_1 = 0, Z) \\ &\quad + E(Y_1(0,1)|Z)\,\Pr(D_2 = 1|D_1 = 0, Z) \text{ under unconfoundedness} \\ &\neq E(Y_1(0, D_2)|D_1 = 1, Z) \\ &= E(Y_1(0,0)|Z)\,\Pr(D_2 = 0|D_1 = 1, Z) \\ &\quad + E\big(Y_1(0,1)\big)\,\Pr(D_2 = 1|D_1 = 1, Z) \end{aligned} \qquad (3)$$

In (3), the probability weights Pr(·) serve as the source of inequality between the two terms when practice adoption decisions are correlated due to complementarities. To illustrate this, note that if the farmer receives payment for practice 1, the probability of receiving the payments for practice 2 may be higher, and thus $\Pr(D_2 = 1|D_1 = 1, Z) > \Pr(D_2 = 1|D_1 = 0, Z)$. In addition, complementarities may imply that a farmer is likely to adopt practice 1 if they already receive payment for practice 2. Hence, payments for one practice may not only lead to the adoption of that practice, but also increase the rate of adoption for the other practice, and as such $E(Y_1(0,1)|Z) > E(Y_1(0,0)|Z)$. We would then have

$$E(Y_1(0, D_2)|D_1 = 1, Z) > E(Y_1(0, D_2)|D_1 = 0, Z), \tag{4}$$

which contradicts (2). In other words, the farmers who are untreated cannot be an unbiased control group for those treated, even after controlling for farmers and farm characteristics included in *Z*.

Thus, following previous literature, we use an adjustment for the inverse propensity score weighting procedure for multi-valued treatments (e.g., Imbens, 2000; Cattaneo, 2010; McCaffrey *et al.*, 2013) to obtain an estimate for the ATT. Let $p_{d_2|d_1}(Z) = \Pr(D_2 = d_2|D_1 = d_1, Z)$ be the probability of receiving payments for practice 2, conditional on the payment status for practice 1 and covariates *Z*. Under the assumption of unconfoundedness, we have

$$E(Y_1(0, D_2)|D_1 = 1, Z) = E\left(Y_1 \frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}\middle|D_1 = 0, Z\right), \tag{5}$$

where $\frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$ is an adjusted IPSW.

3.3.2 Estimation

One way to estimate (5) and calculate the ATT would be to estimate $p_{D_2|1}(Z)$ and $p_{D_2|0}(Z)$ individually using, say, a logit model, use the fitted values to calculate IPSWs for each farmer in the dataset, and then estimate $E\left(Y_1 \frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}\middle| D_1 = 0, Z\right)$ using ordinary least squares. We use this procedure to estimate the results presented in Appendix 3.7.1. However, our dataset contains a relatively small number of treated units, particularly farmers who receive payment for cover crops or nutrient management. This can lead to overfitting the IPSW when considering jointly the treatment status of two practices. When this happens, the denominator of $\frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$ can become very small, producing large weight estimates and subsequently unstable adjusted adoption decisions $Y_1 \frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$.

Regression adjustment offers another means of estimating ATT that does not suffer from stability problems. Note first that we can rewrite the RHS of (5) as:

$$
\begin{aligned}
E\left(Y_1 \frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}\middle| D_1 = 0, Z\right) &= \frac{E\left(Y \frac{P_{D_2|D_1=1,Z}}{P_{D_2|D_1=0,Z}}(1-D_1)|Z\right)}{P(D_1=0|Z)} \\
&= E(Y \frac{P_{D_2=1|D_1=1,Z}}{P_{D_2=1|D_1=0,Z}} \frac{1}{P(D_1=0|Z)} D_2(1-D_1)|Z) \\
&+ E(Y \frac{P_{D_2=1|D_1=1,Z}}{P_{D_2=1|D_1=0,Z}} \frac{1}{P(D_1=0|Z)} (1-D_2)(1-D_1)|Z) \\
&= E(Y \frac{P_{D_2=1|D_1=1,Z}}{P_{D_1=0|D_2=1,Z}} D_2(1-D_1|Z) \\
&+ E\left(Y \frac{P_{D_2=0|D_1=1,Z}}{P_{D_1=0|D_2=0,Z}}(1-D_2)(1-D_1)\middle|Z\right) \\
&= P_{D_2=1|D_1=1,Z} E(Y|D_2=1, D_1=0, Z) \\
&+ P_{D_2=0|D_1=1,Z} E(Y|D_2=0, D_1=0, Z).
\end{aligned} \tag{6}
$$

This weighting scheme is analogous to a bivariate regression adjustment, where D_2, or the treatment status of the second practice, is included in the covariates. Define:

$$g(D_2, Z) = E(Y|D_1 = 0, D_2, Z). \quad (7)$$

then

$$\begin{aligned} E(g(D_2, Z)|D_1 = 1, Z) &= E(Y(0, D_2)|D_1 = 1) \\ &= P_{D_2=0|D_1=1,Z}\, g(0, Z) + P_{D_2=1|D_1=1,Z}\, g(1, Z). \end{aligned} \quad (8)$$

We estimate $g(0, Z)$ by regressing the adoption decision of the first practice (no-till) on the covariates Z for fields that do not receive payment for either no-till or the second practice (cover crops or nutrient management). We collect the data for the analysis of additionality under complementary practices from multiple sources. The main dataset comes from the U.S. Department of Agriculture's Agricultural Resource Management Survey (ARMS). The survey contains information on field-level cropping practices, field features and resource use, and farm-level finance and farmers' personal demographics. The survey is divided into three phases. The first phase determines whether the farmer and farm qualify as a potential participant in phases II and III. In phase II, the respondent answers survey questions related to their production of a specific major commodity on a randomly drawn field that year. The chosen commodity changes from year to year. Questions in phase II ask about conservation practice adoption and related information, application of nutrients, and field features, among other aspects of production. Phase III of the survey collects data at the farm level, which includes, but is not limited to, commodity marketing and income, operating and capital expenditures, farm assets and debts, and farmer characteristics. The three phases are conducted in order starting in early summer (phase I), fall (phase II), and late winter (phase III).

ARMS uses a stratified sampling design, which means that farms are grouped into strata by regions or by states (in cases of states that have a larger sampled population), farm sales category, and commodity specialty. Due to the structured nature of selection, each observation in a stratum has a probability weight that represents their selection probability, which ensures the representativeness of farms in different regions, size, and crop specialty. In this analysis, we use ARMS data from three years: 2016 (corn), 2017 (spring wheat, winter wheat and durum wheat), and 2018 (soybean), as those are among the most common crops throughout the US (combined production is around 53% of total crop production) and are therefore the targets of the majority of conservation assistance programs (NASS, 2017).

From the phase II field-level survey, we collect information on conservation practice adoption, particularly whether the farmer has adopted no-till, nutrient management, or cover crops, whether those practices receive any type of conservation funding (EQIP, CSP, CRP, or other federal funding), the year those practices are applied, and if adoption of the practice is a part of compliance requirements. We also collect data on overall soil quality, which includes wetland and erosion status of the soil (i.e., whether the field is identified as wetland and/or highly erodible). Following Claassen et al. (2018), we obtain information on whether manure has been applied to the field, and finally, whether the farmer owns the field or not. The relationship between conservation practices adoption and land ownership has been studied extensively (see Prokopy et al., 2008 and Knowler & Bradshaw, 2007 for a review and summary). In general, landowners have more incentives to invest in conservation practices due to the long-term benefits for their land regarding soil health and productivity. Claassen et al. (2018) collect data on manure application due to the practice's relation to nutrient management, which entails identifying the quantity, scheduling, and techniques of fertilizer or manure application.

From the phase III farm-level survey, we obtain data on total acres in operation, farmers' demographics, including age, education (i.e., whether the farmer has a college degree or not), and whether farming is the main source of income for the respondent's household or not. We do not use data on race and gender since most observations (>90%) are white and male. We then merge the data in the field- and farm-level surveys together. We use only observations from farmers that respond to both the field- and farm-level surveys. The retention rate in each of the three years of the surveys we use ranges from 33% to 42%. Overall, we have 1,110 observations for 2016, 1,292 for 2017, and 1,210 for 2018, for a total of 3,612 observations. Due to the nature of wheat as either a grain crop or cover crops, there are concerns that wheat farmers might be less inclined to adopt cover crops than soybean or corn farmers (Frankenfield, 2023; SARE, n.d.). We find that around 17% of all cover crops adopters are wheat farmers. In fact, wheat farmers grow the crop for multiple purposes, depending on their priorities (Klein & McClure, 2020). Therefore, our dataset includes wheat farmers even when we examine cover crop additionality.

Following Claassen et al. (2018), we collect external data that ARMS does not cover to account for additional drivers of practice adoption. We use county-level data on 2017 population density from the Census Bureau and ArcGIS hub (Esri, 2022; U.S. Census Bureau, n.d.). We collect state-level information on slope and soil productivity index—particularly for corn, soybean and small grains—from the Soil Geographic Database of the USDA, using the Gridded Soil Survey Geographic (gSSURGO) database. The data is then joined with the counties shapefile from the Census Bureau to obtain county-level information on soil productivity and slope. As federal financial assistance for neighboring farms may affect the decision-making process of the farmers (Claassen et al., 2018), we also collect data on CRP and EQIP payments for conservation practices at the county level. In addition, we calculate the average payments for neighboring counties for each county in the main dataset. County-level CRP payments come from the Farm Service Agency of USDA, while we extract the EQIP payments from the Financial Assistance Program Data Dashboard of the NRCS.

In accordance with USDA practice in using the ARMS dataset, we include expansion weight variables to ensure the sample is representative of the population. We also include replicate weights provided in the dataset to better estimate standard errors. The ARMS User Guide suggests using 30 weight variables, which are given in the phase III data. For more details on the expansion and replicate weights, refer to the ARMS User Guide (Katchova, Barton & Jones, 2021). Finally, we incorporate the weights in our models using the jackknife estimation method per the suggestion of USDA, as it allows for the replication of estimation results.

Table 3.1 contain the summary statistics of the variables that are covariates in our treatment models, including continuous and binary ones. Besides those variables, our models also include indicators for crops grown (soybean/corn, or wheat) and indicators for whether the farmer adopts a conservation practice as part of a compliance requirement. As our analysis focuses on the additionality and the potential complementarity between different conservation payments, we are also interested in the statistics of farmers who adopt no-till, cover crops, and nutrient management. Table 3.2 contains the summary statistics on the adoption of these three practices with regard to their financial subsidy status. we examine the adoption decision of no-till, cover crops and nutrient management with and without financial assistance for the practice. In total, approximately 56% of respondents in the dataset adopt no-till, suggesting its high popularity among farmers. In addition, among those who adopt, only around 23% of farmers report receiving some type of financial assistance to adopt no-till. This may be due to the cost-saving advantages of no-till, therefore indicating the low dependency of the practice on financial assistance. Cover crops, in contrast, are much less popular; only 10% of responders adopt the practice. Of those who adopt, nearly 27% rely on federal financial assistance. Nutrient management's popularity lies between no-till and cover crops; around 22% of respondents adopt the practice, with approximately 25% of adopters receiving financial assistance.

Table 3.3 and Table 3.4 present the prevalence of no-till and cover crops, and no-till and nutrient management individual and co-adoption.

Table 3.1 and Table 3.2 for the list and summary statistics of the covariates. In a similar manner, we estimate $g(1, Z)$ by regressing the adoption decision of the first practice on the covariates for fields untreated (unpaid) for no-till but treated for the second practice. Parameter estimates for $g(0, Z)$ and $g(1, Z)$ for both the no-till – cover crops and no-till – nutrient management models can be found in Appendix 3.7.3, Table 3.17 and Table 3.18. We then weight the fitted values of $g(0, Z)$ and $g(1, Z)$ by the associated probability of treatment status of practice 2 to calculate the expression on the second line of (8). Averaging this term over fields treated for no-till yields the ATT estimate.

We compare the estimates of ATT from the regression adjustment procedure against an "unadjusted model" that estimates additionality as $ATT = 1 - E(Y_1(0, D_2)|D_1 = 0, Z)$, where the second term is mean adoption of no-till among untreated fields. Recall from (2) that this estimate of the treatment effect will be biased in the presence of complementarities. We estimate the unadjusted model by regressing the no-till adoption decision on the covariates for only untreated fields. Parameter estimates for this model can be found in Appendix 3.7.2, column (1) of Table 3.11 and Table 3.14.

3.4 Results

Table 3.5 shows the estimated ATT measures for no-till. The unadjusted additionality estimate for no-till is 23.8%, meaning that 23.8% of farmers who adopt no-till would not have adopted the practice without payment. If we control for potential correlation in adoption decisions with cover crops and nutrient management using the regression adjustment model, we find estimates of additionality equal to 24.8% and 22.9%, respectively. The difference between the unadjusted and adjusted models are insignificant for both practice pairs (no-till – cover crops and no-till – nutrient management), indicating that neither second practice exhibits a correlation with no-till. Hence, we do not find evidence that additionality estimates that do not account for potential correlation in adoption decisions are overstated.

Table 3.5. Additionality estimates of no-till, unadjusted and adjusted for potential correlation with cover crops or nutrient management with regression adjustments.

Model	N	Mean adoption rate of nonpayment no-till fields	Additionality	95% confidence interval*
Unadjusted	469	0.762	0.238	[0.182 – 0.293]
Regression adjustment – cover crops	469	0.752	0.248	[0.132 - 0.364]
Regression adjustment – nutrient management	469	0.771	0.229	[0.156 – 0.302]

*95% confidence interval of additionality estimate is obtained via bootstrap.

We also estimate the additionality of payments for cover crops and nutrient management, with no-till as the second practice. As shown earlier, no-till adoption enjoys significantly higher popularity than either cover crops or nutrient management. Therefore, those farmers may have different characteristics than farmers who adopt cover crops or nutrient management as their first practice. Table 3.6 shows the additionality estimates for each practice.

Table 3.6. Additionality estimates of cover crops and nutrient management, unadjusted and adjusted for potential correlation with no-till with regression adjustments.

Practice	Model	N	Mean adoption rate of nonpayment fields	Additionality	95% confidence interval*
Cover crops - no-till	Unadjusted	100	0.553	0.447	[0.464 - 0.641]
	Regression adjustment	100	0.555	0.445	[0.458 - 0.652]
Nutrient management - no-till	Unadjusted	199	0.719	0.281	[0.658 - 0.780]
	Regression adjustment	199	0.699	0.301	[0.625 - 0.772]

*95% confidence interval of additionality estimate is obtained via bootstrap.

The unadjusted additionality estimates are 0.447 for cover crops and 0.281 for nutrient management. The results indicate that among the three common practices—no-till, cover crops and nutrient management—cover crops would benefit the most from payment programs. Controlling for the potential correlation with no-till adoption, the cover crops additionality estimate becomes 0.445. Thus, the difference between the unadjusted and adjusted additionality estimates of the cover crops – no-till model is insignificant, similar to the no-till – cover crops model. The 95% confidence interval of the estimates also largely intersect with each other. Therefore, we find no evidence of complementarity between no-till and cover crops, whether the farmer adopts no-till or cover crops first.

Similar to the cover crops – no-till model, the nutrient management – no-till model estimates show no significant differences between the unadjusted and regression adjustment model. The additionality estimate of the regression adjustment model is 0.301, which is 2% higher than the unadjusted estimate. Nevertheless, similar to the no-till – nutrient management model, the 95% confidence intervals overlap and hence our estimates do not give conclusive evidence of correlation between nutrient management and no-till adoption.

In Appendices 0 and 0, we perform a robustness check by estimating the additionality using an adjusted inverse propensity score method. The results show moderate complementarity between both no-till and cover crops and no-till and no-till and nutrient management among no-till farmers, suggesting an overstatement of traditional additionality estimates. However, when the order is switched and no-till becomes the second practice, the results show strong substitution relationship between cover crops and no-till, and nutrient management and no-till. This phenomenon, combined with the large, estimated values of the propensity scores and the wide 95% confidence interval of the additionality estimates in some models, renders the results unstable and unreliable.

3.5 Discussion and Conclusion

This paper studies the additionality of common conservation practices including no-till, cover crops and nutrient management in the context of potential correlation between the practices. We incorporate the potential correlation between the practices by considering the likelihood of their co-adoption. We achieve this by re-weighting the adoption decision of one practice (no-till) using the adjusted inverse propensity score method. Our results show no significant differences between additionality estimates after controlling for potential correlations in adoption decisions for no-till, cover crops, and nutrient management.

We perform a robustness check using an IPSW approach to adjust for the likelihood of co-adopting two practices. The results show complementary relationship between no-till and cover crops, and no-till and nutrient management. However, when we reverse the order of practices adoption, the estimates indicate substitution relationship between these two pairs of practices. This inconsistency, combining with large propensity scores and 95% confidence intervals of the additionality estimates render the IPSW model results unstable and unreliable. Our results seem contradictory to the agronomy literature. Past work shows the synergy between these three practices with respect to soil health and productivity (Blanco-Canqui *et al*., 2015; Pittelkow, *et al*., 2015; Tonitto *et al*., 2006). This seems to undermine our findings of no correlation among these practices, at least in the context of additionality.

However, recent literature demonstrates the low adoption rate of those three practices, despite proven benefits (Reimer *et al*., 2019; Plastina *et al*, 2018; USDA, 2021). This corroborates with our results that indicate low co-adoption rates for no-till, cover crops and nutrient management. Our analysis helps understand more in depth the effectiveness of conservation programs such as EQIP or CSP. However, the limitation of the data may render our estimates not completely unbiased. Specifically, the number of farmers voluntarily adopting cover crops and nutrient management are relatively small compared to no-till. This in turn creates a limited dataset on farmers who co-adopt two practices and consequently unstable weights. In addition, information on practice costs and benefits can be useful, as there are evidence that perceived costs and benefits can be an important factor in practice adoption decisions (see e.g. McCollum *et al*., 2022; Piñeiro *et al.*, 2020). Future research could extend the study with a richer dataset on various practices.

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3.7 Appendix

3.7.1 Estimations of adjusted propensity score

In this section, we present the results of the treatment effects models used to estimate the proposed adjusted inverse propensity score, or the term $\frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$ in equation (4). We use no-till as the first practice and cover crop or nutrient management as the second practice. We will first consider no-till and cover crops.

No-till and cover crops

We estimate the probabilities $p_{D_2|D_1}(Z)$ using a standard logit model. Formally, we perform a logit regression of the treatment status of practice 2 on the covariates, conditioned on the associated treatment status of practice 1. Specifically, the model that estimates the numerator $p_{D_2|1}(Z)$ takes the form:

$$
\begin{aligned}
&Finan\ payment\ cover\ crop \\
&\qquad = const + mostly\ farmer + age + college + owned\ field \\
&\qquad + highly\ erodible + wetland + productivity + manure \\
&\qquad + \log operation\ size + EQIP\ per\ acre \qquad (6) \\
&\qquad + EQIP\ per\ acre\ neighbor + CRP\ per\ acre \\
&\qquad + CRP\ per\ acre\ neighbor + density(2017) + corn\ soybean \\
&\qquad + compliance + \epsilon \quad if\ finan\ payment\ no - till = 1
\end{aligned}
$$

where $corn\ soybean$ is the indicator of whether the field is a corn or soybean field, and ϵ is the error term. Similarly, the model that estimates the denominator $p_{D_2|0}(Z)$ is:

$$
\begin{aligned}
&Finan\ payment\ cover\ crop \\
&\qquad = const + mostly\ farmer + age + college + owned\ field \\
&\qquad + highly\ erodible + wetland + productivity + manure \\
&\qquad + \log operation\ size + EQIP\ per\ acre \qquad (7) \\
&\qquad + EQIP\ per\ acre\ neighbor + CRP\ per\ acre \\
&\qquad + CRP\ per\ acre\ neighbor + density(2017) + corn\ soybean \\
&\qquad + compliance + \epsilon \quad if\ finan\ payment\ no - till = 0
\end{aligned}
$$

Table 3.7 contains the parameter estimates for the numerator $p_{D_2|1}(Z)$ (column 1) and denominator $p_{D_2|0}(Z)$ (column 2), where the second practice is cover crops.

Table 3.7. Results of the propensity score weighting model for no-till and cover crops

VARIABLES	(1) propensity score numerator	(2) propensity score denominator
Mostly farmer	1.790	-0.760
	1.818)	(0.970)
Age	-0.0438	-0.0188
	(0.0528)	(0.0356)
College	-0.737	0.0675
	(1.220)	(0.980)
Owned field	0.361	0.240
	(0.922)	(0.836)
Highly erodible	1.614	1.078
	(1.027)	(0.872)
Wetland	1.585	-0.179
	(2.002)	(1.107)
productivity	7.365	-1.355
	(6.491)	(4.859)
Manure	-0.709	1.683**
	(1.565)	(0.680)
Log operation size	0.0364	-0.183
	(0.410)	(0.192)
EQIP per acre (self)	0.00305	8.63e-05
	(0.00233)	(0.00162)
EQIP per acre (neighbor)	-6.56e-06	0.000718
	(0.00127)	(0.00251)
CRP per acre (self)	0.00686	0.0129
	(0.0646)	(0.0152)
CRP per acre (neighbor)	-0.0141	-0.00762
	(0.0444)	(0.0186)
Density (2017)	0.00504**	-0.00403
	(0.00227)	(0.00444)
Corn/soybean	-0.233	0.0738
	(1.079)	(0.991)
Compliance Cover crops	5.117***	3.543***
	(1.775)	(0.952)
Constant	-6.295	-2.763
	(5.000)	(2.606)
Observations	469	2,950

Table 3.7, column (1) shows that among those who receive a financial payment for no-till, county population density and the compliance status (whether the farmer adopts cover crop to satisfy a compliance requirement) have a positive impact on the financial payment status for cover crop. Column (2) consists of the coefficient estimates of the same treatment model for those who do not receive a financial payment for no-till. For this subset of sample, applying manure on the field increases the likelihood of being paid for cover crop adoption. This may be due to the common concern of nutrient loss from leaching and runoff after manure application, and how cover crop can help reduce this loss. In addition, cover crops can also help improve soil health and structure, which further contributes to the efficient use of nutrients (University of Illinois Extension, n.d.). Similar to the sample subset where farmers do not receive payment for no-till, those who adopt cover crop as part of a compliance requirement are also more likely to receive payment for the practice. This may be to assist farmers in offsetting the cost associated with implementing the practice. Fields whose soil is classified as highly erodible tend to have a higher probability of receiving payment, however the impacts are not highly statistically significant.

We use the results of these two models combined to estimate the value of the adjusted inverse propensity score for each farmer in the whole dataset. The adjusted inverse propensity score ranges from 0 to around 2,280, with a median of around 1.0, a mean of 2.4, and a standard deviation of 41. Given these values, the values of the weighted adoption decision of no-till range from 0 to around 485, with a mean of 1.3 and median of 0.8. Table 3.8 contains the statistics of the adjusted inverse propensity scores and the weighted adoption decision of no-till, as we assume no-till is the first practice that appears in equation (4).

Table 3.8. Statistics summary of adjusted inverse propensity score and weighted adoption decision of no-till, accounting for potential correlation with cover crop

Parameter	N	Mean	Median	Standard deviation	Min	max
Adjusted inverse propensity score	3,419	2.40	0.98	40.94	0	2,278.81
Weighted adoption decision of no-till	3,419	1.27	0.80	12.43	0	485.06

No-till and nutrient management

We also estimate a treatment effects model to estimate additionality for no-till and nutrient management (with no-till being the first practice). We estimate the adjusted inverse propensity scores in a similar manner as above. The models that estimate the IPSW $\frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$ for no-till and nutrient management are analogous to the no-till and cover crop models, represented by equations (6) and (7). However, rather than cover crops, nutrient management acts as the second practice, and thus the dependent variable is the financial payment status of nutrienent management. Table 3.9 contains the coefficient estimates for two sub-models that we use to estimate the numerator and denominator of the adjusted inverse propensity score $\frac{p_{D_2|1}(Z)}{p_{D_2|0}(Z)}$.

Table 3.9. Results of the propensity score weighting model for no-till and nutrient management

VARIABLES	(1) propensity score numerator	(2) propensity score denominator
Mostly farmer	0.971	-0.756
	(2.061)	(0.803)
Age	-0.00646	-0.0264
	(0.0328)	(0.0225)
College	0.423	-0.499
	(0.815)	(0.482)
Owned field	-0.475	0.450
	(0.597)	(0.572)
Highly erodible	0.755	-1.017
	(0.838)	(1.005)
Wetland	0.638	1.878
	(1.249)	(1.356)
Productivity	7.646**	1.715
	(3.734)	(1.802)
Manure	0.394	1.596**
	(1.185)	(0.600)
Log operation size	0.295	0.411**
	(0.263)	(0.192)
EQIP per acre (self)	0.00167	0.000252
	(0.00188)	(0.00146)
EQIP per acre (neighbor)	-0.000395	-0.00331*
	(0.00163)	(0.00163)
CRP per acre (self)	0.0569*	-0.0193*
	(0.0314)	(0.0110)
CRP per acre (neighbor)	-0.0554**	0.0161*
	(0.0269)	(0.00914)
Density (2017)	-0.000381	0.000413
	(0.00280)	(0.00215)
Corn/soybean	-2.239***	0.701
	(0.812)	(0.582)
Compliance Nutrient mgm	3.620***	4.445***
	(1.301)	(0.565)
Constant	-7.114**	-6.958***
	(2.604)	(2.132)
Observations	469	2,950

Table 3.9, column (1) contains the results of the sample subset of farmers who receive a payment for no-till. It shows that higher soil productivity index is linked to a higher probability of receiving a financial payment for nutrient management. The amount of CRP payment in the neighboring county also has a negative impact on the likelihood of receiving payment, while the value of CRP payment in the given farm's county tends to increase the chance of receiving payment for the practice. Among those who already received a payment for and adopted no-till, corn and soybean fields are less likely to receive payment for nutrient management.

Column (2) reports the results of farmers in the dataset who do not receive any payment for no-till. For this sample subset, soil productivity index does not have a significant impact on the likelihood of receiving payment for nutrient management, while the impacts of CRP payment amount in the given field's county and neighboring county are reversed, though not significant. The application of manure increases the chance of receiving payment for nutrient management, which is a consistent result in both sub-models, though its coefficient is only statistically significant in the second sub-model (fields that do not receive payment for no-till). This is intuitive, as proper nutrient management programs can help optimize the use of manure, while minimizing its potential negative impacts on the environment (National Institute of Food and Agriculture – USDA, n.d.). Those who adopt nutrient management to satisfy a compliance requirement are also more likely to receive payment for the practice. Similar to the cover crop treatment model, the coefficients of the compliance requirement are highly statistically significant in both sub-models. This indicates the consistency of the influence of compliance requirements on the financial payment status of practices. Table 3.10 shows the statistics of adoption decision of no-till, adjusted for potential correlation with nutrient management.

Table 3.10. Statistics summary of adjusted inverse propensity score and weighted adoption decision of no-till, accounting for potential correlation with nutrient management

Parameter	N	Mean	Median	Standard deviation	Min	max
Adjusted inverse propensity score	3,419	3.72	0.93	41.10	0	1,192.69
Weighted adoption decision of no-till	3,419	3.3	0.64	41.19	0	1,192.69

3.7.2 Estimates of additionality with and without assumption of complementarity

In this section, we present the results of the models used to estimate the ATT, or the additionality of a practice, accounting for possible complementarity. We compare our estimates against a non-weighted model which estimates additionality as $1 - E(Y_1(0, D_2)|D_1 = 0, Z)$, where the second term is mean adoption of the first practice (no-till in our analysis) among untreated fields as in (2) above. We estimate this term by regressing the adoption decision of the first practice, in this analysis no-till on the covariates for untreated fields. Specifically, the non-weighted model takes the form:

$$\begin{aligned} no - till = {} & const + mostly\ farmer + age + college + owned\ field \\ & + highly\ erodible + wetland + productivity + manure \\ & + \log operation\ size + EQIP\ per\ acre \\ & + EQIP\ per\ acre\ neighbor + CRP\ per\ acre \\ & + CRP\ per\ acre\ neighbor + density(2017) + corn\ soybean \\ & + compliance + \epsilon\ \ if\ \ finan\ \ payment\ no - till = 0 \end{aligned} \tag{8}$$

The weighted model replaces the adoption decision with the weighted adoption decision, and can be written as:

$$
\begin{aligned}
weighted\ no - till \\
&= const + mostly\ farmer + age + college + owned\ field \\
&+ highly\ erodible + wetland + productivity + manure \\
&+ \log operation\ size + EQIP\ per\ acre \\
&+ EQIP\ per\ acre\ neighbor + CRP\ per\ acre \\
&+ CRP\ per\ acre\ neighbor + density(2017) + corn\ soybean \\
&+ compliance + \epsilon\ \ if\ \ finan\ \ payment\ no - till = 0
\end{aligned} \tag{9}
$$

We evaluate the results of the pair no-till and cover crop first, and then no-till and nutrient management.

No-till and cover crops

Table 3.11 presents the results of the two treatment effects models of the pair no-till and cover crop, with no-till as the first practice, and cover crop the second practice.

Table 3.11. Results of the treatment model for no-till and cover crops

VARIABLES	(1) Non-complementary	(2) Complementary
Mostly farmer	0.0392	0.0939
	(0.0487)	(0.182)
Age	0.000435	-0.00548
	(0.00144)	(0.00982)
College	-0.0205	-0.0716
	(0.0356)	(0.103)
Owned field	0.00366	0.0906
	(0.0303)	(0.128)
Highly erodible	0.0996	0.368
	(0.106)	(0.387)
Wetland	-0.0779	-0.0107
	(0.0794)	(0.296)
Productivity	0.312	1.278
	(0.202)	(0.968)
Manure	0.0430	0.103
	(0.0496)	(0.123)
Log operation size	0.0297	0.00751
	(0.0195)	(0.0527)
EQIP per acre (self)	4.27e-05	3.53e-05
	(0.000122)	(0.000120)
EQIP per acre (neighbor)	6.96e-05	1.91e-05
	(4.99e-05)	(5.53e-05)
CRP per acre (self)	0.00192*	-0.000603
	(0.000983)	(0.00324)
CRP per acre (neighbor)	-0.00162	-0.00160
	(0.00111)	(0.00185)
Density (2017)	-3.34e-05	-0.000359***
	(8.21e-05)	(0.000113)
Corn/soybean	-0.237***	-0.360***
	(0.0415)	(0.120)
Compliance No-till	0.681***	0.830***
	(0.0335)	(0.262)
Constant	0.0729	0.319
	(0.114)	(0.566)
Observations	2,950	2,950
R-squared	0.320	0.034

Column (1) contains the results of the non-weighted model, which does not account for potential complementarity between no-till and cover crop. The results show that among the untreated fields (fields that do not receive any payment for no-till adoption), satisfying a compliance requirement is strongly linked to adoption decision, which is intuitive. Corn and soybean fields are less likely to adopt no-till than wheat fields. The field operation size has a positive impact on no-till adoption, though the effects are not significant. Similarly, EQIP and CRP payment amounts seem to increase the chance of adopting no-till, though their impacts are non-significant.

Column (2) presents the coefficient estimates of the weighted model. Similar to the non-weighted model, compliance satisfaction is highly positively linked to adoption of no-till, while corn and soybean fields are less likely adopt no-till, which seems to be at odds with Claassen *et al.* (2018). However, while they study the additionality of conservation tillage, we assess the additionality of no-till in a more recent dataset, which may bring about the differences. County population density also has a negative impact on no-till adoption.

We then use the estimates from Table 3.11 to calculate the expected outcome for each farmer in the dataset. Averaging these over the treated no-till fields then yields the ATT shown in equation (1). Column (1) results allow us to estimate the ATT without weighting the adoption decision of no-till, and column (2) results are used to find the ATT accounting for potential complementarity between the two practices, which in this case is no-till and cover crop. The estimate of additionality without accounting for potential complementarity would be overstated if it is larger than the additionality estimate from the weighted model. Table 3.12 shows the results of the ATT of two models.

Table 3.12. Additionality estimation of no-till with and without adjustment for potential correlation with cover crops adoption

Model	N	Mean adoption rate of nonpayment no-till fields	Additionality	95% confidence interval*
Non-weighted	469	0.762	0.238	[0.182 – 0.293]
Weighted	469	0.813	0.187	[-5.497 – 5.871]

*95% confidence interval of the additionality estimates are obtained using bootstrap.

Table 3.12 shows that, on average, the additionality of no-till measured by the ATT is 0.238 for the non-weighted model and 0.187 for the weighted model. This means that, on average, 23.8% of farmers who receive payment for no-till would not have adopted the practice without payments in the non-weighted model. The figure for the weighted model is 18.7%, which is a difference of 5.1 percentage points from the unweighted estimate. This indicates that the estimate of additionality for no-till will be overstated by 5.1% if one does not account for its potential complementary with cover crops. Therefore, our results suggest mild evidence of complementarity between no-till and cover crops adoption in practice. However, the large range of the 95% confidence interval suggests instability of the estimate. We thus encounter the issue of overfitting as described in section 0, which renders this model unreliable.

Similar to the regression adjustment method, we perform a reverse model where no-till is the second practice, and cover crops is the first. The additionality results can be found in Table 3.13.

Table 3.13. Additionality estimation of cover crops with and without adjustment for potential correlation with no-till adoption

Model	N	Mean adoption rate of nonpayment cover crops fields	Additionality	95% confidence interval*
Non-weighted	100	0.553	0.447	[0.343 – 0.518]
Weighted	100	0.454	0.546	[0.579 – 0.791]

*95% confidence interval of the additionality estimates are obtained using bootstrap. The confidence interval for this model however is not reliable, as there are too few observations (too few treated cover crops fields) for the bootstrap procedure to run properly.

Table 3.13 shows that the additionality of cover crops measured by the ATT is 0.447 for the non-weighted model and 0.546 for the weighted model. Thus, the weighted model estimate is almost 10 percentage points larger than the unweighted one, indicating strong substitutability between the two practices. It means that those who are paid for and adopt cover crops will be much less likely to adopt no-till, which is contradictory to the previous no-till – cover crops model and to agronomy literature. Therefore, while the estimates of this model do not encounter a large 95% confidence interval issue, their contradictory nature does not provide us meaningful conclusions about the correlation between the two practices.

No-till and nutrient management

Table 3.14 presents the coefficient estimates of the unweighted and weighted treatment effects models, where no-till is the first practice and nutrient management is the second.

Table 3.14. Results of the treatment model for no-till and nutrient management

VARIABLES	(1) Non-complementary	(2) Complementary
Mostly farmer	0.0392	-0.193
	(0.0487)	(0.223)
Age	0.000435	0.0102**
	(0.00144)	(0.00455)
College	-0.0205	-0.0619
	(0.0356)	(0.144)
Owned field	0.00366	-0.150
	(0.0303)	(0.143)
Highly erodible	0.0996	-0.0426
	(0.106)	(0.154)
Wetland	-0.0779	0.314
	(0.0794)	(0.388)
Productivity	0.312	0.271
	(0.202)	(0.356)
Manure	0.0430	0.212
	(0.0496)	(0.226)
Log operation size	0.0297	0.0947**
	(0.0195)	(0.0411)
EQIP per acre (self)	4.27e-05	0.000329
	(0.000122)	(0.000789)
EQIP per acre (neighbor)	6.96e-05	5.22e-05
	(4.99e-05)	(0.000137)
CRP per acre (self)	0.00192*	0.00110
	(0.000983)	(0.00520)
CRP per acre (neighbor)	-0.00162	0.00169
	(0.00111)	(0.00536)
Density (2017)	-3.34e-05	-0.000238
	(8.21e-05)	(0.000219)
Corn/soybean	-0.237***	-0.396*
	(0.0415)	(0.225)
Compliance No-till	0.681***	0.553***
	(0.0335)	(0.0827)
Constant	0.0729	-0.652
	(0.114)	(0.549)
Observations	2,950	2,950
R-squared	0.320	0.009

Column (1) shows the results of the unweighted model and is the same as column (1) in Table 9. Column (2) presents the coefficient estimates of the weighted model where we account for the potential complementary or substitution between no-till and nutrient management adoption. Consistent with other models, fields that meet compliance requirements are highly significantly more likely to adopt no-till. After weighing the adoption decision however, the results show that corn and soybean fields are not significantly less likely to adopt no-till than wheat fields, or nor does the population density negatively impact the adoption likelihood. The farmer's age and the operation size of the field have statistically significant positive effects on the probability of adopting no-till.

Table 3.15 contains the estimates of additionality for no-till for the non-weighted and weighted models, using the estimates obtained from Table 3.13 in a similar manner to the estimation of additionality for the no-till and cover crops model.

Table 3.15.Additionality estimation of no-till with and without adjustment for potential correlation with nutrient management adoption

Model	N	Mean adoption rate of nonpayment no-till fields	Additionality	95% Confidence interval
Non-weighted	469	0.762	0.238	[0.182 – 0.293]
Weighted	469	0.825	0.175	[-23.748 – 24.097]

*The 95% confidence interval of the additionality estimate is imputed using bootstrap.

Table 3.15 presents the ATT, additionality of no-till, accounting for its potential correlation with nutrient management is 17.5%, while the estimate is 23.8% when we do not assume any correlation between them, which is a difference of 6.3 percentage points. The result indicates that, without accounting for the complementarity between no-till and nutrient management, the additionality estimate of no-till is overstated by around 6.3%, and hence that no-till and nutrient management are potentially complementary. Thus, the payment and adoption of one practice can increase the likelihood of adopting another practice with less payment necessary to incentivize the adoption of the second practice. Nevertheless, similar to the no-till and cover crops model, the 95% confidence interval of the no-till and nutrient management model is unreliably large, thus indicating overfitting issues. The results of the reverse model for nutrient management – no-till can be found in Table 3.16.

Table 3.16. Additionality estimation of no-till with and without adjustment for potential correlation with nutrient management adoption

Model	N	Mean adoption rate of nonpayment no-till fields	Additionality	95% Confidence interval
Non-weighted	199	0.719	0.281	[0.219 – 0.343]
Weighted	199	0.523	0.477	[0.265 – 0.689]

*The 95% confidence interval of the additionality estimate is imputed using bootstrap.

The additionality estimate of nutrient management is 0.281, without controlling for its potential correlation with no-till. On the other hand, the estimate is 0.477 when we account for potential correlation between them, which is a difference of negative 19.6 percentage points. The result suggests a strong substitution relationship between nutrient management. They show that without accounting for the substitutability between nutrient management and no-till, the additionality estimate of nutrient management is understated by 19.6%. Similar to the reverse cover crops – no-till model, these results contradict the no-till – nutrient management model and also agronomy literature. As such, we do not rely on these results for robust conclusions about the relationship between no-till and nutrient management.

3.7.3 Regression adjustment models results

Table 3.17. Results for regression adjustment weights estimates for no-till and cover crops.

VARIABLES	(1) g_0_z	(2) g_1_z
Mostly farmer	0.0522	-0.383
	(0.0527)	(0.741)
Age	0.000284	0.00719
	(0.00151)	(0.0189)
College	-0.0157	-0.0921
	(0.0357)	(0.605)
Owned field	-0.00195	0.0805
	(0.0308)	(0.404)
Highly erodible	0.105	0.0244
	(0.109)	(0.644)
Wetland	-0.0813	0.115
	(0.0785)	(0.607)
Productivity	0.324	0.148
	(0.195)	(2.017)
Manure	0.0311	0.357
	(0.0514)	(0.533)
Log operation size	0.0286	-0.0599
	(0.0196)	(0.339)
EQIP per acre (self)	3.42e-05	9.38e-07
	(0.000108)	(0.00169)
EQIP per acre (neighbor)	9.36e-05*	4.66e-06
	(5.48e-05)	(0.00132)
CRP per acre (self)	0.00185*	-0.00818
	(0.000998)	(0.0209)
CRP per acre (neighbor)	-0.00168	0.0109
	(0.00112)	(0.0218)
Density (2017)	-3.72e-05	-0.000120
	(8.35e-05)	(0.00195)
Corn/soybean	-0.237***	-0.329
	(0.0407)	(0.603)
Compliance No-till	0.685***	0.569
	(0.0348)	(0.499)
Constant	0.0806	0.591
	(0.118)	(2.712)
Observations	2,911	39
R-squared	0.320	0.700

Table 3.18. Results for regression adjustment weights estimates for no-till and nutrient management.

VARIABLES	(1) g_0_z	(2) g_1_z
Mostly farmer	0.0423	-0.0706
	(0.0503)	(0.213)
Age	0.000319	0.00547
	(0.00149)	(0.00562)
College	-0.0157	-0.215*
	(0.0364)	(0.111)
Owned field	0.00249	-0.00438
	(0.0311)	(0.159)
Highly erodible	0.104	-0.0507
	(0.107)	(0.226)
Wetland	-0.0691	0.0272
	(0.0809)	(0.125)
Productivity	0.311	0.512
	(0.208)	(0.619)
Manure	0.0447	-0.000738
	(0.0521)	(0.122)
Log operation size	0.0298	0.0244
	(0.0195)	(0.0661)
EQIP per acre (self)	3.70e-05	0.000445
	(0.000120)	(0.000318)
EQIP per acre (neighbor)	7.06e-05	-0.00118
	(5.01e-05)	(0.000805)
CRP per acre (self)	0.00182*	-0.00178
	(0.000974)	(0.00739)
CRP per acre (neighbor)	-0.00152	0.000912
	(0.00110)	(0.00792)
Density (2017)	-4.05e-05	0.00126*
	(8.32e-05)	(0.000615)
Corn/soybean	-0.232***	-0.578**
	(0.0423)	(0.240)
Compliance No-till	0.677***	0.884***
	(0.0358)	(0.117)
Constant	0.0745	0.240
	(0.115)	(0.515)
Observations	2,867	83
R-squared	0.314	0.791