ABSTRACT

Title of dissertation:	WIND POWER DEVELOPMENT IN THE UNITED STATES: EFFECTS OF POLICIES AND ELECTRICITY TRANSMISSION CONGESTION
	Claudia Hitaj, Doctor of Philosophy, 2013
Dissertation directed by:	Professor Kenneth E. McConnell Department of Agricultural and Resource Economics

In this dissertation, I analyze the drivers of wind power development in the United States as well as the relationship between renewable power plant location and transmission congestion and emissions levels. I first examine the role of government renewable energy incentives and access to the electricity grid on investment in wind power plants across counties from 1998-2007. The results indicate that the federal production tax credit, state-level sales tax credit and production incentives play an important role in promoting wind power. In addition, higher wind power penetration levels can be achieved by bringing more parts of the electricity transmission grid under independent system operator regulation. I conclude that state and federal government policies play a significant role in wind power development both by providing financial support and by improving physical and procedural access to the electricity grid.

Second, I examine the effect of renewable power plant location on electricity transmission congestion levels and system-wide emissions levels in a theoretical

model and a simulation study. A new renewable plant takes the effect of congestion on its own output into account, but ignores the effect of its marginal contribution to congestion on output from existing plants, which results in curtailment of renewable power. Though pricing congestion removes the externality and reduces curtailment, I find that in the absence of a price on emissions, pricing congestion may in some cases actually increase system-wide emissions.

The final part of my dissertation deals with an econometric issue that emerged from the empirical analysis of the drivers of wind power. I study the effect of the degree of censoring on random-effects Tobit estimates in finite sample with a particular focus on severe censoring, when the percentage of uncensored observations reaches 1 to 5 percent. The results show that the Tobit model performs well even at 5 percent uncensored observations with the bias in the Tobit estimates remaining at or below 5 percent. Under severe censoring (1 percent uncensored observations), large biases appear in the estimated standard errors and marginal effects. These are generally reduced as the sample size increases in both N and T.

WIND POWER DEVELOPMENT IN THE UNITED STATES: EFFECTS OF POLICIES AND ELECTRICITY TRANSMISSION CONGESTION

by

Claudia Hitaj

Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2013

Advisory Committee:
Professor Kenneth E. McConnell, Chair
Professor Roberton Williams, III
Professor Marc Nerlove
Professor Erik Lichtenberg
Professor Maureen Cropper

Dedication

To my family.

Acknowledgments

I would like to thank Ted McConnell, my adviser and Dissertation Committee Chair, for his support and guidance. He is a great mentor to me. I am also thankful to the members of my Dissertation Committee, Marc Nerlove, Rob Williams, Erik Lichtenberg, and Maureen Cropper, for their advice and comments on my research throughout my graduate studies.

I thank the faculty and graduate students at AREC for their support, with special thanks to fellow students Romina Ordoñez and Yoanna Kraus Elsin.

I gratefully acknowledge the US Environmental Protection Agency, which provided funding for the last three years of my graduate studies under the STAR Gradudate Fellowship.[1]

[1]This dissertation was developed under STAR Fellowship Assistance Agreement No. FP-91716901-0 awarded by the US Environmental Protection Agency (EPA). It has not been formally reviewed by EPA, and the views expressed in this dissertation are solely those of Claudia Hitaj.

Table of Contents

List of Figures

List of Abbreviations and Variables

AC	Alternating current
AR(1)	Auto-regressive process of order one
CO2eq	Carbon dioxide equivalent
EIA	Energy Information Administration of the US Department of Energy
ERCOT	Electric Reliability Council of Texas
FE	Fixed effects
FERC	Federal Energy Regulatory Commission
GIS	Geographic information system
IEEE	Institute of Electrical and Electronics Engineers
ISO	Independent system operator
IV	Instrumental variables
kWh	Kilo-Watt hour
LMP	Locational marginal price
LPM	Linear probability model
m	Meter
ME	Marginal effects
mph	Miles per hour
MW	Mega-Watt
MWh	Mega-Watt hour
OLS	Ordinary least squares
OPF	Optimal power flow
PJM	PJM Interconnection (a Regional Transmission Organization)
PM	Particulate matter
PTC	Production tax credit
RE	Random effects
REC	Renewable energy credit
SO2	Sulfur dioxide
RPS	Renewable portfolio standard
RTO	Regional transmission organization
US	United States

a_i	Abatement-specific production incentive per unit of installed capacity at location i
c	Levelized marginal investment cost
$f_i(\cdot)$	Fraction of utilized capacity
k_i	Installed wind power capacity in (MW) at location i
k_i^*	Optimal installed capacity at location i in the Firm Problem
k_i^s	Optimal installed capacity at location i in the Social Planner Problem taking into account congestion
k_i^{sa}	Optimal installed capacity at location i in the Social Planner Problem taking into account congestion and emissions
k_i^t	Optimal installed capacity at location i in the Firm Problem with a congestion tax
r_i	Energy subsidy per unit of installed capacity at location i
t_i	Congestion tax per unit of installed capacity at location i

Chapter 1

Introduction

The government of the United States is seeking to increase the share of electricity generated from renewable energy sources to mitigate climate change and strengthen energy security. Despite government interest in promoting renewable power, there has been no comprehensive quantitative analysis at the national level of how federal and state policies, as well as access to the electricity grid, affect wind power. In addition, the literature has paid little attention to the details of integrating wind power into the existing electricity transmission infrastructure. In particular, how does transmission congestion affect regional output from renewable power plants, and what emissions reductions are actually achieved?

There is great variability in the type and level of renewable energy incentives offered at the state-level. Incentives include sales, property and corporate tax credits, production incentives, and renewable portfolio standards. Controlling for wind capacity, population density, land values, electricity transmission line coverage and grid regulation type, I estimate in Chapter 2 the effects of state and federal renewable energy incentives on investment in wind power across counties from 1998-2007 via random effects Tobit, Probit, and ordinary least squares instrumental variables regression. Based on the results, I provide first estimates of the relative cost-effectiveness of these various incentives in promoting investment in wind power.

The importance of government subsidies for renewable power is highlighted in Chapter 2. However, subsidies for renewable power are not the most efficient way of reducing emissions in the power sector. Subsidizing electricity generation by renewable power plants reduces the price of electricity and thus increases consumption and emissions relative to the alternative of pricing emissions at conventional power plants and thereby increasing the price of electricity. In addition, since many subsidies are set at the state rather than the federal level, several inefficiencies are introduced.

First, because of differences in subsidies across states, renewable power is not necessarily deployed in areas with high renewable energy potential and adequate transmission capacity. Second, subsidies do not take into account that the abatement achieved by renewable power plants varies across locations. A renewable power plant at one location may substitute for an old, high-emissions coal plant and thus achieve greater abatement than a renewable power plant at a different location that substitutes for a cleaner natural gas plant. Third, state-level subsidies contribute to the clustering of renewable power plants in states with the highest levels of incentives, which leads to curtailment of renewable power due to transmission congestion. Chapter 3 is concerned with the latter two points.

In Chapter 3, I examine the effect of renewable power plant location on electricity transmission congestion levels and system-wide emissions levels. Two externalities come into play: A congestion externality (1), since new renewable power plants do not take into account the effect of their marginal contribution to congestion on output from existing plants, and an emissions externality (2), since greenhouse gas emissions from conventional power plants are not priced according to their marginal social cost. I develop a model to examine the interaction of these two externalities.

The model shows that, in contrast to individual profit-maximizing firms, a social planner installs smaller sized power plants at some locations to minimize curtailment and reduce idle capacity. The socially optimal outcome can be achieved with the institution of a congestion price. The model also demonstrates that regional energy subsidies that incentivize the clustering of renewable plants in particular areas are rendered less effective, since the resulting increase in transmission congestion contributes to renewable power curtailment. Finally, I present the counter-intuitive result that the institution of a congestion charge, in the absence of a price on emissions, may in some cases increase system-wide emissions, despite the overall increase in renewable power output and reduction in conventional power output. Two instruments, a congestion price and an emissions price, are necessary to ensure optimal investment in and location of new renewable power plants.

Chapter 3 also contains a simulation study of optimal power flow in a stylized grid, the IEEE 30 bus test system. The simulations reveal that clustering of renewable plants contributes to transmission congestion and that new renewable plants can affect output at existing plants. Finally, the simulations make apparent that the abatement achieved by a renewable power plant depends crucially on which types of conventional power plants are forced to reduce output depending on the arragement of the plants within the grid.

Chapter 4 can stand alone as an econometric paper, though it addresses an issue that arises in the empirical analysis of the drivers of wind power development in

Chapter 2. In this chapter, I examine how the Tobit model performs in finite sample when the dependent variable is severely censored, and determine the percentage bias in the estimates of the coefficients, standard errors, marginal effects, and disturbance standard deviation. The Monte Carlo method is used to analyze the effect on Tobit estimates of varying the percentage of uncensored observations from 63 to 1 percent in different sample sizes with $N \in \{1000, 2000, 3000, 4000, 5000\}$ and $T \in \{1, 2, 3, 8\}$. I find that the Tobit model performs quite well even up to 5 percent uncensored observations. However, when only 1 percent of the observations are uncensored, bias appears in the estimates of the standard errors and marginal effects, in particular.

Chapter 2

Wind Power Development in the United States

Abstract

This paper analyzes the drivers of wind power development in the United States, focusing on government renewable energy incentives and access to the electricity grid. The effects of wind capacity, electricity transmission line coverage and grid regulation, as well as state and federal subsidies from 1998-2007 are estimated via random effects Tobit, Probit, and ordinary least squares instrumental variables regression. The results indicate that the federal production tax credit, state-level sales tax credit and production incentives play an important role in promoting wind power. In addition, higher wind power penetration levels can be achieved by bringing more parts of the electricity transmission grid under independent system operator regulation. This paper concludes that state and federal government policies play a significant role in wind power development both by providing financial support and by improving physical and procedural access to the electricity grid.

Keywords: Wind power; Renewable energy policy; Electricity grid

2.1 Introduction

The United States (US) is striving to increase the share of electricity generated from renewable energy sources to mitigate climate change and strengthen energy security [1]. One of the most promising renewable energy sources in the US is wind. In 2008, wind power contributed 42 percent of all new generating capacity [2]. Most states have several policies in place to promote renewable energy, but state variability on the level, duration, and combination of policies is extensive. Despite government interest in promoting renewable energy, to date there has been no comprehensive quantitative analysis at the national level of how federal and state policies, as well as access to the electricity grid, affect wind power. This paper seeks to fill that void.

States employ various forms of incentives for renewable energy, including corporate, sales, and property tax credits, as well as production incentives (awarded on a ¢/kWh basis) and renewable portfolio standards. Wind plants across the US also benefit from the federal production tax credit. As each incentive is associated with a different cost and a different impact on additional investment in wind power, these incentives will vary in their cost-effectiveness. Given that the federal and state governments are interested in supporting renewable energy, it is important to identify the effect of each policy instrument on wind power development.

This paper applies several estimation techniques to identify the effect of state and federal renewable energy incentives and access to the electricity transmission grid on annual additions to installed wind power capacity across counties from 1998-2007. The panel Tobit model allows for censoring of the dependent variable (annual capacity additions in MW), since for most counties and time periods the dependent variable is zero. This paper applies two techniques to control for the potential endogeneity of state policies, which can occur when states pass policies to support an already existing wind power industry. First, the panel Tobit regression is run on a reduced sample that excludes states with investment occurring before any policy was offered. Second, this paper employs instrumental variables in the ordinary least squares (OLS) setting to control for the potential endogeneity of state policies. All models include regressors to control for county windiness, income, population density, distance to electricity demand centers, and technological improvement in wind power plant design.

The regression results are robust across all models. The federal and state production incentives, as well as the sales tax credit emerge as important drivers of wind power development, with the production incentive registering as 2.5 times more cost-effective than the sales tax credit. The most cost-effective way of increasing wind power investment involves a regulatory change that expands coverage of or creates additional regional transmission organizations (RTOs), which coordinate transmission at a regional level to reduce operating inefficiencies. Expanding transmission line coverage also increases additions to wind power capacity.

The existing literature on the effects of renewable energy policies on wind power consists mainly of case studies and exploratory analyses with very few empirical investigations. Bird et al. (2005) [3] provide an overview of policies and market factors driving wind power development in 12 key states. Gouchoe et al. (2002) [4] conduct case studies on financial incentives in six states. Much of the literature focuses on the effect of renewable portfolio standards (RPS) on wind power development. Langniss and Wiser (2003) [5] investigate the implementation of an RPS in Texas, Wiser et al. (2004) [6] evaluate the design and impacts of 13 state RPS policies, Wiser et al. (2007) [7] provide an overview of federal RPS proposals and investigate possible relationships between state and federal RPS policies, and Chen (2009) [8] synthesize and review the results of 31 studies on the costs and benefits of RPS policies.

Previous empirical studies have focused on the effect of an RPS on renewable energy electricity generation. Carley (2009) [9] uses state-level data from 1998 to 2006. State subsidy policies including grants, loans, and rebates are collapsed into a subsidy index and corporate, property, personal, and sales tax credits are collapsed into a tax incentive index. The results indicate that renewable portfolio standards do not significantly predict the percentage of electricity generation from renewable energy but do increase the total amount of renewable energy generation.

Adelaja and Hailu (2007) [10] estimate the effect of an RPS on wind capacity installations across the fifty states in 2008, and conclude that the effect is significantly positive. Menz and Vachon (2006) [11] analyze the effect of an RPS, public benefits funds, mandatory green power options, fuel generation disclosure rules and retail choice on installed wind power capacity in 35 states in 2003 using OLS. Their results indicate a positive relationship between an RPS and wind power development.

Kneifel (2008) [12], following Menz and Vachon (2006) [11], estimates the effect of an RPS and other policies on total non-hydropower renewable capacity for

1996-2003 using OLS, again finding a positive effect. Yin and Powers (2010) [13] undertake the most comprehensive study of the effect of an RPS on wind power development, since they take into account the heterogeneity among RPS policies across states. The results suggest that RPS policies have had a significant and positive effect on in-state renewable energy development.

This paper builds on the existing case study literature and the empirical analyses by providing a quantitative analysis of the drivers of wind power. It faces the same main limitation as previous empirical studies - a low level of cross-sectional variation in policy incentives set at the state level. However, this paper represents several improvements. First, policy incentives are allowed to vary over time, which is not the case in Menz and Vachon (2006) [11] and Adelaja and Hailu (2007) [10]. Second, this is the first paper to account for grid deregulation status and transmission line coverage, and allow both to vary at the county level. Finally, most of the control variables, including windiness, vary at the county level. To my knowledge, this is the first paper to use county-level data from 1998 to 2007, allow for varying degrees of a policy among states, include federal as well as state incentives, identify the separate effects of each type of policy instrument, and explicitly account for wind capacity, access to the electricity grid, and grid deregulation status.

2.2 Determinants of Wind Power Profitability

The profitability and feasibility of a wind power plant at a given location are determined by several factors. The windiness of the area is crucial to profitability, as the power in wind is proportional to the cube of its speed, so doubling the wind speed causes power to increase by a factor of eight [14].

Next to wind speed, constancy and reliability affect the capacity factor of wind plants. Most wind plants run 65-90 percent of the time, but not necessarily at full capacity, since the wind does not blow steadily all the time. A capacity factor of 25-40 percent is common [15]. Wind plants do not operate when wind speeds are too low or when they are too high during storms, as there is a risk of damaging the turbine. The Energy Information Administration (EIA) distinguishes between 7 classes of wind power at a height of 50 meters (Table 2.1) [16]. Wind blows up to 12.5 miles per hour (mph) in power class 1 and over 26.6 mph in power class 7. In general, sites with a wind power rating of 4 or higher are preferred for large scale wind plants [15].

Table 2.1: Classes of Wind Power Density at 50 Meters

Wind Power Class	Wind Power Density (W/m^2)	Speed m/s (mph)
1	0-200	0.0-5.6 (0.0-12.5)
2	200-300	5.6-6.4 (12.5-14.3)
3	300-400	6.4-7.0 (14.3-15.7)
4	400-500	7.0-7.5 (15.7-16.8)
5	500-600	7.5-8.0 (16.8-17.9)
6	600-800	8.0-8.8 (17.9-19.7)
7	800-2000	8.8-11.9 (19.7-26.6)

Source: [17]

Another important factor is distance to the electricity transmission grid. The greater is the distance between the plant and the grid, the higher the cost to the plant owner, since new plants bear the costs of connecting to the grid [18]. Figure 2.1 shows the location of wind power plants in Wyoming. The plants are clustered alongside transmission lines, instead of locating in areas with higher wind potential.

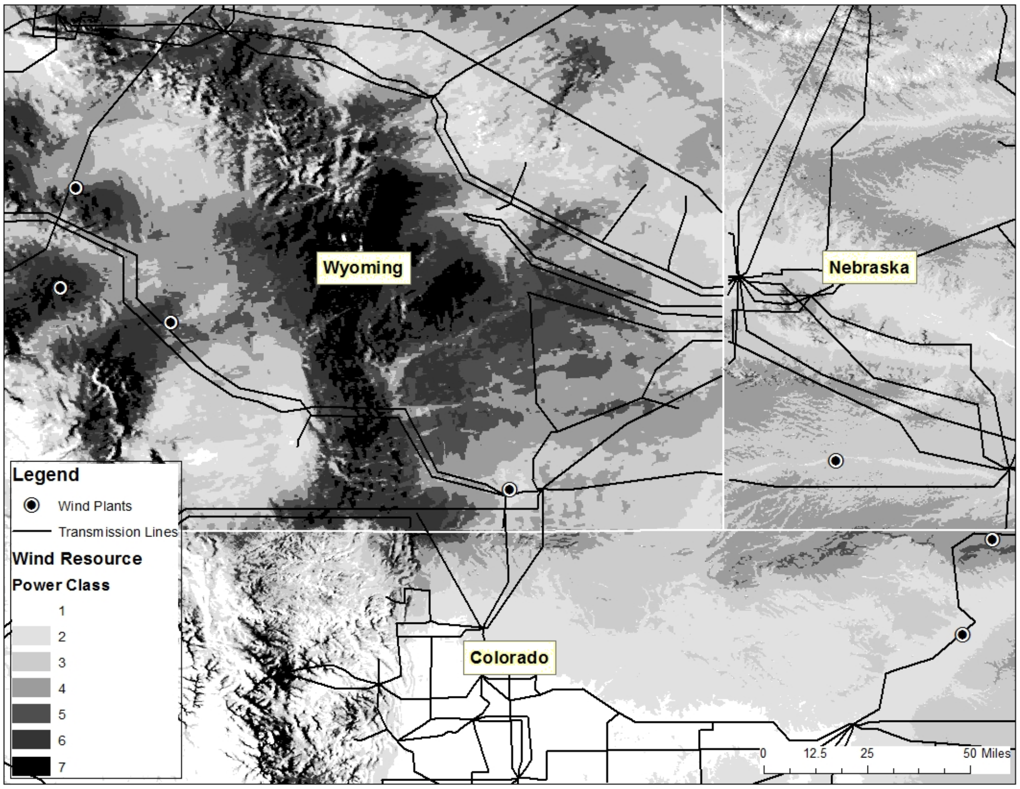

Figure 2.1: Wind Plant Location and the Transmission Grid
Wind power plants in Wyoming, Nebraska, and Colorado locate alongside the electricity grid, foregoing locations with greater wind potential.

2.2.1 Policy Incentives

State and federal incentives have a considerable effect on the profitability of wind plants. The main federal incentive is the renewable energy production tax credit (PTC), currently at 2.1 cents per kilowatt-hour (kWh). It was first instituted with the Energy Policy Act of 1992. After expiring in 2001, it was extended six times for one or two years at a time, and actually expired twice. The latest extension in 2009 allows the PTC to expire in 2012. The importance of the PTC for the wind power industry is evidenced by the boom-and-bust cycle of new plants in the past 10 years, following the expirations and short-term extensions of the PTC [19].

A variety of state incentives exist, mostly in the form of tax exemptions and credits. The level, combination, and duration of incentives vary significantly across states. Tables A.2 and A.3 in the Appendix list the renewable energy policies by state.

A production incentive offered by a state government or a utility provides cash payments based on the number of kWh generated by a wind power plant, usually around 1-3 ¢/kWh. It is earned on an annual basis and varies with the amount of electricity produced. Some are offered as a corporate tax credit, which can also take the form of a tax credit for a percentage of equipment and installation costs.

All property tax incentives and the vast majority of sales tax incentives are offered as tax exemptions rather than credits. A property tax incentive excludes all or part of the added value of a renewable energy system from the valuation of the property for taxation purposes [20]. A sales tax incentive exempts or refunds the sales tax on the purchase of wind turbine equipment and installation services. While the sales tax incentive is realized only once during the initial construction period, the property tax incentive is realized annually.

State-level renewable portfolio standards require utilities to obtain a certain percentage of their electricity from renewable energy sources. This policy places the burden on utilities to incentivize electricity generation from renewable energy sources. Failure to comply results in financial penalties on a per MWh basis.[1] Utilities could, for example, enter into power-purchasing agreements with wind plants

[1]The average penalty is 49.63 $/MWh, ranging from 10 $/MWh in Montana to 62.13 $/MWh in Maine, Massachusetts, New Hampshire, and Rhode Island. The penalties are significantly larger than the price of a renewable energy credit (REC). In 2008, the weighted average price of a REC was 4.48 $/MWh in Pennsylvania, one of three states requiring that REC pricing is disclosed to the public [21]. In the voluntary REC market, the national price of RECs for wind power remained below 5 $/MWh in 2007 [22].

or offer production incentives on a ¢/kWh basis. Thus, a wind power plant could receive financial incentives not only from the federal and state government but also from the utility company it sells its electricity to.

The variability of state-level policy incentives has led to a potentially inefficient allocation of wind plants across the US. The importance of policy incentives for wind power development is made apparent in Figure 2.2. Wind power plants are clustered along the Southwest border of Minnesota, while greater wind resources are available in neighboring South Dakota. Minnesota was the first state to offer a 1¢/kWh production incentive for wind energy in 1997, which could explain the high level of wind power development.

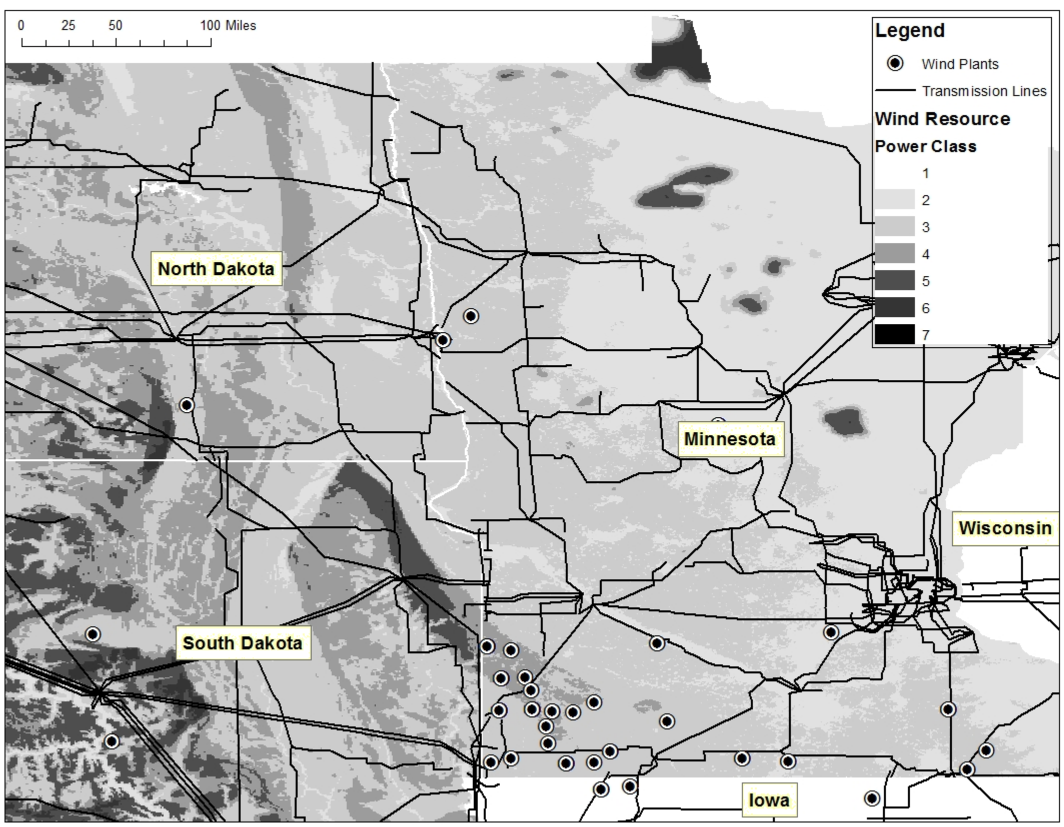

Figure 2.2: Wnd Plant Location and State-Level Incentives
Wind power plants cluster along the Southwest border of Minnesota, while greater wind resources are available in neighboring South Dakota.

2.2.2 Intermittency

The transmission system operator must balance the changing demand of electricity consumers with the supply of electricity at every second, since electricity cannot be stored. While traditional power plants are capable of nearly perfectly predicting their supply, wind plants suffer from the intermittency of wind. There is a cost associated with balancing wind energy and keeping back-up capacity.

In a review of the literature on wind integration costs, DeMeo et al. (2005) [23] conclude that the impacts of wind variability on system operating costs are not negligible but are relatively modest at less than 10 percent of the wholesale energy value. Estimates of the total operating cost impact of wind power range from 1.85 to 4.97 $/MWh of wind power for 3.5 to 15 percent wind penetration, but could be as low as 2.92 $/MWh for 29 percent penetration [23]. The costs depend on wind forecasting, the size of the associated balancing authority, and the generation mix and fuel costs. Integration costs are reduced in markets with sub-hourly dispatch cycles of 5 to 15 minutes [24]. At higher penetration levels, transmission system operators begin to incur significant additional expenses to provide back-up and balancing capacity to deal with the variability of wind. These levels of penetration have not yet been reached in the US, indicating that there is still growth potential.

2.2.3 Regional Transmission Organizations

In 2000, the Federal Energy Regulatory Commission (FERC) supported the creation of RTOs, also called independent system operators (ISOs), which coordinate transmission at a regional level to reduce operating inefficiencies. Several RTOs were created in the 2000s, though large parts of the grid are still operated by utilities. A map of RTOs can be found in Figure A.1 of the Appendix.

What type of grid a wind power plant interconnects to is an important factor for profitability. In a grid operated by an RTO, access to congested lines could be broader than in a grid operated by a utility that also owns generation facilities. Furthermore, RTO-operated grids are typically larger and more efficient than those operated by utilities, since RTOs can reduce costs through improved grid reliability, reduced reserve requirements, increased market liquidity, and coordinated planning for new generation and transmission resources [24, 25, 26]. Larger grids are better able to handle an intermittent resource like wind energy, since lack of wind in one area can be compensated by wind blowing in another area. Finally, costs to the wind plant resulting from inadvertent schedule deviations are typically lower under RTO regulation than under utility regulation [24].

2.3 Empirical Strategy

2.3.1 Estimation Sample

Many states have at least some incentive policies in place for renewable and clean energy. Typically, a state government decides on a menu of policies ranging from tax incentives to renewable portfolio standards. At first glance, it is unclear how each policy instrument contributes to wind power development. Econometric analysis can help identify the separate effect of each policy instrument on wind power development at a particular location.

One method of investigating the effect of policies is to look at firm-level data. In this case, each observation would be a firm that could own one or several wind power plants in different locations. The problem with this type of analysis is that, by definition, only those locations that have proved attractive to a wind power investor are included in the sample. Locations with perhaps poor policy incentives are not part of the sample. In order to get a more complete picture of the problem, it is necessary to include in the sample locations that have not managed to attract wind power investors.

For this reason, all locations are included in the sample analyzed in this paper. Since there could theoretically be an infinite number of potential locations for wind power plants, for simplicity, the county is chosen as the unit of analysis. Each county has a different level of attractiveness in terms of profitability to potential investors.

Counties that are technically infeasible locations for wind power plants are excluded from the sample, such as counties with an average wind power class less than or equal to 1, as well as counties with a population density greater than 2,100 population per square mile.

2.3.2 Assumptions

The model is based on several assumptions. First, the electricity price is assumed to be exogenous - that is, any additional wind power capacity will have no effect on the electricity price. Second, there is always demand for added generation capacity due to population and GDP growth in all three interconnects (Western, Eastern, and Texas). Third, no grid is completely saturated with wind power, i.e. no grid is unable to accept additional wind power due to system stability constraints.

Fourth, electricity industry deregulation has made it possible to completely separate electricity production from transmission and distribution. This is particularly true of investment in wind power, since in the 1998 to 2007 period 99 to 88 percent, respectively, of additional capacity came from independent power producers that are engaged solely in electricity generation (Figure 2.3) [27]. Only a minority of investment came from utilities, some of which may own transmission/distribution facilities.[2] Furthermore, utility investment in wind power picks up only in 2004, well after the start of deregulation in 1996, when FERC required all public utilities that own or operate transmission facilities to offer an open access transmission tariff to any supplier [28]. By 2004, deregulation of the industry is well underway and generation occurs separately from transmission/distribution.

Given these assumptions, investment in wind generation subject to transmission losses can be separated from ownership and operation of transmission and distribution lines. The transmission and distribution grid is therefore exogenous to a firm's investment decision. Only variables that affect a firm's decision of the location and size of wind power plants matter.

The state policy variables may violate the exogeneity assumption. It is possible that policy incentives are endogenous, if (1) they are passed to support an

[2] In 1998 for the electricity industry as a whole (not just limited to wind power plants), 16 percent of the utilities were involved in both generation and transmission/distribution, 45 percent in transmission/distribution only, and 34 percent in generation only (including independent power producers) [28].

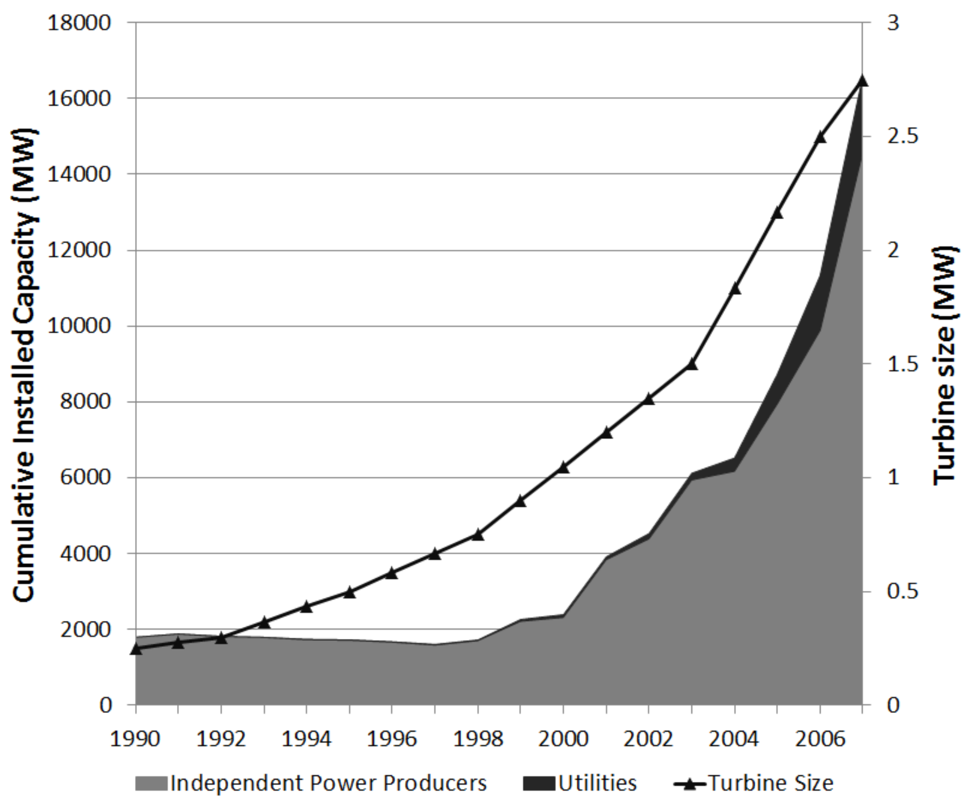

Figure 2.3: Cumulative Installed Wind Power Capacity (MW) by Independent Power Producers & Utilities and Turbine Size (MW)
Source: [27] and [29]

already existing wind industry; or (2) if they are only passed by states with high wind potential. This paper addresses both sources of endogeneity. However, the second source of endogeneity is mitigated by the fact that policies are geared towards renewables in general, and may be driven by other technologies, such as solar power. In addition, county-level windiness controls for any bias in the estimates of state policies that might occur without the presence of this control. That is, endogeneity arising from the fact that states with high wind power potential may institute generous incentives is controlled for by the inclusion of the wind power class variable, which varies across counties.

2.3.3 Econometric Models: Tobit and Instrumental Variables

The dependent variable y_{it} is the addition to existing capacity (if any) in county i in period t. For most counties and for most time periods this will be zero, since in 2007 only 122 out of 2,152 counties in the sample host wind plants. Since y_{it} takes on the value of zero with positive probability and is close to continuous for $y_{it} > 0$, the most appropriate model is the censored regression or corner solution model. For this type of limited dependent variable, traditional estimation techniques, such as OLS, lead to inconsistent estimators.

The panel Tobit estimators are obtained by maximum likelihood. This paper uses a random effects model rather than a fixed effects model, since the number of time periods T is small compared to the number of counties N. Parameter estimates obtained by maximum likelihood estimation of a nonlinear fixed effects model are inconsistent if no sufficient statistic for the fixed effects exists, as is the case for panel Tobit. As $N \to \infty$, the fixed effects (incidental parameters) are estimated inconsistently, since each fixed effect depends on only T observations. This is the incidental parameters problem first analyzed by Neyman and Scott (1948) for the linear regression model [30].

Let the vector X_{it} consist of the explanatory variables discussed above. Then for the $i = 1, \ldots, N$ counties and $t = 1, \ldots, T$ time periods the model to be estimated is as follows. Define latent wind power capacity additions y^*_{it} as

$$\begin{aligned} y^*_{it} &= X_{it}\beta + \epsilon_{it} \\ \epsilon_{it} &= \nu_i + \eta_{it}. \end{aligned}$$

The observed variable is

$$y_{it} = \begin{cases} y^*_{it} & \text{if} \quad y^*_{it} > 0 \\ 0 & \text{if} \quad y^*_{it} \leq 0. \end{cases}$$

The error term ϵ_{it} is composed of a time-invariant county-specific random effect ν_i and an idiosyncratic error η_{it} that varies over time and across counties. Assume that $\forall\, i \neq j, t \neq s$

$$\begin{aligned} \mathbb{E}\left[\nu_i \nu_j\right] &= 0, \qquad \nu_i &\sim& \; N(0, \sigma^2_\nu) \\ \mathbb{E}\left[\eta_{it}\eta_{is}\right] &= 0, \qquad \eta_{it} &\sim& \; N(0, \sigma^2_\eta) \end{aligned}$$

and that the county-specific random effect ν_i is orthogonal to the covariates X_{it}. Any unobserved time-invariant county-specific variables that affect wind power development and that are not included in the estimation would be contained in the error term ν_i. For example, ν_i could include the willingness of a county's residents to accept wind turbines in their view-shed, though this is likely to vary throughout the county and may change over time. It is difficult to determine whether the unobserved characteristics are correlated with any of the included independent variables. Willingness to accept might be partly captured by income and population density. However, the regression equation already includes several control variables, justifying the assumption that the county-specific effect ν_i is orthogonal to the covariates

X_{it}.

The assumption of zero covariance is not trivial. For a firm, the total costs of setting up two plants in two neighboring counties are likely to be less than the total costs of setting up two plants in two counties separated by a great distance. The cost savings are due to economies of scale in construction and maintenance. Similarly, profits are not completely separable over time. The total costs to the firm of setting up a second plant in a county already containing one plant are likely to be less than the total costs of setting up a second plant in a different county. Thus, the optimal wind capacity to install (and thus the error term in an econometric model) could be correlated over space and time.

Even outside the economies-of-scale argument, for the case when several firms are involved, there is potential for cost savings. For a new firm entering a county with existing wind plants, costs can be smaller due to smoother proceedings with local government, since employees are more experienced in dealing with wind plants, and the availability of a more experienced work force. However, these types of cost reductions are likely to be much smaller when the wind plants are owned by different firms rather than a single firm.

While the potential for correlation of errors is acknowledged, since only 14 percent of firms in the dataset own more than one wind plant and the potential cost reductions are small compared to total costs, it is assumed that errors are uncorrelated. However, ownership data is available only for 45 percent of the sample.

The severe degree of censoring in the panel Tobit models estimated in this paper does not present a problem from a theoretical point of view, but could have finite sample implications. The panel sample considered consists of only close to 1 percent uncensored observations across counties and over time. How the random-effects Tobit model handles this type of severe censoring in finite sample is explored in Chapter 4. The study finds that for $T = 8$ and $N = 2000$ when only 1 percent of the observations are uncensored, the bias in the estimates of the coefficients, standard errors, marginal effects, and disturbance standard deviation remains below 5 percent.

Under these assumptions, maximum likelihood estimation leads to consistent and efficient estimates. When the residuals are serially dependent, Tobit estimators are still consistent, though inefficient [31]. However, including the lag dependent variable as a regressor could lead to endogeneity, unless the errors follow an autoregressive process of order one (AR(1)). Similarly, there is potential for endogeneity in the policy variables. To account for endogeneity of the lag dependent variable and the policy variables, an instrumental variables (IV) model based on random-effects OLS is employed. The severity of policy endogeneity is also tested by estimating the Tobit model on a reduced sample that excludes states with a pre-trend in investment occurring before policies are offered.

As yet, there is no computationally accessible method of using instrumental variables in a panel random-effects Tobit model. As both the IV and Tobit models have their strengths and weaknesses, this paper draws conclusions based on a comparison of the significance and magnitude of the coefficients estimated in both models.

2.4 Data

2.4.1 Wind Power Plants

The dependent variable is the addition in MW to existing installed wind capacity in county i in year t. For most counties and for most time periods, the dependent variable is zero. County area is included as a control variable, since larger counties can physically host more wind turbines than smaller counties.

Information on existing wind plants in the US built in the period 1975-2007 was obtained from the EIA [32]. The dataset includes information on the generating capacity, number of turbines, and geographic information system (GIS) location. Figure A.2 in the Appendix depicts a low-resolution map of US wind resources and power plants.

About 94 percent of wind capacity was installed after 1990, 91 percent after 1998, and 85 percent after 2000 (Figure 2.3). Figure 2.4 shows the wind power installations by state. Texas, Iowa, and California have the most wind power capacity, though growth in California has recently stalled.

2.4.2 Transmission Grid Variables

Two variables are included to measure access to the electricity grid. The total length of transmission lines (calculated as the sum of lengths in miles of all lines passing through the county) divided by the county area in square miles is a measure of a county's transmission line coverage. The second variable measuring access to the grid is an indicator variable for the presence of an RTO regulator. The

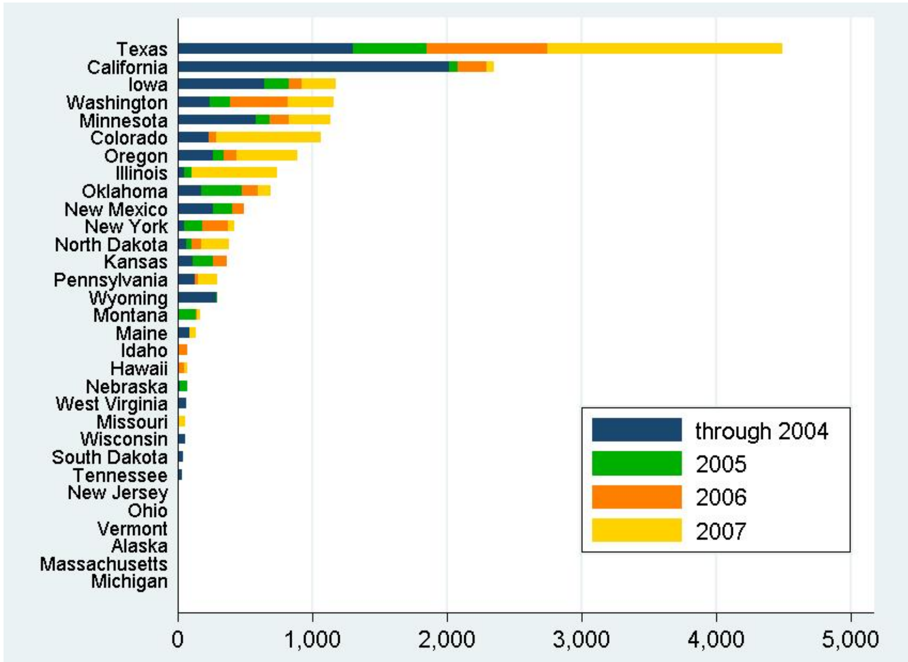

Figure 2.4: Wind Power Capacity Installations (MW) by State

transmission grids regulated by RTOs are not confined to state boundaries, so this indicator variable varies across counties and over time.

The GIS map of the electricity transmission grid for the contiguous US comes from the National Renewable Energy Laboratory, which obtained it from the Federal Emergency Management Agency [17]. The map is somewhat dated (from 1993), but there has been little expansion of the grid since 1990.[3]

2.4.3 Policy Variables

Next to access to the electricity grid, the main regressors of interest are the state and federal tax incentives. The regression includes variables for state-level sales, corporate, and property tax incentives, renewable portfolio standards, pro-

[3] Capital investment in grid expansion has decreased steadily since the 1970s and decreased by one half from 1994 to 1998 [33].

duction incentives, and the federal production tax credit. Information on state incentive policies for renewable energy was obtained from the Database on State Incentives for Renewables and Efficiency [20].

The presence of the state-level corporate tax credit is measured by an indicator variable, since the format of the tax credit varies considerably across states. The sales tax incentive is 100 percent in all states that offer this incentive, but the tax rate varies from 4-7 percent across states. The variable capturing the sales tax incentive equals the appropriate tax rate and is equal to zero for states not offering the incentive. Property tax incentives are measured as the assessed valuation reduction in percent, ranging from 50-100 percent.

The incentives mentioned above have different spatial implications. Corporate and property tax incentives only apply within the state they are offered in. The benefit of a sales tax exemption extends beyond the borders of a state that offers this type of incentive. Wind power plants in neighboring states can purchase turbine parts in states that offer sales tax exemptions.

Any production incentive offered by a state or by a utility to its distribution region is measured in ¢/kWh. Utilities that institute production incentives for renewable energy are typically responding to consumer demand for green electricity or state-mandated renewable portfolio standards. Production incentives offered by state governments have an effect only on within-state wind power development, while those offered by utilities can cross state borders, since the distribution grid of power companies is not confined to state boundaries. This variable thus varies across counties.

The RPS consists of a target standard and an implementation year, such as 20 percent by 2025. It is converted into one variable, by linearly increasing the standard from 0 percent to the target percentage from the announcement year to the implementation year. The effect of an RPS is also not bounded within the state.[4] The linearized RPS variable for border counties (county centroid is within 60 miles of a state border) takes on the value of the RPS in its own or neighboring state, whichever is larger. Thus, the RPS variable varies across counties rather than just states. The linearized RPS variable excludes portions of the state's RPS that are set aside for other technologies, such as solar, and are thus not available to wind power.

2.4.4 Wind Capacity

The main control variable to include is the wind power class, since the windiness of a location is an important factor for productivity. Wind class GIS data for most US states was obtained from the National Renewable Energy Laboratory [17]. The wind maps of high resolution (200m cell size) give the wind power class defined by the annual average wind speeds. The county wind power class is calculated as a spatial average based on this high resolution data.

Wind data for Texas was obtained from the Alternative Energy Institute at West Texas A&M University [34].[5] Minnesota wind data was obtained from the Minnesota Department of Commerce [35]. High resolution wind data for Alabama,

[4] Iowa is surrounded by states with ambitious RPS laws, which has had a positive effect on wind power development.

[5] I thank the Alternative Energy Institute for sharing GIS data on wind capacity in Texas.

Florida, Georgia, Louisiana, Mississippi, and South Carolina are unavailable. The low-resolution wind map (Figure A.2) shows that these states have very limited wind resources, below the minimum wind speed level necessary to generate electricity. This can justify the exclusion of these states from the estimation sample.

2.4.5 Control Variables

The state annual average retail price of electricity was obtained from the EIA and controls for the positive relationship between price and profits of electricity suppliers [36]. County annual per capita income for the sample period was obtained from the Bureau of Economic Analysis [37].

State and county GIS data were obtained from the Environment and Systems Research Institute [38]. The dataset includes county-level population density from 2000 (for years 1998-2002) and from 2005 (for years 2003-2007), county area, and county average land value (measured as the sales of agricultural products per farm in 1997 in thousands of dollars). Distance to the nearest city, which controls for access to electricity demand centers, was calculated based on county and city GIS data.

Finally, it is important to control for technological changes in wind turbines and plant designs over time. Figure 2.3 shows how turbine sizes have increased over the sample period. This paper accounts for technological change with a third-order polynomial time trend.[6]

[6] The regression results are robust to accounting for technological change using average turbine size over time. The annual average turbine size (capacity in MW) over time was obtained from the Department of Energy [29].

2.4.6 Instruments

In the IV model, the state policies are instrumented with the ratio of Democrats to Republicans in the state lower and upper houses (varying over time and across states) and in the US House and Senate (varying over time only) [39], the percentage of US House representatives by state voting for the Waxman/Markey Climate Bill[7] (varying across states only) [40], and the state marginal damages of sulfur dioxide pollution (varying across states only) [41].

The state-level marginal damages of sulfur dioxide (SO2) pollution represent each state's conceivable interest in reducing SO2 pollution, and are a good measure of a state's willingness to adopt policies that promote renewable energy as an alternative to conventional energy, which contributes to SO2 pollution [41]. A House Representative voting for the Waxman/Markey Climate Bill gives another indication of constituent interest in promoting renewable energy. Finally, the ratio of Democrats to Republicans in state and federal legislatures is likely to be higher in areas that favor promoting renewable energy. Tests on the validity of the instruments for the state policies and the lag dependent variable are presented in Table 2.4.

2.5 Results and Discussion

Summary statistics for the 1998-2007 period can be found in Table A.1 in the Appendix. In 2007, wind power plants were installed in 122 of the 2,152 counties

[7]H.R. 2454 (111th): American Clean Energy and Security Act of 2009 sponsored by Representatives Waxman and Markey

included in the regression sample. The table divides the sample into two subsets: county-time observations with positive and zero installed wind power capacity. The subset of county-time observations with positive installed wind capacity has a significantly higher wind power class, higher levels of all policy incentives, higher income, land value, and electricity price, smaller distance to the nearest city, and is more likely to have an RTO-regulated electricity grid.

Panel data analysis is based on the period 1998-2007, since 91 percent of wind power investment occurred after 1998. As a robustness check, several models are considered, including the Tobit, panel OLS, Probit, and linear probability model (LPM). The results are presented in Table 2.3. The Tobit model allows for censoring of the dependent variable, since yearly additions to capacity are non-zero for only 1 percent of the observations. While the Tobit, Probit, and OLS models use random effects, as a robustness check the LPM uses county fixed effects with errors clustered at the state level. The IV model results that control for the potential endogeneity of state policies and the lag dependent variable are presented in Table 2.4.

Two samples are analyzed via Tobit regression. Column (1) of Table 2.3 presents the estimates for the full sample, while column (2) presents the estimates for a reduced sample that excludes 11 states that exhibit a pre-trend in investment.[8] The Tobit estimates of the two samples are very similar with the same significance level, indicating that the endogeneity bias is relatively small. The Tobit and OLS estimates (Columns (1), (2), and (3) of Table 2.3) coincide in sign and significance

[8] In AK, CA, CO, IL, ME, NE, NM, PA, SD, WI, and WY wind power investment occurred before any state renewable energy policy was offered.

level, though not in magnitude, since the OLS model does not take into account censoring of the dependent variable. The Probit model does not perform well, but the LPM identifies the production incentive, the federal production tax credit, and RTO regulation as important drivers of wind power investment, confirming the results of the Tobit model. The LPM necessarily excludes variables that do not vary over time, since the model includes county fixed effects. These results provide an important robustness check, since the identification of policy variables relies on variation over time only and not across counties.

Though the instruments are arguably crude, the joint significance of the instruments in the first stage is very high, passing the 1 percent significance level in the case of each policy measure. With these instruments all policy measures prove endogenous at 1 percent significance based on endogeneity tests (Column (5) of Table 2.4). However, none of the five policy variables remain significant, when they are instrumented at the same time, perhaps because the instruments are not strong enough. I limit myself to instrumenting three policy measures at a time. While the coefficient estimates do not change much across the different models, the significance of the coefficients does. This indicates that there is not enough variation in the instruments. In all models, the corporate tax credit is no longer significant, but the sales and property tax credits and the production incentive are significant in some models. Surprisingly, the coefficient on the property tax credit is significantly negative.[9]

[9] An exemption from local property taxes is comparable to a subsidy of $15,840, assuming a 1 MW plant at a cost of $1,650,000 and a property tax rate of 0.96 percent [42, 43]. The property tax credit for renewable energy is one of the first policy measures instituted in many states, several years ahead of any other state or federal measure. By itself, the property tax credit may not have

Finally, including the lag dependent variable as an explanatory variable can introduce bias, unless the error term is exactly an AR(1) process. Column (4) of Table 2.4 presents the results for instrumenting for the lag dependent variable with lags of other covariates. The additional instruments for lag log capacity additions are the lag state upper and lower house ratios of Democrats to Republicans, lag electricity price, lag RTO regulated grid, and lag federal production tax credit. Here, the lag log capacity additions are no longer significant. However, the null hypothesis of exogeneity could not be rejected with a p-value of 0.3750, indicating that including the lag dependent variable does not introduce a significant amount of bias through endogeneity.

While the instruments pass the valid instrument test in the cases presented in Table 2.4, this is not the case when the policies are instrumented one at a time. It appears that the instruments are only valid for the sales and property tax credit, as well as the production incentive.[10] This may explain why the corporate tax credit and renewable portfolio standard, when instrumented, are not significant.

The main result is that the policies remain significant and the coefficients do not change much between the IV approach and the standard OLS approach. This suggests that, while endogeneity is a concern, the bias is not substantial. The sales tax credit and production incentive, in particular, are significant determinants of

---

been enough to incentive wind power development. In addition, community and local government approval may not be gained, if local disamenities resulting from the wind plant are not offset by the proceeds from the property tax. This may explain why the coefficient is not significantly positive.

[10] The null hypothesis of valid instruments for the corporate tax credit, the renewable portfolio standard, and lag log capacity additions is rejected with p-values of 0.0047, 0.0027, and 0.0063, respectively. The null hypothesis of valid instruments cannot be rejected for the production incentive, sales, and property tax credit with p-values of 0.5192, 0.4647, 0.2564, respectively.

wind power investment, while the positive effect of the corporate tax credit (though identified as significant in the Tobit model) is questionable.

Overall, I conclude that the endogeneity bias in the Tobit model is likely relatively small, since the Tobit estimates do not change much when excluding states with a pre-trend in investment. This bias may be smaller than the bias present in the IV model, which suffers from weak instruments and does not account for censoring of the dependent variable. For this reason, more weight is given to the Tobit estimates.

Based on the Tobit model estimates in column (1) of Table 2.3, annual installed capacity increases by 27.8 percent for a one unit increase in the wind power class. The federal PTC also has a large and significant effect, with annual capacity additions increasing by 24.2 percent in a PTC expiration year. This type of federal support for wind power on a per kWh basis proves to play an important role in wind power development.

Access to the electricity grid emerges as a key factor for wind power development. If a county's electricity grid is regulated by an RTO, annual capacity additions increase by 20.0 percent. The total length of transmission lines (calculated as the sum of lengths of all lines passing through the county) normalized by the county area is a measure of electricity grid coverage and is inversely related to distance to the grid. As expected, it is positively related to wind power development, since a higher ratio of lines to county area would improve access to the grid by reducing the distance from any given location in the county to the grid. Doubling the county average 0.142 miles of transmission line per square mile would lead to a 10.8 percent increase in annual installed capacity. While both variables measuring grid access are important, a significant boost to wind power development can be achieved even without costly expansion of the grid. The government can improve access by requiring RTO-regulation in all regions. Of course, expansion of the grid is required to tap into more remote wind resources and accommodate increases in generation capacity.

The corporate and sales tax incentives, as well as the production incentive, all have positive and significant coefficient estimates. Property tax incentives appear to have no or even a negative effect on wind power development. The presence of corporate tax credits increases annual capacity additions by 21.9 percent. In the IV model, the effect is 4.9 percent (column (1) of Table 2.4), though censoring of the dependent variable is not taken into account. An increase in the production incentive by 1 ¢/kWh would increase annual capacity additions by 20.0 percent (Tobit) or 8.7 percent (IV). Finally, increasing the sales tax credit by one additional percentage point would increase annual capacity additions by 4.2 percent (Tobit) or 1.0 percent (IV).

2.5.1 Cost-Effectiveness of Various Policies

Table 2.2 presents estimates of the cost-effectiveness of several policies for increasing wind power penetration. The most cost-effective way of increasing wind power investment involves an expansion of coverage or creation of additional RTOs. Counties with grids that are regulated by RTOs can expect a 20 percent increase in annual additions to installed wind power capacity. This increase in wind power can be achieved at a modest organizational cost to regulators and power plant owners.

Given assumptions on investment costs, it is possible to compare the cost-effectiveness of the sales tax and production incentive. A 1 MW turbine cost \$1,650,000 in 2005 [42]. If a sales tax reduction of 1 percent were offered, this would cost the state \$16,500 and would lead to an annual capacity increase of 4.2 percent. The same turbine operating at a 35 percent capacity factor would generate $0.35 \cdot 24 \cdot 365 = 3,066$ MWh/year = 3,066,000 kWh/year. A 1¢/kWh production incentive would cost the government \$30,660 per year and would achieve a 20 percent increase in annual capacity additions. The production incentive achieves a 0.652 percent increase in annual capacity additions per thousand dollars spent, while the sales tax incentive achieves only 0.255 percent.

The corporate tax credit comes in various forms. In order to perform a cost-effectiveness calculation, it is assumed that the corporate tax credit amounts to 50 percent of equipment and installation costs, estimated here at \$1,650,000 for a 1 MW wind plant. The corporate tax credit thus provides \$825,000 to a 1 MW wind plant and results in an increase in annual capacity additions by 21.9 percent. This amounts to a 0.0265 percent increase in annual capacity additions per thousand dollars spent.

The average county has 0.142 miles of transmission line per square mile area. With an average county size of 1,147 square miles, this amounts to 163 miles of transmission lines for the average county. Increasing the coverage by 10 percent to 0.156 miles of lines per square mile would require installation of an additional 16 miles of transmission lines and would result in a total cost of $24 million, assuming a transmission line installation cost of $1.5 million per mile [44]. The benefit of expanding transmission line coverage would be an increase in annual capacity additions by 1.03 percent. Assuming the installation cost of additional transmission lines could be spread over 20 years, the increase in transmission line coverage achieves a 0.000858 percent increase in annual capacity additions per thousand dollars spent. Expanding transmission coverage is therefore several orders of magnitude less cost-effective than either the production incentive or the sales tax credit. However, this cost estimate assumes that the transmission lines would be randomly placed over the county. In reality, a single well-placed transmission line could result in significant additional wind capacity coming on line. Expanding transmission capacity, though expensive, will eventually become necessary to increasing investment in wind power.

Table 2.2: Cost-Effectiveness of Selected Policies

Policy	Annual capacity additions (%) per thousand dollars spent
RTO regulated grid	20.0[a]
Production incentive	0.652
Sales tax credit	0.255
Corporate tax credit	0.0265
Transmission line coverage	0.000858

[a] This estimate assumes that establishing an RTO or becoming a member in an RTO imposes no organizational costs on regulators and power plant owners.

2.5.2 Limitations

Some care must be taken when interpreting the results, since there are limitations to the models and estimation procedures. First, it is unclear how the Tobit model performs when the number of uncensored observations is small relative to the number of censored observations, though the Monte Carlo study in Chapter 4 indicates that the Tobit model performs reasonably well. Second, the sample is relatively small with only 2,152 counties included in each regression. The estimates are consistent only as $N \to \infty$ with fixed T. Third, there are omitted variables, such as land cover (distinguishing between differing degrees of vegetation cover), investor expectations, and community opposition, leading to omitted variable bias.

While the IV approach addresses the endogeneity problem, the issue of censoring remains. As yet, there is no computationally accessible method of using instrumental variables in a panel random-effects Tobit model. The endogeneity bias present in the Tobit model is likely relatively small, since the Tobit estimates for the full sample are very similar to those for the reduced sample excluding states with a pre-trend in investment. It is unclear to what extent the IV model suffers from weak instrument bias and misspecification by ignoring the issue of censoring. For this reason, the conclusions of this paper are based more heavily on the Tobit results, though the IV results are also considered, as both the IV and Tobit models have their strengths and weaknesses.

Though it is argued that wind plant ownership is separate from transmission infrastructure ownership, 1 percent (1998) to 12 percent (2007) of wind plant capacity is owned by utilities. The dataset does not contain information on whether these utilities also own transmission lines. Given this possibility, the separation between generation and transmission, and in fact the separation between supply and demand, is not complete. Ignoring this incomplete separation would attenuate the effect of the variables measuring access to the grid, since utilities that simultaneously own wind plants and transmission lines will have an incentive to ease the interconnection process both procedurally and financially.

The main limitation lies in the relatively small degree of cross-sectional variation for those types of policy incentives that are set at the state rather than the county level. These include corporate, property, and sales tax incentives. With respect to these policy incentives, this paper faces the same limitation as previous empirical studies. However, this paper represents several improvements. First, the policy incentives vary over time, as not all previous empirical studies have allowed. Second, the production incentive, linearized renewable portfolio standard, and grid deregulation status vary at the county level. Finally, the control variables of windiness and transmission line coverage vary at the county level as well. With this increase in cross-sectional variation, the separate effect of these policy instruments on wind power development can be more credibly identified.

2.6 Conclusion

With strong growth rates in the past three years, the wind power industry is set to become an important player in the electricity industry. The federal production tax credit and the state-level corporate tax credit, sales tax incentive, and production incentives emerge as significant drivers of wind power development, of which the production incentive ranks as the most cost-effective.

Access to the electricity grid is another important factor for wind power development. Higher wind power penetration levels can be achieved very cost-effectively by bringing more parts of the electricity transmission grid under RTO regulation. RTOs introduce competitive wholesale markets for electricity, facilitate the interconnection procedures for wind plants, adapt schedule deviation penalties to the physical requirements of wind power technology, and provide supply scheduling that is closer to real time than in grids regulated by local utilities. Expanding the grid to include more remote windy areas, though expensive, could also significantly impact wind power development.

This paper concludes that state and federal government policies play a significant role in wind power development both by providing financial support and by improving access to the electricity grid. Further deregulation of the electricity industry is likely to improve the ability of wind power to contribute to the US electricity generation portfolio. In view of the importance of state incentives for wind power, future research could focus on whether the variability of state-level policy incentives has led to a potentially inefficient allocation of wind plants across the US.

Table 2.3: Wind Power Capacity 1998-2007

Dependent Variable	Log capacity additions (MW)			Capacity additions (0/1)	
	Tobit marginal effects		OLS	Probit ME	LPM
	(1)	(2)	(3)	(4)	(5)
Lag log capacity additions (MW)	0.0543***	0.0385*	0.222***	0.0000681	0.00774
	(2.86)	(1.82)	(28.46)	(1.29)	(0.87)
Wind power class	0.245***	0.248***	0.0220***	0.000233*	
	(6.73)	(5.70)	(7.24)	(1.76)	
Corporate tax credit (0/1)	0.198**	0.306***	0.0334***	0.000305	0.0104
	(2.16)	(2.95)	(3.67)	(1.14)	(1.27)
Sales tax credit	0.0409***	0.0599***	0.00396***	0.0000408	0.000107
(sales tax rate in %)	(3.44)	(4.33)	(3.03)	(1.56)	(0.13)
Property tax credit	-0.0214	-0.0673	-0.0113*	-0.0000224	-0.000787
(% reduction of assessed value)	(-0.34)	(-0.78)	(-1.80)	(-0.35)	(-0.12)
Production incentive (¢/kWh)	0.182***	0.226***	0.0220***	0.000183	0.00317**
	(4.50)	(4.78)	(4.90)	(1.60)	(2.14)
Linearized renewable portfolio	-0.00458	-0.000325	0.000138	-0.00000433	-0.000713*
standard (%)	(-0.69)	(-0.04)	(0.13)	(-0.63)	(-1.85)
PTC expiration year (0/1)	0.217***	0.204***	0.0229***	0.000313	0.00555**
	(3.86)	(3.17)	(3.69)	(1.52)	(2.36)
Transmission line coverage	0.725***	0.670**	0.0808***	0.000679	
(miles/square mile area)	(3.02)	(2.14)	(3.83)	(1.55)	
RTO regulated grid (0/1)	0.182***	0.175**	0.0162**	0.000215	0.00549*
	(3.05)	(2.42)	(2.45)	(1.48)	(1.90)
Electricity price (retail, ¢/kWh)	0.0635***	0.0758***	0.00623***	0.0000613*	0.00741***
	(4.17)	(4.28)	(3.49)	(1.68)	(3.01)
Income per capita (millions)	0.00666*	0.00502	0.00125**	0.00000619	-0.000278
	(1.67)	(0.69)	(2.33)	(1.19)	(-0.89)
Population density	-0.000537**	-0.000930**	-0.0000678***	-0.000000502	-0.0000171
(population/square mile)	(-2.32)	(-2.29)	(-3.84)	(-1.40)	(-0.16)
Distance to nearest city (miles)	-0.00173	-0.00140	-0.000183	-0.00000173	
	(-0.79)	(-0.57)	(-0.99)	(-0.74)	
Agricultural sales/farm	0.000171	0.0000779	0.0000366*	0.000000179	
(thousands, 1997)	(1.08)	(0.44)	(1.91)	(0.97)	
County area (square miles)	0.0000369**	0.0000165	0.00000416**	3.56e-08	
	(2.14)	(0.65)	(2.40)	(1.39)	
Time index	-0.0200	0.0464	0.00358	-0.0000300	0.000783
	(-0.18)	(0.36)	(0.30)	(-0.27)	(0.32)
Time index squared	-0.00150	-0.0154	-0.00182	7.70e-08	-0.000408
	(-0.07)	(-0.63)	(-0.75)	(0.00)	(-0.65)
Time index cubed	0.000428	0.00119	0.000180	0.000000324	0.0000308
	(0.35)	(0.86)	(1.24)	(0.27)	(0.73)
Constant			-0.0956***		-0.0209
			(-4.84)		(-0.58)
Observations	21520	15840	21520	21520	21520
Number of counties	2152	1584	2152	2152	2152
Uncensored observations	205	141		205	
Error structure	RE	RE	RE	RE	FE, errors clustered by state

*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level
Z-statistics in parentheses. Marginal effects (ME) conditional on the dependent variable greater than zero are reported for the Tobit and Probit models. LPM stands for linear probability model, RE for random effects, and FE for fixed effects. To control for policy endogeneity, the Tobit model in column (2) excludes counties in states with a pre-trend in investment, i.e. wind power investment occurring before renewable energy policies were offered.

Table 2.4: Wind Power Capacity 1998-2007: Instrumental Variables

Dependent Variable Log capacity additions (MW)	IV (1)	IV (2)	IV (3)	IV (4)	Exogeneity test p-value
Lag log capacity additions (MW)	0.220*** (26.03)	0.224*** (27.15)	0.221*** (25.05)	-0.149 (-0.57)	0.3750
Wind power class	0.0283*** (7.40)	0.0340*** (6.06)	0.0298*** (5.33)	0.0453*** (4.72)	
Corporate tax credit (0/1)	0.0474 (1.11)	0.0349 (0.79)	0.0628*** (2.73)	0.0537 (1.36)	0.0002
Sales tax credit (sales tax rate in %)	0.0101 (1.35)	0.0144** (2.39)	0.0135 (1.54)	0.0197*** (3.01)	0.0001
Property tax credit (% reduction of assessed value)	-0.0354** (-2.20)	-0.0801*** (-3.27)	-0.0553 (-1.23)	-0.112*** (-3.45)	0.0002
Production incentive (¢/kWh)	0.0832** (2.36)	0.0227*** (3.57)	0.0618 (1.01)	0.0330*** (3.44)	0.0003
Linearized renewable portfolio standard (%)	-0.000410 (-0.32)	0.00161 (1.34)	0.000350 (0.16)	0.00301* (1.90)	0.0009
PTC expiration year (0/1)	0.0289*** (4.14)	0.0282*** (4.12)	0.0283*** (4.03)	0.0254*** (3.41)	
Transmission line length (miles/square mile area)	0.0851*** (3.56)	0.0949*** (3.79)	0.0903*** (3.49)	0.127*** (3.72)	
RTO regulated grid (0/1)	0.0375** (2.28)	0.0278** (2.22)	0.0303 (1.56)	0.0403*** (2.75)	
Electricity price (retail, ¢/kWh)	0.00772*** (3.36)	0.00529** (2.26)	0.00730*** (2.82)	0.00553** (2.34)	
Income per capita (millions)	0.000921 (1.57)	0.000868 (1.47)	0.000874 (1.48)	0.00144* (1.93)	
Population density (population/square mile)	-0.0000630*** (-3.12)	-0.0000710*** (-3.53)	-0.0000645*** (-3.13)	-0.0000986*** (-3.43)	
Distance to nearest city (miles)	-0.000170 (-0.85)	-0.000144 (-0.72)	-0.000152 (-0.76)	-0.000199 (-0.93)	
Agricultural sales/farm (thousands, 1997)	0.0000452** (2.15)	0.0000384* (1.86)	0.0000419* (1.90)	0.0000594** (2.26)	
County area (square miles)	0.00000212 (1.08)	0.00000249 (1.28)	0.00000199 (1.06)	0.00000388* (1.72)	
Time index	0.00680 (0.53)	0.00862 (0.66)	0.00653 (0.51)	0.0198 (1.26)	
Time index squared	-0.00374 (-1.33)	-0.00293 (-1.09)	-0.00324 (-1.11)	-0.00520 (-1.61)	
Time index cubed	0.000314* (1.86)	0.000256 (1.60)	0.000281 (1.58)	0.000390** (2.03)	
Constant	-0.120*** (-5.06)	-0.105*** (-4.75)	-0.116*** (-4.52)	-0.139*** (-4.19)	
Observations	19910	19910	19910	19909	
Test for valid instruments (p-value)	0.8707	0.9883	0.8988	0.3939	

Instruments: State lower house ratio Democrats/ Republicans, state upper house ratio Democrats/ Republicans, House Democrats/ Republicans, Senate Democrats/ Republicans, percentage House representatives voting for Waxman/Markey Climate Bill, marginal damages of SO2 pollution by state.
Additional instruments for lag log capacity additions (column 4) are the lag state upper and lower house ratio of Democrats/Republicans, lag electricity price, lag RTO regulated grid, and lag federal production tax credit.
*** Significant at 1 percent level, ** Significant at 5 percent level, * Significant at 10 percent level
Z-statistics in parentheses. Shaded cells indicate instrumented variables.

Chapter 3

Renewable Power Effects on Electricity Transmission Congestion and Emissions

Abstract

This paper examines the effect of renewable power plant location on electricity transmission congestion levels and system-wide emissions levels in a theoretical model and a simulation study. A new renewable plant takes the effect of congestion on its own output into account, but ignores the effect of its marginal contribution to congestion on output from existing plants, which results in curtailment of renewable power. A model is developed to examine this externality and shows that a social planner installs smaller sized power plants to minimize curtailment than individual profit-maximizing firms would. The model also examines the interaction of the congestion and emissions externalities. In the absence of a price on emissions, pricing congestion usually reduces system-wide emissions, though there are exceptions. Power flow simulations using the modified IEEE 30 bus test system reveal that clustering of renewable plants contributes to transmission congestion, and that new renewable plants can affect output at existing plants. Regional energy subsidies that incentivize the clustering of renewable plants in particular areas are rendered less effective, since they contribute to renewable power curtailment.

Keywords: Transmission congestion; Renewable power; Electricity grid; Emissions;

Optimal power flow

3.1 Introduction

The United States (US) government has various policies in place, both at the federal and state level, that promote the production of electricity using renewable energy sources, in order to mitigate climate change and promote energy security. While the US possesses an abundance of renewable energy sources, such as wind, solar, and geothermal, renewable power plants are not necessarily deployed in areas with high renewable energy potential, in part due to differences across states in the types of incentives offered [45].

The patchwork of state incentives for renewable power contributes to a sub-optimal distribution of renewable power plants across the electricity transmission grid in terms of optimal use of both renewable energy and transmission resources. Renewable power plants cluster in areas that offer the most generous portfolio of government incentives, which can lead to transmission congestion. During very windy or sunny periods, the joint power output of renewable plants can exceed the capacities of transmission lines that connect the plants with electricity demand centers. Congestion manifests itself as curtailment of power from all producers that are not granted access to a congested line by the grid operator to maintain grid stability.

A congestion pricing mechanism is in effect in only some parts of the US electricity grid to allow for efficient transmission capacity allocation among power producers.[1] With their zero fuel costs, renewable power plants can underbid conventional power plants for access to a congested line. Renewable power plants are thus affected by transmission congestion only in areas with a high concentration of renewable power plants. Congestion pricing acts as a signal to reduce curtailment by dis-incentivizing clustering of plants.

When curtailment at renewable power plants is reduced, system-wide emissions are expected to decrease in tandem with the reduction in output at conventional power plants. However, this result does not hold uniformly and depends on the configuration of the grid and the substitution patterns between output from renewable and conventional power plants. This paper attempts to analyze the connection between the congestion and emissions externalities. Understanding how renewable power plants affect and are affected by congestion and how the congestion and emissions externalities interact is vital to mitigating climate change in an efficient manner. As the US seeks to increase renewable power capacity in the long run, these questions will become more important.

The literature on the integration of renewable power plants into the transmission grid is focused mainly on the issue of intermittency [46, 47, 48, 49, 50, 51]. As opposed to conventional plants, renewable power plants are unable to predict and accurately control output, since they rely on nature to provide wind or solar energy as a fuel source. Intermittency at the hourly and sub-hourly level must be balanced with other fast-ramping power plants - usually natural gas plants.

[1]The US is a leader in this regard, since power markets are still operated under a single price of electricity rather than location-dependent pricing in much of the rest of the world, including most notably Europe.

Less attention has been given to the relationship between transmission congestion and renewable power generation, though several recent studies focus on the issue. Førsund et al. (2008) examine how phasing in wind power in Norway affects transmission congestion and crowding-out of hydropower [52]. Woo et al. (2011) show that high wind generation and low electricity demand in the Electric Reliability Council of Texas (ERCOT) West Zone lead to congestion and zonal electricity price differences [53]. Phillips and Middleton (2012) develop an optimization model for the geospatial arrangement and cost minimization of wind power generation and transmission infrastructure [54]. They find that the costs of integrating a certain amount of wind in the ERCOT electricity grid can be reduced by up to 50% by jointly optimizing investment in wind plants and transmission capacity. Blumsack and Xu (2011) analyze the emissions impacts of incremental investments in wind power in the Western US using a generation dispatch model that incorporates the impacts of transmission constraints [55]. They find that the location of wind plants changes the utilization of transmission assets, which affects system-level emissions, with wind investment in *some* locations leading to slight increases in overall emissions. Finally, a study for the Austrialian Clean Energy Council (2010) compares the costs of achieving 20% wind power penetration levels by 2020 for different arrangements of wind power plants across the grid, and finds that costs are highest for scenarios with highly concentrated wind power development, requiring significant investment in transmission capacity [56].

None of the studies investigates the theory or empirics of how the transmission congestion externality affects renewable power output and the level of emissions, and only a few of them offer recommendations for policy improvements. This paper aims to fill that void. First, the paper develops a theoretical model of the transmission congestion externality problem, capable of analyzing how state-level subsidies exacerbate the congestion externality problem by contributing to the clustering of renewable power plants in certain areas of the grid. Second, the paper demonstrates the effect of the transmission congestion externality on power plant output through a series of simulations of power flow in an electricity grid for different levels of electricity demand and wind speed. Both the theoretical model and the simulation study show that total renewable power output is higher when renewable power plants are more evenly distributed across potential sites in the grid. In the absence of a price on emissions, instituting a congestion price will usually reduce system-wide emissions, though this result depends crucially on the distribution of abatement potential and the potential to cause congestion across locations.

An optimal government policy would be a uniform carbon price to address the pollution externality in conjunction with a congestion price to address the congestion externality. In the absence of a national carbon price, renewable energy subsidies represent a sub-optimal solution to the pollution externality. Current incentives can be improved by addressing the effect of the subsidies on congestion levels and the effect of congestion levels on emissions reductions. The goal of the paper is to highlight how ignoring the effect of congestion on renewable power output and emissions levels renders government incentives for renewable power less effective.

The paper first defines the relationship between electricity transmission congestion and renewable power plant location in Section 3.2. A theoretical model examining the transmission congestion externality is developed in Section 3.3. Power output for conventional and wind plants for different levels of electricity demand and wind speed are simulated in Section 3.4. After a discussion of possible policy responses in Section 3.5, the paper concludes with Section 3.6.

3.2 Transmission Congestion and Renewable Power Plant Location

3.2.1 Electricity Transmission Congestion

Congestion occurs when power flow over a transmission line exceeds line capacity, leading to higher local marginal electricity prices in the electricity demand center, since more electricity must be supplied by local generators rather than less expensive, distant generators. Expanding line capacity does not remove the congestion externality and only temporarily eases congestion, since the expanded line capacity may induce other developers to invest in the area.

In the remainder of the paper, wind power will be used as the main example of renewable power plants, but the results apply to solar power plants as well. Both types of plants do not have complete control over output and must rely on nature to supply adequate amounts of fuel to produce power. Thus, for the purpose of analyzing the transmission congestion and emissions externalities, the term wind power plant will be used essentially interchangeably with the term renewable power plant.

Wind power plants are more susceptible to transmission congestion than conventional power plants for two reasons. First, wind power must be transported over greater distances to meet sufficient demand, since it is typically windy at night when electricity demand is low.[2] Second, conventional power plants are better connected with demand centers. This is because many conventional power plants, such as coal and nuclear plants, were built in the 1950s in tandem with the transmission grid. The grid connects coal reserves in the Appalachians with demand centers along the East Coast, but does a poorer job at connecting windy areas in the Midwest with large cities. Table B.1 in the Appendix shows the average transmission line coverage around the plant for different plant types, with wind plants locating in areas with the lowest coverage. For these two reasons, wind power is transmitted over long distances, which makes it more susceptible to congestion problems.

Transmission congestion is similar to road traffic congestion. As electricity flow over the line increases, more and more electrical energy is dissipated as heat, which is produced by the current I flowing through the line resistance R.[3] While transmission congestion results in electricity flow losses, road traffic congestion results in longer travel times. Without intervention of the grid operator, electricity flow that exceeds the line's capacity would result in the line overheating and flow stopping completely. Grid operators intervene to ensure electricity flow does not exceed some limit. Thus, the share of output from a power plant that reaches customers at the other end of the line gradually decreases due to losses and eventually plateaus due to intervention of the grid operator restricting flow to some limit.

Currently, congestion pricing is in effect in only some parts of the US electricity

[2] In contrast, solar power output tends to be positively correlated with electricity demand.
[3] Losses are equal to I^2R

grid.[4] Transmission systems are able to price congestion, if they operate based on locational marginal prices (LMPs), i.e. prices that are determined for each node rather than a single price for the entire grid. Without transmission congestion, the price of electricity is the same across all nodes of the grid. When congestion occurs, the price of meeting an additional MW of demand at one end of the line is higher than at the other.

As an essentially zero marginal cost plant, wind plants can underbid most conventional power plants that have non-zero fuel costs. In competing for access to a congested line, wind plants thus compete with other wind plants and slow-ramping plants, such as coal, that are unable to ramp down fast enough once wind speed picks up. Since wind plants earn a federal production tax credit for every unit of electricity produced, LMPs can be negative (up to negative the production tax credit).

3.2.2 Renewable Power Plant Location and Congestion

When deciding on optimal plant location, wind power developers take several factors into account, including the area windiness, distance to the electricity grid, available state incentives, as well as expected power output given current and future transmission constraints. Once the wind power plant is built, power output depends on wind speed and transmission congestion levels, but the wind plant cannot be relocated if congestion levels prove too high. The presence of a congestion externality

[4]These include the grids operated by the regional transmission organizations California ISO, Midwest ISO, PJM, New York ISO, and New England ISO.

means that developers take into account the average cost of transmission congestion in siting their wind plants but disregard their marginal impact on output from existing wind plants.

The portfolio of renewable energy incentives offered by state governments varies widely from state to state, which can lead to a potentially inefficient allocation of wind plants across the US in terms of optimal use of both wind and transmission resources [45]. Wind power plants are clustered in the McCarney region of western Texas. About 84% of installed wind power capacity is located in the West zone of ERCOT [57]. On windy days, transmission constraints become an issue. Electricity prices can drop below zero with wind power plants bidding up to the negative of the federal production tax credit, in order to gain access to congestion transmission lines. This was true on June 19, 2012, when record wind generation occurred. Figure 3.1 shows the total wind generation and settlement prices for four zones in ERCOT at 15 minute intervals throughout the day of June 19, 2012.

3.2.3 Evidence of Wind Power Curtailment

Grid operators can resort to wind power curtailment in the event of transmission constraints. In 2009, Midwest ISO curtailed about 200,000 MWh of wind power or 1% of wind generation [58]. Curtailment as a percentage of potential wind power output in ERCOT was much higher. In 2009, ERCOT curtailed 3,842,000 MWh, which amounts to 16% of potential wind power generation, with monthly averages ranging from 24-28% of potential wind generation from February-April, to about

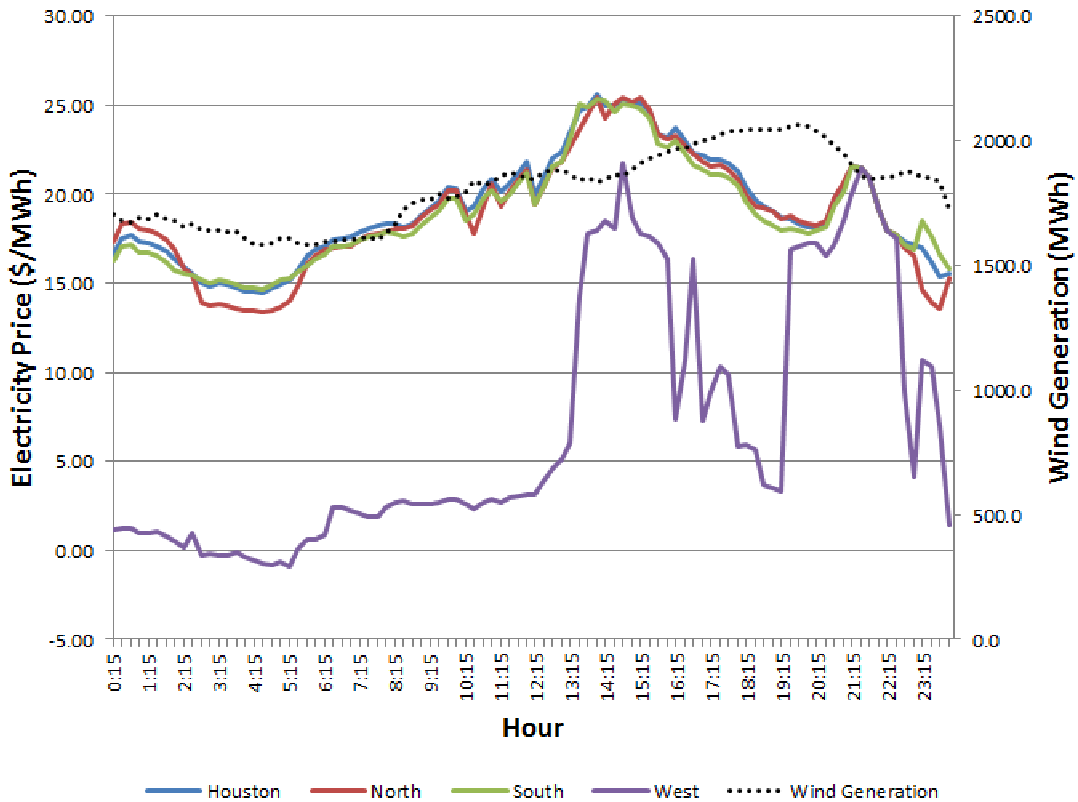

Figure 3.1: Electricity Prices and Wind Generation in ERCOT on June 19, 2012 Electricity prices in the West zone, which hosts 84% of wind power capacity in ERCOT, dropped below zero from 2:45 to 5:15am on June 19, 2012, a particularly windy day. Wind generation remained high throughout the day, but congestion eased somewhat as electricity demand in the West zone increased. In the absence of congestion, prices in all four zones would be the same.

10-18% in January and from May-November and 6% in December [58, 59].

Curtailment is a much larger issue in ERCOT due to several factors (Table 3.1). First, ERCOT produces a larger share of its electricity from wind than Midwest ISO, with the shares amounting to 6.2% and 2.9% in 2009, respectively [60, 61].[5] Second, the degree of wind power plant concentration is slightly higher in ERCOT than in Midwest ISO. In 2009, about 87% of wind capacity was located in ERCOT's West zone. In Midwest ISO, 84% of wind power capacity was installed in the Western

[5] In 2012, ERCOT and Midwest ISO generated 9.2% and 8.2% (in the Fall), respectively, from wind.

Table 3.1: Wind Power Capacity, Output, and Curtailment in ERCOT and Midwest ISO

	ERCOT	Midwest ISO
Wind power curtailment (MWh)	3,842,000	200,000
Wind power curtailment (% of potential output)	16	1
Installed wind capacity (%)	11	5.1
Electricity generated from wind (%)	6.2	2.9
Installed wind capacity located in West (%)	87	84
Installed wind capacity (% of total capacity in West)	62	20
Load in West (%)	7.4	22.7

Source: [60, 59, 61, 58]

region. Third and most importantly, the imbalance between installed wind power capacity and load (electricity demand) in ERCOT's West zone was much larger than in Midwest ISO's Western region. In ERCOT, 62% of generating capacity in the West zone was wind, but only 7.4% of load was located in the West [59]. In Midwest ISO, 20% of generating capacity in the West was wind, and 22.7% of load was located in the West [61]. Thus, a much greater share of electricity produced by wind power plants had to be exported in ERCOT than in Midwest ISO, making wind power in ERCOT more susceptible to transmission congestion. This explains why a much larger share of wind power was curtailed in ERCOT (16%) than in Midwest ISO (1%).

Wind plants in Midwest ISO may have much greater abatement potential than wind plants in ERCOT, since coal plants generated 74% of electricity in Midwest ISO in 2009, compared with 37% in ERCOT. Natural gas and nuclear plants contributed 42% and 14% to electricity generated in ERCOT. System-wide emissions rates in ERCOT are thus lower than in Midwest ISO, since coal plants have the highest emissions rates. Thus, while the amount of wind power curtailment in ERCOT is higher than in Midwest ISO, the difference in terms of emissions abatement potential may be lower. The cost of curtailment in Midwest ISO is high due to the high system-wide emissions rate. In Minnesota, as the portion of electricity generated by wind grew from 4% to 10% from 2006 to 2009, electric sector carbon-dioxide emissions fell by more than 10%, or 4 million tons [62].

3.3 Model

The model developed in this section examines how individual wind power plant location affects output at other wind power plants by contributing to electricity transmission congestion. Individual firms acting independently to maximize profits do not address this externality, but a social planner who maximizes profits across all wind plants does. The optimal congestion charge is derived that would induce individual firms to choose the socially optimal amount of capacity to install at each location. A regional renewable energy subsidy is found to exacerbate the congestion externality by contributing to clustering of wind plants in certain areas of the grid. Finally, the effect on system-wide emissions of instituting a congestion price is examined.

3.3.1 Model Setup and Assumptions

Assume there are n potential wind plant sites within a stylized electricity grid, to which conventional fossil fueled generators are connected. It is assumed that each wind plant is owned by a different firm. Wind power output is a function of wind speed, total load, installed capacity, congestion, and location. Congestion, as it affects wind plants, depends on total wind power output and is independent of conventional power output, since wind power plants can always underbid conventional power plants. Thus, competition among wind power plants for transmission capacity affects wind power output.

Several simplifying assumptions are made. First, the levelized marginal investment cost c for each unit of capacity k_i is assumed to be constant with $0 < c < 1$.[6] Second, load and wind speed are assumed to remain constant, which means that, without congestion, electricity generation would depend only on installed capacity. Third, the price of electricity for the given load level is set to one.

A developer building a new wind plant does not take into account the effect of building its new plant on output of existing wind plants, resulting in idle capacity at existing wind plants. A social planner would build a smaller or potentially no plant at that location, in order to reduce congestion and minimize the amount of idle capacity.

Electricity output from a wind plant is modeled as the fraction of utilized capacity multiplied by installed capacity. The fraction of capacity used to produce electricity can be described by $f_i(k_1, \ldots, k_n)$, where $0 \leq f_i \leq 1$ and k_i is the installed capacity at location i. If there is no transmission congestion, $f_i = 1$ and installed capacity at location i is fully utilized to produce the electricity output $f_i \cdot k_i$. Since the price of electricity is normalized to one, the total value of capacity $(1 \cdot f_i \cdot k_i)$ is

[6]The levelized marginal investment cost is based on an assumed utilization rate, which depends on transmission congestion. In this model, the cost c is not updated once investment is made and transmission congestion is realized.

the same as total electricity output ($f_i \cdot k_i$).

Since installed capacities at other locations $j \neq i$ affect output at location i, $f_i(\cdot)$ is a function of $k_1, \ldots, k_n$. The installed capacities k_i and k_j have a different effect on the fraction of utilized capacity at other locations, since transmission congestion depends on the grid configuration. How output of a wind plant affects output at other plants depends on how electricity flows through the grid. For this reason, the fraction of utilized capacity is indexed by i.

At low levels of capacity k_i, the wind plant at location i can operate at full capacity and $f_i = 1$. As the transmission lines heat up, the fraction of output produced that can be sold to customers is reduced, since electrical energy dissipates as heat.[7] Eventually, line capacity is reached, and additional units of wind power capacity at location i have no effect on output from that plant. In general, $\partial f_i / \partial k_i \leq 0$ and $\partial^2 f_i / \partial k_i^2 \leq 0$.

Initially, low levels of capacity k_j may not affect output of the plant at location i. The plants at both locations i and j are trying to access the same line, but the plant at location j has better access to the line. As k_j increases, output at location i goes to zero. Once output from location j has completely displaced output from location i, the line capacity constraint becomes binding for the plant at location j. The negative congestion externality is reflected in $\partial f_i / \partial k_j \leq 0$, $\partial^2 f_i / \partial k_j^2 \leq 0$. It is assumed that $\partial^2 f_i / \partial k_i \partial k_j \leq 0$, i.e. the effect of k_i on f_i decreases with increasing levels of k_j.

[7] In practice, a plant's price bid is multiplied by a loss factor, depending on how output from the plant contributes to system losses. A loss factor greater than 1 means that the plant contributes to losses.

Firms maximize profits disregarding the effect of their own wind plant output on output from existing plants through congestion. The social planner takes this externality into account and maximizes profits for all firms. Initially, the benefits in terms of emissions reductions of wind power plants are not incorporated into the model, such that the resulting overall level of installed wind power capacity does not necessarily induce the socially optimal level of emissions reductions. In this simplified model, comparisons between the distribution of wind plants induced by profit-maximizing firms and a social planner are still possible, and any results derived from these comparisons are independent of whether or not total installed capacity is optimal in terms of emissions reductions.

3.3.2 Modeling the Transmission Congestion Externality

The following analysis shows that a social planner installs smaller wind plants than individual profit-maximizing firms would. Only if the grid is uncongested are the installed capacities in the social planner problem equal to those in the firm problem.

Firm Problem

Since installed capacity k_i at each location i is common knowledge, and firms are assumed to profit-maximize taking other firms' strategies as given, the solution to the firm problem is a Nash Equilibrium. Firms maximize

$$\max_{k_i} \quad f_i(k_1, \ldots, k_n)k_i - ck_i$$

Let k_i^* denote the level of capacity that satisfies the first order condition:

$$f_i(k_1^*, \ldots, k_n^*) + k_i^* \frac{\partial f_i}{\partial k_i}(k_1^*, \ldots, k_n^*) - c = 0. \tag{3.1}$$

The Nash equilibrium level of capacity at location i is implicitly given by

$$k_i^* = \frac{c - f_i(k_1^*, \ldots, k_n^*)}{\frac{\partial f_i}{\partial k_i}(k_1^*, \ldots, k_n^*)}.$$

Social Planner Problem

The social planner selects capacity at each location $i = 1, \ldots, n$ to maximize total profits:

$$\max_{k_1, \ldots, k_n} \quad \sum_{i=1}^{n} \left(f_i(k_1, \ldots, k_n)k_i - ck_i\right).$$

Let k_i^s denote the socially optimal level of capacity at location i that satisfies the i^{th} first order condition:

$$f_i(k_1^s, \ldots, k_n^s) + \sum_{i=1}^{n} \frac{\partial f_i}{\partial k_i}(k_1^s, \ldots, k_n^s) \cdot k_i^s - c = 0. \tag{3.2}$$

The socially optimal level of capacity at location i is implicitly given by

$$k_i^s = \frac{c - f_i(k_1^s, \ldots, k_n^s) - \sum_{j \neq i} k_j^s \cdot \frac{\partial f_j}{\partial k_i}(k_1^s, \ldots, k_n^s)}{\frac{\partial f_i}{\partial k_i}(k_1^s, \ldots, k_n^s)}.$$

Comparing the Nash equilibrium condition given by equation 3.1 with the social optimum given by equation 3.2, it is clear that $k_i^* = k_i^s$ only if $\sum_{j \neq i}(\partial f_i / \partial k_j) \cdot k_j = 0$ for all i. The term $\sum_{j \neq i}(\partial f_i / \partial k_j) \cdot k_j$ captures the congestion externality. Only in the absence of a congestion externality is the Nash equilibrium equal to the social optimum.

Since $(\partial f_j / \partial k_i) \leq 0$ and $k_j \geq 0$, the congestion externality term can only equal zero if all partial derivatives are equal to zero or if nonzero, the corresponding k_j is equal to zero. Thus, if the amount of wind capacities installed at locations $i = 1, \ldots, n$ are small compared with load and line capacity, then it may indeed be true that $(\partial f_j / \partial k_i) = 0$ for all $j \neq i$, i.e. there is no congestion. In this case, the Nash equilibrium level of capacity at all locations is the same as the social optimum and $k_i^* = k_i^s$ for all i. If, however, the grid configuration is such that line capacity presents a real constraint to wind power output, i.e. there is potential for congestion, then $(\partial f_j / \partial k_i) < 0$ and $k_j > 0$ for some $i \neq j$. In this case, firms acting individually would not achieve the social optimum and $k_i^* > k_i^s$. In general, $k_i^s \leq k_i^*$ for all i. The proof is in Section B.1 in the Appendix.

3.3.3 Optimal Congestion Charge

Suppose firms are held responsible for congestion they cause that results in reductions in output at other wind plants. An optimal congestion charge would be set in such a way that profit-maximizing firms achieve the socially optimal level of installed capacity at each of the $i = 1, \ldots, n$ locations.

Firm Problem

Firms must pay a congestion charge t_i per unit of installed capacity k_i.

$$\max_{k_i} \quad f_i(k_1, \ldots, k_n)k_i - t_i k_i - ck_i$$

Let k_i^t denote the level of capacity that satisfies the first order condition:

$$f_i(k_1^t, \ldots, k_n^t) + k_i^t \frac{\partial f_i}{\partial k_i}(k_1^t, \ldots, k_n^t) - t_i - c = 0. \tag{3.3}$$

Comparing equation 3.3 with equation 3.2, it follows that the optimal congestion charge is given by

$$t_i = -\sum_{j \neq i} k_j^t \cdot \frac{\partial f_j}{\partial k_i}(k_1^t, \ldots, k_n^t).$$

Since $\partial f_j / \partial k_i \leq 0$, the congestion charge t_i is greater or equal to zero. The optimal congestion charge is equal to the sum of marginal damages from congestion induced by the wind plant at location i. The charge allows the wind plant at location i to fully internalize the effect of its output on output from all other wind plants.

3.3.4 Regional Renewable Energy Subsidy

Suppose an energy subsidy were offered in a region based on the amount of capacity installed. Depending on the size of the subsidy, this can represent a significant draw to a particular region.

Assume that the electricity grid stretches over several jurisdictions, and that Region A offers an energy subsidy of size r. Region A is defined as containing all locations $i \in I_A \subset I = \{1, \ldots, n\}$. The subsidy at location i is thus defined as

$$r_i = \begin{cases} r & \text{if } i \in I_A \\ 0 & \text{if } i \notin I_A \end{cases}$$

Firms maximize

$$\max_{k_i} \quad f_i(k_1, \ldots, k_n)k_i + (r_i - c)k_i$$

Let k_i^r denote the level of capacity that satisfies the first order condition:

$$f_i(k_1^r, \ldots, k_n^r) + k_i^r \frac{\partial f_i}{\partial k_i}(k_1^r, \ldots, k_n^r) + r_i - c = 0. \tag{3.4}$$

The subsidy is an incentive for increased investment in wind power in Region A. Comparing equations 3.4 and 3.1, it follows that $k_i^r > k_i^*$ for all $i \in I_A$ and $k_j^r = k_j^*$ for all $j \notin I_A$. The proof is in Section B.1 in the Appendix.

Congestion induced by regional renewable energy subsidies prevents wind power capacity from being fully utilized. If the subsidy is capacity-based, as in the example above, then part of the subsidy is wasted. The same holds true for production-based subsidies, since electricity production from wind plants displaces production from other wind plants rather than conventional plants.

3.3.5 How Congestion Affects Emissions Reductions by Renewable Power Plants

This section investigates the interaction of the congestion and emissions externalities. The main question is whether the institution of a congestion charge reduces or increases system-wide emissions in the absence of a price on emissions, such as carbon dioxide.

Suppose an abatement-specific production incentive a_i were offered for wind power. The subsidy amount varies across wind plant locations according to the amount of emissions reductions achieved at conventional power plants for a given grid configuration and load level. The subsidy reduces the price per kWh of wind power relative to conventional power. In terms of the amount of investment in wind capacity, this subsidy is equivalent to pricing pollution at conventional power plants, since that increases the price per kWh of conventional power relative to wind power.

The abatement-specific production incentive a_i is given exogenously and is defined to induce optimal levels of abatement given the costs of wind power and the benefits of reducing emissions. However, the optimality of a_i depends on congestion levels, since a wind power plant may substitute for different sets of conventional power plants (with different emissions rates) when there is congestion than when the grid is uncongested. If $(a_1, \ldots, a_n)$ is defined as optimal in the uncongested grid, then a_i achieves only second-best levels of abatement if the grid is congested. Optimality would require jointly determining a_i and k_i taking congestion into account, which is beyond the scope of this paper. This model is meant to provide a first illustration of how the congestion and emissions externalities interact.

This model makes the simplifying assumption that congestion alters the level of output of wind plants (quantity effect) but does not alter which conventional plants the wind plants displaces (quality effect). With this assumption, abatement potential does not depend on congestion levels and $(a_1, \ldots, a_n)$ induces optimal abatement regardless of congestion levels.

Firm Problem: Abatement-Specific Production Incentive

Suppose the government offers a production incentive that is location-specific, such that the firm receives $a_i = 1 + subsidy_i > 1$ per unit of output. The subsidy is a function of the emissions reductions at conventional power plants achieved by a wind plant at location i per unit of output for a given grid configuration and load level. Firms maximize

$$\max_{k_i} \quad a_i f_i(k_1, \ldots, k_n) k_i - c k_i.$$

Let k_i^a denote the level of capacity that satisfies the first order condition:

$$a_i f_i(k_1^a, \ldots, k_n^a) + a_i k_i^a \frac{\partial f_i}{\partial k_i}(k_1^a, \ldots, k_n^a) - c = 0. \tag{3.5}$$

The optimal capacity at location i is given implicitly by

$$k_i^a = \frac{\frac{c}{a_i} - f_i(k_1^a, \ldots, k_n^a)}{\frac{\partial f_i}{\partial k_i}(k_1^a, \ldots, k_n^a)}.$$

Social Planner Problem: Abatement-Specific Production Incentive

The social planner selects capacity at each location $i = 1, \ldots, n$ to maximize total profits:

$$\max_{k_1, \ldots, k_n} \quad \sum_{i=1}^{n} \left(a_i f_i(k_1, \ldots, k_n) k_i - c k_i\right).$$

Let k_i^{sa} denote the socially optimal level of capacity at location i that satisfies the i^{th} first order condition:

$$a_i f_i(k_1^{sa}, \ldots, k_n^{sa}) + \sum_{j=1}^{n} a_j k_j^{sa} \frac{\partial f_i}{\partial k_j}(k_1^{sa}, \ldots, k_n^{sa}) - c = 0. \tag{3.6}$$

The socially optimal level of capacity at location i is given implicitly by

$$k_i^{sa} = \frac{\frac{c}{a_i} - f_i(k_1^{sa}, \ldots, k_n^{sa}) - \frac{1}{a_i} \sum_{j \neq i} a_j k_j^{sa} \cdot \frac{\partial f_j}{\partial k_i}(k_1^{sa}, \ldots, k_n^{sa})}{\frac{\partial f_i}{\partial k_i}(k_1^{sa}, \ldots, k_n^{sa})}.$$

The set of installed capacities $(k_1^{sa}, \ldots, k_n^{sa})$ represents the socially optimal level in terms of managing both the congestion and emissions externalities.[8] Subsidizing wind power according to each plant's potential to reduce emissions at conventional plants is equivalent to pricing emissions at the conventional plants, since in both

[8] Abatement would be suboptimal without the simplifying assumption that the per-unit abatement potential of wind plants is independent of congestion (i.e. the types of conventional plants the wind plant substitutes for does not change with changes in congestion levels).

cases the relative production costs of the wind and conventional plants are realigned.

Again, $k_i^a = k_i^{sa}$ for all i only if the grid is uncongested. In general, $k_i^a \geq k_i^{sa}$ for all i. The proof is analogous to the proof that $k_i^* \geq k_i^s$ in Section B.1.

Subsidizing wind power according to its abatement potential changes the weights the social planner puts on output from plant i as compared with output from other plants $j \neq i$. As compared with k_i^s, the per-unit cost of the wind plant at location i is reduced by the factor $1/a_i$, and the congestion externality term is scaled by a_j/a_i. The social planner is thus capable of capturing any trade-offs between congestion and abatement. For example, if the plant at location i causes large amounts of congestion but has high abatement potential, then one would expect $k_i^{sa} > k_i^s$.

3.3.5.1 Pricing Congestion in the Absence of a Price on Emissions

When wind power is not subsidized according to its abatement potential, how the institution of a congestion pricing mechanism would change system-wide emissions depends on the configuration of the grid. With an optimal congestion charge (ignoring the location-specific abatement potential of wind plants), profit-maximizing firms choose the socially optimal level of capacity, i.e. $k_i^t = k_i^s$ for all i. The institution of a congestion charge results in capacity (and thus output) being reduced at some locations to ease congestion and to increase output at other locations. How this distribution of increases and decreases in output compares with the distribution of abatement potential across locations depends on the configuration of the grid in question. Thus, how the institution of a congestion charge would change system-wide emissions is uncertain. However, it is possible to draw some general conclusions from the model.

Suppose a_i is close to 1 and $a_j = \bar{a} >> 1$ for all $j \neq i$, i.e. the abatement potential of location i is very small relative to other locations and the distribution of abatement potential is skewed to the left. If location i causes non-zero congestion externalities, then instituting a congestion charge would lead to a reduction in output at location i in favor of an increase in output at other locations $j \neq i$. Since i has low abatement potential relative to locations $j \neq i$, the institution of a congestion charge would lead to a reduction in system-wide emissions.

Suppose $a_i >> \bar{a} = a_j \approx 1$ for all $j \neq i$, i.e. the abatement potential of location i is very large relative to other locations and the distribution of abatement potential is skewed to the right. If location i causes large congestion externalities, then instituting a congestion charge would lead to a large reduction in output at location i in favor of a large increase in output at all other locations $j \neq i$. Since i has high abatement potential relative to other locations, the effect on system-wide emissions is uncertain. It is clear that total wind power output increases under a congestion charge. However, the abatement increase achieved through the increase in output from low-abatement locations j may not be sufficient to make up for the large abatement decrease due to the large reduction in output from high-abatement location i. In this case, system-wide emissions may increase.

If location i causes small congestion externalities, then a congestion charge would result in a small reduction in output at location i in favor of an increase in

Table 3.2: Congestion Charge Effect on Emissions

Abatement potential of i	Congestion potential of i		Effect of congestion charge	System-wide emissions
Relatively low	> 0	$\Rightarrow$	$k_i \downarrow$ $output_{-i} \uparrow$	Down
Relatively high	High	$\Rightarrow$	$k_i \downarrow\downarrow$ $output_{-i} \uparrow\uparrow$	? Likely up
	Low	$\Rightarrow$	$k_i \downarrow$ $output_{-i} \uparrow$	? Likely down

output at all other locations. Since total wind output increases under a congestion charge, it is likely that the total abatement resulting from the increases in output at locations $j \neq i$ is sufficient to make up for the reduction in abatement at location i. In this case, system-wide emissions decrease. Table 3.2 summarizes these results.

In general, if abatement potential and the potential to cause congestion are negatively correlated, pricing congestion would likely reduce system-wide emissions. If the correlation is positive and both distributions are skewed to the right, pricing congestion could *increase* system-wide emissions. If the correlation is positive and both distributions are skewed to the left, pricing congestion would likely reduce system-wide emissions. In general, pricing congestion should reduce system-wide emissions, since it leads to an increase in overall output from wind plants, unless abatement potential and the potential to cause congestion are positively correlated and both distributions are skewed to the right.

It is important to note that pricing congestion will not always reduce system-wide emissions. In order to address both the congestion and emissions externalities, two instruments are needed - a congestion price and an emissions price.

3.4 Simulation: Wind Power Plants in the IEEE 30 Bus Test System

The following simulation study examines how the location decisions of wind power developers can affect congestion levels and electricity output at existing wind power plants. A new wind plant connecting to a grid is found to reduce output at existing plants, if they are induced to cluster in one area offering a regional renewable energy subsidy. The same number of wind plants installed at different, more distributed locations across the grid does not result in a reduction in utilized capacity through congestion. The size of the reduction in emissions achieved through wind power depends on the emissions rates of the conventional power plants. Different configurations of wind power plants across the grid result in different reductions in emissions.

3.4.1 Modified IEEE 30 Bus Test System

This paper uses a standard power flow test case - the modified IEEE 30 bus test system,[9] representing a portion of the American Electric Power system in the Midwest in 1961 [63]. The original 30 bus test system was first used by Alsac and Stott in 1974 [64] and later entered in IEEE Common Data Format by Rich Christie in 1993 [63]. The modified IEEE 30 bus test system is based on [64].[10] In addition, generator locations, costs and limits and bus areas are from [65]. This modified IEEE 30 bus test system is used widely in power flow analysis. Figure 3.2 shows the configuration of the IEEE 30 bus test system.

[9] IEEE stands for the Institute of Electrical and Electronics Engineers.

[10] Branch parameters rounded to nearest 0.01, shunt values divided by 100 and the shunt on bus 10 moved to bus 5

The IEEE 30 bus system consists of 30 buses (nodes), 41 branches (transmission lines), 6 generators, and 21 loads (demand centers). It is divided into three areas, which are interpreted as three states offering different renewable energy incentives. The bus data including the load for real and reactive power[11] are given in Table B.2 in the Appendix. The largest load (94.2 MW) is at bus 5 in Area A. The total generating capacity of the grid is 335 MW, while load is 283.4 MW. Table B.3 shows generator capacity limits and operating costs, which are assumed to be quadratic in power output P according to the function $f_P^i(P) = c_0^i + c_1^i P + c_2^i P^2$ for each of the $i = 1, \ldots, 6$ generators. At most capacity levels the generators in Area A are the least costly, while those in Area C are the most expensive. The transmission line capacity limits are given in Table B.4.

The capacities of the generators in the modified IEEE 30 bus test system range from 35 to 80 MW, which is small compared with the 500 to 2,000 MW capacity range of most fossil-fueled power plants. However, the test system is consistent within itself. Multiplying generator capacities and bus loads by some factor, while proportionally increasing line capacities, does not change the dispatch order. Similarly, while 30 distribution buses will cover only a small area, the 30 bus test system can also represent 30 transmission buses in a large region, where smaller connections between the buses are ignored. For these reasons, the IEEE 30 bus test system can be applied to the case of wind plants locating within a regional transmission grid

[11] When a coil or capacitor is connected to an alternating current (AC) power supply, it stores electrical energy during a quarter of an AC cycle and releases it back into the AC power supply in the next quarter phase. Though there is no net energy flow over one complete AC cycle, the back and forth flow of energy in each quarter cycle, called reactive power, heats up the wires, and is thus regarded by grid operators as a load.

that covers parts of three different states, represented by Areas A, B, and C.

3.4.2 Optimal Power Flow

To determine which generators are dispatched to meet the electricity load, the optimal power flow (OPF) is solved with the Matlab package MATPOWER developed by [66]. The OPF describes how to meet electricity demand at least cost while satisfying the physical constraints of the grid. The cost minimization objective function and constraints are presented in Section B.2 in the Appendix. The constraints include that supply equals demand at each bus and that the branch flow limits are not exceeded.

The optimal power flow in the baseline case of the modified IEEE 30 bus test system is depicted in Figure 3.2. The generators at buses 2 and 27 are operating at full capacity, and the branches from buses 21 to 22 and 15 to 23 are congested. The LMP ranges from 4.30 $/MWh at bus 23 to 5.02 $/MWh at bus 5. The objective function value, i.e. the total cost of producing electricity to meet demand, is 982.51 $/hour.

3.4.3 Simulation: Wind Plants Connect to the Grid

Area C is now assumed to provide a renewable energy subsidy. Three wind plants connect to the grid, and all are induced to locate in Area C due to the incentive. The wind plants at buses 24 and 25 have 21 MW capacity and the wind plant at bus 29 has 30 MW capacity. Due to the zero marginal operating costs, a wind plant

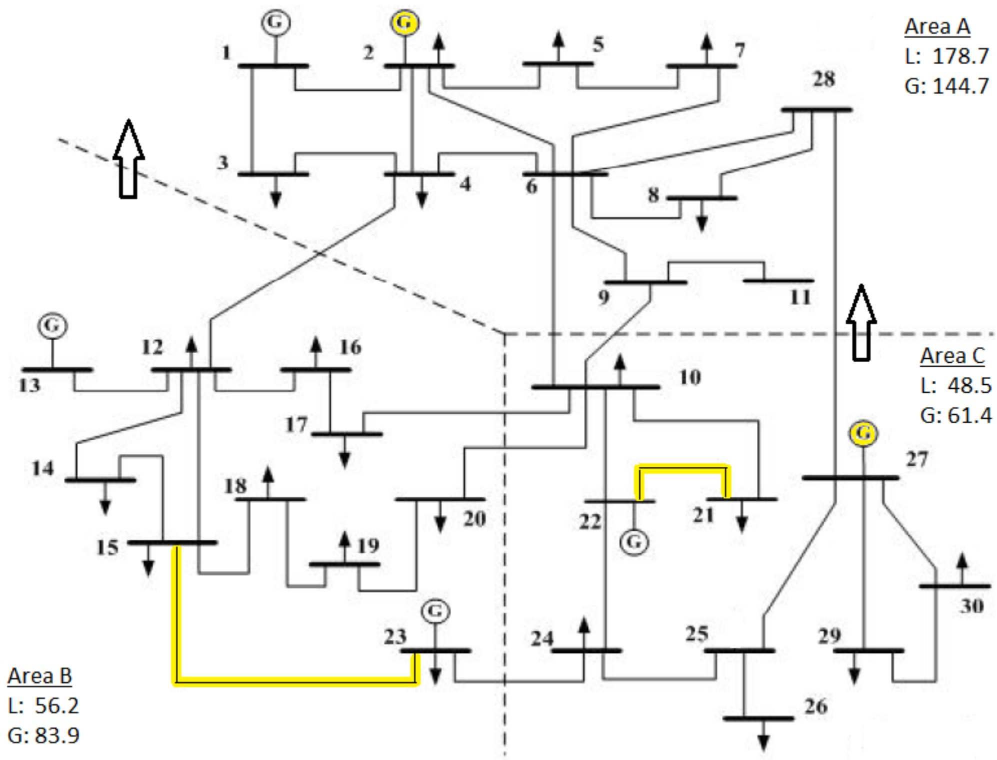

Figure 3.2: Optimal Power Flow in the Baseline Case
Highlighted generators and branches are operating at capacity.

will always be able to underbid one of the other conventional power plants, which have positive marginal operating costs. Wind power will be curtailed only when power cannot be transported to demand centers due to transmission congestion. In the OPF, the wind power plants operate at full or near-full capacity (column 2 of Table 3.3), though 6 branches are congested as compared with 2 branches in the baseline no-wind case (Table 3.4).

Next, a fourth wind plant with 30 MW capacity is added to the grid in Area C at bus 30. In the OPF, it operates at full 30 MW capacity, but the wind plant at bus 29 operates at only 13.51 MW capacity, while it was previously operating at full 30 MW capacity (column 3 of Table 3.3). This demonstrates the case of a congestion externality. The developer of the plant at bus 30 does not take into account the

Table 3.3: Optimal Power Flow Results in High Wind Speed Case: Generator Output (MWh)

	Bus Number (Capacity)	Baseline	Three Wind Plants (clustered)	Four Wind Plants (clustered)	Four Wind Plants (unclustered)
Conventional plants	Bus 1 (80 MW)	64.70	71.66	68.52	45.96
	Bus 2 (80 MW)	80.00	80.00	80.00	61.03
	Bus 22 (50 MW)	28.93	26.48	26.52	23.43
	Bus 27 (55 MW)	55.00	7.65	0.00	22.41
	Bus 23 (30 MW)	26.02	0.00	0.00	16.81
	Bus 13 (40 MW)	35.33	34.67	35.21	17.38
	Total	289.98	220.45	210.26	187.02
Wind plants	Bus 24 (21 MW)	0.00	20.09	19.75	21.00 (Bus 7, 21 MW)
	Bus 25 (21 MW)	0.00	21.00	18.32	21.00 (Bus 28, 21 MW)
	Bus 29 (30 MW)	0.00	30.00	13.52	30.00 (Bus 16, 30 MW)
	Bus 30 (30 MW)	0.00	0.00	30.00	30.00 (Bus 30, 30 MW)
	Total	0.00	71.09	81.60	102.00
Total cost	($/hr)	982.51	727.70	690.07	558.11

Table 3.4: Optimal Power Flow Results in High Wind Speed Case: Branch Constraint Shadow Prices

From bus	To bus	Baseline	Three Wind Plants (clustered)	Four Wind Plants (clustered)	Four Wind Plants (unclustered)
6	8	0	9.70	11.86	0
16	17	0	0	0	0.16
21	22	0.22	4.96	5.59	0
15	23	0.50	0	0	0
22	24	0	7.30	7.86	0
23	24	0	0.26	0.32	0
24	25	0	0.79	3.50	0
27	29	0	1.10	2.76	0
6	28	0	0	0	0.24

All other branches are unconstrained with a shadow price equal to zero.

effect of the plant's power output on congestion levels that affect other wind power plants - here most significantly the plant at bus 29. The branch constraint shadow prices (i.e. congestion prices) are presented in Table 3.4. With the addition of the fourth wind plant at bus 30, congestion increases on all 6 already congested branches.

Adding a fourth wind plant at bus 30 means that over half of the wind power plant capacity at bus 29 remains idle. Of course, output at the conventional power plants is also affected, notably the plants at buses 23 and 27. Since wind power plants represent the cheaper alternative, the reduction in output at the more expensive conventional power plants is beneficial to consumers. The plants at buses 23 and 27 may over time be mothballed or shut down completely.

A different distribution of four wind plants across the potential wind plant sites results in a different reduction of output for the conventional power plants. Column 4 of Table 3.3 shows the OPF results for the case where four wind plants are more uniformly distributed across the grid. Two wind plants of 21 MW capacity connect to buses 7 and 28 in Area A, which is where the greatest electricity demand is located, and two wind plants of 30 MW capacity connect to buses 16 and 30 in Areas B and C, respectively. All four plants operate at full capacity, as opposed to the case of clustered plants presented in column 3 of Table 3.3. The conventional power plants produce 210.25 MWh and 187.02 MWh in a given hour in the clustered and unclustered case, respectively.

If all conventional power plants had the same emissions rate, the unclustered case would result in a greater reduction in emissions than the Nash equilibrium case. If the emissions rates of the plants at buses 23 and 27 were significantly higher than those of the other plants, it may be the case that the clustered plants case results in lower total emissions despite the lower wind power output.

While the effect of the distribution of wind power plants across potential sites on the total emissions produced by the conventional power plants in an hour for a given level of electricity demand is unclear, it is certain that the distribution induced by a social planner would result in greater or equal wind power output than the distribution induced by individual firms, since the social planner takes congestion into account. Given that conventional power plants have non-zero emissions, it is likely that the distribution of wind plants induced by a social planner would result in lower emissions.

3.4.4 Generator Output for Different Wind Speed and Load Levels

Wind does not blow constantly all the time. In fact, it is usually windy at night, when electricity demand is low. This is why transmission bottlenecks present such a problem to wind power plants. When demand is low but wind power plant output is high, electricity must be transported over greater distances to reach a sufficient amount of demand. Table 3.5 shows the generator output for different load levels and wind speeds in the case of four wind plants connected to the grid in Area C at buses 24, 25, 29, and 30. Four load levels are considered - 25%, 50%, 75%, and 100% of the original load, which occur with 21%, 17%, 38%, and 25% probability. Low, medium, and high wind speeds have a certain probability of occurring at different load levels. The assumed joint probability of wind speed and load levels is given in the second row of Table 3.5. High wind speeds are most likely to occur during hours of low electricity load. This joint distribution is one of many possible distributions.

Based on the joint probability of wind speed and load level, each column in Table 3.5 occurs with a certain probability. The expected output of each generator is presented in Table 3.6 for the baseline, three wind plants, and four wind plants scenarios. Expected output for the generator at bus 27 is significantly reduced from 31.46 MWh to 11.96 MWh for a given hour with the addition of four wind plants in Area C. The addition of a fourth wind plant at bus 30 reduces expected wind plant output at bus 29 from 17.24 to 13.24 MWh for a given hour due to transmission congestion. Total expected wind output in the unclustered case is higher than in the clustered case, since the overall congestion level is lower.

Table 3.5: Generator Output for Different Load and Wind Speed Levels: Four Wind Plants Clustered Case

	Low Wind Speed				Medium Wind Speed				High Wind Speed			
Load Level	25%	50%	75%	100%	25%	50%	75%	100%	25%	50%	75%	100%
Probability (joint)	0.04	0.04	0.28	0.04	0.05	0.05	0.10	0.20	0.10	0.05	0.03	0.03
Conventional plants												
Bus 1 (80 MW)	9.12	32.07	43.80	59.75	0	25.63	40.95	62.71	0	17.36	39.49	68.52
Bus 2 (80 MW)	17.72	44.44	58.32	77.30	5.02	36.97	54.95	80	0	27.45	53.37	80
Bus 22 (50 MW)	10.93	18.60	22.67	26.20	7.30	16.41	22.31	26.55	8.15	23.81	29.19	26.52
Bus 27 (55 MW)	0	1.17	25.43	40.13	0	0	8.27	11.83	0	0	0	0
Bus 23 (30 MW)	0	6.23	15.27	20.23	0	0.94	11.37	11.66	0	0	0	0
Bus 13 (40 MW)	0	6.97	16.90	32.63	0	1.84	14.52	31.28	0	0	13.67	35.21
Total	37.77	109.47	182.38	256.23	12.31	81.80	152.38	224.03	8.15	68.63	135.73	210.26
Wind plants												
Bus 24 (7,14,21 MW)	7.00	7.00	7.00	7.00	14.00	14.00	14.00	14.00	14.59	20.35	21.00	19.75
Bus 25 (7,14,21 MW)	7.00	7.00	7.00	7.00	14.00	14.00	14.00	14.00	16.44	18.69	20.30	18.32
Bus 29 (10,20,30 MW)	10	10	10	10	13.19	15.20	17.28	19.36	10.36	10.99	11.75	13.52
Bus 30 (10,20,30 MW)	10	10	10	10	20	20	20	20	24.85	27.58	30	30
Total	34.00	34.00	34.00	34.00	61.19	63.20	65.28	67.36	66.24	77.61	83.05	81.60
Total cost ($/hr)	74.81	282.84	539.83	839.07	19.84	194.72	431.50	722.99	12.31	161.24	381.57	690.07

Generator capacities at each bus are given in parentheses. Low and medium wind speeds are modeled as a reduction wind plant capacity by two-thirds and one-third, respectively, as compared with the high wind speed case. A 21 MW plant thus has a capacity of 7 MW in the low wind speed case and 14 MW in the high wind speed case.

Table 3.6: Expected Generator Output for Different Wind Speed and Load Levels

	Bus Number (Capacity)	Baseline	Three Wind Plants (clustered)	Four Wind Plants (clustered)	(unclustered)
Conv. plants	Bus 1 (80 MW)	45.11	39.50	37.79	33.40
	Bus 2 (80 MW)	59.09	52.00	50.21	45.13
	Bus 22 (50 MW)	22.92	20.82	20.70	18.23
	Bus 27 (55 MW)	31.46	18.68	11.96	19.21
	Bus 23 (30 MW)	15.38	9.79	8.85	11.40
	Bus 13 (40 MW)	18.33	15.85	15.34	11.98
	Total	192.29	156.65	144.85	139.35
Wind plants	Bus 24 (7,14,21 MW)		12.23	11.89	12.35 (Bus 7, 21 MW)
	Bus 25 (21 MW)		12.60	11.94	12.24 (Bus 28, 21 MW)
	Bus 29 (30 MW)		17.24	13.24	17.24 (Bus 16, 30 MW)
	Bus 30 (30 MW)			17.36	16.34 (Bus 30, 30 MW)
	Total		42.07	54.44	58.17

3.5 Optimal Policy

Wind power curtailment as a result of congestion represents an inefficiency on two counts. First, government subsidies are partially wasted, since wind power capacity is not fully utilized. Second, curtailment means that available wind power is not used to replace production from conventional power plants that produce emissions. This represents a lost opportunity for reducing air pollution.

The point of renewable energy subsidies is to reduce pollution by increasing the portion of electricity generated through renewable resources. When wind power is curtailed due to transmission constraints, conventional power plants, which over time might have shut down in the absence of congestion, remain operational, delaying the transition to cleaner electricity.

The optimal government policy would be the institution of a carbon price in conjunction with marginal cost pricing of electricity transmission congestion, such as exists in some regional transmission organizations today. The carbon price (and prices or caps on other air pollutants) would ensure that air pollution externalities are appropriately internalized rather than through the roundabout method of subsidizing renewable power, disregarding each plant's contribution to emissions reductions. Marginal cost congestion pricing across the entire grid would ensure efficient use of congested lines. With the removal of the air pollution externality through the carbon price, there is no need to pay special attention to the adverse effect of congestion on wind power as opposed to conventional power.

In the absence of a national carbon price, congestion pricing usually reduces system-wide emissions, but this depends crucially on relative abatement potential of the various affected renewable power plants. In the absence of both a national carbon price and congestion pricing, the government should take into account the effect of regional renewable energy subsidies on transmission congestion levels through clustering of wind plants. It is important to note that congestion pricing alone does not guarantee a reduction in emissions. Two instruments - a price on congestion and a price on emissions - are necessary to appropriately deal with the two externalities.

3.6 Conclusions

This paper models the effect of individual renewable power plant location on total system-wide renewable power output by examining the electricity transmission congestion externality. The model developed in this paper shows that a social planner taking the congestion externality into account would build smaller renewable power plants in areas with an already high penetration of renewable power than individual firms would, thereby reducing renewable power curtailment. In addition, state-level renewable energy subsidies contribute to transmission congestion, since they induce clustering of wind power plants.

While the location decision of any type of power plant affects output at other plants, this paper is concerned with renewable power plants in particular, for two reasons. First, they are more susceptible to transmission congestion than conventional power plants due to constraints in expanding the existing transmission grid infrastructure. Second, curtailment at renewable power plants results in a reduction in abatement.

A simulation of optimal power flow in the modified IEEE 30 bus test system shows that the location of a new renewable power plant affects congestion levels and output at existing plants. If renewable power plants are drawn to an area through a renewable energy subsidy, the clustering of plants leads to higher congestion levels and lower total renewable power output than otherwise. This means that current state-level subsidies are less effective because of transmission congestion, since part of the installed renewable power capacity remains idle during congested hours.

Renewable energy subsidies are intended to correct for the lack of price on air pollution from conventional power plants. The goal is to change the energy mix to reduce overall air pollution levels. Which type of plant a renewable power plant substitutes for depends upon the configuration of the electricity grid in question. Transmission congestion may mean that the dirtiest coal plants continue operating, while cleaner natural gas plants make way for renewable plants. Renewable power plant developers do not take into account which types of plants their power will substitute for given the configuration of the grid. This is why renewable energy subsidies are less efficient at abating emissions than a policy that prices emissions at conventional plants.

An optimal policy would take the form of a national carbon price to address the carbon emissions externality in conjunction with congestion pricing across all areas of the grid. In the absence of a carbon price, system-wide emissions should usually be reduced by the institution of congestion pricing, though there are notable exceptions. In the absence of both a carbon price and congestion pricing, state-level incentives could be improved if they take into account the effect of the incentive on renewable power plant location, which in turn affects congestion and abatement levels.

Chapter 4

Severe Censoring in the Tobit Model

Abstract

This paper studies the effect of the degree of censoring on random-effects Tobit estimates in finite sample, with a particular focus on severe censoring, when the percentage of uncensored observations reaches as low as 1 percent. The Monte Carlo method is used to analyze the effect of varying the percentage of uncensored observations from 63 to 1 percent in different sample sizes of $N \in \{1000, 2000, 3000, 4000, 5000\}$ and $T \in \{1, 2, 3, 5, 8\}$. The results show that the Tobit model performs well even at 5 percent uncensored observations with the bias in the estimated coefficients, standard errors, marginal effects, and disturbance standard deviation remaining at or below 5 percent for most combinations of T and N. Under severe censoring (1 percent uncensored observations), large biases - mostly under 100 percent - appear in the estimated standard errors and marginal effects. These are generally reduced as the sample size increases in both N and T.

Keywords: Tobit; Panel data; Monte Carlo; Censoring; Finite sample; Marginal effects

4.1 Introduction

In some lines of research, it is quite common for the dependent variable in an econometric analysis to be severely censored. In marketing, response rates to untargeted direct mailings may often only reach 0.5 percent, depending on the product or service advertised [67]. Similarly, the participation rate in voluntary government programs, such as for environmental conservation or energy efficiency, can be quite low. When researchers are faced with a severely censored dependent variable, the temptation is there to drop the censored observations and focus on the sub-sample of uncensored observations, because of uncertainty about how the econometric models for dealing with censored data perform in finite sample. This would be a mistake, since results from the analysis of the sub-sample of uncensored observations would not be generalizable to the whole population.

This paper performs a Monte Carlo analysis of the Tobit model in finite sample to determine the degree of bias in the estimates of the coefficients, standard errors, disturbance standard deviation, and marginal effects for varying degrees of censoring. Knowledge about the presence or absence of bias in the Tobit estimates should be useful to applied economists in various fields dealing with severely censored data.

While there is no theoretical reason for the degree of censoring to affect Tobit estimates asymptotically, it is unclear how the estimates behave in a finite sample with severe censoring. Literature on the effect of the degree of censoring on the coefficient estimates is scarce. Greene (2004) [68] investigates the incidental parameters problem in the *fixed effects* Tobit model. As part of this study he finds that changing the degree of censoring from 20 to 64 percent has little effect on the coefficient estimates. This study, however, does not look at the case of more severe censoring. Cramer et al. (1999) [69] analyze the effect of severe censoring (99.5 percent), but their results are not based on generated data. Instead, they use a given dataset from a bank on the rate of switching from savings to investment accounts and find that the coefficient estimates do not change dramatically with the degree of censoring. However, the true value of the coefficient is unknown, as is the direction of the bias, since some coefficient estimates first increase and then decrease with the degree of censoring. Neither of these two studies adequately addresses the issue of severe censoring in the Tobit model in finite sample. This paper aims to fill that void.

The Monte Carlo study in this paper sheds light on how the maximum likelihood estimator of the Tobit model behaves in finite sample when the dependent variable is severely censored. Several scenarios are analyzed. The percentage of uncensored observations changes from 1.1 (severe) to 5.1, 16, 37, and 63. The number of individuals varies from $N = 1000$ to 2000, 3000, 4000, and 5000. Finally, the cross-sectional case is considered ($T = 1$) as well as the random-effects panel cases with $T = 2$, 3, 5, and 8. In all scenarios, the bias in percent is calculated for the coefficient estimates, standard errors, marginal effects, and the disturbance standard deviation.

This paper finds that the Tobit model performs quite well overall even in the case of more severe censoring. With 5 percent uncensored observations, the Tobit estimates are largely unbiased for all combinations of T and N considered. With only 1 percent uncensored observations, estimates of the marginal effects should be treated with caution in most cases. Significant bias is present for $T = 1$, 2, and 3. Only for $T = 5$ and $N \geq 3000$ as well as $T = 8$ and $N \geq 2000$ is the bias in the estimates of the marginal effects low. Here, the marginal effects are underestimated by up to 12 percent, and can thus provide a lower bound on the true effect.

4.2 Tobit Model

A dependent variable is censored if it is continuous but bounded from above and/or below. The values of the dependent variable outside of the threshold are unknown and are recorded as equal to the threshold. Censoring in this regard is the result of data observability. For example, the concentration of air or water pollutants may be undetectable under a certain threshold as given by the measuring technology. The pollutant concentration variable is thus censored from below at the detection threshold.

A similar type of censoring is exhibited in the corner solution model, though it is not the result of data observability. Here, the dependent variable is the solution to an optimization problem. It equals the corner solution (usually zero) with positive probability and is continuous elsewhere. For example, the dependent variable could measure the optimal amount of investment in renewable power in mega-watts in county i in period t. For the vast majority of county-time observations, this is zero, i.e. it is not optimal to invest in renewable power. Annual household expenditures on durable goods, such as cars or housing, are another example.

When the dependent variable is continuous but bounded from above or below, ordinary least squares (OLS) estimation leads to slope coefficient estimates that are biased toward zero, since variation in the regressors is not fully captured by variation in the dependent variable due to the constraints imposed by censoring.[1] The Tobit model was developed by James Tobin to deal with this type of nonlinearity [71].

It is important to note that the coefficient estimates in the Tobit model represent the marginal effect of an independent variable x on the unobserved latent censored variable y^* and thus can not be interpreted as the marginal effect of x on the observed dependent variable y, as in the linear regression model. Rather, the coefficients reflect the combination of (1) the change in y of those above the limit, weighted by the probability of being above the limit, and (2) the change in the probability of being above the limit, weighted by the expected value of y if above [72]. The marginal effect of x on y depends on all coefficient estimates as well as on the estimate of the disturbance standard deviation.

This study investigates the finite sample bias of severe censoring for different sample sizes of varying T and N. The Tobit maximum likelihood estimator assumes normality and homoskedasticity, and is inconsistent when the disturbance is non-normal or heteroskedastic [73, 74]. Similarly, when the residuals are serially dependent, the maximum likelihood estimator is still consistent, though inefficient [31]. How the Tobit model behaves in finite sample with severe censoring, when any of these assumptions is violated, is worth asking but beyond the scope of this paper.

[1] In fact, the bias in the OLS slope estimates can be corrected by dividing OLS slopes by the proportion of nonlimit observations in the sample [70].

4.3 Experimental Setup of the Monte Carlo Study

Consider the latent model

$$y_{it}^{*} = c + \beta x_{it} + \delta d_{it} + \alpha_i + \epsilon_{it} \tag{4.1}$$

for $i = 1, \ldots, N$ individuals and $t = 1, \ldots, T$ time periods. The observed variable is

$$y_{it} = \begin{cases} y_{it}^{*} & \text{if} \quad y_{it}^{*} > 0 \\ 0 & \text{if} \quad y_{it}^{*} \leq 0. \end{cases}$$

The sample log likelihood for $i = 1, \ldots, N$ individuals over $t = 1, \ldots, T$ time periods is given by equation 4.2. The function $\lambda(\cdot)$, known as the inverse Mills ratio, is defined as $\lambda(\cdot) \equiv \frac{\phi(\cdot)}{\Phi(\cdot)}$.

$$\begin{aligned} \ln L = \sum_{i=1}^{N} \Bigg[\sum_{t=1}^{T} \mathbf{1}_{[y_{it}=0]} \ln \left(1 - \Phi \left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma} \right) \right) + \\ + \mathbf{1}_{[y_{it}>0]} \ln \left(\sigma^{-1} \phi \left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma} \right) \right) \end{aligned} \tag{4.2}$$

The data of N individuals over T time periods are generated according to the following specifications, which are based on [68].

1. $x_{it} \sim N(0, 1)$ is a continuous variable.

2. $d_{it} = \mathbf{1}[e_{it} > 0]$ where $e_{it} \sim N(0, 1)$ is an indicator variable.

3. $\epsilon_{it} \sim N(0, \sigma)$ is the error term, and the variance $\sigma = 1$.

4. $\alpha_i = 0.3u_i$ where $u_i \sim N(0,1)$ is the individual effect.

5. The coefficients are set as $\beta = 1$ and $\delta = 1$.

6. Varying the constant $c \in \{-4, -3, -2, -1, 0\}$ changes the percentage of uncensored observations from 1 to 63.

7. The latent variable is generated as $y^*_{it} = c + \beta x_{it} + \delta d_{it} + \alpha_i + \epsilon_{it}$. For cross-sectional data with $T = 1$, the latent variable is $y^*_i = c + \beta x_i + \delta d_i + \epsilon_i$.

8. The observed censored variable is $y_{it} = \max\{0, y^*_{it}\}$ and $y_i = \max\{0, y^*_i\}$ in the cross-sectional case.

The x variable is generated at the beginning of the study and remains fixed throughout. In each of the 1000 replications, error terms are (re-)generated and a random-effects Tobit model is estimated using the statistical software package STATA. The Monte Carlo study is strictly replicable.[2]

As in [68], the results of the Monte Carlo experiments are presented as the average of 1000 replications of the estimated bias in the estimates, measured against the true values. The bias is reported in percent. The true values of $\beta = \delta = \sigma = 1$ are known, but the true parameter values of the marginal effects and the standard errors do not exist and are estimated with the data.

The standard error of β and δ, averaged over all replications, is compared with the "true" standard error, which is taken as the standard deviation of the distribution of the estimated β and δ over all replications.

[2]The code for the Monte Carlo study as well as the seed for the random number generator are available from the author upon request.

4.3.1 Marginal Effects

Three types of marginal effects are considered: The marginal effect of x or d on the latent dependent variable y^* (1), the marginal effect of x or d on the expected censored variable y conditional on $y > 0$ (2) and unconditional on y (3). They are derived, respectively, from the three conditional mean functions given by equations 4.3, 4.4, and 4.5.

Which type of marginal effect is of interest for a particular study depends on the context. In the corner solution model, the marginal effect of the independent variables on the latent variable y^* will usually be uninteresting, since censoring is a byproduct of the maximization problem rather than due to data observability issues. When the dependent variable is censored in the traditional sense due to observability, the marginal effect of the independent variables on y^* could be of primary interest. As any of the three types of marginal effects can be of interest depending on the research question, this paper reports percentage bias for all three types.

$$\mathbb{E}\left[y_{it}^*|x_{it}, d_{it}, \alpha_i\right] = c + \alpha_i + \beta x_{it} + \delta d_{it} \tag{4.3}$$

$$\mathbb{E}\left[y_{it}|x_{it}, d_{it}, \alpha_i\right] = (c + \alpha_i + \beta x_{it} + \delta d_{it}) \cdot \Phi\left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma}\right) + \\ + \sigma \cdot \phi(c + \alpha_i + \beta x_{it} + \delta d_{it}) \tag{4.4}$$

$$\mathbb{E}\left[y_{it}|x_{it}, d_{it}, \alpha_i, y_{it} > 0\right] = c + \alpha_i + \beta x_{it} + \delta d_{it} + \sigma\lambda\left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma}\right) \quad (4.5)$$

The marginal effects of x and d on the latent unobserved variable y^* are derived from equation 4.3. They are simply equal to the corresponding coefficients, similar to the standard linear regression model, and are given by equations 4.6 and 4.7. The true value of these marginal effects is known, since $\beta = \delta = 1$.

$$\frac{\partial \mathbb{E}\left[y^*_{it}|\alpha_i, x_{it}, d_{it}\right]}{\partial x_{it}} = \beta \quad (4.6)$$

$$\frac{\partial \mathbb{E}\left[y^*_{it}|\alpha_i, x_{it}, d_{it}\right]}{\partial d_{it}} = \delta \quad (4.7)$$

The unconditional marginal effects $ME_x(y)$ and $ME_d(y)$, derived from equation 4.4, are given by equations 4.8 and 4.9.

$$ME_x \equiv \frac{\partial \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it}\right]}{\partial x_{it}} = \beta \cdot \Phi\left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma}\right) \quad (4.8)$$

$$\begin{aligned} ME_d &\equiv \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it} = 1\right] - \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it} = 0\right] = \\ &= (c + \alpha_i + \beta x_{it} + \delta)\left[\Phi\left(\frac{c + \alpha_i + \beta x_{it} + \delta}{\sigma}\right) - \Phi\left(\frac{c + \alpha_i + \beta x_{it}}{\sigma}\right)\right] + \\ &\quad + \sigma\left[\phi\left(\frac{c + \alpha_i + \beta x_{it} + \delta}{\sigma}\right) - \phi\left(\frac{c + \alpha_i + \beta x_{it}}{\sigma}\right)\right] \end{aligned} \quad (4.9)$$

The conditional marginal effects $ME_x(y > 0)$ and $ME_d(y > 0)$ are derived from equation 4.5 and are given by equations 4.10 and 4.11.

$$ME_x(y > 0) \equiv \frac{\partial \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it}, y_{it} > 0\right]}{\partial x_{it}} =$$
$$= \beta \left\{ 1 - \lambda\left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma}\right)\left[\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma} + \lambda\left(\frac{c + \alpha_i + \beta x_{it} + \delta d_{it}}{\sigma}\right)\right]\right\} \tag{4.10}$$

$$ME_d(y > 0) \equiv \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it} = 1, y_{it} > 0\right] - \mathbb{E}\left[y_{it}|\alpha_i, x_{it}, d_{it} = 0, y_{it} > 0\right] =$$
$$= \delta + \sigma\left[\lambda\left(\frac{c + \alpha_i + \beta x_{it} + \delta}{\sigma}\right) - \lambda\left(\frac{c + \alpha_i + \beta x_{it}}{\sigma}\right)\right] \tag{4.11}$$

The estimated and "true" marginal effects of x and d on the observed censored dependent variable are calculated as the average marginal effect at each $N \times T$ data-point rather than once at the data means. The estimated version uses the estimated values of β, δ, and σ, while the "true" version uses the true values of $\beta = \delta = \sigma = 1$ and also includes the true individual effects α_i. These data-point-average marginal effects are then averaged again over all the replications to produce the final values, upon which the percentage bias calculations are based.

4.4 Results

Table 4.1 demonstrates the effect of censoring on Tobit estimates for varying N for the cross-sectional case with $T = 1$. For 63, 37, and 16 percent uncensored observations, the percent bias in the Tobit estimates of the coefficients, standard errors, marginal effects, and the variance remains below 1 percent and only occasionally reaches 5 percent. As the degree of censoring increases such that only 5 and 1 percent of the observations are uncensored, bias appears in the estimates of the marginal effects on the observed censored variable y (though not on y^*, these marginal effects are the coefficients, which are largely unbiased). When 5 percent of the observations are uncensored, the Tobit model performs well only for $N \geq 3000$. Under severe censoring (1 percent uncensored observations), the Tobit model does not perform well in finite sample with $N \leq 5000$, since the marginal effects are biased up to 150 percent. With $N \geq 4000$, the bias of the marginal effects conditional on $y > 0$ drops below 10 percent, but estimates of the marginal effects unconditional on y remain biased upwards of 37 percent. Thus, for $T = 1$ under severe censoring, estimates of the marginal effects on the observed censored dependent variable should be treated with caution.

Table 4.2 shows the effect of censoring on Tobit estimates for varying N and fixed $T = 2$. In a small sample of $N = 1000$, the Tobit model performs quite well even up to 5 percent uncensored observations. Estimates of the coefficients, standard errors, marginal effects, and the variance are biased by only 0 to 5 percent. However, at 1.1 percent uncensored observations the percentage bias of the estimates is large, particularly for the indicator variable. The marginal effects unconditional on y are biased upwards by 768 percent, and the standard error is inflated by a factor of 19. The estimated coefficient of the continuous variable is unbiased, but the bias shows up in the marginal effects, which are inflated by 218 and 121 percent.

For $T = 2$, the estimates do not consistently improve with increased N and decreased censoring, though there is a general tendency. The bias in the marginal effects unconditional on y is reduced to around 16 percent for $N = 5000$ and $c = -4$. The bias in the marginal effects conditional on $y > 0$ is even lower, at 9 percent for the continuous variable and 1 percent for the indicator variable. The standard error of δ, which is inflated for $N = 1000$ and $c = -4$, is initially reduced with increasing N but then turns increasingly negative, thereby underestimating the true standard error.

In general for $T = 2$, under severe censoring with only 1.1 percent uncensored observations, the marginal effects are biased upwards and the standard errors are biased as well, though the direction of the bias depends on N. For small N, the standard error of the indicator variable is overestimated, but in all other cases the standard errors are underestimated. Attenuation in the estimates of the standard errors could lead to faulty inference about variable significance due to inflated Wald test statistics.

Table 4.3 presents the Monte Carlo results for $T = 3$, varying N, and varying degrees of censoring. Again, the Tobit model performs quite well for up to 5 percent uncensored observations ($c = -3$), though with some attenuation in the standard error estimate of the indicator variable at 16 percent uncensored observations. Most of the bias for the severe censoring case appears as an overestimation of the marginal effects unconditional on y and an underestimation of the standard errors. A positive result is that the estimated marginal effects conditional on $y > 0$ are unbiased for $T = 3$ and $N \geq 2000$.

For $T = 5$ and $T = 8$, only the results for the severe censoring case are reported in Tables 4.4 and 4.5, respectively, since the Tobit estimates for uncensored observations of 5 percent or more are effectively unbiased. For $T = 5$ and $N \leq 2000$, the standard errors are underestimated and the marginal effects are overestimated for both the continuous and binary dependent variables. For $N \geq 3000$, the estimates are largely unbiased. Similarly, for $T = 8$ and $N \geq 2000$, the bias in the estimates of the marginal effects in the severe censoring case remains below 12 percent.

A caveat for the interpretation of these results relates to the number of replications. Particularly in the case of severe censoring ($c = -4$), convergence in the numerical computation of the maximum likelihood could not be achieved after 30 iterations in some of the 1000 replications. Table 4.6 reports the percentage of replications, which produced no results due to non-convergence. The analysis above is based on those replications, in which convergence was achieved. For example in the worst case encountered here with $T = 8$, $c = -4$, and $N = 5000$, about 50 percent of the replications produced no results. The estimates reported for this case are thus based on only 500 replications.

4.5 Conclusions

This paper is the result of an econometric problem encountered in determining the drivers of wind power in the United States [45]. Optimal investment in wind power for a particular county in a particular year is usually zero - the corner solution to an optimization problem. It was unclear *a priori* how the Tobit model would handle censoring of the dependent variable exceeding 98 percent in finite sample. A review of the literature provided an unsatisfactory answer to this question, which prompted the research in this paper.

Overall, the Tobit model performs well in finite sample with even up to 5 percent uncensored observations for all combinations of $T \in \{1, 2, 3, 5, 8\}$ and $N \in \{1000, 2000, 3000, 4000, 5000\}$ considered. Under severe censoring with 1 percent uncensored observations, the percentage bias can be large, in particular for the standard errors and marginal effects on the observed censored dependent variable.

For the case of severe censoring (1 percent uncensored observations), the following results hold. For researchers interested in the marginal effect of the independent variables on the unobserved latent dependent variable y^*, the Tobit model provides reasonably unbiased coefficient estimates for $T = 1$ and $N \geq 2000$, $T = 2$ and $N \geq 3000$ (with attenuated standard errors), $T = 3$ and $N \geq 2000$ (with attenuated standard errors), $T = 5$ and $N \geq 1000$ (with attenuated standard errors), and $T = 8$ and $N \geq 2000$. In general, the estimates of coefficients and standard errors are largely unbiased for any T and $N \geq 3000$ for the case of severe censoring.

For researchers interested in the marginal effect of the independent variables on the observed censored variable y, unconditional on y, the Tobit model provides reasonably unbiased estimates of this type of marginal effect in the case of severe censoring (1 percent uncensored observations) for $T = 5$ and $N \geq 3000$, and $T = 8$ and $N \geq 2000$. The estimates of this marginal effect are biased for $T = 1$, 2, and 3.

If the marginal effect of the independent variables on the observed censored variable y, conditional on $y > 0$, is of interest, the Tobit model provides reasonably unbiased estimates of this type of marginal effect in the severe censoring case (1 percent uncensored observations) for $T = 1$ and $N \geq 4000$, $T = 2$ and $N \geq 5000$, $T = 3$ and $N \geq 2000$, $T = 5$ and $N \geq 3000$, and $T = 8$ and $N \geq 2000$.

The Monte Carlo results presented here for combinations of $T \in \{1, 2, 3, 5, 8\}$ and $N \in \{1000, 2000, 3000, 4000, 5000\}$ should be of use to applied economists facing severely censored data. For those combinations of T and N that do produce biased estimates, the direction of the bias can be useful to provide upper or lower bounds on estimates.

Table 4.1: Effect of Censoring on Tobit Estimates for $T = 1$ (Percent Bias)

		$c = 0$	$c = -1$	$c = -2$	$c = -3$	$c = -4$
	Uncensored (%)	63	37	16	4.9	1.0
$N = 1000$	β	0.217	0.118	0.37	0.294	2.3
	$SE(\beta)$	0.696	-0.642	0.0615	-1.54	-2.52
	ME_x	0.218	0.232	1.38	12.4	150
	$ME_x(y > 0)$	0.567	0.683	1.69	4.89	29.6
	δ	0.173	0.281	0.457	1.83	-14
	$SE(\delta)$	-4.51	-1.63	-0.79	-5.02	15.4
	ME_d	0.314	0.564	1.79	20.2	97.5
	$ME_d(y > 0)$	0.394	0.623	1.13	4.1	-7.22
	σ	-0.212	-0.379	-0.644	-2.04	-6.67
$N = 2000$	β	0.0589	0.192	0.185	-0.144	-0.874
	$SE(\beta)$	-1.31	-4.77	-2.77	-1.32	-1.62
	ME_x	0.0795	0.363	0.648	5.53	81.8
	$ME_x(y > 0)$	0.216	0.458	0.901	2.27	10.4
	δ	0.158	0.395	0.206	0.992	-0.509
	$SE(\delta)$	0.965	0.119	5.07	-2.63	7.87
	ME_d	0.251	0.63	0.815	10.4	75.4
	$ME_d(y > 0)$	0.293	0.659	0.463	1.96	4.79
	σ	-0.161	-0.167	-0.36	-1.15	-3.71
$N = 3000$	β	0.161	0.19	0.135	0.122	0.549
	$SE(\beta)$	-0.772	-1	-2.8	-4.52	0.454
	ME_x	0.15	0.308	0.386	4.81	80.2
	$ME_x(y > 0)$	0.31	0.311	0.579	1.39	5.76
	δ	0.0646	0.198	-0.0341	0.463	4.91
	$SE(\delta)$	-2.79	-2.42	-0.905	-2.79	-2.47
	ME_d	0.109	0.363	0.377	7.01	72.5
	$ME_d(y > 0)$	0.132	0.377	0.155	1.43	12.6
	σ	-0.0283	0.00603	-0.174	-0.482	-1.69
$N = 4000$	β	-0.00631	-0.066	-0.0352	-0.109	0.0247
	$SE(\beta)$	-0.0759	4.03	-0.747	-0.22	-3.81
	ME_x	0.00106	-0.125	-0.056	1.96	54.1
	$ME_x(y > 0)$	0.0691	0.131	0.355	1.08	4.1
	δ	0.0277	-0.0892	-0.145	-0.231	2.2
	$SE(\delta)$	4.61	2.16	-1.15	-1.82	-0.589
	ME_d	0.0645	-0.0962	0.0582	3.66	45.3
	$ME_d(y > 0)$	0.0852	-0.079	-0.109	0.046	6.65
	σ	-0.0997	-0.162	-0.179	-0.475	-1.34
$N = 5000$	β	0.0534	0.138	0.149	0.14	0.863
	$SE(\beta)$	0.137	0.471	1.25	1.36	0.469
	ME_x	0.0752	0.198	0.535	2.72	48.3
	$ME_x(y > 0)$	0.145	0.321	0.348	0.75	3.45
	δ	0.127	0.136	0.25	0.177	3.21
	$SE(\delta)$	-1.48	-0.183	-2.6	0.649	-3.65
	ME_d	0.185	0.209	0.671	3.47	36.6
	$ME_d(y > 0)$	0.213	0.247	0.475	0.741	8.02
	σ	-0.124	-0.123	-0.0852	-0.186	-0.776

Shaded cells indicate bias in excess of 10 percent.

Table 4.2: Effect of Censoring on Tobit Estimates for $T = 2$ (Percent Bias)

		$c = 0$	$c = -1$	$c = -2$	$c = -3$	$c = -4$
	Uncensored (%)	63	37	16	5.1	1.1
$N = 1000$	β	0.0971	0.146	0.169	0.0301	0.171
	$SE(\beta)$	1.85	1.9	1.62	0.176	-13.1
	ME_x	0.469	-0.425	-2.15	-2.49	218
	$ME_x(y > 0)$	0.241	0.39	0.942	5.63	121
	δ	0.0868	0.197	0.269	0.9	21.5
	$SE(\delta)$	3.14	4.24	4.58	-4.47	1930
	ME_d	0.567	-0.389	-2.19	1.84	768
	$ME_d(y > 0)$	-0.0378	-0.552	-0.811	-0.814	110
	σ	-0.0143	-0.0443	-0.209	-2.28	-10.5
$N = 2000$	β	0.0207	-0.00902	0.0771	0.33	-0.259
	$SE(\beta)$	1.64	0.63	-3.15	-0.603	-10.9
	ME_x	0.404	-0.693	-2.66	-4.42	37.5
	$ME_x(y > 0)$	0.155	0.289	0.657	3.66	41.6
	δ	0.033	-0.0625	-0.0172	0.348	3.3
	$SE(\delta)$	-0.365	4.63	-0.865	-2.97	77.2
	ME_d	0.502	-0.792	-3.02	-3.2	66.3
	$ME_d(y > 0)$	-0.0825	-0.985	-1.38	-1.52	13.4
	σ	-0.165	-0.196	-0.205	-1.45	-5.62
$N = 3000$	β	0.0858	0.115	0.158	-0.0201	0.401
	$SE(\beta)$	-0.793	-3.28	0.821	2.61	-22.7
	ME_x	0.511	-0.361	-2.2	-5.15	29.2
	$ME_x(y > 0)$	0.137	0.185	0.299	1.58	25.6
	δ	0.264	0.326	0.35	0.473	1.76
	$SE(\delta)$	-0.357	-1.07	2.23	4.51	-5.76
	ME_d	0.769	-0.219	-2.42	-4.38	17.2
	$ME_d(y > 0)$	0.169	-0.449	-0.811	-1.05	4.35
	σ	-0.026	-0.0259	0.0122	-0.638	-2.82
$N = 4000$	β	0.0485	0.0938	-0.0344	0.0197	-0.332
	$SE(\beta)$	0.301	0.0685	1.68	0.96	-11.9
	ME_x	0.451	-0.511	-2.93	-5.28	6.27
	$ME_x(y > 0)$	0.113	0.208	0.263	1.48	12.8
	δ	0.0508	0.032	-0.0689	0.425	0.387
	$SE(\delta)$	-0.643	-1.07	-1.75	-2.17	-6.53
	ME_d	0.521	-0.648	-3.25	-4.86	7.49
	$ME_d(y > 0)$	-0.0848	-0.84	-1.49	-1.08	-2.68
	σ	-0.0761	-0.0473	-0.116	-0.548	-3.66
$N = 5000$	β	0.0178	0.0739	-0.0205	0.0897	0.423
	$SE(\beta)$	2.29	-0.742	0.105	0.571	-22.9
	ME_x	0.375	-0.589	-3.03	-5.22	15.9
	$ME_x(y > 0)$	0.0569	0.161	0.218	1.15	9.27
	δ	-0.127	-0.0956	-0.267	0.223	1.61
	$SE(\delta)$	1.63	1.42	-0.82	-3.01	-20
	ME_d	0.283	-0.834	-3.57	-5.47	16.3
	$ME_d(y > 0)$	-0.342	-1.02	-1.73	-1.14	1.29
	σ	0.0261	0.00454	-0.0453	-0.312	-2.45

Shaded cells indicate bias in excess of 10 percent.

Table 4.3: Effect of Censoring on Tobit Estimates for $T = 3$ (Percent Bias)

		$c = 0$	$c = -1$	$c = -2$	$c = -3$	$c = -4$
	Uncensored (%)	63	37	16	5.1	1.1
$N = 1000$	β	-0.0523	-0.0965	0.0332	0.222	3.16
	$SE(\beta)$	1.73	-1.28	-3.38	-9.46	-33.2
	ME_x	0.342	-0.791	-3.3	-3.31	162
	$ME_x(y > 0)$	-0.00388	0.133	1.45	4.05	31.9
	δ	0.0883	-0.0726	-0.556	0.0856	11.1
	$SE(\delta)$	-1.56	-2.22	-13.1	-8.59	488
	ME_d	0.57	-0.772	-3.81	-1.4	302
	$ME_d(y > 0)$	-0.0353	-0.979	-2.12	-1.39	41.2
	σ	-0.0495	-0.149	-0.636	-1.54	-4.44
$N = 2000$	β	0.0873	0.128	0.193	-0.044	0.786
	$SE(\beta)$	3.09	1.99	1.03	-2.8	-46.9
	ME_x	0.459	-0.435	-2.46	-4.85	50.5
	$ME_x(y > 0)$	0.159	0.198	0.486	0.87	9.65
	δ	0.0243	0.134	-0.0657	0.0487	1.88
	$SE(\delta)$	1.56	-1.18	-6.42	-2.96	-13.2
	ME_d	0.468	-0.496	-3.07	-4.76	37.6
	$ME_d(y > 0)$	-0.15	-0.705	-1.33	-1.1	3.13
	σ	0.0216	0.0204	-0.0202	-0.246	-2.67
$N = 3000$	β	0.0201	0.0908	0.155	0.193	0.488
	$SE(\beta)$	-2.1	1.43	-8.02	-0.289	-37.2
	ME_x	0.406	-0.519	-3.31	-5.28	22
	$ME_x(y > 0)$	0.0712	0.178	1.22	1.27	9.26
	δ	0.0199	0.032	-0.722	-0.0961	1.71
	$SE(\delta)$	-2.39	-1.2	-18.3	-1.53	-14.2
	ME_d	0.471	-0.654	-4.43	-5.83	24.6
	$ME_d(y > 0)$	-0.143	-0.852	-2.42	-1.5	0.442
	σ	-0.0423	-0.0145	-0.503	-0.381	-3.11
$N = 4000$	β	-0.013	0.0412	0.0505	-0.0569	1.09
	$SE(\beta)$	1.1	-0.811	-4.3	3.72	-25.8
	ME_x	0.35	-0.612	-3.2	-6.28	13.2
	$ME_x(y > 0)$	-0.00175	0.0835	0.638	0.519	5.68
	δ	-0.0706	-0.0931	-0.548	-0.358	1.25
	$SE(\delta)$	3.21	1.71	-16	0.665	-10.1
	ME_d	0.343	-0.817	-4.05	-6.96	6.12
	$ME_d(y > 0)$	-0.278	-1.03	-2.14	-1.83	1.26
	σ	0.0354	0.0337	-0.222	-0.121	-1.21
$N = 5000$	β	-0.0273	0.0119	0.142	0.0593	0.753
	$SE(\beta)$	2.22	4.16	-8.32	3.09	-46.9
	ME_x	0.344	-0.64	-3.04	-5.87	22.3
	$ME_x(y > 0)$	-0.0188	0.0544	0.769	0.6	4.56
	δ	-0.0441	-0.0535	-0.482	-0.0523	1.39
	$SE(\delta)$	0.906	-0.244	-23.6	0.42	-23.7
	ME_d	0.378	-0.784	-3.97	-6.53	17.2
	$ME_d(y > 0)$	-0.242	-0.989	-2.04	-1.45	1.96
	σ	0.00026	0.00151	-0.255	-0.162	-1.23

Shaded cells indicate bias in excess of 10 percent.

Table 4.4: Effect of Sample Size on Tobit Estimates for 1.1 Percent Uncensored Observations and $T = 5$ (Percent Bias)

	N=1000	N=2000	N=3000	N=4000	N=5000
β	3.73	2.82	-0.316	0.136	0.046
$SE(\beta)$	-75.8	-78.8	0.553	-14.5	1.6
ME_x	204	121	-4.25	-2.77	-6.3
$ME_x(y > 0)$	8.72	3.86	2.53	2.8	1.99
δ	3.99	2.3	0.431	0.958	0.321
$SE(\delta)$	-44.1	-59.3	1.98	-6.01	-2.19
ME_d	200	104	-4.01	-2.01	-7.04
$ME_d(y > 0)$	24.2	13.4	-1.08	-0.471	-1.05
σ	-0.111	0.946	-1.14	-1.15	-0.788

Shaded cells indicate bias in excess of 10 percent.

Table 4.5: Effect of Sample Size on Tobit Estimates for 1.1 Percent Uncensored Observations and $T = 8$ (Percent Bias)

	N=1000	N=2000	N=3000	N=4000	N=5000
β	12.2	0.366	-0.238	0.126	0.0636
$SE(\beta)$	-92.1	-3.34	-2.99	0.963	1.7
ME_x	597	0.844	-5.72	-5.62	-7.02
$ME_x(y > 0)$	6.07	1.62	1.07	0.823	0.272
δ	11.4	0.573	0.425	0.504	0.182
$SE(\delta)$	-85	-4.73	-4.15	-2.96	7.74
ME_d	459	-5.93	-7.28	-8.84	-11.7
$ME_d(y > 0)$	69.1	0.474	-0.546	-0.217	-0.469
σ	8.48	-0.278	-0.493	-0.199	0.0949

Shaded cells indicate bias in excess of 10 percent.

Table 4.6: Missing Results Due to Non-Convergence (Percent of Replications)

	Censoring	$N = 1000$	$N = 2000$	$N = 3000$	$N = 4000$	$N = 5000$
$T = 1$	$c = -4$	32.4	8.9	2.2	0.4	0.1
$T = 2$	$c = -3$	0.1	0	0	0	0.1
	$c = -4$	4.1	4.6	7.4	9.5	13.6
$T = 3$	$c = -4$	2.3	6.0	14.7	18.6	23.1
$T = 5$	$c = -4$	4.8	13.8	22.3	28.3	36.1
$T = 8$	$c = -4$	13.6	24.3	35.8	49.0	50.6

The values above show the percentage of replications, in which convergence for the numerical computation of the maximum likelihood was not achieved after 30 iterations due to discontinuous regions or non-concavity. Combinations of T, c, and N, which are not shown above, have zero missing results. For example in the case of $T = 1$, $c = -4$, and $N = 1000$, the Tobit results presented in this paper are based on the 676 out of 1000 replications, for which convergence could be achieved.

Chapter 5

Conclusion

Transitioning to a cleaner electricity generation mix is an important step towards mitigating climate change. While some form of government intervention is necessary to remove the externality associated with emissions in the power sector, it is important that policies be both effective and cost-effective. For example, subsidies for renewable power could lead to a situation where the clustering of renewable power plants results in curtailment, thereby negating cost-effectiveness. In addition, if the output from these renewable power plants substitutes for output from a hydropower plant rather than a conventional plant, then the policy is ineffective, since the overall goal of reducing emissions in the power sector has not been achieved. Policy design is therefore crucial to mitigating climate change efficiently.

This dissertation inquires into several aspects of renewable energy policy. Chapter 2 provides an empirical analysis of the drivers of wind power development in the United States and presents estimates of the cost-effectiveness of various policies. Chapter 3 offers a more detailed discussion of policy design. It finds that reductions in both electricity transmission congestion and system-wide emissions levels can be achieved by revising renewable energy policies to take into account their effect on plant location. Finally, Chapter 4 deals with an econometric issue, severe censoring in the Tobit model, that arises from the empirical analysis in Chapter 2.

The federal production tax credit and the state-level corporate tax credit, sales tax incentive, and production incentives emerge as significant drivers of wind power development, of which the production incentive ranks as the most cost-effective. Next to these direct subsidies for renewable power, access to the electricity grid is another important factor for wind power development. Higher wind power penetration levels can be achieved cost-effectively by bringing more parts of the electricity transmission grid under the control of Regional Transmission Organizations, which introduce competitive wholesale markets for electricity and provide supply scheduling closer to real time than in grids regulated by local utilities. Expanding the grid to include more remote windy areas is the most expensive way to encourage the development of wind power. This step may be necessary to achieve large-scale emissions reductions in the power sector. The main conclusion is that state and federal government policies play a significant role in wind power development both by providing financial support and by improving access to the electricity grid.

The effect of renewable power plant location on electricity transmission congestion and system-wide emissions levels is examined in a model and simulation study in Chapter 3. Without a price on congestion, there is no signal to prevent the development of areas with high concentrations of renewable power plants that then suffer from transmission congestion resulting in curtailment of renewable power. Similarly, the lack of a price on emissions means that investment in renewable power is not directed towards locations with large abatement potential. Only the combination of a national price on carbon and a congestion charge can ensure optimal use of existing transmission infrastructure to achieve optimal reductions in emissions.

Finally, Chapter 4 analyzes how the Tobit model performs in finite sample for differing degrees of censoring. Overall, the Tobit model performs well in finite sample with even up to 5 percent uncensored observations for all combinations of $T \in \{1, 2, 3, 5, 8\}$ and $N \in \{1000, 2000, 3000, 4000, 5000\}$ considered. Under severe censoring with 1 percent uncensored observations, the percentage bias can be large, in particular for the standard errors and marginal effects on the observed censored dependent variable. The estimates of coefficients and standard errors are largely unbiased for all T considered and $N \geq 3000$. Estimates of the marginal effect of the independent variables on the observed censored variable y, unconditional on y, are unbiased for $T = 5$ and $N \geq 3000$, and $T = 8$ and $N \geq 2000$. Estimates of these marginal effects conditional on $y > 0$ are unbiased for $T = 1$ and $N \geq 4000$, $T = 2$ and $N \geq 5000$, $T = 3$ and $N \geq 2000$, $T = 5$ and $N \geq 3000$, and $T = 8$ and $N \geq 2000$.

This dissertation contributes to the discussion of renewable energy policy by analyzing the performance of various policies in supporting wind power and highlighting the effect of renewable power plant location on transmission congestion and emissions levels. Understanding how renewable power plants affect and are affected by congestion and how the congestion and emissions externalities interact is vital to mitigating climate change in an efficient manner. As the portion of electricity generated from renewables is set to increase in the long run, these issues will gain in importance.

Chapter A

Appendix

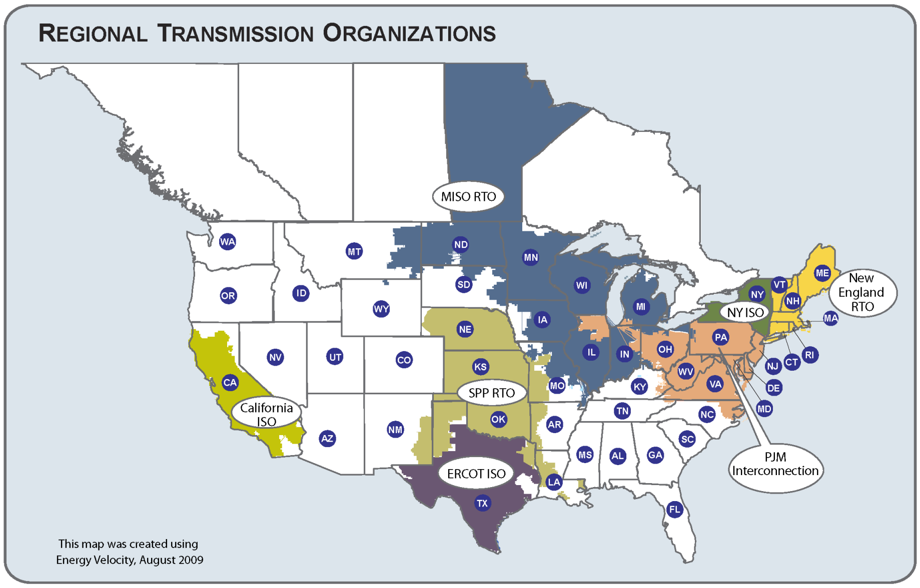

Figure A.1: Regional Transmission Organizations and Independent System Operators
Source: [75]

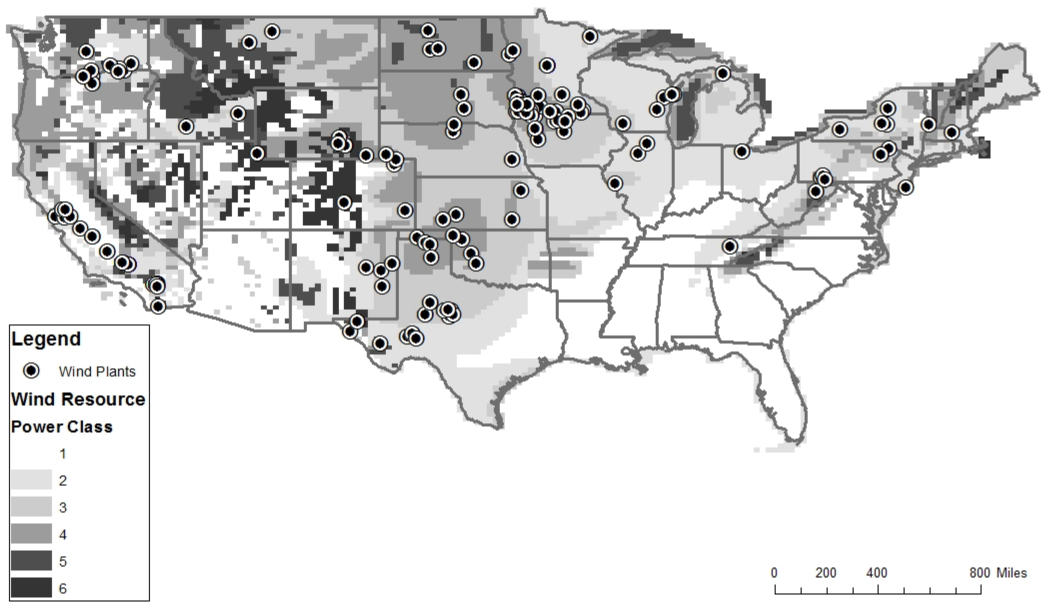

Figure A.2: United States Map of Wind Plants and Wind Power Class

Table A.1: Summary Statistics: 1998-2007

Top row: Zero Investment Bottom row: Positive investment	Varies Over+	Mean	Std. Dev.	Minimum	Maximum
Log capacity additions (MW)	CT	0***	0	0	0
		1.15	1.84	0	6.47
Wind power class	C	1.91***	0.93**	1	4.9
		2.54	0.98	1.02	5
Corporate tax credit (0/1)	ST	0.16***	0.367***	0	1
		0.373	0.484	0	1
Sales tax credit	ST	0.875***	2.04***	0	6.5
(sales tax rate in %)		1.87	2.75	0	6.5
Property tax credit	ST	0.42***	0.478	0	1
(% reduction of assessed value)		0.646	0.46	0	1
Production incentive (¢/kWh)	CT	0.179***	0.588***	0	3
		0.36	0.699	0	3
Linearized renewable portfolio	CT	10.8***	45.4***	0	305
standard (%)		30.7	77.9	0	305
PTC expiration year (0/1)	T	0.302***	0.459***	0	1
		0.219	0.414	0	1
Transmission line length	C	0.142	0.153***	0	1.27
(miles/square mile area)		0.154	0.216	0	1.22
RTO regulated grid (0/1)	CT	0.429***	0.495*	0	1
		0.675	0.469	0	1
Electricity price (retail, ¢/kWh)	ST	6.86***	1.85***	4	21.3
		7.66	2.45	4.3	21.3
Income per capita (millions)	CT	2.4***	6.91***	0.00385	140
		4.23	13.1	0.0128	131
Population density	CT	114	245	0.1	2070
(population/square mile)		101	255	0.7	2040
Distance to nearest city (miles)	C	16.7**	13.3***	0	63.3
		15.6	11.7	0	47.7
Agricultural sales/farm	C	106***	134***	0	1790
(thousands, 1997)		171	186	5.96	1240
County area (square miles)	C	1140***	1520***	24.8	20100
		1550	1740	288	8160

+ Variables vary across states (S), counties (C), or over time (T).

Over the 1998-2007 period, there are 20,908 observations with zero installed capacity (top row) and 612 observations with positive installed capacity (bottom row). In 2007, wind power plants were installed in 122 of 2,152 counties.

Differences in means and standard deviations may be significant at the 1% (***), 5% (**), or 10% (*) level. The difference in means is tested with a t-test allowing for unequal variances. The difference in variance (standard deviation) is tested with Bartlett's test.

Table A.2: Government Policies for Renewable Energy

State	Renewable Portfolio Standard		Prod. Incentive (¢/kWh)		Sales Tax Incentive[a]		Property Tax Incentive		Corporate Tax Credit		
	Level (%)	Year	Level	Year	Rate (%)	Year	Level	Year	Level	Year	Limit
Alaska											
Arizona	10.5 by 2025	2006			5.6	1997	80	2008			
Arkansas											
California	33 by 2020[c]	2003	1.6	2006							
Colorado	27 by 2020	2004					50	2001			
Connecticut	20 by 2020	1998									
Delaware	21.5 by 2027	2005									
Georgia			3[b]	2000							
Hawaii	40 by 2030[c]	2001							20% E&I costs	1990	$500,000
Idaho			2	2002	6[e]	2005	100	2007			
Illinois	18.8 by 2026	2007					100	2007			
Indiana							100	1975			
Iowa	1.1 by 1997	1983	1.0-1.5[d]	2005	5	1999	100	1978			
Kansas	20 by 2020	2009					100	1999			
Kentucky			3[b]	2000	6	2008			30% income tax credit	2009	$1,000
Maine	10 by 2017	1999			5[e]	2006					
Maryland	18 in 2022	2004	0.85[d]	2007							
Massachusetts	24 by 2030	1997			5	1977	100	1975			
Michigan	10 by 2015	2008									
Minnesota	25 by 2020	2007	1	1997	6.5	1998	100	1992			
Missouri	14.7 by 2021	2008									
Montana	15 in 2015	2005	2	2002			100	2001			
Nebraska					5.5	2007					
Nevada	23.5 by 2025[c]	1997					50	1997			
New Hampshire	16 by 2025	2007									

[a] All states offering a sales tax credit set the credit level at 100% (removing the sales tax), but differ in their sales tax rate.
[b] Only counties serviced by the Tennessee Valley Authority utility.
[c] California: 20% by 2010 and 33% by 2020; Hawaii: 10% by 2010, 15% by 2015, 25% by 2020, and 40% by 2030; Massachusetts: standard increases by 1% per year after 2009; Nevada: 5.7% by 2005, 23.5% by 2025.
[d] Offered as a corporate tax credit.
[e] Idaho and Maine offer a sales tax refund, all other states offer a sales tax exemption.
E&I refers to equipment and installation costs.

Table A.3: Government Policies for Renewable Energy (Cont'd)

State	Renewable Portfolio Standard		Prod. Incentive (¢/kWh)		Sales Tax Incentive[a]		Property Tax Incentive		Corporate Tax Credit		
	Level (%)	Year	Level	Year	Rate (%)	Year	Level	Year	Level	Year	Limit
New Jersey	17.9 by 2021	1999									
New Mexico	9.4 by 2020	2004	1[d]	2002							
New York	20.7 by 2015	2004					100	1977			
North Carolina	11.5 of 2021	2007	3[b]	2000							
North Dakota		2006					78	2001	15% E&I costs	2001	
Ohio	12 by 2024	2008			5.5	1973	100	1978			
Oklahoma			0.25-0.75[d]	2003							
Oregon	25 by 2025	2007	2	2002			100	1976			
Pennsylvania	7.5 by 2021	2004					100	2006			
Rhode Island	14 by 2019	2004			7	2005					
South Carolina											
South Dakota							100	2003			
Tennessee			3	2000			67	2003			
Texas	4.4 by 2014[c]	1999					100	1981	100% E&I costs	1982	
Utah			0.35[d]	2001	4.65	2004					
Vermont					6	1999	100	1975			
Virginia			3[b]	2000							
Washington	15 by 2020	2006	2	2002	6.5	2001					
West Virginia							75	2001	30% tax credit	2001	
Wisconsin	9.6 by 2015	1999			5	2009	100	2003			
Wyoming					4	2003					
Alabama[e]			3[b]	2000							
District of Columbia[e]	17.5 by 2023	2005									
Florida[e]			1[d]	2007			80	2009			
Louisiana[e]											
Mississippi[e]			3[b]	2000							

[a] All states offering a sales tax credit set the credit level at 100% (removing the sales tax), but states differ in their sales tax rate.
[b] Only counties serviced by the Tennessee Valley Authority utility.
[c] Montana: 5% in 2008, 10% in 2010 15% in 2015; Texas: 2,280 MW by 2007, 3,272 MW by 2009, 4,264 MW by 2011, 5,256 MW by 2013, 5,880 MW by 2014.
[d] Offered as a corporate tax credit.
[e] Alabama, District of Columbia, Florida, Louisiana, and Mississippi are excluded from the sample due to missing data on wind capacity.
E&I refers to equipment and installation costs.

Chapter B

Appendix

Table B.1: Mean Transmission Line Coverage and Emissions by Fuel Source in PJM

Fuel	Line coverage	Emission (lbs/h) PM	SO2	Annual CO2eq emission (tons)	Year	Obs.
Coal	0.54	153.02	406.94	4,699,991	1973	90
Oil & Other	0.47	47.82	62.55	562,389	1974	79
Natural Gas	0.53	9.81	7.96	189,962	1994	113
Waste	0.44	85.25	17.33	7,800	1991	31
Nuclear	0.43	0	0	122	1979	17
Hydro	0.78	0	0	0	1952	37
Wind	0.20	0	0	0	2005	12

B.1 Proofs

The capacities of the wind plants installed by the social planner taking into account transmission congestion are less than or equal to those installed by individual profit-maximizing firms. In general, $k_i^s \leq k_i^*$ for all i.

Proof. Suppose the contrary were true and $k_i^s > k_i^*$ for all i even though all locations cause congestion externalities, i.e. $\sum_{j \neq i}(\partial f_i/\partial k_j) \cdot k_j < 0$ for all i. Since $\partial f_i/\partial k_i \leq 0$ and $\partial f_i/\partial k_j \leq 0$, it follows that $f_i(k_1^s, \ldots, k_n^s) \leq f_i(k_1^*, \ldots, k_n^*) \leq 1$. With $\partial^2 f_i/\partial k_i^2 \leq 0$ and $\partial^2 f_i/\partial k_i \partial k_j \leq 0$, it follows that $\frac{\partial f_i}{\partial k_i}(k_1^s, \ldots, k_n^s) \leq \frac{\partial f_i}{\partial k_i}(k_1^*, \ldots, k_n^*) \leq 0$. This means the first two terms of equation 3.1 are less than or equal to the first two terms of equation 3.2. The third term of the equation 3.2 is strictly less than zero. It follows that equation 3.2 is strictly less than equation 3.1.

However, both equations are equal to zero, which is a contradiction. It follows that $k_i^s \leq k_i^*$ for all i. ■

A capacity-based subsidy offered in Region A contributes to clustering of wind plants. Comparing equations 3.4 and 3.1, it follows that $k_i^r > k_i^*$ for all $i \in I_A$ and $k_j^r = k_j^*$ for all $j \notin I_A$.

Proof. Suppose the contrary were true and $k_i^r < k_i^*$ for all i even though $r_i > 0$ for $i \in I_A$. With $\partial f_i/\partial k_i \leq 0$ and $\partial f_i/\partial k_j \leq 0$, it follows that $f_i(k_1^*, \ldots, k_n^*) \leq f_i(k_1^r, \ldots, k_n^r)$. Since $\partial^2 f_i/\partial k_i^2 \leq 0$ and $\partial^2 f_i/\partial k_i \partial k_j \leq 0$, it follows that $\frac{\partial f_i}{\partial k_i}(k_1^*, \ldots, k_n^*) \leq \frac{\partial f_i}{\partial k_i}(k_1^r, \ldots, k_n^r) \leq 0$. Finally, $r_i - c \geq c$. Thus, the first two terms of equation 3.4 are greater or equal to the first two terms of equation 3.1. For $i \in I_A$, the third term of equation 3.4, $r_i - c$, is strictly greater than the third term of equation 3.1. This is a contradiction, since both equations are equal to zero for all i. Thus, $k_i^r \geq k_i^*$ for all i. ■

B.2 Optimal Power Flow

The objective function of the optimal power flow problem is the summation of individual quadratic cost functions f_P^i and f_Q^i of real and reactive power injections, respectively, for each generator:

$$\min_{\Theta, V_m, P_g, Q_g} \sum_{i=1}^{n_g} f_P^i(P_g^i) + f_Q^i(Q_g^i)$$

subject to equality constraints, inequality constraints, and variable limits, where Θ and V_m are the $n_b \times 1$ vectors of voltage angles and magnitudes, and P_g and Q_g

are the $n_g \times 1$ vectors of generator real and reactive power injections. In the case of the IEEE 30 bus test system, the number of buses n_b is 30, and the number of generators n_g is 6, and the number of branch lines n_l is 41.

The equality constraints are the full set of $2 \times n_b$ nonlinear real and reactive power balance equations, such that supply in real and reactive power equals demand *at each bus.*

$$P_b(\Theta, V_m) + P_d = C_g P_g \tag{B.1}$$

$$Q_b(\Theta, V_m) + Q_d = C_g Q_g \tag{B.2}$$

The sparse $n_b \times n_g$ generator connection matrix C_g is defined such that its $(i, j)^{\text{th}}$ element is 1 if generator j is located at bus i and 0 otherwise.

The inequality constraints consist of two sets of n_l branch flow limits, one for the *from* end and one for the *to* branch:

$$|F_f(\Theta, V_m)| \leq F_{\max} \tag{B.3}$$

$$|F_t(\Theta, V_m)| \leq F_{\max} \tag{B.4}$$

The flows $F(\Theta, V_m)$ can be flows of apparent power $S(\Theta, V_m)$ in MVA, real power $P(\Theta, V_m)$ in MW, or current $I(\Theta, V_m)$ in A. When all branch flow constraints are slack, the system is uncongested.

The variable limits include an equality constraint on any reference bus angle and upper and lower limits on all bus voltage magnitudes and real and reactive power injections:

$$\begin{aligned}
\theta_i^{\text{ref}} &\le \theta_i \le \theta_i^{\text{ref}}, \quad i \in \mathcal{I}_{\text{ref}} && \text{(B.5)} \\
\nu_m^{i,\min} &\le \nu_m^i \le \nu_m^{i,\max}, \quad i = 1, \ldots, n_b && \text{(B.6)} \\
p_g^{i,\min} &\le p_g^i \le p_g^{i,\max}, \quad i = 1, \ldots, n_g && \text{(B.7)} \\
q_g^{i,\min} &\le q_g^i \le q_g^{i,\max}, \quad i = 1, \ldots, n_g && \text{(B.8)}
\end{aligned}$$

B.3 Modified IEEE 30 Bus Test System Data

Table B.2: Bus Data

Bus	Load (MW)		Bus	Load (MW)	
	Real	Reactive		Real	Reactive
1	0	0	16	3.5	1.8
2	21.7	12.7	17	9	5.8
3	2.4	1.2	18	3.2	0.9
4	7.6	1.6	19	9.5	3.4
5	94.2	0	20	2.2	0.7
6	0	0	21	17.5	11.2
7	22.8	10.9	22	0	0
8	30	30	23	3.2	1.6
9	0	0	24	8.7	6.7
10	5.8	2	25	0	0
11	0	0	26	3.5	2.3
12	11.2	7.5	27	0	0
13	0	0	28	0	0
14	6.2	1.6	29	2.4	0.9
15	8.2	2.5	30	10.6	1.9

Table B.3: Generator Data

Area	Bus	Cost coefficients			Power output (MW)	
		c_0	c_1	c_2	P_{min}	P_{max}
A	1	0	2	0.02	0	80
	2	0	1.75	0.0175	0	80
B	13	0	3	0.025	0	40
	23	0	3	0.025	0	30
C	22	0	1	0.0625	0	50
	27	0	3.25	0834	0	55

Note: Operating costs for each of the $i = 1, \ldots, 6$ generators are given by the quadratic cost function $f_P^i(P) = c_0^i + c_1^i P + c_2^i P^2$.

Table B.4: Branch Data

From bus	To bus	Resistance	Reactance	Total line charging susceptance
1	2	0.0192	0.0575	0.0528
1	3	0.0452	0.1652	0.0408
2	4	0.057	0.1737	0.0368
3	4	0.0132	0.0379	084
2	5	0.0472	0.1983	0.0418
2	6	0.0581	0.1763	0.0374
4	6	0.0119	0.0414	09
5	7	0.046	0.116	0.0204
6	7	0.0267	0.082	0.017
6	8	0.012	0.042	09
6	9	0	0.208	0
6	10	0	0.556	0
9	11	0	0.208	0
9	10	0	0.11	0
4	12	0	0.256	0
12	13	0	0.14	0
12	14	0.1231	0.2559	0
12	15	0.0662	0.1304	0
12	16	0.0945	0.1987	0
14	15	0.221	0.1997	0
16	17	0.0524	0.1923	0
15	18	0.1073	0.2185	0
18	19	0.0639	0.1292	0
19	20	0.034	0.068	0
10	20	0.0936	0.209	0
10	17	0.0324	0.0845	0
10	21	0.0348	0.0749	0
10	22	0.0727	0.1499	0
21	22	0.0116	0.0236	0
15	23	0.1	0.202	0
22	24	0.115	0.179	0
23	24	0.132	0.27	0
24	25	0.1885	0.3292	0
25	26	0.2544	0.38	0
25	27	0.1093	0.2087	0
28	27	0	0.396	0
27	29	0.2198	0.4153	0
27	30	0.3202	0.6027	0
29	30	0.2399	0.4533	0
8	28	0.0636	0.2	0.0428
6	28	0.0169	0.0599	0.013

Bibliography

[1] WH. Energy and environment. The White House, Washington, DC, 2009.

[2] AWEA. Annual wind industry report: Year ending 2008. American Wind Energy Association, 2009.

[3] Lori Bird, Mark Bolinger, Troy Gagliano, Ryan Wiser, Matthew Brown, and Brian Parsons. Policies and market factors driving wind power development in the United States. *Energy Policy*, 33(11):1397 – 1407, 2005.

[4] S. Gouchoe, V. Everette, and R. Haynes. Case studies on the effectiveness of state financial incentives for renewable energy. NREL/SR-620-32819, National Renewable Energy Laboratory, Raleigh, NC, 2002.

[5] O. Langniss and R. Wiser. The renewable portfolio standard in Texas: An early assessment. *Energy Policy*, 31:527–535, 2003.

[6] R. Wiser, K. Porter, and R. Grace. Evaluating experience with renewables portfolio standards in the United States. Lawrence Berkeley National Laboratory, LBNL-54439, 2004.

[7] R. Wiser, C. Namovicz, M. Gielecki, and R. Smith. Renewables portfolio standards: A factual introduction to experience from the United States. Lawrence Berkeley National Laboratory, LBNL-62569, 2007.

[8] Cliff Chen, Ryan Wiser, Andrew Mills, and Mark Bolinger. Weighing the costs and benefits of state renewables portfolio standards in the United States: A comparative analysis of state-level policy impact projections. *Renewable and Sustainable Energy Reviews*, 13(3):552 – 566, 2009.

[9] Sanya Carley. State renewable energy electricity policies: An empirical evaluation of effectiveness. *Energy Policy*, 37:3071–3081, 2009.

[10] Soji Adelaja and Yohannes Hailu. Projected impacts of renewable portfolio standards on wind industry development in Michigan. Land Policy Institute, Michigan State, December 2007.

[11] Fredric C. Menz and Stephan Vachon. The effectiveness of different policy regimes for promoting wind power: Experiences from the states. *Energy Policy*, 34:1786–1796, 2006.

[12] Joshua Kneifel. Effects of state government policies on electricity capacity from nonhydropower renewable soruces. Unpublished manuscript, University of Florida, 2008.

[13] Haitao Yin and Nicholas Powers. Do state renewable portfolio standards promote in-state renewable generation. *Energy Policy*, 38(2):1140–1149, 2010.

[14] IEA. Renewable energy essentials: Wind. International Energy Agency, Paris, 2008.

[15] AWEA. Wind energy basics. American Wind Energy Association, 2009.

[16] EIA. Renewables and alternate fuels: Wind. Energy Information Administration (EIA), 2008.

[17] NREL. Dynamic maps, GIS data, and analysis tools. National Renewable Energy Laboratory, 2008.

[18] K. Porter, S. Fink, C. Mudd, and J. DeCesaro. Generation interconnection policies and wind power: A discussion of issues, problems, and potential solutions. Exeter Associates, Inc. for the National Renewable Energy Laboratory (NREL), 2009.

[19] Mark Bolinger and Ryan Wiser. Wind power price trends in the United States: Struggling to remain competitive in the face of strong growth. *Energy Policy*, 37(3):1061 – 1071, 2009.

[20] DSIRE. Database on state incentives for renewables and efficiency. Solar Center, North Carolina State University, 2009.

[21] PAPUC. Pennsylvania alternative energy credit program pricing. Pennsylvania Public Utility Commission, 2011.

[22] DOE. The green power network - renewable energy certificates (REC) prices. Department of Energy, Washington, DC, 2011.

[23] Edgar DeMeo, William Grant, Michael R. Milligan, and Matthew J. Schuerger. Wind plant integration: Costs, status, and issues. IEEE Power & Energy Magazine, 2005.

[24] B. Kirby and M. Milligan. Facilitating wind development: The importance of electric industry structure. National Renewable Energy Laboratory Technical Report NREL/TP-500-43251, 2008.

[25] IRC. The value of independent regional grid operators. ISO/RTO Council, 2005.

[26] FERC. Order No. 2000 - Regional transmission organizations. Federal Energy Regulatory Commission, Washington, DC, 1999.

[27] EIA. Electric power annual. Energy Information Administration, Department of Energy, 2009.

[28] EIA. The changing structure of the electric power industry 2000: An update. Energy Information Administration, Department of Energy, DOE/EIA-0562(00), 2000.

[29] DOE. 20% Wind energy by 2030: Increasing wind energy contribution to U.S. electricity supply. Department of Energy, 2008.

[30] J. Neyman and E.L. Scott. Consistent estimates based on partially consistent observations. *Econometrica*, 16:1–32, 1948.

[31] Peter M. Robinson. On the asymptotic properties of estimators of models containing limited dependent variables. *Econometrica*, 50(1):27–41, 1982.

[32] EIA. Form EIA-860 database annual electric generator report. Energy Information Administration, Department of Energy, 2009.

[33] M. Shahidehpour. Investing in expansion: The many issues that cloud transmission planning. *Power and Energy Magazine, IEEE*, 2(1):14–18, Jan-Feb 2004.

[34] AEI. Detailed GIS wind class map. Alternative Energy Institute, West Texas A&M University, 2004.

[35] MDC. GIS wind map. Energy Info Center, Minnesota Department of Commerce, 2006.

[36] EIA. Electric power annual 2007: 1990-2007 average price by state by provider (EIA-861). Energy Information Administration, Department of Energy, 2009.

[37] BEA. Regional data: Local area personal income. Bureau of Economic Analysis, Department of Commerce, Washington, DC, 2010.

[38] ESRI. United States issue of the ESRI data & maps series. Environmental Systems Research Institute. Available: U.S. Government Information, Maps & GIS Services Collection, University of Maryland Library, 2006.

[39] NCSL. Composition of state legislatures, by political party affiliation. National Conference of State Legislatures, Denver, CO, 2011.

[40] GovTrack. H.R. 2454 (111th): American Clean Energy and Security Act of 2009 (on passage of the bill). Govtrack.us by Civic Impulse, LLC, 2009.

[41] A.B. Chupp. Environmental constituent interest, green electricity policies, and legislative voting. *Journal of Environmental Economics and Management*, 62:254–266, 2011.

[42] Black and Veatch. 20% Wind energy penetration in the United States: A technical analysis of the energy resource. Black & Veatch Project 144864, Walnut Creek, CA, 2007.

[43] Tax Foundation. Property taxes on owner-occupied housing, by county, ranked by taxes as a percentage of home value, 2007 - 2009 (three-year average). Tax Foundation, Washington, DC, 2010.

[44] AEP. Transmission facts. American Electric Power, Columbus, OH, 2008.

[45] Claudia Hitaj. Wind power development in the United States. *Journal of Environmental Economics and Management*, forthcoming, 2013.

[46] Alan D. Lamont. Assessing the long-term system value of intermittent electric generation technologies. *Energy Economics*, 30(3):1208 – 1231, 2008.

[47] Marc Beaudin, Hamidreza Zareipour, Anthony Schellenberglabe, and William Rosehart. Energy storage for mitigating the variability of renewable electricity sources: An updated review. *Energy for Sustainable Development*, 14(4):302 – 314, 2010.

[48] Elaine K. Hart and Mark Z. Jacobson. A Monte Carlo approach to generator portfolio planning and carbon emissions assessments of systems with large penetrations of variable renewables. *Renewable Energy*, 36(8):2278 – 2286, 2011.

[49] David Dallinger and Martin Wietschel. Grid integration of intermittent renewable energy sources using price-responsive plug-in electric vehicles. *Renewable and Sustainable Energy Reviews*, 16(5):3370 – 3382, 2012.

[50] Brian Tarroja, Fabian Mueller, Joshua D. Eichman, and Scott Samuelsen. Metrics for evaluating the impacts of intermittent renewable generation on utility load-balancing. *Energy*, 42(1):546 – 562, 2012.

[51] Emmanouil Voumvoulakis, Georgia Asimakopoulou, Svetoslav Danchev, George Maniatis, and Aggelos Tsakanikas. Large scale integration of intermittent renewable energy sources in the greek power sector. *Energy Policy*, 50(0):161 – 173, 2012.

[52] F.R. Førsund, B. Singh, T. Jensen, and C. Larsen. Phasing in wind-power in Norway: Network congestion and crowding-out of hydropower. *Energy Policy*, 36(9):3514–3520, 2008.

[53] C.K. Woo, J. Zarnikau, J. Moore, and I. Horowitz. Wind generation and zonal-market price divergence: Evidence from texas. *Energy Policy*, 39(7):3928 – 3938, 2011.

[54] Benjamin R. Phillips and Richard S. Middleton. Simwind: A geospatial infrastructure model for optimizing wind power generation and transmission. *Energy Policy*, 43(0):291 – 302, 2012.

[55] Seth Blumsack and Jianhua Xu. Spatial variation of emissions impacts due to renewable energy siting decisions in the Western U.S. under high-renewable penetration scenarios. *Energy Policy*, 39(11):6962 – 6971, 2011.

[56] CEC. Transmission congestion and renewable generation. Clean Energy Council, Victoria, Australia, 2010.

[57] ERCOT. Capacity, demand, and reserves report. Electric Reliability Council of Texas, 2011.

[58] NREL. Examples of wind energy curtailment practices. National Renewable Energy Laboratory Subcontract Report NREL/SR-550-48737, 2010.

[59] PUCT. 2009 State of the market report. Public Utility Commission of Texas, 2010.

[60] ERCOT. 2009 Annual report. Electric Reliability Council of Texas, 2010.

[61] David Patton. 2009 State of the market report Midwest ISO. Midwest ISO Independent Market Monitor, 2010.

[62] Michael Goggin. Wind power is a reliable technology that provides societal and consumer benefits. www.minnpost.com, January 31, 2013.

[63] UWEE. Power systems test case archive. University of Washington Department of Electrical Engineering, 2011.

[64] O. Alsac and B. Stott. Optimal load flow with steady state security. *IEEE Transactions on Power Apparatus and Systems*, 93:745–751, 1974.

[65] R.W. Ferrero, S.M. Shahidehpour, and V.C. Ramesh. Transaction analysis in deregulated power systems using game theory. *IEEE Transactions on Power Systems*, 12:1340–1347, 1997.

[66] R.D. Zimmerman, C.E. Murillo-Snchez, and R.J. Thomas. MATPOWER steady-state operations, planning and analysis tools for power systems research and education. *IEEE Transactions on Power Systems*, 26:12–19, 2011.

[67] NMOA. Average direct mail response rate. National Mail Order Association, Minneapolis, MN, 2010.

[68] W.H. Greene. Fixed effects and bias due to the incidental parameters problem in the Tobit model. *Econometric Reviews*, 23:125–147, 2004.

[69] M. Cramer, P.H. Franses, and E. Slagter. Censored regression analysis in large samples with many zero observations. Econometric Institute Research Report 9939/A, 1999.

[70] W.H. Greene. On the asymptotic bias of the ordinary least squares estimator of the Tobit model. *Econometrica*, 49:505–513, 1981.

[71] James Tobin. Estimation of relationships for limited dependent variables. *Econometrica*, 26:24–36, 1958.

[72] John F. McDonald and Robert A. Moffit. The uses of Tobit analysis. *The Review of Economics and Statistics*, 62:318321, 1980.

[73] A. Arabmazar and P. Schmidt. An investigation of the robustness of the Tobit estimator to non-normality. *Econometrica*, 50:1055–1063, 1982.

[74] A. Arabmazar and P. Schmidt. Further evidence on the robustness of the Tobit estimator to heteroskedasticity. *Journal of Econometrics*, 17:253–258, 1981.

[75] FERC. Regional transmission organizations (RTO)/ Independent system operators (ISO). Federal Energy Regulatory Commission, 2009.