Wind Turbine Shutdowns and Upgrades in Denmark: Timing Decisions and the Impact of Government Policy

Jonathan A. Cook
Nexant, Inc.
jonathancook@nexant.com

C.-Y. Cynthia Lin
University of California at Davis
cclin@primal.ucdavis.edu

Selected Paper prepared for presentation at the 2015 Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, CA, July 26-68

Wind Turbine Shutdowns and Upgrades in Denmark: Timing Decisions and the Impact of Government Policy*

Jonathan A. Cook[†] C.-Y. Cynthia Lin [‡]

May 2015

Abstract: Shutting down and/or upgrading existing productive assets are important economic decisions for the owners of those assets and are also the fundamental decisions that underlie the development of new, growing industries. This paper develops a dynamic structural econometric model of wind turbine owners' decisions about whether and when to add new turbines to a pre-existing stock, scrap an existing turbine, or replace old turbines with newer versions (i.e., upgrade). We apply our model to owner-level panel data for Denmark over the period 1980-2011 to estimate the underlying profit structure for wind producers and evaluate the impact of technology and government policy on wind industry development. Our structural econometric model explicitly takes into account the dynamics and interdependence of shutdown and upgrade decisions and generates parameter estimates with direct economic interpretations. Results from the model indicate that the growth and development of the Danish wind industry was primarily driven by government policies as opposed to technological improvements. The parameter estimates are used to simulate counterfactual policy scenarios in order to quantify the effectiveness of the Danish feed-in-tariff and replacement certificate programs. Results show that both of these policies significantly impacted the timing of shutdown and upgrade decisions made by turbine owners and accelerated the development of the wind industry in Denmark.

Keywords: wind energy, dynamic structural econometric model
JEL codes: Q42, L90

---

*The authors are tremendously thankful for the help of Dr. Preben Nyeng at Energinet.dk for his help in understanding the Danish electricity market, access to turbine ownership data and connections to other experts in the field. We thank Chad Syverson for valuable comments. We also received helpful comments from conference participants at the U.S. Association of Energy Economics North American conference and the Harvard Environmental Economics Program Research Workshop, and from seminar participants at UC-Davis and Texas A&M. Lin is a member of the Giannini Foundation for Agricultural Economics. All errors are our own.

[†]Nexant, Inc.; jonathancook@nexant.com

[‡](Corresponding Author), Agricultural and Resource Economics, University of California at Davis, One Shields Avenue, Davis, CA 95616; cclin@primal.ucdavis.edu

1 Introduction

Due to concerns about climate change, fossil fuel price volatility, energy security, and possible fossil fuel scarcity, governments at many levels around the world have begun implementing policies aimed at increasing the production share of renewables in the electricity sector. These support policies have taken several different forms (e.g., Renewable Portfolio Standards, feed-in-tariffs, tax credits, etc.) and proponents argue that they are necessary for these nascent industries to continue to develop technological improvements, achieve economies of scale and compete with existing industries. Wind energy was one of the earliest renewable generation technologies to be promoted and its maturity and low costs relative to other renewables has made it a leading option for many countries in the early phases of pursuing climate goals.

For policymakers, an important long-run question related to the development of renewable industries is how government policies affect decisions regarding the scrapping or upgrading of existing assets. How much of the shutdowns and upgrades can be attributed to the policies as opposed to other market trends? How do policies affect the timing of owner decisions and the subsequent path of the industry?

This paper aims to shed some light on these questions by developing a dynamic structural econometric model of wind turbine shutdowns and upgrades in the context of Denmark and using it to estimate the underlying profit structure for turbine owners. In particular, we model wind turbine owners' decisions about whether and when to add new turbines to a pre-existing stock, scrap an existing turbine, or replace old turbines with newer versions (i.e., upgrade). Shutting down and/or upgrading existing productive assets are important economic decisions for the owners of those assets and are also the fundamental decisions that underlie the development of new, growing industries.

To date, empirical research addressing the economics of wind energy has tended to focus on production costs, investment decisions or policy options for increasing the penetration of wind energy in electricity grids. Engineering studies have regularly calculated the cost of producing electricity from wind turbines and compared it with existing fossil-fuel generators (Darmstadter, 2003; Krohn et al., 2009). The consensus among these studies is that although generating costs associated with wind power have been steadily declining, market penetration of wind energy has remained fairly low in most countries due to the relatively low prices of coal and natural gas. Policy research has been aimed at describing the policies that have been implemented (Allison and Williams, 2010), evaluating the abilities of different wind energy policies to promote new investments (Agnolucci, 2007), or comparing the policies of different countries with emerging wind industries (Klaassen et al., 2005). Munksgaard and Morthorst (2008) provide an excellent description of the trends in feed-in-tariffs and the market price of electricity in Denmark and attempt to forecast future investments in wind energy based on an estimated internal rate of return. Jacobsson and Johnson (2000) come at the problem from a technology innovation and diffusion perspective, in which they provide an analytical framework for examining the process of technical change in the electricity industry. Mauritzen (2014) estimates a reduced-form model of wind turbine scrapping decisions. We build on the work of Mauritzen (2014) by developing and estimating a dynamic structural econometric model, by utilizing additional data and by extending the model to include both shutdown and upgrade decisions.

We apply our model to owner-level panel data for Denmark over the period 1980-2011 to estimate the underlying profit structure for wind producers and evaluate the impact of technology and government policy on wind industry development. Our structural econometric model explicitly takes into account the dynamics and interdependence of shutdown and upgrade decisions and generates parameter estimates with direct economic interpretations. Results from the model indicate that the growth and development of the Danish wind industry was primarily driven by government policies as opposed to technological improvements. The parameter estimates are used to simulate counterfactual policy scenarios in order to quantify the effectiveness of the Danish feed-in-tariff and replacement certificate programs. Results show that both of these policies significantly impacted the timing of shutdown and upgrade decisions made by turbine owners and accelerated the development of the wind industry in Denmark.

2 The Danish Wind Industry

For many countries, questions regarding shutdown and upgrade decisions will become increasingly relevant in the near future as existing turbines approach the end of their expected lifetimes (usually around 20 years) and technology continues to improve. This is already the case in Denmark, where a concerted effort to transition away from fossil fuels began in the late 1970's soon after the first oil crisis. Since then, the long-term energy goal of the Danish government has been to have 100% of the country's energy supply come from renewable sources. With a long history of designing turbines that stretches back to the late 19^{th} century (Heymann, 1998), wind power was the leading technological choice to offset electricity production from fossil fuels. To this end, the Danish government implemented several policies designed to encourage wind investments throughout the country. As a result of this sustained policy goal, Denmark became a leader in both turbine design and installed wind capacity during the 1980s and 1990s and has one of the most mature modern wind industries in the world.

We focus on the wind industry in Denmark over the period 1980-2011, and use data from a publicly available database containing all turbines constructed in Denmark during that time period (DEA, 2012). Ownership information for each turbine was obtained from a professional colleague at Energinet.dk so that a panel dataset at the owner level could be constructed and used to estimate the structural model.

Figure 1 provides snapshots of the development of the Danish wind industry for the years 1980, 1990, 2000, and 2010. Each dot on the map represents a single wind turbine, with the size and color of the dot corresponding to the size of the turbine. Looking at the maps, two distinct phases of wind industry development are evident: (1) a boom in the installations of new turbines during the 1990s and (2) significant increases in turbine size during the 2000s. During our period of study there were significant improvements in turbine technology as well as changes to the structure of the electricity markets and wind policies.

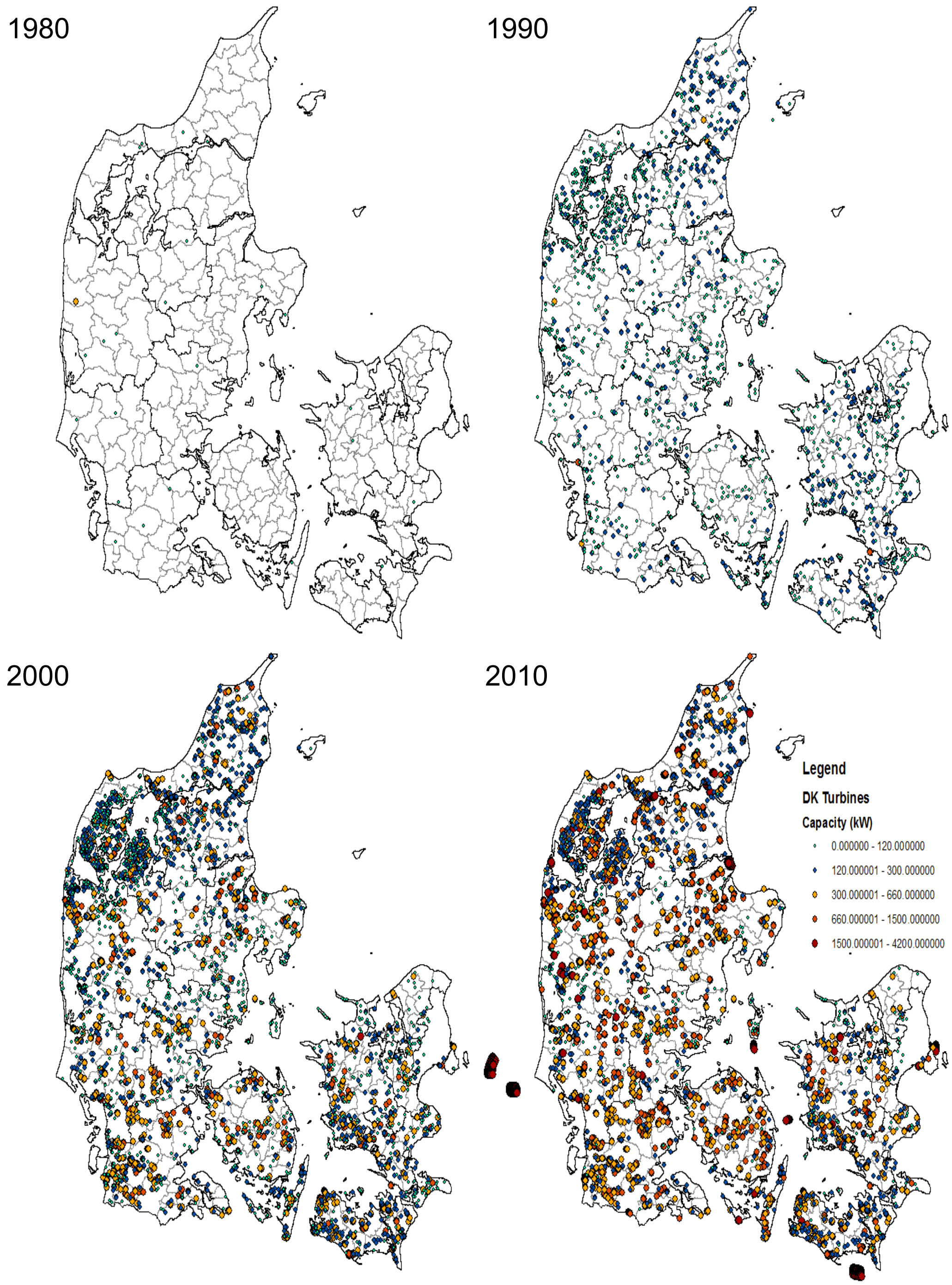
In terms of ownership, the Danish wind industry has been remarkably decentralized throughout its history. Of the roughly 2,900 turbine owners during over the period 1980-2011, the vast majority (~90%) own two or fewer turbines.[1] We therefore focus on turbine owners who own two or fewer turbines.

An interesting feature of Danish wind development was that it was not led by a few large firms constructing large, centralized wind farms. Instead, the vast majority of wind turbines in the country were installed and owned by individuals or local cooperatives. This decentralized development resulted in 80% of all turbines in Denmark being owned by wind cooperatives in 2001 (Mendonça et al., 2009). This trend has changed in more recent years as more utility-scale wind projects have come online, but the fact that there are so many early turbine owners provides a healthy sample size for the structural model employed.

Our analysis makes use of several turbine-specific and national level variables that likely have an impact on turbine management decisions. Included in the Energinet.dk data are the capacity of each turbine, the date it was installed and the location of the turbine. Capacity enters directly into all specifications, while the installation date can be used to calculate the age of each turbine throughout the study period. We also include variables for government policy and for the state of wind turbine technology, each of which we describe in detail below. In our dynamic structural econometric model, we assume the state variables evolve as a finite state first-order Markov process.

[1] In particular, of the 2,924 total turbine owners in the country during the period of study (1980-2011), 2,565 (88%) own 2 or fewer turbines.

Figure 1: Snapshots of Installed Wind Turbines in Denmark



2.1 Government Policy

We focus on two important policies that the Danish government has implemented on the wind industry: (1) the feed-in-tariff for electricity generated by wind turbines and (2) the replacement certificate scheme for incentivizing turbine owners to scrap old turbines and replace them with new ones. Since the late 1970s, the Danish government has supported wind development by paying wind turbine owners a supplement to the electricity production price, called a feed-in-tariff. Prior to the liberalization of the power market[2] in 1999, the payment was a fixed amount guaranteed for a significant portion (if not all) of a turbine's useful life. After liberalization, the payment took the form of a fixed amount that would be paid to owners on top of the electricity price determined in the competitive wholesale market. The amount of these payments has been adjusted over time as more wind power came online (see Table 1). The level of the feed-in-tariff is determined by the date a turbine was built.[3]

Table 1: Danish Feed-in-Tariff Policies

Date Range	**Level of Subsidy**
Before Jan. 1, 2000	DKK 0.60/kWh price guarantee for 10 years, DKK 0.10/kWh price guarantee for next 20 years
Jan. 1, 2000 – Dec. 31, 2002	DKK 0.43/kWh price guarantee for 22,000 load hours
Jan. 1, 2003 – Feb. 20, 2008	Feed-in-tariff up to DKK 0.10 over market price with maximum payment of DKK 0.36/kWh
Feb. 21, 2008 – present	Feed-in-tariff of DKK 0.25/kWh for 22,000 load hours

Source: Mauritzen (2014)

[2]Before 1999, Danish municipal utilities were vertically integrated and operated as regulated natural monopolies so that the price of electricity for retail customers was set at a level that allowed the utility to recouperate the cost of generating, transmitting and distributing electricity to its customers. After liberalization in 1999, Denmark joined the Nordic regional market (NordPool) and began using locational marginal pricing together with a Dutch auction mechanism (2^{nd} price auction) to determine wholesale prices.

[3]Massive increases in wind capacity (and generation) can have an impact on wholesale prices specifically, on particularly windy days, the wholesale price can become negative as zero-marginal cost wind becomes the marginal source of generation and the market actually pays buyers to use excess wind production. Negative wholesale prices are relatively infrequent even with 25% of the countrys generation coming from wind. In Denmark, however, because of the incentive policies for wind production, turbine owners are insulated from any investment incentives this may cause because the feed-in-tariff guarantees the price they will receive for production (leaving the government to figure out how to deal with any differences between that price and the actual market price).

Table 2: Danish Replacement Certificate Program

Date Range for Scrapping	Eligible Capacities	Value of Scrapping Certificate
Mar. 3, 1999 – Dec. 31, 2003	< 150 kW	DKK 0.17/kWh over market price for 12,000 peak-load hours with maximum price of DKK 0.60/kWh
Dec. 15, 2004 – Feb. 20, 2008	< 450 kW	DKK 0.12/kWh over market price for 12,000 peak-load hours with maximum price of DKK 0.48/kWh
Feb. 21, 2008 – Dec. 31, 2011	< 450 kW	DKK 0.08/kWh over market price for 12,000 peak-load hours with maximum price of DKK 0.38/kWh

Source: Denmark (2008)

Also beginning in 1999, the government created a replacement certificate program to incentivize the upgrading of older, lower capacity turbines to newer, larger turbines. Eligible turbine owners who scrapped their turbines during the program received a certificate that would grant an additional price supplement for a new turbine that was constructed (see Table 2). These scrapping certificates were given out through the end of 2011 and could be sold to other prospective turbine owners.

In our dynamic structural econometric model, we assume that both of these government policies evolve as a finite state first-order Markov process. From the perspective of turbine owners, the evolution of both of these policies over time was uncertain at the beginning of the study period, due to the democratic nature of lawmaking and uncertainty about the evolution of the Danish wind industry and fuel prices for other forms of electricity generation. Although the basic strategy of reducing the feed-in-tariff over time was likely known by turbine owners, the exact timing and values of either of the support policies could not have been perfectly anticipated. We therefore model future values of these policies as uncertain from the point of view of the turbine owners in any given year of our period of study. We use empirical probabilities to estimate a turbine owner's expectation of future values of these policies conditional on current values of these policies and on current values of other state variables.

2.2 State of Wind Turbine Technology

For our measure of the state of wind turbine technology in Denmark, we use the levelized cost of energy in Denmark. Levelized cost of energy is defined as the total present value cost of a turbine divided by the total amount of electricity it produces in its lifetime. The levelized cost can be thought of as the price that electricity would have to be sold at in order for a new generator to break even over the lifetime of the project.

Levelized cost is calculated by summing the total costs of an electricity-generating asset over the course of its expected lifetime divided by the total amount of electricity the asset is expected to produce. Total costs include initial capital costs, fuel costs, and operation and maintenance costs. Levelized costs are typically calculated over 20-40 year lifetimes and discount all costs back to the present.

A general equation for levelized cost *leco* is given by:

$$lcoe = \frac{\sum_{t=1}^{T} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{T} \frac{E_t}{(1+r)^t}} \tag{1}$$

where, for each time t from $t = 1$ to $t = T$, I_t denotes investment cost, M_t denotes maintenance cost, F_t denotes fuel cost, and E_t denotes electricity output at time t, and r is the discount rate. In the case of wind, fuel costs are zero and operation costs are low, so the bulk of the cost is the cost of the turbine itself. Total electricity generation in kWh is usually estimated by specifying a capacity factor representing the fraction of time the turbine will actually be producing electricity and multiplying that number by the capacity of the turbine in kW and the number of hours in a year (which is 8760 hours).

One of the primary purposes of the levelized cost of energy is to allow developers to evaluate potential projects on a prospective basis. The actual number is very much dependent on the assumptions that are made, but it is meant to give an idea of the likelihood of a project breaking even. For example, if the levelized cost of energy for a potential wind project is a lot higher than the current price of electricity, then that project does not look very promising.

Our estimates of the levelized cost of energy are from Lantz, Hand, and Wiser (Lantz et al., 2012). In particular, we use the estimates of the levelized cost of energy for onshore wind turbines in Denmark from the Danish Energy Agency (DEA, 1999) for each year over the period 1980 to 1999, which were the years when these estimates were available, and we use the lower bound of the remaining estimates in Lantz et al. (2012) for each year over the period 2000 to 2010. We extrapolated the levelized cost for 2011 using data from the years 2004-2010. We convert the units of levelized cost are to Danish krone per MWh.

Because we eventually discretize the levelized cost of energy into 3 bins for use in our structural model, our results are robust to any imprecision in our estimates of the levelized cost of energy owing to our merging estimates from multiple sources and our extrapolating the values for the year 2011.

We assume that all turbines built in the same year have the same levelized cost. The levelized cost therefore serves as a signal to owners about the costs associated with installing a new turbine that year. As technology improved over time, the cost of generating electricity from wind turbines has declined because of economies of scale and learning.

The purpose of including levelized cost of energy in our model is to capture the development of wind turbine technology over time. The idea is that as technology improves, turbine costs will decline and capacity factors will increase, both of which will lead to a lower levelized cost of energy. As long as the levelized cost of energy for each year is calculated using similar methodology and assumptions, then what the levelized cost is capturing is the time path of turbine costs, which we are arguing is driven by developments in turbine technology. We are assuming that the levelized cost of energy is exogenous from the point of view of a small wind farm owner and that an individual owners investment decisions do not impact the levelized cost of energy.

We model the future values of technology as uncertain from the point of view of the turbine owners. Moreover, because we are studying the decisions of turbine owners with small numbers of turbines (rather than large energy companies), we argue that the evolution of these variables is taken as given by each individual turbine owner and the owner's decisions have zero impact on the future values of these variables. We use empirical probabilities to estimate a turbine owner's expectation of future values of technology conditional on current values of technology and on current values of other state variables.

3 Econometric Models

3.1 Preliminary Reduced-Form Models

To complement our structural model, we first estimate several preliminary reduced-form discrete response models to analyze turbine owners' decisions to scrap, add and/or upgrade turbines. To examine the scrapping decision, we estimate logit, probit and linear probability models at both the owner and turbine levels using a binary dependent variable y_{it} which equals 1 if owner i scraps a turbine in period t. We also estimate a fixed effects logit model at the owner level using an owner fixed effect α_i. The specifications for these models are given by:

$$\text{Logit:} \qquad Pr(y_{it} = 1) = 1 - F\left(-\left(\beta_0 + x_{it}'\beta\right)\right) \tag{2}$$

$$\text{Probit:} \qquad Pr(y_{it} = 1) = \Phi\left(\beta_0 + x_{it}'\beta\right) \tag{3}$$

$$\text{Linear Probability:} \qquad Pr(y_{it} = 1) = \beta_0 + x_{it}'\beta \tag{4}$$

$$\text{Fixed Effects Logit:} \qquad Pr(y_{it} = 1) = 1 - F\left(-\left(\beta_0 + x_{it}'\beta + \alpha_i\right)\right). \tag{5}$$

Notes: In Equation 2, $F(\cdot)$ denotes the logistic cumulative distribution function. In Equation 3, $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

To examine the decisions to add a turbine and to upgrade a turbine, we estimate two additional sets of logit, probit, linear probability, and fixed effects logit models at the owner level where the binary dependent variable y_{it} equals 1 if owner i adds a turbine in period t and where the binary dependent variable y_{it} equals 1 if owner i upgrades a turbine in period t, respectively.

Explanatory variables x_{it} in each model include turbine/owner specific characteristics, government policies, as well as aggregate statistics including GDP per capita as a measure of income, total installed wind capacity, the largest installed turbine for a given year and the levelized cost of wind energy in Denmark. The largest installed turbine and levelized cost are used as measures of the state of wind turbine technology. As technology improved over time, turbine size has steadily increased, while the cost of generating electricity from wind turbines has declined because of economies of scale and learning.

The primary advantage of the reduced-form models are that we can use continuous variables without having to discretize them and, because state-space constraints are less of a concern, we can include many covariates. However, the reduced-form models only estimate the per-period probability of shutting down or upgrading, and therefore do not have a clear structural interpretation. As we explain below, because the payoffs from shutting down or upgrading turbines depend on market conditions such as the state of technology and government policies that vary stochastically over time, a turbine owner who hopes to make a dynamically optimal decision would need to account for the option value to waiting before making an irreversible decision to shut down or upgrade a turbine (Dixit and Pindyck, 1994). The parameters in the reduced-form models are therefore confounded by continuation values. We now develop a dynamic structural econometric model which better and more explicitly captures the dynamic and interdependent nature of a turbine owner's shutdown and upgrade decisions.

3.2 Structural Model of Wind Turbine Shutdowns and Upgrades

We model the decision to add, scrap or upgrade a wind turbine using a dynamic structural econometric model. Various methods for estimating dynamic structural models have been developed (Rust, 1988; Keane and Wolpin, 1994; Pakes et al., 2007; Bajari et al., 2007, 2009), and these methods have been applied various topics including bus engine replacement (Rust, 1987), nuclear power plant shutdown decisions (Rothwell and Rust, 1997), water management (Timmins, 2002), oil investment timing decisions (Lin, 2013), air conditioner purchase (Rapson, 2014), copper mining decisions (Aguirregabiria and Luengo, 2014), the cement industry (Ryan, 2012), and fisheries (Huang and Smith, 2014). To our knowledge, this paper is the first application to the wind industry.

Applying a dynamic structural econometric model to micro-level data allows one to model the decision to shut down or upgrade a wind turbine as a dynamic optimization problem at the individual level and enables one to study the impact of government policies and technological progress on those decisions. This "bottom-up" style of modeling is in direct contrast to many previous "top-down" approaches to examining trends in the wind industry and the structural nature of the model gives insights into key economic and behavioral parameters. Understanding the factors that influence individual decisions to invest in wind energy and how different policies can affect the timing of that decision is important for policies both in countries that already have mature wind industries as well as those that are earlier in the process of increasing renewable electricity generation (e.g. most of the U.S.).

There are several advantages to using a dynamic structural model to analyze the shutdown and upgrade decisions of wind turbine owners. First, unlike reduced-form models, a structural approach explicitly models the dynamics of shutdown and upgrade decisions. Wind turbines are long-term productive assets that degrade over time and are costly to replace in terms of money, time and effort. With an existing turbine, owners are locked into a fixed output capacity and feed-in-tariff. Meanwhile, technology and government policies are changing over time. Because the payoffs from shutting down or upgrading turbines depend on market conditions such as the state of technology and government policies that vary stochastically over time, a turbine owner who hopes to make a dynamically optimal decision would need to account for the option value to waiting before making an irreversible decision to shut down or upgrade a turbine (Dixit and Pindyck, 1994). Using a dynamic model allows an owner's decision to scrap or upgrade a turbine to be based not only on the condition of the existing turbine, but also on the current and expected future states of technology and policy.

A second advantage of the structural model is that with the structural model we are able to estimate the effect of each state variable on the expected payoffs from shutting down or upgrading a turbine, and are therefore able to estimate parameters that have direct economic interpretations. In the reduced-form model, we estimated the effect of these variables on the per-period probability of shutting down or upgrading. In contrast, the dynamic model accounts for the continuation value, which is the expected value of the value function next period. With the structural model we are able to estimate parameters in the payoffs from shutting down or upgrading, since we are able to structurally model how the continuation values relate to the payoffs from shutting down or upgrading.

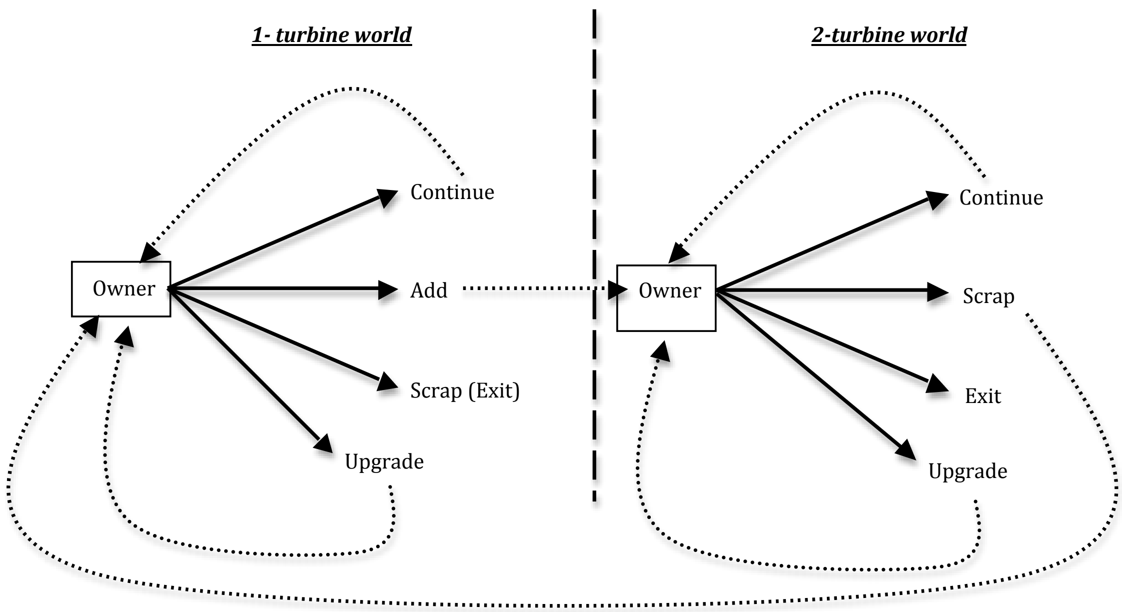
A third advantage of our structural model is that we are able to model the interdependence of the shutdown, addition and upgrade decisions. In particular, we model the value function for owners of one turbine and the value function for owners of two turbines separately, but allow them to depend on each other. Since an owner of one turbine has the option of becoming an owner of two turbines by adding a new turbine, the value of being an owner of one turbine depends in part on the value of being an owner of two turbines. Similarly, since an owner of two turbines has the option of becoming the owner of one turbine by scrapping one of his turbines, the value of being an owner of two turbines depends in part on the value of being an owner of one turbine.

A fourth advantage of our structural model is that we can use the parameter estimates from our structural model to simulate various counterfactual policy scenarios. We use our estimates to simulate the Danish wind industry in absence of government policy, and compare the actual development of the industry in the presence of government policy with this counterfactual development in the absence of policy.

Our structural model allows for owners to have up to two turbines at any particular time and the available actions depend on how many turbines are in operation, as depicted in Figure 2. As mentioned, 88% of turbine owners own 2 or fewer turbines during the period of study (1980-2011).

We build upon previous structural dynamic models by modeling two interdependent value functions, reflecting interdependent shutdown, adding and upgrading decisions. The basic idea is to have a model with two "worlds", such that when an owner has one operating turbine he/she is in the one-turbine world and moves to the two-turbine world if and when a second turbine becomes operational. The interdependence of the shutdown, adding and upgrading decisions is depicted in Figure 2. We model the decisions of owners beginning in the year in which their first wind turbine was built, conditional on having built a turbine so that all owners begin in the one-turbine world. Each period (year), an owner decides whether to continue producing with a single turbine, add a new turbine, upgrade to a new turbine, or scrap their existing turbine (exit the market). If the owner decides to add, then they move to the two-turbine world in the following period, where they have a slightly different set of possible actions. In the two-turbine world, owners can either continue producing with two turbines, scrap one of their existing turbines or scrap both of their turbines. Scrapping a turbine and adding a turbine in the same period constitutes an upgrade and if an owner scraps a single turbine, they move back to the one-turbine world.

Figure 2: Conceptual Framework for the Dynamic Structural Model of Interdependent Scrapping, Adding and Upgrading Decisions



Each agent in our model is a turbine owner who owns and operates no more than two wind turbines in any given period (year). In each period t, the each turbine owner i choices an action $d_{i,t} \in \{0, 1, 2, ..., 9\}$. The choice set available to agent i depends upon the world that an owner is in during that period, as listed in Table 3 below. In each period t, an owner of one turbine can decide to continue without any shutdown, addition or upgrade; add a small turbine; add a medium turbine; add a large turbine; upgrade to a small turbine; upgrade to a medium turbine; upgrade to a large turbine; or scrap his turbine. In each period t, an owner of two turbines can decide to continue without any shutdown or upgrade; upgrade one turbine to a small turbine; upgrade one turbine to a medium turbine; upgrade one turbine to a large turbine; scrap one turbine; or scrap both turbines.

Table 3: Actions Available to Turbine Owners Owning One and Two Turbines

Action	**One-turbine world**	**Two-turbine world**
Continue ($d_{i,t}$ = 1)	x	x
Add small turbine ($d_{i,t}$ = 2)	x	
Add medium turbine ($d_{i,t}$ = 3)	x	
Add large turbine ($d_{i,t}$ = 4)	x	
Scrap only one turbine ($d_{i,t}$ = 5)		x
Upgrade to small turbine ($d_{i,t}$ = 6)	x	x
Upgrade to medium turbine ($d_{i,t}$ = 7)	x	x
Upgrade to large turbine ($d_{i,t}$ = 8)	x	x
Scrap all turbines (exit) ($d_{i,t}$ = 9)	x	x

The payoff for each turbine owner i in each period t depends on state variables $x_i t$ that vary across individuals and/or time. Each state variable is discretized based on observed values in the data. Original capacity (cap_kw_i), original turbine age ($turbine\_age_{i,t}$), original feed-in-tariff ($orig\_fit_i$), and original levelized cost ($orig\_lcoe_i$) are state variables for the capacity, age, feed-in-tariff, and levelized cost, respectively, of the first turbine. New capacity (cap_kw2_i), new turbine age ($turbine\_age2_{i,t}$), new feed-in-tariff ($orig\_fit2_i$), and new levelized cost ($orig\_lcoe2_i$) are state variables for the capacity, age, feed-in-tariff, and levelized cost, respectively, of the second turbine for owners of two turbines. We also include state variables for the current period replacement subsidy ($rep\_subsidy_{i,t}$) and the current period levelized cost ($lcoe_t$).

We assume that the state variables evolve as a finite state first-order Markov process. We also assume, as is standard in discrete time models, that actions that change an owner's stock of turbines (add, upgrade, exit) do not affect the values of state variables until the following period. The values of the "New" state variables, corresponding to the second turbine, are set to zero for owners of one turbine. If and when an owner owning one turbine chooses to add a second turbine, these variables starting the period after the second turbine is added are set equal to their respective values at the time the second turbine is added. If an owner owning two turbines scraps one of his turbines, which in the data is always the older turbine, then the "Original" state variables take on the values of the "New" state variables and the "New" state variables are again set to zero.

For each owner i, the per-period payoff function to owning one turbine is $U^I(d_{i,t}, x_{i,t}, \epsilon_{i,t}\ ; \theta)$, which depends on the action $d_{i,t}$ taken, the value of the relevant state variables $x_{i,t}$, the vector of shocks $\epsilon_{i,t}$ to each of agent i's payoffs, and the parameters θ such that:

$$U^{I}\left(d_{i,t}, x_{i,t}, \epsilon_{i,t}\ ;\theta\right) = \begin{cases} \pi^{I,c}(x_{i,t}) + \epsilon_{i,t}^{I,c} & \text{if } d_{i,t} = 1 \text{ (Continue)} \\ \pi^{I,a}(x_{i,t}) + \epsilon_{i,t}^{I,a} & \text{if } d_{i,t} \in \{2,3,4\} \text{ (Add, } k = 1,2,3) \\ \pi^{I,u}(x_{i,t}) + \epsilon_{i,t}^{I,u} & \text{if } d_{i,t} \in \{6,7,8\} \text{ (Upgrade, } k = 1,2,3) \\ \pi^{I,e}(x_{i,t}) + \epsilon_{i,t}^{I,e} & \text{if } d_{i,t} = 9 \text{ (Exit),} \end{cases} \tag{6}$$

where owners can choose to add or upgrade to a small ($k = 1$), medium ($k = 2$) or large ($k = 3$) turbine and the respective payoff to doing so includes a distinct error term for each of these actions, and where the deterministic components $\pi^{I,j}(\cdot)$ of the per-period payoff functions are defined as:

$$\begin{aligned} \pi^{I,c}(x_{i,t}) &= \gamma_1 cap\_kw_i + \gamma_2 turbine\_age_{i,t} + \gamma_3 orig\_fit_i + \gamma_4 lcoe\_orig_i \\ \pi^{I,a}(x_{i,t}) &= \gamma_1 cap\_kw_i + \gamma_2 turbine\_age_{i,t} + \gamma_3 orig\_fit_i + \gamma_4 lcoe\_orig_i + C_i \\ \pi^{I,u}(x_{i,t}) &= \gamma_1 cap\_kw_i + \gamma_2 turbine\_age_{i,t} + \gamma_3 orig\_fit_i + \gamma_4 lcoe\_orig_i + \alpha_1 rep\_subsidy_{i,t} + \rho_2 \\ \pi^{I,e}(x_{i,t}) &= \alpha_1 rep\_subsidy_{i,t} + \alpha_2 lcoe_t + S_i^{I}. \end{aligned} \tag{7}$$

In Equation 7, the γ coefficients represent the effects on per-period payoffs to operating the turbine of turbine capacity (γ_1), turbine age (γ_2), the feed-in-tariff received by the owner[4] (γ_3), and the levelized cost of wind energy at the time the turbine was installed (γ_4). Since we do not have any data on maintenance or operating costs, we assume that all operating and maintenance costs are captured by the state of technology when the turbine was built ($lcoe_{i,t}$) and the age of the turbine. The feed-in-tariff received by the owner ($orig\_fit_i$) is assumed to be locked in for the life of the turbine upon connection to the grid.

In the payoff $\pi^{I,a}(\cdot)$ for adding a turbine, the C_i term represents the total discounted cost associated with buying and constructing an additional turbine. Separate specifications of the model were run using costs that vary by capacity ($C_i = \tau_1 cap\_kw_i$) and costs that are constant ($C_i = \rho_1$).

In the payoff $\pi^{I,e}(\cdot)$ to exiting, we include the current period levelized cost of wind energy as a proxy for (the negative of) the value that could be obtained by selling a replacement certificate. We expect replacement certificates to be more valuable when turbines are cheaper to build (i.e. low values of $lcoe_t$) and demand for new investments is high. The S_i^I term represents the scrap value to exiting. Separate specifications of the model were run using scrap values that vary by capacity ($S_i^I = \tau_2 cap\_kw_i$) and scrap values that are constant

[4]The level of the feed-in-tariff is locked in upon construction of the turbine.

$(S_i^I = \rho_3)$.

Per-period payoffs in the two-turbine world (Equation 8) are very similar, except that a slightly different set of options are available – namely, owners cannot add a third turbine, but can instead choose to scrap the older of their two turbines:

$$U^{II}(d_{i,t}, x_{i,t}, \epsilon_{i,t}\ ; \theta) = \begin{cases} \pi^{II,c}(x_{i,t}) + \epsilon_{i,t}^{II,c} & \text{if } d_{i,t} = 1 \text{ (Continue)} \\ \pi^{II,s}(x_{i,t}) + \epsilon_{i,t}^{II,s} & \text{if } d_{i,t} = 5 \text{ (Scrap one turbine)} \\ \pi^{II,u}(x_{i,t}) + \epsilon_{i,t}^{II,u} & \text{if } d_{i,t} \in \{6,7,8\} \text{ (Upgrade, } k = 1,2,3) \\ \pi^{II,e}(x_{i,t}) + \epsilon_{i,t}^{II,e} & \text{if } d_{i,t} = 9 \text{ (Exit),} \end{cases} \tag{8}$$

where the deterministic components $\pi^{II,j}(\cdot)$ of the per-period payoffs are defined as:

$$\begin{aligned} \pi^{II,c}(x_{i,t}) &= \gamma_1 cap\_kw_i + \gamma_2 turbine\_age_{i,t} + \gamma_3 orig\_fit_i + \gamma_4 lcoe\_orig_i \\ &\quad + \beta_1 cap\_kw2_i + \beta_2 turbine\_age2_{i,t} + \beta_3 orig\_fit2_i + \beta_4 lcoe\_orig2_i \\ \pi^{II,s}(x_{i,t}) &= \beta_1 cap\_kw2_i + \beta_2 turbine\_age2_{i,t} + \beta_3 orig\_fit2_i + \beta_4 lcoe\_orig2_i + S_i^{II,s} \\ &\quad + \alpha_1 rep\_subsidy_{i,t} + \alpha_2 lcoe_t \\ \pi^{II,u}(x_{i,t}) &= \gamma_1 cap\_kw_i + \gamma_2 turbine\_age_{i,t} + \gamma_3 orig\_fit_i + \gamma_4 lcoe\_orig_i \\ &\quad + \beta_1 cap\_kw2_i + \beta_2 turbine\_age2_{i,t} + \beta_3 orig\_fit2_i + \beta_4 lcoe\_orig2_i \\ &\quad + \alpha_1 rep\_subsidy_{i,t} + \rho_2 \\ \pi^{II,e}(x_{i,t}) &= \alpha_1 rep\_subsidy_{i,t} + \alpha_3 lcoe_t + S_i^{II,e}. \end{aligned} \tag{9}$$

In the payoff $\pi^{II,e}(\cdot)$ to exiting, we include the current period levelized cost of wind energy as a proxy for (the negative of) the value that could be obtained by selling a replacement certificate. We expect replacement certificates to be more valuable when turbines are cheaper to build (i.e. low values of $lcoe_t$) and demand for new investments is high. In one specification we allow the coefficient α_2 for owners of one turbine to differ from the coefficient α_3 for owners of two turbines; in the other specifications we assume that these coefficients are the same.

The $S_i^{II,s}$ term represents the scrap value to scrapping the first turbine and is equal to the scrap value S_i^I to owners of one turbine from scrapping their one turbine and exiting. Separate specifications of the model were run using scrap values that vary by capacity ($S_i^{II,s} = \tau_2 cap\_kw_i$) and scrap values that are constant ($S_i^{II,s} = \rho_3$).

The $S_i^{II,e}$ term represents the scrap value to owners of two turbines from scapping both turbines and exiting. Separate specifications of the model were run using scrap values that vary by capacity ($S_i^{II,e} = \tau_2 cap\_kw_i + \tau_3 cap\_kw2_i$) and scrap values that are constant ($S_i^{II,e} = \rho_3$).

In each period t, each turbine owner i chooses action $d_{i,t}$ to maximize the present discounted value of his entire stream of expected per-period payoffs. Letting $\epsilon_{i,t}$ denote a vector of the time-t shocks for all possible actions $d_{i,t}$ for turbine owner i, and using the payoff functions in Equations 6 and 8, we can write out the value function for the owner of one turbine and the value function for the owner of two turbines, respectively. The value $V^I(\cdot)$ of owning one turbine depends on the value $V^{II}(\cdot)$ of owning two turbines, and is given by:

$$V^I(x_{i,t}, \epsilon_{i,t}\,; \theta) = \max_{d_{i,t}} \left\{ \begin{array}{l} \pi^{I,c}(x_{i,t}) + \epsilon_{i,t}^{I,c} + \beta E[V^I(x_{t+1}, \epsilon_{t+1}) \mid x_t, \epsilon_t, d_{i,t}, \theta] \\ \pi^{I,a}(x_{i,t}) + \epsilon_{i,t}^{I,a} + \beta E[V^{II}(x_{t+1}, \epsilon_{t+1}) \mid x_t, \epsilon_t, d_{i,t}\theta] \\ \pi^{I,u}(x_{i,t}) + \epsilon_{i,t}^{I,u} + \beta E[V^I(x_{t+1}, \epsilon_{t+1}) \mid x_t, \epsilon_t, d_{i,t}, \theta] \\ \pi^{I,e}(x_{i,t}) + \epsilon_{i,t}^{I,e} \end{array} \right\}. \tag{10}$$

Similarly, the value $V^{II}(\cdot)$ of owning two turbines depends on the value $V^I(\cdot)$ of owning one turbine, and is given by:

$$V^{II}(x_{i,t}, \epsilon_{i,t}\,; \theta) = \max_{d_{i,t}} \left\{ \begin{array}{l} \pi^{II,c}(x_{i,t}) + \epsilon_{i,t}^{II,c} + \beta E[V^{II}(x_{t+1}, \epsilon_{t+1}) \mid x_t, d_{i,t}, \epsilon_t, \theta] \\ \pi^{II,s}(x_{i,t}) + \epsilon_{i,t}^{II,s} + \beta E[V^I(x_{t+1}, \epsilon_{t+1}) \mid x_t, d_{i,t}, \epsilon_t, \theta] \\ \pi^{II,u}(x_{i,t}) + \epsilon_{i,t}^{II,u} + \beta E[V^{II}(x_{t+1}, \epsilon_{t+1}) \mid x_t, d_{i,t}, \epsilon_t, \theta] \\ \pi^{II,e}(x_{i,t}) + \epsilon_{i,t}^{II,e} \end{array} \right\}.$$

As standard in many dynamic structural models, we make the following conditional independence assumption:

$$Pr(x_{i,t+1}, \epsilon_{i,t+1}, d_{i,t}, \theta) = Pr(x_{i,t+1} \mid x_{i,t}, d_{i,t}, \theta)\, Pr(\epsilon_{i,t+1} \mid \theta)\,. \tag{11}$$

The transition probabilities $Pr(x_{i,t+1} \mid x_{i,t}, d_{i,t}, \theta)$ are estimated non-parametrically from the data for all possible state and action combinations. For turbine age, we kept track of actual age and increment it deterministically each year, then determine which discretized bin the actual age falls into. Substituting the conditional independence assumption into the value functions yields:

$$V^{I}\left(x_{i,t},\epsilon_{i,t}\,;\theta\right)=\max_{d_{i,t}}\left\{\begin{array}{l}\pi^{I,c}(x_{i,t})+\epsilon_{i,t}^{I,c}+\beta\int\tilde{V}^{I}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{I,a}(x_{i,t})+\epsilon_{i,t}^{I,a}+\beta\int\tilde{V}^{II}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{I,u}(x_{i,t})+\epsilon_{i,t}^{I,u}+\beta\int\tilde{V}^{I}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{I,e}(x_{i,t})+\epsilon_{i,t}^{I,e}\end{array}\right\}\tag{12}$$

for owners of one turbine, and:

$$V^{II}\left(x_{i,t},\epsilon_{i,t}\,;\theta\right)=\max_{d_{i,t}}\left\{\begin{array}{l}\pi^{II,c}(x_{i,t})+\epsilon_{i,t}^{II,c}+\beta\int\tilde{V}^{II}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{II,s}(x_{i,t})+\epsilon_{i,t}^{II,s}+\beta\int\tilde{V}^{I}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{II,u}(x_{i,t})+\epsilon_{i,t}^{II,u}+\beta\int\tilde{V}^{II}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},\theta\right)\\ \pi^{II,e}(x_{i,t})+\epsilon_{i,t}^{II,e}\end{array}\right\}$$

for owners of two turbines, where:

$$\tilde{V}^{j}(x_{i,t+1})=\int V^{j}(x_{i,t+1},\epsilon_{i,t+1};\theta)dPr(\epsilon_{i,t+1}\mid\theta)=E_{\epsilon}\left[V^{j}(x_{i,t+1},\epsilon_{i,t+1};\theta)\right]\quad\text{for } j=I,II.$$

Making the assumption that each shock in $\epsilon_{i,t}$ is i.i.d. extreme value (type 1) across owners i, actions $d_{i,t}$ and time t, we can then write the expressions for $\tilde{V}^{j}(x_t)$ as:

$$\tilde{V}^{I}(x_{i,t})=\ln\left(\sum_{d}\exp\left(\delta^{I,d}\left(x_{i,t},\tilde{V}^{\ddagger}\right)\right)\right)\tag{13}$$

and:

$$\tilde{V}^{II}(x_{i,t})=\ln\left(\sum_{d}\exp\left(\delta^{II,d}\left(x_{i,t},\tilde{V}^{\ddagger}\right)\right)\right),\tag{14}$$

where:

$$\delta^{j,d}\left(x_{i,t},\tilde{V}^{\ddagger}\right)=\pi^{j,d}+\beta\int\tilde{V}^{\ddagger}(x_{i,t+1})dPr\left(x_{i,t+1}\mid x_{i,t},d,\theta\right)\quad\text{for } j=I,II.$$

In Equations 13 and 14, the $\tilde{V}^{\ddagger}$ terms are either $\tilde{V}^{I}(x_{i,t+1})$ or $\tilde{V}^{II}(x_{i,t+1})$ depending upon the world that an owner is in and the action taken (similar to Equation 12). These expressions for $\tilde{V}^{j}$ are fixed points that can be solved with numeric methods simultaneously and then used to estimate the probability of a given action conditional on the realization of a particular combination of state variables. These choice probabilities take the following multinomial logit form:

$$Pr\left(d_{i,t} = \tilde{d} \mid x_{i,t}, \theta\right) = \frac{\exp\left(\delta^{u,\tilde{d}}\left(x_{i,t}, \tilde{V}^{\ddagger}\right)\right)}{\sum_d \exp\left(\delta^{j,d}\left(x_{i,t}, \tilde{V}^{\ddagger}\right)\right)} \quad \text{for } j = I, II. \tag{15}$$

After obtaining the model predictions for the choice probabilities as functions of the state variables and the unknown parameters θ, the parameters can then be estimated using maximum likelihood. In the context of the model, the parameter estimates define a profit structure for wind turbine owners that is used to conduct counterfactual policy simulations.

4 Results

4.1 Preliminary Reduced-Form Results

We first present the results of our preliminary reduced-form models. Summary statistics for the explanatory variables used in the reduced-form models are shown in Table 4.

Table 4: Summary Statistics for Variables in Reduced-Form Models

Variable	Mean	Std. Dev.	Min.	Max.	N
Turbine added at time t (dummy)	0.0423	0.2012	0	1	87810
Turbine scrapped at time t (dummy)	0.0056	0.0744	0	1	87810
Turbine upgraded at time t (dummy)	0.0008	0.0274	0	1	87810
Levelized Cost of Wind Energy (DKK/MWh)	627.2	356.1	341.4	1600	33
Largest Installed Turbine in DK (kW)	1381.4	1265.6	30	4200	35
Total Installed Wind Capacity in DK (MW)	1323.5	1413.5	0.1	3927	35
DK Annual Wind Generation (GWh)	2621.7	2989.5	0	9840	35
GDP per capita (Thousand DKK)	193.1	82.3	57.7	321.3	35
Population (Millions)	5.3	0.1	5.1	5.6	35

The results of the discrete response models (logit, probit, linear probability and fixed effects logit) of an owner's decision to scrap a turbine are shown in Table 5. The dependent variable in these models is a binary outcome variable that is equal to one if an owner shuts down any of his/her turbines in a given year. In each model, the replacement schemes have a significant effect on the probability of an owner shutting down at least one turbine. Owners were also more likely to scrap turbines in years with higher feed-in-tariffs and better existing technology.

Table 5: Reduced-Form Results for Owner-Level Scrapping Decisions

Dependent variable is probability of scrapping turbine				
	(1) Logit	(2) Probit	(3) Linear Probability	(4) Fixed Effects Logit
Feed-In-Tariff (DKK/kWh)	0.103**	0.094**	0.130**	10.97**
	(0.008)	(0.007)	(0.009)	(0.780)
Replacement Certificate (DKK/kWh)	0.255**	0.217**	0.520**	27.11**
	(0.0192)	(0.0124)	(0.0301)	(1.463)
Owner Has Multiple Wind Farms (dummy)	0.015**	0.017**	0.028**	1.616**
	(0.002)	(0.002)	(0.006)	(0.143)
Number of Active Turbines For Owner	0.0002**	0.0002**	0.0010**	0.0211**
	(0.000)	(0.000)	(0.0003)	(0.0052)
Largest Installed Turbine In DK (kW)	0.003**	0.003**	-0.000	0.362**
	(0.001)	(0.001)	(0.000)	(0.077)
Total Installed Wind Capacity in DK (MW)	-0.0003**	-0.0002**	0.0006	-0.0173
	(0.000)	(0.000)	(0.0005)	(0.0097)
Previous year's DK capacity (MW)	0.045**	0.0403**	0.062**	4.753**
	(0.004)	(0.004)	(0.004)	(0.465)
Previous year's DK electricity production (GWh)	-0.014**	-0.012**	-0.016**	-1.449**
	(0.002)	(0.002)	(0.004)	(0.202)
Year	0.004**	0.003**	-0.001**	0.465**
	(0.001)	(0.001)	(0.000)	(0.076)
Constant			1.727**	
			(0.477)	
Number of observations	40,636	40,636	40,636	40,636

Notes: Robust standard errors are in parentheses. Marginal effects are reported for the logit and probit models. The fixed effects logit model includes owner fixed effects. Significance codes: ** p<0.01, * p<0.05.

Similar models of the scrapping decision were estimated using the turbine-level data. These results are shown in Table 6. At the turbine level, we are able to include turbine specific characteristics such as turbine age, wind quality, cumulative electricity production, the capacity factor over the lifetime of the turbine, and whether the turbine is privately owned. A dummy variable for whether the owner of a particular turbine has multiple wind farms (defined as more than one site) is also included. Again, the replacement subsidy has a large impact on the likelihood of a turbine being scrapped and higher feed-in-tariffs are associated with a higher prevalence of scrapping. Older turbines are more likely to be scrapped, as are bigger turbines. The wind quality available at the site of a turbine does not have a significant impact on whether or not a turbine is scrapped.

Table 6: Reduced-Form Results for Turbine-Level Scrapping Decisions

Dependent variable is probability of scrapping turbine	(1) Fixed-effects Logit	(2) Logit	(3) Probit
Feed-In-Tariff (DKK/kWh)	0.205**	0.162**	0.149**
	(0.033)	(0.020)	(0.017)
Replacement Certificate (DKK/kWh)	0.598**	0.296**	0.273**
	(0.135)	(0.031)	(0.026)
Privately Owned Turbine (dummy)	-0.011**	-0.016**	-0.011*
	(0.003)	(0.005)	(0.005)
Age Of Turbine	0.006**	0.004**	0.003**
	(0.001)	(0.000)	(0.000)
Turbine Capacity (MW)	0.042**	0.010	0.012**
	(0.005)	(0.006)	(0.004)
Capacity Factor Over Lifetime Of Turbine	0.002	-0.007	-0.0167
	(0.012)	(0.021)	(0.019)
Owner Has Multiple Wind Farms (dummy)	0.007**	0.014**	0.013**
	(0.003)	(0.003)	(0.003)
Cumulative Production From Turbine (MWh)	-0.004**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)
Wind Quality (kW/m^2)	0.015	0.020	0.031*
	(0.010)	(0.015)	(0.013)
Largest Installed Turbine In DK (kW)	0.016**	0.016**	0.014**
	(0.002)	(0.004)	(0.002)
Total Installed Wind Capacity In DK (MW)	0.021**	0.009**	0.009**
	(0.005)	(0.002)	(0.002)
Residential Price Of Natural Gas (DKK/Nm^3)	0.007	-0.002	-0.003
	(0.005)	(0.007)	(0.006)
Year	-0.007**	0.003	0.003*
	(0.001)	(0.002)	(0.001)
Constant	14.53**		
	(2.037)		
Number of observations	100,560	100,560	100,560
Number of turbines	6,410	6,410	6,410

Notes: Robust standard errors are in parentheses. Marginal effects are reported for the logit and probit models. The fixed effects model includes owner fixed effects. Significance codes:** p<0.01, * p<0.05.

Table 7 presents the results of the discrete response models (logit, probit, linear probability and fixed effects logit) of the decision to add turbines using owner-level data. According to the results, the replacement subsidy has either a negative or insignificant effect on the probability of adding a turbine while the feed-in-tariff does not have a robust signigicant effect. Neither policy is significant when owner fixed effects are added.

Table 7: Reduced-Form Results for Owner-Level Adding Decisions

	Dependent variable is probability of adding a turbine			
	(1)	(2)	(3)	(4)
	Logit	Probit	Linear Probability	Fixed Effects Logit
Level Of Feed-In-Tariff (DKK/kWh)	0.031**	0.025*	-0.042**	1.779
	(0.012)	(0.012)	(0.011)	(0.911)
Replacement Certificate (DKK/kWh)	-0.014	-0.006	-0.034*	2.105
	(0.013)	(0.013)	(0.014)	(1.334)
Levelized Cost (DKK/MWh)	-0.000	-0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.007)
Owner Has Multiple Wind Farms (dummy)	0.050**	0.050**	0.175**	4.447**
	(0.002)	(0.002)	(0.011)	(0.328)
Total Installed Capacity in DK (MW)	0.0003**	0.0004**	0.0031**	-0.0379
	(0.000)	(0.000)	(0.0007)	(0.0268)
Previous Year's DK capacity (MW)	0.0075	0.0021	-0.0129**	-0.0493
	(0.0054)	(0.0053)	(0.0037)	(0.4231)
Previous year's DK electricity production (GWh)	-0.008**	-0.006*	0.001	-0.545*
	(0.003)	(0.003)	(0.001)	(0.234)
GDP Per Capita (Thousands DKK)	0.0006**	0.0004**	0.0009**	0.0475**
	(0.0002)	(0.0001)	(0.0001)	(0.0122)
Population (Millions)	0.225**	0.252**	1.006**	23.716**
	(0.047)	(0.048)	(0.169)	(4.017)
Year	-0.009**	-0.008**	-0.030**	-0.859**
	(0.002)	(0.001)	(0.005)	(0.118)
Constant			53.90**	
			(8.415)	
Observations	40,636	40,636	40,636	5,827
R-squared			0.184	

Notes: Robust standard errors are in parentheses. Marginal effects are reported for the logit and probit models. The fixed effects logit model includes owner fixed effects. Significance codes: ** p<0.01, * p<0.05.

Table 8 presents the results of the discrete response models (logit, probit, linear probability and fixed effects logit) of the decision to upgrade turbines using owner-level data. According to the results, both the replacement certificate and the feed-in-tariff have either a positive or insignificant effect on the probability of upgrading an existing turbine.

According to the preliminary reduced-form results, both the replacement certificate and the feed-in-tariff had robust positive effects the probability of scrapping a turbine, but less robust effects on the probability of adding or upgrading turbines. However, the reduced-form models are static models, and therefore do not capture the dynamics of the shutdown and upgrade decisions. Moreover, the separate reduced-form models of scrapping, adding and upgrading do not capture the interdependent nature of these decisions. The prelim-

Table 8: Reduced-Form Results for Owner-Level Upgrade Decisions

Dependent variable is probability of upgrading an existing turbine				
	(1)	(2)	(3)	(4)
	Logit	Probit	Linear Probability	Fixed Effects Logit
Level Of Feed-In-Tariff (DKK/kWh)	0.005	0.005	0.011**	4.364
	(0.011)	(0.006)	(0.004)	(2.869)
Replacement Certificate (DKK/kWh)	0.020	0.018	0.034**	10.479*
	(0.039)	(0.017)	(0.007)	(4.353)
Levelized Cost	-0.000	-0.000	0.000	-0.337**
	(0.001)	(0.000)	(0.000)	(0.089)
Owner Has Multiple Wind Farms (dummy)	0.005	0.004	0.008*	18.791
	(0.009)	(0.004)	(0.003)	(1015.05)
Total Installed Capacity Of Turbines in DK (MW)	0.000	0.000	0.002**	0.015
	(0.000)	(0.000)	(0.001)	(0.025)
Previous Year's DK capacity (MW)	-0.000	0.000	0.005**	-0.048
	(0.002)	(0.002)	(0.002)	(1.170)
Previous year's DK electricity production (GWh)	-0.000	-0.000	-0.000	0.058
	(0.001)	(0.001)	(0.000)	(0.558)
GDP Per Capita (Thousands DKK)	0.000	0.000	0.000	0.095
	(0.000)	(0.000)	(0.000)	(0.049)
Population (Millions)	0.312	0.284	-0.018	200.415**
	(0.629)	(0.286)	(0.016)	(70.856)
Year	-0.006	-0.005	0.000	-3.472*
	(0.011)	(0.005)	(0.000)	(1.650)
Constant			-0.354	
			(0.441)	
Observations	40,636	40,636	40,636	989
R-squared			0.056	

Notes: Robust standard errors are in parentheses. Marginal effects are reported for the logit and probit models. The fixed effects logit model includes owner fixed effects. Significance codes: ** p<0.01, * p<0.05.

inary reduced-form results therefore potentially provide a misleading measure of the effects of government policy. We now turn to the results of our dynamic structural econometric model which better captures the dynamic and interdependent nature of a turbine owner's shutdown, addition and upgrade decisions, and therefore better measures the effects of government policy.

4.2 Structural Results

Summary statistics for the variables used in our dynamic structural econometric model are shown in Table 9 and the bins used to discretize the variables are shown in Table 10.

Table 9: Summary Statistics for Variables in Structural Model

Variable	Mean	Std. Dev.	Min.	Max.
Capacity (kW)	487.9	507	10	6000
Installation Date	Aug. 13, 1994	6.46 years	Jan. 1, 1978	Oct. 17, 2011
Turbine-specific Feed-in-tariff (DKK/kWh)	0.5	0.1	0.1	0.6
Turbine-specific Levelized Cost (DKK/MWh)	627.2	356.1	341.4	1599.7

Table 10: Discretized Values for State Variables in Structural Model

Variable	Value Range	Discrete Value
Capacity (kW)	0-450	1
	451-750	2
	>750	3
Turbine Age	0-9	1
	10-19	2
	>19	3
Feed-in-tariff (DKK/kWh)	0.25	1
	0.43	2
	0.60	3
Levelized Cost (DKK/MWh)	0-525	1
	526-700	2
	>700	3
Replacement Certificate (DKK/kWh)	0.08	1
	0.12	2
	0.17	3

We estimate three specifications of our dynamic structural econometric model. The three specifications vary in the way they model new turbine costs, scrap values and the value of selling a replacement certificate. In Specification 1, new turbine costs and scrap values are assumed to be proportional to the size of the turbine, and replacement certificates are assumed to have the same value in a given time period for both owners of one turbine and owners of two turbines. Specification 2 keeps the assumption that new turbine costs and scrap values depend on turbine capacity, but allows for the value of replacement certificates to be different for owners of one turbine and owners of two turbines. Lastly, Specification 3 assumes that new turbine costs and scrap values are constant and that the value of the replacement certificates are the same for both owners of one turbine and owners of two turbines.

The parameter estimates for these three specifications of our dynamic structural econometric model are reported in Table 11. Because the state variables are discretized, the estimates are not interpretable as marginal effects, but should instead be interpreted as relative contributions to the profits of turbine owners.

Table 11: Results of Dynamic Structural Econometric Model

Parameter	**Variable**	**Description**	(1)	(2)	(3)
γ_1	*cap_kw*	Capacity of Turbine 1	0.682	0.682	0.166**
			(0.415)	(0.418)	(0.036)
γ_2	*turbine_age*	Age of Turbine 1	-0.083*	-0.083*	-0.066
			(0.041)	(0.041)	(0.036)
γ_3	*orig_fit*	Feed-in-tariff for Turbine 1	0.316*	0.316*	0.223**
			(0.136)	(0.137)	(0.045)
γ_4	*orig_lcoe*	LCOE for Turbine 1	-0.153**	-0.153**	-0.154**
			(0.026)	(0.026)	(0.022)
β_1	*cap_kw*2	Capacity of Turbine 2	-0.124	-0.123	0.012
			(1.293)	(2.722)	(0.046)
β_2	*turbine_age*2	Age of Turbine 2	-0.168	-0.166	0.037
			(0.240)	(0.249)	(0.106)
β_3	*orig_fit*2	Feed-in-tariff for Turbine 2	0.317	0.314	0.011
			(0.524)	(0.964)	(0.052)
β_4	*lcoe_orig*2	LCOE for Turbine 2	-0.194	-0.192	0.019
			(0.209)	(0.213)	(0.043)
α_1	*rep_subsidy*	Replacement Certificate	1.466**	1.467**	1.121**
			(0.114)	(0.115)	(0.290)
α_2	$lcoe_t$	(Negative of) value of replacement certificate	-0.119	-0.118	-0.467
			(0.377)	(0.385)	(0.811)
α_3	$lcoe_t$	(Negative of) value of 2nd replacement certificate		-0.034	
				(2.091)	
τ_1	*cap_kw*2	(Negative of) cost of adding new turbine	-0.192	-0.193	
			(0.210)	(0.209)	
τ_2	*cap_kw*	Scrap value of turbine 1	3.719**	3.717**	
			(0.654)	(0.659)	
τ_3	*cap_kw*2	Scrap value of turbine 2	-0.621*	-0.676**	
			(0.300)	(0.224)	
ρ_1	constant	(Negative of) cost of adding new turbine			-6.150**
					(0.835)
ρ_2	constant	(Negative of) cost of upgrading			-9.064**
					(2.046)
ρ_3	constant	Scrap value of exiting			-2.285
					(2.407)

Notes: Standard errors are in parentheses. Significance codes:** p<0.01, * p<0.05.

Examining the results gives us a sense of the relative impacts of different variables on the profits of wind turbine owners and the importance of the policies put into place by the Danish government. The signs of the γ and β coefficients on the payoffs from operating a turbine show that higher profits are generated by younger turbines with higher capacities that were built during periods of high feed-in-tariffs and low levelized costs.[5]

In all specifications the feed-in-tariff is a significant source of revenues. A change in the level of the feed-in-tariff (e.g., from low (0.25 DKK/kWh) to medium (0.43 DKK/kWh), or from medium (0.43 DKK/kWh) to high (0.60 DKK/kWh)) has approximately 1.5 to 2 times the effects on per-period payoffs as a decrease in the level of the levelized cost of energy, the indicator of technology (e.g., from high (¿100 DKK/kWh) to medium (76-100 DKK/kWh), or from medium (76-100 DKK/kWh) to low (0-75 DKK/kWh)), where the levels are determined by the bins in Table 10.

Likewise, replacement certificates comprise a significant share of the payoffs to scrapping or upgrading existing turbines in all three specifications. A change in the level of the replacement certificate (e.g., from low (0.08 DKK/kWh) to medium (0.12 DKK/kWh), or from medium (0.12 DKK/kWh) to high (0.17 DKK/kWh)) has approximately 7 to 9.5 times the effects on per-period payoffs as a decrease in the level of the levelized cost of energy, the indicator of technology (e.g., from high to medium, or from medium to low). Our results therefore indicate that the growth and development of the Danish wind industry was primarily driven by government policies as opposed to technological improvements.

Looking across the three specifications, we see that the scrap value of turbines is positive and is larger for higher capacity turbines, while adding new turbines or upgrading carries with it a significant cost that is not significantly affected by the capacity of the new turbine. Comparing the magnitudes of the coefficients for adding (ρ_1) and upgrading (ρ_2) in Specification 3 indicates that upgrading is the more costly of the two actions.

4.3 Policy Simulations

One of the primary benefits of estimating a structural model is that it allows for simulations of counterfactual policy scenarios that can tell us more about the magnitudes of policy impacts. In this section, we present the results of simulations we ran over the time period of our data set (1980-2011) for several different policy scenarios. Specifically, the counterfactual policy scenarios we evaluate are:

1. What would have happened without the replacement certificate program?

2. What if the feed-in-tariff was designed to decline as a turbine ages instead of remaining flat through the lifetime of the turbine?

[5] Parameters for owners of one turbine are estimated much more precisely likely due to fact that there is a relatively small sample of owners owning two turbines.

3. What would have happened if there was no feed-in-tariff at all?

4. What would have happened without both the replacement certificate program and the feed-in-tariff?

Simulations were conducted by imposing restrictions on the relevant government policy state variables corresponding to each policy scenario and using the significant parameter estimates from Specification 3 of the model. For the simulations involving either no replacement certificate program, no feed-in-tariff (or both), this process entailed setting the value of those variables equal to zero for all owners in all time periods. In the simulation with a declining feed-in-tariff, we specify a feed-in-tariff that declines according to the age of a turbine as shown in Table 12.

Table 12: Simulated Feed-in-Tariff Policy

Turbine Age	**Level of Subsidy**S
0 to 8 years	DKK .60/kWh price guarantee
9 to 16 years	DKK .43/kWh price guarantee
>16 years	DKK .10/kWh price guarantee

The parameters and new state variables were used to generate new transition and choice probabilities conditional on the combination of state variables faced by an owner.[6] Beginning with the first observed value of the state variables for each owner from the actual data, we simulated the action for that period by drawing from the choice probabilities and the state variables for the next period by drawing from the transition probabilities. Based on the state variables drawn for the next period, we then simulated the action for that period and the state variables for the subsequent period, and so on until the last year of our data set (2011).

Once the simulated data was created, we calculated various summary statistics for comparison to the actual, observed data. These statistics of interest include the total discounted payoffs for turbine owners (i.e., the present discounted value of the entire stream of payoffs for each turbine owner), the number of new turbines added, the number of turbines that were scrapped, the number of upgrades made, the average age of turbines scrapped, and the total number of replacement certificates issued. We also calculate, for the turbines in the final year of the data set (2011), the average age of these turbines and the distribution of these turbines' capacities.

[6]Because many of the state variables are exactly determined by the action an owner takes, transition probabilities in the policy simulations are based on the remaining stochastic variables in the simulation: replacement subsidy, levelized cost of wind energy, feed-in-tariff.

For each counterfactual policy scenario, we run 100 independent simulations. The means and standard deviations are then calculated over the 100 independent simulations for each of the summary statistics. These means and standard deviations are reported in Table 13.

Table 13: Results of Simulations of Counterfactual Policy Scenarios

	Actual Data	No Replacement Certificate	Declining Feed-In-Tariff	No Feed-In-Tariff	No Replacement Certificate + No Feed-In-Tariff
Total discounted payoffs (percentage of actual)	100	34.2	38.4	5.03	4.05
		(0.51)	(0.52)	(0.21)	(0.17)
Total number of turbines scrapped	214	2,343	2,334	2,351	2,351
		(8.21)	(8.59)	(6.43)	(5.81)
Total number of turbines upgraded	13	2	2	1	1
		(1.32)	(1.24)	(0.83)	(0.85)
Total number of turbines added	129	32	31	17	17
		(5.88)	(5.77)	(4.20)	(3.71)
Turbines scrapped by owners of 1 turbine	180	2,297	2,889	2,326	2,326
		(7.08)	(7.74)	(4.85)	(4.57)
Turbines scrapped by owners of 2 turbines	34	46	45	25	25
		(9.12)	(9.07)	(6.56)	(6.01)
Average age of turbines scrapped	16	3	3	2	2
		(0.04)	(0.04)	(0.03)	(0.03)
Total number of replacement certificates issued	213	n/a	101	67	n/a
		n/a	(8.46)	(7.39)	n/a
Average age of turbines in 2011	13	5	5	2	2
		(0.44)	(0.37)	(0.32)	(0.33)
Number of small turbines in 2011	423	4	2	2	2
		(1.33)	(1.09)	(0.70)	(0.82)
Number of medium turbines in 2011	1291	18	17	2	2
		(4.25)	(4.03)	(1.23)	(1.37)
Number of large turbines in 2011	472	62	71	51	50
		(3.95)	(5.13)	(2.87)	(2.93)

Notes: The table reports, for each policy scenario, the means and standard deviations over 100 simulations. Means are rounded to the nearest whole number. Standard deviations are in parentheses.

Examining the results in Table 13, there are several noticeable differences between the policy simulations and the actual data. First, total discounted payoffs for turbine owners are significantly higher in the actual data than in any of the simulations. This result suggests that both the replacement certificate policy and feed-in-tariff provided windfall gains to small turbine owners. In particular, total discounted payoffs would have been only 30% of the actual payoffs if there were no replacement certificate and only 5% of the actual payoffs if there were no feed-in-tariff. In the absence of both policies, total discounted payoffs would have been only 4% of the actual payoffs.

A second result is that in all policy simulations, owners choose to scrap more and add fewer turbines than in the actual data. This is likely because the value of owning turbines and the value associated with waiting for future periods before scrapping are significantly lower in the absence of these policies, since both the replacement certificates and feed-in-tariff have positive values for turbine owners. As a consequence, many owners scrap their turbines and exit the industry, rather than add new turbines.

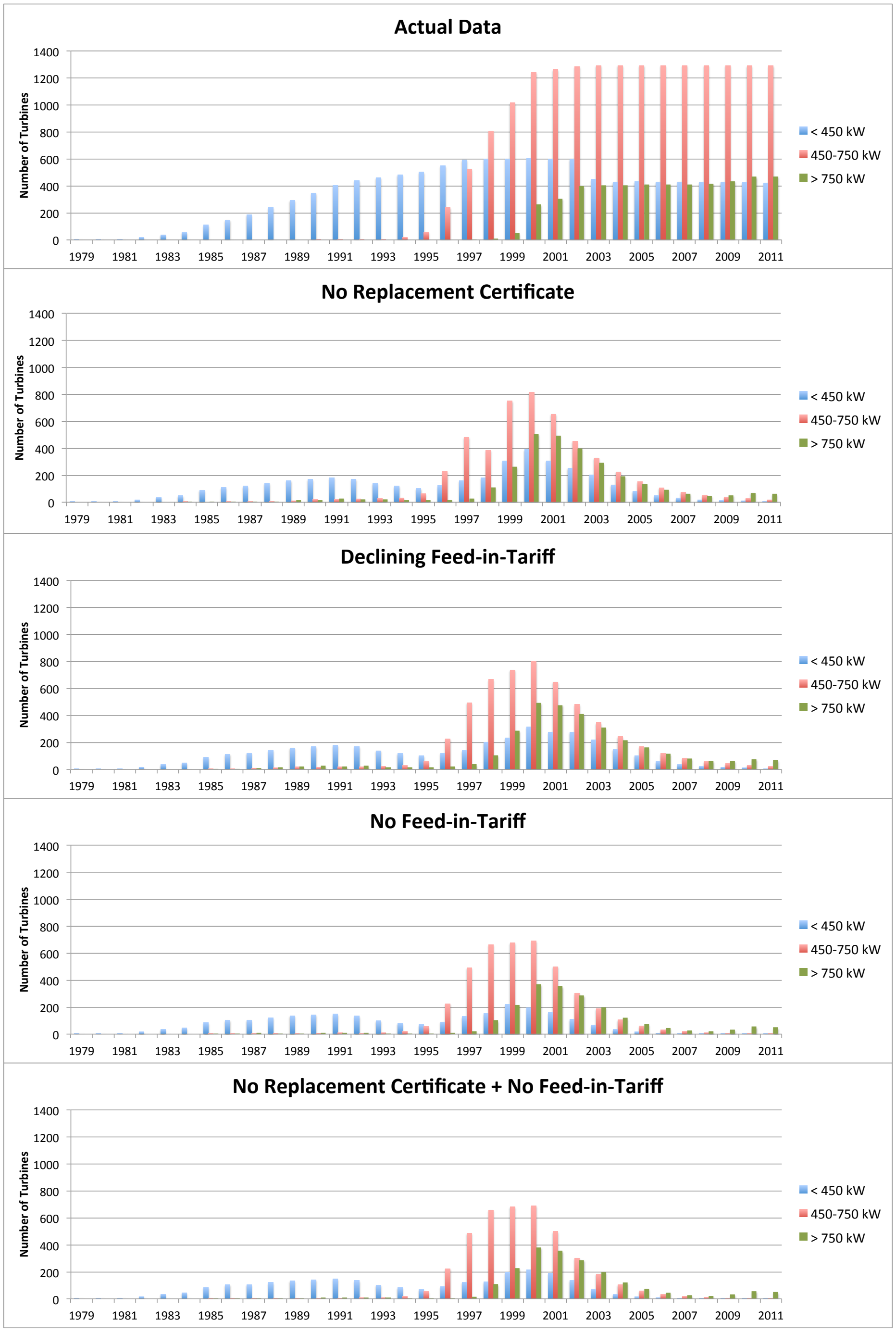
From the simulated data, we can also examine the evolution of the Danish wind industry under the different policy scenarios. Figure 3 shows the number of small (< 450 kW), medium (450 - 750 kW) and large (> 750 kW) wind turbines that existed in each year from 1980-2011 for the actual data as well as under each policy simulation. Overall, fewer turbines exist in the simulations except for rapid growth in the number of medium-sized turbines during the boom years of the industry between 1990-2000.

5 Conclusion

This paper develops a dynamic structural econometric model of wind turbine ownership that is used to estimate a profit structure for wind energy producers in Denmark. Results from the model indicate that the growth and development of the Danish wind industry was primarily driven by government policies as opposed to technological improvements. Results from policy simulations show that both the replacement certificate and flat feed-in-tariff policies generated windfall profits for existing turbine owners and resulted in more turbine additions and upgrades than would have otherwise occurred. Both of these policies significantly impacted the timing of shutdown and upgrade decisions made by turbine owners and accelerated the development of the wind industry in Denmark.

Without the policies, the benefits to owning a turbine would have been significantly reduced. In particular, total discounted payoffs would have been only 30% of the actual payoffs if there were no replacement

Figure 3: Evolution of Wind Industry Under Different Policy Scenarios



certificate and only 5% of the actual payoffs if there were no feed-in-tariff. In the absence of both policies, total discounted payoffs would only have been 4% of the actual payoffs. Without these policies, most small-scale wind turbine owners would have exited the industry before the end of 2011.

The results from the policy simulations can be used to assess Denmark's wind policies from several different perspectives. The driving forces behind renewable energy development in Denmark for 35 years have been energy security and green growth that have manifested themselves in a series of energy and climate goals (Energinet.dk, 2010; Meyer, 2004). To these ends, the feed-in-tariff was the primary tool chosen to incentivize new investments in wind turbines, while the replacement certificate program was created to allow the expansion of wind power to take place along with the decommissioning of older and less appropriately sited wind turbines.

Evaluated on the basis of their stated goals, the feed-in-tariff and replacement certificate policies have been a rousing success, though their ability to achieve other objectives is not quite as clear. Due to the fixed nature of feed-in-tariff incentives over the lifetime of a turbine, the policy became increasingly expensive for the government as the number of turbines grew throughout the 1980s and 1990s. Implementing a declining feed-in-tariff would have reduced government expenditures, but would also have resulted in the addition of fewer turbines.

Other relevant economic questions include whether or not the policies improved welfare from a social standpoint and understanding any equity impacts. We have seen that the welfare of owners with small numbers of turbines was improved by the policies, but the effects on larger owners and electricity consumers could not be estimated. Because our sample only contains those turbine owners who operate a maximum of two turbines at any one time and because installed wind capacity continued to grow in Denmark through the 2000s, the results of the policy simulations suggest that new installations in the absence of government policy would have been dominated by investments in larger wind farms from new entrants as opposed to decentralized investments made by small-scale turbine owners. This is to say, over time the Danish wind industry would have shifted toward larger wind farms that were owned by fewer numbers of people. Without the feed-in-tariff and replacement certificate program, it is likely that nearly all early turbine owners would have exited the industry by the end of 2011.

The focus of our paper is on the shutdown, addition and upgrade decisions of existing turbine owners, as shutting down and/or upgrading existing productive assets are important economic decisions for the owners of those assets and are also the fundamental decisions that underlie the development of new, growing industries. We do not model the original entry decision for an owner, but instead condition upon it. Because the location of turbines are pre-determined by municipal wind plans (DEA, 2009), we can plausibly argue that the probability of entry was driven by factors exogenous to the Danish feed-in-tariff and replacement certificate programs, and therefore that our estimates of the effects of the Danish feed-in-tariff and replacement certificate programs are not biased towards zero even though we condition upon entry. However, if the entry decision is affected by the Danish feed-in-tariff and replacement certificate programs, our estimates of the effects of these policies on total discounted payoffs are a lower bound on the total benefits of the policies and the actual benefits of these policies may be even greater than what we estimate. In this case, the large lower bound values for the total benefits of the policies that we estimate are still meaningful since they suggest that the actual benefits of these policies may be at least as large. We hope to model the entry decision in future work.

The dynamic structural econometric model we develop in this paper can be applied to any set of interdependent shutdown and upgrade decisions. Our application to the Danish wind industry has important implications to the design of renewable energy policies worldwide.

References

Paolo Agnolucci. Wind electricity in Denmark: A survey of policies, their effectiveness and factors motivating their introduction. *Renewable and Sustainable Energy Reviews*, 11(5):951–963, 2007. ISSN 1364-0321. doi: 10.1016/j.rser.2005.07.004.

Victor Aguirregabiria and Andres Luengo. A microeconometric dynamic structural model of copper mining decisions. 2014.

Gary Allison and John Williams. The effects of state laws and regulations on the development of renewable sources of electric energy. Technical report, NEPI, 2010.

Patrick Bajari, C Lanier Benkard, and Jonathan Levin. Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370, 2007.

Patrick Bajari, Victor Chernozhukov, Han Hong, and Denis Nekipelov. Identification and efficient semiparametric estimation of a dynamic discrete game. Technical report, Working paper, University of Minnesota.[203], 2009.

Joel Darmstadter. The economic and policy setting of renewable energy: Where do things stand? Discussion Paper dp-03-64, Resources For the Future, 2003.

DEA. Wind power in denmark. technology, policies and results. Technical report, Danish Energy Agency [DEA], 1999.

DEA. Wind turbines in denmark. Technical report, Danish Energy Agency [DEA], 2009.

DEA. Register of wind turbines. Technical report, Danish Energy Agency [DEA], 2012. URL `http://www.ens.dk/EN-US/INFO/FACTSANDFIGURES/ENERGY_STATISTICS_AND_INDICATORS/OVERVIEWOFTHEENERGYSECTOR/REGISTEROFWINDTURBINES/Sider/Forside.aspx`.

Denmark. Promotion of renewable energy act, 2008. URL `http://www.ens.dk/en-US/Info/Legislation/Energy_Supply/Documents/Promotion%20of%20Renewable%20Energy%20Act%20-%20extract.pdf`.

Robert K Dixit and Robert S Pindyck. *Investment under Uncertainty*. Princeton University Press, 1994.

Energinet.dk. Wind power to combat climate change: How to integrate wind energy into the power system. Online, 2010.

Matthias Heymann. Signs of hubris: The shaping of wind technology styles in Germany, Denmark, and the United States, 1940-1990. *Technology and Culture*, 39(4):641–670, 1998. ISSN 0040-165X. doi: 10.2307/1215843. ArticleType: research-article / Full publication date: Oct., 1998 / Copyright © 1998 Society for the History of Technology.

Ling Huang and Martin D Smith. The dynamic efficiency costs of common-pool resource exploitation. *American Economic Review*, 104(12):4071–4103, 2014.

Staffan Jacobsson and Anna Johnson. The diffusion of renewable energy technology: an analytical framework and key issues for research. *Energy policy*, 28(9):625–640, 2000.

Michael P. Keane and Kenneth I. Wolpin. The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte carlo evidence. *The Review of Economics and Statistics*, 76(4):648–672, 1994. ISSN 0034-6535. doi: 10.2307/2109768. ArticleType: research-article / Full publication date: Nov., 1994 / Copyright © 1994 The MIT Press.

Ger Klaassen, Asami Miketa, Katarina Larsen, and Thomas Sundqvist. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics*, 54(2–3):227–240, 2005. ISSN 0921-8009. doi: 10.1016/j.ecolecon.2005.01.008.

Soren Krohn, Poul Erik Morthorst, and Shimon Awerbuch. *The Economics of Wind Energy*. EWEA, 2009.

Eric Lantz, Ryan Wiser, and Maureen Hand. The past and future cost of wind energy. *IEA wind task*, 26, 2012.

C.-Y. Cynthia Lin. Strategic decision-making with information and extraction externalities: A structural model of the multi-stage investment timing game in offshore petroleum production. *Review of Economics and Statistics*, 95(5):1601–1621, 2013.

Johannes Mauritzen. Scrapping a wind turbine: Policy changes, scrapping incentives and why wind turbines in good locations get scrapped first. *Energy Journal*, 2014.

Miguel Mendonça, Stephen Lacey, and Frede Hvelplund. Stability, participation and transparency in renewable energy policy: Lessons from Denmark and the United States. *Policy and Society*, 27(4):379–398, 2009. ISSN 1449-4035. doi: 10.1016/j.polsoc.2009.01.007.

Niels I Meyer. Renewable energy policy in denmark. *Energy for sustainable development*, 8(1):25–35, 2004.

Jesper Munksgaard and Poul Erik Morthorst. Wind power in the Danish liberalised power market–policy measures, price impact and investor incentives. *Energy Policy*, 36(10):3940–3947, 2008.

Ariel Pakes, Michael Ostrovsky, and Steven Berry. Simple estimators for the parameters of discrete dynamic games (with Entry/Exit examples). *The RAND Journal of Economics*, 38(2):373–399, 2007. ISSN 0741-6261. ArticleType: research-article / Full publication date: Summer, 2007 / Copyright © 2007 The RAND Corporation.

David Rapson. Durable goods and long-run electricity demand: Evidence from air conditioner purchase behavior. *Journal of Environmental Economics and Management*, 68(1):141–160, 2014.

Geoffrey Rothwell and John Rust. On the optimal lifetime of nuclear power plants. *Journal of Business & Economic Statistics*, 15(2):195–208, 1997.

John Rust. Optimal replacement of GMC bus engines: An empirical model of harold zurcher. *Econometrica*, 55(5):999–1033, 1987. ISSN 0012-9682. doi: 10.2307/1911259. URL `http://www.jstor.org/stable/1911259`. ArticleType: research-article / Full publication date: Sep., 1987 / Copyright © 1987 The Econometric Society.

John Rust. Maximum likelihood estimation of discrete control processes. *SIAM journal on control and optimization*, 26(5):1006–1024, 1988. ISSN 0363-0129.

Stephen P Ryan. The costs of environmental regulation in a concentrated industry. *Econometrica*, 80(3): 1019–1061, 2012.

Christopher Timmins. Measuring the dynamic efficiency costs of regulators' preferences: Municipal water utilities in the arid west. *Econometrica*, 70(2):603–629, 2002.