

**Three Essays on Energy Policy and Investment**

by

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A dissertation submitted in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
(Economics)  
in the University of Michigan  
2017

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## ACKNOWLEDGEMENTS

I thank my advisor, Ryan Kellogg, for his guidance and encouragement. Through our regularly scheduled meetings, I learned a great deal about the research process and how to conduct careful economics research. I also thank my dissertation committee of Dan Ackerman, Ying Fan, and Catie Hausman for their helpful comments and suggestions and for being very generous with their time, particularly this past winter. Several other economists at the University of Michigan contributed to my dissertation, especially Shaun McRae and Francine LaFontaine who advised me earlier in my studies.

I am grateful for the use of the Michigan Census Research Data Center and for help using this data from J. Clint Carter, Margaret Levenstein, Francine LaFontaine, and Jagadeesh Sivadasan. I also thank the Michigan Institute for Teaching and Research in Economics for purchasing the data I used in my second chapter. Finally, I thank Rackham Graduate School for a fellowship that enabled me to focus on research this fall.

I am also thankful for the support of family and friends during my doctoral studies. My parents were always supportive regardless of my career ambitions. My college roommates provided some much needed perspective. Both my research and my overall graduate school experience benefitted from excellent colleagues, especially Paul Brehm, Eric Chyn, Adam Dearing, Alan Griffith, Yeliz Kacamak, Andrew Litten, Gail Lucasan, Bryan Stuart, Evan Taylor, Eleanor Wilking, and Chenyu Yang. Finally, I owe a special thanks to my partner, Christopher Sullivan. In addition to providing valuable feedback, he was a constant source of love and encouragement throughout my doctoral studies. Thank you, Chris, for everything.

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## ABSTRACT

In three chapters, this dissertation studies firm investment decisions in contexts informative for the design of energy policy. The first chapter studies electricity-intensive manufacturers' decision to buy machinery and equipment; the second and third chapters study developers' decision to build new wind energy projects.

The first chapter investigates the relationship between electricity price volatility and the investment dynamics of manufacturers. I first find that electricity-intensive manufacturers respond to higher electricity prices by reducing their capital expenditures. I then use a dynamic model of manufacturer investment with capital adjustment costs to study the implications of this response for efficiency. I find that policies that reduce electricity price volatility, such as building transmission to integrate electricity markets, increase aggregate productivity by allowing these firms to better match capital to where it is most productive.

The second chapter examines the effect on wind energy investment of awarding subsidies as non-refundable tax credits rather than as grants. The non-refundable production tax credit (PTC) is a large subsidy for wind energy. Firms can only use the PTC to reduce their taxes, an important restriction since the subsidy is large relative to their tax bill. Taking advantage of a temporary program that allowed wind developers to choose between the PTC and a cost-based, grant subsidy, I use a revealed preference approach to infer how developers trade off non-refundable tax credits and grants. I find that wind developers substantially discounted non-refundable tax-credits relative to grants, and I show that offering the PTC as a grant would increase investment by up to ten percent.

The third chapter is joint work with Chenyu Yang and studies the relationship between policy uncertainty and wind energy investment. We focus on uncertainty about the same PTC studied in chapter two. This subsidy was typically extended for only a few years at a time, and, at each expiration, the industry faced uncertainty about whether the subsidy would be renewed. Using wind project-level data, we verify that investment responded to these potential expirations. However, we find that uncertainty did not affect project size, ruling out one channel through which uncertainty may have reduced efficiency.

## CHAPTER 1 ELECTRICITY PRICES AND MANUFACTURING INVESTMENT

This chapter uses confidential data from the U.S. Census. Any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.

### 1.1 INTRODUCTION

The U.S. is pursuing several policy changes that will affect electricity markets. Some of these changes are motivated by environmental objectives, e.g. carbon pricing, mandates to reduce power plant emissions, and subsidies for renewable energy; others are motivated by economic objectives, e.g. wholesale electricity market restructuring, the introduction of capacity markets, and investment in large-scale electricity transmission projects. Regardless of their objective, the effect of these policy changes on electricity price levels and volatility will influence the investment decisions of electricity users.

I study the impact of electricity price volatility on the allocation of capital across energy-intensive manufacturers to learn about how these policies affect manufacturing efficiency. A key to understanding this impact is that these manufacturers are capital intensive and find it costly to adjust their capital stock. If electricity prices increase for an energy-intensive manufacturing plant, the plant is unlikely to move to an area with lower prices even though electricity is an appreciable share of its operating cost. Many of its costs are sunk, and it would need to disrupt its production to relocate or reduce capacity. These adjustment costs imply that electricity price changes can create cross-sectional dispersion in the marginal

revenue product of capital across plants. The manufacturer facing an electricity price increase must either i.) pay costs to decrease its capital stock appropriately, or ii.) operate with a capital stock that is above the level it would choose were there no adjustment costs, or iii.) employ some combination of the two. It is these second and third options that create dispersion in the observed marginal product of capital. In a static model, this dispersion is a sign of inefficiency because aggregate output would increase if capital were better allocated across plants.

This marginal product of capital dispersion may be efficient in a dynamic model, and Asker, Collard-Wexler and De Loecker (2014) use a dynamic investment model with capital adjustment costs to show that most of the cross-country and cross-industry differences in dispersion in the marginal revenue product of capital can be explained by differences in the volatility in productivity. In their model, to decrease static misallocation, policymakers must either decrease adjustment costs or reduce the volatility of productivity. A limitation of this result for policy is that Asker, Collard-Wexler and De Loecker's productivity shock is a residual that captures many shocks to production; it is not clear whether policy can play a role in reducing its volatility. In contrast, my model links dispersion in the marginal product of capital to observed volatility in electricity prices - volatility that is directly affected by public policy.

I first use exogenous variation in electricity prices and restricted access U.S. Census data on investment to confirm that plants change their capital stock in response to electricity price changes. To isolate the effect of electricity prices, I use variation from the interaction between natural gas price changes and regional differences in electricity generation capacity. Geographic differences and accumulated investment decisions have led to regional differences in the share of electricity generators that use coal, natural gas, or renewable resources as their fuel source. Natural gas prices changed substantially from 1997-2013, and these regional differences in generation capacity imply that an increase in gas prices will increase electricity prices differentially across regions: the larger the share of natural gas generation, the bigger

the price increase. I find that a 10 percent increase in electricity prices is associated with a 3 percent reduction in capital expenditures on machinery, equipment, and structures for these manufacturers, suggesting electricity and capital are complements in their production function.

To link firm investment responses to dispersion in the marginal product of capital, I next develop a dynamic model of manufacturer production and investment and estimate it using U.S. Census data on plant-level capital expenditures and electricity use. I model plants as price-takers that take their productivity as given and face costs to adjusting their capital stock. Many energy-intensive manufacturing industries produce tradable, homogenous products and are well-approximated as price-takers, and I use the largest of these industries, the paper mill industry, to estimate the model. I begin by estimating the production function for these manufacturers. I then nest this production function in a single-agent, dynamic investment model and use simulated method of moments to recover estimates of the adjustment cost parameters.

Using this model, I simulate a counterfactual that approximates the effect of complete electricity market integration, and I find modest but economically significant effects on manufacturer profits. I present a counterfactual that captures the intuition that complete market integration would remove all but the national-level shocks to electricity prices. In this counterfactual, I leave mean electricity prices unchanged and adjust the electricity price process to reflect only national-level price shocks, a change that reduces the volatility of electricity prices by 83 percent. I find that dispersion in the marginal product of capital falls by 4.4 percent and profits increase by 1.8 percent. Most of the effect on profits is due to manufacturers holding more capital (1.2 percent) and using it more efficiently, rather than a fall in realized adjustment costs. While small in percentage terms, this is a sizable effect for a change in the second moment of electricity prices. The size of these industries also implies this effect is economically significant: annually, the paper industry accounts for over twenty-five billion dollars of GDP while energy-intensive manufacturing as a whole accounts

for over three hundred billion dollars. Feasible policies that move the U.S. toward more integrated electricity markets include large-scale investments in electricity transmission and market redesigns that increase electricity trading, such as the one studied by Mansur and White (2012).

This chapter contributes to the literature that examines the causes of marginal product of capital dispersion by relating dispersion to changes in an observed input price. Hsieh and Klenow (2009) compare manufacturing in the U.S. with that in China and India, and find that the U.S. having a better allocation of factors across plants can explain much of the aggregate Total Factor Productivity (TFP) difference between these countries. The idea that reducing factor misallocation could make these economies dramatically more productive is a powerful one, and it has led to several papers examining the causes of this dispersion (e.g. Midrigan and Xu (2014) for financial frictions, Peters (2013) for imperfect competition). This chapter is most similar to Asker, Collard-Wexler and De Loecker (2014) in that it models dispersion as being caused by the interaction between capital adjustment costs and exogenous shocks to profitability. While Asker, Collard-Wexler and De Loecker (2014) focus on dispersion caused by variation in productivity, I look at dispersion caused by variation in the price of a key input. Dispersion caused by electricity prices is particularly interesting because electricity markets are heavily regulated and public policy plays an important role in shaping these prices.

This chapter also contributes to the environmental economics literature by establishing that energy-intensive manufacturers decrease their capital expenditures in response to electricity price increases. This finding complements that of Kahn and Mansur (2013), who find that electricity prices matter for the location and employment decisions of energy-intensive manufacturers. Coupled with my finding that manufacturers face capital adjustment costs, the investment response I find implies a wedge between the short and long run effects of electricity price changes on manufacturing activity. This is consistent with Pindyck and Rotemberg (1983), who use a dynamic model to find that significant capital adjustment



costs can rationalize conflicting estimates of the elasticity of energy demand.

This chapter proceeds as follows. Section 2 describes U.S. Census and Energy Information Administration data. Section 3 defines the relevant markets and describes the energy-intensive manufacturing industries. Section 4 describes the electricity price variation. Section 5 presents regression results that motivate the structural model. Section 6 describes the model of production and investment. Section 7 presents the counterfactual simulation of a reduction in the volatility of electricity prices. Section 8 concludes.

## 1.2 DATA

I use detailed survey data from the U.S. Census to form an unbalanced panel of manufacturing plants. The panel is annual and spans from 1997 through 2013.<sup>1</sup> An advantage of these data is that they contain information on plant-level electricity use, and I supplement this plant-level data with energy price and electricity data from the U.S. Energy Information Administration (EIA). I will also use publicly available data on the business cycle and prices to control for other factors affecting investment.

Two plant-level datasets form the backbone of my unbalanced panel: the Census of Manufacturers (CMF) and the Annual Survey of Manufacturers (ASM). The CMF surveys all manufacturing plants every five years while the ASM surveys a sample of manufacturers in every year. A new sample for the ASM is chosen every five years and followed in the years intervening the CMF. The questions in the ASM are a subset of those asked in the CMF, so I can combine the two datasets to create a plant-level panel. Because the ASM is only a sample of plants, this panel is unbalanced, and plants that operate continuously over the period will appear in as little as four or as many as seventeen years. To find the year of entry and exit for each plant, I use another Census dataset that has the operating status of all plants in all years, the Longitudinal Business Database (LBD).

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<sup>1</sup>1997 is the year the Census began using the North American Industry Classification System (NAICS) to assign plants to industries. Prior to 1997, the Census classified plants into industries using the Standard Industrial Classification (SIC) system, and it is difficult to match industries across systems. 2013 is the last year for which data is available.

A novel feature of these plant-level data is that they allow me to construct two variables that will be useful in estimation: total quantity of electricity used and an average electricity price for each plant. I separately observe the total quantity of electricity purchased, generated, and sold for each plant, and this allows me to construct the total quantity used as purchased plus generated less sold. I also observe the cost of purchased electricity, which I divide by quantity purchased to construct an average electricity price.<sup>2</sup> One limitation is that the price I construct is an average price rather than a marginal price, and it will better approximate the marginal price for plants that operate continuously or face high costs of shifting their production to off-peak hours.<sup>3</sup> It is unusual to observe electricity data at this level, and these data serve two important roles in my analysis. First, the plant-level relationship between electricity use and output is informative for how electricity enters the production function. Second, a plant-level measure should be a more accurate measure of the electricity prices these manufacturers face than alternative measures, such as utility-level average prices.

I use EIA data on natural gas spot prices and electricity generation capacity to map underlying shifts in natural gas prices to variation in plant-level electricity prices. Most electricity in the U.S. is produced by either natural gas or coal burning generators, and the impact of natural gas price changes on electricity prices should depend on which type of generators an area relies on. My measure of natural gas prices is the annual average of daily

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<sup>2</sup>The relevance of this price should not vary with whether the plant can generate its own electricity. Nearly all plants purchase some electricity, and plants with generators usually have the ability to sell electricity back into the grid

<sup>3</sup>This average price corresponds to the marginal price if there are no fixed charges and a constant marginal price per kWh. In reality, industrial contracts can have fixed charges, varying marginal prices, and demand charges. Industrial users can either purchase electricity directly from wholesalers or from their local utility. In either case, the contract may have a fixed charge and marginal rates that vary by delivery voltage, time of use, and quantity demanded. Contracts with lower marginal rates for higher voltage electricity are common, though the differential is usually a small fraction of the price. Prices can also vary by time of use, with higher prices during periods of peak demand. Within an industrial contract, the marginal cost for electricity typically does not vary by quantity; however, users may be able to choose among a menu of contracts, some more favorable when the quantity demanded is higher. According to Davis et al. (2013), decreasing block pricing - in which the price schedule slopes down in quantity - was once common practice. The 1978 Public Utilities Regulatory Policies Act (PURPA) attempted to discourage this practice, and it is now less common. Finally, contracts with local utilities usually include a demand charge. This charge is based on the maximum use over a set time period, for example the highest use hour for the month.

NYMEX prices for one-month natural gas futures at Henry Hub, Louisiana. I also construct a panel with each region's share of natural gas generation capacity, i.e. the total natural gas generation capacity, divided by the total generation capacity, using data from EIA Form-860.

To control for other factors affecting investment, I use national and local measures of business cycle and industry-level output prices. In regression specifications, I control for state-level unemployment and total employment using annual data from the Bureau of Labor Statistics (BLS). I also control for the aggregate business cycle using data on U.S. GDP from FREDUSE. In the dynamic model, the effects of the business cycle are mediated through output prices. As my measure of output prices, I use industry-specific annual price indices from the NBER-CES; these price indices are constructed by the Bureau of Economic Analysis (Becker, Gray and Marvakov, 2016*b*).<sup>4</sup>

### 1.3 INDUSTRY SELECTION AND RELEVANT MARKETS

#### 1.3.1 INDUSTRY DEFINITION, SELECTION, AND RELEVANT MARKETS

I define industries at the six-digit NAICS code level so that, within these industries, plants produce a closely related set of products. NAICS industries are based on the similarity of production processes, with the six-digit level the most specific classification.<sup>5</sup> Take, for example, the six-digit NAICS code 322122, Newsprint Mills. It falls under the four-digit NAICS code, Pulp, Paper, and Paperboard Mills, which, itself, falls under the three-digit NAICS code Paper manufacturing. The gain from a narrow definition is that it improves production function estimates, as plants within an industry are more homogenous. The trade-offs are that I have less statistical power, and that I may be excluding competitors in closely related industries. Limiting the sample to firms that are price-takers alleviates

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<sup>4</sup>According to e-mail correspondence with the BEA Industry Economic Accounts, most of the underlying pricing data comes from the BLS. The BLS samples establishments in each industry and collects monthly price data from these establishments. The survey is voluntary and initiated by a field economist (BLS, n.d.).

<sup>5</sup>NAICS codes change slightly every five years, and I use 2012 NAICS codes for my analysis. For my sample of industries, the only change is that a few 2012 codes combine industries that show up as having multiple distinct NAICS codes in 1997, 2002, and 2007.

the second concern, since the impact of competing industries on firm behavior will be fully captured in the market price. Henceforth, I treat the relevant product market for producers in each industry as synonymous with the industry e.g. iron and steel for NAICS 331111, Iron and Steel Mills; and broadwoven fabric for NAICS 313210, Broadwoven Fabric Mills.

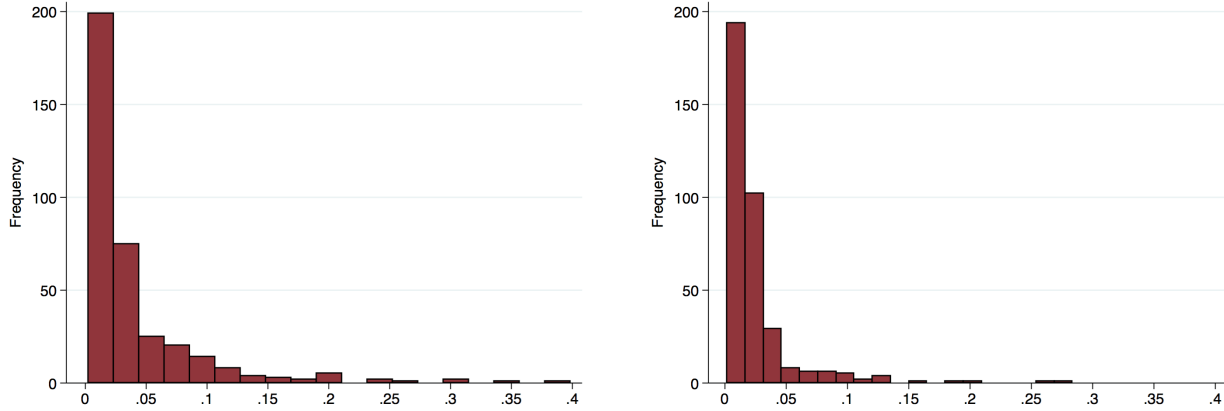
To focus on industries where manufacturers respond to electricity prices, I limit my analysis to the seventy industries for which electricity is a significant share of costs. For most manufacturing industries electricity is a small share of total costs, with purchased electricity accounting for just over one percent of costs for the median industry. However, Figure 1.1 shows this distribution has a long right tail. Purchased electricity is four percent of costs for the ninety-fifth percentile and twenty-two percent of costs for the most electricity-intensive industry, aluminum (U.S. Census, 2002). The same is true of electricity as a share of value-added, a measure of output that excludes materials costs. If materials costs are nearly fixed across producers and over time, the ratio of electricity costs to value-added will be more relevant to investment behavior than the ratio of electricity costs to total costs. In practice these two ratios are highly correlated, and I will use both to select industries. Because some manufacturers generate their own electricity, I use the sum of two variables as my measure of electricity costs: the cost of purchased electricity, and the cost of purchased fuels for heat, power, and electricity generation.<sup>6</sup> The seventy industries for which this sum is over five percent of value-added and over three percent of total costs form my sample of energy-intensive manufacturers.

When I estimate the dynamic model, I make two restrictions that limit my sample to twenty-six industries where plants are well approximated as price-takers. The first is that the relevant geographic market is national or global. This restriction allows me to use national-level prices for output and national concentration measures as a proxy for market concentration. To distinguish these industries, I focus on transportation costs, which I

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<sup>6</sup>I use the sum of salaries and wages, materials, and capital expenditures as my cost measure. Total costs should technically include employee benefits, rental payments, and miscellaneous operating expenses, but I only observe these variables in some years.

Figure 1.1: Variation in the importance of electricity by industry



(a) Electricity & Fuels over Value-Added

(b) Electricity & Fuels over Total Cost

Data from the 2002 EC. One ob. per industry,  $n = 363$ . Aluminum ( $ef/va = 0.57$ ) excluded from (a).

expect to be the limiting factor in market size. Most energy-intensive industries produce non-perishable, intermediate goods that they sell to other manufacturers, so I expect buyers to be price-sensitive and willing to purchase these goods from the location with the lowest price (inclusive of transportation costs). I determine market size using data from the Census Commodity Flow Survey (CFS), and I classify industries with an average domestic mileage shipped greater than five hundred miles as being tradable, i.e. competing in national or global output markets.<sup>7</sup> The second restriction is that the industries have a national Herfindahl-Hirschman index (HHI) less than 1000.<sup>8</sup> The cutoff of 1000 corresponds to the level below which the Department of Justice considers an industry unconcentrated (U.S. DOJ and FTC, 1997). My measure of HHI is the national, 50-firm HHI from 2002. Because these industries compete in geographically large output markets, national concentration should be a good

<sup>7</sup>The CFS is a detailed survey that includes the origin and destination for all shipments made by a sample of plants. The survey is over a four-week period, with plants recording this information for one week each quarter. I focus on the primary product by value for each NAICS industry and determine market size using the average domestic mileage shipped from the 2002 CFS. I define industries as serving large markets if their average mileage shipped is greater than five-hundred miles. This cutoff is chosen because it is highly correlated with the measure used to define highly tradable industries in Allcott and Keniston (2014) (a measure, itself, based on elasticities from Holmes and Stevens (2014)).

<sup>8</sup>The HHI is a commonly used measure of market concentration, and it is the sum of the squared market shares of firms competing in a market. For example, monopoly results in an HHI of 10,000, while a symmetric duopoly would have an HHI of 5,000 ( $50^2 + 50^2$ ).

proxy for true market concentration.

At this point, I have the twenty-six industries where firms compete in national or global output markets, produce relatively homogenous goods, and have little if any market power. Of the 70 energy-intensive industries, this is the subset of industries I expect to be most sensitive to electricity prices changes. I summarize twenty of them in Table 1.1. The first thing to note is that these industries make up an economically significant share of the economy: they accounted for 150 billion dollars in value-added in 2002. Electricity and fuels (E&F) make up around five percent of their total costs and ten percent of their value-added. I could estimate the dynamic model for all twenty-six of these industries, but, for computational tractability, I will estimate it for only the largest industry, "Paper (except Newsprint) Mills."

Table 1.1: Electricity shares for the tradable industries in my energy-intensive sample

NAICS	Industry	Total VA (bn)	HHI	E&F/TC	E&F/VA
325199	All Oth. Basic Organic Chemical Mfg	21.8	238	0.07	0.15
313210	Broadwoven Fabric Mills	6.2	223	0.03	0.07
335991	Carbon and Graphite Product Mfg	1.1	606	0.05	0.09
327120	Clay Building Material and Refractories Mfg	4	858	0.10	0.11
311411	Frozen Fruit, Juice, and Vegetable Mfg	5.7	533	0.03	0.05
327992	Ground or Treated Mineral and Earth Mfg	1.8	726	0.10	0.09
332111	Iron and Steel Forging	2.3	184	0.03	0.09
313240	Knit Fabric Mills	1.9	742	0.03	0.07
331410	Nonferrous Metal (except Al) Smelting and Refining	2.1	219	0.05	0.12
331318	Oth. Aluminum Rolling, Drawing, and Extruding	3.5	734	0.03	0.07
325180	Oth. Basic Inorganic Chemical manufacturing	13.2	668	0.12	0.17
327212	Oth. Pressed and Blown Glass and Glassware Mfg	3.7	552	0.10	0.11
322121	Paper (except Newsprint) Mills	29.9	810	0.07	0.10
322130	Paperboard Mills	13.2	749	0.12	0.20
325211	Plastics Material and Resin Mfg	21	443	0.05	0.12
327110	Pottery, Ceramics, and Plumbing Fixture Mfg	2.7	935	0.05	0.05
321219	Reconstituted Wood Product Mfg	3	498	0.07	0.15
331513	Steel Foundries (except Investment)	1.7	488	0.07	0.11
325212	Synthetic Rubber Mfg	3.7	744	0.05	0.07
313310	Textile and Fabric Finishing Mills	5.6	308	0.03	0.07

Data from the 2002 Economic Census. Of the 37 tradable industries in my sample of electricity intensive industries, 26 have an HHI<1000; this table lists 20 of them. Value-added is in real 2012 billions of dollars. Total cost is the sum of all costs, including employee benefits, rental payments, and miscellaneous expenditures. HHI is the 50 firm concentration ratio for the entire U.S. E&F is the total cost of purchased electricity plus the total cost of purchased fuels for heat, or electricity generation. For these industries, the cost of purchased electricity is just over half of the sum of purchased electricity and purchased fuels.

### 1.3.2 RELEVANT MARKETS FOR ELECTRICITY

National or global output markets contrast with regional electricity markets. I define the relevant product market as electricity: electricity is homogenous up to changes in delivery voltage, and these changes have only a minor impact on price. I define the relevant geographic market as the Environmental Protection Agency's (EPA's) eGRID subregions. The twenty-two eGRID subregions are pictured in Figure 1.2. The data the EPA provides at the eGRID subregion level are frequently used to estimate the pollution and carbon emitted when electricity is consumed at a given location. Even within the subregions, transmission constraints can result in significant price differentials. These eGRID subregions are a compromise between narrowly defined regions, such as Power Control Areas, across which there is substantial trading, and larger regions, such as NERC regions, within which electricity prices can vary widely.

### 1.4 ELECTRICITY PRICE VARIATION

I study the relationship between annual, average electricity prices and annual investment.<sup>9</sup> Understanding this relationship requires variation in annual electricity prices, and the period from 1997-2013 saw significant swings in both absolute and relative levels of these prices. National price data from the EIA (2016*b*) shows that annual, industrial electricity prices increased by twenty-five percent from 1999 to 2008 before falling ten percent from 2008 to 2012. EIA state-level data shows that relative electricity prices changed as well. When the 48 states of the continental U.S. are ranked by their electricity price in each year, the median change in rank between 1998 and 2008 was 4, and the 90<sup>th</sup> percentile was 19; between 2008 and 2012, the median was 6, and the 90<sup>th</sup> percentile was 20.<sup>10</sup> These price changes tended

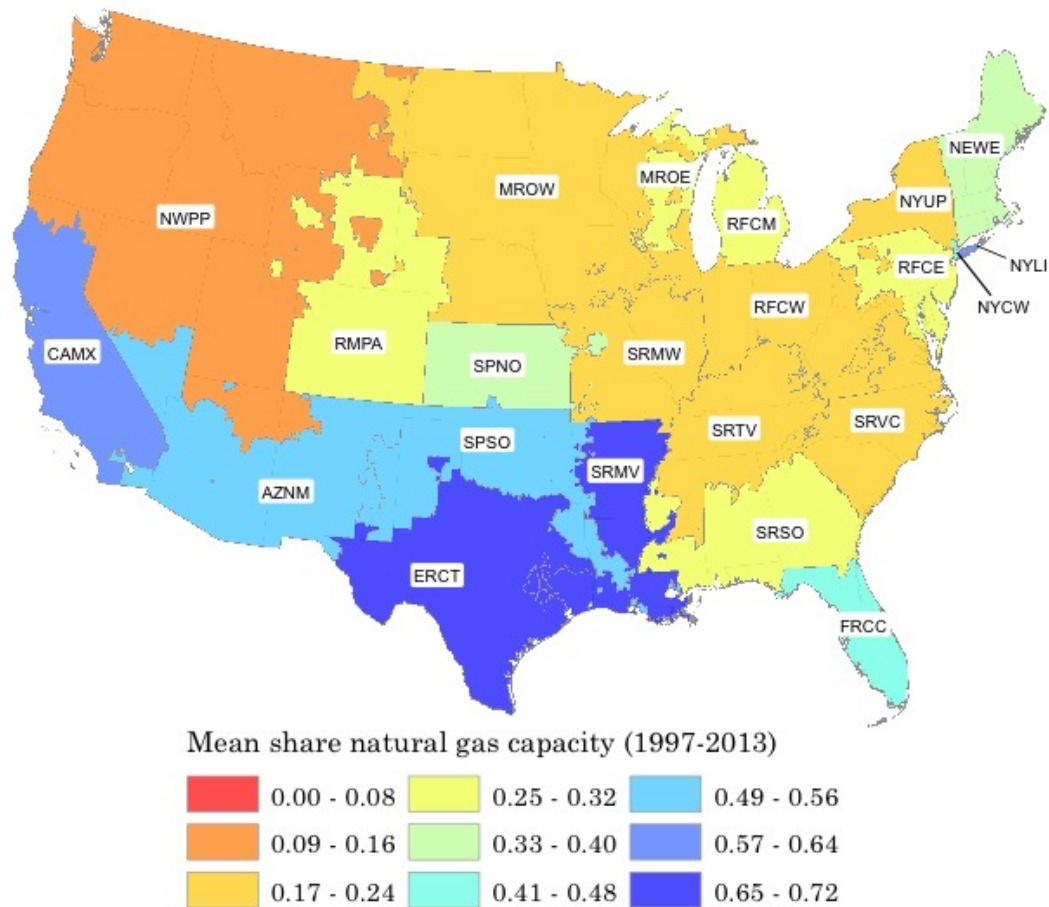
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<sup>9</sup>I do not expect investment be very responsive to shorter run, e.g. monthly or daily, variation in electricity prices, and my data is ill-suited to studying responses at this granularity.

<sup>10</sup>I would prefer to report statistics about eGRID region-level price changes, but the EIA reports annual, average prices at the state level.



Figure 1.2: Regional variation in natural gas generation capacity (22 eGRID regions)



to be gradual, occurring over several years.

Given these swings in national and regional level prices, it is not surprising that I see variation in my plant-level electricity price data. Table 2.2 shows the mean electricity price in my sample was 8 cents per kWh with a standard deviation of 3 cents. The within-plant standard deviation of electricity prices over the period was 1.7 cents, confirming the aggregate pattern of significant time series variation in electricity prices.

Table 1.2: Summary statistics

Variable	Mean	SD	Within-plant SD	N
Electricity price	0.080	0.031	0.017	162,000
Log (capital expenditures, in 1000s)	6.3	2.1	1.07	146,000
Share gas '95	0.18	0.204	0	162,000
Natural gas price	5.3	2.3	-	162,000
Share gas '95 X gas price	0.94	1.24	0.376	162,000

N = 162,000. Sample is 70 energy-intensive industries from 1997-2013. Plants are not weighted when calculating means and standard deviations. Within-plant SD is the mean across plants of the within-plant standard deviation in electricity prices. All prices in real 2012 dollars.

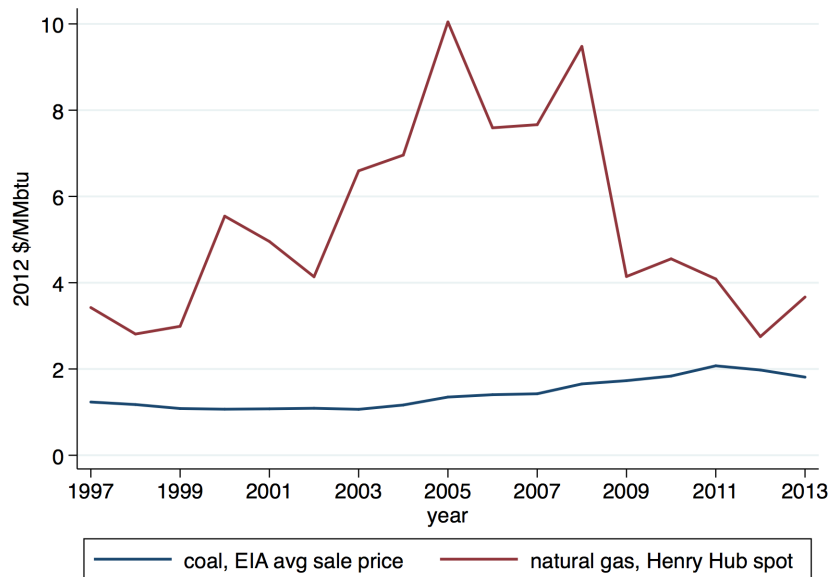
Natural gas price changes were a major cause of variation in electricity prices, and they provide the exogenous variation I use in estimation. Generation makes up about two-thirds of the cost of producing electricity (EIA, 2015*a*), and fuel prices are the most variable component of electricity prices. Figure 1.3 shows that gas prices more than doubled from 1998 to 2008 before falling back to 1998 levels in 2012.<sup>11</sup> Though we may worry that some of this variation was due to the business cycle, Appendix Figure A.2 shows that the overall correlation between natural gas prices and the business cycle was low. The decrease in prices in the latter half of the period was largely due to increased production from hydraulically fractured wells (Hausman and Kellogg, 2015). As shown in the figure, average coal prices varied more smoothly over the period.<sup>12</sup> In addition to creating time-series variation in electricity prices, the interaction between changes in the natural gas price and regional stocks of electricity generation capacity provides exogenous, cross-sectional variation in electricity

<sup>11</sup>Appendix Figure A.1 shows that oil prices varied substantially and diverged from natural gas prices in the second half of the period; however, outside of New England, oil is only a small share of electricity fuel costs.

<sup>12</sup>My coal price measure is not directly comparable since it is not a spot price. Coal prices experience more regional variation than natural gas prices, and coal is more likely to be sold using long-term contracts (Morris, 2013; EIA, 2016*a*). Using state-level EIA data on industrial electricity prices, I find that regional coal prices explain less of the electricity price variation than national natural gas prices.

prices. The key insight is that a change to the price of natural gas differentially affects regions based on the type of generators they use to generate electricity. For example, the Pacific Northwest relies on hydropower and coal for most of its electricity generation; whereas, California relies heavily on natural gas. When the gas price rises, electricity prices increase in both regions, but they increase by more in California since it is more reliant on natural gas for electricity generation. Figure 1.2 shows how the share of electricity generation capacity that uses natural gas as a fuel varies by region. Regional variation in generation stocks is caused by which form of generation was the most cost effective when the region added generation and persistent geographic differences in suitability for the different types of generation, e.g. Wyoming has large coal deposits and is thus more likely to use coal generators.

Figure 1.3: Natural gas and coal prices from 1997-2013



Henry Hub gas prices in \$/MMbtu from Bloomberg. Coal prices are average mine sales prices in \$/short ton; I convert them to MMbtu using EIA’s 2005 estimate of 20.214 MMbtu/short ton (EIA, 2016c).

Other sources of variation in plant-level electricity prices include changes in electricity price schedules or changes in policy. Some of the observed variation in electricity prices is likely explained by differences in rate schedules and the frequency with which utilities adjust

prices. It may also be from plants moving along a price schedule; a schedule with a fixed cost will lead to average price changes when plants increase or decrease their electricity consumption. Two salient facts, previously documented in Davis et al. (2013), are that there is significant dispersion in plant-level average electricity prices, even within narrowly defined geographic regions, and that there is a negative correlation between plant size and its average electricity price.<sup>13</sup> Energy policy also affected electricity prices over the period. In the late 1990s and early 2000s, several states restructured their electricity markets to increase competition, a policy that shifted prices away from average cost and toward marginal cost (Borenstein and Bushnell, 2015). Many states also began mandating a minimum fraction of generation from renewable resources in an effort to move away from fossil fuel generation. Presumably these renewable portfolio standards raised electricity prices in states that adopted them, though empirical evidence on the extent of the price increase is mixed (Fischer, 2010).

## 1.5 MOTIVATING EVIDENCE

Before estimating the dynamic model, I first document that plants decrease their capital stock in response to higher electricity prices. Ex ante, it is not obvious that a plant will decrease capital expenditures in response to an electricity price increase. First, as shown in Table 1.1, electricity typically accounts for less than ten percent of costs for even the most energy-intensive manufacturers, so plants may not be very sensitive to these prices. Second, capital and electricity may not be complements in production. In particular, if production is Cobb-Douglas in all inputs and has constant returns to scale, the optimal plant-level capital stock is independent of electricity prices. Plants may also respond to electricity price increases by investing in more efficient machines, in which case investment might rise when electricity prices increase.

I begin by estimating linear models of the contemporaneous effect of electricity prices on

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<sup>13</sup>Davis et al. (2013) use the same plant level data from the ASM matched to utility-level data from the EIA for 1963-2000.

investment for my sample of seventy energy-intensive industries. These estimates capture the average short-run effect of electricity price changes on investment. For plant  $i$ , in year  $t$ , my primary specification is the following:

$$i_{it} = \beta_0 + \beta_1 P_{it}^e + \gamma X_{it} + \alpha_t + \delta_n + \phi_n t + \psi_n * P_t^g + \mu_r + \lambda_r * lgdp_t + \epsilon_{it} \quad (1.1)$$

where  $i_{it}$  is the log of total capital expenditures,  $P_{it}^e$  is the plant electricity price in levels, and  $\beta_1$  is the coefficient of interest. I use the log rather than the level of capital expenditures because my sample includes plants of varying sizes.<sup>14</sup> Using the log necessitates dropping the ten percent of plant-year observations with expenditures of zero; however, results are robust to alternative treatments of zero expenditure observations.<sup>15</sup>

I control for several co-determinants of investment, including the business cycle, plant age and size, year, industry, and region. The vector  $X_{it}$  includes the annual, state-level unemployment rate, log of annual state employment, plant age, and log average plant size.<sup>16</sup> I also include year fixed effects,  $\alpha_t$ , so the coefficient is identified off changes in a plant's price relative to the average price for that year. I allow for industry-specific trends in investment by including industry intercepts,  $\delta_n$ , and a linear time trend for each industry,  $\phi_n t$ . While year fixed effects control for the average impact of the natural gas price on investment, some industries, such as the petrochemicals industry, use natural gas for feedstock and are more sensitive to this price. I allow for industry-specific impacts of the natural gas price on investment by including an interaction between industry indicators and the natural gas spot price,  $\psi_n * P_t^g$ . I include region fixed effects,  $\mu_r$ , to control for unobserved regional differences that are constant over time. I also allow for regional differences in the impact of the aggregate

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<sup>14</sup>If I used the level of capital expenditures as the dependent variable, my model would imply that a small plant and a large plant would change their investment by the same absolute amount e.g. 500 dollars, in response to a one cent increase in electricity prices. This model implies that small and large plants facing the same electricity price increase adjust their investment by the same amount in percentage terms.

<sup>15</sup>For example, using the log (capital expenditures+1) as the dependent variable or estimating a tobit model.

<sup>16</sup>Using the county-level unemployment rate and log employment as the measure of local business cycle shocks leads to similar estimates for the electricity price coefficient. My measure of plant size is the average value of shipments across all of the plant's observations (in real \$2012).

business cycle on investment by including region by business cycle interactions,  $\lambda_r * lgdp_t$ .<sup>17</sup> To control for time-invariant, unobserved differences across plants, I also estimate a model with plant fixed effects.

Throughout, I weight observations by average plant size and cluster standard errors by region.<sup>18</sup> The rationale for weighting is that I will later estimate instrumental variables models, and the instrument is more powerful for larger plants. I weight each observation by the mean of the total value of shipments across all observations for a plant.<sup>19</sup> I cluster my standard errors at the level of eGRID regions, and there are twenty-two regions.<sup>20</sup>

I find that an electricity price increase is associated with a moderate and statistically significant decrease in capital expenditures. I present these results in Table 1.3. The point estimate from (1) implies that the elasticity of investment with respect to electricity prices is -0.21. Column 2 shows that the estimated coefficient on electricity prices is not sensitive to the inclusion of local business cycle measures or plant age, variables that, for computational tractability, I will not include in the dynamic model. Column 3 shows that including industry-by-year fixed effects has little effect on the estimated coefficient.

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<sup>17</sup>My measure of the aggregate business cycle is de-trended log U.S. GDP.

<sup>18</sup>I report results from unweighted regressions in Appendix Table A.1.

<sup>19</sup>I choose total shipments rather than value-added because the mean of value-added can be negative.

<sup>20</sup>Reported standard errors are not bias-corrected for a small number of clusters; I will update them to account for this bias in future versions.

Table 1.3: OLS estimates

	Log capital expenditures				
	(1)	(2)	(3)	(4)	(5)
Electricity price	-2.665***	-2.777***	-2.660***	-1.186*	-1.19
	(0.824)	(0.859)	(0.817)	(0.632)	(0.807)
Electricity priceXtradable					-2.224**
					(1.078)
Year FE	X	X		X	X
Region FE	X	X	X		X
Plant FE				X	
State business cycle	X		X	X	X
RegionXbusiness cycle	X		X	X	X
Plant age	X		X		X
Industry FE	X	X			X
Industry linear time trend	X	X		X	X
IndustryXgas price	X	X		X	X
IndustryXyear FE			X		
Plant-years	146,000	146,000	146,000	146,000	146,000
Plants	24,000	24,000	24,000	24,000	24,000

The mean of electricity prices is 0.08, so implied elasticities (at the mean) range from -0.09 to -0.22. Tradable is an industry-level indicator for producing tradable products, and the direct effect of tradability on investment is not separately identified from the industry intercepts. When I allow the relationship between electricity prices and investment to vary by tradability, I find an elasticity of -0.27 for more tradable industries; -0.09 for less tradable. Industries are defined at the 6-digit NAICS level; state business cycle is two variables: annual state unemployment and log of total employment; business cycle is de-trended log US GDP; and gas price is the Henry Hub spot price for natural gas. All specifications weighted by plant size, as measured by average total value of shipments. SE clustered by region. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

When I include plant fixed effects in Column 4, I find a smaller, less precisely estimated coefficient. While one explanation for the discrepancy is that the main specification

is capturing unobserved heterogeneity across plants, I think the more likely explanation is measurement error in electricity prices. Because the fixed effects estimator uses less of the variation in electricity prices, the ratio of noise to signal and, thus, the size of any measurement error induced bias, should be higher for this specification. A related explanation is that within-plant variation in electricity prices includes more of the short-run variation caused by plants shifting up and down their electricity price schedules rather than the longer-run variation investment responds to. Dynamic effects could also explain this discrepancy since lagged or anticipatory effects of electricity price changes on investment will show up in the mean plant investment level, and thus attenuate my estimate toward zero.

Finally, when I allow the relationship between electricity prices and investment to depend on tradability, I find that the impact of an electricity price increase is larger for industries producing tradable goods. Point estimates from (5) imply an elasticity of investment with respect to electricity prices of -0.22 for industries producing tradable goods, and -0.09 for industries that do not. This is intuitive since tradable goods manufacturers are competing in larger output markets and are likely less able to pass local cost increases on to consumers.

### 1.5.1 INSTRUMENTING FOR ELECTRICITY PRICES

Even with the inclusion of the above control variables, my estimate of the coefficient on electricity prices may be capturing the effect of other variables correlated with electricity prices; three examples are manufacturer bargaining power, local demand shocks, and unobserved regulation. First, we may worry the estimated coefficient is capturing the effect of good management, since large electricity users sometimes negotiate rates for power. Better-managed plants might have both higher investment levels and lower electricity prices. Second, local demand shocks may affect both investment decisions and electricity prices in a way not fully captured by the state business cycle controls. The effect of an increase in local demand on electricity prices would likely be a short-run increase in price, as more costly generators turn



on to meet increased demand.<sup>21</sup> The effect of local demand on manufacturer investment is ambiguous as manufacturers might benefit from an increase in local demand for their products or be harmed by increases in land and labor costs. Finally, a state might simultaneously implement environmental policy that affects both electricity prices and other manufacturing costs. For example, a program regulating NO<sub>x</sub> pollution would increase production costs and investment decisions directly, in addition to indirectly through an increase in electricity prices. Overall, the direction of the bias is ambiguous, but the above stories motivate the use of the instrumental variables estimator.

The potential for measurement error in electricity prices also motivates the use of the instrumental variables estimator. I construct the electricity price variable as the ratio of two survey question responses: the total cost of purchased electricity and the total quantity of electricity purchased. If plant managers round their responses, this variable will be measured with error, and this measurement error will cause my estimate of  $\beta_1$  to be attenuated toward zero.<sup>22</sup> The discrepancy between the OLS and fixed effects estimates in Table 1.3 also suggests that measurement error may be an issue.

The exogenous variation discussed in Section 1.4 motivates instrumenting for electricity prices with the regional share of natural gas generation capacity in 1995, interacted with the natural gas spot price. This instrument is similar to the fuel price by generation share interactions used in Kahn and Mansur (2013). Throughout, I condition on the overall impact of natural gas prices on investment, as well as time-invariant regional differences in investment. I use natural gas shares in 1995 rather than contemporaneous shares to avoid capturing the effect of regional changes correlated with changing natural gas capacity. Natural gas generation capacity did increase significantly during the early 2000s, and these changes are

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<sup>21</sup>In the medium to long-run, this effect is counteracted by more generation coming online. In traditional, regulated markets, the additional cost of building new generation is spread evenly over the expected lifetime of the generator. In restructured electricity markets, the price is set by the operating cost of the marginal generator. In either case, we should expect new generation to dampen any price effect.

<sup>22</sup>If respondents correctly report the quantity of electricity purchased but report the cost of purchased electricity with random error, this measurement error will be classical. If the measurement error is due to rounding or random error in both responses, the measurement error will not be classical, but the intuition should still go through that the error leads to attenuation bias which the IV addresses.

discussed in more detail in Appendix Section A.3. Figure 1.2 shows that this instrument is to some extent comparing southern to northern regions, and I include region by aggregate business cycle interactions to control for the possibility that these regions had different growth patterns that affected investment. The inclusion of these interactions has very little effect on the point estimate and increases precision. While it is likely more transitive than a permanent policy change, I expect variation in electricity prices due to changes in the price of natural gas to be quite persistent.

When I instrument for electricity prices using the gas generation capacity share by gas price interaction, I find a ten percent increase in electricity prices leads to a three percent reduction in contemporaneous capital expenditures. The first four columns in Table 1.4 report IV estimates. These estimates are consistently larger than the OLS estimates, and the coefficients are less precisely estimated. Point estimates are fairly stable across specifications, and the implied elasticities range from -0.27 to -0.34. The first-stage is weak when I allow the effect of electricity prices on investment to differ by tradability, and I find a negative point estimate for the tradability interaction and very wide confidence intervals (unreported). Column 5 reports the first-stage. The point estimate implies that a 1 standard deviation increase in the share gas by gas price interaction is associated with a 0.25 standard deviation increase in electricity prices.<sup>23</sup>

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<sup>23</sup>Another reasonable IV would be the interaction between natural gas generation capacity and lagged natural gas spot prices, with the rationale that it takes time to pass through cost shocks to electricity prices. This IV has a slightly weaker, but still strong, first stage, and larger estimates of the effect of electricity prices on investment. Results from this IV are presented in Table A.2.

Table 1.4: IV estimates

Dependent variable	Log capital expenditures				FS: Electricity price
	(1)	(2)	(3)	(4)	(5)
Electricity price	-3.754**	-3.437*	-3.358*	-4.235***	
	(1.79)	(1.94)	(1.93)	(1.60)	
Share gas '95Xgas price					0.640***
					(0.067)
Year FE	X	X		X	X
Region FE	X	X	X		X
Plant FE				X	
State business cycle	X		X	X	X
RegionXbusiness cycle	X		X	X	X
Plant age	X		X		X
Industry FE	X	X			X
Industry linear time trend	X	X		X	X
IndustryXgas price	X	X		X	X
IndustryXyear FE			X		
Plant-years	146,000	146,000	146,000	146,000	146,000
Plants	24,000	24,000	24,000	24,000	24,000
First Stage F	87	78	86	99	-

The mean of electricity prices is 0.08, so implied elasticities (at the mean) range from to -0.27 to -0.34. Column (5) shows the first stage for (1) where, for ease of reading, the dependent variable is the electricity price in cents rather than dollars. Share gas '95Xgas price is the regional share of natural gas generation in 1995 interacted with the natural gas spot price. Industries are defined at the 6-digit NAICS level; state business cycle is two variables: annual state unemployment and log of total employment; business cycle is de-trended log US GDP; and gas price is the Henry Hub spot price for natural gas. All specifications weighted by plant size, as measured by average total value of shipments. SE clustered by region. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

The mean level of investment for an energy-intensive manufacturing plant is over a half million dollars a year, so these estimates translate into a substantial reduction in investment

in levels in response to an increase in relative electricity prices.

## 1.6 MODEL

With evidence that manufacturer investment responds to electricity price changes, I next develop a dynamic model that captures the key features of manufacturers' investment decisions. In this model, plant managers face costs to adjusting their capital stock and choose investment based on their expectations about future prices and productivity. To understand how these decisions respond to changes in the exogenous state variables, I need to know how plants use capital in production; I first estimate industry-specific production functions. Taking these production parameters as given, I subsequently estimate the dynamic model to recover estimates of the capital adjustment parameters.

### 1.6.1 PRODUCTION FUNCTION

Because a Cobb-Douglas function cannot match the investment response I see in the data, I model production as Leontief in capital-labor and electricity. The literature typically models production as either Cobb-Douglas in all inputs or Cobb-Douglas in all inputs except materials. Cobb-Douglas functions assume the elasticity of substitution between inputs is one, so any effect on the desired capital stock of an increase in electricity prices must come through an overall reduction in output (for more detail, see Appendix Section A.5). Thus, a Cobb-Douglas function would need to have strongly decreasing returns to scale to match the observed decrease in investment in response to an electricity price increase. I instead estimate a production function that assumes the elasticity of substitution between capital and labor is one, and the elasticity of substitution between capital-labor and electricity is zero. While I would prefer to estimate rather than assume these elasticities, input elasticities of substitution are notoriously difficult to estimate (Chirinko, Fazzari and Meyer, 2011).<sup>24</sup>

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<sup>24</sup>I hope to estimate the elasticities of substitution between capital, labor, and electricity in future work. Although this will be difficult, defining industries less narrowly, e.g. at the 4-digit NAICS code level instead of the 6-digit level, and incorporating outside data should help. For example, Raval (2015) uses an identification

For comparison, I will also present estimates from a Cobb-Douglas production function in Appendix Section A.6.

### 1.6.1.1 LEONTIEF PRODUCTION FUNCTION

I model production at plant  $i$  in year  $t$  as a function of capital, labor, and electricity. I allow for a plant-specific productivity shock that is observed by plant managers,  $\omega_{it}$ , as well as, potentially serially correlated, measurement error in output,  $\epsilon_{it}$ .

$$Y_{it} = \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}\} e^{\epsilon_{it}} \quad (1.2)$$

Note that, while plant managers make their decisions in response to  $\omega$ , I do not observe this productivity shock in the data. One limitation of this production function is that the productivity shock affects only capital and labor, not electricity. The underlying assumption is that all plants are equally good at using electricity in production. Because we typically think productivity grows over time, this assumption is consistent with the fact that output and energy use in the paper industry (and energy-intensive manufacturing as a whole) were flat over the period, while both capital and labor declined steadily (Becker, Gray and Marvakov, 2016a). Because there is no substitution between electricity and capital, this production function also precludes plants investing in more energy-efficient machines, a behavior the negative relationship between electricity prices and investment suggests is less important.

I measure capital in dollars and construct it from investment using the perpetual inventory method, a construction discussed in more detail in Appendix Section A.1.2. My measure of labor is total salaries and wages.<sup>25</sup> Finally, I measure electricity in MWh and construct it as electricity purchased, plus electricity generated, less electricity sold.

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strategy relying on cross-sectional variation in local wages to estimate the elasticity of substitution between capital and labor for U.S. manufacturing.

<sup>25</sup>The rationale for using the wage bill is that it captures both quantity and quality of labor. The tradeoff is that the wage bill can pick up geographic differences in wages. If a worker with the same productivity has different wages in two locations this difference will show up in  $\omega$ . If manufacturing labor is relatively mobile and located in low cost-of-living locations, the wage bill will be a better measure. Fox and Smeets (2011) also find that the wage bill does a good job of explaining labor's contribution to production.

First, I estimate the electricity coefficient. I do not observe output, but I do observe total revenues and an industry-specific price index.<sup>26,27</sup> Because I assume these firms compete in the same perfectly competitive output market, I can take total revenues, equal to  $P_t Y_{it}$ , and divide them by the price index,  $P_t/P_b$ , to find a measure that is proportional to output.<sup>28</sup> Perfectly variable labor, electricity, and materials ensure that all arguments of the production function always bind, so the following equation will always hold.

$$P_t Y_{it} = P_t e^{\beta_1} E_{it}^{\beta_E} e^{\epsilon_{it}} \quad (1.3)$$

$$P_t Y_{it} \left( \frac{P_b}{P_t} \right) = P_b Y_{it} = P_b e^{\beta_1} E_{it}^{\beta_E} e^{\epsilon_{it}} \quad (1.4)$$

I next take logs of both sides to linearize equation (1.4).

$$\tilde{y}_{it} = \tilde{\beta}_1 + \beta_E e_{it} + \epsilon_{it} \quad (1.5)$$

where lower case letters denote logs. Because I cannot separate output from the base price,  $P_b$ ,  $\tilde{y}_{it}$  equals the log of output plus the log of the base price, and  $\tilde{\beta}_0$  is the log of the electricity argument constant plus the log of the base price. Because I have assumed that  $\epsilon_{it}$  is measurement error that does not affect plant manager's decisions, I can estimate this equation using OLS.

Relying again on both arguments of the production function binding, I divide by the price index and take logs to find an equation for output as a function of capital and labor.

$$\tilde{y}_{it} = \tilde{\beta}_0 + \beta_K k_{it} + \beta_L l_{it} + \omega_{it} + \epsilon_{it} \quad (1.6)$$

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<sup>26</sup>For some industries, I observe quantities every five years in the Census of Manufacturers.

<sup>27</sup>Specifically, I observe the total value of shipments. I also observe the value of final goods inventories at the beginning and end of each year, so I could construct the value of final goods produced as the total value of shipments plus the change in inventories. In practice, I found this measure that incorporates inventories to be very noisy.

<sup>28</sup>Using industry-specific price indices is one approach to overcome the problem of not observing quantities. In most cases, the underlying assumption necessary for consistent estimates is that any deviations of the plant-level price from the industry price are uncorrelated with inputs (Petrin and Sivadasan, 2013).

Though this equation is linear in the parameters, the levels of capital and labor are positively correlated with unobserved productivity, and the OLS estimator will be inconsistent. This is because managers of more productive plants will, all else equal, employ more inputs. Rather than use OLS, I estimate the production function coefficients for labor using the first-order conditions. I then estimate the capital coefficient using techniques from the industrial organization literature.

For notational simplicity, I did not include materials in the above production function. Assuming a constant materials price, the production function in Equation 1.2 is consistent with a production function that uses a fixed fraction of materials to produce each unit of output. In estimation, I do not constrain the function to be fixed-proportion in materials, which here means I estimate  $\beta_M$  in Equation 1.7 rather than assuming it is one.

$$Y_{it} = \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}, e^{\beta_2} M_{it}^{\beta_M}\} e^{\epsilon_{it}} \quad (1.7)$$

I measure materials in dollars, assume real materials prices are constant, and regress log output on the log cost of purchased materials to estimate the materials coefficient.<sup>29</sup>

I next estimate the labor coefficient,  $\beta_L$ , using conditions from the plant manager's profit maximization problem. I assume labor has no adjustment costs and all firms face the same wage rate, assumptions that simplify the dynamic model. Given these assumptions, the techniques I will use to estimate the capital coefficient cannot identify the labor coefficient (Bond and Soderbom, 2005). Instead, I rely on estimating the first order condition which will hold exactly under these assumptions. Because I assume  $\epsilon$  is measurement error in output, plant managers solve the following problem:

$$\max_{L,E,M} P_t \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}, e^{\beta_2} M_{it}^{\beta_M}\} - L_{it} - P_{it}^E E_{it} - M_{it} \quad (1.8)$$

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<sup>29</sup>I observe an industry-year level price index for materials, and estimates with and without normalizing by the index are very similar. I choose not to normalize by the index since I assume materials prices are constant.

where  $\epsilon$  does not enter. Let  $Y_{it}^* \equiv \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}, e^{\beta_2} M_{it}^{\beta_M}\} = Y_{it} e^{-\epsilon_{it}}$ .

The marginal benefit of an extra unit of labor is the marginal product of labor given the productivity and capital stock, and the marginal cost is the cost of increasing all inputs proportionally so that all arguments exactly bind.

$$\text{Marginal Benefit} \quad \beta_L \frac{P_t Y_{it}^*}{L_{it}} = 1 + \frac{\beta_L E_{it}}{\beta_E L_{it}} P_{it}^E + \frac{\beta_L M_{it}}{\beta_M L_{it}} \quad \text{Marginal Cost} \quad (1.9)$$

Rearranging gives an expression for  $\beta_L$ .

$$\beta_L = \frac{L_{it}}{P_t Y_{it}^*} \frac{1}{\left(1 - \frac{E_{it} P_{it}^E}{\beta_E P_t Y_{it}^*} - \frac{M_{it} P_M}{\beta_M P_t Y_{it}^*}\right)} \quad (1.10)$$

I do not observe  $P_t Y_{it}^*$  and instead observe  $P_t Y_{it}$ . Substituting observed revenues into Equation 1.10 gives the following expression:

$$\beta_L = \frac{L_{it}}{P_t Y_{it}} \left( e^{-\epsilon_{it}} - \frac{P_{it}^E E_{it}}{\beta_E P_t Y_{it}} - \frac{P_M M_{it}}{\beta_M P_t Y_{it}} \right)^{-1} \quad (1.11)$$

Since this equation is monotonic, but not linear, in  $\epsilon$ , I use the median across all observations as my estimate of  $\beta_L$ .

$$\hat{\beta}_L = \text{median} \left\{ \frac{L_{it}}{P_t Y_{it}} \left( 1 - \frac{P_{it}^E E_{it}}{\beta_E P_t Y_{it}} - \frac{P_M M_{it}}{\beta_M P_t Y_{it}} \right)^{-1} \right\} \quad (1.12)$$

where the 1 follows from  $\text{median}(e^{-\epsilon}) = e^{-\text{median}(\epsilon)} = e^0 = 1$ .

If the production function were Cobb-Douglas in all inputs, the first order condition would equate the labor coefficient to its expenditure share. The optimality condition for this Leontief production function equates the labor coefficient to the scaled-up labor expenditure share, where the scaling up accounts for the drag on output of also needing to increase electricity and materials simultaneously. A convenient feature of this estimator is that output enters only as total revenues, a quantity I observe.



Capital in my model is a dynamic input for two reasons: there is a one period time to build, and plants face costs to adjusting their capital stock.<sup>30</sup> Therefore, I do not expect a plant’s capital stock to satisfy its static first-order condition. Instead, I rely explicitly on capital being dynamic to create variation in the observed capital stock across plants facing the same productivity shock: the variation necessary to identify the capital coefficient. This estimation strategy follows the industrial organization literature on production function estimation (see Olley and Pakes (1996), Levinsohn and Petrin (2003), Akerberg, Caves and Frazer (2015), and Collard-Wexler and De Loecker (2016)), and relies on four additional assumptions. Two of these assumptions are about how productivity evolves over time. The first is that productivity evolves exogenously according to an AR(1) process.

$$\omega_{it} = \mu + \rho\omega_{it-1} + \xi_{it} \tag{1.13}$$

The second is that plant managers cannot forecast the innovation to productivity,  $\xi_{it}$ . Thus,  $\mathbb{E}[\xi_{it}|\mathcal{I}_{t-1}] = 0$  where  $\mathcal{I}_{t-1}$  denotes the plant manager’s information set at time  $t - 1$ . The other two assumptions are important for using material demand to control for unobserved productivity.<sup>31</sup> One is that material demand is monotonically increasing in productivity. Given perfectly variable labor, electricity, and materials, this assumption is intuitive. A positive productivity shock will give a plant manager an incentive to increase labor as it becomes more productive, and he will simultaneously increase electricity and materials proportionally. The second, stronger assumption is that productivity is the only unobservable entering the material demand equation. Taken together, these last two assumptions allow for the inversion of the material demand function.

Given these assumptions, material input demand can be expressed as a function of capital, productivity, output prices, and electricity prices and inverted to find the productivity shock,

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<sup>30</sup>A one period time to build means that investment in period  $t$  does not become productive until period  $t + 1$ .

<sup>31</sup>These assumptions allow me to separate  $\omega$  from the measurement error  $\epsilon$ . The functional form of my production function suggests avoiding these assumptions by using Equation 1.5 to estimate  $\epsilon$ . I elect to use inverted material demand to separate the two because I expect this method to be more robust.

$\omega$ .

$$m_{it} = g(k_{it}, P_t, P_{it}^E, \omega_{it}) \quad (1.14)$$

$$\omega_{it} = g^{-1}(k_{it}, P_t, P_{it}^E, m_{it}) \quad (1.15)$$

while  $g^{-1}(\cdot)$  is unknown, I can approximate it with a polynomial in the four state variables. Returning to the linearized equation, (1.6), I subtract off my estimates of the contribution of labor and electricity to production,  $\hat{\beta}_L l$ .

$$y_{it}' = \tilde{y}_{it} - \hat{\beta}_L l_{it} = \tilde{\beta}_0 + \beta_K k_{it} + \omega_{it} + \epsilon_{it} \quad (1.16)$$

$$= \tilde{\beta}_0 + \beta_K k_{it} + g^{-1}(k_{it}, P_t, P_{it}^E, m_{it}) + \epsilon_{it} \quad (1.17)$$

For every guess of the constant and capital coefficient, I can now find the implied productivity shocks and estimate the AR(1) process to find the productivity innovations,  $\xi$ . I then use the fact that capital at  $t$  lies in  $\mathcal{I}_{t-1}$  to form the moment I use to estimate  $\beta_K$ :

$$\mathbb{E}[\xi_{it} k_{it}] = 0 \quad (1.18)$$

Recent work by Collard-Wexler and De Loecker suggests using investment as an instrument to address measurement error in capital caused by mismeasurement of depreciation. While using lagged investment to form the moment addresses measurement error, it is less efficient. Because one period of investment explains less of the overall variation in capital, using lagged investment rather than capital to form the moment may also exacerbate the effect of any remaining endogeneity caused by not fully separating  $\omega_{t-1}$  from the productivity innovation,  $\xi_t$ . For example, in my model, this endogeneity could result from  $\omega$  not actually following an AR(1) process. For these reasons, I use the capital moment for my main specification and present estimates found using a lagged investment moment in Appendix Section A.7 as a robustness check.

### 1.6.1.2 DISPERSION IN THE MARGINAL PRODUCT OF CAPITAL FOR THE LEONTIEF FUNCTION

One complication caused by the Leontief functional form is that the increase in revenues from an additional unit of capital is always zero.<sup>32</sup> Thus, looking at dispersion in the marginal product of capital is not informative about efficient capital allocation. Instead, I use an optimality condition from the plant's maximization problem with no adjustment costs to construct a similar measure. If all inputs are perfectly variable, the plant's problem is

$$\max_{L,E,M} P_t \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}, e^{\beta_2} M_{it}^{\beta_M}\} - L_{it} - P_{it}^E E_{it} - M_{it} - R_K K_{it} \quad (1.19)$$

where  $L$  is payroll, measured in dollars,  $E$  is electricity, measured in MWh, and  $M$  is materials, measured in dollars. If a plant increases its capital stock, it will also increase both electricity and materials so that no inputs are wasted. How much these other inputs must be increased depends on the ratio of their coefficients to the capital coefficient. Therefore, the marginal cost of an additional unit of capital is its rental rate plus the cost of increasing materials and electricity proportionally.

$$\text{Marginal Benefit} \quad \beta_K \frac{P_t Y_{it}}{K_{it}} = R_K + \frac{\beta_K E_{it}}{\beta_E K_{it}} P^E + \frac{\beta_K M_{it}}{\beta_M K_{it}} \quad \text{Marginal Cost} \quad (1.20)$$

Moving everything that varies to the left gives an equation that should hold if there are no adjustment costs.

$$\beta_K \frac{P_t Y_{it}}{K_{it}} - \frac{\beta_K E_{it}}{\beta_E K_{it}} P^E - \frac{\beta_K M_{it}}{\beta_M K_{it}} = R_K \quad (1.21)$$

In this model,  $R_K$  is common across all plants. If there are no adjustment costs (including the time to build for capital), the left hand side of Equation 1.21 should be constant across all plants, and I refer to this standard deviation as dispersion in the marginal revenue product

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<sup>32</sup>If we assume firms are already choosing inputs such that no inputs are wasted.

of capital.

### 1.6.1.3 PRODUCTION FUNCTION ESTIMATES

I report my estimates of the production function parameters in Table 1.6. Perhaps the most striking result is the that the capital coefficient is larger than the labor coefficient. To confirm this high capital coefficient is reasonable, I compare the ratio of annual payroll to the real capital stock for manufacturing as a whole to the same ratio for the paper industry. This ratio is 0.31 across all manufacturing but only 0.12 for paper, confirming that this industry is exceptionally capital intensive.<sup>33</sup>

Table 1.5: Production function estimates

$Y_{it} = \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}\} e^{\epsilon_{it}}$					
	Estimate	SE		Estimate	SE
$\beta_K$	0.562	(0.033)	$\beta_0$	2.05	(0.37)
$\beta_L$	0.303	(0.013)	$\beta_1$	4.60	(0.35)
$\beta_E$	0.634	(0.028)			

Estimated using 2,400 plant-years for NAICS 322121, Paper (except Newsprint) Mills. I estimate  $\beta_M$  to be 0.93 with a SE of 0.022. SE bootstrapped by drawing plants with replacement.

I also find a good deal of curvature in electricity. This estimate may be biased downward by unobserved heterogeneity in the types of products produced, since smaller plants may produce more niche, less energy-intensive products. Another possible explanation is measurement error in electricity use.

Finally, I find decreasing returns to scale. This is comforting since I am not modeling these plants as facing downward sloping demand curves. Instead, it is increasing marginal cost

<sup>33</sup>I do this comparison using publicly available data from the NBER CES on all manufacturing industries from 1997-2011.

curves that pin down plant size for these manufacturers. For the Cobb-Douglas specification, reported in Appendix A.6, I estimate the returns to scale to be 0.85 with a standard error of 0.03.

## 1.6.2 DYNAMIC MODEL

Having estimated the profit function, I now move to the dynamic model in which plant managers choose investment based on expectations about the future. The goal of the dynamic model is to recover estimates of the costs plants face in adjusting their capital stock. These costs will be informative about the difference between the short and long run response of manufacturers to electricity price changes as well as the potential welfare gains from reducing electricity price volatility.

### 1.6.2.1 CAPITAL ADJUSTMENT COSTS

I follow Asker, Collard-Wexler and De Loecker (2014) in modeling plants as facing both fixed and convex costs to adjusting their capital stock. The fixed cost of adjusting,  $\lambda$ , does not depend on the size of investment. It is a fraction of profits earned in the current period, and it captures the disruption costs to production of installing new capital. I also include a convex cost of adjusting,  $\zeta$ , which increases linearly in a plant's investment rate ( $I/K$ ). Cooper and Haltiwanger (2006) find a combination of convex and non-convex costs can match both the lumpiness and serial correlation found in plant-level investment data. Both of these costs also capture the idea that investment is at least partially irreversible.<sup>34</sup>

I assume capital takes one period to become productive and follows the law of motion

$$K_{i,t+1} = I_{it} + (1 - \delta)K_{it} \tag{1.22}$$

For plant  $i$  in year  $t$ , the costs of choosing investment level  $I_{it}$  given current capital level  $K_{it}$

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<sup>34</sup>Though I do not model a plant manager as selling capital for less than she bought it for, the fixed adjustment cost, coupled with depreciation, generates a similar pattern of inaction in the data.

and exogenous states  $X_{it}$  are the following:

$$C(I_{it}, K_{it}) = I_{it} + \lambda \mathbb{I}\{I_{it} \neq 0\} \pi(K_{it}, X_{it}) + \frac{\zeta}{2} \left( \frac{I_{it}}{K_{it}} \right)^2 K_{it} \quad (1.23)$$

This formulation treats positive and negative investment symmetrically, but, because capital depreciates, plants will have positive investment much more frequently. As Asker, Collard-Wexler and De Loecker (2014) did, I will measure investment as total capital expenditures, which will always be positive. Cooper and Haltiwanger (2006) define investment as capital expenditures less retirements,<sup>35</sup> and they find that roughly ten percent of plant-year observations have negative gross investment. I observe information on retirements in the CMF (every 5 years) and will use this information to examine the sensitivity of my results to ignoring retirements in future versions.

### 1.6.2.2 EXOGENOUS STATES

I model plants as responding to five exogenous states: log output prices, log productivity, log electricity prices, log natural gas prices, and regional share of natural gas. Two of these states are common to all plants in a given year: natural gas prices and output prices. All plants within a region have the same natural gas generation share, and both electricity prices and productivity vary at the plant level.

I model the non-electricity price states as evolving independently according to AR(1) processes.

$$x_{t+1} = \mu_x + \rho_x x_t + \xi_{it}^x \quad \text{for } x = p, \omega, s^g, p^g \quad (1.24)$$

where  $p_t$  is the log output price,  $\omega_{it}$  is log productivity,  $s_{rt}^g$  is the natural gas share,  $p_t^g$  is the log gas price, and  $\xi^x$  is i.i.d  $\sim \mathcal{N}(0, \sigma_x^2)$ . I allow electricity prices to depend on both the

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<sup>35</sup>Cooper and Haltiwanger (2006) also use U.S. Census data, and they define retirements as the answer to the question “gross value of depreciable assets sold, retired, scrapped, destroyed, etc.” This question was asked every year over the period they study.

regional share of natural gas and the price of natural gas. I also allow for correlation between shocks to the price of natural gas and electricity prices. For computational tractability, I do not include region or plant-specific intercepts. The electricity price process is

$$p_{it}^e = \alpha_0 + \alpha_1 p_{i,t-1}^e + \alpha_2 s g_{r,t-1} X p_{t-1}^g + \alpha_3 s g_{r,t-1} + \alpha_4 p_{t-1}^g + \xi_{it}^e \quad (1.25)$$

$$p_t^g = \gamma_0 + \gamma_1 p_{t-1}^g + \xi_t^g \quad (1.26)$$

where  $(\xi^e, \xi^g) \sim$  bivariate normal with a variance covariance matrix  $\Sigma = \begin{bmatrix} \sigma_e^2 & \rho \\ \rho & \sigma_g^2 \end{bmatrix}$  where  $\rho$  is the covariance between the  $\xi^e$  and  $\xi^g$ .

This setup nests four assumptions that are worth highlighting. The first is that plants cannot invest in their productivity. While a richer model would allow firms to affect their productivity, allowing for this behavior makes the plant's problem significantly more complicated. Assuming productivity is exogenous is more reasonable for my industries because they produce non-differentiated products and research and development makes up a small fraction of their total capital expenditures.<sup>36</sup> The second assumption is that any cost changes due to changes in the natural gas price or electricity prices are not passed through to output prices. Since these producers are price-takers operating in large markets, assuming manufacturers do not pass through electricity price shocks to prices is a reasonable approximation, particularly for manufacturers that compete internationally. There are likely aggregate shocks that affect both output and electricity prices, and my model can be relaxed to allow these shocks to be passed through to output prices. The third assumption is that the regional share of natural gas generation follows an AR(1) process. As shown in Appendix Figure A.3, an AR(1) process is a much better approximation for the second half of the sample. Many areas added combined-cycle natural gas plants and retired coal plants in the early 2000s,

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<sup>36</sup>The National Science Foundation (NSF) Business R&D and Innovation Survey (BRDIS) collects information on domestic R&D capital expenditures as a fraction of total capital expenditures. For paper, basic chemicals, and primary metals, domestic R&D was 2.2, 1.5, and 1.3, percent of total capital expenditures, inclusive of R&D (NSF, 2015).

and this led to large jumps in natural gas capacity. From 2003 onward, natural gas shares were stable. Finally, I assume the volatility of the shocks to these price processes is constant over the length of the period. This precludes changes such as the financial crisis of 2008 and 2009 from affecting the size of the shocks to natural gas or output prices.

I estimate all five processes using OLS. I report estimates and describe estimation in more detail in Appendix Section A.8.

### 1.6.2.3 VALUE FUNCTION

Because I assume electricity, labor, and materials are perfectly variable, these inputs can be chosen optimally conditional on the capital stock and exogenous states each period. I denote profits conditional on the optimal choice of variable inputs as  $\pi(K_{it}, X_{it})$ . The value function can then be expressed as

$$V(K_{it}, X_{it}) = \max_{I_{it}} \pi(K_{it}, X_{it}) - C(I_{it}, K_{it}) + \beta \mathbb{E}_{\xi} [V(K_{i,t+1}, X_{i,t+1})] \quad (1.27)$$

$$\text{s.t.} \quad K_{it} = I_{it} + (1 - \delta)K_{it}$$

$$C(I_{it}, K_{it}) = I_{it} + \frac{\zeta}{2} \left( \frac{I_{it}}{K_{it}} \right)^2 K_{it} + \lambda \mathbf{1}\{I \neq 0\} \pi(K_{it}, X_{it})$$

where  $\pi(K_{it}, X_{it})$  is the output price times the estimated production function, less the cost of inputs. Note that I do not allow for entry or exit. Because there is no fixed cost of operation and marginal product of inputs goes to infinity as inputs go to zero, plants will always find it profitable to operate.<sup>37</sup>

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<sup>37</sup>In future versions, I plan to extend the model to include a fixed cost of operation and allow for plant exit.



#### 1.6.2.4 IDENTIFICATION AND ESTIMATION

I follow Cooper and Haltiwanger (2006) and Asker, Collard-Wexler and De Loecker (2014) by estimating the two adjustment cost parameters using simulated method of moments. Specifically, I guess adjustment costs parameters, solve for the value function given these parameters, and use it to simulate plant investment over time.<sup>38</sup> I then calculate moments of the simulated data and match them to the moments in the actual data. I weight by an estimate of the optimal weighting matrix and use a minimum distance criterion to find the adjustment cost parameters that come closest to matching the empirical moments. Because I rely on simulating to the stationary distribution, a limitation of using this estimation procedure is that I cannot allow for a trend in productivity or output prices.<sup>39</sup>

I match four moments in the data that are informative about my adjustment cost parameters: the serial correlation in investment, the covariance between the investment rate and the regional share of natural gas by log gas price interaction, the fraction of observations with an investment rate ( $I/K$ ) less than one percent, and the fraction of observations with an investment rate greater than twenty percent.

Table 1.6: Moments used to estimate adjustment costs

Serial correlation in $I/K$	0.275
Correlation between $I/K$ , share gasXlog pgas	-0.030
Fraction of observations with $I/K < .01$	0.179
Fraction of observations with $I/K > 0.2$	0.037

Moments for the paper industry, based on 2,400 plant-years.

Mean  $I/K$  is 6 percent, median  $I/K$  is 3 percent.

The first moment is the serial correlation in the investment rate ( $I/K$ ). All else equal,

<sup>38</sup>For more detail, see Appendix Section A.9.

<sup>39</sup>When simulating the dynamic model, I adjust the intercepts of these price processes to ensure there are no trends. As a robustness check, I will test the sensitivity of my results to using moments that are less informative about the parameters but also less sensitive to a trend in productivity.

high fixed costs of adjusting will lead to low serial correlation because investment will be made in infrequent bursts, while convex adjustment costs will lead to high serial correlation as plants respond to shocks with small, frequent changes. My second moment is the covariance between the investment rate and the regional share natural gas by gas price interaction.<sup>40</sup> Changes in this interaction affect electricity prices that, in turn, affect expected profitability for these manufacturers. This moment is informative because larger adjustment costs will dampen this correlation between investment and profitability shocks. The final two moments I match are points on the CDF of the investment rate distribution, and they are particularly informative about the size of the fixed cost. First, I match the fraction of observations with an investment rate less than one percent. While the moment most closely linked to the model would be fraction of observations with zero investment, I find that smaller plants disproportionately have zero investment, and I choose the moment I do to avoid picking up scale effects.<sup>41</sup> Many observations near zero are indicative of high fixed costs. Second, I match the rate of large investment spikes: the fraction of observations with investment rates greater than twenty percent. Because high fixed costs give plants an incentive to cluster their investment to avoid multiple disruptions, I expect investment spikes to be positively associated with the fixed adjustment cost parameter.

One complication is that my measure of investment is total capital expenditures, and it is always greater than zero. While consistent with using the perpetual inventory method to construct the capital stock, this setup has the unappealing feature of bounding the rate at which can plants reduce their capital stock by the depreciation rate. Cooper and Haltiwanger (2006) stress the importance of observing retirements in measuring investment, though an argument can be made that retirements are sufficiently captured by depreciation. While the inclusion of retirements is at least debatable, my measure of investment would ideally capture capital sales. The Census stopped collecting information on used capital sales in

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<sup>40</sup>For ease of interpretation, I report the correlation in the table even though I match the covariance in estimation.

<sup>41</sup>This also suggests we should not take the model in Equation 1.23 literally; instead, it captures the main features of these adjustment costs.

1988.

### 1.6.2.5 ADJUSTMENT COST ESTIMATES

$$C(I_{it}, K_{it}) = I_{it} + \lambda \mathbb{I}\{I_{it} \neq 0\} \pi(K_{it}, X_{it}) + \frac{\zeta}{2} \left( \frac{I_{it}}{K_{it}} \right)^2 K_{it} \quad (29, \text{revisited})$$

I estimate large convex adjustment costs and small fixed adjustment costs. Table 1.7 presents the estimated adjustment costs. The convex parameter estimate implies that an investment rate of twenty-percent will result in adjustment costs that are ten percent of the capital stock, about half the cost of the investment itself. This estimate seems high but plausible since less than four percent of the plant-year observations in my sample have an investment rate of at least twenty percent. When I estimate these costs for the Cobb-Douglas production function, I find a similar value for the fixed cost and a much higher value for the convex cost.

Table 1.7: Adjustment costs

Parameter	Estimate
$\lambda$	0.0025
$\zeta$	5.0

Leontief function; paper industry

These estimates are not easily comparable to those in Asker, Collard-Wexler and De Loecker (2014) since these authors estimate costs for manufacturing as a whole and estimate them at the monthly level. If I do a rough conversion of their numbers to the annual level, the results imply that they find much higher fixed costs and slightly lower convex costs than what I find for the paper industry.<sup>42</sup>

<sup>42</sup>They estimate the same adjustment cost function at the monthly level and estimate  $\zeta^m$  to be 17.4 and  $\lambda^m$  to be 0.09.

## 1.7 COUNTERFACTUAL

Electricity market integration decreases electricity price volatility by smoothing out local shocks to supply and demand. There is currently interest in policies to increase market integration because it can smooth the short-run fluctuations in supply caused by intermittent renewable generation. Any integration pursued for this motive will also reduce the longer-term supply and demand fluctuations relevant to my analysis. An example of a recent policy that increases integration by facilitating electricity trading is the introduction of the energy imbalance market in the Western Interconnection: a market started in 2014 that has expanded to eight Western states (California ISO, 2016).

I simulate a counterfactual in which I remove all but the national component of electricity price volatility. This counterfactual approximately captures the upper bound on the effect of aggressively integrating electricity markets. It is an upper bound because some of the eliminated plant-level variation would undoubtedly remain after market integration. Although electricity market integration would likely change price levels, I leave the average electricity price level unchanged to focus on the effect of the change in the variance of these prices.

To perform this counterfactual, I begin by identifying the national variation that I will allow to remain in the plant-level price process. As introduced in Section 1.6.2.2, this process is

$$p_{it}^e = \alpha_0 + \alpha_1 p_{i,t-1}^e + \alpha_2 s g_{r,t-1} X p_{t-1}^g + \alpha_3 s g_{r,t-1} + \alpha_4 p_{t-1}^g + \xi_{it}^e \quad (1.25, \text{revisited})$$

I estimate this process and use the residual to estimate the national-level variation. Because I do not include plant-intercepts in the price process, I begin by removing any variance due to constant, unobserved heterogeneity across plants by regressing  $\hat{\xi}_e$  on plant fixed effects,  $\kappa_i$ .

$$\hat{\xi}_{it}^e = \kappa_i + \nu_{it} \quad (1.28)$$

I then separate the remaining variance in the plant-process error into a national and plant-specific component by regressing  $\hat{\nu}_{it}$  on time fixed effects,  $\gamma_t$ .

$$\hat{\nu}_{it} = \gamma_t + \eta_{it} \tag{1.29}$$

I construct a counterfactual price process by scaling down the variance of the error in the electricity price process accordingly and setting the natural gas share process to that of the weighted average natural gas share. I then match the empirical regional distribution of the paper plants in my sample and simulate their investment behavior under both the original and the lower variance price processes.<sup>43</sup>

When I simulate the electricity prices and paper plant investment under the counterfactual price process, I find that, relative to under the original electricity price process, electricity prices are about 20 percent as volatile, dispersion in the marginal product of capital falls by 4.4 percent, and industry profits rise by 1.8 percent. That only 17 percent of electricity price volatility is explained by national-level shocks is surprising, and I use state-level electricity prices to verify that it is not entirely an artifact of my plant-level electricity price variable.<sup>44</sup> I also find that capital is 1.2 percent higher under the lower volatility price process, and only 19 percent of the change in profits is due to lower realized adjustment costs.

Because even the most integrated markets will still have some time-varying difference in prices across plants, e.g. due to shifts along price schedules, I also present an alternative counterfactual that assumes none of the plant-level electricity price volatility is removed by market integration. Instead, I only remove volatility explained by eGRID region level price changes. To implement this counterfactual, I follow the same steps as above through Equation 1.29. I then take the residual from this equation,  $\hat{\eta}_{it}$ , and regress it on eGRID

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<sup>43</sup>Specifically, I conduct 100 simulations under each price process. For each simulation, I simulate 1000 periods of data and calculate statistics based on the last 200 periods.

<sup>44</sup>When I demean the seventeen years of EIA state-level industrial electricity prices by state and regress them on year fixed effects, I find an  $R^2$  of 0.34. If I estimate a state-level price process that is analogous to my plant-level process, regress the residual from this process on state fixed effects, and then regress the second residual on year fixed effects, I find an  $R^2$  of 0.13.

region by year fixed effects. This allows me to determine what fraction of the non-national variation in electricity prices is at the regional level versus the plant level. I then scale-down the fraction of non-national variation explained by region to convert it to the fraction of total variation, and I adjust the standard deviation of the error term in the price process accordingly, a reduction of thirteen percent.

In this more conservative counterfactual, I find that, relative to the original price process, electricity prices are about eighty percent as volatile, dispersion in the marginal product of capital falls by 1.1 percent, and industry profits rise by 0.6 percent. Eight percent of the change in profits is due to changes in adjustment costs, and the industry holds about 0.3 percent more capital.

## 1.8 CONCLUSION

In this chapter, I establish that energy-intensive manufacturers decrease their investment in response to electricity price increases. I also find that decreasing the volatility of electricity prices increases these manufacturers' aggregate productivity and profits.

By linking variation in electricity prices to dispersion in the marginal product of capital caused by dynamic inputs, this chapter allows us to think about a particular cause of this dispersion and whether it is dynamically efficient. At least some of this dispersion could be reduced by policies to integrate regional electricity markets, policies such as investing in electricity transmission or adopting electricity market designs that facilitate trading. Mansur and White (2012) find that moving to a centralized market design led to substantial gains in electricity market efficiency. Factoring in the benefits to manufacturing would only increase the argument for integration.

More generally, this chapter is informative about the contribution of input price shocks to dispersion in the marginal product of capital. I find that reducing the volatility of an input price can have a measurable effect on this dispersion. This finding is notable because electricity is not a very large share of costs, even for the energy-intensive manufacturers I

study, and it motivates studying dispersion caused by changes in the price of other inputs, chiefly labor and materials.

This chapter leaves open several questions for future work. First, I abstract from firms' ability to invest in energy efficiency, in part because my data are not directly informative about these investments. Future work could use data from the Manufacturing Energy Consumption Survey (MECS) to incorporate these investments as one channel by which these manufacturers respond to electricity price increases. I also expect there to be significant heterogeneity in the impact of electricity prices on manufacturing industries. Exploring this heterogeneity will shed light on which industries stand to lose or gain the most from policies that address climate change.

## CHAPTER 2 WIND TAX EQUITY FINANCING

### 2.1 INTRODUCTION

Each year the Federal Government spends billions subsidizing wind energy investment, and these subsidies have contributed to rapid growth in this industry. Wind electricity generation capacity in 2012 was over ten times that of 2002, and wind is expected to be an important part of the Environmental Protection Agency's (EPA) new Clean Power Plan. While prior work has studied the impact of wind energy subsidies on emissions, this chapter studies the differential impact of awarding subsidies in the form of non-refundable tax credits, as opposed to grants or refundable tax credits.

Non-refundable tax credits are ubiquitous as a subsidy form, and their non-refundability causes the subsidy's benefit to differ across taxpaying and non-taxpaying firms. The most common type of tax credit, non-refundable tax credits are used to subsidize a wide range of activities, including research and development, education, and retirement savings (Erb, 2015). While grants and refundable tax credits can be used regardless of how much is owed in taxes, non-refundable credits cannot reduce a firm's tax bill below zero.<sup>1</sup> As a result, a ten-thousand dollar, non-refundable tax credit will be worth ten-thousand to a firm that owes more than ten-thousand in taxes, but worth less to a firm that does not.

This distinction is important in wind energy, where firms often receive more in subsidy than they owe in taxes. Wind projects receive a large, non-refundable tax credit for every

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<sup>1</sup>Technically, the alternative minimum tax (AMT) prevents firms from reducing their taxes to zero, but the key is that there is a hard lower bound which firms cannot use non-refundable tax credits to go below.



unit of electricity they generate, measured in mega-watt-hours (MWh). Three features of wind energy make the credit being non-refundable particularly salient: the per-MWh subsidy is large, roughly forty percent of a typical MWh price; most wind developers specialize in renewable energy projects, all of which generate non-refundable tax credits; and the industry is in its takeoff stage, with many new entrants that are not yet profitable.<sup>2</sup> Thus, the constraint that these firms must owe taxes to use the subsidy frequently binds. Wind developers can carry forward unused tax credits to future years, but discounting makes this option unattractive. Further, firms are prohibited by law from selling the credits. Instead, they usually partner with large investors who finance part of a wind project in return for the tax credits it generates, an arrangement known as tax equity financing.

Relative to a world where wind subsidies are awarded as refundable tax credits or grants, there are several reasons to suspect that using tax equity financing to transfer tax credits results in inefficiency. First, transaction costs may be high since each tax equity deal occurs at the individual project-level and requires coordination between at least two, and often three, parties and their attorneys. Second, only a few large investors provide the bulk of tax equity financing, so market power may lead to an inefficiently low quantity of tax equity deals. Third, by law, tax equity investors must bear at least some risk, and overcoming information asymmetries about project quality may be costly. Finally, the need for tax equity financing may affect market structure by raising costs differentially for new entrants relative to established developers. New entrants may be disproportionately affected because they are both less likely to be paying taxes and more likely to be perceived as high-risk tax equity partners. This last effect could dampen both competition and innovation.

Rather than attempting to measure each of these inefficiencies, I estimate the “price” wind developers using tax equity financing receive for their tax credits. Despite its importance to the industry, we have limited information about this price because the terms of

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<sup>2</sup>The same firm usually acts as both the owner and developer of a wind project: in my sample, two-thirds of projects have exactly the same owner and developer and several others are joint ventures in which one firm is both an owner and a developer. For this reason, I refer to both the owner and developer as the project developer unless the distinction is important.

contracts between project developers and investors are unobserved. If every wind developer receives a price of one dollar for a dollar in non-refundable tax credits, the market is efficient. Transaction costs, market power, and information asymmetries will all lead to wind developers receiving a price below one dollar. Though this price is only suggestive of the absolute level of inefficiency, it is the relevant metric for another outcome that matters to policymakers: the amount of wind energy investment for each dollar spent on subsidy. I will also estimate how the price developers receive from “selling” their tax credits varies with developer experience. This difference in price would provide evidence as to whether providing a non-refundable tax credit subsidy acts as a barrier to entry in this industry.<sup>3</sup>

In 2009, the U.S. Government introduced a program that allowed wind developers to choose between the non-refundable tax credit subsidy and a cash grant subsidy, and I use observed choices to infer the price wind developers receive for their tax credits. My analysis directly estimates how much wind developers value each dollar of non-refundable tax credits compared to one cash dollar. In equilibrium, this value will equal the price wind developers receive from transferring their non-refundable tax credits using tax equity financing.<sup>4</sup> The program, which ran from 2009-2012, was unexpected and explicitly temporary. It allowed wind projects to choose between an up-front, cash grant equal to a fraction of project installation costs, and a production-based, non-refundable tax credit over the first ten years of operation. Since utility-scale wind projects usually take several years to plan and build, project characteristics are plausibly exogenous to the subsidy program. I develop a model of the choice of subsidy as a function of project characteristics and the price of non-refundable tax credits, and I use a revealed preference approach to estimate this price from observed choices. For example, I expect wind projects in high wind, low cost regions like Texas to pre-

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<sup>3</sup>In reality, a tax-equity investor provides a loan to the wind developer in exchange for non-refundable tax credits, depreciation deductions, and the loan’s repayment over a period of several years. The terms of this loan relative to debt financing implicitly define an average price paid for each dollar of non-refundable tax credits. For more information on these transactions, see Appendix Section B.1.

<sup>4</sup>During this period, nearly all of the wind developers in my sample were using tax equity financing to monetize their tax credits, so, by revealed preference, they did not value them higher than this price. Conversely, a developer would value tax credits at no less than it sell them to a tax equity investor for.

fer the production-based subsidy, and I expect wind projects in low wind, high cost regions like Massachusetts to prefer the cost-based grant. Somewhere in between, projects will be indifferent between the two subsidies, and where this point lies will be depend on developers' willingness to trade-off non-refundable tax credits and cash.

I estimate that wind project developers value each dollar of non-refundable tax credits at \$0.86 in cash, on average, and this discounting can lead to a substantial reduction in wind energy investment. Because my analysis requires converting non-refundable tax credits to their present value, this estimate is sensitive to the assumed discount rate.<sup>5</sup> However, even at the upper bound of plausible discount rates, a real rate of ten percent, I find wind developers value non-refundable tax credits at a slight discount relative to cash. I also find that firms building their first wind project have particularly low valuations for non-refundable tax credits relative to cash, which suggests that this subsidy form may act as a barrier to entry. Using a back-of-the-envelope calculation, based on a uniform valuation of \$0.86 and a supply elasticity from Johnson (2014), I find that moving to refundable tax credits or grants would have increased investment over the period from 2009-2012 by as much as ten percent.

By focusing on the impact of subsidy type on investment, this chapter fits into the environmental economics literature on the relationship between dollars spent on wind energy subsidies, investment in wind energy, and emission reductions. While recent work has focused on measuring the benefits of wind subsidies in terms of emission reduction, e.g. Cullen (2013), this work focuses on how subsidy form affects the link between dollars spent and investment. More narrowly, previous studies have also examined the wind production tax credit (PTC) and its effect on investment. In a paper published shortly after the PTC was enacted, Kahn (1996) argues that the PTC will be ineffective because it will force wind developers to use more equity and less debt to finance their projects, thus raising financing costs. He finds that structuring the PTC as a cash payment rather than a non-refundable tax credit would lower financing costs by 10 percent. Metcalf (2010) constructs the user cost of capital for wind

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<sup>5</sup>The production subsidy is awarded over the first ten years of project operation, and I use a discount factor to convert the subsidy into its present value at the date of project completion.

energy investment under the various tax policies in place from 1990-2007. When he examines the response of investment to changes in this cost of capital, he finds the PTC played an important role in stimulating investment. Twenty years after it was enacted, the consensus is that the PTC helped spur the growth of wind energy, but the question of the consequences of giving it as a non-refundable tax credit remains. This chapter re-visits Kahn's critique of the PTC using data on individual wind projects.

This chapter also relates to two strands of the public finance literature on using non-refundable tax credits to subsidize investment. The first is work from the early 1980s on safe-harbor leasing. In 1981, the U.S. government adopted a rule that allowed firms to essentially divorce actual ownership of an asset from ownership for tax purposes. The purpose of this rule, known as safe-harbor leasing, was to facilitate use of the Investment Tax Credit (ITC) by non-taxpaying firms. This policy sparked interest in the distinction between refundable and non-refundable tax credits, with Warren Jr. and Auerbach (1982) positing that we should allow a non-taxpaying firm to use tax credits if their purpose is to provide a subsidy, but not if their purpose is to reduce capital taxation. Politically unpopular, safe-harbor leasing was quickly repealed (Owers and Rogers, 1985). More recently, there have been papers studying the efficiency of the Low-Income Housing Tax Credit (LIHTC). This credit is similar to the wind PTC in that it is non-refundable and most housing developers cannot use the credits themselves. However, the LIHTC is an investable tax credit, which means it is transferable. Thus, developers do not need to employ a workaround such as tax equity financing to sell them (Desai, Dharmapala and Singhal, 2010). Making the PTC investable is another option available to policymakers.

## 2.2 INSTITUTIONAL DETAILS

### 2.2.1 TAX SUBSIDIES FOR WIND INVESTMENT

#### 2.2.1.1 PRODUCTION TAX CREDIT

Historically, the largest federal subsidy for wind energy has been the production tax credit (PTC), a per megawatt-hour (MWh) subsidy that wind projects receive for their first ten years of operation. The PTC was enacted 1992 and is adjusted annually for inflation. Wind project developers have long struggled to make full use of the credit given its size in relation to their tax liability; in 2012 the PTC was \$22/MWh while a typical wholesale price for electricity was \$50/MWh. Unused PTCs can be rolled over and used to reduce tax liability in future years.<sup>6</sup>

The U.S. Congress typically renews the PTC for a few years at a time and re-visits the decision to extend the credit near the end of this window. Importantly, the PTC was not in danger of expiring during my sample period (2009-2012).<sup>7</sup> Since projects that qualify for the PTC receive it for the full ten years even if the program is subsequently allowed to expire, expectations about future renewals should not have a direct effect on the expected value of the PTC.

#### 2.2.1.2 ACCELERATED AND BONUS DEPRECIATION

The federal government also subsidizes investment in wind energy through its treatment of depreciation deductions.<sup>8</sup> Projects qualify for 50 percent bonus depreciation which allows

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<sup>6</sup>DSIRE: Database of State Incentives for Renewables and Efficiency (2015) notes that credits can be carried back one year and carried forward up to twenty years.

<sup>7</sup>The last time the credit came within a year of expiring was in 2008, before my sample begins, and all of the projects in my sample were under construction by the start of 2011 (U.S. Department of Energy, 2014).

<sup>8</sup>Companies pay income taxes on net income, so they are allowed to deduct costs from their taxable income. Depreciation deductions allow a firm to deduct a fixed investment cost from its taxable income over the course of the investment's useful life. For example, suppose a wind project with no salvage value has an expected useful life of twenty years. Then a developer using straight-line depreciation would deduct 1/20<sup>th</sup> of the project installation cost from its taxable income each year for twenty years. One way the government can subsidize investment is by shortening the tax life over which depreciation occurs. If this life is shortened to five years, then the developer would deduct 1/5<sup>th</sup> of the cost each year for the first five years

half of a project's installation cost to be deducted from taxable income in the first year. The remaining 50 percent is depreciated over a five-year tax life using 200 percent declining balance depreciation, a method in which the fraction deducted in the first year is roughly four times as large as the fraction deducted in the last year. From September 2010 through December 2011 the bonus depreciation for wind projects was increased to 100 percent, so the entire cost could be deducted in the first year (IRS, 2011).<sup>9</sup> While these favorable depreciation rules applied to most kinds of capital, wind projects are particularly affected by depreciation rules due to their cost structure; most of their costs are sunk costs paid when the project is installed.

The implicit subsidy from these depreciation rules relative to twenty year straight-line depreciation can easily be as large as the PTC. While these rules lower the cost of investing in wind energy, they exacerbate the problem of having more non-refundable tax credits than tax liability by directly reducing taxable income in the first few years of operation. Like PTCs, unused depreciation deductions can be carried over and used in future years.

### **2.2.2 TAX EQUITY FINANCING AS A MEANS OF TRANSFERRING TAX SUBSIDIES**

It is illegal to sell tax credits and depreciation deductions, so wind developers use a workaround called tax equity financing to transfer them to another firm with the tax liability to use them.

*Most renewable energy projects in the United States have been financed in the past largely with tax equity. The US government pays as much as 65% of the capital cost of such projects through tax incentives. Few developers can use the incentives directly, so they barter them in tax equity transactions to raise capital for their projects.* - 2010 Project Finance Newswire (Chadbourne and Parke, LLP, 2010)

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and zero thereafter. While in both cases the entire cost of the investment is deducted from taxable income, the present value of the deductions is higher in the second case. Bonus depreciation, which allows additional depreciation deductions in the first year, and declining balance depreciation, which allows a larger fraction of the investment to be depreciated in earlier years, are other ways of providing an investment subsidy through the treatment of depreciation deductions. While none of these methods allow more than one-hundred percent of the cost to be deducted, shifting forward the timing of deductions creates a subsidy.

<sup>9</sup>In empirical work, I only apply the 100 percent bonus to projects that began operating in 2011 since property had to both be acquired and placed in service after September 2010 to qualify

A typical tax equity financing arrangement involves forming a Limited Liability Company that owns the project. Both the wind developer and the tax equity investor put up equity for this joint venture, and the tax credits, depreciation deductions, and cash generated by the project are split between the two. The transaction, discussed in more detail in Appendix B.1, is set up so that the investor's stake in the project becomes very low once the tax incentives are exhausted, usually about ten years after project construction. This "flip" structure substantially reduces the risk the investor bears.

The developer and investor would like to have a transaction that transfers all the tax credits and depreciation deductions to the investor without the investor bearing any risk. The IRS, on the other hand, prohibits the tax incentives from going to a party without a true equity stake. In 2007, the IRS created a safe harbor provision that allowed these transactions as long as they stayed within certain bounds. This provision allows for up to ninety-nine percent of the tax credits and depreciation deductions to go to the tax equity investor during these transactions (IRS, 2007).

The majority of tax equity is provided by a handful of financial firms, and a small number of suppliers might lead to market power or an inelastic short-run supply curve, both of which are consistent with a substantial share of the subsidy going to the investors. As of 2011, there were fifteen tax equity investors active in renewable energy (U.S. Partnership for Renewable Energy Finance, 2011). Suppliers are limited to corporations with large and reliable levels of tax liability since a typical transaction will generate significant tax credits for ten years. While many non-financial firms satisfy these requirements, they have been slow to enter: a 2012 *WSJ* article by Ryan Tracy discusses the U.S. Government's efforts to encourage companies like Walt Disney Co. and Exxon Mobil Corp. to supply tax equity. This reluctance to enter is likely because providing tax equity requires writing complex contracts and evaluating renewable energy projects. While firms could develop expertise in these areas, they may not want to pay the fixed cost to do so given the expectation the PTC might soon be phased out.

### 2.2.3 A TEMPORARY GRANT PROGRAM

The financial crisis of made it difficult to finance any investment, but wind projects were particularly affected due to their reliance on tax equity financing. In late 2008, many of the firms supplying tax equity lost their appetite for risk and had lower levels of tax liability on which to use tax incentives; consequently, the supply of tax equity financing fell. At the same time, the Obama Administration wanted to use the stimulus as an opportunity to encourage investment in renewable electricity and energy efficiency. To address this lack of financing and stimulate investment, the American Recovery and Reinvestment Act (ARRA) of 2009 instituted the Section 1603 Treasury Grant Program. This program provided wind developers with the option of electing the PTC, a cash grant equal to 30 percent of project installation costs, or an Investment Tax Credit (ITC) equal to 30 percent of project installation costs. Projects could choose between the three but could not take more than one (Bolinger et al., 2009).

I will focus on the choice between the PTC and the grant, called a Section 1603 Grant, since I expect developers to always prefer the grant to the ITC. While the grant and the ITC are for identical amounts, the grant is in cash and developers do not need to owe taxes to use it.<sup>10</sup> The option to take the ITC was likely included because commercial solar projects that had previously been eligible for the 30 percent ITC were also eligible for the 1603 Grant Program (U.S. Department of Energy, 2011). It may have also been included in the expectation that it would remain after the grant program had been phased out; as of 2013, new wind projects were not eligible for the grant but could still elect the ITC (Bolinger and Wiser, 2013).

The Section 1603 Program was put into law in February 2009 and began awarding grants in September 2009. All projects completed in 2009, regardless of whether they were completed before the ARRA was passed, were eligible for the grant. The grant program was

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<sup>10</sup>Projects claim the ITC in the year in which the project begins commercial operation (Bolinger, 2014), so even projects that are under construction for multiple years should not have a reason to prefer the ITC.



scheduled to last only a few years, and the last eligible projects are those for which construction was started by the end of 2011 and completed by 2016. As of December 2013, over \$12 billion in Section 1603 Grants had been awarded to wind projects (U.S. Department of Treasury, 2013).

## 2.3 DATA

I use data on all generators with a nameplate capacity 1 MW or greater that began operation in 2009 through 2012.<sup>11</sup> Some locations have multiple generators, and I combine generators with the same plant and operating date into one observation. I now call each observation a project. Because I only observe realized electricity generation at the plant level, I drop cases where a plant contains multiple wind projects (roughly ten percent of wind projects).

Data on existing wind generators come from the U.S. Energy Information Administration (EIA) Form 860. Operators of electricity generators are required by law to submit Form 860 if they i) have at least 1 MW of nameplate generation capacity and ii) are located at a facility connected to the local or regional power grid. These data provide a snapshot of all operating generators as of December 31<sup>st</sup> of each year. Form 860 records the nameplate, location, and date of initial operation for each generator. It also lists what sector the generator operator falls in: regulated utility, independent power producer, industrial, or commercial.<sup>12</sup> I supplement the Form 860 data with data from the American Wind Energy Association (AWEA) project database. These data include information on the wind project owner and developer. They also includes the height, diameter, and brand of wind turbines used. I find a match in the AWEA data for every project in my sample of data from Form 860. I use the AWEA data to construct measures of wind project owner and developer experience. For each project, I count how many projects that owner has previously completed since 2000. I do the same thing for each developer. Some projects are joint ventures, and I apportion

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<sup>11</sup>U.S. Energy Information Administration (n.d.) defines nameplate capacity as the maximum rate of electricity production for a generator as rated by the manufacturer.

<sup>12</sup>Examples for the last two categories would be generators operated by manufacturing plants (industrial) and hospitals (commercial).

them equally to each party for counting purposes.

Data on Section 1603 Awards come from the U.S. Department of Treasury and includes the grant recipient, grant date, and amount awarded. I match these data to Form 860 data using the grant recipient name, state, and award date. I only observe whether a project took a 1603 Grant; I have no corresponding data on the PTC. Since projects cannot take both the grant and the PTC, I assume all projects that did not take the grant took the PTC. I think this assumption is reasonable given the size of these subsidies, but it is important for me to drop projects built by cooperatives, universities, and government entities that not eligible for the subsidies. I identify these projects based on plant and utility name in the Form 860 and AWEA data. Projects built by publicly owned utilities are also ineligible and are identified and dropped based on the name and indicator for regulated utilities in Form 860 along with information on the utilities' websites (Bolinger, Wisser and Darghouth, 2010).

I use annual data on construction industry wages from the Bureau of Labor Statistics (BLS). The wages used are for "construction laborers" and are at the Metropolitan and Non-Metropolitan Statistical Area level. These are converted into county level wages and merged onto projects by county. Annual wage numbers are from May of each year. While building times vary, the developer Iberdrola finds it typically takes six months to a year to go from the beginning of construction to operation (Renewables, 2015). With this in mind, I lag wages by six months; for example, I use 2010 wages for projects that began operation in the second half of 2010 or the first half to 2011.

I do not observe land prices and instead use a measure of housing prices used in Albouy and Lue (forthcoming) and Albouy et al. (2016). The measure is the log difference, controlling for observable housing characteristics, in housing prices between a location and the U.S. mean. It is at the Public Use Microdata Area (PUMA) level for the year 2000. I merge this measure onto wind project data by zip code. When zip codes are missing, I match observations based on county and geographic coordinates.

The final sample used for estimation is 215 projects greater than 10 MW built by inde-

pendent power producers from 2009-2012. In total, these projects account for 21,964 MW of capacity. This is sixty-three percent of the total wind capacity added from 2009-2012, and thirty-seven percent of total U.S. wind generation capacity as of 2012.<sup>13</sup>

Data on installation costs and annual generation will be discussed in Section 2.5.

## 2.4 MODEL

I adopt a static model in which wind developers take project characteristics as given and choose the subsidy with the highest expected value. Critically, the model allows for wind developers to value a dollar in non-refundable tax credits at less than a dollar in cash. It also nests the possibility that project developers treat cash and non-refundable tax credits as equivalent, something we would expect if these firms had ample tax liability on which to use the subsidy. I will later use the model to recover an estimate of this valuation for a dollar in non-refundable tax credits, a parameter I denote as  $p$ .

Each wind developer chooses the subsidy with the highest expected present value. *Under full capture of the subsidy*, i.e. if non-refundable tax credits are treated as cash, the expected present value of choosing the PTC would be the following:

$$\mathbb{E}PV_{PTC_i} = \sum_{t=1}^{10} \beta^t (\mathbb{E}[MWh\ generated_{it}] * PTC)$$

where  $\beta$  is the real discount factor,  $MWh\ generated_{it}$  is annual generation for project  $i$  in year  $t$ , and  $PTC$  is the \$22/MWh subsidy. If a developer chooses a 1603 Grant, it receives a grant equal to thirty percent of project installation costs. It also loses the ability to deduct fifteen percent of project installation costs from its taxes as depreciation deductions. Thus, under full capture, the present value of choosing the grant would be the following:

$$PV_{Grant_i} = 0.3 * C_i - 0.15 * k_1 * C_i$$

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<sup>13</sup>Aggregate capacity data come from EIA's Electric Power Annual.

where  $k_1$  is a known constant given the marginal tax rate,  $\tau$ , and discount factor,  $\beta$ .

Wind developers may value a dollar in non-refundable tax credits or depreciation deductions at less than a dollar, so I allow them to value a dollar of tax incentives at  $p \in [0, 1]$ .<sup>14</sup> This parameter corresponds to the following thought experiment: what is the lowest price at which a wind developer would be willing to sell me a dollar in non-refundable tax credits? For developers with more credits than they owe in taxes, I expect this valuation to equal the price they receive for their tax credits in tax-equity transactions. Taking  $(p, \beta, \tau)$  as given, the developer chooses between the two subsidies to maximize its expected present value.

$$\max \left\{ \sum_{t=1}^{10} \beta^t * p * (\mathbb{E}[MWh\ generated_{it}] * PTC) , 0.3 * C_i - p * 0.15 * k_1 * C_i \right\}$$

Suppose  $\mathbb{E}[MWh\ generated_{it}]$  is a constant  $M_i$ . This approximates reality as, while production varies from year to year, the main driver of variability is weather patterns that are difficult to forecast in advance. Then the decision reduces to

$$\max \left\{ p * k_2 * M_i , 0.3 * C_i - p * 0.15 * k_1 * C_i \right\}$$

where  $k_2$  is a known constant given the discount factor, and  $M_i$  is expected annual generation. This formulation makes it clear that project installation cost ( $C$ ) and expected annual generation ( $M$ ) are the project characteristics driving the subsidy choice. All else equal, higher cost projects will be more likely to choose the grant while more productive projects will be more likely to choose the PTC. In addition, choosing the grant will become more attractive as wind developers' valuation for tax credits,  $p$ , decreases. A visual representation of this is shown in Figure 2.1. As  $p$  decreases, the line in  $(C, M)$  space at which projects are indifferent between the Grant and the PTC rotates upward, and more projects choose the grant.

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<sup>14</sup>Because firms also need to be paying taxes to use depreciation deductions, I expect a developer to, on average, have the same valuation for depreciation deductions as it does for non-refundable tax credits.

Figure 2.1: Illustration of the Model

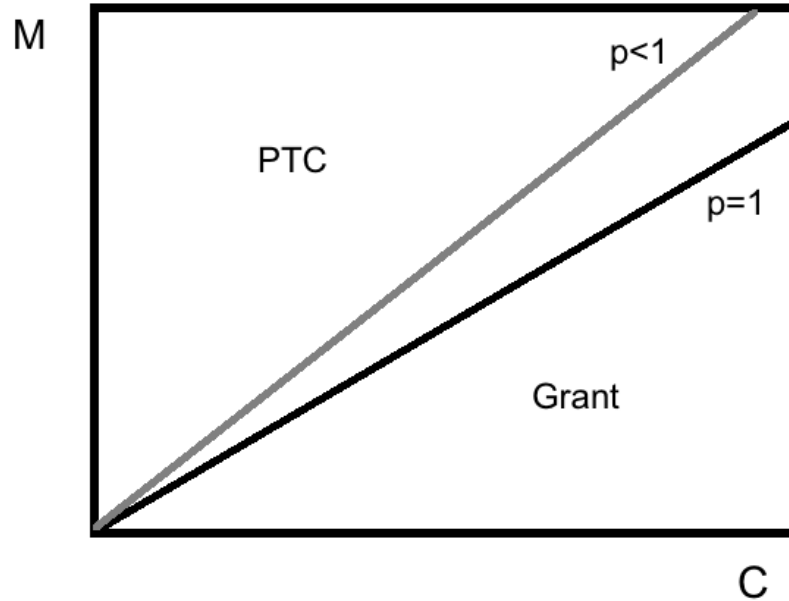


Figure depicts regions in  $(C, M)$  space for which each subsidy is chosen.

The key timing assumption is that each project's characteristics are determined prior to the subsidy choice. This rules out the possibility that a developer decides to take a 1603 Grant for a project and then uses more expensive turbines than it would have if it had chosen to take the PTC. The justification for this assumption is that the grant program was unexpected and wind projects have long planning horizons. Prior to construction, a developer had to obtain the necessary regulatory approval, measure wind speeds for an extended period of time, arrange to purchase turbines, and, typically, negotiate a power purchase agreement (PPA). Therefore, I expect any impact of the subsidy on project characteristics to be small: an example of a feasible change might be a project planning to take the grant purchasing more insurance its the turbines. If higher costs primarily buy more production, then the distortions caused by the grant and the PTC should not be very different.

This framework also assumes that which subsidy is chosen does not affect ex-post operation decisions. With regard to production decisions, wind generators are price-takers and have very low marginal costs, so a project will generally produce as much electricity as pos-

sible.<sup>15</sup> Wind developers also face the decision of when to exit, and wind projects usually last twenty to thirty years (American Wind Energy Association, 2014). Because exit occurs after the PTC is exhausted, the subsidy choice should not interact with exit decisions.

The model treats each project decision as independent. This assumption rules out the possibility that a developer making a subsidy decision for one project internalizes its effect on tax liability to use on other projects. This is more problematic in cases where self-sheltering the tax benefits is a feasible option.<sup>16</sup> The majority of my sample is independent power producers specializing in renewable projects, and I expect them to be using tax equity financing for most projects regardless of which subsidy they choose: even with the grant, tax equity can be used to transfer depreciation deductions.<sup>17</sup> Self-sheltering should also be less desirable for large projects, and, for this reason, I limit the main sample for analysis to projects over 10 MW. Using tax equity financing for only the PTC also raises the possibility of a dynamic decision in which taking the PTC and developing a relationship with a tax equity investor for one project lowers the cost of using tax equity financing for future projects. Since each tax equity deal typically requires project specific contracting, I expect the returns to using tax equity for multiple projects to be limited.

Some other considerations not captured by the model are the interaction of the subsidy decision with other policies and desired ownership structure. Though I am not aware of any examples, state level policies may interact with the subsidy decision.<sup>18</sup> Which subsidy is more appealing may also depend on desired ownership structure, and I abstract from this

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<sup>15</sup>While still rare, periods of very low and even negative prices are becoming more common (Huntowski, Patterson and Schnitzer, 2012); it seems unlikely a new entrant would enter a location where the expectation is for significant periods of negative prices.

<sup>16</sup>Bolinger, Wisser and Darghouth (2010) find that several projects in 2009 took the grant and elected to self-shelter the depreciation deductions rather than use tax equity financing. They posit this option may be particularly attractive to smaller projects.

<sup>17</sup>This is also the justification for not including a fixed cost of tax-equity financing in the model. Any fixed costs will not affect the subsidy choice if projects use tax equity financing regardless.

<sup>18</sup>The grant should also be more attractive to projects using government subsidized energy financing since the use of this financing leads to a reduction in the PTC while the 1603 Grant amount remains unchanged. Using a list of loan guarantees from McArdle (2011), I verified that none of the projects in my sample received subsidized financing as part of the Department of Energy (DOE) Section 1703 or 1705 loan programs as of October 2011, but there are other programs that provide subsidized financing.

consideration. To receive the PTC, the same firm must act as both the owner and operator of the project, but, if the project is sold in the first ten years of operation, the new owner can take the PTC. The 1603 Grant allows for leasing since the owner and operator need not be the same, but it puts restrictions on selling the project for the first few years. Particularly for larger projects, most projects are owned and developed by the same company and unlikely to be sold or leased.

## 2.5 KEY EXPLANATORY VARIABLES AND PARAMETERS

This section describes how I construct the key characteristics driving the subsidy decision: project installation cost ( $C$ ) and expected electricity production ( $M$ ). It also describes how I choose the discount factor,  $\beta$ , and the marginal tax rate,  $\tau$ , values I use in constructing the constants multiplying  $C$  and  $M$ .

### 2.5.1 INSTALLATION COSTS

I do not observe installation costs, but I do observe grant amounts for projects that elected 1603 Grants. Since the grant equals thirty percent of installation costs, I multiply grant amounts by 100/30 to construct the installation cost for each project.<sup>19</sup> Projects have an incentive to overreport costs on their grant applications, but, while reported costs may be slightly higher than true costs, I do not expect large deviations from true costs since these projects are often audited.<sup>20</sup> Figure 2.2 plots these costs against capacity. Costs are well approximated by constant returns to scale. I find the mean cost per kW of nameplate capacity among projects built from 2009-2011 to be 2,240 dollars. This is similar to the cost per kW of 2,200 dollars that Bolinger and Wiser (2013) report for 2009-2011.<sup>21</sup> Table 2.2

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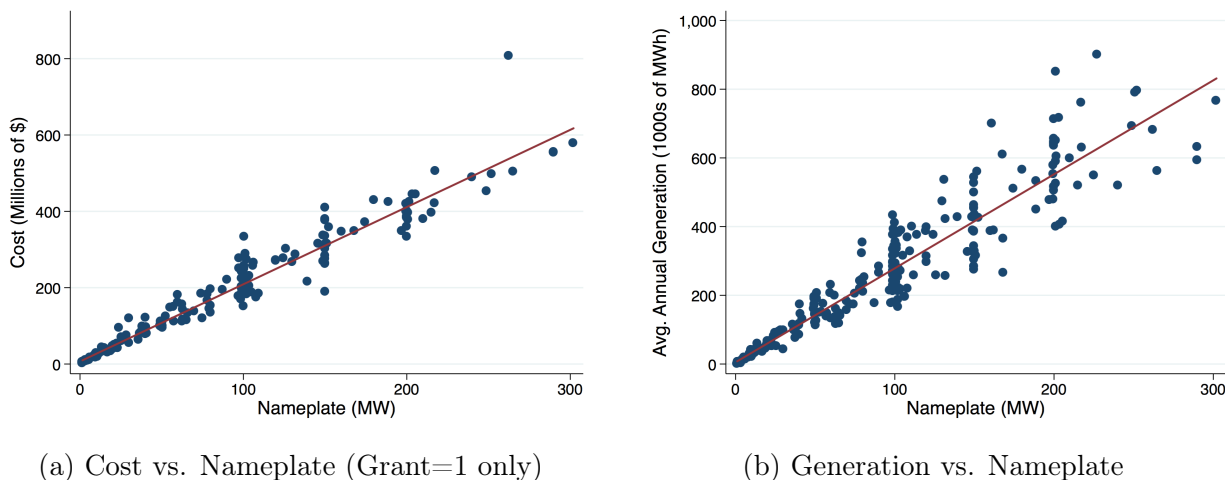
<sup>19</sup>These costs include only grant-qualifying costs; Bolinger, Wiser and Darghouth (2010) estimate that grant-qualifying costs account for only 95% of total installed project costs. These grant-qualifying costs should be what is relevant for both the grant amount and depreciation deductions as a rule of thumb for grant-qualifying costs is costs that are depreciable.

<sup>20</sup>[Look for citation beyond individual audit reports]

<sup>21</sup>The 2012 Wind Market Intelligence Report reports a capacity-weighted average cost for each year; 2,200 is an unweighted average across the three years.

shows costs along with other project characteristics.

Figure 2.2: Cost and Generation vs. Project Size



Because I do not observe costs for projects that took the PTC, I use observed factors affecting cost to estimate a selection model. To give an indication of the effect of these factors on cost, I regress cost per kW of nameplate capacity on nameplate, nameplate squared, turbine hub height and rotor diameter, turbine manufacturer,<sup>22</sup> construction wages, house prices, region fixed effects, a cubic time trend, and wind developer experience and experience squared. Wind turbine prices are a major driver of cost changes over time, and the time trend should capture some of their effect.

Table 2.1 presents results from this regression for my sample of IPPs as well as a larger sample that includes grant eligible IOUs. The point estimates for the nameplate coefficients indicate a period of increasing returns to scale that tapers off and turns negative around 175 MW.<sup>23</sup> Costs are higher in the Northeast, and Suzlon, an Indian turbine manufacturer, is associated with lower costs. The negative coefficient on hub height is unexpected, and the point estimate of -11 implies a one standard deviation increase in hub height is associated with a 0.2 standard deviation decrease in cost. Hub heights were increasing over this time

<sup>22</sup>While I observe the turbine manufacturer(s) for all projects, I only include indicators for manufacturers used by at least by at least ten projects in my sample.

<sup>23</sup>A joint test that the nameplate coefficients are 0 gives a p-value of 0.12, but this test is only valid if a selection on observables assumption holds.



period, so the estimate may be due to a time trend not picked up by the time controls. The estimated coefficients on the construction wage and housing price variables both have the expected sign, and there does not seem to be a strong relationship between developer experience and cost.

Table 2.1: Regression of cost/kW of nameplate on observable characteristics

	Sample of IPPs $\geq$ 10 MW		Grant eligible $\geq$ 10MW	
Nameplate	-2.531*	(1.261)	-2.037	(1.241)
Nameplate <sup>2</sup>	0.00723	(0.00480)	0.00507	(0.00490)
Hub height	-11.00***	(3.052)	-12.36***	(3.003)
Rotor diameter	4.365***	(1.243)	4.438***	(1.174)
Housing-cost differential	301.3	(198.1)	178.5	(219.9)
Median construction wage	15.09*	(8.652)	14.64	(8.946)
Developer experience	-1.084	(5.639)	0.804	(6.019)
Developer experience <sup>2</sup>	-0.0786	(0.106)	-0.106	(0.114)
Great Lakes	-94.66	(74.94)	-80.82	(89.95)
Interior	41.66	(102.8)	-12.54	(106.4)
Northeast	269.0***	(95.58)	234.3**	(97.66)
t	-207.0***	(44.97)	-183.3***	(45.40)
t <sup>2</sup>	-160.1***	(24.52)	-147.3***	(25.14)
t <sup>3</sup>	30.90	(21.41)	20.85	(25.05)
Turbine manufacturers	X		X	
Constant	2,649***	(277.2)	2,726***	(275.3)
Observations	165		175	
R-squared	0.517		0.474	
Mean dep. var	2,136		2,147	

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1. SE clustered by state (30 clusters). All costs from 1603 grant data. Dummy variables for the wind turbine manufacturers Clipper, GE, Gamesa, Siemens, and Suzlon are also included. Developer experience is the number of prior projects completed since 2000. West is the omitted region. t is time in quarters. All grant eligible includes projects built by IOUs and projects in the Southeast and HI.

## 2.5.2 GENERATION

I next construct a generation measure for each project using realized levels of annual generation. Data come from EIA Form 923 for years 2010-2014, so I have two to five full years of data for each project. I assign each project its average realized generation for the time I observe it operating, starting with the first full year after completion. I divide average annual generation by nameplate and  $365 \times 24$  to construct project capacity factors. There are a few large outliers, so I drop the seventeen projects that lie below the 1<sup>st</sup> or above the 99<sup>th</sup> percentiles of the capacity factor distribution.

Table 2.2 shows that the mean capacity factor for my sample is 0.321.<sup>24</sup> Of projects electing the PTC, the mean capacity factor is 0.366. For those taking the grant it is 0.308. The p-value for a t-test of equivalence of means across the two groups is  $<0.001$ . While projects taking the PTC have higher capacity factors on average, there is considerable overlap in the distributions of capacity factors of the projects taking each subsidy.

## 2.5.3 OTHER PARAMETERS

Following Bolinger and Wiser (2013), I use a real discount rate of seven percent.<sup>25</sup> As the grant decision is comparing an upfront subsidy to a stream of payments over time, I expect the discount rate to be an important parameter in my analysis, and I present results for other discount rates as a robustness check. Discount rates are related to costs of capital, and it is unlikely all developers discount future payments at the same rate. My model assumes a constant discount rate, but limiting my analysis to independent power producers, a relatively similar set of firms, should reduce the scope for unobserved heterogeneity in discount rates to bias estimates.

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<sup>24</sup>This is similar to the capacity factor of 0.313 that Bolinger and Wiser (2013) find for all new projects that began operation in 2009-2011. (The 2012 Wind Market Intelligence Report reports a capacity-weighted average capacity factor for each year, and the 0.321 is an unweighted average across the three years for IPP projects over 10 MW) This similarity should be expected given both were constructed using EIA data.

<sup>25</sup>Bolinger and Wiser (2013) use this discount rate when constructing levelized PPA prices for the 2012 Wind Market Intelligence Report (p.49)

As is standard practice in analyses of this industry, I use a 35 percent corporate tax rate for calculating the value of depreciation deductions.<sup>26</sup> The PTC is adjusted annually for inflation: the value used for each year is the original value of the PTC in \$/MWh multiplied by an inflation factor and rounded to the nearest dollar. Since all present values are in 2012 dollars, I use the unrounded 2012 value of \$22.1985/MWh (IRS, 2012). Depreciation deductions are not adjusted for inflation, so I assume an annual inflation rate of two percent to construct their expected present value.

## 2.6 IDENTIFICATION AND ESTIMATION

Variation in project characteristics affects the present values of each subsidy, and where projects switch from the PTC to the grant as cost increases or generation decreases identifies wind developers' valuation for non-refundable tax credits. This parameter is nearly indistinguishable from the discount factor, which I will assume rather than estimate. I pool across projects by assuming that each developer in my sample has the same valuation for non-refundable tax credits. In later specifications, I allow for heterogeneity in valuations by assuming each valuation is a known, up to parameters, function of observable characteristics.

Because I only observe costs for projects that elected the grant, I follow Heckman (1979) and estimate a selection model. I expect the error terms to be proportional to project size, so I divide both installation costs and generation by nameplate capacity. Let  $C_i$  = installation cost/nameplate,  $M_i$  = average annual generation/nameplate.<sup>27</sup> Then the two equations to be estimated jointly are

$$C_i = X_i\gamma + \sigma_u u_i \tag{2.1}$$

$$G_i = \mathbb{1}\left(0.3C_i - p * 0.15k_1C_i + \sigma_\epsilon \epsilon_i > p * k_2M_i\right) \tag{2.2}$$

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<sup>26</sup>The marginal tax rates for taxable income over \$100,000 are between 0.34 and 0.39, and flatten out at 0.35 for the highest levels of income. The 0.35 rate is used for all income over \$18,333,333 (Center, 2014). Bolinger, Harper and Karcher (2007) refers to it as the "standard industry assumption for Federal corporate tax rate." (p. 61)

<sup>27</sup>I divide by nameplate measured in kW, so the units of  $C_i$  are \$/kW.

where  $C_i$  is observed if and only if  $G_i = 1$ , and  $X_i$  are the observed determinants of cost. I assume  $u_i, \epsilon_i$  are i.i.d. bivariate standard normal with  $cov(u, \epsilon) = \lambda$ . I do not need to normalize  $\sigma_u$  or  $\sigma_\epsilon$  to one as the selection equation, (2), is denominated in dollars.

Now, the rate at which projects with different generation and predicted costs trade-off the two subsidies identifies the valuation parameter,  $p$ . Variation in project generation ( $M$ ) conditional on observed cost shifters is used to identify the degree of selection.<sup>28</sup>

The technical condition for identification is that generation and the observed determinants of cost are independent of the error terms ( $X_i, M_i \perp\!\!\!\perp \epsilon_i, u_i$ ), and the biggest threat to identification is selection on which potential projects are constructed. Because I am limiting my analysis to projects that were actually built, I expect at least some positive correlation between  $u_i$  and  $M_i$ . All else equal, a project with higher unobserved costs will need to have higher expected generation to justify building it. The same logic suggests a negative correlation between observed determinants of cost and unobserved costs ( $X_i$  and  $u_i$ ).

I expect the bias in the valuation parameter due to selection on which projects are built to be small for two reasons. First, a breakdown of project characteristics by region, shown in Table 2.3, suggests that the market price for wind energy plays a larger role in determining project viability i.e. high-cost, low productivity projects are being built in the Northeast at the same time that low-cost, high productivity projects are being built in the interior of the

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<sup>28</sup>Expected generation,  $M_i$ , is the excluded variable that enters the selection equation but not the equation determining  $C_i$ . In the canonical selection model described in Heckman (1979), i.e.

$$\begin{aligned} C_i &= X_{1i}\gamma_1 + \sigma_u u_i \\ G_i &= \mathbb{1}\left(X_{2i}\gamma_2 + \sigma_\epsilon \epsilon_i > 0\right) \end{aligned}$$

if the observed variables entering both equations are the same, it is difficult to separate the effect of a regressor on selection ( $\gamma_2$ ) from its effect on the outcome ( $\gamma_1$ ) and the model is identified by functional form assumptions alone. For example, a regressor might be associated with high observed costs either because it increases costs or because it makes the grant less desirable, thus raising the bar for unobservables,  $u$ , at which a project takes the grant and has its cost observed. My model imposes more structure than the canonical model because cost enters the grant equation directly with a known coefficient. However, allowing for a non-zero  $\lambda$  (note that, unlike the canonical model, a non-zero  $\lambda$  does not imply no selection) means we still need an excluded variable. Without it, we can only pin down the relative impact of the regressors since the regressors jointly having a larger effect on costs is indistinguishable from a higher value of  $\lambda$ . Expected generation serves as this excluded variable that shifts around the subsidy decision, but does not affect project costs per MW of capacity.

country. Second, a positive correlation between expected generation and unobserved costs should directly bias my estimate of the error correlation parameter,  $\lambda$ , not my estimate of the valuation parameter,  $p$ . The intuition is that a positive correlation between generation and unobserved costs weakens the relationship between generation and the subsidy decision, rather than moving the cutoff generation level at which projects switch from the grant to the PTC. When there is a positive correlation between generation and unobserved costs and the model assumes it is zero, the true parameters will over predict choosing the grant for projects with low expected generation, and under predict the grant for projects with high expected generation. While lowering the valuation parameter,  $p$ , shifts all projects toward the grant regardless of generation level, increasing the correlation parameter,  $\lambda$ , will flatten the relationship between generation and the subsidy decision by shifting high generation projects toward the grant and low generation projects toward the PTC. Thus, increasing  $\lambda$  from its true value allows the model to fit the observed pattern while altering  $p$  does not.

Though potentially problematic, any bias from measurement error in expected generation also appears to be small. As shown in Appendix B.3, within project variation in annual generation is considerably smaller than across project variation, and estimates are virtually identical when the most recent year of generation data (2014) is excluded. This suggests that measurement error is not leading to much attenuation, as I would expect the magnitude of the error to decrease with additional years of data at a rate of  $1/T$ . As another check, I re-estimate the model using a different measure of expected generation. Rather than use the average of generation across all observed years, I regress generation in the first year after completion on the average of generation across all subsequent years. I then use the predicted value as my measure of expected generation. Since generation in the first year and average generation in later years should be unbiased estimates of expected generation,<sup>29</sup> using only variation in one measure that can be explained by the other resembles the instrumental variables strategy used by Shapiro (2015). Using this alternative measure leads to very

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<sup>29</sup>This assumes the differences between observed and expected generation in each year are white noise, a reasonable assumption if variation is driven primarily by weather.

similar estimates.

## 2.7 RESULTS

Table 2.2 shows there is substantial variation in electricity production and cost per kW of capacity among wind projects built from 2009-2012. The mean capacity factor for the sample is 0.31 with a standard deviation of 0.07. Costs are only observed for projects that took the grant, and the mean cost per kW of capacity for these projects is \$2,136/kW with a standard deviation of \$343/kW. Table 2.2 also shows that seventy-seven percent of projects in the sample chose the grant. When all grant eligible projects are considered, this number is seventy-two percent. The decrease is explained by Investor Owned Utilities (IOUs) being much less likely to choose the grant: among the twenty-two eligible IOU projects over 10 MW, only four took the grant. This may be because IOUs have tax liability on which to use the tax credits or face a lower cost of capital. The grant may also result in lower rate base, an unattractive feature for IOUs subject to rate of return regulation. Beyond a difference in grant take-up, including projects built by IOUs or located in the Southeast or Hawaii has little effect on aggregate statistics.

Table 2.2: Summary statistics

	Sample of IPPs $\geq$ 10MW				
	mean	std dev	min	max	N
Nameplate	102.2	68.9	10	302	215
Capacity Factor	0.321	0.070	0.180	0.506	215
Cost/kW	2,136	343	1,257	3,312	165
Grant	0.772	0.420	0	1	215
	All grant eligible $\geq$ 10MW				
	mean	std. dev	min	max	N
Nameplate	103.2	72.6	10	444	246
Capacity Factor	0.322	0.068	0.163	0.506	246
Cost/kW	2,167	390	1,257	3,966	177
Grant	0.724	0.448	0	1	246

IPP stands for Independent Power Producer. Sample of all grant eligible includes an additional 22 Investor Owned Utility (IOU) projects, 6 IPP projects in the Southeast, and 3 IPP projects in HI. Cost is the installation cost per kW of nameplate capacity, in 2012 dollars; it is only observed for projects that elect the grant.

Table 2.3 shows there are clear regional patterns in project characteristics: on average, the coasts have higher costs and less productive projects than the Interior and Great Lakes regions. As expected, projects in the Interior region, which tend to have both higher capacity factors and lower costs, are much less likely to take the grant than projects in the Northeast, where production is lower and costs are higher. Considerable regional variation in the price of wind energy likely explains why projects are being built simultaneously in both regions.



Table 2.3: Variation in  $C, M$  by region for IPPs $\geq 10$ MW

<i>Region</i>	<i>Nameplate</i>		<i>Capacity Factor</i>		<i>Grant = 1</i>	<i>Cost/kW</i>	
	N	Mean	Mean	Std. Dev	N	Mean	Std. Dev
Great Lakes	25	145	0.310	0.050	18	2,028	290
Interior	92	111	0.373	0.069	57	2,087	296
Northeast	28	72	0.274	0.056	25	2,337	408
Southeast	6	62	0.299	0.044	6	2,380	342
West	70	87	0.283	0.067	65	2,132	344
Total	221	101	0.320	0.070	171	2,145	345

All 6 projects built in the Southeast took the grant and are excluded from the main sample.

Table 2.4 shows that more productive projects are significantly less likely to take the grant. This is comforting since variation in generation shifting around the subsidy decision is essential to identifying the model. While much of the variation in generation is regional, column (2) shows that this relationship between generation and subsidy choice holds within region as well. Controlling for a time trend in column (3) has little impact on the estimated coefficient. Finally, the addition of cost controls - nameplate and its square; turbine hub height, rotor diameter, and manufacturer; area construction wages and house prices; and developer experience and its square - in column (4) leads to a modest decrease in the effect. The estimated coefficient on capacity factor in (4) is statistically different from zero and implies a one standard deviation increase in capacity factor is associated with an eight percent decrease in the probability a project takes the grant (seventy-two percent of projects in my sample took the grant).

Table 2.4: Regression of Grant=1 on project capacity factor

	(1)	(2)	(3)	(4)
Capacity Factor	-1.915	-1.335	-1.262	-1.178
	(0.40)	(0.47)	(0.46)	(0.47)
Region FE		X	X	X
Time trend			X	X
Cost controls				X
N	215	215	215	215

Sample is IPPs $\geq$ 10 MW. Avg. marginal effects from a probit. SE clustered by state (31 clusters). Time trend is a third degree polynomial in quarter of operation. Cost controls are turbine height, rotor diameter, turbine manufacturer dummies; housing price differentials and construction wages; and wind developer experience and experience squared.

The selection model estimates in Table 2.5 are consistent with larger projects using tax equity financing to sell credits at a price of \$0.85-0.90 while smaller projects use their own tax liability and thus have a lower valuation for non-refundable credits. These estimates are from the selection model outlined in Section 2.6, and a derivation of the likelihood function is provided in Appendix B.2. The primary sample is independent power producer (IPP) wind projects over 10 MW, and I estimate  $p$  to be 0.86. This estimate is marginally statistically different from one, with a p-value of 0.07. When I estimate the model using the entire sample of IPP projects, I find a  $p$  of 0.81. This suggests that the valuation parameter is heterogenous, with developers of smaller projects having lower valuations for non-refundable tax credits. One explanation of this difference is that the fixed cost of using tax equity financing is a greater share of the total subsidy for small projects. As a result, developers of these projects may elect to instead slowly use the tax credits on their own tax liability.<sup>30</sup>

<sup>30</sup>Recall that unused, non-refundable tax credits and depreciation deductions can be carried over for up to twenty years, but waiting to use the credits reduces the value of the subsidy since developers discount the future.

Smaller projects may also have lower bargaining power, which results in a lower valuation for tax credits, or higher overall borrowing costs, which the model will capture as a lower valuation parameter. Limiting the sample to projects over 20 MW leads to an estimate of the valuation parameter that is nearly identical to that found for the primary sample. Estimates of other parameters are very similar as well. I take the similarity of estimates for the sample of projects over 10 MW and the sample of projects over 20 MW as evidence that any impact of project size on the grant decision is negligible once projects are over 10 MW in size.

Overall, estimates for the other parameters are reasonable and relatively consistent across the three samples. I estimate the standard deviation of the unobservables affecting costs,  $\sigma_u$ , to be 298. This seems large but plausible given predicted costs have a mean of 2,033 and a standard deviation 285. The estimated standard deviation of unobservable factors affecting the subsidy decision,  $\epsilon$ , is 187. This seems large as I would not expect many other factors beside cost and generation to be important to the decision. Two things  $\epsilon$  is likely capturing are i) differences between expected and realized generation and ii) heterogeneity in  $p$ , and I will later estimate a model that allows  $p$  to vary with observable characteristics. The correlation between these two unobservables,  $\lambda$  is imprecisely estimated to be -0.09. Note that being unable to reject  $\lambda$  equal to 0 is not the same as being unable to reject selection. The model explicitly incorporates selection by including cost in the selection equation, so selection is a positive correlation between the composite error term in the grant equation  $((0.3 - 0.15 * p * k_1)\sigma_u u_i + \sigma_\epsilon \epsilon_i)$  and the error term in the cost equation ( $u_i$ ). Finally, the estimated coefficients in the cost equation look similar to those found in Table 2.1.<sup>31</sup>

All three sets of results in Table 2.5 assume a real discount rate of seven percent. This value is chosen for the main specification because it is used in the 2012 Wind Market Report to construct levelized electricity prices from power purchase agreements. The ex-ante analysis

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<sup>31</sup>I include fewer control variables when estimating the selection model: specifically, I use an indicator variable for a Chinese or Indian turbine manufacturer rather than the six indicator variables for different turbine manufacturers, and I exclude the variable on construction wages, which is highly correlated with the housing price variable. Estimation of the selection model with the same controls as Table 2.1 converges and produces very similar estimates to those reported here.

of the subsidy choice performed in Bolinger et al. (2009) assumes a nominal discount rate of seven and a half percent but also presents results assuming five and ten percent nominal rates. Estimates of the valuation for non-refundable tax credits,  $p$ , are sensitive to the choice of discount rate, and estimates assuming different rates are shown in Table 2.6. At a real discount rate of 5 percent, I estimate  $p$  to be 0.79 while I estimate  $p$  to be nearly 1 (0.97) if I assume a real discount rate of ten percent.

Table 2.5: Selection Model Estimates

	Sample $\geq 10$ MW		All IPP Sample		Sample $\geq 20$ MW	
Tax-credit valuation ( $p$ )	0.86	(0.078)	0.81	(0.082)	0.87	(0.052)
SD cost unobservable ( $\sigma_u$ )	298	(26)	310	(35)	297	(32)
SD choice unobservable ( $\sigma_\epsilon$ )	151	(36)	183	(43)	150	(38)
Unobservables corr. ( $\lambda$ )	-0.090	(0.293)	0.009	(0.358)	-0.149	(0.350)
Nameplate	-3.5	(1.2)	-4.2	(1.4)	-2.1	(2.1)
Nameplate <sup>2</sup>	0.011	(0.0047)	0.013	(0.0053)	0.0067	(0.0071)
Hub height	-10.6	(4.6)	-14.6	(3.9)	-9.4	(4.5)
Rotor diameter	1.3	(3.2)	0.2	(2.9)	0.3	(3.5)
Chinese or Indian turbines	-327	(132)	-351	(139)	-288	(200)
Housing cost differential	233	(223)	228	(184)	185	(226)
Developer experience	-8.5	(7.0)	-5.8	(8.4)	-11.2	(7.0)
Developer Experience <sup>2</sup>	0.08	(0.16)	0.04	(0.19)	0.13	(0.16)
Great Lakes	-35	(98)	-34	(118)	-35	(100)
Interior	-68	(130)	-110	(116)	-65	(133)
Northeast	309	(108)	247	(123)	315	(135)
Constant	3,141	(332)	3,612	(232)	3,034	(376)
N	215		239		195	

The two equations are  $C_i = X_i\gamma + \sigma_u u_i$  and  $G_i = \mathbb{1}(0.3C_i - p * 0.15k_1 C_i + \sigma_\epsilon \epsilon_i > p * k_2 M_i)$ . From nameplate onward are estimates for  $\gamma$ . Estimates assume a real discount rate of 7 percent. IPP projects only. Chinese or Indian turbines is an indicator for turbines from a Chinese or Indian manufacturer. Developer experience is the number of prior projects completed by the developer since 2000. West is the omitted region. A third degree polynomial in quarter of operation is included in all specifications. Robust SEs, clustered by state (31 clusters); the likelihood function still assumes independent observations.  $\lambda$  is  $cov(u, \epsilon)$ , not the covariance between the error in the cost eqn and the composite error in the selection eqn.

Table 2.6: Estimates of  $p$  under different discount rates

$r$	5	6	7	8	9	10
$p$	0.79	0.82	0.86	0.89	0.93	0.97
	(0.098)	(0.089)	(0.078)	(0.069)	(0.062)	(0.061)

Sample is the 215 projects over 10MW built by IPPs. The controls used are the same as those used in Table 2.5. SE clustered by state.

I also estimate a model that allows an owner's valuation for non-refundable tax credits to vary with observed owner characteristics. The characteristic *owner flow* is the number of projects completed by the same owner during a fifteen month period surrounding project completion. The idea is to capture that owners with a higher ratio of non-refundable tax credit subsidy to tax liability might have a lower valuation for tax credits either because they are less able to use some of the tax credits themselves or have lower bargaining power relative to tax equity investors. For the same reasons, first time owners may also have a lower valuation for tax credits. The results presented in B.2 are consistent with this intuition as I find building more projects concurrently and being a first time owner reduce the estimated valuation non-refundable tax-credit valuation,  $p_i$ . However, if there is heterogeneity in the valuation parameter, it is also possible that owners building lots of projects concurrently are building out projects with the lowest  $p_i$  to take advantage of the grant program. Similarly, to the extent being a first time owner raises the cost of building a project in a way not captured by a second degree polynomial in developer experience, the estimated decrease in  $p_i$  for first time owners, which shifts them toward the grant, could just be picking up higher costs, which also shift projects toward the grant. Overall, my results are inconclusive, but consistent with the use of non-refundable tax credits acting as a barrier to entry and rapid expansion in this industry.

Table 2.7: Estimates allowing for heterogeneity in  $p$ 


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$$p = \alpha_0 + \alpha_1 * owner\_flow + \alpha_2 * first\_project$$

$\alpha_0$	1.002	(0.063)	$\sigma_u$	294	(23)
$\alpha_1$	-0.022	(0.008)	$\sigma_\epsilon$	157	(40)
$\alpha_2$	-0.196	(0.076)	$\lambda$	-0.20	(0.41)

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Nameplate	-3.29	(1.14)	Dev. experience <sup>2</sup>	0.075	(0.158)
Nameplate <sup>2</sup>	0.0103	(0.0046)	Great Lakes	-28	(89)
Hub height	-10.14	(4.54)	Interior	-52	(128)
Rotor diameter	1.33	(3.15)	Northeast	313	(108)
Chinese or Indian turbines	-331	(133)	t	-174	(63)
Housing cost differential	250	(217)	t <sup>2</sup>	-215	(46)
Dev. experience	-8.31	(6.86)	t <sup>3</sup>	76	(35)
Constant	3,100	343	N	215	

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Estimates assume a real discount rate of 7 percent. Sample is the 215 projects over 10MW built by IPPs. *owner flow* is the number of projects completed by the same owner in the quarter of project completion and the two quarters before and after (a 15 mo. period). *first project* is an indicator for whether the wind project was the first project completed by an owner since 2000. SE clustered by state.

## 2.8 CONCLUSION

These estimates suggest that wind developers discount non-refundable tax credits relative to grants, and that moving to awarding subsidies as grants or refundable tax credits could have a substantial impact on investment. Empirical results cannot speak to whether this result reflects an inefficiency or just a transfer of some of the subsidies for wind investment

to tax equity investors. The number of firms supplying tax equity financing and their size relative to the firms building wind projects make the presence of market power and thus efficiency losses a distinct possibility. Even if the result is coming only from a transfer from wind developers to investors, political considerations mean a substantial share going to tax equity investors could still have an impact on the supply of renewable energy generation and the perceived effectiveness of these subsidies.

The point estimate of \$0.86 from Table 2.5 can be used to do a back-of-the-envelope calculation of the potential impact on investment of using non-refundable tax credits as opposed to grants. Suppose investment in wind energy only responds to the share of the subsidy that goes to wind developers. Using data from 1999-2007, Johnson (2014) estimates a long-run supply elasticity for renewable electricity generation of 2.67. Combining this estimate with the assumption of no demand response, I find that moving from non-refundable tax credits to grants, i.e. wind developers responding to a PTC of \$22/MWh as opposed to \$18.92/MWh, would result in an increase in investment of ten percent.<sup>32</sup> In reality, I would expect some demand response since, while the price of electricity is rarely determined by wind generators, the state premiums for renewable energy would be affected.

Estimating wind developers' valuation for non-refundable tax credits using data from 2009-2012 raises the question of generalizability, as these estimates are from a time when we might expect this valuation to be particularly low. The financial crisis reduced the supply of tax equity financing, and concern that new projects could not obtain this financing was a major motivation for introducing the grant program. On the other hand, the grant program itself reduced demand for tax equity. Even if this was a case where this valuation for non-refundable tax credits was particularly low, this confluence of large subsidies, a growing industry, and an economic downturn could easily happen again. The government frequently uses subsidies to jumpstart new industries or technologies, and early market participants often take some time to become profitable. Awarding subsidies in the form of non-refundable

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<sup>32</sup>This calculation assumes a price of wind energy, inclusive of the subsidy, of \$80/MWh.



tax credits in these cases not only reduces their value to firms without tax liability, but it also distorts the price of investment across firms based on their other activities. While industries may respond with clever solutions like the tax equity contracts prevalent in wind energy, these solutions will still necessitate another actor whose inclusion may result in transaction costs, the exercise of market power, and coordination problems.

## CHAPTER 3 WIND POLICY UNCERTAINTY

From a work with Chenyu Yang

### 3.1 INTRODUCTION

Whether a policy designed to increase private investment succeeds depends on firms' expectations about future policy. Several subsidies designed to encourage investment alternate from being offered to not offered: for example, the Investment Tax Credit, a policy typically used to stimulate investment in recessions, and the Generalized System of Preferences, a trade policy intended to help exporters in developing countries. Firms might shift up investment to take advantage of the an investment credit if they think it is likely to expire. On the other hand, firms might not pay the sunk cost to start exporting if they expect their current, preferential treatment to be discontinued.

We study the relationship between investment behavior and policy uncertainty in the context of a large subsidy for investing in wind energy. In 1992, the U.S. government introduced a production tax credit (PTC) to encourage investment in renewable energy. Wind generators received the credit if they began operation while it was in place, and, starting in the late 1990s, the subsidy was typically renewed by Congress for only a few years at a time. In the lead up to each expiration, there was uncertainty about whether or not the policy would be renewed or revert to no subsidy, and the subsidy was allowed to revert to no subsidy four times (Sherlock, 2015). These few short periods of no PTC saw uncertainty about whether it would be reinstated. To learn about how policy uncertainty affects the

level and timing of investment, we use data on all wind projects built from 2001-2014 and the dates of potential changes to subsidy status.

Three features make this a good setting to study policy uncertainty: whether the subsidy is available has a large impact on wind project profits, the policy and corresponding expectations are straightforward, and the benefit of the subsidy to the firm is easy to calculate. One challenge in studying uncertainty is that its effects are often of second-order importance; for example, lowering the mean of the tax rate will likely affect investment more than lowering the variance of the tax rate. The subsidy we study is a per-unit subsidy equal to about a third of the output price, so, if uncertainty has important effects in this setting, we would expect them to be detectable. Secondly, the policy is narrow, and the expectation over the period was that either the full subsidy or no subsidy would be in place. This contrasts with policies like a healthcare bill, e.g. the Affordable Care Act (ACA), with many interacting pieces. Even if the ACA is repealed, it is unlikely to be replaced with the status quo prior to its enactment. Finally, the subsidy we study is a per-unit subsidy based on the quantity of electricity generated, and we can use data on realized electricity generation to translate the benefit from the subsidy into dollar terms for each wind project.

We have two main findings that we hope to build upon in future work: i. uncertainty affected the number of wind projects constructed in periods surrounding potential expirations ii. uncertainty did not appear to distort project sizes. Using data on the date wind projects began operation, we find that the number of projects completed increases in the months just prior to PTC expirations and falls in the months following. In and of itself, this finding does not tell us how uncertainty affected the total wind generation capacity built over the period, and this is a question we hope to answer in future work. In contrast, we do not find evidence that uncertainty affected wind project sizes, implying that any efficiency losses from building the wrong size projects are likely small. This result is surprising as we might expect a wind project developer to choose to build a smaller project that could be finished quickly if there were less than six months to a potential subsidy expiration. However, we

also find that expected construction time increases only weakly in project size, a finding that may explain why we do not see a size distortion.

If future work, we plan to develop a structural model of how firms make the decision to build new wind projects. We can use the model and observed investment decisions to infer what expectations about the probability of PTC renewal are consistent with the observed behavior. Then, we can simulate a counterfactual where we change firms' expectations about the probability the subsidy will be renewed. Using the counterfactual, we can answer questions such as how much investment levels would change absent uncertainty and whether uncertainty affected the amount of new wind generation per tax dollar spent on the subsidy. We can also examine which features of this setting are driving our findings.

This chapter fits into a large literature on investment under uncertainty and a much smaller literature on the relationship between policy uncertainty and investment. As in the investment under uncertainty literature (e.g. Dixit and Pindyck (1994)), the irreversibility of wind project investment causes expectations about future states to affect current investment decisions. Unlike much of that literature, the uncertainty here is about a discrete state variable, a policy that jumps between two states, as opposed to a continuous state variable that evolves according to a non-stationary, brownian motion process. Hasset and Metcalf (1999) show that this distinction is important, and, in our setting, increases in uncertainty may actually increase total investment. While we cannot conclude how uncertainty affected total investment, we do establish that PTC uncertainty affected either investment levels, the timing of investment, or both.

Our study also builds on two existing papers on the effect of PTC uncertainty on the wind power industry, and our main contribution relative to these papers is to use wind-project-level data on realized investment. These data allow us to examine how the number and size of wind projects change surrounding potential PTC expirations. First, Grobman and Carey (2003) develop a model where a social planner chooses between investing in wind and investing in fossil fuel electricity generation technology. They simulate the model to find

that total wind generation capacity is sensitive to changes in the probability of transitioning between PTC states. Barradale (2010) takes a more qualitative approach to understanding the effects of uncertainty. She surveys wind industry participants to learn their beliefs about the PTC and the probability it will be renewed, and she finds that the main channel through which uncertainty affects investment is by inhibiting contracting between utilities and the wind project owners.<sup>1</sup> While we do not model contracting, our findings are consistent with this mechanism.

The next sections proceed as follows. Section 2 describes the key features of the wind industry, PTC, and the history of policy changes associated with the PTC. Section 3 describes the wind project data. Section 4 presents results on how the size and number of wind project change surrounding subsidy expirations, and Section 5 concludes.

### 3.2 INDUSTRY

Wind projects often take years to build and have substantial sunk costs, and these two features make expectations about future conditions an important consideration in the decision to build a project. Prior to construction, wind project developers must decide on an appropriate site, apply and receive the required permits, measure wind speeds at the relevant height, negotiate an order for wind turbines, and have the turbines delivered. Most wind projects also simultaneously arrange for financing and sign a contract, known as a power purchase agreement, to sell their output to the local utility. Construction itself usually takes between two months and a year.<sup>2</sup> These planning and construction costs are largely sunk.

Wind projects' cost structure makes it optimal for them to produce as much electricity as possible, so a production subsidy will not affect operation decisions for a completed project. Wind generators do not require fuel, and operations and maintenance costs are low relative

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<sup>1</sup>Most wind developers sign a power purchase agreement to sell power to a utility prior to beginning construction.

<sup>2</sup>This estimate is based on FAA data on expected construction times. EWEA (n.d.) benchmarks construction of a 10 MW wind project taking as little as two months and a 50 MW wind project as taking about six months.

to the price of electricity.<sup>3</sup> Most wind project developers sign a power purchase agreement up-front to sell a project's output at a fixed price. The remaining wind projects sell into deregulated markets where a wind generator is unlikely to be the marginal generator setting the market price. Because projects have such low marginal costs and are essentially price-takers, wind project operators only restrict output when required to do so by a grid operator trying to balance supply and demand. Thus, the only major decision a wind developer makes after operation is when to exit, an action rarely taken by projects less than fifteen years old. In our setting, this implies that the production tax credit does not affect wind project operation decisions.

### 3.2.1 PRODUCTION TAX CREDIT

The production tax credit (PTC) is a large subsidy for investing in wind energy. Eligible projects receive a per-unit subsidy for electricity generated in their first ten years of operation. The subsidy amount is adjusted annually for inflation: when the credit was introduced in 1993, it was \$0.015/kWh, while in 2016 it was \$0.023/kWh (DSIRE, 2016). For comparison, a typical price for wholesale wind-generated electricity in 2016 is \$0.06/kWh, making the subsidy a sizable share of wind project revenues.

Although it is a per-unit subsidy, projects receive the PTC if and only if it is in place when they begin operation, so there is a discontinuity in project payoffs across a change in PTC status. For most of the period we study, projects received the credit for ten years as long as they were "placed in service" while the credit was in place.<sup>4</sup> Thus, a wind developer that started a project while the PTC was in place but finished it and began operation while it was not would not receive the subsidy. In principal, that project would also not receive the subsidy if it was later reinstated. However, on the few occasions when the PTC lapsed and was reinstated, it was reinstated retroactively. As a result, every otherwise qualified wind

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<sup>3</sup>Bolinger and Wiser (2013) finds these costs are about \$0.01/kWh, and wholesale prices of wind power (inclusive of subsidy) are usually at least \$0.05/kWh.

<sup>4</sup>In 2013, the rules were modified to allow projects that were substantially under construction with the credit in place to receive the credit for ten years (Sherlock, 2015).

project that began operation between when the PTC was enacted and 2014 were eligible to receive it.

Table 3.1: Timeline for Expirations and Extensions of the Production Tax Credit

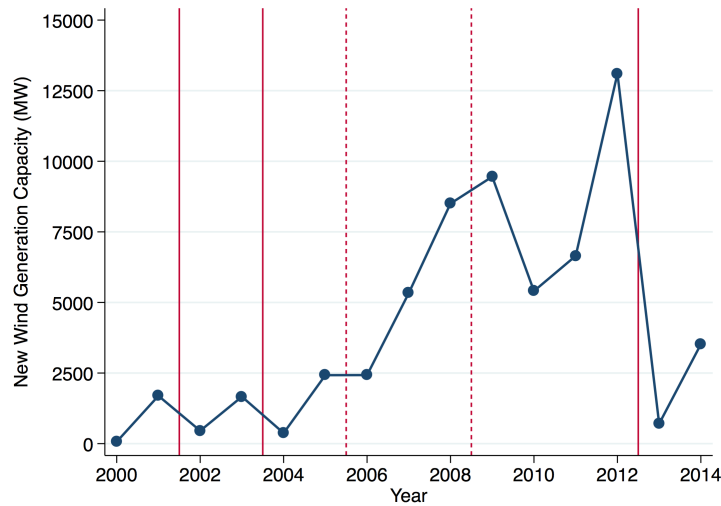
Action	Year	Date	Extended to	Act
Expired	1999	Jul 30		
Extended	2000	Dec 17	Dec 31, 2001	Ticket to Work & Work Incentives Improvement Act of 1999
Expired	2001	Dec 31		
Extended	2002	Mar 9	Dec 31, 2003	Job Creation & Worker Assistance Act of 2002
Expired	2003	Dec 31		
Extended	2004	Oct 4	Dec 31, 2005	Working Families Tax Relief Act of 2004
Extended	2005	Aug 8	Dec 31, 2007	Energy Policy Act of 2005
Extended	2006	Dec 20	Dec 31, 2008	Tax Relief and Health Care Act of 2006
	2007			
Extended	2008	Oct 3	Dec 31, 2011	Emergency Economic Stabilization Act of 2008
Extended <sup>1</sup>	2009	Feb 17	Dec 31, 2012	American Recovery & Reinvestment Act of 2009
	2010			
	2011			
Expired	2012	Dec 31		
Extended <sup>2</sup>	2013	Jan 2	Dec 31, 2014	American Tax Payer Relief Act of 2012

Notes: <sup>1</sup>Also gave projects the option of electing the PTC, the ITC, or a cash grant equivalent to the ITC (through Dec. 31, 2011). <sup>2</sup>Also modified eligibility to be based on the “begun construction” date rather than the “placed in service” date. Information on expirations and renewals from Sherlock (2015).

There was often uncertainty about whether the PTC would be available the following year, and data on new wind capacity suggest that this uncertainty affected wind developers’ investment decisions. As Table 3.1 shows, the PTC was often extended for only a few years at

a time, and it was even allowed to expire four times before later being re-instated. Figure 3.1 depicts U.S. Energy Information Administration data on annual additions of wind capacity. For the three expirations pictured, capacity additions ticked up in the year prior to the December expiration date and fell the following year. A similar but less pronounced pattern is visible in 2005 when the PTC came within a few months of expiring; the PTC was set to expire in December 2005 and was extended in August of 2005. This pattern does not appear around the near expiration in 2008; however, 2009 coincided with the introduction of a federal subsidy that may have propped up wind energy investment.<sup>5</sup>

Figure 3.1: New U.S. Wind Capacity and PTC Expirations (in red)



Dotted line: PTC came within 5 months of expiration

### 3.3 DATA

Our base data set comes from U.S. Energy Information Administration (EIA) Form 860 and includes the size and operation date of all utility-scale wind projects completed from 2001 through 2014. All wind projects larger than 1 MW are required by law to complete this survey annually. Our measure of wind project size is the nameplate capacity variable,<sup>6</sup> and

<sup>5</sup>As described in Chapter 2, the federal government introduced a program in 2009 that allowed new wind projects to choose between the PTC and a cash grant worth thirty percent of installation costs.

<sup>6</sup>U.S. Energy Information Administration (n.d.) defines nameplate capacity as the maximum rate of electricity production for a generator as rated by the manufacturer; a 5KW wind turbine in ideal wind



our measure of operation date is the month and year the project reports beginning operation.

We use data from the Federal Aviation Administration (FAA) to construct measures of the length and predictability of wind project construction times. All wind projects must file FAA Form 7460-2 within five days of the project reaching its greatest height. This date corresponds to the day the turbines are put up, and thus provides a measure of when projects are nearly complete. All structures over 200 feet must also receive FAA approval prior to construction, and about half of the projects in our sample meet this requirement. To apply for the requisite aeronautical study, wind developers are required to file FAA Form 7460-1, and they typically file it three months to a year in advance of when they plan to start construction (FAA, n.d.). This form asks for an expected construction start and end date, and thus provides a measure of expected construction time for the subset of wind projects that file it.

Though we have not successfully matched all wind projects to their corresponding FAA records, the data we have matched allow us to compare the two measures wind project completion across the datasets. We match FAA data to EIA Form 860 data using wind project name and state, and we verify matches using latitude and longitude data. All wind projects should appear in both datasets. However, it is challenging to match across the two since projects must be matched by name, and the EIA name can correspond to all or part of three fields in the FAA data. The FAA data is also at the turbine level, while the EIA data is at the generator level, so there are many FAA observations for each EIA observation. With minimal by-hand matching, we have matched 261 of the 520 wind projects that began operation after 2008. Figure 3.2 plots histograms of the date matched projects reached their tallest height in the FAA data and the date they began operation the EIA data. The date wind turbines are erected likely falls near the date a project begins operation since testing is the only task that must be completed in the interim.<sup>7</sup> The matched data largely corroborates

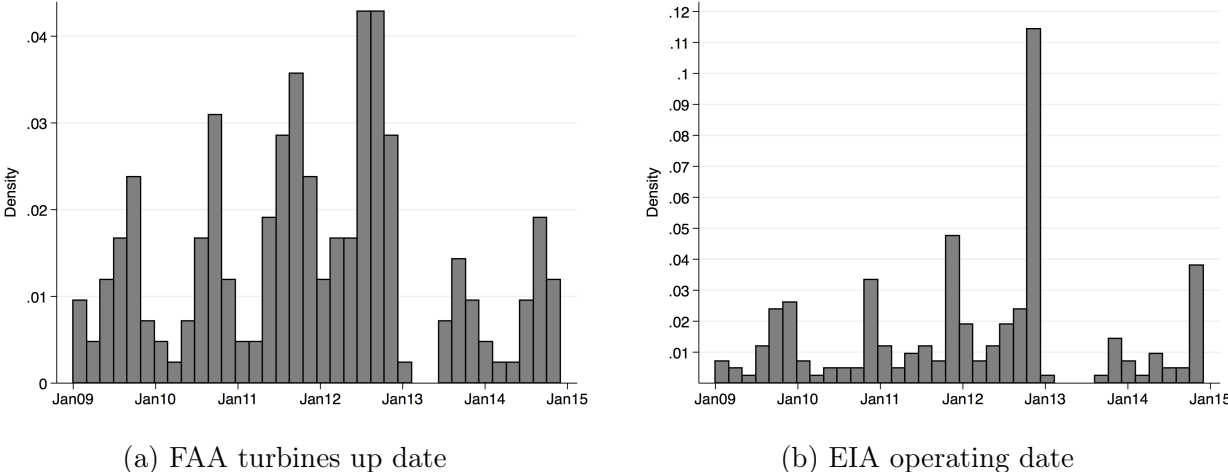
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conditions will generate 5 kWh an hour.

<sup>7</sup>According to Idziak (2014), it is important for wind systems to undergo testing after construction and prior to being energized.

this as the mean and median length of time between these two events is three months. The prevalence of December operation dates in the EIA data seems plausible given that the most common months for projects to reach maximum height are August, September, and October. The data exhibit clear seasonality, likely because many wind projects start construction when the ground thaws in the spring and then finish construction before the winter.

Figure 3.2: Comparison of FAA and EIA data for 212 wind projects



FAA turbines up is the date a project lists as reaching its maximum height. EIA operating date is the month the project begins operating in EIA Form 860.

### 3.4 DESCRIPTIVE FIGURES AND REGRESSIONS

We next establish some basic patterns in the data that will inform an eventual model of wind project investment decisions. First, the number of wind projects completed increases in the months prior to a PTC expiration and falls in months subsequent. Second, the size of completed projects does not appear to change surrounding expirations. Taken together, these two results imply that the changes in aggregate wind generation capacity surrounding expirations are explained by changes in the number, rather than the composition of, projects completed. We also find construction time increases in project size, but a doubling of project size does not lead to a doubling of expected construction time. Finally, the variance of construction times conditional on project size is high, and comparing actual to expected

operating dates indicates that wind developers face uncertainty about how many months of construction will be needed to build a wind project.

We find that the number of projects built increases before a PTC expiration and falls afterward. Figures 3.3a and 3.3c plot the number of projects that begin operation each quarter. The apparent spike in projects at the end of 2007 corresponds to a sustained increase in the number of projects built per quarter, an increase reflected in the different scales on the two graphs. The number of new projects appears to increase before each of the three expirations shown and fall thereafter. To test this hypothesis, we collapse the dataset to the quarterly level and regress the number of projects built each quarter on an indicator for being near an expiration, quarter fixed effects, and a third degree polynomial in quarter of operation. All three PTC expirations occurred on December 31, so the indicator for being before an expiration corresponds to the last two quarters of that year. Similarly, the indicator for after an expiration corresponds to the first two quarters of the subsequent year. Table 3.2 shows that we find statistically and economically significant increases prior to expirations and decreases afterward. Results are qualitatively similar if we define the windows surrounding expirations as either one quarter or the entire year on each side.

Table 3.2: Quarterly projects completed on expirations

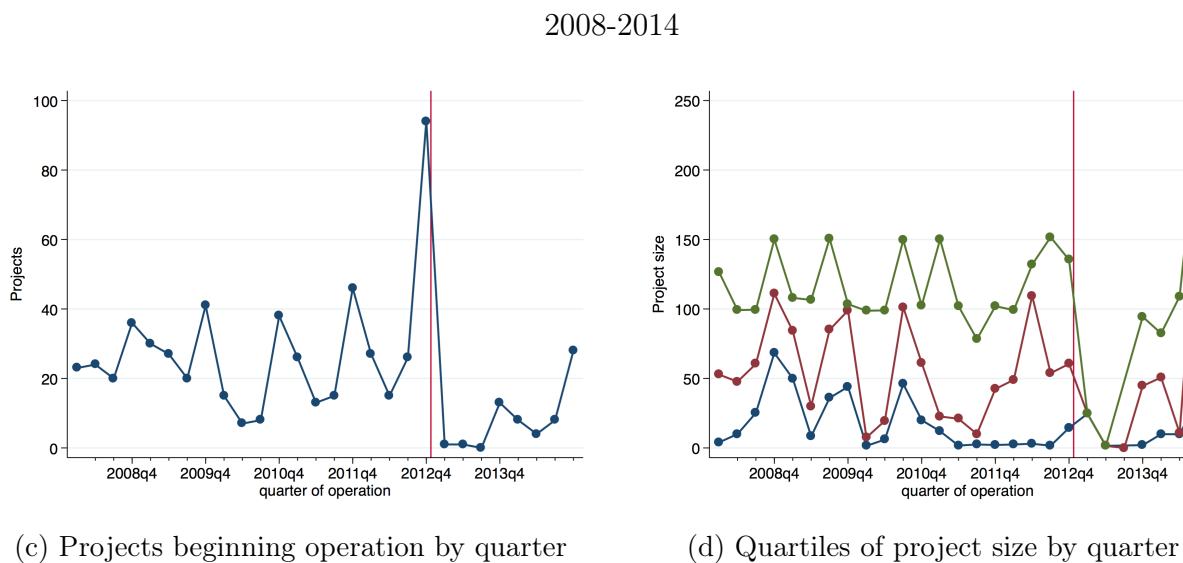
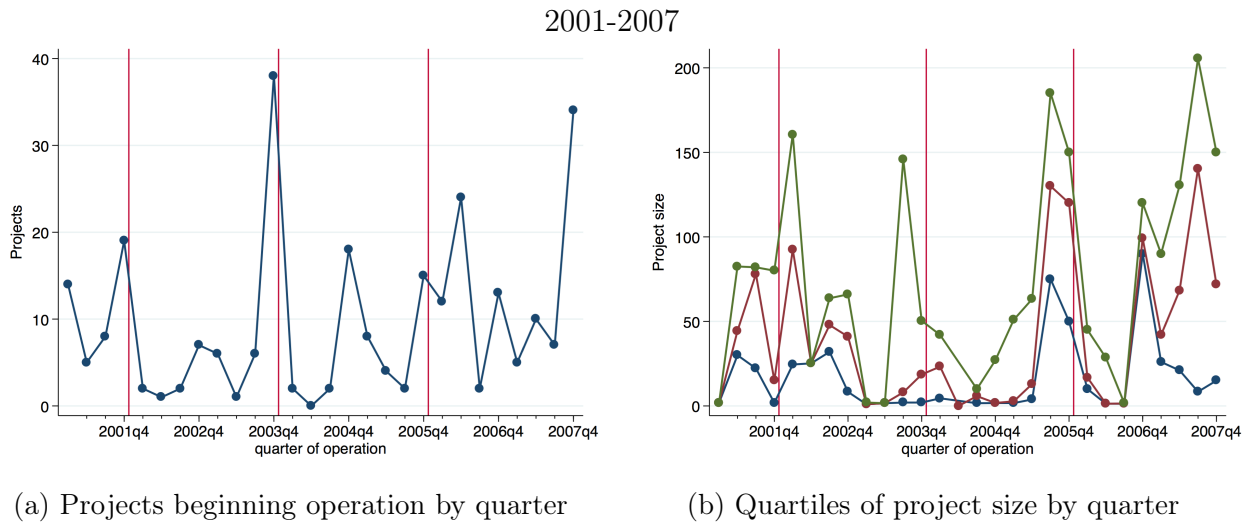
Before expiration	20.67	20.20
	(8.93)	(9.04)
After expiration	-7.87	-6.50
	(3.42)	(3.66)
N	56	56
Dependent var.	mean 15.73	std. dev. 16.10

Dependent variable is the number of wind projects completed in that quarter. Newey-west SE (lag 8) in parentheses. All specifications include quarter fixed effects and a cubic in quarter of operation.

In contrast, there is not a clear change in project size surrounding expirations. Figures 3.3b and 3.3d plot the quantiles of completed project size over time. Though the data is somewhat noisy, there does not appear to be a clear change near expirations. We test for an effect of expirations on size by regressing project size on an indicator for completion in the six months leading up to a PTC expiration, along with quarter of operation dummies and a third degree polynomial in quarter of operation. We find a small negative point estimate, suggesting that projects built in the lead up to expirations are slightly smaller. This estimate is not statistically significant, and we can rule out effects greater than 0.3 standard deviations of project size at the five percent level. These results are robust to defining the period surrounding expirations differently and alternative controls. The analogous test for projects completed immediately after an expiration similarly finds no effect; in this case, the coefficient is imprecisely estimated, and the point estimate is close to zero. Taken together, these two observations imply that the pattern in Figure 3.1 is explained by changes in the number of projects completed surrounding expirations rather than changes in the size of

completed projects.

Figure 3.3: Number and size of projects surrounding PTC expirations

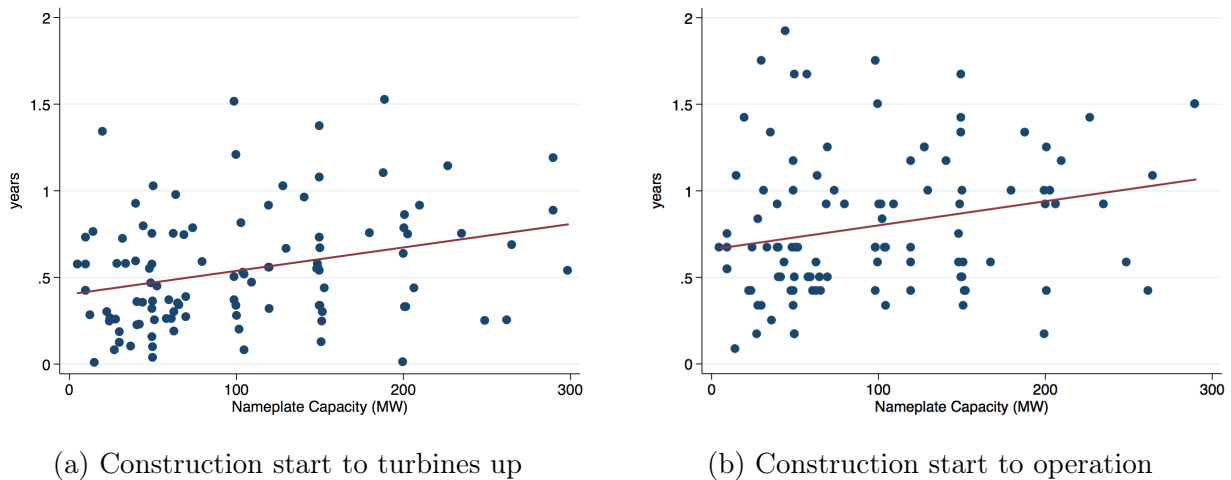


Measure of size is nameplate capacity; for b) and d), projects appear in quarter they began operation.

Measures of construction time increase slowly in project size, and this may explain why we do not see obvious changes in project size surrounding expirations. Figure 3.4a plots a construction time measure that is the difference between the date construction was expected to start, from FAA Form 7680-1, and the date a wind project reaches its maximum height, from FAA Form 7680-2. While all wind projects must report the date they reach maximum

height, only a subset of projects (those over 200 feet) must report expected construction start and end dates. Figure 3.4b is the same plot but with a different measure of construction time: the realized difference between the date construction was expected to start and when the project began operation. In both cases, average construction time increases gradually in project size.

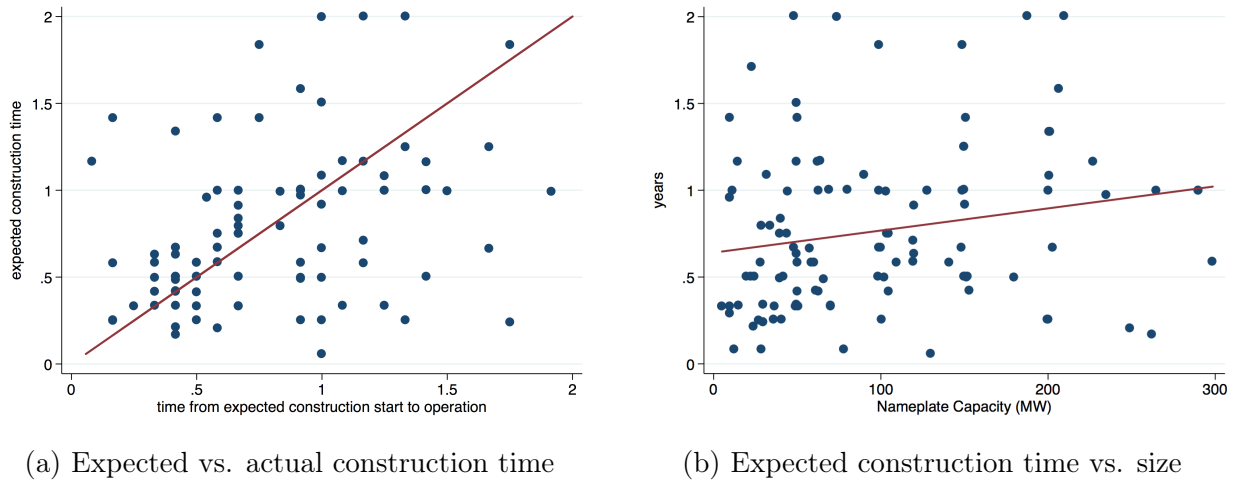
Figure 3.4: Relationship between size and measures of construction time



Comparing expected to actual construction times suggests that wind developers themselves cannot perfectly forecast project construction times. The FAA representative we spoke with told us that wind projects often run into unanticipated delays, for example, hitting rock or gas when drilling foundations, or trouble with leasing agreements. Figure 3.5a plots expected construction time against actual construction time, where our measure of actual construction time is the difference between the expected construction start date and the date the EIA lists the project as beginning operation. Many observations lie off the forty-five degree line, though they appear to be roughly centered around it. This pattern is consistent with wind developers not knowing exactly how long construction will take ex ante, even if their expectations of construction time are correct on average. Figure 3.5b verifies that expected construction time increases in project size at a similar rate to those in Figure 3.4. Wind developers building a project of a given size also expect substantial

deviations in construction time from the average time for that size. An inability to forecast how long construction takes should make it more difficult for wind developers to respond to uncertainty about a PTC renewal by shifting potential projects forward in time.

Figure 3.5: Comparison to expected construction time



### 3.5 CONCLUSION

We find that the number of wind projects constructed increases prior to, and decreases after, dates the production tax credit (PTC) expired. Because the PTC was ex-post in place continuously throughout the period (it was retroactively renewed after each of the expirations we observe), these changes suggest that uncertainty about its status affected wind developers' investment decisions. We find little evidence that uncertainty affected project size, perhaps because construction times are only weakly related to project size.

While our results suggest that uncertainty did not affect project size, uncertainty may have increased costs by giving wind developers an incentive to rush projects that might otherwise finish after a potential PTC expiration. Once we perform a more comprehensive, by-hand matching of the FAA to EIA data, our construction time measures can be used to test whether projects built just prior to a PTC expiration had shorter construction times, conditional on observables. If construction times do not change surrounding expirations,

then increased costs from rushing are unlikely to be a channel through which uncertainty reduced efficiency.

In future work, we plan to develop a model that can match the patterns described in this chapter. We plan to use the model to study how uncertainty about PTC renewals over the period affected government expenditures per MW of new wind generation capacity.



## APPENDICES

## APPENDIX A

### A.1 DATA APPENDIX

#### A.1.1 SAMPLE SELECTION

My base data set is an unbalanced panel of all plant-year observations from the ASM and CMF from 1997-2013. I begin by dropping observations that are administrative record observations (most variables for these observations are imputed) and observations the Census identifies as having known errors. Throughout, I convert variables measured in dollars to 2012 dollars using the urban chained CPI less energy.

The first step is to identify energy-intensive industries. I take observations in my base data set and classify them into industries using 2012 NAICS codes. I then classify industries as energy-intensive based on the sum of two variables: the cost of purchased electricity and the cost of fuel for heat, power, and electricity generation. If the ratio of this sum to value-added is greater than five percent, and the ratio of the sum to total costs is greater than three percent, I classify the industry as energy-intensive. I calculate these ratios across all observations in each industry. I define total costs as the sum of salaries and wages, materials (including electricity and fuels), and capital expenditures. Total costs should also include employee benefits, rental payments, and miscellaneous operating expenses, but I do not observe these variables in all years. 70 of the 364 industries in my sample meet this criteria for being energy-intensive.

I often observe a plant operating in multiple industries over the course of the panel. For

purposes of identifying a plant as energy-intensive, I classify each plant as belonging to its modal industry. In the case of a tie, I assign the plant to its earliest observed industry. I then keep all observations for all plants with a modal industry that is energy intensive. In the remaining sample, twenty-one percent of plants appear as operating in more than one industry over the period. Thus, I still have observations for plants that are not operating in an energy-intensive industry in my sample: seven percent of plant-year observations correspond to a different industry than the plant's modal industry, and not all of these industries are energy intensive. My impression is that these industry changes are primarily explained by shifts from one industry to a closely related one, e.g. Alkalies and chlorine manufacturing to All other basic inorganic chemical manufacturing, rather than complete misclassification or large changes in operation.

Once I have determined which industries are energy intensive, I next drop plant-years with missing or large outlier observations for key variables. I first drop plant-years with missing or negative values for total value of shipments, salaries and wages, employment, and materials. I also drop plant-years with large outliers for the electricity price variable. Specifically, I trim the distribution of electricity prices by dropping observations below the 0.5<sup>th</sup> and above the 99.5<sup>th</sup> percentile. I also drop plant-years that are large outliers relative to neighboring observations. To identify these observations, I construct year on year changes in electricity prices in both directions. I then drop observations that are in the 1 percent tails of the year-on-year change in price distributions for changes in both directions. If an observation only borders one other observation, I drop it if the change in that direction is in the 1 percent tails of the change distribution. Finally, I drop observations for plants with a zip code that does not match their state or a bordering state. While the existence of this discrepancy sounds troubling, it is likely due to plant managers reporting a corporate headquarters rather than the plant level address.

For the regressions in Section 1.5, I make the additional restriction that plants have at least two non-zero capital expenditures observations in my data. This restriction drops

very few plants and prevents the sample from changing when I include plant fixed effects in regressions with the log of capital expenditures as the dependent variable.

To estimate the dynamic model, I take all the observations from the above sample with a modal industry of NAICS 322121 - Paper (except Newsprint) Mills.<sup>8</sup> From this sample, I drop observations that are non-consecutive, have missing values for the capital stock, or have zero or negative values for total electricity use. Compared to the paper plant observations I use in regressions, the resulting sample contains just over 60 percent of the unique paper industry plants and over 90 percent of the total value of shipments. Thus, plants in my sample tend to be larger than plants in the industry as a whole.

Some of the Census data I use in my analysis are imputed. The Census often imputes responses that are left blank. From 2002 onward, these observations are typically flagged; however, they are not flagged before 2002. Beyond dropping administrative records, I do not drop these imputed observations from my data. They tend to disproportionately occur for small plants, and imputation is done in a variety of ways. For more on the extent of imputation in the CMF, see White, Reiter and Petrin (2012).

### A.1.2 CONSTRUCTING THE CAPITAL STOCK

I construct the capital stock using the perpetual inventory method. In my data, I observe information on two types of capital. The first is structures, and the second is machinery and equipment. I observe plant-level investment for each type in every year a plant appears in my sample (because the ASM surveys a subset of manufacturing plants, I do not observe all plants in all years). To apply the perpetual inventory method, I need two additional pieces of information about each type of capital: an initial value for each plant and the rate at which it depreciates. I observe book values of capital every five years in the CMF, and I use the book value of capital at the beginning of the year in the earliest year I observe it to initialize

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<sup>8</sup>Given the focus on adjustment costs, the drop based on non-zero capital expenditures could be problematic; however, it has almost no bite once I drop non-consecutive observations.

the perpetual inventory calculation.<sup>9</sup> If the perpetual inventory breaks down due to a year where a plant does not appear in my sample or has missing investment data, I restart the calculation the next time I observe the book value of capital. I assume a depreciation rate of three percent for structures and ten percent for machinery and equipment; I base these choices on depreciation tables from the U.S. BEA (BEA, n.d.). While plants use physical capital in production, I measure capital and investment in dollars. Since the price of capital varies over time, I use industry-specific investment price deflators from the NBER-CES to convert investment in different years into comparable units. To deflate the book value of capital, I assume an equal fraction of capital is purchased in every year since the plant began operation.

## **A.2 MOVEMENT OF NATURAL GAS PRICES WITH OIL PRICES AND THE BUSINESS CYCLE**

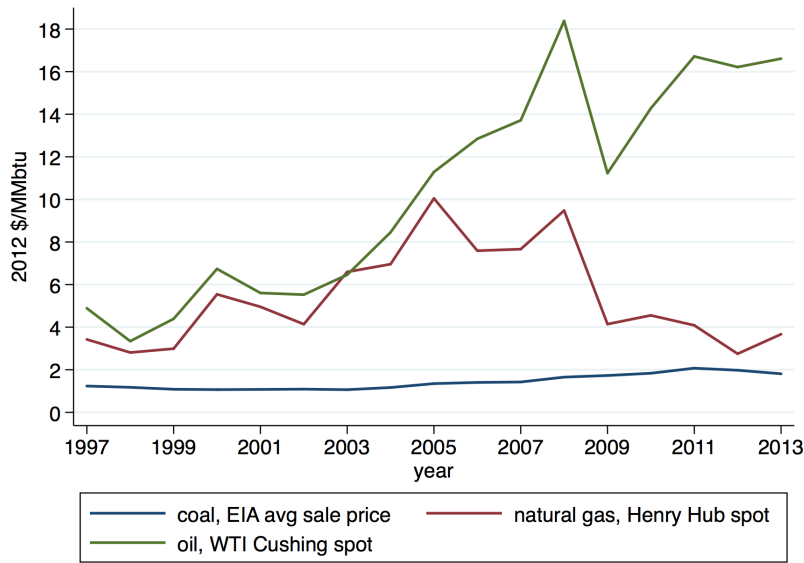
While most electricity is generated using coal or natural gas, some areas, particularly New England and Florida, still use oil to generate electricity. Oil prices diverged from both natural gas and coal prices over the second half of the period.

Natural gas prices increased leading up to the financial crisis and subsequently fell in 2009. I will control for the aggregate business cycle explicitly in regressions and via output prices in the dynamic model; however, the fall in natural gas prices continuing beyond the economic recovery suggests that increased production from hydraulically fractured wells may have been the primary cause. Over the entire period, the covariance between natural gas prices and the business cycle was low.

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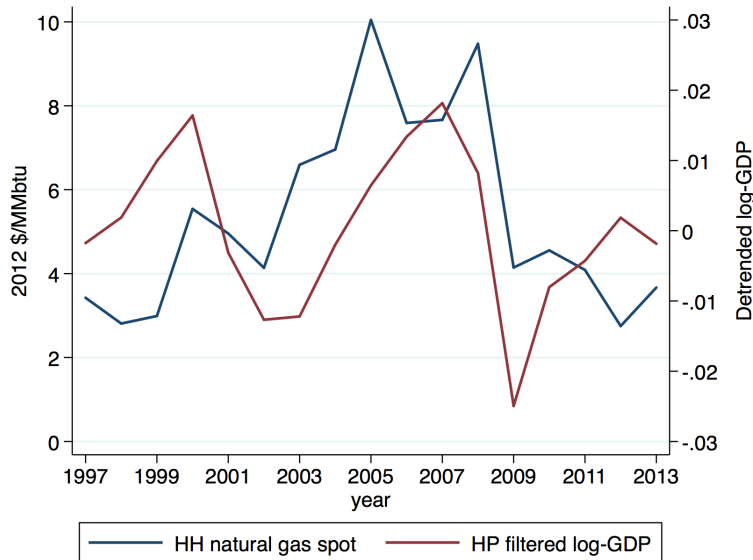
<sup>9</sup>The book value is the acquisition cost (including installation) of the capital, less depreciation. It is not necessarily the market value of the asset.

Figure A.1: Natural gas and coal prices from 1997-2013



Henry Hub gas prices in \$/MMbtu from Bloomberg. Coal prices are EIA average mine sales prices in \$/short ton and oil prices are Cushing, OK WTI spot prices in \$/barrel; both are converted to \$/MMbtu using EIA’s estimates of 20.214 MMbtu/short ton (EIA, 2016c) and 5.8 MMbtu/barrel (EIA, 2015b)

Figure A.2: Natural gas prices and the business cycle from 1997-2013



Henry Hub gas prices in \$/MMbtu from Bloomberg. Log annual real GDP from U.S. Bureau of Economic Analysis (n.d.), detrended using a hp-filter with  $\mu = 6$ .

### A.3 EVOLUTION OF NATURAL GAS GENERATION SHARES

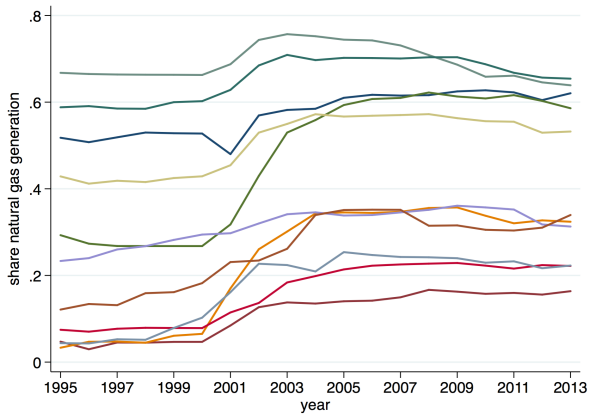
The late 1990s and early 2000s saw a significant expansion in natural gas generation capacity. Advances in gas turbine technology were the primary cause of this growth, though low natural gas prices and the elimination of natural gas price controls also contributed (Bautista, 1996). More stringent, national regulation of criteria air pollutants likely also contributed by forcing retrofits and retirements of coal plants. My identification strategy relies on natural gas generation shares being exogenous to firm investment decisions. I use natural gas shares in 1995 for the instrumental variables specification and contemporaneous natural gas shares in the dynamic model. In either case, we might be concerned that changes in the growth of natural gas shares are due to changes in regional economic conditions that also affect investment.<sup>10</sup> The graphs below show that natural gas generation capacity was flat surrounding 1995. They also show the ubiquity of the early 2000s increase: all but a handful of regions added natural gas generation at this time. That so much of the increase occurred at once suggests that natural gas generation capacity was not primarily responding to regional differences in economic conditions. Using data on state-level unemployment rates merged onto eGRID regions, I find that regions with higher unemployment rates were less likely to add natural gas capacity but that this effect is statistically insignificant.<sup>11</sup>

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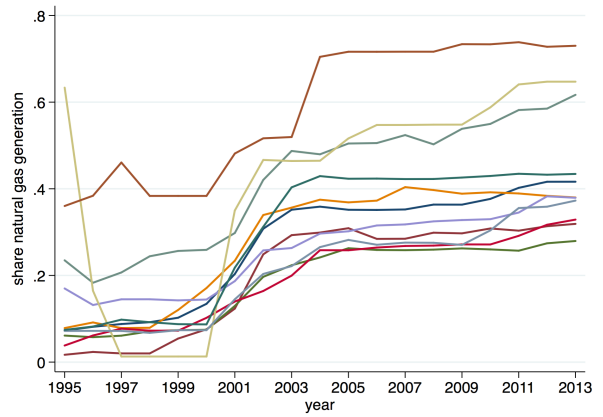
<sup>10</sup>For the 1995 natural gas shares this is less obvious; however, states with high 1995 natural gas shares may be those that grew the most during the early 1990s. If this growth carried into my sample period, and affected investment in a way not captured by the region fixed effects, it could bias my estimates.

<sup>11</sup>To conduct this test, I merge state level unemployment rates onto electricity generator-level data. I then collapse the generator data to the eGRID level, taking an average of the unemployment rates within a region. I regress changes in natural gas capacity shares on this unemployment rate variable as well as year and eGRID fixed effects.

Figure A.3: Natural gas share generation capacity by eGRID region: 1995-2013



(a) 11 Westernmost eGRID regions



(b) 11 Easternmost eGRID regions



## A.4 ADDITIONAL REGRESSION SPECIFICATIONS

### A.4.1 UNWEIGHTED OLS ESTIMATES

Table A.1: OLS estimates, unweighted

	(1)	(2)	(3)	(4)	(5)
electricity price	-3.888***	-3.962***	-3.911***	-2.090***	-3.115***
	(0.351)	(0.354)	(0.344)	(0.238)	(0.360)
elec priceXtradable					-1.582***
					(0.506)
Year FE	X	X		X	X
Region FE	X	X	X		X
Plant FE				X	
State business cycle	X		X	X	X
RegionXbusiness cycle	X		X	X	X
Plant age	X		X		X
Industry FE	X	X			X
Industry linear time trend	X	X		X	X
IndustryXgas price	X	X		X	X
IndustryXyear FE			X		
Plant-years	146,000	146,000	146,000	146,000	146,000
Plants	24,000	24,000	24,000	24,000	24,000

Tradable is an industry-level indicator for producing tradable products. The mean of electricity prices is 0.08, so implied elasticities (at the mean) range from -0.17 to -0.31. For non-tradables, this elasticity is -0.25; for tradables, it is -0.38. Industries are defined at the 6-digit NAICS level; state business cycle is two variables: annual state unemployment and log of total employment; business cycle is de-trended log US GDP; and `ngas_spot` is the Henry Hub spot price for natural gas. SE clustered by region. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## A.4.2 LAGGED GAS PRICE INTERACTION IV ESTIMATES

Table A.2: IV estimates with lagged gas price interaction

Dependent variable	Log capital expenditures				Electricity price (cents)
	(1)	(2)	(3)	(4)	(5)
Electricity price	-11.09** (2.97)	-10.23*** (3.63)	-5.980* (3.53)	-10.97* (2.82)	
Share gas '95XLgas price					0.393*** (0.042)
Year FE	X	X		X	X
Region FE	X	X	X		X
Plant FE				X	
State business cycle	X		X	X	X
RegionXbusiness cycle	X		X	X	X
Plant age	X		X		X
Industry FE	X	X			X
Industry linear time trend	X	X		X	X
IndustryXgas price	X	X		X	X
IndustryXyear FE			X		
Plant-years	146,000	146,000	146,000	146,000	146,000
Plants	24,000	24,000	24,000	24,000	24,000
First Stage F	76	51	66	82	-

The mean of electricity prices is 0.08, so implied elasticities (at the mean) range from to -0.48 to -0.89. Column (5) shows the first stage for (1) where, for ease of reading, the dependent variable is the electricity price in cents rather than dollars. Share gas '95XLgas price is the regional share of natural gas generation in 1995 interacted with the lagged natural gas spot price. Industries are defined at the 6-digit NAICS level; state business cycle is two variables: annual state unemployment and log of total employment; business cycle is de-trended log US GDP; and gas price is the Henry Hub spot price for natural gas. All specifications weighted by plant size, as measured by average total value of shipments. SE clustered by region. \*\*\* p<0.01, \*\* p<0.05, \*\*\* p<0.1.

## A.5 DERIVING $\frac{\partial K^*}{\partial p^E}$ WHEN PRODUCTION IS COBB-DOUGLAS

Depending on the production technology, firms can find it optimal to either increase or decrease the quantity of one factor in response to the increase in the price of another factor. This section analytically solves for the sign of  $\partial K/\partial p^E$  if production Cobb-Douglas i.e. the elasticity of substitution between capital and electricity is one.

### A.5.1 NO ADJUSTMENT COSTS

Suppose production is Cobb-Douglas in capital and electricity.

$$f(K, E) = AK^\alpha E^\beta$$

If there are no adjustment costs, firms face input prices  $r_K$  and  $p_e$ , and the price of output is normalized to one, then the static first-order conditions are the following:

$$\begin{aligned} \frac{\partial \pi}{\partial K} &: \frac{\alpha AK^\alpha E^\beta}{K} = r_K \\ \frac{\partial \pi}{\partial E} &: \frac{\beta AK^\alpha E^\beta}{E} = p_E \end{aligned}$$

These first order conditions imply the following input demand functions:

$$K^* = \left( \frac{\alpha AE^\beta}{r_K} \right)^{\frac{1}{1-\alpha}} \tag{A1}$$

$$E^* = \left( \frac{\beta AK^\alpha}{p_E} \right)^{\frac{1}{1-\beta}} \tag{A2}$$

Substituting in Equation A2 into A1 gives the following:

$$\begin{aligned}
K^* &= \left(\frac{\alpha A}{r_K}\right)^{\frac{1}{1-\alpha}} \left(\frac{\beta A}{p_E}\right)^{\frac{\beta}{(1-\beta)(1-\alpha)}} K^{*\frac{\alpha\beta}{(1-\beta)(1-\alpha)}} \\
K^* &= \left[\left(\frac{\alpha A}{r_K}\right)^{\frac{1}{1-\alpha}} \left(\frac{\beta A}{p_E}\right)^{\frac{\beta}{(1-\beta)(1-\alpha)}}\right]^{\frac{(1-\alpha)(1-\beta)}{1-\alpha-\beta}} \\
K^* &= \left(\frac{\alpha A}{r_K}\right)^{\frac{1-\beta}{1-\alpha-\beta}} (\beta A)^{\frac{\beta}{1-\alpha-\beta}} p_E^{\frac{1-\alpha-\beta}{\beta}}
\end{aligned}$$

Taking the derivative of  $K^*$  with respect to the price of electricity,  $p_E$ :

$$\frac{\partial K^*}{\partial p_E} = (1 - \alpha - \beta) \frac{1}{\beta} \left(\frac{\alpha A}{r_K}\right)^{\frac{1-\beta}{1-\alpha-\beta}} (\beta A)^{\frac{\beta}{1-\alpha-\beta}} p_E^{\frac{1-\alpha-2\beta}{\beta}}$$

The sign of this term depends on  $1 - \alpha - \beta$  but is only informative if we have decreasing returns to scale. If  $\alpha + \beta < 1$ , then  $\frac{\partial K^*}{\partial p_E} < 0$ . If  $\alpha + \beta > 1$ , the Hessian is no longer positive-semidefinite and  $K^*$  is no longer a maximum. If  $\alpha + \beta$  is equal to 1, the above equation is undefined. If there are constant returns to scale, any firm facing lower input costs could expand and serve the whole market.

### A.5.2 ADJUSTMENT COSTS

Suppose production is still Cobb-Douglas in capital and electricity, but firms now face costs to adjusting their capital stock  $\gamma(K - K_{t-1})^2$ . For simplicity, capital is productive immediately, and there is no depreciation or uncertainty. The problem is now dynamic since the choice of capital today will affect adjustment costs next period.

$$\max \sum_{t=0}^{\infty} \beta^t [AK_t^\alpha E_t^\beta - r_K K_t - p_E E_t - \gamma(K_t - K_{t-1})^2]$$

Now the first order conditions are the following:

$$\begin{aligned} \frac{\partial L}{\partial K_t} &: \alpha AK_t^{\alpha-1} E_t^\beta - r_K - 2\gamma(K_t - K_{t-1}) = 2\beta\gamma(K_{t+1} - K_t) \\ \frac{\partial L}{\partial E_t} &: AK_t^\alpha E_t^{\beta-1} - p_E = 0 \end{aligned}$$

Notice the first order condition for  $E_t$  is identical and implies the same input demand function:

$$E_t^* = \left( \frac{\beta AK_t^\alpha}{p_E} \right)^{\frac{1}{1-\beta}}$$

The capital first order condition now depends on past and future values of capital since the cost of adjusting to today's choice will depend on  $K_{t-1}$ , and today's choice will affect the cost of adjusting to  $K_{t+1}$  next period.

The effect of a one time electricity price change should be similar, with the difference that it may take place over several periods instead of all at once. If the cost to adjusting was fixed instead of convex, the plant would adjust immediately, but might not find it profitable to adjust at all.

## A.6 COBB-DOUGLAS PRODUCTION FUNCTION

I also present Cobb-Douglas production function estimates for comparison. I found implausibly high estimates of the adjustment cost parameters when I used the Cobb-Douglas function in the dynamic model, and I did not simulate counterfactuals for this function. My expectation is that the effect of electricity price volatility on dispersion in the marginal product of capital for this function is smaller than what I find for the Leontief function.

This function models production at plant  $i$  in year  $t$  as Cobb-Douglas in capital, labor, and electricity. I again allow for a plant-specific productivity shock that is observed by plant

managers,  $\omega_{it}$ , as well as, potentially serially-correlated, measurement error in output,  $\epsilon_{it}$ .

$$Y_{it} = e^{\gamma_0} K_{it}^{\gamma_K} L_{it}^{\gamma_L} E_{it}^{\gamma_E} e^{\omega_{it}} e^{\epsilon_{it}} \quad (\text{A3})$$

To estimate this function, I follow a similar procedure to that described in Section 1.6.1.1. I estimate both the labor and electricity coefficients using the first order conditions, and I estimate the capital coefficient using techniques from the production function literature. My estimator for the labor coefficient is

$$\hat{\gamma}_L = \text{median} \left\{ \frac{L_{it}}{P_t Y_{it}} \left( 1 - \frac{M_{it}}{P_t Y_{it}} \right)^{-1} \right\} \quad (\text{A4})$$

Analogously, my estimator for the electricity coefficient is the following:

$$\hat{\gamma}_E = \text{median} \left\{ \frac{P_t^E E_{it}}{P_t Y_{it}} \left( 1 - \frac{M_{it}}{P_t Y_{it}} \right)^{-1} \right\} \quad (\text{A5})$$

To estimate the capital coefficient, I follow the same procedure of guessing a capital coefficient, finding the implied productivity shocks, and forming the moment that these shocks are uncorrelated with current capital described in Section 1.6.1.1. The only difference is that I subtract off the estimated share of output attributable to electricity and labor as I did labor in Equation 1.16. Table A.3 reports the estimated coefficients.

Table A.3: Cobb-Douglas estimates

$Y_{it} = e^{\gamma_0} K_{it}^{\gamma_K} L_{it}^{\gamma_L} E_{it}^{\gamma_E} e^{\omega_{it}} e^{\epsilon_{it}}$					
	Estimate	SE		Estimate	SE
$\gamma_K$	0.524	(0.031)	$\gamma_E$	0.082	(0.005)
$\gamma_L$	0.242	(0.007)	$\gamma_0$	2.18	(0.35)

Estimated using 2,400 plant-years for NAICS 322121, Paper (except Newsprint) Mills. SE bootstrapped by drawing plants with replacement.

## A.7 PRODUCTION FUNCTION ESTIMATES USING A LAGGED INVESTMENT MOMENT

Table A.4: Production function estimates, lagged investment moment

Leontief			Cobb-Douglas		
$Y_{it} = \min\{e^{\beta_0} K_{it}^{\beta_K} L_{it}^{\beta_L} e^{\omega_{it}}, e^{\beta_1} E_{it}^{\beta_E}\} e^{\epsilon_{it}}$			$Y_{it} = e^{\gamma_0} K_{it}^{\gamma_K} L_{it}^{\gamma_L} E_{it}^{\gamma_E} e^{\omega_{it}} e^{\epsilon_{it}}$		
	Estimate	SE		Estimate	SE
$\beta_K$	0.605	(0.062)	$\gamma_K$	0.569	(0.058)
$\beta_L$	0.303	(0.013)	$\gamma_L$	0.242	(0.007)
$\beta_E$	0.634	(0.028)	$\gamma_E$	0.082	(0.005)
$\beta_0$	2.05	(0.37)	$\gamma_0$	1.63	(0.70)
$\beta_1$	4.60	(0.35)			

Estimated using 2,400 plant-years for NAICS 322121, Paper (except Newsprint) Mills. For the Leontief production function, I estimate  $\beta_M$  to be 0.93 with a SE of 0.022. SE bootstrapped by drawing plants with replacement.

## A.8 ESTIMATES FOR THE EXOGENOUS STATE AR(1) PROCESSES

I estimate all price processes using OLS. I do not correct for any bias induced by including the lagged dependent variable as a regressor.

$$x_{t+1} = \mu_x + \rho_x x_t + \xi_{it}^x \quad \text{for } x = p, \omega, s^g, p^g \quad (1.24, \text{revisited})$$

where  $p_t$  is the log output price,  $\omega_{it}$  is log productivity,  $s_{rt}^g$  is the natural gas share,  $p_t^g$  is the log gas price, and  $\xi^x$  is i.i.d  $\sim \mathcal{N}(0, \sigma_x^2)$ .

For natural gas, I use data on Henry Hub Contract 1 spot prices in real 2012 dollars from 1995-2013. For output prices, I use annual price indices from the NBER-CES for 1990-2011,

and I estimate the output price process separately by industry.<sup>12</sup>

Log Natural Gas Price			Log Output Price		
Parameter	Estimate	SE	Parameter	Estimate	SE
$\rho_g$	0.71	(0.16)	$\rho_p$	0.83	(0.15)
$\mu_g$	0.46	(0.26)	$\mu_p$	0.023	(0.019)
$\sigma_g$	0.31	-	$\sigma_p$	0.084	

Newey-west SE in parentheses (5 year lag). Output prices are for NAICS 322121 - Paper (except Newsprint) Mills

To calculate the share of natural gas generation in each region, I use generator level data from EIA Form 860. I match these generators to eGRID regions using zip codes. I then calculate the share of natural gas generation capacity as a fraction of total generation capacity in each region in each year. I drop Alaska and Hawaii and estimate the AR(1) process using OLS. I estimate the share process using my sample of manufacturers, so observations in regions with more manufacturing plants with more weight; in the table below, I report the unweighted estimates which are slightly noisier.

I invert out productivity shocks,  $\omega$ , during production function estimation. I then regress productivity shocks on their lags to estimate the productivity process. The estimates I report below are for the Leontief production function; estimates are virtually identical for the Cobb-Douglas production function.

<sup>12</sup>Time periods are chosen based on data availability: 1994 is the first year I observe HH gas prices and 2011 is the last year of data in the NBER-CES database.



Share Natural Gas			Log Productivity		
Parameter	Estimate	SE	Parameter	Estimate	SE
$\rho_g$	0.98	(0.008)	$\rho_p$	0.82	(0.025)
$\mu_g$	0.018	(0.004)	$\mu_p$	-	-
$\sigma_g$	0.034	-	$\sigma_p$	0.27	(0.019)

Share natural gas SEs clustered by region. Productivity SEs are bootstrapped by drawing plants with replacement. In estimation, I estimated a non-zero constant for the productivity process; however, I did not disclose it and so cannot report it.

Finally, I estimate the log electricity price process using plant-level data on all energy-intensive manufacturers that produce tradable products. However, I do not report these estimates to avoid disclosing information on another sample. Below I report estimates of this price process for the paper industry to provide a sense of the magnitude of these coefficients.

$$p_{it}^e = \alpha_0 + \alpha_1 p_{i,t-1}^e + \alpha_2 s g_{r,t-1} X p_{t-1}^g + \alpha_3 s g_{r,t-1} + \alpha_4 p_{t-1}^g + \xi_{it}^e \quad (1.25, \text{revisited})$$

Parameter	Estimate	SE
$\alpha_1$	0.825	(0.025)
$\alpha_2$	0.101	(0.079)
$\alpha_3$	-0.053	(0.099)
$\alpha_4$	-0.006	(0.024)
$\alpha_0$	-0.504	(0.087)

Estimates for paper industry; not used in estimation. SE clustered by region.

## A.9 SIMULATED METHOD OF MOMENTS

I use simulated method of moments to solve for adjustment cost parameters. This requires solving for the value function at each guess of the parameters. I discretize the problem and solve for the value function using value function iteration. I grid the capital stock on a log scale and use 800 states, so that the distance between two adjacent states is just under two percent. I constrain plant managers to choose one of these states when making their optimization decision. I grid all exogenous states beside natural gas generation shares equal distance apart on a log scale; natural gas shares I grid evenly. I use 7 electricity price states, 5 productivity states, 3 final goods price states, 3 share natural gas states, and 3 natural gas price states. This leaves me with a total of 756,000 states. I model the exogenous states as continuous and linearly interpolate the value-function to calculate the value for each state.

After I solve for the value function, I use it to simulate data from the model. I simulate data for the number of unique plants in my sample of paper manufacturers. To do the simulation, I must assign each plant to a region, and I assign plants to regions to match the empirical distribution of the industry. I next draw an initial capital stock, simulate the model for 1000 periods, and use the last 200 periods to construct my simulated moments. I then match these moments to the moments in the Census data.

## APPENDIX B: WIND TAX EQUITY FINANCING

### B.1 TAX EQUITY FLIP PARTNERSHIP

The most commonly used arrangement for tax equity financing is known as the Institutional Investor Flip structure.<sup>13</sup> In it, a wind developer and a tax equity investor set up a Limited Liability Company (LLC) for the project. Since an LLC is treated as a partnership by the IRS, the LLC does not pay its own income taxes; instead, its owners count their share of its profits, losses, credits, and deductions on their income taxes. While the share of these distributions a partner receives is usually proportional to its interest in the LLC, this need not be the case, and it is not in an Institutional Investor Flip. Instead, a special allocation of these distributions is made, and a Safe Harbor provision in IRS Revenue Procedure 2007-65 allows for the allocations outlined below.

The deal has three stages. In the first, the developer receives all cash payments and the institutional investor receives all the tax incentives.<sup>14</sup> This phase usually lasts until the developer recovers the capital it initially contributed to the project. Next, the investor receives all distributed cash and all tax incentives until it reaches its target rate of return - the "flip" point. At this point, the project enters the third stage where the majority of both cash and tax incentives go to the developer, but the investor still receives at least five percent of both. The developer often buys out the institutional investor's share when this

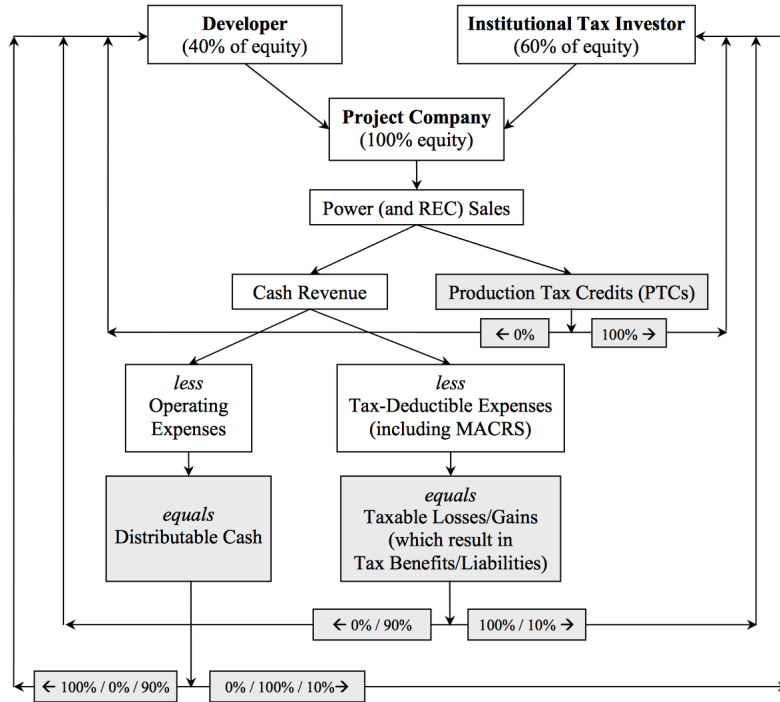
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<sup>13</sup>This section draws heavily from Bolinger, Harper and Karcher (2007). It also uses information from Hecimovich and Stevens (2012), IRS (2007), and Laurence (2014).

<sup>14</sup>Technically this share of tax incentives must be capped at 99 percent for the project to qualify for Safe Harbor.

stage is reached.

Figure B.1: Institutional Investor Flip



(Figure copied directly from Bolinger, Harper, and Karcher (2007, p. 24))

## B.2 DERIVATION OF THE LIKELIHOOD FUNCTION

Let  $C_i$  = installation cost/nameplate/1000,  $M_i$  = annual generation/nameplate/1000. Then the two equations to be estimated are

$$C_i = X_i \gamma + \sigma_u u_i \tag{B1}$$

$$G_i = \mathbb{1} \left( 0.3C_i - p * 0.15k_1 C_i + \sigma_\epsilon \epsilon_i > p * k_2 M_i \right) \tag{B2}$$

where  $C_i$  is observed if and only if  $G_i = 1$ . Assume  $u_i, \epsilon_i$  are i.i.d.  $\mathcal{N}(0, 1)$  with  $cov(u, \epsilon) = \lambda$ .

$$\begin{pmatrix} u_i \\ \epsilon_i \end{pmatrix} \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \lambda \\ \lambda & 1 \end{bmatrix} \right)$$

Since the equation determining subsidy choice is in dollars, there is no need to normalize one of the variances  $(\sigma_u, \sigma_\epsilon)$  to 1.

Since  $C_i$  is observed if and only if  $G_i = 1$ , the likelihood of observation  $i$  is

$$f(C_i, G_i | X_i, M_i; \theta) = f(C_i, G_i = 1 | X_i, M_i; \theta)^{G_i} * Pr(G_i = 0 | X_i, M_i; \theta)^{1-G_i}$$

where  $\theta = (p, \gamma, \sigma_1^2, \sigma_2^2)$ .

1. Starting with the first component  $f(C_i, G_i = 1 | X_i, M_i; \theta)$ :

$$f(C_i, G_i = 1 | X_i, M_i; \theta) = Pr(G_i = 1 | X_i, M_i, C_i; \theta) * f(C_i | X_i, M_i; \theta)$$

i)  $Pr(G_i = 1 | C_i, X_i, M_i; \theta)$

$$\begin{aligned} &= Pr\left(C_i * (0.3 - 0.15 * p * k_1) + \sigma_\epsilon \epsilon_i > p * k_2 M_i\right) \\ &= Pr\left(\epsilon_i > \frac{1}{\sigma_\epsilon} (p * k_2 M_i - C_i * (0.3 - 0.15 * p * k_1))\right) \end{aligned}$$

Since  $C_i = X_i \gamma + \sigma_u u_i$ , each  $X_i, C_i, \gamma$  implies a unique  $u_i = 1/\sigma_u * (C_i - X_i \gamma)$ , so  $Pr(G_i = 1 | C_i, X_i, M_i; \theta) = Pr(G_i = 1 | C_i, u_i, M_i; \theta)$ . Using properties of bivariate normal random variables,  $F_{\epsilon|u}() \sim \mathcal{N}(\lambda u, 1 - \lambda^2)$ .

$$\begin{aligned} &= Pr\left(\epsilon_i > \frac{1}{\sigma_\epsilon} (p * k_2 M_i - C_i * (0.3 - 0.15 * p * k_1))\right) \\ &= 1 - \Phi\left(\left[\frac{1}{\sigma_\epsilon} (p * k_2 M_i - C_i * (0.3 - 0.15 * p * k_1)) - \lambda u_i\right] / \sqrt{1 - \lambda^2}\right) \\ &= \Phi\left(\left[\frac{1}{\sigma_\epsilon} (C_i * (0.3 - 0.15 * p * k_1) - p * k_2 M_i) + \lambda u_i\right] / \sqrt{1 - \lambda^2}\right) \end{aligned}$$

ii)  $f(C_i|X_i, M_i; \theta)$

$$= \frac{1}{\sigma_u} \phi\left(\frac{C_i - X_i\gamma}{\sigma_u}\right)$$

Putting together i) and ii) gives

$$f(C_i, G_i = 1|X_i, M_i; \theta) = \Phi\left(\left[\frac{1}{\sigma_\epsilon}(C_i * (0.3 - 0.15 * p * k_1) - p * k_2 M_i) + \lambda u_i\right] / \sqrt{1 - \lambda^2}\right) * \frac{1}{\sigma_u} \phi\left(\frac{C_i - X_i\gamma}{\sigma_u}\right)$$

2. Now the second component  $Pr(G_i = 0|X_i, M_i, ; \theta)$ :

$$\begin{aligned} Pr(G_i = 0|X_i, m_i, ; \theta) &= Pr\left((X_i\gamma + \sigma_u u_i) * (0.3 - 0.15 * p * k_1) + \sigma_\epsilon \epsilon_i < p * k_2 M_i\right) \\ &= Pr\left(X_i\gamma * (0.3 - 0.15 * p * k_1) + \sigma_u u_i * (0.3 - 0.15 * p * k_1) + \sigma_\epsilon \epsilon_i < p * k_2 M_i\right) \\ &= Pr\left(\sigma_u u_i * (0.3 - 0.15 * p * k_1) + \sigma_\epsilon \epsilon_i < p * k_2 M_i - X_i\gamma * (0.3 - 0.15 * p * k_1)\right) \end{aligned}$$

The bivariate normal assumption on  $(u, \epsilon)$  implies  $(0.3 - 0.15 * p * k_1)\sigma_u u_i + \sigma_\epsilon \epsilon_i \sim \mathcal{N}(0, (0.3 - 0.15 * p * k_1)^2 \sigma_u^2 + \sigma_\epsilon^2 + 2(0.3 - 0.15 * p * k_1)\sigma_u \sigma_\epsilon \lambda)$ . Let  $(0.3 - 0.15 * p * k_1)^2 \sigma_u^2 + \sigma_\epsilon^2 + 2(0.3 - 0.15 * p * k_1)\sigma_u \sigma_\epsilon \lambda \equiv \mathbb{V}$ .

$$Pr(G_i = 0|X_i, M_i; \theta) = \Phi\left(\frac{p * k_2 M_i - X_i\gamma * (0.3 - 0.15 * p * k_1)}{\sqrt{\mathbb{V}}}\right)$$

3. Putting the components together:

$$\begin{aligned} f(C_i, G_i|X_i, M_i; \theta) &= f(C_i, G_i = 1|X_i, M_i; \theta)^{G_i} * Pr(G_i = 0|X_i, M_i, ; \theta)^{1-G_i} \\ &= \left[\Phi\left(\left[\frac{1}{\sigma_\epsilon}(C_i * (0.3 - 0.15 * p * k_1) - p * k_2 M_i) + \frac{\lambda}{\sigma_u}(C_i - X_i\gamma)\right] / \sqrt{1 - \lambda^2}\right) * \frac{1}{\sigma_u} \phi\left(\frac{C_i - X_i\gamma}{\sigma_u}\right)\right]^{G_i} * \Phi\left(\frac{p * k_2 M_i - X_i\gamma * (0.3 - 0.15 * p * k_1)}{\sqrt{\mathbb{V}}}\right)^{1-G_i} \end{aligned}$$

4. Taking the log:

$$\begin{aligned} \ell_i(C_i, G_i | X_i, M_i; \theta) = & G_i \log \left( \Phi \left( \left[ \frac{1}{\sigma_\epsilon} (C_i * (0.3 - 0.15 * p * k_1) - p * k_2 M_i) + \frac{\lambda}{\sigma_u} (C_i - X_i \gamma) \right] / \sqrt{1 - \lambda^2} \right) \right) \\ & + G_i \log \left( \frac{1}{\sigma_u} \phi \left( \frac{C_i - X_i \gamma}{\sigma_u} \right) \right) + (1 - G_i) \log \left( \Phi \left( \frac{p k_2 M_i - X_i \gamma * (0.3 - 0.15 p k_1)}{\sqrt{\mathbb{V}}} \right) \right) \end{aligned}$$

$$\text{where } \mathbb{V} \equiv (0.3 - 0.15 * p * k_1)^2 \sigma_u^2 + \sigma_\epsilon^2 + 2(0.3 - 0.15 * p * k_1) \sigma_u \sigma_\epsilon \lambda.$$

I assume observations are drawn independently from the same joint distribution, so the joint likelihood I use for estimation is the following:

$$\ell(\mathbf{C}, \mathbf{G} | X_i, M_i; \theta) = \frac{1}{N} \sum_{i=1}^N \ell_i(C_i, G_i | X_i, M_i; \theta)$$

### B.3 ESTIMATES OF AVERAGE ANNUAL GENERATION

For estimation, I use a measure of average annual generation for each project. To construct this, I average across realized annual generation for 2010-2014. I only use generation numbers from full years after a project began operation. This means the average is over two to five years of data for each project. The following table breaks down projects by the number of observed years of generation.  $cf_i$  is the average capacity factor for project  $i$  across all years of observed generation. The table reports the mean and standard deviation of this value across projects. It also reports the mean across projects of the within project standard deviation of annual generation across years.

Years of generation	Projects	Capacity factor ( $cf_i$ )	SD $cf_i$	Within project SD $cf_{it}$
2	55	0.328	0.068	0.019
3	54	0.321	0.077	0.020
4	38	0.330	0.071	0.026
5	68	0.312	0.064	0.026
Total	215	0.321	0.070	0.023

#### B.4 REGION DEFINITIONS

Table B.1: Regions used as explanatory variables

<i>Region</i>	<i>States</i>
Great Lakes	IL, IN, MI, OH, WI
Interior	CO, IA, KS, MN, MO, MT, ND, NM, NE, OK, SD, TX, WY
Northeast	CT, MA, ME, NH, NJ, NY, PA, RI, VT
Southeast	AL, AR, DE, FL, GA, KY, LA, MD, MS, NC, SC, TN, VA, WV
West	AZ, CA, ID, NV, OR, UT, WA

Regions are from Berkeley Labs 2012 Wind Market Intelligence Report. Projects in AK and HI are not assigned to any region and all eligible projects built in the Southeast elected the grant; projects in these regions are not included in the empirical analysis.



## B.5 HETEROGENEITY IN VALUATION BY YEAR OF PROJECT COMPLETION

I also estimate a model that allows owners' valuation for non-refundable tax credits to vary depending on the year the wind project began operation. Point estimates suggest that this valuation,  $p_i$ , was lowest for projects completed in 2010 and increased over time as the economy recovered. The estimate for 2009 of 0.99 is counterintuitive, but a plausible explanation is that projects completed in early 2009 already had tax equity deals for the PTC lined up before the introduction of the grant program. While they were technically eligible for the grant program, these projects may not have seriously considered it.

Table B.2: Estimates allowing for heterogeneity in  $p$  by year

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$$p = \alpha_0 + \alpha_1 * 2010 + \alpha_2 * 2011 + \alpha_3 * 2012$$

$\alpha_0$	0.985	0.071	$\sigma_u$	296	24
$\alpha_1$	-0.218	0.095	$\sigma_\epsilon$	146	31
$\alpha_2$	-0.170	0.089	$\lambda$	-0.144	0.275
$\alpha_3$	-0.137	0.096			

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Nameplate	-3.6	1.4	Developer experience <sup>2</sup>	0.08	0.14
Nameplate <sup>2</sup>	0.011	0.005	Great Lakes	-35	115
Hub height	-10.1	5.3	Interior	-62	117
Rotor diameter	1.2	2.7	Northeast	302	91
Indian/Chinese turbine manuf	-336	153	t	-202	49
Housing cost differential	243	217	t <sup>2</sup>	-204	48
Developer experience	-8.6	6.7	t <sup>3</sup>	75	40
Constant	3,120	384	N	215	

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Estimates assume a real discount rate of 7 percent. Sample is projects over 10MW built by IPPs. 2010 is an indicator for if the project began operation in 2010; 2009 is the omitted year. SE clustered by state.

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