QUEEN'S UNIVERSITY

Plugging In To Green Energy

The Demand for Renewable Energy

in the US and Ontario

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I review markets for green energy to assess the impact of changes in policy and prices on customer participation. I estimate several models and conclude that a one cent increase in the price for green energy causes a greater than one percent fall in the number of customers in the market. I also find that states with Feed-in Tariff policies have half to one percent higher customer participation rates than those without such policies.

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1. INTRODUCTION

The electricity we demand in our modern lives must be produced every minute of every hour of every day. Historically, this production occurred in large centralized plants that generated power as it was demanded. Much of this power was produced by burning fossil fuels—and emitting greenhouse gases—to produce steam. While large scale production of this nature still has its place, the combined pressures of fuel scarcity and climate change have led to new interest in producing power from cleaner, renewable resources. This shift towards renewable energy has been abetted by government policies aimed at curbing emissions and by the interest of consumers who choose to purchase renewable electricity.

Consumers who buy renewable electricity do not receive a different type of power in their homes, as all consumers are connected to the same electricity grid. Their power is "green" because their utility company supplies them with "environmental attributes." Renewable energy facilities—powered by wind, solar, small scale hydro, biomass and other sources deemed to be environmentally friendly—feed energy into the grid like any other electricity producer, but each megawatt of energy produced at these facilities creates a by-product called an environmental attribute. It is the environmental attributes which are sold to consumers as green energy.

Green energy sales accounted for less than one percent of all electricity sales in the US in 2009, but sales have been steadily growing across North America. [1] Recently the Ontario Power Authority (OPA) has begun to investigate the possibility of selling environmental attributes in Ontario. This program would use the environmental attributes the OPA has collected through contracts it holds for renewable energy, which include the Province of Ontario's Feed-in Tariff program.[2]

[1] (Bird & Sumner, Green Power Marketing in the United States: A Status Report, 2010)
[2] A Feed-in Tariff offers a guaranteed price for production from renewable facilities.

To date, there has been little research on the price sensitivity of consumers in the market for green energy. Research into green energy markets has typically centered on addressing shortcomings in the wholesale market. The focus of this paper is to examine residential households' demand for renewable energy. I offer insight into the impact of changes in prices and income on demand and characterize the differences between states with different renewable energy policies.

Using newly available data from U.S., I assess the effect of changes in prices and income on the number of consumers who choose to buy green energy. I first estimate a generalized estimating equation to measure the influence of income and prices on the proportion of customers who buy green energy, controlling for differences in state policies. The results from this model show that a one cent increase in green energy prices causes a half a percentage point fall in participation rates. I use an instrumental variable technique with both simultaneous and single equation models to control for the endogeneity of prices and customer numbers. These results show that a one cent increase in the green premium causes a greater than one percent fall in the number of green customers. In addition, states with Feed-in Tariffs (FIT) or Renewable Portfolio Standards (RPS)[3] have approximately one percent higher green customer numbers than those that have no such policies. It appears that state level policies which aim at increasing production have a positive impact on the up-take of green energy by demanders. I hypothesize that large capacity additions might positively affect the demand for renewable energy by attracting media—and consumer—attention, but I find no evidence to support this hypothesis.

The next Section presents some background on markets for renewable energy in Ontario and in the United States. Section 3 reviews some existing research on the demand for renewable energy and outlines some of the challenges of modeling this market. Section 4 presents the data and

[3] An RPS program mandates that a utility purchase a minimum quantity of renewable energy in a given year.

Section 5 the results. Section 6 offers some concluding remarks for Ontario and suggests some areas for further research.

2. BACKGROUND AND CONTEXT

To measure the demand for green energy, it is important to understand some of the structural features of green energy markets. In this section I outline the structure of renewable energy markets, present some details relevant for Ontario, and discuss some of the policies which have shaped renewable energy markets in the U.S.

2.1 GREEN POWER AND RENEWABLE ENERGY

Renewable energy, green power, and green energy all refer to electricity which has been generated from renewable facilities, which include solar, wind, biogas, biomass and small scale hydroelectric facilities. The energy is renewable because the fuel used to produce it originates either from a renewable source or from the waste of some other process. For example, biogas facilities combust gases which have been extracted from decaying organic material (such as methane) to produce steam. Other renewable generators produce steam by capturing waste heat. Such facilities, along with more widely known renewable energy generators such as wind turbines and solar collectors, are deemed to be qualifying renewable facilities through state statutes.

The energy that these qualifying facilities produce is tracked and traded in North America with Renewable Energy Certificates (RECs).[4] Each qualifying facility is registered in a REC tracking system; one REC is issued for every megawatt of renewable energy each registered facility produces. RECs are tracked with a unique serial number, and are retired within the tracking system when the renewable attributes they contain are sold to a final consumer.[5]

[4] RECs are also referred to as Green Energy Certificates or Green Tags.
[5] This is designed to prevent double counting of environmental attributes.

RECs are sold to a number of customers including utilities and marketers who sell green power. These resellers ensure that each customer's demand for green electricity is met with RECs. In addition, RECs are bought by large commercial or industrial customers directly, and they are also converted into carbon offsets and sold in the offset market. In this context, the trade in RECs is the same as trade in renewable energy. To analyze the residential demand for renewable energy, therefore, I review some important features of REC markets. For example, states which have legislated that a certain portion of energy must be met with renewable production (through an RPS policy, for example) require utilities to show compliance with RECs. Customers in states with an RPS policy are therefore served by a utility who must sell a prescribed amount of green energy. It is likely that such customers will face different green energy options compared with customers in states that do not have an RPS policy.

The definition of a REC (for compliance in RPS programs) depends on state legislation, but the content of a REC varies with each state's emissions policies. Most REC definitions in state statutes follow broadly the same pattern: "all renewable or environmental attributes associated with the production of electricity from eligible renewable resources." [6] RECs are distinguished by direct attributes, including energy source, generation technology, plant location and certificate vintage. RECs also contain *derived attributes*—avoided emissions—which depend critically on local emissions policy.

Specifically, carbon caps or emissions standards can eliminate the avoided emissions contained in a REC, since renewable energy that replaces non-renewable energy will, under a binding cap, shift emissions to another polluter. A renewable generator will reduce overall

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[6] (Environmental Tracking Network of North America, 2008) See for example, the California Public Utility Commission (CPUC Decision 08-08-028) which defines REC as including "all renewable and environmental attributes associated with the production of electricity from the eligible renewable resources, including any avoided emissions of pollutants to the air, soil, or water; any avoided emissions of carbon dioxide . . . or any other GHGs that have been determined by the United Nations International Panel on Climate Change, or otherwise by law, to contribute to the actual or potential threat of global climate change; and to the reporting rights to these avoided emissions…". There is a footnote that explains that avoided emissions may have no value for GHG compliance purposes.

emissions if the energy it produces replaces energy that would otherwise be produced by a fossil fueled—and emitting—generator. For a REC to contain an emissions reduction value, the REC must encourage generation above what would be built without the REC. Further, there must be no carbon cap in place: under a carbon cap, production from a renewable facility will make the cap less binding on others, but will not reduce emissions.[7] The potential for a REC to contain avoided emissions attributes changes its potential uses, in turn affecting its value.[8] As a consequence, the difference in value between a REC produced in a region with a carbon cap and one produced in a region with no carbon cap will affect the price of green energy in those regions.

The market for green energy is complicated because many states have introduced large subsidization programs for renewable energy. Normally one expects that high cost, non-renewable energy would induce new supply from renewable sources. Rare however has the price of non-renewable energy been sufficiently high to induce this supply response. Places with strong green constituencies have instead elected to subsidize the supply of renewable energy. The justification for subsidies is partly exculpatory (we will produce fewer emissions than we have been producing) and partly sold to the public as "economic development." The argument is that the regions which develop the capacity to produce wind mills and solar panels will export this technology to regions which adopt green technology in the future.

Subsidization generally takes two forms: Feed-in Tariff (FIT) policies and Renewable Portfolio Standards (RPS) policies. The former offers independent green energy producers guaranteed rates for the energy they supply. This encourages the proliferation of wind turbines and solar collectors, as can be seen throughout rural Ontario since the introduction of the FIT program, for example. An RPS policy is a contract with the government for an established energy supplier to

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[7] For more detail, see Gillenwater, Redefining RECs-Part 1: Untangling Attributes and Offsets, 2008 and Gillenwater, Redefining RECs-Part 2: Untangling Certificates and Emissions Markets, 2008. Emissions policies often include special provisions for electricity generators to account for this feature.

[8] Carbon cap policies with alternative compliance payments will limit the emissions value a REC might contain.

purchase a minimum quantity of renewable energy each year. Under such a scheme, a green household can agree to pay its supplier an above-market price for energy with the understanding that the supplier acquires that power from green sources. Green households are able to purchase power in states which do not have an RPS policy in place, but compared to green households in states with an RPS policy these households may make different choices, even if both households face the same prices. FIT and RPS policies thus play a central role in shaping the choices consumers face in the market for green energy.

2.2 CONTEXT FOR ONTARIO

Since the Electricity Restructuring Act of 2004, Ontario's electricity industry has shifted from promoting competition between generators to ensuring adequacy and reliability through long term planning. The government aims to become a North American leader in reducing emissions and enhancing the availability of renewable energy sources, and to that end it has laid out plans to phase out coal production, stimulate conservation and demand management, and encourage the construction of new renewable energy facilities.[9]

In 2009 the Provincial government introduced the province's Feed-in Tariff (FIT) program with the passage of the Green Energy and Green Economy Act.[10] The Ontario Power Authority (OPA) has the responsibility of developing and executing contracts to implement the FIT program, and has already added approximately 16 MW of new capacity through the FIT program and 47 MW through the microFIT program (for projects of 10 kW or less). Over 3000 MW of new capacity is also under development.[11] The OPA has collected environmental attributes from production under the FIT program and from its contracts with other renewable energy producers.

[9] (Ontario Ministry of Energy, 2010)
[10] The Green Energy and Green Economy Act (GEA) also contains legislation to streamline approvals and grid connection processes for renewable energy projects.
[11] (Ontario Power Authority, June 10, 2011)

Interest in studying renewable electricity markets derives in part from the potential entry of the OPA into the renewable energy market. The OPA has been directed by the Province of Ontario to proceed with a pilot program to track, sell and audit a limited number of environmental attributes collected through the Feed-in Tariff program. [12] Before beginning the pilot program the OPA has expressed interest in developing its understanding of the market for green energy.[13] In this report, I use new data from the U.S. to analyze market demand and prices for green energy. My conclusions are drawn from customer participation and prices for green energy in the U.S., but they might serve as a starting point to understand how changes in prices and income affect customer participation in Ontario.

2.3 GREEN ENERGY MARKETS IN THE U.S.

Renewable energy is a small but growing segment in the U.S. electricity market. Before reviewing some the policies which have shaped the market for renewable energy, I present some statistics from 2009 to illustrate the size and scope of this market:[14]

- 0.8% of total power sales in the U.S. were for green power products.
- Residential customers accounted for 54% of regulated green pricing programs and 69% of competitive green energy sales.
- Average participation in utility green pricing programs was 2.0%.
- The average price in utility green pricing programs was 1.75 cents per kWh.
- Consumers spent an average of $5.40 per month on green power.

States have introduced a number of policies aimed at encouraging the production of renewable energy. These include Renewable Portfolio Standards (RPS), Feed-in Tariffs (FIT), and policies which allow consumers to generate their own electricity and pay only for the additional

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[12] (Ministry of Energy, February 17, 2011)
[13] Currently, consumers in Ontario have the option of buying renewable energy products offered by Bullfrog Power, Just Energy, and Direct Energy. These retailers offer green products by purchasing and retiring RECs on behalf of their green customers.
[14] These statistics are drawn from Bird & Sumner, Green Power Marketing in the United States: A Status Report, 2010.

energy they consume (net-metering programs). These initiatives are not limited to the state level: Austin Texas, for example, has announced plans to become carbon neutral by 2020 in part through purchasing renewable energy for municipal facilities.[15] I discuss FIT and RPS policies below, as RPS policies have been the most common policy in the U.S. and FIT policies have special relevance for Ontario.

A Renewable Portfolio Standard (RPS) requires state utilities to meet a specific fraction of their electricity sales with renewable energy. For example, California has set goal of producing 33% of all its electricity with renewable energy by 2020, and New York has a goal of producing 29% of its electricity from renewable sources by 2015. While these RPS policies may appear unduly optimistic, it turns out that other jurisdictions, especially in Europe, have set and reached similar or even higher targets. Both Denmark and Finland, for example, each currently produce around 30% of their energy with renewable resources. Germany currently produces 15% and has set a target of 25% to 30% by 2020. Italy produces 17% and Spain 21%, while the UK produces 5% and has a goal of 15% by 2015.[16] These jurisdictions surely face different political climates and resource capabilities, but their accomplishments demonstrate that seemingly unattainable goals may not be so far out of reach.

RPS policies require utilities to comply with the standard by purchasing RECs, which are defined through state statutes.[17] Definitions in most states are similar, but discrepancies between states have led to drastic differences in REC prices. For example, while RECs are typically traded for $5 to $10, RECs from solar energy in New Jersey have traded at over $400.[18] I expect that high prices for RECs will translate into higher prices for renewable energy at the retail level, which in turn will affect green customer numbers.

[15] City of Austin Resolution 20070215-023, February 15, 2007.
[16] (REN21, 2010)
[17] Some states allow utilities to purchase RECs from other regions, referred to as Tradable RECs.
[18] (Bird & Sumner, Green Power Marketing in the United States: A Status Report, 2010)

While not as common as RPS programs, several states and utilities have adopted Feed-in Tariffs.[19] These programs offer guaranteed payments for the power produced by qualifying renewable facilities. Washington State, for example, introduced a FIT for solar, wind, and biogas facilities in 2005, with payments ranging from twelve to fifty-four cents per kWh.[20] Although FIT policies are not as widespread as RPS programs, they have a direct impact on the availability of renewable energy, which in turn will affect the prices utilities charge. The introduction of a FIT generally increases renewable energy production, raising the number of RECs available and putting downward pressure on prices. However, utilities that must pay for the FIT program may set higher prices for green energy to recoup some of their costs. At the same time, FIT programs attract publicity, which could affect demand by raising consumer awareness about renewable energy.

Another important modeling consideration is the introduction of wholesale competition in a number of states in the early 2000s. Some of these markets failed to function satisfactorily (perhaps most vivid was California), while others successfully introduced competition in the generation and retail sides of the electricity market. Deregulation has added another dimension to analyzing energy markets: states which have introduced competition have allowed customers to sign up with retailers of their choice. Deregulated and non-deregulated states may experience differences in customer participation in green energy markets if competitive retailers in deregulated states are more or less effective at promoting green energy than regulated utilities in regulated states.

2.4 LESSONS LEARNED

Fledgling markets for green energy in the U.S. have faced a number of challenges, including defining the content of RECs and using RECs to finance new projects. The costs developers and utilities face for verifying, monitoring, and contracting for RECs have varied considerably on

[19] These include California; Gainesville, Florida; Oregon; two utilities in Vermont; Washington; and several utilities in Wisconsin.
[20] (Couture & Cory, 2009)

account of discrepancies in REC definitions between states.[21] These transaction costs primarily affect a utility's ability to meet RPS targets, as there is little evidence to suggest that consumers prefer one type of REC over another.[22] However, differences in REC prices will affect the price for green energy at the retail level.[23]

Defining RECs and the environmental attributes they contain has not been without controversy. Some critics have suggested that RECs do not represent bundles of environmental attributes, but rather that they are financial vehicles to encourage the construction of additional renewable capacity. This perspective implies that when RECs are paid to facilities which would be built even in the absence of REC payments, they are inefficient subsidies.[24] Why? If RECs encourage renewable generation, they should only encourage generation that cannot be economically built. The owner of a generator which would be built even without revenue from REC sales would receive REC payments simply for owning capacity. Unless REC sales increase the construction of additional facilities, they are simply a subsidy for capacity. If RECs are in fact subsidies, retail consumers who buy green energy are not in fact buying a commodity. Rather, they are making an incentive payment to renewable energy producers. This distinction could affect retailer's ability to market "green energy."

The view of RECs as incentive payments leads to the issue of financing new renewable energy projects: because renewable generation typically involves high costs for initial construction but relatively low costs for operation, producers might prefer an upfront payment rather than an uncertain stream of revenue from REC sales. This hampers the ability of RECs to encourage the construction of new capacity. As more participants have entered the REC market, however,

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[21] (Sovacool, 2011)
[22] Many green sales programs offer specific types of green energy: a customer who signs up with Minnesota Power's WindSense Program, for example, will be sure to receive RECs purchased from wind farms only. (U.S. Department of Energy, 2011)
[23] For example, the city of Talahasee in Florida offers renewable energy from Solar at a premium of over 11 cents, while offering a blended renewable energy product at a premium of one and a half cents. (U.S. Department of Energy, 2011)
[24] See Gillenwater, Redefining RECs-Part 1: Untangling Attributes and Offsets, 2008.

producers and consumers have established a better understanding of REC prices. This understanding has made it easier for developers to obtain long term contracts for RECs, which has in fact allowed RECs to serve as financial instruments encouraging the construction of new generation.[25]

3. THEORY AND METHODS

I turn now to some previous analyses on renewable energy markets before outlining my approach to modeling renewable energy demand. I review a paper prepared by the National Renewable Energy Laboratory (NREL) which forecasts green energy demand in the U.S. and I present some conclusions from two survey papers on customer attitudes toward green energy. Using some consumer demand theory, I outline some modeling issues before describing the econometric methods I use in the rest of the paper.

3.1 PREVIOUS RESEARCH

The NREL has published an analysis of the supply and demand balance of renewable energy in the U.S. This study uses RPS targets and present day growth rates in voluntary renewable energy sales to forecast demand to 2015. [26] Linearly extrapolating from current growth rates makes for a simple forecast but ignores the factors which influence final demand. A model which includes these factors, while making forecasting more difficult, will measure the impact of price changes on final demand.

A 1999 survey by the NREL on consumer attitudes to renewable energy found that 70% of consumers were willing to pay at least five dollars per month for renewable energy and that 21%

[25] (Bird & Holt, Emerging Markets for Renewable Energy Certificates: Opportunities and Challenges, 2005)
[26] (Bird, An Examination of the Regional Supply and Demand Balance for Renewable Electricity in the United States through 2015, 2009)

would pay fifteen dollars or more. The survey also revealed that consumers were poorly informed about the option to purchase renewable energy: of consumers who were not active in the renewable energy market (those who were not purchasing and had not enquired about purchasing green energy) 61% reported that they were not familiar with the term "green energy."[27]

The NREL recently updated this survey, finding that 80% of consumers in the US cared about renewable energy. Moreover, 26% would be willing to spend five to twenty dollars more per month for renewable energy (five percentage points higher than the 21% who would pay fifteen dollars or more in 1999). Of these consumers 7% had purchased at least some renewable energy for their home. Only 14%, however, were aware that they could purchase renewable energy. Given the twelve percentage point gap between those who were willing to pay for green energy and those who were aware that they could, the NREL concluded that consumer awareness has played a central role in determining the number of customers who purchase green energy.[28]

3.2 OBJECTIVE AND CHALLENGES

Economic theory suggests that more consumers will buy green energy if the price falls or if their income increases. In addition, I hypothesize that the price consumers are currently paying for grey electricity (that is, regular non-renewable electricity) might also affect incentives to buy green energy. A higher price for grey power might increase the likelihood that consumers seek out alternative options. Alternatively, higher grey power prices might lower the participation rate if consumers try to minimize their electricity bill. I include several variables which proxy for the average consumer's awareness of the availability of green energy. Part of this awareness probably derives from state policies affecting green energy markets (such as FIT or RPS programs), as the adoption of these policies in key areas might attract media attention. Additionally, the construction of large new renewable projects could be featured in local media, raising customer awareness

[27] (Farhar, 1999)
[28] (Rogers, 2011)

about the option to purchase green energy. Thus I use FIT policies, RPS policies, and renewable capacity additions to proxy for differences in consumer awareness.

The choice to introduce renewable energy subsidy programs may not be exogenous: states might only introduce these policies if they already have a significant number of green customers. The data disputes this theory, however. Comparing average participation rates in states that adopt a FIT before and after the policy is introduced suggests that the introduction of FIT policies increases green customer participation rates. Average participation in residential green energy markets before the introduction of a FIT policy is just over seven-tenths of a percent, while after the FIT policy is introduced participation rates increase to almost two percent (see Table 1). Lest this increase be attributed to overall increases in customer participation, observe that the introduction of an RPS policy has had no effect on the average customer participation rate. In fact, the average participation rate has fallen following the introduction of an RPS policy, from seven-and-a-half-tenths to six-tenths of a percent (see Table 1). T-tests for statistical significance suggest that customer participation rates have statistically increased in states which have introduced a FIT policy, while they have remained unchanged in states which have introduced an RPS policy. (The t-test for equivalence of means produced a p—value of .0095 when comparing the means before and after the introduction of a FIT policy and .4396 when comparing the means before and after the introduction of an RPS policy.)

Table 1: Customer Participation Before and After RPS and FIT Policies are Introduced

	Customer Participation (%)	
	Before	After
FIT	0.72	1.89
RPS	0.75	0.63

I turn now to a review of the models. I use a panel of data to exploit differences between states in the timing of the introduction of new policies. I account for correlation over time and fixed effects by using variance estimators robust to serial correlation and regional dummy variables which account for inherent regional differences. These regional differences primarily reflect the propensity to install renewable capacity, which is influenced by elements such as wind speed and exposure to sunshine.[29]

Figures 3 and 4 in Appendix A show the availability of sun and wind in the U.S. Using state level fixed effects (a dummy variable for each state) would account for these differences but would make estimation intractable. I control for the more broadly defined U.S. census regions of West, Midwest, South and Northeast with regional dummy variables, as the potential availability of various renewable energy sources is correlated with these regions: Figure 3 shows that more sun is available in the West, for example, than in the Northeast. Similarly, Figure 4 shows that more wind is available in the Midwest than in the South. Including regional dummy variables will therefore control, in part, for the differences in each region's ability to produce renewable energy.

In order to examine the relationship between the proportion of customers who buy green energy and average income and prices, I use an estimation framework that can accommodate a dependent variable bounded between zero and one. The traditional approach—using log transformations—is intractable because of the limited variation in prices and participation rates. One of the seminal papers on estimating models with this kind of dependent variable and without resorting to log transformations used quasi-likelihood methods to estimate a General Linear Model (GLM). [30] However, the GLM framework cannot handle observations correlated through time. To handle such time dependence I rely on a generalized estimating equation (GEE). The GEE framework can also be estimated with quasi-likelihood methods, and the application of GEE to panel data is well documented. [31]

[29] (Short, Balir, Heimiller, & Singh, 2003)
[30] (Papke & Wooldridge, 1996)
[31] (Hardin & Hilbe, 2003)

To estimate this equation I specify the participation rate as a function of the price of green power, average personal income, as well as dummy variables for states with FIT, RPS, and deregulation policies. To produce consistent estimates these variables are assumed to be exogenous.[32] To test the effect of new capacity additions I include the capacity variable in several specifications: in megawatts, as a percentage of total capacity and as a percent change from the previous period.

The estimated equation represents an average across all states. However, the coefficient estimates are difficult to interpret because the model is non-linear: the effect of changes in each variable depends on the level of the variable itself. One method to interpret the results is to record how the estimated participation rate changes when one of the variables of interest changes, with all other variables at the mean. For example, I measure the average impact of a one cent increase in green energy prices by evaluating the equation at the mean price and at a price one cent higher, while holding all other variables at their mean. The change in the estimated participation rate reflects the average impact of a one cent increase in the green energy price.

To obtain coefficient estimates that are simpler to interpret, I also model the number of green customers directly.[33] I estimate the impact of changes income and prices on green customer numbers using an instrumental variable approach and controlling for different state policies. This estimation framework will account for the time dependence between observations, fixed regional effects, and the endogeneity of price and quantity.

I examine both demand and supply together using a three stage estimation routine. This estimation routine accounts for both the endogeneity of prices and customer numbers, and the correlation between the unobserved errors in the demand and supply relationships. This correlation arises because some states have both high green customer numbers and high renewable

[32] The assumption that the price is exogenous to the participation rate is valid only if prices affect the number but not the proportion of green customers in each state.
[33] I use the log of the number of green customers so that coefficient estimates reflect percent changes.

energy production levels connected to some unobserved factor. For example, if higher capacity increases customer participation because customers choose to live in a region with higher renewable energy levels, then the level of capacity might have a systematic effect on demand. This correlation, were it ignored, would lead biased coefficient estimates.

To specify the demand equation I include variables on the price of green and grey power, income and income squared, as well as FIT, RPS, and deregulation policy dummies. For the supply side, I include variables on green energy production and state GDP. While large capacity additions might affect demand, through, for example, coverage in local media, I assume that the production of green energy does not affect the average customer's choice to buy green power.[34]

To conduct inference I turn to a single equation framework, as robust standard errors are difficult to obtain in a three-stage least squares estimation routine. I maintain the same specification for demand from the simultaneous equation estimation above and specify a single equation instrumental variable model. The instruments are drawn from the supply relationship in the simultaneous equations model. This single equation model captures only the demand side of the market, but inference is robust to arbitrary heteroskedasticity and correlation within each state over time. Estimation is accomplished with a general method of moments estimator in conjunction with a cluster weight matrix. Such estimation is readily performed in Stata using the IVREG2 estimator package.[35]

4. DATA

Drawing on the economic theory outlined above, I obtained the following data: the number of green customers and the participation rate in residential green energy markets; prices, both for green and grey power; renewable energy production and capacity in each state; policy indicators

[34] A scatter plot between customer participation and renewable energy production shows no obvious relationship between the two variables.

[35] (Baum, Schaffer, & Stillman, 2002)

for FIT, RPS, and deregulation; and some exogenous variables to control for customer characteristics, including income and state GDP. I discuss each of these variables below. As far as I am aware, I am the first to use this data on green customer numbers to study the effect of price changes on the residential demand for green energy.

I calculated the proportion of residential green customers in each state (the green energy market participation rate) by dividing the number of green customers by the total number of customers in each state.[36] I obtained this data at the utility level from the Energy Information Administration (EIA) website. The participation rate includes all residential green customers, but it does not take into account how much renewable energy each customer buys.[37] Customers can typically sign up to purchase a fixed block or a percentage of their total consumption. In fact, the average renewable sales per customer was approximately half that of all (grey power) customers.[38] However, because data on green sales was only available for three years, my analysis used data on green customer numbers (which was available for the period from 2001 to 2009).

I obtained data on the premium for green energy in each state from the list of green pricing programs on the U.S. Department of Energy's Green Power Network website. Using the start date for each program I formed an average of all programs available in each state each year. I constructed the price of grey power (that is, the retail price of regular non-renewable electricity) from data on the sales (in MWh) and revenue (in dollars) for all utilities in each state. The price is simply the revenue divided by the sales, converted into cents per kWh. The EIA has also collected sales and revenue data for green pricing programs since 2007. However, numerous errors in this data, as well as the short time period for which it was available, prevented its use in this analysis.

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[36] Customers refer to households that a utility meters and bills.

[37] 99% of residential customers purchase green energy through their local utility or marketer rather than through wholesale REC markets (Rogers, 2011).

[38] The t-test for equivalence between average green energy sales and average sales to all residential customers has a p-value of zero to four places.

Summary statistics for customer participation, green premiums and grey power prices for residential consumers can be found in Table 2.

I created several variables using data from the Database of State Incentives for Renewable Energy (DSIRE). I created dummy variables for states which have Feed-in Tariff (FIT) programs as well as dummy variables for states with mandated Renewable Portfolio Standards (RPS). To account for differences between regulated versus competitive states, I used information available on the EIA's website on electricity market restructuring to construct a dummy variable for states which have introduced market reforms. These include states with wholesale power markets and with retail competition. A map of restructuring initiatives in the U.S. can be found in Figure 5 in the Appendix.

I constructed variables on renewable and non-renewable generation capacity from data available from the EIA, using existing capacity to 2001 and additions each year from 2001 to 2009. I obtained data on nameplate capacity of each generator in each state, which I classified into non-renewable (coal, petroleum, natural gas and conventional hydro) and renewable (wind, solar, bio energy and small scale hydro). I used this classification to construct a measure of nameplate renewable capacity, as a total number of megawatts and as a percentage of total generation capacity for each state in each year. This measure does not reflect the capacity factors of different generation technologies, but only the installed nameplate capacity: this value is likely to reflect media attention and consumer awareness of renewable energy projects in the state. I also classified data on generator level production by renewable and non-renewable production and formed a variable for renewable production as a percent of total production in each state. Summary statistics for the capacity and production variables can be found in Table 3.

I used the capacity and production variables together to construct a measure of capacity utilization. I divided renewable production by renewable capacity multiplied by the number of hours in a year. This is a coarse measure of state level productive efficiency: states with higher utilization rates have produced more energy from their capacity. This variable, however, reflects neither the capacity factors of different types of generation, nor differences in the generation mix between states.

I obtained several other variables to account for consumer and producer attributes. These included state GDP (in constant 2005 dollars) and average personal income (Average earnings per job), both of which I obtained from the US Bureau of Economic Analysis website. I also obtained the most recent census data (2001) on the percentage of each state's population living in urban areas. These variables constitute all the data used in the analysis below.

5. ANALYSIS AND RESULTS

Before estimating the models discussed above, I present some summary statistics and time series plots of the data to illustrate some differences between states with FIT and RPS policies. Data on customer participation and green energy premiums is plotted over time in Figure 1. This data is divided into three categories: states which have introduced a FIT policy, states which have introduced an RPS policy and states which have introduced neither. [39] The first plot in Figure 1 shows that the green premium has been high in states with FIT policies and has been declining in states with RPS policies. Overall, the average price for green energy ranged from 1.7 to 2.2 cents per kWh. However, the prices in these categories were not statistically different: t-tests for equivalence of means between RPS and non-RPS states and between FIT and non-FIT states produced p-values of .47 and .96 respectively.

[39] The RPS and FIT states include only those states which have introduced the RPS or FIT program; the neither FIT nor RPS classification includes only those states which have not announced plans to introduce FITs or RPS programs.

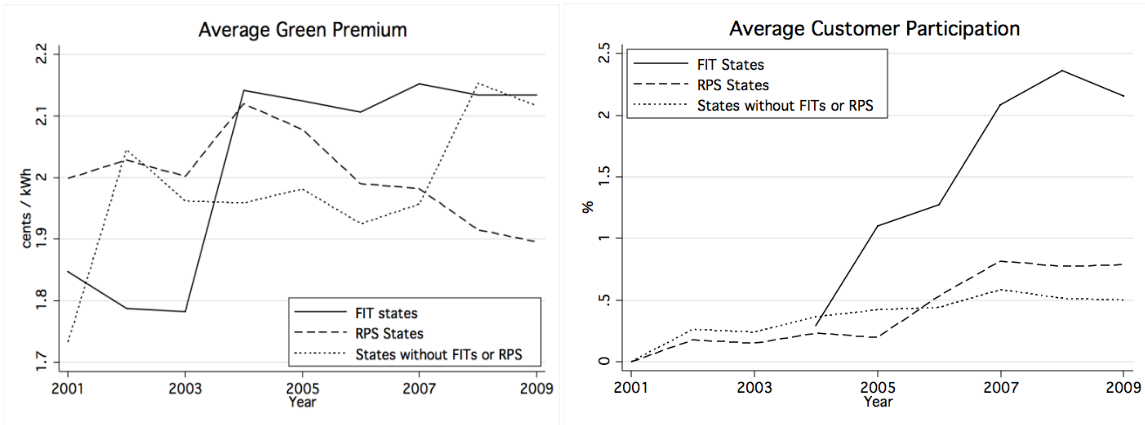

Figure 1: Green Premium and Participation 2001-2009

The second plot in Figure 1 shows the customer participation rate in green pricing programs. This series is plotted by the same three categories: states with FIT policies, states with RPS policies, and states with neither policy. The participation steadily increased in all three categories over the period. Moreover, participation was higher in states with RPS programs and much higher in states with FIT policies—the participation rate in states with FIT policies reached a maximum of two-and-a-half percent versus a rate under one percent in RPS states. The participation rates were statistically different between states with and without these policies: t-tests for equivalence between FIT and non-FIT states and RPS and non-RPS states produced p-values of zero to three significant digits.

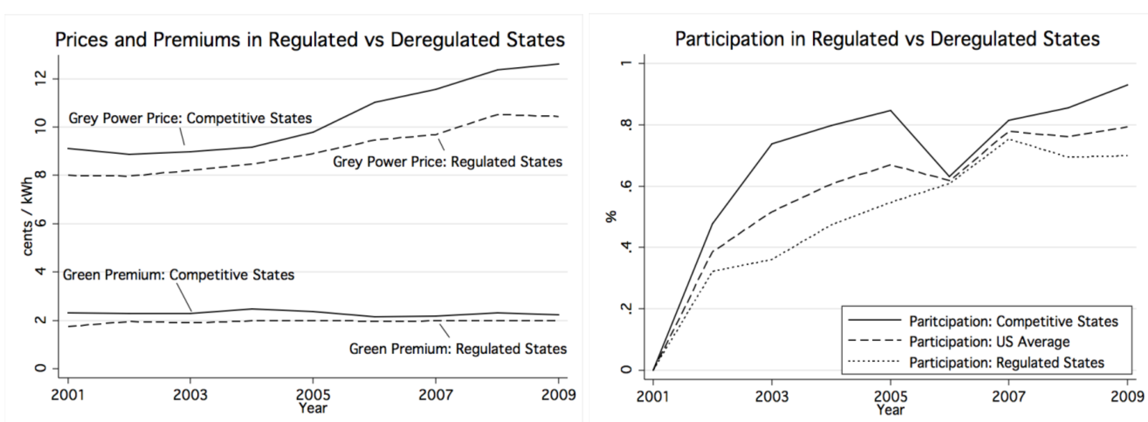

Figure 2: Green Premium and Participation, Regulated and Deregulated States 2001-2009

Using the same data, Figure 2 presents prices and participation rates which are divided into two different categories: states with competitive electricity markets and states with regulated electricity markets. [40] The first panel in Figure 2 shows that the grey power price and the green premium have been higher in states which have attempted deregulation than in those which have remained regulated. The second panel in Figure 2 shows that these states also have had higher participation rates. The p-value for the t-test for the equivalence of average participation rates was 0.0591; for the green premium, 0.0174; and for the grey power price, 0.0000. These t-tests suggest that while the participation rate may not have been statistically different between these categories, the prices certainly were.

Table 2: Participation and Premiums in Green Energy Market

		Participation (%)		Premium (cents/kWh)			Grey Power Price (cents/kWh)
STATES	No. of States	Max	Average	Min	Max	Average	Average
ALL	51	7.06	0.57	0.2	7.3	2.04	9.61
with RPS	22	2.95	0.627	0.2	7.3	2.17	11.92
with FIT	6	7.06	1.85	1.36	4	2.2	10.93
no FIT & no RPS	19	3.53	0.37	0.5	5	1.99	8.17
Deregulated	21	7.06	0.678	0.2	7.3	2.28	10.38
Regulated	30	3.53	0.496	0.5	4.55	1.94	9.07

Table 2 presents summary statistics for prices and participation rates. A few states had very high participation rates (Oregon had the highest rate, 7.06 percent), and others had high green premiums (Arizona had the highest price, over 7 cents per kWh). Recall that the green premium was highest in states with FIT policies; Table 2 shows that states with FIT or RPS policies also had above average grey power prices. The t-test for equivalence between grey power prices in FIT

[40] The deregulated variable includes states which later abandoned deregulation reforms.

states and non-FIT states produced a p-value of .49, suggesting that these prices were not statistically different. In states with an RPS policy, the t-test for equivalence to states without an RPS policy produced a p-value of zero to four significant digits, which suggests that grey power prices were statistically higher in states with RPS policies.

Table 3 presents summary statistics on renewable capacity and production as a proportion of total capacity and production in each state. States with FIT policies had above average renewable production and capacity levels and states without FIT or RPS policies had lower than average renewable production and capacity. States which introduced competition had higher levels of renewable production and capacity compared to regulated states. These features could explain why grey power prices and renewable participation rates were higher in states with FIT policies even though these states also had higher prices for green energy. If participation rates depend on consumer awareness as much as prices, states with high renewable energy levels might also have high participation rates.

Table 3: Renewable Production and Capacity

STATES	No. of States	Production (% of total)	Capacity (% of total)
ALL	51	2.43	5.41
with RPS	19	4.92	7.43
with FIT	22	5.23	9.93
no FIT & no RPS	6	1.16	4.45
Deregulated	21	3.20	6.92
Regulated	30	1.89	4.35

To examine this data more systematically, I pursue the methods laid out in Section 3. I present the results from two types of models to measure the impact of changes in income, prices, and renewable capacity on customer participation. First, I present the results from the GEE model, which measures the proportion of renewable energy customers as a function of average personal income and the price of green power. I included dummy variables for Feed-in Tariffs, RPS policies, and deregulated electricity markets, as well as data on capacity to test the hypothesis that capacity additions influence demand.[41] Estimating this model for all states produced the results presented in the first two columns of Table 4. I also estimated the model controlling for regional effects (using the census regions of Northeast, South, Midwest, and West), the results of which are presented in the last two columns of Table 4.

In both the pooled regression and the regional effects regression, all variables were significant at the ten percent level, while only income, income squared, the renewable capacity utilization rate and the constant term were significant at the five percent level. The regional effects regression included dummy variables specific to each region, which were all significant at the 10% level. The standard errors in Table 4 are robust to misspecification of the within group correlation.[42]

Table 4: XTGEE Estimation Results

	POOLED		REGION EFFECTS	
	Coefficient	Std. Err.	Coefficient	Std. Errr.
greenpremium	-0.3986	0.2180	-.3415	.2432
income	0.2365	0.0518	.2014	.0523
income ^{2}	-0.0018	0.0004	-.0014	.0004
FIT	0.9224	0.5432	.6880	.5323
greenutilization	0.0052	0.0022	.0050	.0023
const.	-11.7528	1.3960	-10.7068	1.3814
no. obs.				305

Comparing the two sets of results, it is clear that the coefficient on the green premium is smaller (in absolute value) and the coefficient on the FIT policy variable is much smaller after

[41] I also included the percent of each state's population living in urban areas, however this variable was insignificant in all models.
[42] (Hardin & Hilbe, 2003, pp. 84-86)

controlling for regional effects, while the coefficients on the other variables are similar. The interpretation of these coefficients is difficult because the non-linearity causes the effect of each variable to change as the variable itself changes. To interpret these results I observed the change in predicted outcomes while changing some variables and holding others at their means. In the pooled model, with each variable at its average, a one thousand dollar increase in average income increased the participation rate by one-tenth of a percent. Similarly, a one penny increase in the green premium caused participation rates to fall by half a percentage point. Finally, states with a FIT policy had, on average, half a percent higher participation rates.

The renewable capacity variable was insignificant in the model, whether specified in megawatts, as a fraction of the total capacity or as a percent change from the previous period. I therefore omitted capacity from the model, concluding that after controlling for income, prices, and state policies, capacity additions do not affect the average participation rate. I found the utilization rate to be significant, however (recall that this variable is based on the energy generated as a percentage of the total available capacity each year). In addition, the grey power price was insignificant and so was omitted. Both the RPS and deregulation dummies were insignificant after including the FIT policy dummy. I tested several lag lengths for the autoregressive error structure, settling on one lag. Additional lags prevented the model from converging (recall that there are only 8 years of observations).

To test the sensitivity of these results I estimated the model omitting several states. California and Texas have very high participation rates, Oregon has a high participation rate and a Feed-in Tariff, while Vermont has a high green premium. Omitting each of these states changed the results only modestly, and in a predictable direction (for example, omitting Vermont lowered the coefficient on the green premium, while omitting Oregon lowered the coefficient on the FIT policy variable). As these omissions produced little change in the overall results, the conclusions drawn above do not appear to depend on any one state.

Above I outlined two models in which the dependent variable is the log of green customers: in the first a system of equations is used to isolate demand from supply, while in the second robust standard errors are obtained by estimating the demand equation alone. The first approach ensures that the specification of demand and supply is reasonable, while the second ensures that inference will be valid. Both of these models are linear, making the estimated coefficients easier to interpret than those from the non-linear GEE model.

To specify the simultaneous equation model, I included variables on the prices of green and grey power, personal income, FIT and RPS policies, and deregulation initiatives. On the supply side I specified the price of green power as a function of renewable production, state GDP, and FIT and RPS policies. For identification I assumed that renewable energy production had no effect on demand and that average personal income had no effect on supply.

Table 5: Simultaneous Equation Estimation Results

	POOLED		REGION EFFECTS	
	Coefficient	Std. Err.	Coefficient	Std. Err.
demand				
greenpremium	-2.0710	.3530	-1.9724	.2997
ln (*greyprice*)	2.2694	.9255	1.2836	.4966
income	.1439	.0592	.1602	.0561
income ^{2}	-.0016	.0005	-.0017	.0005
RPS	.9486	.2840	1.5840	.2972
FIT	1.4889	.3691	1.2027	.3765
const.	14.1815	3.1332	12.8586	1.9009
supply				
ln(*greencustomers*)	-.7484	.3439	-.7545	.3544
ln(*renewableproduction*)	.1550	.1475	.1639	.4597
FIT	1.0761	.5178	.8519	.5153
RPS	.9500	.5055	1.1369	.4597
Deregulated	-.3279	.2331	-.3122	.2222
const.	5.6162	1.2712	6.7493	1.2725
no. obs.				265

In this regression the standard errors do not take into account the time dependence within states and therefore conducting inference using the reported standard errors is inadvisable. However, the coefficient estimates are consistent. The results from this estimation are presented in Table 5. The first two columns present the results for all states, while the last two columns present the results with the inclusion of regional effects. The coefficient estimates show that higher prices for green power tend to lower the number of green customers and that higher average income tends to raise the number of green customers. Moreover, states with FIT or RPS policies have higher green customer numbers.

Interpreting the coefficients in this model is simpler than the GEE model because the dependent variable is the log of green customers. The coefficients therefore measure the percent change in green customer numbers arising from unit changes in the independent variables. In the pooled model, for example, a one cent increase in the green premium is associated with a two percent decline in customer numbers. States with RPS and FIT policies have one to one-and-a-half percent higher green customer numbers, respectively.

The inclusion of regional effects leads to coefficient estimates which are only slightly different from those estimated in the pooled model (see Table 5). Both of the price coefficients are smaller with the inclusion of regional effects, while income effects are larger (in absolute value). Moreover, the difference between states with and without RPS policies is larger with regional effects, while the difference between states with and without FIT policies is smaller. None of the coefficients in the supply curve are significantly different when regional effects are included. For this modeling exercise, therefore, these regions may not be too dissimilar.

Using the same specification for the demand equation I estimated a single equation model to obtain robust estimates of the standard errors. To account for the endogeneity of the green premium I used the log of state GDP, FIT and RPS dummy variables, the log of residential electricity prices, and the log of renewable capacity as instruments.[43] This model was estimated in conjunction with a weight matrix that accounted for time dependence within states.

The results from the estimation for all states are presented in the first two columns of Table 6. The results from the estimation with the inclusion of regional effects are presented in the second two columns of Table 6. Importantly, the standard errors reported in the Table are robust to heteroskedasticity and to dependence within states: this makes inference feasible.

Table 6: Instrumental Variable Estimation Results

	POOLED		REGION EFFECTS	
	Coefficient	Std. Err.	Coefficient	Std. Err.
greennpremium	-1.3513	.9132	-1.788	1.3980
ln(*greyprice*)	2.7308	1.9981	2.8652	1.8757
income	.2671	.1372	.3153	.2388
income ^{2}	-.0026	.0013	-.0032	.0022
RPS	1.4377	.5852	1.6044	.6100
FIT	.9221	.4136	.7140	.3743
const.	10.5963	5.7372	11.3821	7.1454
no. obs.				265

Tests for statistical significance revealed that only income, income squared, and the FIT and RPS dummy variables were significant (the p-values for the test that that they were individually insignificant were equal to zero to three significant digits). With the inclusion of regional effects, only the two FIT and RPS dummies were significant: the p-values for the t-test that they were insignificant were.056 and .009 respectively. All other variables, including the regional dummy variables, were insignificant at the ten percent level, with p-values for the test that they were zero greater than 0.12.

The results from the pooled model show that a one cent increase in the green premium leads to a greater than one percent fall in the number of green customers. Similarly, a one percent

[43] Renewable capacity was a better instrument than production and the results from the GEE estimation above suggest that capacity may not statistically affect customer demand.

higher price for grey electricity is associated with nearly a three percent increase in green customer numbers (this variable, however, is insignificant at the ten percent level). An increase in income increases customer numbers, though at a declining rate. States with RPS or FIT policies have significantly higher numbers of customers: states with a FIT policy have almost one percent higher customer numbers, while states with an RPS policy have greater than one percent higher customer numbers.

Comparing the coefficients from the three stage least squares estimation with those from the single equation estimation suggests that the single equation model underestimated the impact of changes in green prices and overestimated the impact of changes in the grey power price. The impact of income was also larger (in absolute value) in the single equation regression. Finally, the coefficient on the FIT policy dummy on the demand side was smaller compared with its value in the simultaneous equation, while the coefficient on the RPS policy dummy was larger.

The first stage results for the single equation model are presented in Table 7 in the Appendix. I performed several tests on the instruments to ensure the model was identified. The Kleibergen-Paap under-identification test has a null hypothesis that the equation is under-identified.[44] The p-value for the test statistic in the pooled regression was .0865, suggesting (weak) evidence that the regression was not under-identified. The Hansen J over-identification test has a null that the instruments are valid. [45] The test statistic for the pooled regression produced a p-value of .1638, implying that the instruments were valid. Lastly, the Kleibergen-Paap test for weak instruments has a null hypothesis that the regression is weakly identified.[46] The observed test statistic was 4.60, with a critical value at the 10% level of 19.93, meaning that the estimated equation was weakly identified.[47]

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44 (Kleibergen & Paap, 2006)
45 (Hansen, Heaton, & Yaron, 1996)
46 (Kleibergen & Paap, 2006)
47 The critical values are drawn from Stock & Yogo, 2005.

I tested the sensitivity of these results by omitting some states, including California, Delaware, Oregon and Texas. None of these omissions affected the results significantly: all signs were unchanged and the magnitudes of the coefficients changed only marginally. The omissions changed the results in a predictable manner: omitting Oregon produced a slightly smaller coefficient on the FIT policy dummy, while omitting Delaware produced a larger coefficient on income. Omitting Texas lowered the magnitude of both price coefficients. Overall, there is little reason to believe that any one state had any undue influence on the results.

6. CONCLUSIONS

In this paper I reviewed markets for green energy in the U.S. Using new data on customer numbers, prices for green and grey electricity, and several other variables, I estimated the impact of changes in prices on customer participation, controlling for both FIT and RPS policies. I used a simultaneous equations framework to jointly estimate supply and demand, and I used a single equation instrumental variable method to obtain robust standard errors. I used these robust standard errors to conduct inference. I also estimated customer participation rates as a function of prices, income and state policies using a generalized estimating equation. I found that a one cent increase in prices for green energy caused a greater than one percent fall in customer participation. I found that states with FIT policies have approximately one-and-a-half to one percent higher green customer participation rates than those with no such policies.

There are several directions in which this analysis could be extended. In place of state level data, it would be desirable to use utility level data on customer numbers, prices, and sales to estimate a model with finer granularity. Even better would be to use customer level data, but the availability of such data does not appear imminent. Another potential area for future research is the relationship between the wholesale market for green energy (the market for RECs) and the retail market. It would be instructive to examine the relationship between prices in the wholesale and retail markets to assess competition among retailers. Another area for further research is the relationship between emissions policies and renewable energy markets. Emissions policies (especially carbon caps) affect the emissions value of Renewable Energy Certificates, and this in turn will affect the price of green energy. Studying differences in REC prices between jurisdictions with and without carbon caps could reveal the market value of emissions reductions. Altogether, as markets evolve and as more data becomes available, our understanding of renewable energy markets is bound to improve.

It is undeniable that green energy markets are growing: from small-scale beginnings renewable energy sales have grown to account for almost one percent of all electricity sales in the U.S. Some studies have already found that consumer awareness has played an important role in shaping customer demand, but the price sensitivity of these consumers, until now, has been uncertain. Furthermore, the role of policy in shaping demand should not be underestimated: FIT policies in particular appear to have increased consumer participation in green energy markets, even when the policy's chief aim has been to stimulate supply.

For Ontario, where new initiatives have made the province a leader in environmental policy, the outlook for consumer participation in green energy markets is promising. Demand will grow in the future as more consumers realize that they can buy green power. If prices for green energy in Ontario remain below two cents a kWh, participation rates could reach some of the highest levels in North America. All told, the future of renewable energy looks bright.

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APPENDIX

Table 7: First Stage IVREG2 Estimates

	POOLED		REGIONAL EFFECTS	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
ln(*greyprice*)	2.1477	0.7193	1.0920	0.9033
inc000	-0.0119	0.0678	0.0350	0.0861
inc2	-0.0001	0.0005	-0.0006	0.0007
RPS	-0.0935	0.4086	0.3415	0.3382
FIT	-0.0311	0.3356	-0.1174	0.2761
GDP	-0.0001	0.0000	0.0000	0.0000
ln(*greenncapacity*)	0.0476	0.1077	-0.0232	0.1089
West			-0.5289	0.5135
Midwest			-0.9279	0.3121
Northeast			0.7983	0.5186
const.	10.0324	3.6764	6.5199	4.8112
No. Obs.				265

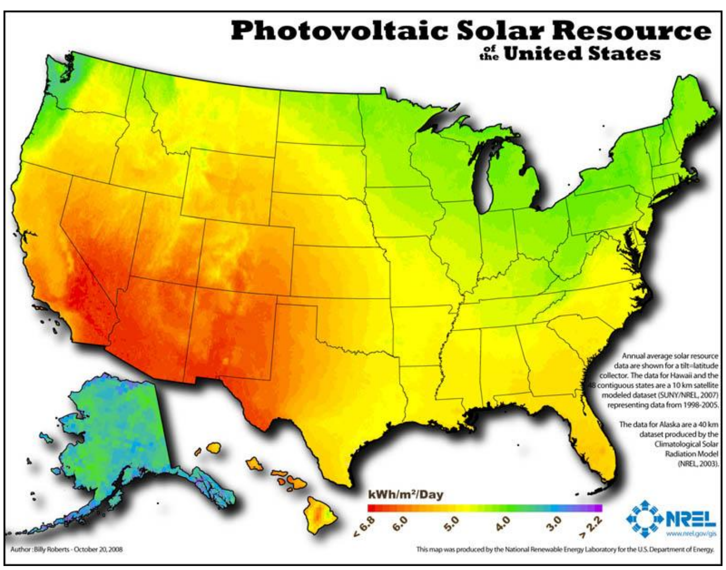


Figure 3: Solar Resource Potential by State, 2008

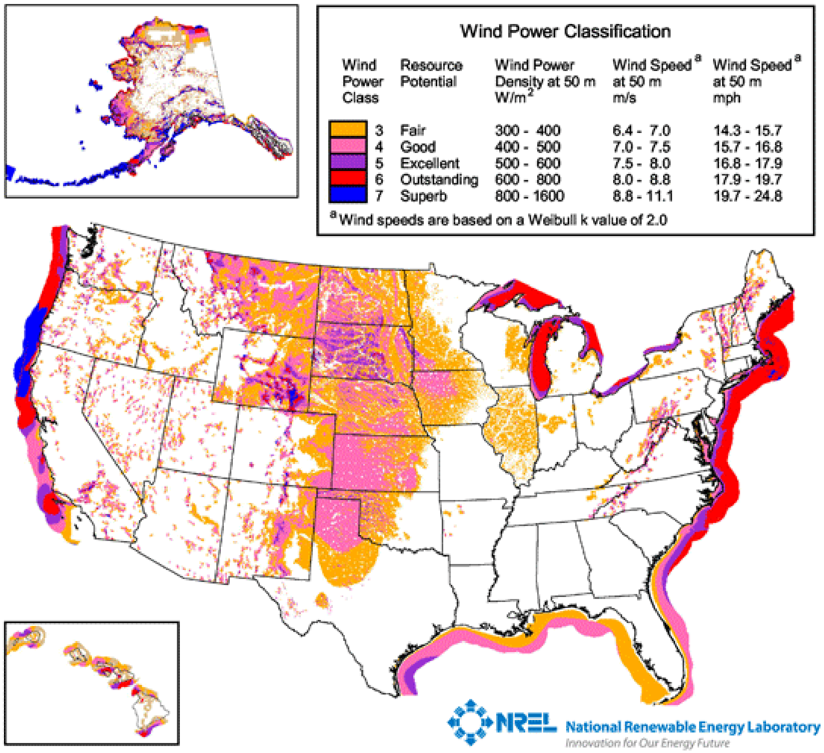
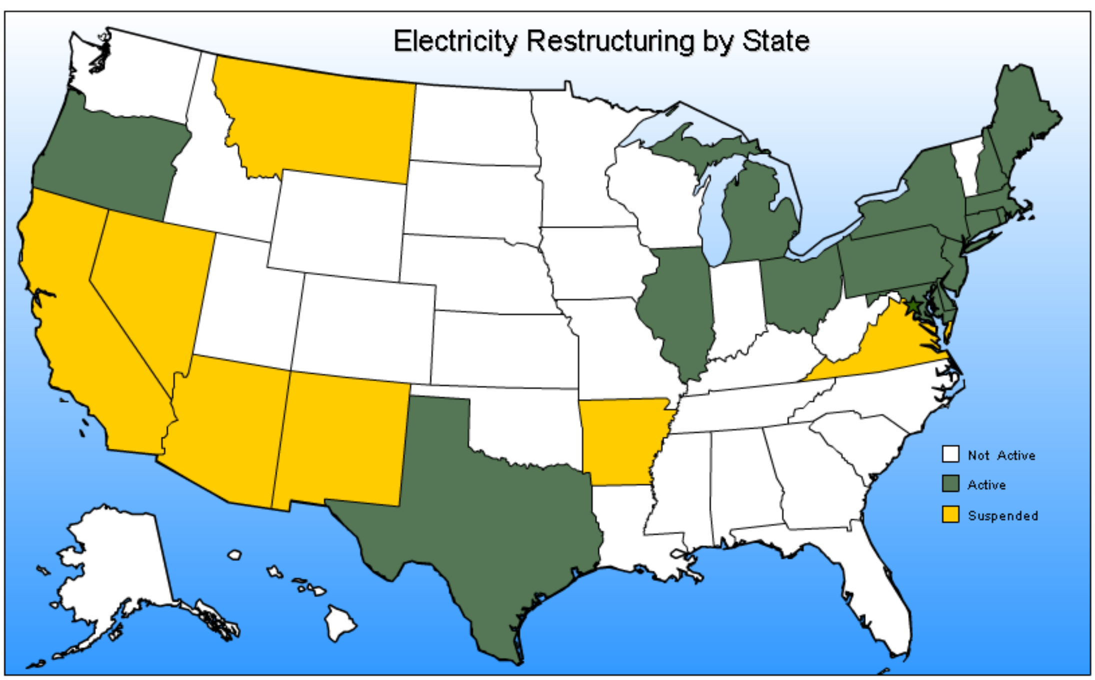


Figure 4: Wind Resource Potential by State, 2010



Source: Energy Information Administration

Figure 5: Electricity Restructuring Status as of June 2011