Diffusion of Solar Technology in Agriculture

by

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Abstract

Solar power provides many benefits to agriculture due to its suitability for remote uses and low maintenance energy production. This thesis studies the diffusion of solar technology in agriculture through two different lenses. First, we examine the factors leading to widespread installation of solar panels through a cross sectional regression. Second, we examine the factors leading farmers in each state to install varying amounts of solar technology through a panel regression. All data are aggregated to the state level. We find that solar radiation, electricity price, wind power potential, utility expenditures, grant programs, and sales tax incentives positively impact the proportion of farms adopting solar technology in each state. Solar radiation, electricity prices, utility expenditures, proportion of agricultural land irrigated, and sales tax incentives are associated with more intense adoption (i.e. more solar panels per thousand farms). We can conclude that there are a broad range of motivations for adopting solar technology in agriculture.

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Introduction

Over time, the growth of solar power has gained momentum and attention. Figure 1 shows electricity generation in billions of kilowatt hours (kWh) from solar energy in the United States [U.S. Energy Information Administration, 2012]. Federal, state, and local governments encourage renewable energy through policies providing public support and favorable regulation. However, we cannot assume that the same policies affect all sectors in the same way. Encouraging solar adoption in agriculture can be done more efficiently if we understand the factors motivating solar installation. Econometric analysis of solar technology adoption can reveal which incentives and conditions are related to higher solar deployment.

Solar diffusion across farms is documented, but the information has not been widely analyzed. Using data from the *On-Farm Renewable Energy Production Survey (2009)* this thesis sets out to answer two questions: 1) What drives a higher proportion of farms to adopt solar technology? and 2) What causes farms in some states to adopt more intensely than others? The first question focuses on the causes for widespread adoption of solar technology while the second question focuses high levels of solar installation measured by the number of installed panels.

This analysis faces some challenges. Using solar power on a farm is, naturally, a farm level decision. However, data are only readily available at the aggregate state level. This deficiency will be explored further in later sections. Due to the aggregate

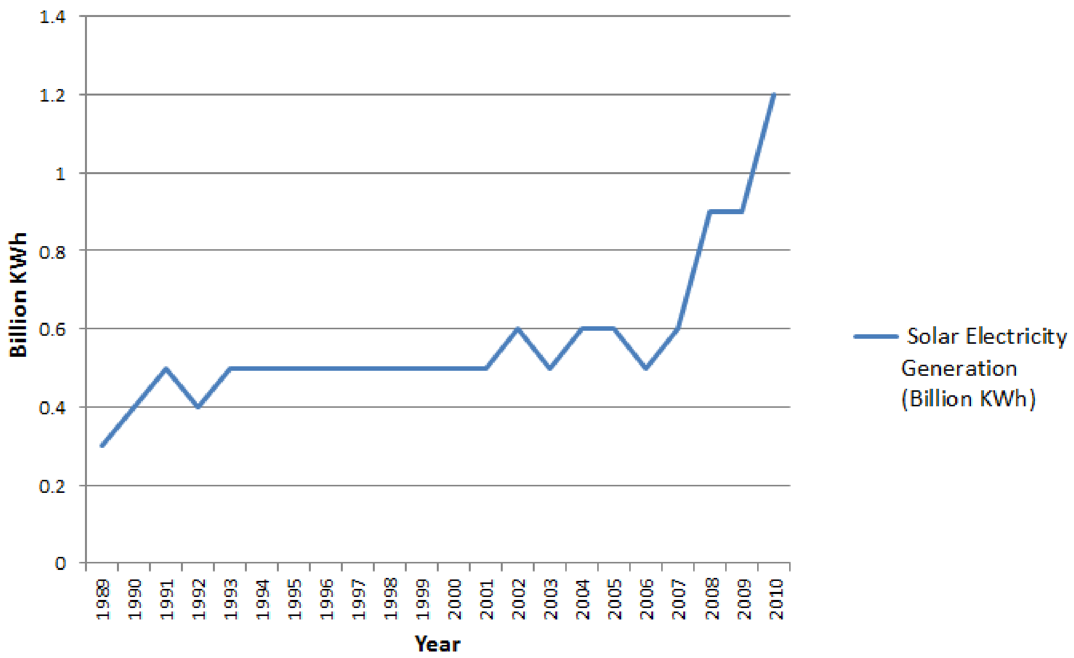

Figure 1: Energy Generation from Solar

nature of the data, the purpose of this thesis is to better understand the state level factors for diffusion of solar. This will help focus research more accurately in the future.

Chapter 1 focuses on the diffusion of solar technolgy. It is not specific to agriculture and covers a basic introduction to solar technology, the importance of state legislation, and causes for diffusion. Chapter 2 focuses on energy use and solar power on farms. Original work begins with chapter 3, which describes the data. Chapters 4 and 5 cover the methods and results from the regressions used to answer the two questions posed above. The thesis concludes with Chapter 6.

Chapter 1

Diffusion of Solar Technology

The United States currently faces considerable energy challenges. Energy related carbon dioxide emissions per capita in the US surpass those of any other country in the Organisation for Economic Co-operation and Development (OECD) [Byrne et al., 2007]. Fossil fuel combustion for electricity generation accounts for 40% of the carbon dioxide emissions in the US according to the Energy Information Administration (EIA) [Fischer and Preonas, 2010]. Solutions for curtailing emissions can be coupled with other goals in creative social projects designed to target multiple problems [Matisoff, 2008]. For example, improving public transportation primarily focuses on fixing traffic problems, but also reduces air pollution. Likewise, renewable energy sources can reduce dependence on foreign energy and stabilize electricity prices while lowering carbon dioxide emissions in the US.

Nationally, renewable energy and energy efficiency can reduce carbon emissions, reliance on fossil fuels, and dependency on foreign energy. All of these effects, however, are externalities. In many instances, markets have failed to accurately value renewable energy development. Markets often disregard positive externalities from renewable energy and, as a result, renewable energy is undervalued. While externalities represent social benefits, increasing energy from renewable sources has the potential to benefit individuals as well. Producing renewable energy can protect customers from the price volatility of conventional sources and offset peak demand allowing customers to avoid high energy costs.

1.1 Solar Technology

Solar energy can be captured in many ways. Each method can be classified into one of two categories: passive and active. Passive solar energy production uses the sun's energy without using special equipment or moving parts. For instance, orienting a building to receive the most natural light instead of lighting with electricity. Active solar techniques use more complicated methods to turn solar energy into other forms of energy like electricity or heat. For example, active solar heating uses pumps or controls to move hot air from solar collectors to buildings [Xiarchos and Vick, 2011]. Solar power applications can also be categorized into solar electric and solar thermal uses. Solar electric applications convert solar energy into electricity and solar thermal applications heat water or air using solar energy.

Solar electric systems, also called solar photovoltaic (PV), convert solar energy into direct current (DC) electricity. When alternating current (AC) electricity is needed, which is usually the case, an inverter is required. The two most common types of PV solar panels are crystalline silicon and thin film [Xiarchos and Vick, 2011]. Crystalline silicon panels are more common and more efficient, averaging about 20% efficiency [Xiarchos and Vick, 2011]. Thin film panels cost less to manufacture because the modules use less than 1% of the silicon that crystalline silicon uses [Xiarchos and Vick, 2011]. They can also generate higher voltage than crystalline silicon [Xiarchos and Vick, 2011].

Solar heating has higher efficiency rates (70-90%) and higher levels of deployment worldwide than solar PV [Xiarchos and Vick, 2011]. Solar hot water systems can use glazed or unglazed flat plate collectors or vacuum tube collectors [Xiarchos and Vick, 2011]. The vacuum tube collectors can heat water to 170-350 degrees Fahrenheit. Solar hot water is the most cost-effective and efficient type of solar power collection, but glazed and unglazed collectors are used for heating air as well [Xiarchos and Vick, 2011].

1.2 Importance of State Policy

State level policy plays a critical role in establishing environmental regulation. While the United States federal government is working to promote green energy, it has been critized for not doing enough to address broad environmental concerns like climate change and promote renewable energy. Literature on renewable energy policy points out the American withdrawal from the Kyoto Protocol under George W. Bush and the perceptions that the US is not an environmentally minded nation [Byrne et al., 2007], [Matisoff, 2008]. However, institutional factors hinder the national government from taking a more active role in climate policy. Federalism, which is an important part of American politics, shifts decisions concerning environmental regulation to state governments so that decisions will be made by politicans close to the people they serve [Cory and Rahman, 2012]. The structure of Congress also makes it difficult to pass bills and interest groups have a strong lobbying presence at the national level [Byrne et al., 2007]. These conditions give states an opportunity to develop policies and try a variety of different approaches to promoting renewable energy and curbing greenhouse gas emissions

[Carley, 2009], [Matisoff, 2008]. State and local policies may also have more stability than national policies due to states' historic leading role in energy matters and lessened pressure from interest groups [Byrne et al., 2007].

Many states developed policy recommendations and strategies in the 1990s and formalized this work as Climate Action Plans (CAPs) [Byrne et al., 2007]. Currently, 32 states have CAPs [U.S. Environmental Protection Agency, 2012]. These plans often include alternative fuel vehicle fleets, public transportation, climate-neutral land use, energy efficiency, renewable energy generation, waste management, and recycling [Byrne et al., 2007]. In addition to making individual state plans, states joined together to make regional goals and policies. In the northeast US, nine states make up the Regional Greenhouse Gas Initiative (RGGI) which adopted an emission reduction schedule to stabilize emissions from 2009-2015 and reduce emissions by 10% by 2020 [Byrne et al., 2007]. Another notable group, the West Coast Governor's Global Warming Initiative (WCGGWI), created a similar program [Byrne et al., 2007]. Even if not part of a regional group, every state has at least one policy to increase energy efficiency or promote renewable energy [Matisoff, 2008].

Even without top down policies from the national and state level, renewable resources would still expand. The US has a strong customer-driven green power market [Byrne et al., 2007]. In the 1990s, utility companies introduced successful programs allowing customers to voluntarily chose electricity from renewable sources for a higher price [Byrne et al., 2007]. A survey in 2006 reported that 77% of respondents thought that developing alternative and renewable energy should be the top priority for US energy policy [Byrne et al., 2007].

At the moment, national policy is a cumbersome tool for promoting renewable energy. State policies and public support are instrumental in encouraging development.

1.3 Diffusion

Diffusion models usually follow an S shaped curve. Figure 1.1 is a basic diffusion graph taken from Rao and Kishore [Rao and Kishore, 2010]. At the beginning of

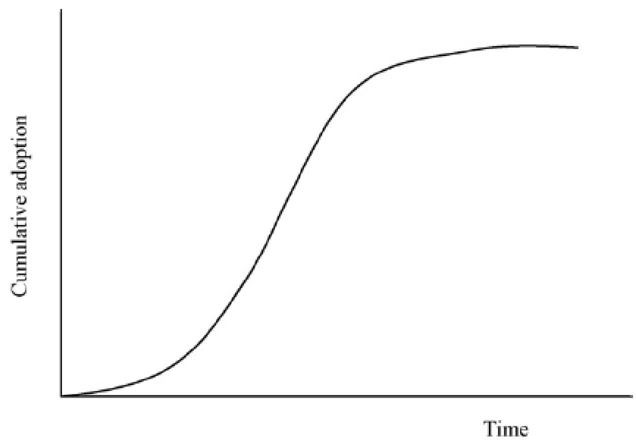

Figure 1.1: Diffusion Graph

the curve, adoption is slow. Gradually, as adoption is encouraged by social factors, advertising, or other means, diffusion picks up and reaches the steep part of the curve. After this explosion of adoption, the curve levels out to market saturation. Market saturation does not mean that 100% of the population owns the new technology, but rather that the portion of the population owning the technology has reached its maximum.

It is very difficult to plot this curve for the diffusion of solar technology. It is possible that the adoption of solar technology is still on the first part of the curve. The early adopters are still buying the technology and we have not reached the drastic upswing in adoption. It is also hard to predict what full market saturation will be for solar technology. It is difficult to predict what percent of households, or in the case of this study, farms, will eventually own solar photovoltaic panels and solar thermal panels. Finding a curve to fit solar diffusion would be useful to policy makers to assess the impacts of their policies and design new programs, but it would be very challenging as well [Rao and Kishore, 2010]. Given the difficulties in tracing this curve for the solar market, we include it here for illustrative purposes and to challenge the reader to consider the potential growth of renewable energy sources in general as the technology improves. Instead of fitting a S curve for the solar market, this thesis examines drivers of diffusion. In the next sections, we will explore the market, policy, and social drivers of diffusion.

1.3.1 Market

Externalities, both postive and negative, cause markets to inaccurately value commodities [Tietenberg, 2004]. Switching from conventional to renewable sources for energy creates positive externalities, including reducing green house gas emissions, that make valuing renewable energy difficult. Although many markets do not accurately value conventional and renewable energy sources, there are market forces that make renewable energy production more attractive. Renewable energy production on farms can protect farmers against price volatility by making farmers less dependent on buying fuel [Byrne et al., 2007]. It can also decrease demand for electricity from the grid during peak pricing hours [Fischer and Preonas, 2010]. On-site energy generation reduces the need for power line extensions and fuel transportation. Renewable energy proves to be economical when used in remote areas for deferrable loads. In the case of solar, defferrable loads are jobs that can be scheduled when sunlight is available, thus energy is conserved at night.

Once the need for renewable energy sources is established, the various methods of producing energy compete to be the most cost-effective alternative. During the 1990s, wind power reached the fastest growth rate of any renewable energy source in the US [Menz and Vachon, 2006]. Much like solar energy, wind energy development is encouraged by economic forces, environmental efforts, and government regulation [Menz and Vachon, 2006]. In a paper on the effectiveness of different policy regimes, Menz showed that the policy regimes of different states had a significant impact on wind power development [Menz and Vachon, 2006]. More specifically, policies affected the amount of wind energy generation present in each state, the growth of wind energy generation, and the number of large wind energy generation projects [Menz and Vachon, 2006]. States with Renewable Portfolio Standard (RPS) policies had higher levels of wind capacity in 2003 and more growth between 1998 and 2003 than states where no RPS policy was in place [Menz and Vachon, 2006]. The driving forces of wind energy development give some insight into what can be expected in the solar energy market.

1.3.2 Policy

With the current climate of environmental concern, renewable energy sources have come to the forefront of energy development. Outside of agriculture, solar electricity production has been growing for a variety of reasons including financial incentives and production requirements from federal, state and local government. Between 2001-2007, solar electricity generation in the United States increased by 12.72%, from 542,760 megawatt hours (MWh) to 611,793 MWh [Doris et al., 2009]. State governments have encouraged solar deployment through a variety of incentives and regulations. Policies that support renewable energy can be created for a variety of reasons. Some policies are designed specifically to increase renewable energy usage and others' main purpose is to reduce air pollutants or carbon emissions with the happy side effect of increasing renewable energy [Fischer and Preonas, 2010].

Incentives offer rewards for voluntary solar energy production. Some popular incentive structures used by states include grants, loans, tax benefits, public benefit funds, and net metering. A plethora of literature exists evaluating the effectiveness of different policy incentives on renewable energy generation (see [Durham et al., 1988], [Carley, 2009] [Doris et al., 2009] [Matisoff, 2008] [Menz and Vachon, 2006] [Murray, 2009]). Durham, Colby, and Longstreth used a probit model to determine whether state tax credits among other control variables have a positive influence on solar adoption in western states [Durham et al., 1988]. They found that the cost of conventional energy sources, level of the state tax credit, educational level of the household head, and number of household residents are all significantly related to adoption of solar water heating devices with the two most significant variables being the level of the state tax credit and price of conventional energy sources [Durham et al., 1988]. In another study, Carley found subsidy programs to be positively related to the percentage of energy from renewable sources as well as the total amount of energy produced from renewable sources in each state [Carley, 2009]. The same paper found tax incentives to be negatively related to both of the dependent variables [Carley, 2009]. Property tax exemptions, tax rebates, credit multipliers, public benefits funds, and net metering were found to have a significant impact on solar power development in a state level fixed effects model by Murray [Murray, 2009].

Net metering and interconnection laws are growing in popularity. These laws require utilities to buy electricity from small producers when excess energy is pushed back into the electrical grid [Matisoff, 2008]. Net metering policies are less likely to expire than grants, subsidies, and tax incentives which gives some assurance to small energy producers [Stoutenborough and Beverlin, 2008]. Since the utility companies are required to buy the electricity, state legislatures have an incentive to pass net metering policies; there is no financial obligation on the part of the government [Stoutenborough and Beverlin, 2008]. Before net meting, under the Public Utility Regulatory Policy Act (PURPA) of 1978, utilities could buy the excess energy for the avoided cost rate or what it would have cost them to produce the electricity themselves [Stoutenborough and Beverlin, 2008]. Net metering policies require utilities to buy the excess electricity at retail rates. This is a significant step forward in making renewable energy cost effective for small producers.

States can also set up specilized funding for renewable energy and energy efficiency programs by instituting a public benefit fund (PBF). These funds collect resources by placing a surcharge on utility bills [Xiarchos and Vick, 2011]. The funds are meant to provide stable, long-run financing for a variety of projects including energy efficiency, clean energy research, low-income household weatherization, and renewable energy projects [Byrne et al., 2007]. Most of the money is used for energy efficiency projects, but some states have dedicated a section of the fund specifically to renewable energy [Byrne et al., 2007], [Xiarchos and Vick, 2011].

In addition to incentives, states also use regulations and requirements to promote renewable energy adoption. One of the most written about forms of regulation is the Renewable Portfolio Standard (RPS). RPS policies require a gradually increasing percentage of electricity produced or sold in the state to come from renewable sources. RPS legislation is a widespread method designed to promote renewable energy use at the state level. Many studies have undertaken to measure the effect of RPS policies on renewable energy use. Each state with a policy chooses a goal percent of renewable energy and a deadline. These goals and deadlines can vary drastically across states, making policies hard to compare. For instance, Washington's RPS requires large utility companies to obtain 15% of their energy from new renewables by 2020 and all cost-effective conservation measures to be taken, whereas Texas' RPS requires $5,880$ Mw of electricity to come from renewables by 2015 and $10,000$ Mw by 2025 [U.S. Department of Energy, 2013]. Given the variety of policies and their relatively recent popularity, it is not surprising that the literature offers no conclusive answer concerning the benefits of RPS. A 2009 study by Carley found that RPS policies do not significantly impact the percentage of energy generated from renewable sources, but that the age of the policy significantly and positively effects the total amount of renewable energy generation [Carley, 2009]. A similar relation was found in the effect of RPS policies on wind power deployment. The effect of RPS policies seemed to increase with their age. This type of relationship makes sense because RPS policies gradually increase the percentage or amount of energy that comes from renewable sources [Menz and Vachon, 2006]. Carley hypothesizes that RPS policies have not had a significant impact due to inadequate policy enforcement, uncertainty over the duration of the policy, unreachable goals, too many exemptions, and too much flexibility offered to utilities [Carley, 2009]. Some RPS policies include solar carve-outs specifying an amount or percent of electricity to come from solar sources. Solar carve-outs were shown to have significant effects on solar energy development [Murray, 2009].

States can also require contractor licensing and equipment certification to protect solar customers from improper installation and faulty equipment.

1.3.3 Networks

For this study, it is important to consider what influences the diffusion of new technologies in general and how these factors will affect diffusion of solar power adoption in agriculture specifically. In addition to responding to policy and financial incentives, technology can also be spread through social avenues. Bollinger and Gillingham conducted a study on diffusion of solar PV panels at the street and zip code level. The study accounted for both environmental preferences and peer effects. They found clustering of solar diffusion at the street and zip code levels [Bollinger and Gillingham, 2010]. More specifically, a 1% increase in the installed base was associated with a roughly 1% decrease in the time between adoptions. The results were highly significant and led the authors to believe that a strong peer effect influences the rate of adoption [Bollinger and Gillingham, 2010]. Interestingly, customers with strong environmental preferences led to increased adoption, but decreased peer effect. Environmentally minded consumers appear to be less effected by their neighbors [Bollinger and Gillingham, 2010].

While it is clear that social connections influence diffusion on a small scale, we have yet to examine regional diffusion across state boundaries. While states may not be directly responsible for building solar arrays, they are responsible for putting policies into place that will encourage or require utility companies and individuals to install renewable energy. Within the state government, renewable energy policies can be passed based on internal determinants (environmental culture of the constituents, natural resource endowment of the state, pollution issues in the state, etc) and also encouraged by diffusion [Matisoff, 2008]. States geographically near each other are likely to face similar challenges and learn from each other's methods. Bureaucrats and politicians are also likely to attend regional conferences and share ideas with neighboring states more often than geographically distance states [Matisoff, 2008]. We see examples of this in the previously mentioned state collaborations such as RGGI and WSCCI. Matisoff used event history analysis to examine when states adopt RPS policies. This study found strong support for the internal determinants model, but did not find evidence of regional diffusion [Matisoff, 2008]. While regional diffusion did not appear to play a role in RPS adoption, states with poor air quality where more likely to consider adopting a

RPS [Matisoff, 2008]. In a 2008 study by Stoutenborough on the diffusion of net metering policies among states, political characteristics were again found to be important. While the effect from neighboring states was not significant, there was clustering based on EPA region showing some information diffusion across state lines [Stoutenborough and Beverlin, 2008].

Chapter 2

Solar Technology in Agriculture

Agriculture holds an interesting, if understudied, place in the solar energy market. In its earliest agricultural applications, solar power was used because is was cost-effective. Using solar power for low power remote energy needs can be cost-effective to farmers by stabilizing energy costs, lowering maintenance costs, and taking away the need for fuel transportation [Xiarchos and Vick, 2011]. Using solar power can be more cost-effective than extending the electrical grid by running new power lines to remote applications [Xiarchos and Vick, 2011]. Agriculture's numerous remote applications caused farmers to be amoung the early adopters of solar power [Xiarchos and Vick, 2011]. While solar serves an important need, the high upfront cost of purchasing and installing solar panels makes adoption difficult.

Despite agriculture's early entry into the market, the use of solar power in agriculture is still small. The average size of a photovoltaic system on a US farm is 4.5 kilowhatts (kW). [Xiarchos and Vick, 2011]. Typically, solar energy faces competition for remote uses from kerosene, diesel, and propane, which are used to power generators when electricity from the grid is not available [Xiarchos and Vick, 2011]. These alternatives come with a cost for transporting the fuel, volatility of fuel prices, risk of fuel spills, noxious fumes and high maintenance demands [Xiarchos and Vick, 2011]. Technological improvements along with renewable energy friendly policies and financing programs are helping make solar more competitive with conventional sources despite its high initial cost. For non-remote uses, the advent of grid connected solar energy generation has also helped solar become more competitive. With grid connected systems, excess energy is no longer wasted, but is instead sold back to the utility company for use by other customers.

Section 1.1 described the difference between solar electric and solar thermal energy. Each type of solar energy generation has unique benefits. Solar heating systems can replace or reduce natural gas and electricity use. Grid connected PV systems reduce the amount of electricity drawn from the grid and offer an opportunity to offset what is used by producing excess electricity during the daylight hours. Off grid energy generation can take the place of natural gas, propane, diesel, batteries, and grid extensions [Xiarchos and Vick, 2011]. Used effectively, solar energy generation has room to grow in agricultural applications.

2.1 Energy Use on Farms

Energy is used everywhere, but residential, industrial, and agricultural sectors all have unique needs and patterns of use. To better understand where solar power can be efficiently produced and used in agriculture, the first step is understanding where and how energy is used in agriculture. In 2008, agriculture used almost one quadrillion British thermal units (Btu) of direct energy [Xiarchos and Vick, 2011]. This energy use resulted in the release of about 76 million tons of carbon dioxide, which is around 1% of total US emissions [Xiarchos and Vick, 2011]. Figure 2.1 shows the end uses for energy used on farms with data from Brown and Elliott's

2005 report [Brown and Elliott, 2005].

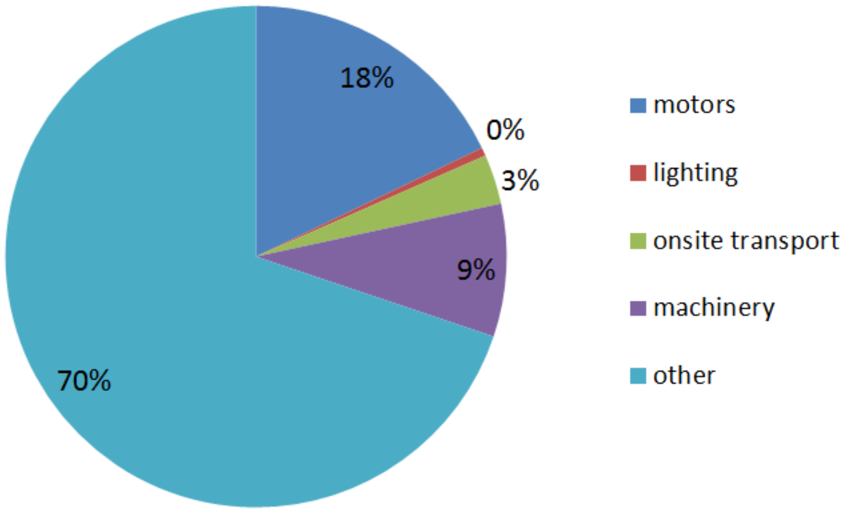

Figure 2.1: Energy Use for All Farm Types

The end use of most energy is unknown, but we can draw some information about the overall enery use on farms from Figure 2.1. Motors and machinery constitute a significant portion of energy use, making up about 27% of total usage. Onsite transport and lighting account for only a small portion of energy use. Irrigation pumps are the primary motor application on farms and drive the promonience of motor energy use [Brown and Elliott, 2005].

Energy costs vary drastically based on farm type. Table 2.1 presents the percent of farm production costs that are spent on energy on different types of farms.

Table 2.1: Energy Expenditure

NAICS* Title	% Energy Expenditures of Total Production Expenditures
Oilseed and Grain Farming	9
Other Crop Farming	9
Greenhouse Nursery and Floriculture	7
Animal Aquaculture	7
Sheep and Goat Farming	7
Beef Cattle Ranching and Farming	7
Dairy Cattle and Milk Production	6
Fruit and Tree Nut Farming	6
Hog and Pig Farming	4
Poultry and Egg Production	3
Cattle Feedlots	2

* North American Industrial Classification System

Source: [Brown and Elliott, 2005]

Each type of farm operation has unique challenges to becoming energy efficient and moving toward renewable sources. On hog, pig, and poultry farms, changing the lighting system to use the most energy efficient type of lights has been shown to decrease the productivity of the animals [Brown and Elliott, 2005]. In cases like this energy efficiency is costly to productivity. Switching to renewable sources would provide a way to offset energy consumption without compromising output.

2.2 Solar Energy Use on Farms

Originally, solar energy was attractive to agricultural applications for its low maintenance, remote uses. While these applications are still well served by using solar, grid connected solar, which supplements energy from the grid instead of replacing it, has expanded in the last decade [Xiarchos and Vick, 2011]. Grid connected solar can cost less to install since it does not require a battery to save the power for later use [Xiarchos and Vick, 2011]. These savings can be important since the initial cost is usually high, ranging from a few hundred to thousands of dollars for PV systems on agricultural operations [Xiarchos and Vick, 2011].

A major use for solar PV systems in agriculture is running motors [Xiarchos and Vick, 2011]. This encompasses a number of different jobs, notably, pumping water for irrigation of fields, watering livestock, pond management and aquaculture. Solar power is also widely used for lighting, electric fencing, and battery charging, as well as feeder, sprayer and sprinkler control [Xiarchos and Vick, 2011]. Pumping water for irrigation and livestock is a good fit for solar power because it is often a remote use with no opportunity for grid connection. The drawbacks of alternative fuel for this type of use have been mentioned earlier and include fuel transportation and price volatility. Solar energy is also well suited for pumping water because when there is plenty of sun, excess water is pumped into a storage tank for later use. This can eliminate the need for batteries, reducing the initial and maintenance costs of the system [Xiarchos and Vick, 2011]. Using solar powered water pumps for livestock watering also keeps the cattle out of the wetlands and waterways [Xiarchos and Vick, 2011].

Solar water and space heaters are useful in several different types of operations. Dairy farms, where up to 40% of the energy used on farm can go towards heating water and cooling milk, as well as other types of livestock operations, require hot water for cleaning pens and equipment [Xiarchos and Vick, 2011]. Hog and poultry farms heat incoming air to keep the animals healthy [Xiarchos and Vick, 2011]. These types of operations need reliable air circulation and ventilation to remove moisture, toxic gases, odors, and dust and thus use large amounts of energy to heat and move air [Xiarchos and Vick, 2011]. The amount of time it takes for the accumulated savings to pay for the solar system varies and is highly dependent on competing energy costs. Xiarchos and Vick report that a solar water heater can face a payback period of 5-20 years when compared to electricity and 15-70 years when compared to natural gas [Xiarchos and Vick, 2011]. For industries like aquaculture where water can be heated to a lower temperature, the time to break even can reduce to 2-5 years [Xiarchos and Vick, 2011]. A solar space heater used to heat fresh air coming into a building can pay for itself in 1-5 years [Xiarchos and Vick, 2011]. Although residential use dominates the market for solar thermal technology, there is ample potential for expansion in agriculture [Xiarchos and Vick, 2011].

2.3 Irrigation

Since motor energy generation is an important use for PV in agriculture, and a large part of this entails pumping water for irrigation and livestock and managing aquaculture, solar irrigation and other water pumping systems will play a role in demand for PV systems. PV pumping systems can pump water from underground wells in addition to surface ponds and streams [Xiarchos and Vick, 2011]. They require little maintenance and are often used in areas without grid access [Xiarchos and Vick, 2011]. Irrigation uses a considerable amount of energy on farms. About 49 million acres of US farmland were pump irrigated in 2008 costing farmers $2.68 billion [Xiarchos and Vick, 2011].

Outside of the United States, solar irrigation systems have made a drastic impact by providing a sustainable, easy-to-maintain method of irrigation in areas with low food security. Solar-powered drip irrigation systems introduced to two villages in northern Benin improved food availability and access and provided the farmers with extra income from better yields to increase consumption during the dry season [Burney et al., 2010]. In this case, drip irrigation was a cost-competitive option due in part to the extreme price volatility of other fuel sources in rural areas and opportunities to purchase the pump as a community and share risks [Burney et al., 2010]. Price volatility also has an impact on irrigation decisions in the US. In a 1982 study, Maddigan, Chern, and Rizy found that the cost of electricity influences the amount of irrigation in agriculture [Maddigan et al., 1982]. Employing solar powered irrigation would help reduce the influence of price fluctuations on irrigation.

2.4 Financing

With the high initial costs associated with installing solar power, farmers and homeowners often look for programs to help finance the purchase. In addition to more traditional avenues of financing, such as commercial bank loans and mortgages, there are programs and policies specific to funding renewable energy generation [Xiarchos and Vick, 2011]. Consumers have multiple options and opportunities for receiving help with the financial challenges associated with solar installation. When making the decision to purchase a solar system, consumers have to consider the cost of the system, the cost of competing fuel, financing options like loans and grants, and incentives from all levels of government such as tax credits and renewable energy certificates [Xiarchos and Vick, 2011].

Some solar technology suppliers allow customers to make group purchases for a discount. Companies offering these deals, like 1 Block Off the Grid, sometimes specialize in neighborhood installations. 1 Block Off the Grid is based in San Francisco and can negotiate up to 48% off the market price [Xiarchos and Vick, 2011]. Other companies work within the agricultural community. Organic Valley, a farmer-owned cooperative, has an agreement with Bubbling Springs Solaron to offer a discount on solar thermal collectors sold to member farms [Xiarchos and Vick, 2011]. This method of financing draws from two of the reasons for diffusion mentioned earlier. First, it changes the market for solar power. With these arrangements, prices for equipment and installation are lowered and solar becomes a more competitive option. Second, these methods use social diffusion. Neighbors and farmers have an incentive to encourage their friends and colleagues to adopt solar technology. Residential solar adoption can follow a clustering pattern and group discounts take advantage of that to draw in more consumers for the supplying companies and lower prices for the consumers.

Many states require utility companies to offer net metering for small scale renewable energy producers. Under this policy, energy used on the farm and energy produced on the farm are aggregated and farmers only pay utility companies for their net energy use. When net metering is combined with time of use (TOU) rates solar producers can see an even bigger payback [Xiarchos and Vick, 2011]. TOU rates are often highest when solar is most productive. If, in addition to selling electricity back at the highest prices, farmers are able to defer their energy use and buy most of their energy during non-peak hours, there can be a considerable advantage. When net metering is not available, farmers can still receive avoided cost payments from utility companies [Xiarchos and Vick, 2011]. Net metering uses market forces to make solar production more attractive. Farmers do not lose excess electricity at a cost to themselves. However, the solar system in question must be grid connected for this method to provide benefits.

In states that have set up a renewable energy credit (REC) trading program, farmers can also help finance their renewable energy systems through energy markets. Each credit usually represents one net megawatt hour of energy generated from an eligible renewable source [Xiarchos and Vick, 2011]. These types of programs are often found in states with RPS policies. RECs allow utilities to meet the RPS requirements without building renewable energy generation systems themselves. Rules for distributing RECs vary from state to state. In some states the renewable energy producer receives the credits for the energy produced and use on-site and and utility company automatically receives the REC for excess electricity [Xiarchos and Vick, 2011]. The RECs awarded to the farmers can be sold separately from the electricity used and tend to carry a higher a price in states with RPS policies [Xiarchos and Vick, 2011]. While RECs are usually not a driving force of small scale solar development, they can help farmers recoup the price of installation [Xiarchos and Vick, 2011]. The combination of high up front costs and a plethora of positive externalities makes renewable energy installations a prime candidate for outside funding.

2.5 National Policies

While the national government in the United States faces challenges and shortcoming in implementing renewable energy policy, there are national programs available to help homeowners and farmers install small scale renewable energy generation systems. These policies will effect all farmers in the US in the same way. A few of the most notable programs are described here.

National policies promoting renewable energy generation have been part of the political landscape for some time. While solar PV was introduced in the late 1950s, the energy crisis in the 1970s spurred solar development [Xiarchos and Vick, 2011]. With this interest in renewable energy, the federal government passed the 1978 Public Utility Regulatory Policies Act (PURPA) which required utility companies to purchase electricity from non-utility producers [Menz and Vachon, 2006]. This allowed grid connected suppliers to receive payment for the excess electricity produced. In 1988, the USDA's National Institute for Food and Agriculture (NIFA) started the Sustainable Agriculture Research and Education (SARE) program making grants for and education about sustainable agriculture available in select regions. The program expanded to the entire nation in 1995 [Xiarchos and Vick, 2011].

The Energy Policy Act of 1992 (EPACT) further opened the market to electricity producers by providing two different financial incentives. It introduced a production tax credit and a renewable energy production incentive [Menz and Vachon, 2006]. In 1996, the act was expanded to require electric utilities to open their transmission lines to all producers [Menz and Vachon, 2006]. In 2005, the Energy Policy Act tripled the personal tax credit for solar systems. Under this version of the EPACT, 30% of the cost of a personal solar PV system is covered [Murray, 2009].

The 2002 farm bill created the USDA Renewable Energy Systems and Energy Efficiency Improvement Program, later renamed the Rural Energy for America Program (REAP), in 2008. This program supplies grants and loan guarantees for energy efficiency and renewable energy systems to farms, ranches, and rural businesses [Xiarchos and Vick, 2011]. The grants available through this program range from $2,500 to $500,000 and can cover up to 25% of system costs. The loan guarantees can cover up to 50% of project costs and range from $5,000 to $10 million [Xiarchos and Vick, 2011]. In 2008, 59 out of 769 REAP projects (7.6%) were for solar energy [Xiarchos and Vick, 2011]. In 2009, there were 1,485 REAP projects and solar had grown to 13%, making up half of the projects for renewable energy [Xiarchos and Vick, 2011].

Federal taxes are also adjusted to reward individuals and businesses for installing renewable energy capacity. The federal investment tax credit provides a tax credit equaling 30% of the cost to install a solar system [Xiarchos and Vick, 2011]. The cost considered does not include any portion paid through subsidies and grants [Xiarchos and Vick, 2011]. The American Recovery and Reinvestment Act of 2009 allows eligible corporations to receive a grant instead of a tax credit [Xiarchos and Vick, 2011]. The IRS also helps commercial owners of solar systems by offering depreciation deductions with 5 year schedules [Xiarchos and Vick, 2011]. This modified accelerated cost-recovery system (MACRS) schedule, which has been in effect since 1986, reduces taxable income for those owning solar and other renewable energy systems [Xiarchos and Vick, 2011]. The Economic Stimulus Act of 2008 and the American Recovery and Reinvestment Act of 2009 furthered this policy by allowing 50% of the installation costs to be depreciated in the first year and the other 50% to be subject to the original 5 year schedule [Xiarchos and Vick, 2011].

The policies listed here are not an exhaustive list of financing opportunities or federal policies. This section is meant to give an idea of type of funding and federal policies available to farmers wishing to install solar power.

Chapter 3

Data

3.1 Data Summary

For this study, we construct two models to examine the diffusion of solar energy systems in agriculture. It is unsurprising, therefore, that there are two dependent variables. The first dependent variable, used for the cross-sectional regression, counts the number of farms per ten thousand that adopt solar technology in each state. The second dependent variable is the cumulative number of solar panels, including PV and thermal, installed per thousand farms at three points in time in each state. This variable is used for the panel regression.

The dependent variables for this project came from the USDA *On-Farm Energy Production Survey (2009)*. These data have been available since 2011, but have not seen significant use in renewable energy literature. Since these data were collected at the state level, the remaining independent variables were also gathered at the state level. Aggregating to the state level creates some challenges. Installing solar panels on farms is a household or business level decision. The characteristics of the decision maker and the farm (i.e. level of education, household size, farm size) are of great interest. The available data, however, record the total number of solar panels on farms in each state. There is no corresponding record of the household characteristics on farms with and without solar. As such, the goals of this project must be aligned with the data. We wish to see which state characteristics lead to higher adoption rates.

Table 3.1 lists the variables used in this project and gives a brief description and the source of information. Each variable will be discussed in more detail in the following two sections covering dependent and indepent variables. Variables are scaled in such a way as to ease interpretation. For instance, *adopt* and *panels* are scaled such that the smallest value leads with a nonzero integer in front of the decimal.

Table 3.1: Variables (Descriptions and Sources)

Name	Description	Source
adopt	farms per $10,000$ farms that adopt solar technology	1) On-Farm R.E. Production Survey 2)Farms, Land in Farms, Livestock Operations 2009 Summary
panels	number of solar panels per $1,000$ farms	1) On-Farm R.E. Production Survey 2)Farms, Land in Farms, Livestock Operations 2001, 2005, and 2009 Summaries
solar radiation	average solar radiation kWh/m^2/day	National Renewable Energy Laboratory
electricity	electricity price (cents per kilowatthour)	Energy Information Administration
diesel	diesel prices by region (dollars per gallon)	Energy Information Administration
wind	potential annual energy (kWh per acre)	[Elliott et al., 1991]
large	% of farms in sales class $\$100,000$ or higher	Census of Agriculture (2002)
utility	% of production expenses spent on utilities	Census of Agriculture (2002 and 2007)
irrigated	acres irrigated per $1,000$ agricultural acres	Census of Agriculture (1997, 2002, and 2007)
grant	number of years since earliest program instated	Database of State Incentives for Renewables and Efficiency (DSIRE)
loan	number of years since earliest program instated	DSIRE
property	number of years since earliest program instated	DSIRE
sales	number of years since earliest program instated	DSIRE
tax	number of years since earliest program instated	DSIRE
credit	number of years since earliest program instated	DSIRE
net metering	number of years since earliest program instated	DSIRE
d04	dummy for 2004	
d09	dummy for 2009	

3.2 Dependent Variables

The *On-Farm Renewable Energy Production Survey (2009)* from the USDA is the motivating dataset for this study. Both of the dependent variables are drawn from this source. Between the two regressions, we wish to explore the diffusion of solar technology in agriculture through two different lenses. First, we wish to see what causes widespread adoption. This is done through a cross sectional regression on the variable *adopt*. The second regression is about the intensity of adoption using *panels* as the dependent variable.

3.2.1 Rate of Adoption

Calculation:

$$adopt = \frac{\text{number of farms using solar panels}}{\text{total number of farms}/10,000}$$

The dependent variable for the cross sectional model, *adopt*, is the proportion of farms per ten thousand farms in each state that installed solar panels. This variable is collected from the *On-Farm Energy Production Survey (2009)* by the USDA
[National Agricultural Statistics Service, 2011]. The total number of farms in each state came from the USDAs *Farms, Land in Farms, and Livestock Operations 2010 Summary* [National Agricultural Statistics Service, 2010].

The data range from 4.3 farms per $10,000$ farms with solar panels in Iowa to 693.33 farms per $10,000$ farms with solar panels in Hawaii. Figure 3.1 shows the rate of adoption in all fifty states. Hawaii, with the maximum adoption, has a noticibly higher rate than the next highest adopters, Alaska and California, with 235.25 and 233.86 panels per $10,000$ farms.

The map in Figure 3.1 shows two clusters of states with high adoption rates.

One cluster is in the southwest part of the country and the other cluster is in the northeast. The southwest cluster corresponds to high levels of solar radiation (see Figure 3.4), but the northeast does not have this advantage. As mentioned in Section 1.2, nine northeast states, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont, make up the Regional Greenhouse Gas Initiative which collectively adopted an emissions reduction schedule. Of those nine states, only Delaware and Maryland have between 10 and 30 farms per $10,000$ that adopted solar power by 2009. The other seven states have above 30 farms per $10,000$ with solar technology. The highest adopter, Vermont, reached 157 farms per $10,000$ with solar technology in 2009.

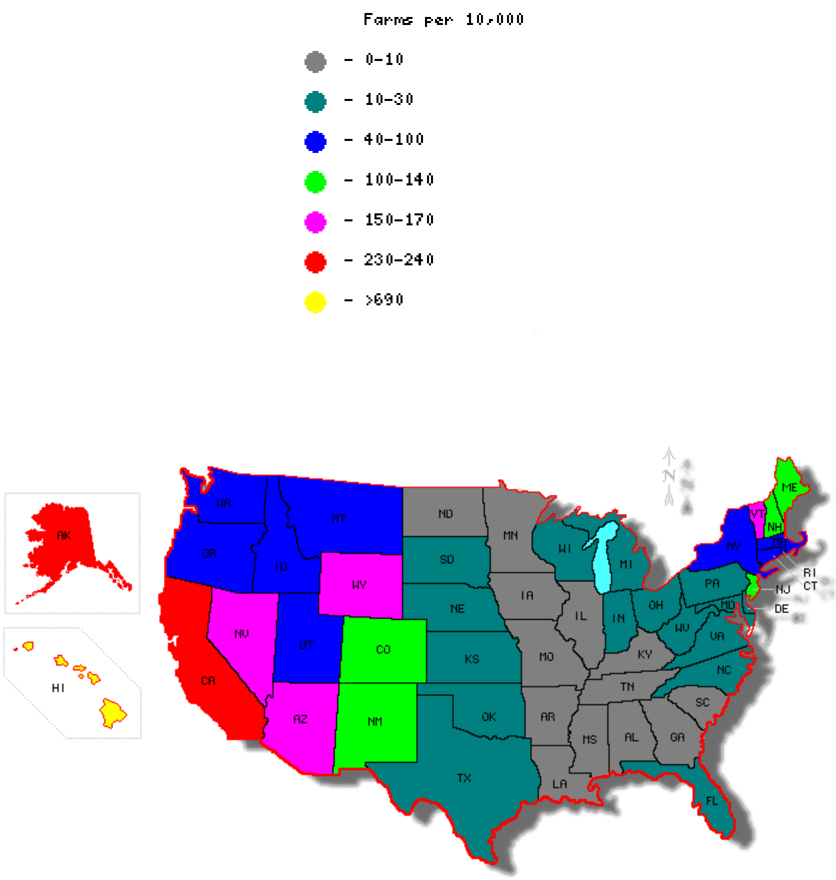

Figure 3.1: Adoption Map

3.2.2 Number of Panels

Calculation:

$$panels = \frac{\text{number of solar panels}}{\text{number of farms}/1,000}$$

The panel regression was built to explain the number of solar panels per thousand farms in each state. This regression is more focused on the intensity of solar use as opposed to the cross sectional regression on the diffusion of the technology.

We have observations on the number of panels in 2000, 2004, and 2009 from the *On-Farm Energy Production Survey (2009)*. The total number of farms came from the 2001, 2005, and 2010 issues of the USDA's *Farms, Land in Farms, and Livestock Operations* publication.

Every state, even those with incomplete data, shows an increase in the number of solar panels from 2000 to 2009. Due to incomplete data, however, Alaska, Connecticut, Delaware, Louisiana, Maryland, New Hampshire, Rhode Island, and West Virginia are not included in the descriptive statistics or regression. Overall, the increase in solar panels is striking. Figure 3.2 shows the total number of solar panels on farms in each year of the study. Only the states included in the regression are represented in the graph.

While the overall increase is impressive, it is important to also consider the distribution of the variable *panels*. Figure 3.3 is a box and whisker plot showing the miniumum, first quartile, median, 3rd quartile and maximum number of panels per thousand farms.

In order for Figure 3.3 to be readable, the states with the three highest panel counts per thousand farms in 2009 could not be included. First, there is California with a sequence of 48.5, 412.8, and $1,179.3$ panels per thousand farms in 2000, 2004, and 2009. Second, New Jersey with 22.5, 244.4, and $1,170$ and then Hawaii

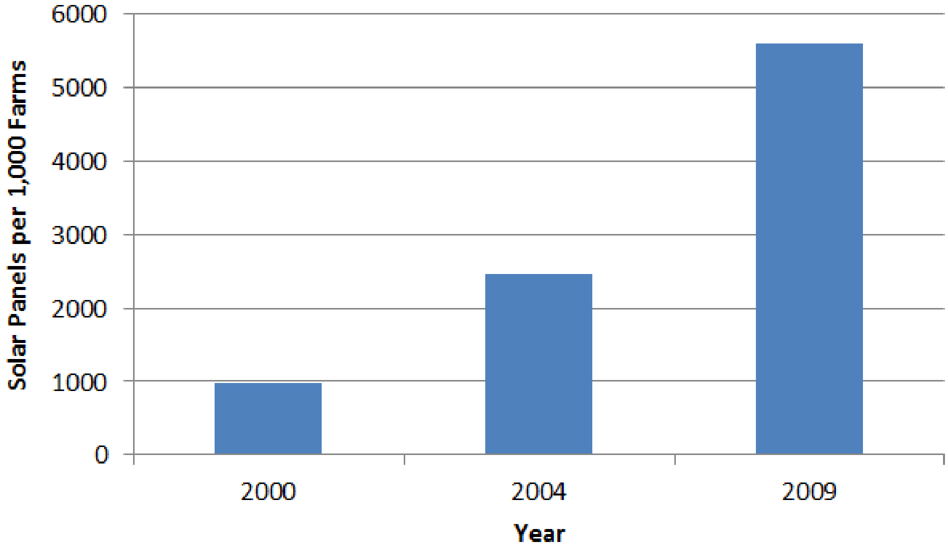

Figure 3.2: Solar Panels in Agriculture

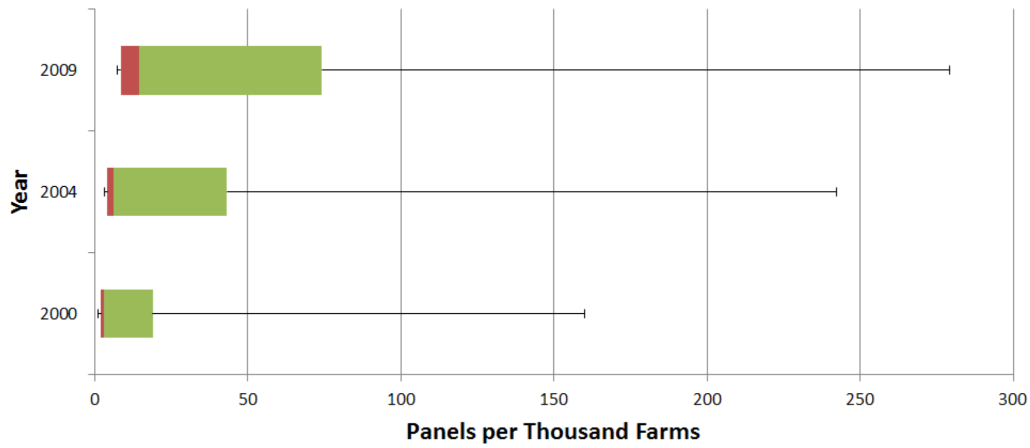

Figure 3.3: Distribution of Panels, Box-Whisker Graph

with a squence of 262.8, 597.8, and 996.9 panels per thousand farms. These values for the year 2009 skewed the whisker of the graph so far as to make the box section unreadable. From Figure 3.3, we can see that the minimum and median are much more stable than the maximum. The growth in the number of solar panels in agriculture seems to be led by increased installation in several top installing states rather than uniform growth across the country.

3.2.3 Comparison of *Adopt* and *Panels*

It is helpful to look at the relationship between *adopt* and *panels*. In Table 3.2, we compare the states with the highest rate of adoption and highest number of panels per farm. We see that New Jersey is number ten in terms of adoption, but jumps to number two in terms of panels per thousand farms. This leads us to believe that the farms in New Jersey that adopt solar do so with great intensity. The same is true for Maine and Massachusetts. Their adoption rates are not in the top ten, they are 11th and 15th respectively, but when the number of panels is considered, they appear on the list. Thus, they must have very concentrated adoption. The farms that do use solar install many panels.

Table 3.2: Top Ten States by *Adopt* and *Panels*

Rank	Adoption	Panels
1	Hawaii	California
2	Alaska	New Jersey
3	California	Hawaii
4	Nevada	Nevada
6	Arizona	Arizona
7	Wyoming	Maine
8	Vermont	Vermont
9	Colorado	Massachusetts
10	New Jersey	Colorado

3.3 Independent Variables

Factors influencing diffusion are grouped into four categories, environmental, market, farm, and policy, which are explained below. The comparative strengths of each group will shed light on the relative effectiveness of policy based incentives and provide direction for future research.

3.3.1 Environmental

The environmental category measures the suitability of each state for solar installation.

Solar Radiation

Solar radiation measures the amount of direct sunlight reaching each state in kilowatt hours per square meter per day (kWh/m^2/day). This variable is meant to capture the environmental suitability of developing solar in each state. The energy collected by solar panels depends not only on the efficiency and size of the solar array, but on the amount of solar radiation available. The National Renewable Energy Laboratory provides measurements of solar radiation across the United States. Figure 3.4 shows a map from the NREL website of average annual solar radiation over the period 1998-2009 [National Renewable Energy Laboratory, 2013].

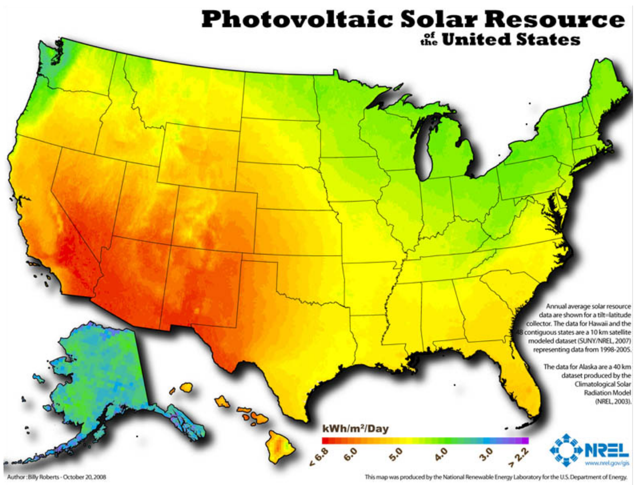

Figure 3.4: Average Annual Solar Radiation

3.3.2 Market

The market category contains variables measuring the prices and availability of competing energy sources. These are substitutes available to farmers to use in place of solar energy.

Electricity

Electricity records the average price in cents per kilowatt hour of electricity across all sectors of consumption. In the cross sectional regression, it is the average price over a ten year period (2000-2009). In the panel regression, *electricity* is the five year average of prices leading up to the year in question. Electricity prices were deflated to 2000 dollars using the consumer price index (CPI) and then averaged over the appropriate time period. *Electricity* is included in order to account for the competition between solar power and electricity from utilities when the application is connected to the grid. When utility companies provide net metering, this may also be the price paid to energy producers for electricity put back into the grid. the inclusion of this variable is not only motivated by theory, but also by empirical evidence. Durham, Colby, and Longstreth found the cost of conventional energy to impact significantly the adoption of residential solar energy systems in western states [Durham et al., 1988].

Diesel

Diesel represents the price of diesel fuel in dollars per gallon in five different regions of the US. The variable was calculated in the same manner as *electricity* with a ten year average for the cross sectional regression and five year averages in the panel regression. Diesel is a substitute power source available to farmers for remote applications were grid connections are unavailable. Prices are not available by state, but are instead calculated by district. Figure 3.5, provided by the Energy Information Administration (EIA), shows the five Petroleum Administration for Defense Districts (PADD) for which diesel prices are reported [U.S. Energy Information Administration, 2013]. Prices are reported separtely for each of the regions within PADD 1. Thus, there are seven different prices in the data set. Diesel prices, like electricity prices, were deflated to 2000 dollars.

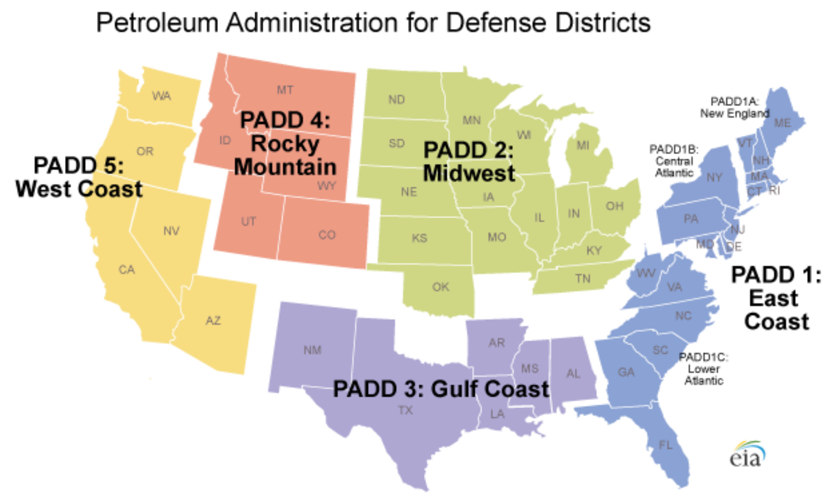

Figure 3.5: PADD Map

Wind

Calculation:

$$wind = \frac{\text{potential annual energy from wind (kWh)}}{\text{total state land in acres}}$$

The previous two variables accounted for competition from conventional energy sources. The variable *wind* measures the potential for wind energy development, helping to assess competition from renewable sources. Wind was the fastest growing source of renewable energy in the United States in the 1990s [Menz and Vachon, 2006]. Wind power continued to have the largest growth percentage for renewable energy from 2001 to 2007 when it grew by 411% [Doris et al., 2009]. The popularity of wind power makes it a strong competitor with solar for share of renewable energy production. Figure 3.6 from Doris et al. shows the growth of wind power in the US from 2001 to 2007 [Doris et al., 2009].

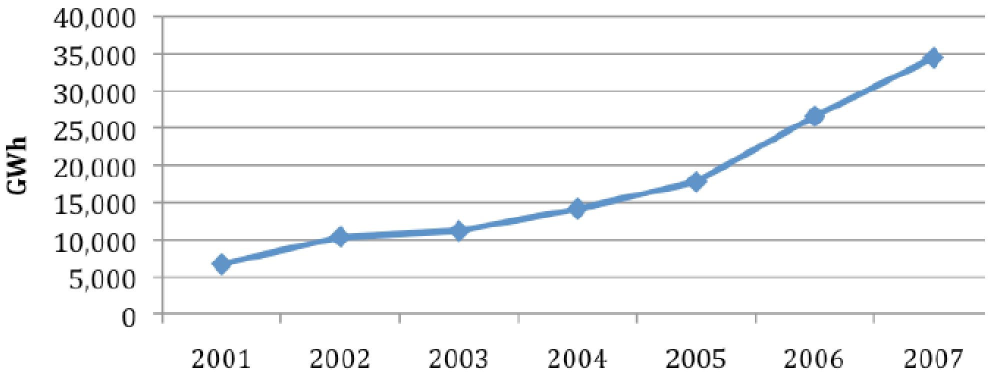

Figure 3.6: US Wind Energy Generation in Gigawatt hours

The variable *wind* measures the potential annual energy production per acre in kilowatt hours (kWh). Wind energy potential was computed by Elliott, Wendell, and Gower in their paper *An Assessment of the Available Windy Land Area and Wind Energy Potential in the Contiguous United States* [Elliott et al., 1991]. The estimates in this paper consider how much energy could be generated from wind if all practical windy areas were developed for wind energy. Practical areas exclude all environmental and urban lands (i.e. national parks and cities), 50% of forest lands, 30% of agricultural land, and 10% of range land. The data used for this variable were published in 1991, but since this variable measures potential power, not generated power, it should be time invariant.

3.3.3 Farm

Since installing solar technology is a farm level decision, it is important to include farm characteristics in the regression. All farm characteristics are aggregated to the state level.

Large

Calculation:

$$large = \frac{\text{farms in sales class over } \$100,000}{\text{total number of farms in state}}$$

Since solar equipment has high initial costs, many studies include income level to explain adoption rates. Since our data is available at the state leve, we include *large* as a proxy for farm income. *Large* denotes the proportion of farms whose market value of agricultural products sold including direct sales is over $\$100,000$.

Utility

The amount of energy needed on farms may influence the decision to adopt solar power. *Utility* measures the share of operating costs spent on utilities. Data was collected from the USDA's Agricultural Census for the years 2002 and 2007. The census was also collected in 1997, but information was not collected for utility costs. Utility data collected in 2002 and 2007 include the cost of electricity, phone, internet, and water, including irrigation [National Agricultural Statistics Service, 2004]. In the panel regression, the data from 2002 are used for the 2000 time step. The data from 2007 are used for the 2009 time step and an average of the 2002 and 2007 data is used for the 2004 time step. The cross sectional regression uses an average of the 2002 and 2007 values to show the average utility expenditure during the time panels were being installed.

Irrigation

Calculation:

$$irrigation = \frac{\text{acres irrigated}}{\text{ag land in thousands of acres}}$$

The variable *irrigated* measures the number of acres irrigated per thousand acres of farmland in the state. Solar power is frequently used for powering irrigation pumps especially in remote locations. Brown and Elliott report that motors are the largest use for energy for all farm types that use irrigation [Brown and Elliott, 2005]. With its high demand for energy, critial role in agriculture, and compatibility with solar energy irrigation is certainly important to consider.

3.3.4 Policy

Statewide policies encouraging solar adoption are divided into several variables in order to determine the most effective policy choices. Each variable counts the number of years a type of program has been available. The year in question in the regression is counted as 1. For instance, if a statewide grant program is started in 1997 and another is started in 2004, the variable *grant* in the cross sectional regression would be 13. The program started in 2004 would not contribute to the dataset.

Programs were counted if they were designed to support renewable or solar energy and would be accessible to farmers. Therefore, policies that only effect utility scale energy production were not included. Also, farmers may have access to general loan programs through banks and farming cooperatives, but these were not included. Only programs that are specifically designed to support solar or renewable energy development were included. All of the programs here are avilable statewide although some are run by non-governmental foundations. Local programs run by cities and utility companies were not included. All of the information on various policies was collected from the Database of State Incentives for Renewables & Efficiency (DSIRE) [U.S. Department of Energy, 2013]. This database displays up to date policies that encourage renewable energy adoption. There is a possibility that programs that were in effect in the study period, but have since expired, are not counted.

These variables are a summarization of the data and lose some detail. Programs within the same category may offer different levels of support. For instance, grant programs may offer different maximum values. Examples of policies are given in the following variable descriptions. They offer insight into typical programs, but are not meant to describe policies in all of the states. Each variable description also includes a color coded map of the United States showing the geographical distribution of the variable.

Policy regimes are measured in several different ways throughout literature on renewable energy development. Trying to balance a understandable model with policy detail is a common challenge. In a 2009 study of RPS policies, Carley uses two variables to describe the policy regime of each state. The first variable counts the number of different types of annual operational subsidy policies. Grant, loan, and rebate programs are all weighted equally in this variable, which has a range of zero to three. The second variable counts the number of different types of annual operational tax incentives taking into account corporate, personal, property, and sales tax policies [Carley, 2009]. Matisoff uses a count variable for the number of state policies incentivizing renewable energy generation as the dependent variable in his 2008 paper on state climate change policies [Matisoff, 2008]. In a paper on wind power development, Menz selected five policies of interest and developed two metrics for measuring each policy. The first was a dummy variable for implementation before 2003 and the second was the number of years each policy was in place in 2003 [Menz and Vachon, 2006].

Grant

The variable *grant* includes grant and rebate programs. These programs fund some of the upfront cost of renewable energy without repayment from the installer. Funded by the state's public benefit fund, the Renewable Energy Resources Trust Fund, the Illinois Department of Commerce and Economics Opportunity (DCEO) runs a state rebate program for solar and wind energy. Residential and commercial solar PV can be awarded a rebate of $1.50 per watt or 25% of project costs with a maximum of a $10,000 rebate. Figure 3.7 shows a sparse distribution of grant programs. The oldest program had been in place for 14 years in 2009. Grant programs are generally found in the east and west, but not in the central part of the country.

Loan

Loan programs usually provide low interest loans for special projects involving energy efficiency improvements and renewable energy installation. The Nebraska Dollar and Energy Savings Loan program is a good example of the incentives available. The Dollar and Energy Savings Loan program started in 1990 with funding from oil overcharge payments collected from Exxon [Energy Bank of Nebraska, 2005] and supported with money from the 2009 American Recovery and Reinvestment Act [U.S. Department of Energy, 2013]. The State Energy Office, in collaboration with various banks, offers loans up to $125,000 for wind, PV, and fuel cells [U.S. Department of Energy, 2013]. Maximum loan amounts for other types of projects vary. Loan programs are more evenly distributed geographically that grant programs. There are several states with loan programs in the central part of the country in Figure 3.8. Minnesota has the oldest loan program, which had been in place for 39 years in 2009.

Property

Property records the number of years since the earliest property tax incentive for solar was installed. Many states, including Connecticut, Nevada, and Montana, have a 100% exemption for renewable energy systems from property taxes. Montana, however, only offers the exemption for the first 10 year of the system's life. The distribution of property tax incentives is shown in Figure 3.9. Property tax incentives fall in to a wide range of age brackets.

Sales

Sales, similar to *property*, corresponds to sales tax incentives. Arizona, California, Connecticut and New York are amoung the states that waive 100% of the state sales tax on eligible equipment. As seen in Figure 3.10, sales tax incentives are, in general, neither as common nor as old as property tax incentives.

Tax

Property tax and sales tax account for some of the tax policies, but there are also personal and corporate tax incentives available to solar installers. These tax incentives are measured in the variable *tax*. Arizona offers a Non-Residential Solar and Wind Tax Credit equal to 10% of installed costs. This credit is targeted specifically toward commercial, industrial, nonprofit, schools, government (local, state, federal, and tribal), agricultural, and institutional interests [U.S. Department of Energy, 2013]. Iowa offers two personal tax credits, one for 15% of costs and the other for $1.50 per kWh hour produced for the first ten years of production [U.S. Department of Energy, 2013]. Tax incentives fall into the newer age categories, under 15 years, and in the oldest bracket, over 25 years. However, there are no tax incentives that have been in place for 16 to 25 years.

Credit

Some states, particularly those with Renewable Portfolio Standards, have set up markets for renewable energy credits. In these states, farms and other small energy producers can sell the credits they accrue for excess energy they produce that is not used on site. Policies that set up specific programs for trading credits where included in the variable along with RPS policies that specifically require trading. Credit trading policies are amoung the newer policies put in place and are spread across the country. Many of the credit trading programs are part of RPS legislation.

Net Metering

While net metering is often mandated by state legislatures, it does not require any finanical obligation from the state and the program will never expire. The variable *net metering* counts the number of years that each state has had a net metering policy. Utility companies sometimes offer their own net metering policies, but this variable only counts statewide mandated net metering. New Hampshire and Minnesota tie for longest standing net metering policies. Both of their policies were enacted in 1983 [U.S. Department of Energy, 2013]. Net metering is the most common incentive. Figure 3.13 clearly shows that the majority of states had net metering policies by 2009. These policies have been installed over time with a wide range of age brackets covered in the graph.

3.3.5 Dummy Variables

Two dummy variables are used in the time series regression to denote the years of the study. The base year is 2000 and dummies, *d04* and *d09*, are included for the years 2004 and 2009.

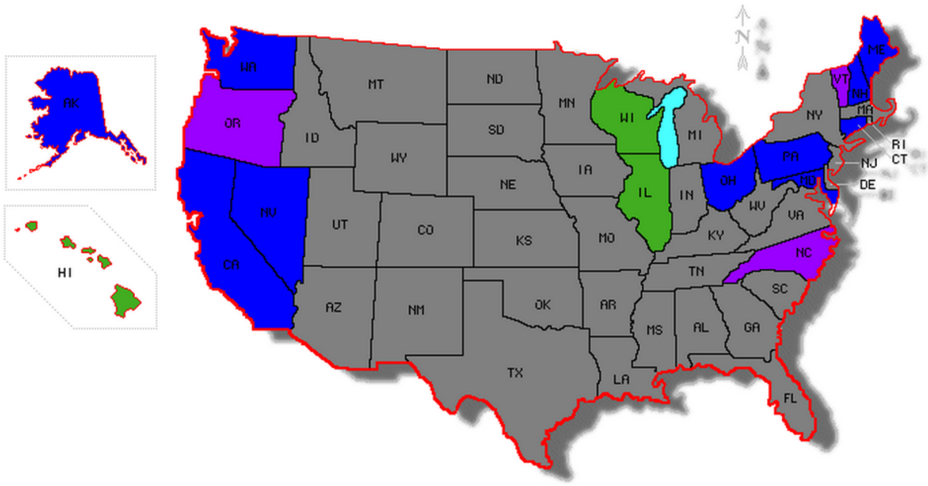

Figure 3.7: *Grant* Map

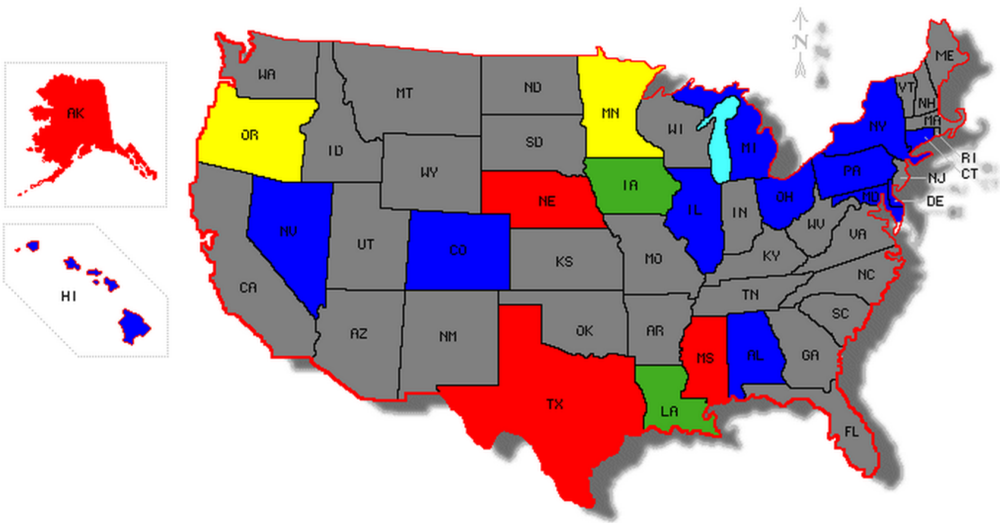

Figure 3.8: *Loan* Map

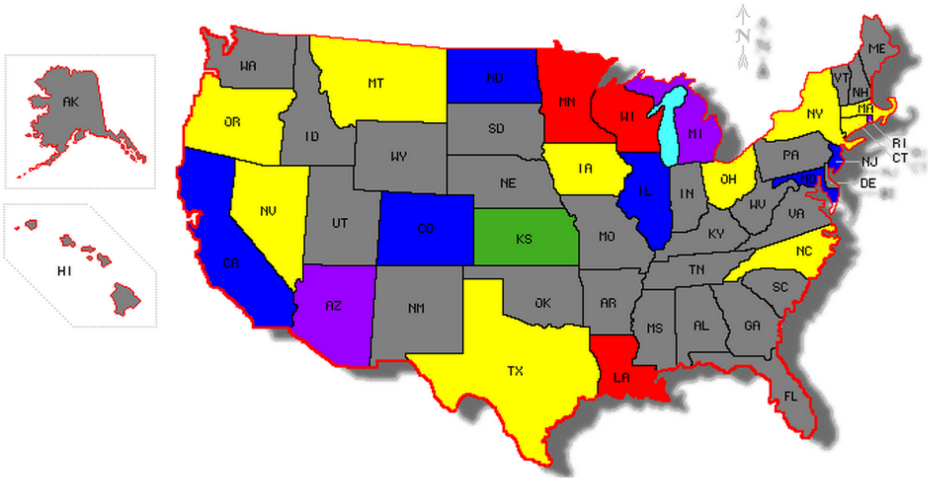

Figure 3.9: *Property* Map

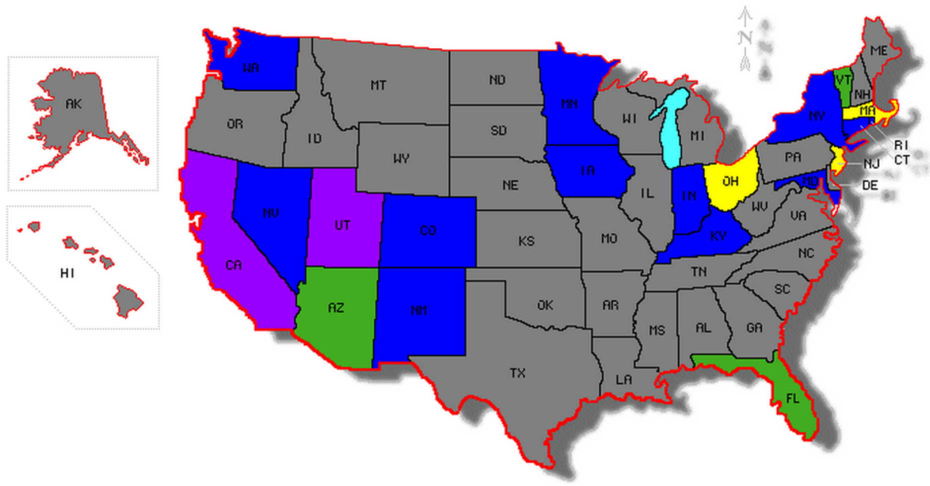

Figure 3.10: *Sales* Map

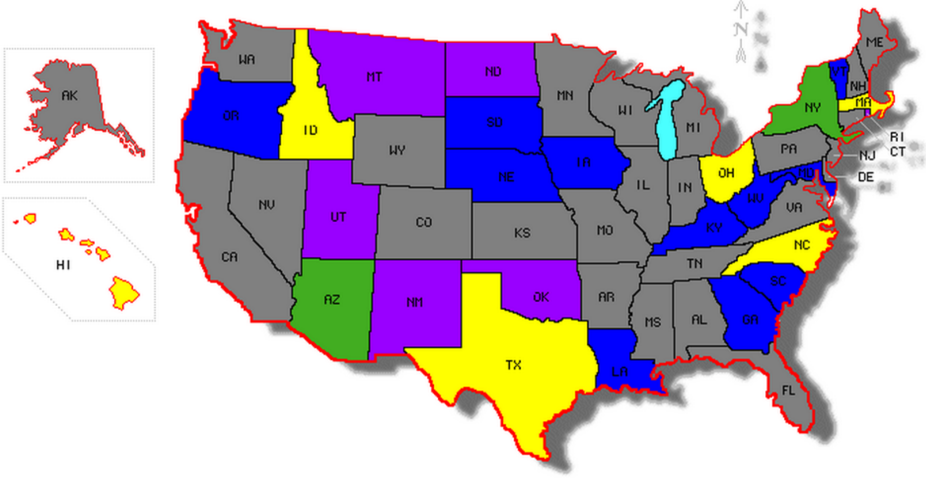

Figure 3.11: *Tax* Map

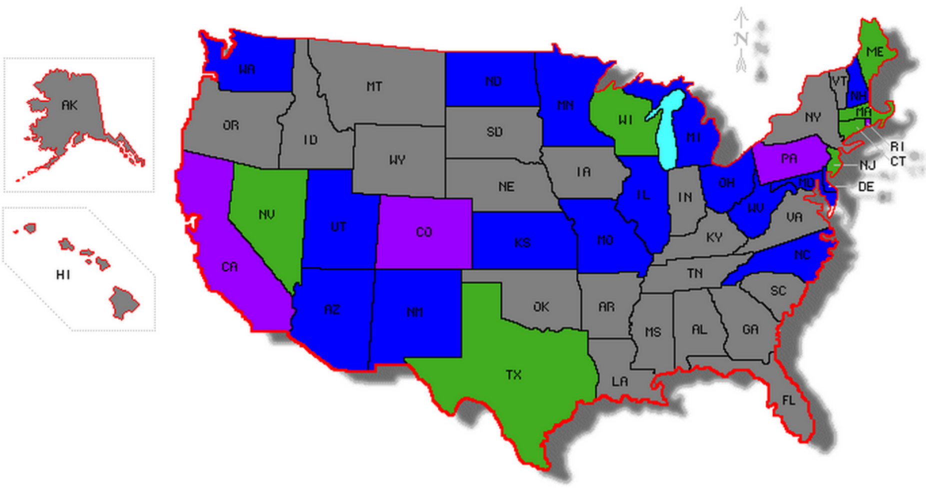

Figure 3.12: *Credit* Map

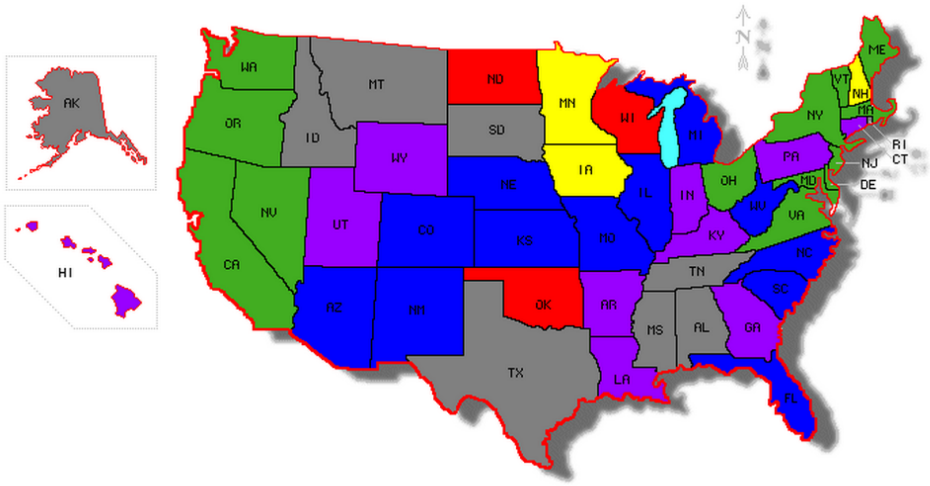

Figure 3.13: *Net Metering* Map

Chapter 4

Cross Sectional Model

4.1 Methods

4.1.1 Data

The complete dataset for the cross sectional regression includes 48 states. Alaska and Hawaii were excluded from the dataset due to missing information regarding wind power potential. Table 4.1 shows the year the data was collected and the expected sign of the coefficients for the independent variables.

4.1.2 Multicollinearity

Before running a regression, we followed the method described by Douglass et al. to test for collinearity [Douglass et al., 2003]. This method uses two tests, the first for degrading collinearity and the second for harmful collinearity. Degrading collinearity is indicated by condition indices over 30. In the event that degrading collinearity is found, the signal to noise ratio is computed for each parameter and compared to a critical value to test for harmful collinearity.

When the condition indices were computed for the entire dataset, the highest value

Table 4.1: Cross Sectional Variables

Variable	Year	Expected Sign
adopt	2009	dependent variable
solar radiation	avg. 1998-2009	+
electricity	avg. 2000-2009	+
diesel	avg. 2000-2009	+
wind	1991	-
large	2007	+
utility	2007	+
irrigation	2007	+
grant	2009	+
loan	2009	+
property	2009	+
sales	2009	+
tax	2009	+
credit	2009	+
net metering	2009	+

was 209.79 with the next highest condition index equal to 41.42. Given these results, signal to noise ratios were computed for each variable and compared to the critical value of 5.035 found in Table 7.9b in Belsley's textbook *Conditioning Diagnostics* [Belsley, 1991]. Eleven out of fifteen variables had inadequate signal to noise ratios. This caused some confusion because signal to noise ratios can denote harmful collinearity, but they can also indicate short data. Not knowing which of these problems was present, we moved to Belsley's recommendation of identifying degrading collinearity by high condition indices coupled with high variance-decomposition proportions. The table of variance-decomposition proportions showed high numbers to be associated with the intercept and *diesel*, 0.98 for both, in conjunction with the index of 209.79 Thus, we dropped *diesel* from the regression and retested for collinearity. The condition index of 41.42 was associated with a variance-decomposition proportion of 0.87 for *solar radiation*. We took the exponential of *solar radiation* and tested for collinearity again. After dropping *diesel* and transforming *solar radiation* (*SR*) to *expSR*, the highest condition index was 19.73. This implies that no degrading collinearity exists in the sample and alleviates the need to check for

harmful collinearity.

4.1.3 Heteroscedasticity

With *diesel* removed from the dataset, the remaining variables were tested for heteroscedasticity using White's Test and the Breusch-Pagan Test. Each test examines a null hypothesis of homoscedasticity and both tests failed to reject that hypothesis.

4.1.4 Joint Significance

The model contains seven variables accounting for state level policies encouraging solar adoption. Preliminary regression results show some, but never all, of the policy variables having a significant impact on adoption rates. To better understand the role of policies in the diffusion of solar technology, the seven policy variables were tested for joint significance. The null hypothesis that all parameter estimates are equal to zero failed to be rejected by a F-test in SAS. The test returned an F-statistic of 1.36 and a p-value of 0.25. We cannot conclude that there is joint significance and instead we must rely on the significance of individual policies.

4.1.5 Model Specification

While we have addressed the problems of multicollinearity and heteroscedasticity, it is still possible that the model is overspecified. An overspecified model can fit the sample data extremely well, but lack predictive power when applied to out of sample data. Since there are no out of sample data to test our model, we turn to the Schwarz Bayesian Criteria (SBC) to identify the variables of most and least importance.

Information criteria, including Akaike's Information Criteria, Bayesian Information Criteria, and Schwarz Bayesian Criteria, use different measures to rate model specifications. SBC is calculated using the following equation.

$$SBC = n \cdot \ln\left(\frac{SSE}{n}\right) + k \ln n$$

where n is the number of observations and k is the number of independent variables including the intercept. Similar to adjusted R^2, this measure penalizes the addition of variables to the model. Each possible model specification can be measured and rated by suitability according to each criteria. In addition to information criteria, there are also heuistic methods (forward selection, backward selection, and stepwise regression) and model diagnostics (root mean square error, adjusted R^2, and Mallows CP) all of which provide ways to choose the best model specification.

We chose to use SBC due to its outstanding performance selecting the correct model when the model is known. The histogram in Figure 4.1 shows the percent each method selects the correct model out of $2,046$ possibilities. The data contained 100 observations. The graph is taken from a paper by Dennis Beal on information criteria methods [Beal, 2007]. The model produced using the SBC is presented in Table 4.2 along with the more inclusive original model.

4.2 Results

As discussed in Section 4.1, we will present results for the general model and the model developed using SBC. Table 4.2 presents the parameter estimates, standard errors, and significance level of the variables. The two models identify mainly the same variables as important.

The first dependent variable, *expSR*, is significant at the 1% level in both regressions. The parameter estimate has the expected sign. When $exp(SR)$ increases by 1, 0.18 more farms per $1,000$ farms, or almost two farms per $10,000$, adopt solar technology. Since *solar radiation* is the only variable in the environmental category, the adoption of solar

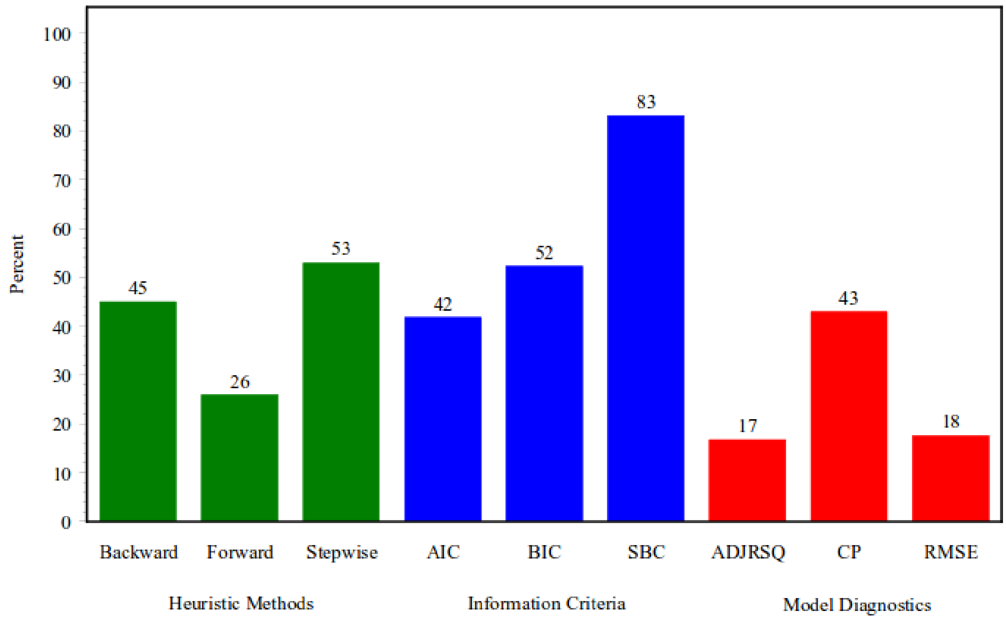

Figure 4.1: Comparitive Accuracy of Model Selection Criteria

technology does rely on environmental factors as expected.

Electricity and *wind* are the only two market variables included in the final model. *Electricity* is highly significant with the expected sign. Recall that *electricity* is a ten year average price. When the price of electricity is higher over an extended amount of time, farmers are more likely to use solar technology to supplement their energy. The first surprising result comes from wind power potential. The variable is significant, but the sign is opposite of what was predicted. Instead of lower adoption in states with better wind resources, we find more adoption. Farmers do not seem to be substituting away from solar when wind power is available for development. Given the small parameter value, however, we see that as the potential annual energy increases by one kilowatt hour per acre, two more farms per ten million will adopt solar technology.

The farm condition variables are less important than expected. *Large* and *irrigation* are insignificant in the general model and do not appear in the SBC model. *Utility*, however, has a very significant impact in both models. The proportion of money spent on utilities turns out to matter much more than the sales class of the farm (*large*) or the amount of land irrigated (*irrigation*). The parameter estimates for *utility* are similar between the two models. In either specification, when the percent of total expenditure spent on utilties increases by 1%, approximately 35 more farms per thousand adopt solar technology.

The policy variables also had a lower significance than expected. Recall that the test for joint significance failed to reject the null hypothesis that all parameters were equal to zero. *Grant* was significant at the 10% level with the expected sign. For each additional year that grant or rebate program is in place, about 3 more farms per ten thousand installed solar technology. Sales tax programs were also significant in both models. The parameter estimates for *grant* and *sales* were positive as expected. Property tax was significant in the SBC model, but not the general model. Its coefficient was surprisingly negative indicating that a longer standing property tax incentive led to less solar power on farms. These results are similar to Carley's results in her 2009 paper. Recall from Section 3.3.4 that she used two variables for policies, one counting subsidy policies (grants, loans, and rebates) and another counting tax policies (sales, property, corporate, and personal). Both variables were significant in a fixed effects variable decomposition model where the dependent variable was the logged share of renewable energy. The tax index was significant with a negative sign and the subsidy variable was significant with a positive sign. They were both significant with the same signs in another regression where the dependent variable was total MWh of renewable energy produced [Carley, 2009]. In this thesis, we see *grant*, a subsidy policy, with a positive sign and *property* with a negative sign in the SBC model. The positive sign on *sales* does not fit the pattern established by Carley, but we have ungrouped our policies, which may cause variation.

Perhaps the most notable policy to fail to reach a significant level was *net metering*. Net metering allows renewable energy producers to automatically receive credit or payment from the utility company for energy put into the grid. Although the literature has a very positive view of this policy (see [Stoutenborough and Beverlin, 2008]), it is possible that the remote uses of solar technology in agriculture prevent farmers from taking advantage of it in a meaningful way.

In both the general model and the SBC model, variables from all four categories, environmental, market, farm, and policy, were significant. The coefficients and levels of significance were also similar across model specifications. By selecting fewer variables the SBC model was able to increase the adjusted R^2 measure as shown in Table 4.2.

Table 4.2: Cross Sectional Results

	General Model		SBC Model	
Adjusted R^2	0.6824		0.7189	
Variable	Parameter Estimate (Standard Error)		Parameter Estimate (Standard Error)	
Intercept	-140.38 (27.20)	***	-138.71 (21.34)	***
exp(solar raditation)	0.18 (0.05)	***	0.18 (0.05)	***
electricity	9.38 (3.25)	***	8.80 (2.68)	***
wind	0.002 (0.91 E$-$03)	*	0.002 (0.74 E$-$03)	**
large	-0.16 (0.39)			
utility	35.06 (7.71)	***	34.20 (6.29)	***
irrigation	-0.003 (0.07)			
grant	3.27 (1.77)	*	3.17 (1.61)	*
loan	-0.01 (0.68)			
property	-0.64 (0.59)		-0.95 (0.38)	**
sales	1.57 (0.74)	**	1.31 (0.61)	**
tax	-0.62 (0.67)			
credit	-0.93 (1.6)			
net metering	-0.07 (0.78)			
*	sig. at 10% level	$p < 0.1$		
**	sig. at 5% level	$p < 0.05$		
***	sig. at 1% level	$p < 0.01$		

Chapter 5

Panel Model

5.1 Methods

5.1.1 Data

The complete dataset for the panel regression includes 41 states and three time periods. Alaska, Connecticut, Delaware, Hawaii, Louisiana, Maryland, New Hampshire, Rhode Island, and West Virginia were excluded from the dataset due to missing information. The resulting dataset is a balanced panel. The dependent variable, *panels*, is the number of solar panels per thousand farms in each state in 2000, 2004, and 2009. Table 5.1 shows the year the data was collected and the expected sign of the coefficients for all of the variables.

5.1.2 Contemporaneous Correlation and Autocorrelation

Contemporaneous correlation was found using the Breusch-Pagan Lagrange Multiplier Test for diagonal covariance matrix. This is corrected by using Panel Corrected Standard Errors (PCSE). The Durbin-Watson test was used to check for autocorrelation. A test statistic of 0.25 indicated positive autocorrelation. Corrections were made for first-order autoregressive errors.

Table 5.1: Panel Variables

Variable	Year	Expected Sign
panels	2000, 2004, 2009	dependent variable
solar radiation	avg. '98-'09 time invariant	+
electricity	avg. '96-'00, '04-'09, '05-'09	+
diesel	avg. '96-'00, '04-'09, '05-'09	+
wind	1991	-
large	1997, 2002, 2007	+
utility	2002, avg. 2002 & 2007, 2007	+
irrigation	1997, 2002, 2007	+
grant	2000, 2004, 2009	+
loan	2000, 2004, 2009	+
property	2000, 2004, 2009	+
sales	2000, 2004, 2009	+
tax	2000, 2004, 2009	+
credit	2000, 2004, 2009	+
net metering	2000, 2004, 2009	+

5.1.3 Heteroscedasticity

The panal data was tested for heteroscedasticity using the Lagrange Multiplier Test for cross-section heteroscedasticity. The test rejected the null hypothesis of homoscedasticity. SHAZAM was used to compute a panel-corrected covariance matrix of the coefficient estimates.

5.1.4 Model Specification

While specification of the general model in the cross sectional study was fairly straight forward, the panel model benefited from closer inspection. Due to the distribution of the dependent variable (see Figure 3.2), it seemed prudent to compare the linear model explaining *panels* with semi-log and log-log models. The results of the linear, semi-log and log-log models are presented in Table 5.2. The log-log model produces the best fit and will hereafter be the general model. In the variable column, a dagger (†) denotes that the natural log of the variable was used in the log-log regression. The double dagger (‡) by *solar radiation* means that the natural log of the *solar radiation* was used in the log-log regression and *exp(solar radiation)* was used in the linear and semi-log models. Any variable without a dagger contains zeros and was linear in all models.

Just as in the cross sectional regression, we use the Schwarz Bayesian Criteria (SBC) to identify the variables of most importance. SBC ranks all combinations of variables by the criteria statistic seen in Section 4.1.5. The model produced using the SBC is presented in the results section along with the more inclusive log-log model.

Table 5.2: Linear, Semi-Log, Log-Log Comparison

	Linear		Semi-Log		Log-Log	
Buse R^2	0.4142		0.7248		0.7335	
Variable	Parameter (S.E.)		Parameter (S.E.)		Parameter (S.E.)	
Intercept	−169.2 (168.1)		−2.88 (0.4751)	***	−8.08 (1.16)	***
solar radiation[‡]	0.26 (0.17)	**	0.37 E−02 (0.95 E−03)	***	3.05 (0.62)	***
electricity[†]	10.02 16.42		0.19 (0.32 E−01)	***	1.23 0.3	***
wind	0.5 E−03 (0.27 E−02)		0.39 E−05 (0.27 E−04)		0.1 E−04 (0.27 E−04)	
large[†]	14.26 (170.6)		1.53 (2.16)		0.46 0.34	
utility[†]	12.87 (9.76)		0.79 (0.18)	***	2.86 (0.66)	***
irrigation[†]	0.47 (0.56)		0.11 E−02 (0.48 E−03)	**	0.13 (0.41 E−01)	***
grant	2.17 4.33		0.76 E−01 (0.76 E−01)		0.74 E−01 (0.8 E−01)	
loan	−0.78 0.57		0.11 E−02 (0.58 E−02)		−0.64 E−02 (0.6 E−02)	
property	−1.82 0.79	**	−0.74 E−02 (0.59 E−02)		−0.31 E−02 (0.54 E−02)	
sales	10.21 (5.16)	**	0.5 E−01 (0.15 E−01)	***	0.53 E−01 (0.16 E−01)	***
tax	−5.83 (3.39)	*	−0.7 E−02 (0.5 E−02)		−0.89 E−02 (0.34 E−02)	***
credit	19.02 (7.26)	***	−0.19 E−01 (0.17 E−01)		−0.22 E−01 (0.21 E−01)	
net metering	2.47 (1.26)	**	0.97 E−03 (0.15 E−01)		0.19 E−02 (0.13 E−01)	
d04	14.62 (7.68)	*	0.99 (0.43 E−01)	***	1.06 (0.44 E−01)	***
d09	30.02 (16.52)	*	1.66 0.12	***	1.82 (0.12)	***
*	sig. at 10% level	$p < 0.1$				
**	sig. at 5% level	$p < 0.05$				
***	sig. at 1% level	$p < 0.01$				

5.2 Results

Once the statstical corrections were made and the best specification choosen, the panel regression produced the following results, shown in Table 5.3.

First, we'll analyze the log-log model. The collection of highly significant variables contains variables from all four categories, environmental, market, farm condition, and policy. *Solar radiation*, *electricity*, *utility*, *irrigation*, *sales*, and *tax* are all significant at the 1% level as are both dummy variables and the intercept. *Solar radiation*, the environmental variable, is unsurprisingly positive and the largest parameter estimate after the intercept. For each percentage increase in *solar radiation* the number of solar panels per thousand farms increases by about 3%. The price of electricity has another big impact on solar installation. For each percentage increase in the price of electricity, the number of panels installed increases by just over 1%. The farm category of variables is also strongly represented in this model. *Utility* and *irrigation* are significant at the 1% level. *Utility* has the next highest effect after *solar radiation*.

All but one of the highly significant variables have the expected positive sign. *Tax* was expected to positively impact the amount of solar adopted, but instead for each addition year of tax policy, the number of solar panels installed per thousand farms decreases by -0.0089%. It should be noted that this variable has a large number of states with no policy, lowering the reliablity of the estimated effect. The positive effect of the policy variable, *sales* is also small. Each additional year that a sales tax incentive is in place only increases the number of solar panels per thousand farms by 0.053%.

The SBC model drastically reduces the number of variables. Even *sales* and *tax*, which were significant in the log-log model, were not selected by the SBC into the parsimonious model. Those variables that were selected retained their significance, but *solar radiation* and *irrigation* moved from the 1% level to the 5% level.

Table 5.3: Panel Results

	Log-Log Model		SBC Model	
Buse R^2	0.7335		0.7015	
Variable	Parameter Estimate (Standard Error)		Parameter Estimate (Standard Error)	
Intercept	-8.08 (1.16)	***	-7.18 (1.7)	***
ln(solar radiation)	3.05 (0.62)	***	1.81 (0.76)	**
ln(electricity)	1.23 0.3	***	1.5 (0.48)	***
wind	0.1 E$-$04 (0.27 E$-$04)			
ln(large)	0.46 0.34			
ln(utility)	2.86 (0.66)	***	2.48 (0.68)	***
ln(irrigation)	0.13 (0.41 E$-$01)	***	0.19 (0.79 E$-$01)	**
grant	0.74 E$-$01 (0.8 E$-$01)			
loan	-0.64 E$-$02 (0.6 E$-$02)			
property	-0.31 E$-$02 (0.54 E$-$02)			
sales	0.53 E$-$01 (0.16 E$-$01)	***		
tax	-0.89 E$-$02 (0.34 E$-$02)	***		
credit	-0.22 E$-$01 (0.21 E$-$01)			
net metering	0.19 E$-$02 (0.13 E$-$01)			
d04	1.06 (0.44 E$-$01)	***	1.04 (0.33 E$-$01)	***
d09	1.82 (0.12)	***	1.88 (0.85 E$-$01)	***
*	sig. at 10% level	$p < 0.1$		
**	sig. at 5% level	$p < 0.05$		
***	sig. at 1% level	$p < 0.01$		

Chapter 6

Conclusion

6.1 Discussion

Table 6.1 shows the significant variables in the general and SBC regressions for the cross sectional and panel models. In three of the four models, variables from all four categories, environmental, market, farm, and policy, were significant. Conditions promoting solar energy are diverse and take into account many different types of incentives.

Table 6.1: Significance Comparison

C.S.	C.S. SBC	Panel	Panel SBC
Intercept	*Intercept*	*Intercept*	*Intercept*
exp(solar radiation)	*exp(solar radiation)*	*ln(solar radiation)*	*ln(solar radiation)*
electricity	*electricity*	*ln(electricity)*	*ln(electricity)*
wind	*wind*		
utility	*utility*	*ln(utility)*	*ln(utility)*
		ln(irrigation)	*ln(irrigation)*
grant	*grant*		
	property		
sales	*sales*	*sales*	
		tax	
		d04	*d04*
		d09	*d09*

The cross sectional regression looks for the reasons why states have different rates of adoption. This regression does not consider how much solar energy each farm installed, but rather the diffusion of solar technology. In the linear model, *solar radiation*, *electricity*, *wind*, *utility*, *grant*, and *sales* were significant. *Solar radiation* is an obvious candidate for significance in each regression; without sufficent sunlight, solar power cannot be an efficient choice. *Electricity* and *utility* show some of the cost of convention energy that is avoided by installing solar. Farms that spend comparatively more on energy, denoted by high *utility* values, can benefit from producing their own energy rather than buying electricty, especially in states with comparatively higher electricity prices. The variable *grant* is a very logical possibility for significance amoung the policy variables. *Grant* includes policies for grant and rebate programs through which farmers receive money for solar or renewable energy projects without repayment. The significance of sales tax is a little harder to explain and the connection may become clearer with more study.

The panel regression modeled the number of solar panels per thousand farms. In this regression, states could achieve a high value for *panels* by having a few farms install large amounts of solar power or by having many farms install moderate amounts of solar power. In this regression, *solar radiation*, *electricity*, *utility*, *irrigation*, *sales*, *tax* and the dummies for year were significant. Refer to Table 6.1 to see where the natural log was applied. Again, *solar radiation* is significant for obvious reasons. The recurring significance of *electricity* and *utility* highlight the importance of avoided cost. Incentives at the time of sale, like *grant* and *sales*, are not as strong in the panel regression, but variables that decrease the payback period of panels, like *utility* and *electricity*, remain highly significant. *Irrigation* brings to light the suitability of solar for pumping water and more genearlly, remote uses. *Irrigation* does not appear significantly in the cross sectional regression. Thus, we know that the proportion of agricultural land that is irrigated does not significantly impact the decision to adopt solar. However, more irrigation can lead to higher intensity adoption. Since *irrigation* is only associated with higher levels of adoption, it provides support to the fact that when solar technology is adopted, it is particularly useful for remote applications.

Grant, which was significant in the cross sectional regression, is no longer significant in the panel model. *Adopt*, the dependent variable in the cross sectional regression, grows as more farms install solar. As some farms may struggle with the high inital cost of solar, financial support for installation may help a significant number of farms over the financial barrier. Since the dependent variable in the panel regression can grow from even growth throughout the state in solar or from a few farms installing many panels, it is not critical that each struggling farm be included. States that rank highly in terms of numbers of panels do not need to insure accessibility by making sure everyone can afford solar, thus *grant* is no longer significant.

In many cases, widespread solar adoption and high intensity solar adoption overlap. Recall Table 3.2 showing the top ten states in terms of solar adoption per ten thousand farms and the top ten states in terms of number of solar panels installed per thousand farms. Just as we see many of the same states in the two lists, we can clearly see several similarities between the models in Table 6.1. The similarities graviate towards variables not entirely controlled by each state. Solar radiation, the price of electricity, utility expeditures, the sales tax are seen in both regressions. Sales tax policies are certainly under the purview of the state while solar radiation and utility expenditures are certainly not. Electricity prices are more complicated as rate changes need approval from public utilities commissions.

In terms of incentives where states are most involved, it seems as though states can target inclusive policies, like grants and rebates, to get many farms involved. Supporting high levels of solar adoption through state policy is a little more complicated. The panel regression points more towards variables that make solar a better competitor to conventional power sources like high electricity prices, significant spending on utilities, and widespread irrigation. Policy variables had a weaker showing. *Sales* was significant in the log-log model, but did not appear in the SBC regression. *Tax* appeared in both, but had a negative effect on solar installation.

6.2 Future Work

There are plenty of opportunities for future research extending from this work. First, as pointed out previously, the data used here is aggregated to the state level and therefore leaves out many possible explanatory variables. A farm level study including variables for income and attitudes towards environmental stewardship would provide more insight into the decision to install solar on farms. Since the decision to install solar is made at the farm level, these characteristics should be considered.

This study could also be improved by using a two stage model. This would allow us to study the following series of questions: 1) What causes widespread adoption of solar technology? and 2) Once a farm has decided to adopt, what causes higher intensity of adoption (i.e. installing more panels per farm)? The first regression would be the cross sectional regression presented here measuring the proportions of farms in each state adopting solar. However, we had to amend question two to read, "What causes high intensity adoption of solar energy?" The data available for independent variables describe state level attributes. We cannot build a dataset to reflect the condition facing only those farms that have choosen to install solar technology. A two staged model with farm level variables would require extensive data collection not within the scope of this thesis.

Beckman and Xiarchos published a study in 2013 of Californian farmers that included the extensions listed above. They used data from the *On-Farm Renewable Energy Production Survey (2009)*, but instead of a state level study, incorporated data at the farm level [Beckman and Xiarchos, 2013]. They found environmental practices, internet connection, and electricity price effect the decision to adopt solar while total value of production and acre value effect the amount of renewable energy installed [Beckman and Xiarchos, 2013].

The policy results presented here offer another avenue of expansion. The policy variables used in this thesis only record the age of each policy. Policies can alternatively be measured by total savings provided to the farmer or policy characteristics. The regressions presented here are also inconclusive concerning ways for states to promote high intensity solar installation. In this study, sales tax policies are frequently the most effective policy in promoting solar, but the parameters are consistently small in magnitude. Further study could examine other ways in which state policy promotes solar or develop new incentive schemes to increase adoption.

There are many ways to expand research in renewable energy sources in agriculture. Data are available, but underutilized. Further study can promote renewable energy by finding effective ways to support farmers and make the technology widely available.

Bibliography

[Beal, 2007] Beal, D. (2007). Information criteria methods in sas for multiple linear regression models. In *SESUG 2007: The Proceedings of the SouthEast SAS Users Group*, Hilton Head, SC.

[Beckman and Xiarchos, 2013] Beckman, J. and Xiarchos, I. M. (2013). Why are california farmers adopting more (and larger) renewable energy operations? *Renewable Energy*, 55:322–330.

[Belsley, 1991] Belsley, D. A. (1991). *Conditioning Diagnostics: Collinearity and Weak Data in Regression.* John Wiley & Sons, Inc.

[Bollinger and Gillingham, 2010] Bollinger, B. and Gillingham, K. (2010). Environmental preferences and peer effects in the diffusion of solar photovoltaic panels. *Revise and Resubmit at Marketing Science.*

[Brown and Elliott, 2005] Brown, E. and Elliott, R. N. (2005). On-farm energy use characterizations. Technical report, American Council for an Energy-Efficient Economy, Washington DC.

[Burney et al., 2010] Burney, J., Woltering, L., Burke, M., Naylor, R., and Pasternak, D. (2010). Solar-powered drip irrigation enhances food security in the sudano-sahel. *Proceedings of the National Academy of Sciences of the United States of America*, 107(5):1848–1853.

[Byrne et al., 2007] Byrne, J., Hughes, K., Rickerson, W., and Kurdgelashvili, L. (2007). American policy conflict in the greenhouse: Divergent trends in federal, regional, state, and local green energy and climate change policy. *Energy Policy*, 35:4555–4573.

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

[Cory and Rahman, 2012] Cory, D. C. and Rahman, T. (2012). *Environmental Justice and Federalism*. Edward Elgar Publishing Inc.

[Doris et al., 2009] Doris, E., McLaren, J., Healey, V., and Hockett, S. (2009). State of the states 2009: Renewable energy development and the role of policy. Technical report, National Renewable Energy Laoratory, Golden Colorado.

[Douglass et al., 2003] Douglass, D. H., Clader, B. D., Christy, J., Michaels, P. J., and Belsley, D. A. (2003). Test for harmful collinearity among predictor variables used in modeling global temperature. *Climate Research*, 24:15–18.

[Durham et al., 1988] Durham, C. A., Colby, B. G., and Longstreth, M. (1988). The impact of state tax credits and energy prices on adoption of solar energy systems. *Land Economics*, 64(4):347–355.

[Elliott et al., 1991] Elliott, D., Wendell, L., and Gower, G. (1991). An assessment of the available windy land area and wind energy potential in the contiguous united states. Technical report, Pacific Northwest Laboratory operated for the U.S. Department of Energy by Battelle Memorial Institute, Washington DC.

[Energy Bank of Nebraska, 2005] Energy Bank of Nebraska (2005). Distribution of oil overcharge settlement funds. Technical report, Nebraska Energy Office, Lincoln NE.

[Fischer and Preonas, 2010] Fischer, C. and Preonas, L. (2010). Combining policies for renewable energy: Is the whole less than the sum of its parts? *International Review of Environmental and Resource Economics*, 4:51–92.

[Maddigan et al., 1982] Maddigan, R. J., Chern, W. S., and Rizy, C. G. (1982). The irrigation demand for electricity. *American Journal of Agricultural Economics*, 64(4):673–680.

[Matisoff, 2008] Matisoff, D. (2008). The adoption of state climate change policies and renewable portfolio standards: Regional diffusion or internal determinants? *Review of Policy Research*, 25(6):527–546.

[Menz and Vachon, 2006] Menz, F. and Vachon, S. (2006). The effectiveness of different policy regimes for promoting wind power: Experiences from the states. *Energy Policy*, 34:1786–1796.

[Murray, 2009] Murray, D. (2009). How do state policies promote solar energy development. honors thesis, University of North Carolina at Chapel Hill.

[National Agricultural Statistics Service, 2004] National Agricultural Statistics Service (2004). 2002 census of agriculture: United States summary and state data. Technical report, United State Department of Agriculture.

[National Agricultural Statistics Service, 2010] National Agricultural Statistics Service (2010). Farms, land in farms, and livestock operations 2009 summary. Technical report, United State Department of Agriculture.

[National Agricultural Statistics Service, 2011] National Agricultural Statistics Service (2011). 2007 census of agriculture: On-farm renewable energy production survey (2009). Technical report, United State Department of Agriculture.

[National Renewable Energy Laboratory, 2013] National Renewable Energy Laboratory (2013). Dynamic maps, GIS data, & analysis tools.

[Rao and Kishore, 2010] Rao, K. U. and Kishore, V. (2010). A review of technology diffusion models with special reference to renewable energy technologies. *Renewable and Sustainable Energy Reviews*, 14:1070–1078.

[Stoutenborough and Beverlin, 2008] Stoutenborough, J. and Beverlin, M. (2008). Encouraging pollution-free energy: The diffusion of state net metering policies. *Social Science Quarterly*, 89(5):1230–1251.

[Tietenberg, 2004] Tietenberg, T. (2004). *Environmental Economics and Policy*. Pearson Addison Wesley, 4 edition.

[U.S. Department of Energy, 2013] U.S. Department of Energy (2013). Database of state incentives for renewables and efficiency.

[U.S. Energy Information Administration, 2012] U.S. Energy Information Administration (2012). Annual energy review.

[U.S. Energy Information Administration, 2013] U.S. Energy Information Administration (2013). Weekly retail gasoline and other prices.

[U.S. Environmental Protection Agency, 2012] U.S. Environmental Protection Agency (2012). Climate change action plans.

[Xiarchos and Vick, 2011] Xiarchos, I. M. and Vick, B. (2011). *Solar Energy Use in US Agriculture Overview and Policy Issues*. United State Department of Agriculture.

Appendix A

Data

A.1 Cross Sectional Data

states	adopt (number of farms per 10,000)	SR (kWh/ m^2/ day)	elec (cents per kilowatthour) average 2000-2009 in 2000 dollars	diesel (dollars per gallon, 2000 dollars, average '00-'09)	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (percent of total expenditure avg '02&'07)
Alabama	6.8041237	4.95	5.95456961	1.85483238	0	9.750515464	2.6
Alaska	235.29412	2.09	10.64093988	2.016967931	missing	11.32352941	4.9
Arizona	164.51613	6.36	7.084003901	2.016967931	137.558219	6.793548387	3.85
Arkansas	8.3503055	4.89	5.686447686	1.85483238	660.902555	16.43584521	2.65
California	233.86503	5.89	10.5863065	2.016967931	591.837567	23.36319018	4.7
Colorado	139.22652	5.72	6.336976812	1.940504839	7251.85585	14.08287293	2.6
Connecticut	53.061224	4.4	11.27168888	2.010858455	1612.52818	104.0408163	2.7
Delaware	16.129032	4.67	7.723506186	2.000345803	1601.05542	39.87903226	2.05
Florida	18.526316	5.26	7.906995728	1.866576572	0	11.01684211	2
Georgia	6.7226891	5.03	6.404708109	1.866576572	27.1748413	14.2289916	2.4
Hawaii	693.33333	5.65	16.02827105	2.016967931	missing	7.04	4.75
Idaho	51.372549	5	4.641469123	1.940504839	1380.09331	16.9254902	4.1
Illinois	7.651715	4.58	6.67983126	1.878429599	1716.8774	30.72559367	1.8
Indiana	20.650407	4.46	5.344473393	1.878429599	0	20.62113821	1.9
Iowa	4.3196544	4.58	5.819029472	1.878429599	15413.6248	35.69978402	1.8
Kansas	17.709924	5.3	5.983182416	1.878429599	20451.0305	21.66259542	1.3
Kentucky	7.8362573	4.58	4.488341035	1.878429599	0	6.926315789	2.4
Louisiana	4.3333333	5	6.632099182	1.85483238	0	10.74	2.15
Maine	119.75309	4.23	10.09348099	2.010858455	2836.04485	9.530864198	3.5
Maryland	16.40625	4.63	7.774157814	2.000345803	479.916303	17.6484375	2.5
Massachusetts	81.818182	4.35	11.1991159	2.010858455	5007.076	10.42857143	3.3
Michigan	13.686131	4.13	6.85181097	1.878429599	1796.73265	14.53649635	2.55
Minnesota	9.0123457	4.34	5.927286432	1.878429599	12905.9174	27.36296296	2.1
Mississippi	5.4373522	4.95	6.506273866	1.85483238	0	10.74704492	2.35
Missouri	8.6111111	4.8	5.648435666	1.878429599	1182.49906	10.96666667	2.15
Montana	79.865772	4.82	5.833678899	1.940504839	10951.8936	21.40939597	3.2
Nebraska	13.771186	5.16	5.2963687	1.878429599	17653.6264	41.47457627	1.85
Nevada	165.58442	5.95	7.813489327	2.016967931	711.713409	19.96753247	6.75
New Hampshire	118.07229	4.26	11.08851458	2.010858455	698.16362	6.891566265	3.2
New Jersey	133.98058	4.54	9.948346987	2.000345803	2124.10599	11.13592233	3
New Mexico	124.63768	6.25	6.527504536	1.85483238	5603.51448	8.15942029	3.45
New York	42.622951	4.18	12.00690013	2.000345803	2055.53328	18.71584699	3.55
North Carolina	19.847328	4.88	6.455066538	1.866576572	224.980353	15.88931298	1.85
North Dakota	9.0625	4.53	5.281964056	1.878429599	27399.2623	35.875	1.9
Ohio	17.356475	4.29	6.524621026	1.878429599	152.964695	16.08010681	2.15
Oklahoma	21.618497	5.25	5.917664077	1.878429599	16512.7583	8.280924855	2.05
Oregon	86.010363	4.92	5.645812256	2.016967931	699.965547	12.11917098	3.2
Pennsylvania	27.373418	4.24	7.535855163	2.000345803	1571.68525	16.85917722	3.15
Rhode Island	98.360656	4.41	10.75274866	2.010858455	1511.42562	9.590163934	3
South Carolina	7.4074074	5.03	5.905818166	1.866576572	51.9344707	6.685185185	2.3

states	adopt (number of farms per 10,000)	SR (kWh/m^2/day)	elec (cents per kilowatthour) average 2000-2009 in 2000 dollars	diesel (dollars per gallon, 2000 dollars, average '00-'09)	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (percent of total expenditure avg '02&'07)
South Dakota	17.460317	4.91	5.920654463	1.878429599	21231.9433	37.91428571	2.2
Tennessee	8.386277	4.71	5.845958342	1.878429599	75.8063819	4.829733164	2.35
Texas	23.151515	5.47	7.626018796	1.85483238	7119.55794	7.103030303	2.35
Utah	80.120482	5.74	5.159971666	1.940504839	456.673597	9.734939759	3.4
Vermont	157.14286	4.15	10.10174282	2.010858455	847.644684	15.4	3.45
Virginia	17.659574	4.72	6.083542507	1.866576572	474.773222	7.931914894	2.2
Washington	51.898734	4.34	5.216891834	2.016967931	775.739039	15.10126582	3.6
West Virginia	11.637931	4.36	4.747386226	1.866576572	325.030452	3.228448276	2.1
Wisconsin	22.564103	4.31	6.542847311	1.878429599	1615.90704	21.34230769	3.2
Wyoming	160	5.32	4.501035628	1.940504839	12023.0731	19.32727273	3.25

states	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
Alabama	12.53544444	0	1	0	0	0	0	0
Alaska	4.238636364	2	17	0	0	0	0	0
Arizona	33.56927203	0	0	10	13	15	4	2
Arkansas	327.9913235	0	0	0	0	0	0	9
California	315.596811	3	0	2	9	0	7	14
Colorado	91.62801917	0	1	1	1	0	6	4
Connecticut	24.7525	1	5	33	3	0	12	10
Delaware	213.3918367	0	1	0	0	0	5	11
Florida	167.7965405	0	0	0	13	0	0	2
Georgia	98.81291262	0	0	0	0	2	0	9
Hawaii	52.35267857	14	2	0	0	34	0	9
Idaho	289.4639474	0	0	0	0	34	0	0
Illinois	17.76981273	13	2	4	0	0	3	3
Indiana	26.83195946	0	0	0	1	0	0	6
Iowa	6.153181818	0	14	32	4	5	0	26
Kansas	59.79974026	0	0	11	0	0	1	1
Kentucky	4.195	0	0	0	2	2	0	6
Louisiana	118.5531677	0	12	16	0	2	0	7
Maine	15.55111111	5	0	0	0	0	11	12
Maryland	45.27073171	5	2	2	2	4	3	13
Massachusetts	44.48653846	0	0	35	33	34	13	13
Michigan	50.0428	0	2	8	0	0	2	2
Minnesota	18.8236803	0	39	18	5	0	3	27
Mississippi	123.860724	0	21	0	0	0	0	0
Missouri	41.23646048	0	0	0	0	0	2	3
Montana	33.11129934	0	0	29	0	8	0	0
Nebraska	187.6876974	0	20	0	0	4	0	1
Nevada	117.1237288	1	1	27	1	0	13	13
New Hampshire	5.280851064	3	0	0	0	0	3	27
New Jersey	130.5164384	0	0	2	30	0	11	11
New Mexico	19.30344186	0	0	0	3	8	3	2
New York	9.578873239	0	3	33	5	12	0	13
North Carolina	26.98546512	7	0	33	0	33	3	5
North Dakota	5.963080808	0	0	3	0	9	4	19
Ohio	2.750652174	1	1	38	38	38	1	11
Oklahoma	15.23555556	0	0	0	0	7	0	22
Oregon	112.5118293	8	30	34	0	4	0	11
Pennsylvania	4.875612903	2	2	0	0	0	6	6
Rhode Island	61.51428571	0	0	10	5	10	6	0
South Carolina	27.02836735	0	0	0	0	4	0	2

states	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
South Dakota	8.554736842	0	0	0	0	0	0	0
Tennessee	7.468348624	0	0	0	0	0	0	0
Texas	38.42343558	0	21	29	0	28	11	0
Utah	102.1751351	0	0	0	6	9	2	8
Vermont	1.881147541	7	0	0	11	1	0	12
Virginia	10.273375	0	0	0	0	0	0	11
Washington	117.2916892	4	0	0	4	0	4	12
West Virginia	0.591621622	0	0	0	0	1	1	1
Wisconsin	24.82177632	11	0	25	0	0	11	18
Wyoming	51.34844371	0	0	0	0	0	0	9

A.2 Panel Data

state	panels (average number of panels per thousand farms)	d04	d09	SR (kWh/ m^2/ day)	electricity (cents per kilowatthour) 2000 dollars 5yr avgs	diesel (dollars per gallon) (2000 dollars) 5 yr avgs	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (% of expenses)
Alabama	0.531914894	0	0	4.95	5.760055643	1.23835759	0	0.1022128	2.8
Alaska	113.7931034	0	0	2.09	10.55281701	1.39223085	missing	0.0810345	3.9
Arizona	160	0	0	6.36	7.731996487	1.39223085	137.55822	0.1342991	3.9
Arkansas	4.958333333	0	0	4.89	6.21903769	1.23835759	660.90255	0.2146458	2.8
California	48.48	0	0	5.89	9.738732312	1.39223085	591.83757	0.2423105	4.8
Colorado	63.55172414	0	0	5.72	6.26790566	1.33102688	7251.8559	0.1584667	2.6
Connecticut	missing	0	0	4.4	10.70357877	1.33290316	1612.5282	0.1183333	2.7
Delaware	0	0	0	4.67	7.149630703	1.34060748	1601.0554	0.4442308	2.5
Florida	3.363636364	0	0	5.26	7.39803847	1.23643141	0	0.1222727	2.1
Georgia	0.44	0	0	5.03	6.662469448	1.23643141	27.174841	0.1521589	2.6
Hawaii	262.8070175	0	0	5.65	13.0634358	1.39223085	missing	0.0814545	4.3
Idaho	18.04081633	0	0	5	4.187184189	1.33102688	1380.0933	0.1974694	4.4
Illinois	4.41025641	0	0	4.58	7.745385491	1.2572543	1716.8774	0.3022338	2
Indiana	2.0625	0	0	4.46	5.540968014	1.2572543	0	0.1938801	2.1
Iowa	0.442105263	0	0	4.58	6.27293343	1.2572543	15413.625	0.3384787	2.1
Kansas	2.90625	0	0	5.3	6.651860885	1.2572543	20451.03	0.2084961	1.5
Kentucky	0.688888889	0	0	4.58	4.326344821	1.2572543	0	0.0636778	2.8
Louisiana	missing	0	0	5	6.3360187	1.23835759	0	0.1525517	2.3
Maine	48.52941176	0	0	4.23	10.13488962	1.33290316	2836.0449	0.1105634	3.3
Maryland	9.274193548	0	0	4.63	7.3057377	1.34060748	479.9163	0.2133871	2.7
Massachusetts	25.24590164	0	0	4.35	10.25504877	1.33290316	5007.076	0.1518033	3
Michigan	3.807692308	0	0	4.13	7.461009518	1.2572543	1796.7326	0.1416226	2.7
Minnesota	2.443037975	0	0	4.34	6.005486262	1.2572543	12905.917	0.2525556	2.4
Mississippi	0.325581395	0	0	4.95	6.188864211	1.23835759	0	0.1173333	2.5
Missouri	1.04587156	0	0	4.8	6.389323934	1.2572543	1182.4991	0.0991376	2.4
Montana	20.36231884	0	0	4.82	5.152117897	1.33102688	10951.894	0.1968705	3.4
Nebraska	2.759259259	0	0	5.16	5.584551986	1.2572543	17653.626	0.3565769	1.9
Nevada	50.66666667	0	0	5.95	6.18457333	1.39223085	711.71341	0.166129	6.3
New Hampshire	133.2258065	0	0	4.26	12.21468763	1.33290316	698.16362	0.0863636	2.9
New Jersey	22.5	0	0	4.54	10.6723423	1.34060748	2124.106	0.1216495	2.9
New Mexico	44.40789474	0	0	6.25	7.049682612	1.23835759	5603.5145	0.1011111	3.2
New York	8.289473684	0	0	4.18	11.427125	1.34060748	2055.5333	0.1886133	3.6
North Carolina	2.789473684	0	0	4.88	6.813932428	1.23643141	224.98035	0.1853153	2.1
North Dakota	0.561056106	0	0	4.53	5.879816158	1.2572543	27399.262	0.2838636	2.2
Ohio	2.3125	0	0	4.29	6.677034406	1.2572543	152.96469	0.1352405	2.4
Oklahoma	1.929411765	0	0	5.25	5.816853053	1.2572543	16512.758	0.0760592	2.2
Oregon	19.825	0	0	4.92	5.048023367	1.39223085	699.96555	0.11685	3.3
Pennsylvania	2.06779661	0	0	4.24	8.039568174	1.34060748	1571.6852	0.1727797	3.3
Rhode Island	25.71428571	0	0	4.41	10.43848197	1.33290316	1511.4256	0.13	3
South Carolina	1.75	0	0	5.03	5.868638096	1.23643141	51.934471	0.0997521	2.5

state	panels (average number of panels per thousand farms)	d04	d09	SR (kWh/ m^2/ day)	electricity (cents per kilowatthour) 2000 dollars 5yr avgs	diesel (dollars per gallon) (2000 dollars) 5 yr avgs	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (% of expenses)
South Dakota	1.353846154	0	0	4.91	6.590565943	1.2572543	21231.943	0.2965741	2.5
Tennessee	2.211111111	0	0	4.71	5.756901081	1.2572543	75.806382	0.0452841	2.6
Texas	2.261061947	0	0	5.47	6.505218095	1.23835759	7119.5579	0.0759439	2.4
Utah	11.80645161	0	0	5.74	5.331270966	1.33102688	456.6736	0.1068387	3.3
Vermont	65.29411765	0	0	4.15	10.51622225	1.33290316	847.64468	0.1983333	3.5
Virginia	2.12244898	0	0	4.72	6.296060642	1.23643141	474.77322	0.0858144	2.4
Washington	14.7	0	0	4.34	4.33306796	1.39223085	775.73904	0.1916216	3.7
West Virginia	2.536585366	0	0	4.36	5.358249117	1.23643141	325.03045	0.0310096	2.2
Wisconsin	11.24675325	0	0	4.31	5.70707979	1.2572543	1615.907	0.2118839	3.4
Wyoming	31.19565217	0	0	5.32	4.542746657	1.33102688	12023.073	0.2058696	3.1
Alabama	0.772727273	1	0	4.95	5.513212707	1.37038605	0	0.1061591	2.6
Alaska	missing	1	0	2.09	10.03714349	1.53895685	missing	0.1145161	4.9
Arizona	242.254902	1	0	6.36	6.976181648	1.53895685	137.55822	0.1168627	3.85
Arkansas	6	1	0	4.89	5.480804045	1.37038605	660.90255	0.1792421	2.65
California	412.8051948	1	0	5.89	10.68378864	1.53895685	591.83757	0.2543506	4.7
Colorado	106.9579288	1	0	5.72	6.029608146	1.45800493	7251.8559	0.1271845	2.6
Connecticut	missing	1	0	4.4	9.405922862	1.52130206	1612.5282	0.1045238	2.7
Delaware	0	1	0	4.67	6.536809939	1.51027201	1601.0554	0.4452174	2.05
Florida	4.697674419	1	0	5.26	7.205684533	1.37876946	0	0.1187674	2
Georgia	2	1	0	5.03	6.061820066	1.37876946	27.174841	0.128	2.4
Hawaii	597.8181818	1	0	5.65	13.67244031	1.53895685	missing	0.0881818	4.75
Idaho	26.48	1	0	5	4.742179868	1.45800493	1380.0933	0.15572	4.1
Illinois	15.71232877	1	0	4.58	6.582189738	1.40461194	1716.8774	0.2667671	1.8
Indiana	4.435075885	1	0	4.46	5.111422062	1.40461194	0	0.1747218	1.9
Iowa	2.051282051	1	0	4.58	5.841048451	1.40461194	15413.625	0.3056299	1.8
Kansas	4.139534884	1	0	5.3	6.025379176	1.40461194	20451.03	0.1708372	1.3
Kentucky	1.152941176	1	0	4.58	4.14751484	1.40461194	0	0.0602235	2.4
Louisiana	missing	1	0	5	6.393257358	1.37038605	0	0.1259191	2.15
Maine	75.83333333	1	0	4.23	9.570122019	1.52130206	2836.0449	0.0943056	3.5
Maryland	missing	1	0	4.63	6.325425889	1.51027201	479.9163	0.1734711	2.5
Massachusetts	53.60655738	1	0	4.35	10.01009901	1.52130206	5007.076	0.1132787	3.3
Michigan	4.92481203	1	0	4.13	6.682171216	1.40461194	1796.7326	0.1220113	2.55
Minnesota	4.085213033	1	0	4.34	5.707898447	1.40461194	12905.917	0.2323559	2.1
Mississippi	1.706161137	1	0	4.95	6.06731763	1.37038605	0	0.1032464	2.35
Missouri	1.669811321	1	0	4.8	5.775961503	1.40461194	1182.4991	0.0888302	2.15
Montana	40.25	1	0	4.82	5.667435942	1.45800493	10951.894	0.1795357	3.2
Nebraska	7.888198758	1	0	5.16	5.267541572	1.40461194	17653.626	0.3267909	1.85
Nevada	106	1	0	5.95	7.486747809	1.53895685	711.71341	0.1936667	6.75
New Hampshire	missing	1	0	4.26	10.50872477	1.52130206	698.16362	0.0744118	3.2
New Jersey	244.4444444	1	0	4.54	9.145062625	1.51027201	2124.106	0.1069697	3

state	panels (average number of panels per thousand farms)	d04	d09	SR (kWh/ m^2/ day)	electricity (cents per kilowatthour) 2000 dollars 5yr avgs	diesel (dollars per gallon) (2000 dollars) 5 yr avgs	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (% of expenses)
New Mexico	78	1	0	6.25	6.601448622	1.37038605	5603.5145	0.0907429	3.45
New York	21.5	1	0	4.18	11.27509688	1.51027201	2055.5333	0.1791944	3.55
North Carolina	6.192307692	1	0	4.88	6.420666728	1.37876946	224.98035	0.1690577	1.85
North Dakota	1.881188119	1	0	4.53	5.258256827	1.40461194	27399.262	0.2913861	1.9
Ohio	12.49676585	1	0	4.29	6.381270471	1.40461194	152.96469	0.1147219	2.15
Oklahoma	4.479041916	1	0	5.25	5.806018733	1.40461194	16512.758	0.0772455	2.05
Oregon	45.975	1	0	4.92	5.534729896	1.53895685	699.96555	0.104675	3.2
Pennsylvania	7.079037801	1	0	4.24	7.59036406	1.51027201	1571.6852	0.1648969	3.15
Rhode Island	missing	1	0	4.41	9.981809133	1.52130206	1511.4256	0.1317647	3
South Carolina	2.868852459	1	0	5.03	5.634204157	1.37876946	51.934471	0.0680328	2.3
South Dakota	4.841772152	1	0	4.91	6.059960804	1.40461194	21231.943	0.3058861	2.2
Tennessee	3.682352941	1	0	4.71	5.510634604	1.40461194	75.806382	0.0452706	2.35
Texas	5.751091703	1	0	5.47	6.853730705	1.37038605	7119.5579	0.0640349	2.35
Utah	49.86928105	1	0	5.74	5.063034082	1.45800493	456.6736	0.1037255	3.4
Vermont	111.875	1	0	4.15	10.31117605	1.52130206	847.64468	0.1823438	3.45
Virginia	6.105263158	1	0	4.72	5.928361225	1.37876946	474.77322	0.0825474	2.2
Washington	37.94285714	1	0	4.34	5.184403478	1.53895685	775.73904	0.1884286	3.6
West Virginia	5.192307692	1	0	4.36	4.873698512	1.37876946	325.03045	0.0334135	2.1
Wisconsin	16.8627451	1	0	4.31	6.023784327	1.40461194	1615.907	0.1820915	3.2
Wyoming	75.86956522	1	0	5.32	4.430152789	1.45800493	12023.073	0.196413	3.25
Alabama	2.680412371	0	1	4.95	6.395926513	2.32535592	0	0.0975052	2.4
Alaska	missing	0	1	2.09	11.24473626	2.48217038	missing	0.1132353	5.9
Arizona	275.2258065	0	1	6.36	7.191826154	2.48217038	137.55822	0.0679355	3.8
Arkansas	8.49287169	0	1	4.89	5.892091327	2.32535592	660.90255	0.1643585	2.5
California	1179.312883	0	1	5.89	10.48882436	2.48217038	591.83757	0.2336319	4.6
Colorado	160.9116022	0	1	5.72	6.644345477	2.40920573	7251.8559	0.1408287	2.6
Connecticut	missing	0	1	4.4	13.13745491	2.48187526	1612.5282	1.0404082	2.7
Delaware	missing	0	1	4.67	8.910202432	2.471874	1601.0554	0.3987903	1.6
Florida	14.52631579	0	1	5.26	8.608306924	2.34013757	0	0.1101684	1.9
Georgia	10	0	1	5.03	6.747596152	2.34013757	27.174841	0.1422899	2.2
Hawaii	996.9333333	0	1	5.65	18.3841018	2.48217038	missing	0.0704	5.2
Idaho	41.49019608	0	1	5	4.540758378	2.40920573	1380.0933	0.1692549	3.8
Illinois	20.19788918	0	1	4.58	6.777472783	2.33956965	1716.8774	0.3072559	1.6
Indiana	9.528455285	0	1	4.46	5.577524723	2.33956965	0	0.2062114	1.7
Iowa	6.090712743	0	1	4.58	5.797010492	2.33956965	15413.625	0.3569978	1.5
Kansas	6.702290076	0	1	5.3	5.940985655	2.33956965	20451.03	0.216626	1.1
Kentucky	5.67251462	0	1	4.58	4.829167229	2.33956965	0	0.0692632	2
Louisiana	missing	0	1	5	6.870941005	2.32535592	0	0.1074	2
Maine	210.7407407	0	1	4.23	10.61683996	2.48187526	2836.0449	0.0953086	3.7
Maryland	missing	0	1	4.63	9.222889739	2.471874	479.9163	0.1764844	2.3
Massachusetts	167.012987	0	1	4.35	12.38813279	2.48187526	5007.076	0.1042857	3.6
Michigan	9.854014599	0	1	4.13	7.021450724	2.33956965	1796.7326	0.145365	2.4
Minnesota	6.987654321	0	1	4.34	6.146674418	2.33956965	12905.917	0.2736296	1.8
Mississippi	2.836879433	0	1	4.95	6.945230101	2.32535592	0	0.1074704	2.2
Missouri	4.972222222	0	1	4.8	5.520909829	2.33956965	1182.4991	0.1096667	1.9

state	panels (average number of panels per thousand farms)	d04	d09	SR (kWh/ m^2/ day)	electricity (cents per kilowatthour) 2000 dollars 5yr avgs	diesel (dollars per gallon) (2000 dollars) 5 yr avgs	wind (potential annual energy (kWh) per acre)	large (% of farms in sales class $100,000 or higher)	utility (% of expenses)
Montana	67.41610738	0	1	4.82	5.999921855	2.40920573	10951.894	0.214094	3
Nebraska	14.78813559	0	1	5.16	5.325195828	2.33956965	17653.626	0.4147458	1.8
Nevada	279.2207792	0	1	5.95	8.140230844	2.48217038	711.71341	0.1996753	7.2
New Hampshire	missing	0	1	4.26	11.66830439	2.48187526	698.16362	0.0689157	3.5
New Jersey	1170	0	1	4.54	10.75163135	2.471874	2124.106	0.1113592	3.1
New Mexico	115.3658537	0	1	6.25	6.453560451	2.32535592	5603.5145	0.0815942	3.7
New York	72.15846995	0	1	4.18	12.73870337	2.471874	2055.5333	0.1871585	3.5
North Carolina	13.54961832	0	1	4.88	6.489466349	2.34013757	224.98035	0.1588931	1.6
North Dakota	3.90625	0	1	4.53	5.305671285	2.33956965	27399.262	0.35875	1.6
Ohio	18.95861148	0	1	4.29	6.667971581	2.33956965	152.96469	0.1608011	1.9
Oklahoma	8.38150289	0	1	5.25	6.02930942	2.33956965	16512.758	0.0828092	1.9
Oregon	132.7202073	0	1	4.92	5.756894616	2.48217038	699.96555	0.1211917	3.1
Pennsylvania	38.92405063	0	1	4.24	7.481346266	2.471874	1571.6852	0.1685918	3
Rhode Island	missing	0	1	4.41	11.52368818	2.48187526	1511.4256	0.0959016	3
South Carolina	4.555555556	0	1	5.03	6.177432175	2.34013757	51.934471	0.0668519	2.1
South Dakota	9.555555556	0	1	4.91	5.781348122	2.33956965	21231.943	0.3791429	1.9
Tennessee	9.008894536	0	1	4.71	6.181282079	2.33956965	75.806382	0.0482973	2.1
Texas	12.7959596	0	1	5.47	8.398306887	2.32535592	7119.5579	0.0710303	2.3
Utah	76.3253012	0	1	5.74	5.25690925	2.40920573	456.6736	0.0973494	3.5
Vermont	185.4285714	0	1	4.15	9.892309592	2.48187526	847.64468	0.154	3.4
Virginia	13.82978723	0	1	4.72	6.238723789	2.34013757	474.77322	0.0793191	2
Washington	55.69620253	0	1	4.34	5.24938019	2.48217038	775.73904	0.1510127	3.5
West Virginia	missing	0	1	4.36	4.621073939	2.34013757	325.03045	0.0322845	2
Wisconsin	33.62820513	0	1	4.31	7.061910295	2.33956965	1615.907	0.2134231	3
Wyoming	135.5454545	0	1	5.32	4.571918467	2.40920573	12023.073	0.1932727	3.4

state	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
Alabama	8.849666667	0	0	0	0	0	0	0
Alaska	2.898913043	0	8	0	0	0	0	0
Arizona	40.27475655	0	0	1	4	6	0	0
Arkansas	259.269726	0	0	0	0	0	0	0
California	319.6652158	0	0	0	0	0	0	5
Colorado	106.7795253	0	0	0	0	0	0	0
Connecticut	21.35833333	0	0	24	0	0	3	1
Delaware	129.3517241	0	0	0	0	0	0	2
Florida	181.9245631	0	0	0	4	0	0	0
Georgia	69.64558559	0	0	0	0	0	0	0
Hawaii	53.45208333	5	0	0	0	25	0	0
Idaho	297.7987395	0	0	0	0	25	0	0
Illinois	12.69588448	4	0	0	0	0	0	0
Indiana	16.51077419	0	0	0	0	0	0	0
Iowa	4.059420732	0	5	23	0	0	0	17
Kansas	56.75402105	0	0	2	0	0	0	0
Kentucky	4.41375	0	0	0	0	0	0	0
Louisiana	118.6211111	0	3	7	0	0	0	0
Maine	17.50314961	0	0	0	0	0	2	3
Maryland	32.69666667	0	0	0	0	0	0	4
Massachusetts	47.05263158	0	0	26	24	25	4	4
Michigan	39.14144231	0	0	0	0	0	0	0
Minnesota	14.10101399	0	30	9	0	0	0	18
Mississippi	100.0130631	0	12	0	0	0	0	0
Missouri	30.70376667	0	0	0	0	0	0	0
Montana	37.06433862	0	0	20	0	0	0	0
Nebraska	152.2749138	0	11	0	0	0	0	0
Nevada	112.315	0	0	18	0	0	4	4
New Hampshire	6.757142857	0	0	0	0	0	0	18
New Jersey	113.7108434	0	0	0	21	0	2	2
New Mexico	19.35761364	0	0	0	0	0	0	0
New York	9.583246753	0	0	24	0	3	0	4
North Carolina	16.99076087	0	0	24	0	24	0	0
North Dakota	4.644771574	0	0	0	0	0	0	10
Ohio	2.353892617	0	0	29	29	29	0	2
Oklahoma	14.97379412	0	0	0	0	0	0	13
Oregon	114.1556977	0	21	25	0	0	0	2
Pennsylvania	5.206363636	0	0	0	0	0	0	0
Rhode Island	55.55	0	0	1	0	1	0	0
South Carolina	18.91446809	0	0	0	0	0	0	0

state	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
South Dakota	8.345340909	0	0	0	0	0	0	0
Tennessee	4.017948718	0	0	0	0	0	0	0
Texas	44.34073077	0	12	20	0	19	2	0
Utah	105.0408621	0	0	0	0	0	0	0
Vermont	2.123134328	0	0	0	2	0	0	3
Virginia	9.929655172	0	0	0	0	0	0	2
Washington	113.8292994	0	0	0	0	0	0	3
West Virginia	0.984166667	0	0	0	0	0	0	0
Wisconsin	22.12759259	2	0	16	0	0	2	9
Wyoming	50.57537572	0	0	0	0	0	0	0
Alabama	12.5037931	0	0	0	0	0	0	0
Alaska	3.046666667	0	12	0	0	0	0	0
Arizona	35.29299242	0	0	5	8	10	0	0
Arkansas	288.1781944	0	0	0	0	0	0	4
California	326.1929963	0	0	0	4	0	2	9
Colorado	83.83993528	0	0	0	0	0	1	0
Connecticut	28.16388889	0	0	28	0	0	7	5
Delaware	183.3339623	0	0	0	0	0	0	6
Florida	179.720198	0	0	0	8	0	0	0
Georgia	81.38411215	0	0	0	0	0	0	4
Hawaii	53.22615385	9	0	0	0	29	0	4
Idaho	278.6883051	0	0	0	0	29	0	0
Illinois	14.21247273	8	0	0	0	0	0	0
Indiana	20.87533333	0	0	0	0	0	0	1
Iowa	4.482933754	0	9	27	0	0	0	21
Kansas	56.74315678	0	0	6	0	0	0	0
Kentucky	2.663115942	0	0	0	0	0	0	1
Louisiana	119.5975796	0	7	11	0	0	0	2
Maine	14.38175182	0	0	0	0	0	6	7
Maryland	39.42829268	0	0	0	0	0	0	8
Massachusetts	45.61538462	0	0	30	28	29	8	8
Michigan	45.1760396	0	0	3	0	0	0	0
Minnesota	16.48007246	0	34	13	0	0	0	22
Mississippi	106.3828054	0	16	0	0	0	0	0
Missouri	34.31803987	0	0	0	0	0	0	0
Montana	32.8803827	0	0	24	0	3	0	0
Nebraska	166.1257081	0	15	0	0	0	0	0
Nevada	118.5163492	0	0	22	0	0	8	8
New Hampshire	5.093333333	0	0	0	0	0	0	22
New Jersey	118.1621951	0	0	0	25	0	6	6

state	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
New Mexico	18.89930649	0	0	0	0	3	0	0
New York	9.824078947	0	0	28	0	7	0	8
North Carolina	29.33966667	2	0	28	0	28	0	0
North Dakota	5.147639594	0	0	0	0	4	0	14
Ohio	2.786643836	0	0	33	33	33	0	6
Oklahoma	15.35765579	0	0	0	0	2	0	17
Oregon	110.9085465	3	25	29	0	0	0	6
Pennsylvania	5.521558442	0	0	0	0	0	1	1
Rhode Island	66.05	0	0	5	0	5	1	0
South Carolina	19.72	0	0	0	0	0	0	0
South Dakota	9.157146119	0	0	0	0	0	0	0
Tennessee	5.277327586	0	0	0	0	0	0	0
Texas	39.03567692	0	16	24	0	23	6	0
Utah	94.05267241	0	0	0	1	4	0	3
Vermont	1.868	2	0	0	6	0	0	7
Virginia	11.50151163	0	0	0	0	0	0	6
Washington	119.9444079	0	0	0	0	0	0	7
West Virginia	0.550277778	0	0	0	0	0	0	0
Wisconsin	24.89690323	6	0	20	0	0	6	13
Wyoming	44.76445993	0	0	0	0	0	0	4
Alabama	12.53544444	0	1	0	0	0	0	0
Alaska	4.238636364	2	17	0	0	0	0	0
Arizona	33.56927203	0	0	10	13	15	4	2
Arkansas	327.9913235	0	0	0	0	0	0	9
California	315.596811	3	0	2	9	0	7	14
Colorado	91.62801917	0	1	1	1	0	6	4
Connecticut	24.7525	1	5	33	3	0	12	10
Delaware	213.3918367	0	1	0	0	0	5	11
Florida	167.7965405	0	0	0	13	0	0	2
Georgia	98.81291262	0	0	0	0	2	0	9
Hawaii	52.35267857	14	2	0	0	34	0	9
Idaho	289.4639474	0	0	0	0	34	0	0
Illinois	17.76981273	13	2	4	0	0	3	3
Indiana	26.83195946	0	0	0	1	0	0	6
Iowa	6.153181818	0	14	32	4	5	0	26
Kansas	59.79974026	0	0	11	0	0	1	1
Kentucky	4.195	0	0	0	2	2	0	6
Louisiana	118.5531677	0	12	16	0	2	0	7
Maine	15.55111111	5	0	0	0	0	11	12
Maryland	45.27073171	5	2	2	2	4	3	13
Massachusetts	44.48653846	0	0	35	33	34	13	13
Michigan	50.0428	0	2	8	0	0	2	2
Minnesota	18.8236803	0	39	18	5	0	3	27
Mississippi	123.860724	0	21	0	0	0	0	0
Missouri	41.23646048	0	0	0	0	0	2	3

state	irrigated (acres irrigated per thousand acres of ag land)	grant/ rebate (years since earliest)	loan (years since earliest)	property (years since earliest)	sales (years since earliest)	tax (years since earliest)	credit (years since earliest)	net metering (years since earliest)
Montana	33.11129934	0	0	29	0	8	0	0
Nebraska	187.6876974	0	20	0	0	4	0	1
Nevada	117.1237288	1	1	27	1	0	13	13
New Hampshire	5.280851064	3	0	0	0	0	3	27
New Jersey	130.5164384	0	0	2	30	0	11	11
New Mexico	19.30344186	0	0	0	3	8	3	2
New York	9.578873239	0	3	33	5	12	0	13
North Carolina	26.98546512	7	0	33	0	33	3	5
North Dakota	5.963080808	0	0	3	0	9	4	19
Ohio	2.750652174	1	1	38	38	38	1	11
Oklahoma	15.23555556	0	0	0	0	7	0	22
Oregon	112.5118293	8	30	34	0	4	0	11
Pennsylvania	4.875612903	2	2	0	0	0	6	6
Rhode Island	61.51428571	0	0	10	5	10	6	0
South Carolina	27.02836735	0	0	0	0	4	0	2
South Dakota	8.554736842	0	0	0	0	0	0	0
Tennessee	7.468348624	0	0	0	0	0	0	0
Texas	38.42343558	0	21	29	0	28	11	0
Utah	102.1751351	0	0	0	6	9	2	8
Vermont	1.881147541	7	0	0	11	1	0	12
Virginia	10.273375	0	0	0	0	0	0	11
Washington	117.2916892	4	0	0	4	0	4	12
West Virginia	0.591621622	0	0	0	0	1	1	1
Wisconsin	24.82177632	11	0	25	0	0	11	18
Wyoming	51.34844371	0	0	0	0	0	0	9