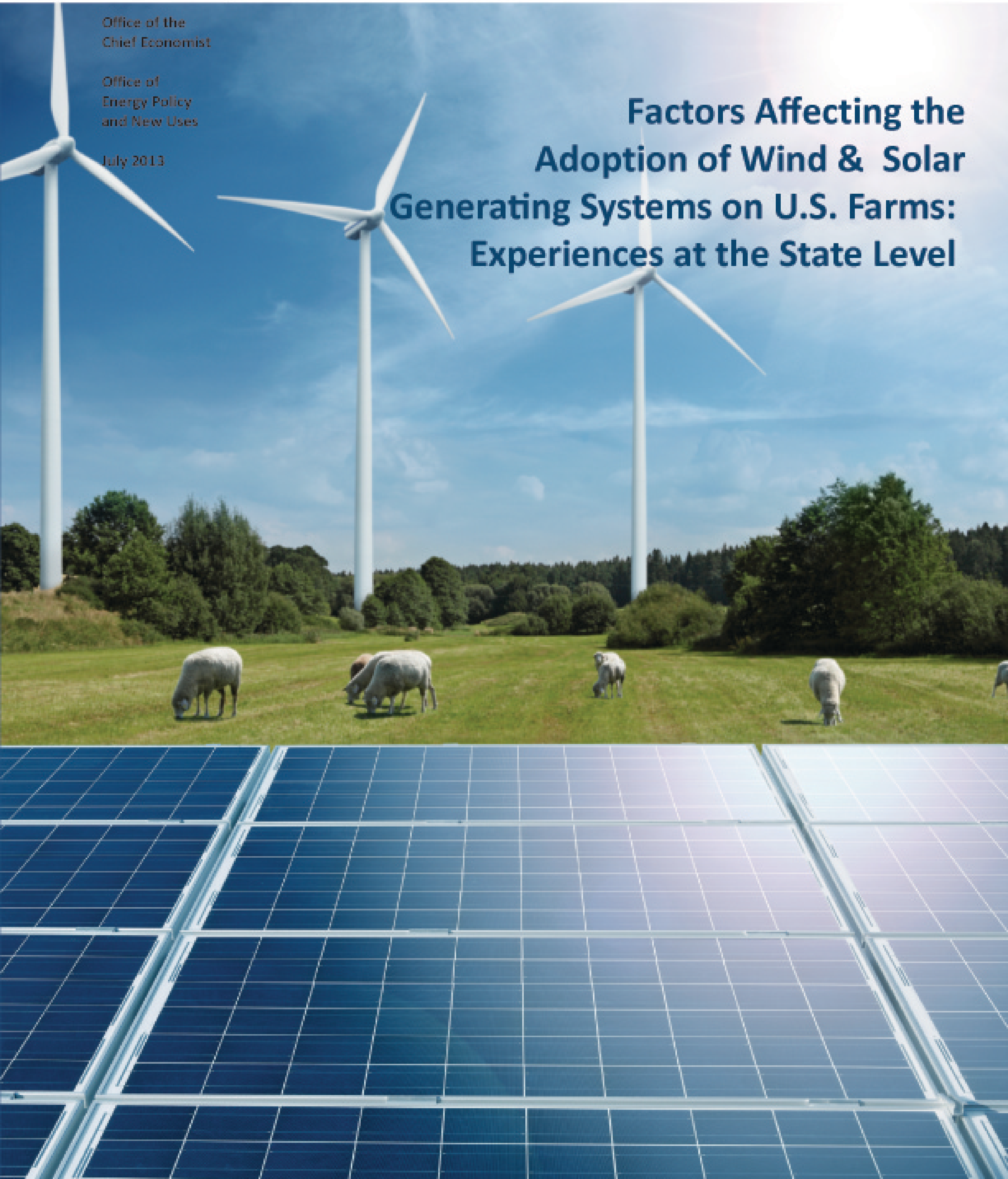
United States
Department of
Agriculture

Office of the
Chief Economist

Office of
Energy Policy
and New Uses

July 2013

Factors Affecting the Adoption of Wind & Solar Generating Systems on U.S. Farms: Experiences at the State Level



Factors Affecting the Adoption of Wind and Solar-Power Generating Systems on U.S. Farms: Experiences at the State Level

Irene M. Xiarchos, Natural Resource Economist and Policy Analyst, Office of Energy Policy and New Uses, Office of the Chief Economist, U.S. Department of Agriculture
William Lazarus, Professor and Extension Economist, Department of Applied Economics, University of Minnesota

Office of Energy Policy and New Uses
Office of the Chief Economist
U.S. Department of Agriculture

Contents

Tables and Figures

Tables

Figures

Acknowledgements

We appreciate the reviews from Robert Yohansson at USDA's Office of the Chief Economist (OCE); Harry Baumes at USDA's Office of Energy Policy New Uses (OEPNU); Jan Lewandrowski at USDA's Climate Change Program Office (CCPO); Donald Buysse, and Dale Hawks at USDA's National Agricultural Statistics Service (NASS); Hansen LeRoy, and Peter Stenberg at USDA's Economic Research Service (ERS); Antony Crooks at USDA's Rural Development (RD); David Buland at USDA's Natural Resource Conservation Service (NRCS); and John Hay at the University of Nebraska. Further contributions we would like to acknowledge include input from Charlie Hallahan and Allison Borchers at USDA's Economic Research Service (ERS), Faye Propsom at USDA's National Agricultural Statistics Service (NASS), and Antony Crooks at USDA's Rural Development (RD). We also appreciate the design assistance from Jennifer Lohr and Brenda Chapin at USDA's Office of the Chief Economist (OCE).

Executive Summary

The study is the first to examine the role of State-level policies such as net metering and Renewable Portfolio Standards (RPS), as well as the role of electric cooperatives, on States' adoption rates of solar and wind systems on U.S. farms. The study found that States with higher energy prices, more organic acres per farm, and more Internet connectivity adopt renewable electricity at higher rates. For solar systems, full farm ownership and solar resources also have a significant and positive relationship with adoption rates.

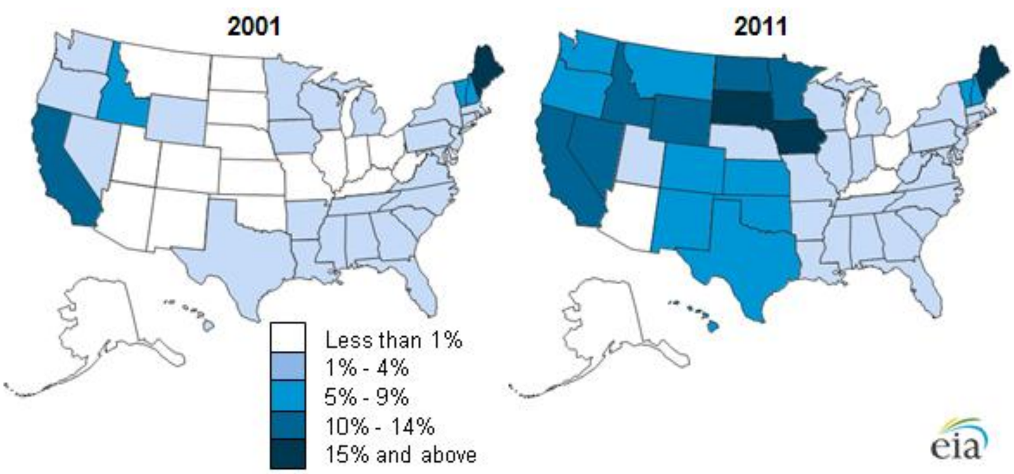
RPS targets are found to increase renewable electricity adoption at the State level. Our result accords with the literature; however, this is the first study to show an impact at the distributed-generation scale. Our study does not find a systematic relationship for State financial instruments, such as rebates, grants, investment tax credits, and production incentives, at least in the form captured by our policy variables. Similarly, net metering and interconnection policies do not seem to influence renewable electricity adoption at the State level. Conversely, electric cooperative prevalence in the State is found to have a negative relationship to renewable electricity adoption share. The interaction of those factors highlights the importance of coordinating approaches in policy formulation to meet Federal and State objectives of increasing renewable energy adoption.

The results of this study can assist States as they further refine and focus their policies to promote renewable electricity, particularly during an era of declining government budgets. A more detailed examination of farm-level data from the On-Farm Renewable Energy Production Survey in combination with policy, institutional, and economic variables at the State level can provide a fuller and more realistic interpretation of the State-level determinants of adoption of wind- and solar-energy technologies.

Introduction

Security, environmental, and economic concerns underlie recent investments in renewable energy technologies and implementation of policies to support renewable energy adoption. Expanded production of renewable electricity can help meet a number of objectives, including increased energy security, reduced risk from rising and volatile energy costs, as well as decreased carbon emissions and other pollutants.[1] Newer renewable electricity sources, however, such as wind, solar, geothermal, and small hydro, count for less than 3 percent of electricity generation, and more conventional renewable sources such as large hydropower and traditional biomass reached just below 8 percent of electricity generation in 2010 (U.S. Energy Information Administration (EIA) 2012).[2] The cost of adopting renewable electricity systems remains high and is still dependent on Federal and State policies. Despite those obstacles, policy support and technological advances have led to a tremendous increase in new renewable capacity in the past decade, primarily in wind energy (Figure 1, U.S. Energy Information Administration 2012). EIA projects further increases by 77 percent from 10 percent in 2010 to 15 percent in 2035.

Figure 1. Renewable Share of Net Electricity Generation by State (excludes Hydroelectric).



Source: U.S. Energy Information Administration (EIA)

[1] Although this report focuses on solar and wind electricity on U.S. farms, the largest contribution of U.S. agriculture to renewable energy continues to be biomass, which, in addition to electricity, is used also for heating/cooling, and transportation. Altogether, biomass accounts for almost 50 percent of renewable energy consumption (U.S. Energy Information Administration 2012). By comparison, hydroelectric is around 30 percent, while wind and solar are less that 18 percent of renewable energy consumption (U.S. Energy Information Administration 2012).

[2] Large hydropower and traditional biomass are considered established sources of renewable electricity and count for almost 9 percent of electricity generation (U.S. Energy Information Administration 2012).

Wind and solar installations are often located on or close to agricultural land. For that reason, and because 40 percent of the total U.S. land area is in agriculture, many leading States in renewable electricity installations are States with large agricultural sectors (National Agricultural Statistics Service, 2009a).[1] Farming operations are also a natural fit for smaller scale renewable electricity applications. Agricultural producers are actually early adopters of renewable powered technology due to its convenience for small and remote power needs. Wind turbines, for example, were used to pump water and for remote electricity generation since the early 1900s and, in the absence of rural electrification, were widely incorporated in agriculture operations by 1930.

At the time, agriculture represented the main market for wind energy systems and continues to present a large market opportunity for sales of small wind systems (less than 100 kilowatts) today (American Wind Energy Association 2011). Stand-alone solar photo-voltaic (PV) systems were introduced in the 1980s and have become the most common form of on-farm electricity generation (National Agricultural Statistics Service 2011). Though those off-grid applications represented the majority of renewable energy use throughout the 1990s, grid-connected systems are now leading the growth in on-farm systems (Xiarchos and Vick 2011).

The 2009 On-Farm Renewable Energy Production Survey (OFREPS) was the first national survey of on-farm renewable energy generation. It addressed only distributed generation of on-farm renewable energy applications owned and operated as part of individual farm operations.[3] It excluded "large wind" systems of 100 kilowatts or more, which are generally commercial applications often located on farms but operated by other business entities under wind rights lease agreements with the farm (National Agricultural Statistics Service 2011).[4] The number of small wind systems has almost doubled since 2001 (American Wind Energy Association 2011), while solar power has increased by 146 percent since 2000 (Sherwood 2010).[5] The OFREPS survey provides insights about renewable electricity in agriculture and factors that influence distributed generation.

Following the examples of Menz and Vachon (2006), Adelaja and Hailu (2008), and Sawyer, et al. (1984), our examination applies specifically to State-level adoption rates of wind and solar systems for farms and evaluates the State factors that might explain the

---

[3] Distributed generation (DG) is an approach that employs small-scale technologies to produce electricity close to the end users of power. DG technologies often consist of modular (and sometimes renewable-energy) generators and provide power onsite with little reliance on the distribution and transmission grid. DG can often provide lower-cost electricity and higher power reliability and security with fewer environmental consequences than can traditional power generators.

[4] This report focuses on wind and solar installations captured in the OFREPS (available at http://www.agcensus.usda.gov/Publications/Energy_Production_Survey/). It excludes anaerobic digesters (also included in the OFREPS), as well as small hydro, and geothermal systems (not examined in the OFREPS).

[5] Until 2009, which frames the study period of the paper, most of the PV installations had been customer sited. 2010 marks the emergence of the utility sector in PV. The share of utility sector installations rose from virtually none in 2006 to 15 percent of all installations in 2009 and 32 percent in 2010 (Sherwood 2010).

States' varying adoption rates.[6] Our main interest lies in identifying policy and institutional influences on State-level adoption differences while controlling for State differences in economics and structural factors in agriculture. The interest on policy variables is nested in the perceived importance of policy in promoting renewable electricity technologies until volume-related costs reach parity with fossil-based technologies. That study is unique in that it focuses on distributed generation on farms, whereas previous State-level work focused primarily on utility-scale installations (Menz and Vachon 2006, Adelaja and Hailu 2008, Yin and Powers, 2010, Shrimali and Kniefel 2011). Small-scale renewables have, up to now, mostly been examined at the household level (Mills and Schleich 2009, Durham et al. 1988, Labay and Kinnear 1981, Willis et al. 2011).

To identify a range of potential factors that might systematically account for State variations, bivariate statistical correlation tests are performed in accordance to Sawyer et al. (1984). Variables that show a significant relationship are used to construct a parsimonious multivariate representation of those relationships in the absence of multi-period observations following Menz and Vachon (2006) and Adelaja and Hailu (2008). Although technology adoption is ultimately an individual farm-level choice, analyzing State-level variables can help explain underlying State variation and evaluate policy effectiveness.

[6] The term adoption rate herein refers to the proportion of farms in each State that installed renewable electricity systems on their operation until 2009, based on the OFREPS survey.

Literature Review

The literature on for renewable electricity varies in at least four ways:

1. Technologies analyzed.
2. Level of aggregation (individual decisionmaker or State-level totals) examined.
3. Sector (utilities, residential users, or farm operators) evaluated.
4. Analytical methods used to evaluate adoption (ordinary least squares regression, limited dependent variable regression, other statistical technique, or simulation).

Analytical methods used in renewable energy adoption research can be characterized as statistical and non-statistical. Most recent statistical technology adoption research has focused on total renewable electricity capacity or generation in the State. At aggregate levels, utility-scale capacity overshadows distributed generation by end-users such as farmers, and consequently, total renewable electricity capacity represents utility-scale capacity in those studies. State-level studies face the disadvantage of relying on secondary data, while studies of individual decisionmakers use data from surveys designed specifically for that purpose. Also, State-level studies generally involve fewer degrees of freedom and narrower ranges of values for the variables, so that consequently they are less likely to find statistically significant results.

Menz and Vachon (2006) was the first State-level evaluation of how utility-scale renewable electricity capacity relates to State policies. They examined the impact of an array of government policies in 39 States on wind energy capacity and its growth from 1998-2003 through hierarchical linear regression analysis. They considered renewable portfolio standards (RPS), generation disclosure, a mandatory green power option, public benefit funds, and choice of electricity source. Their study was conducted in two parts. The first part used bivariate variables for the above policies in existence prior to 2003. The second part used the experience related to each policy expressed as the time since each policy enactment. They found that both renewable portfolio standards (RPS) and green power options were positively related to wind power development. Adelaja and Hailu (2008) furthered the analysis by adding State socioeconomic and political characteristics in addition to renewable energy policies in the examination of State differentials in wind industry development. That study found that RPS has a significant effect on wind development as do the State's wind potential, economic conditions, and political structure.

Yin and Powers (2010) evaluated by means of a fixed effects panel model the presence of an RPS and its stringency (as measured by whether some utilities in the State are exempt from the RPS, whether existing generation when the RPS is implemented is allowed to "count" against the RPS, whether utilities can purchase renewable electricity credits from outside the State to meet part of the RPS, and penalties imposed on non-compliant energy producers). They found that an RPS that requires additional renewable generation above that existing at implementation has a positive impact where the mere presence of a weaker RPS does not. Net metering and interconnection were not found to be effective in increasing renewable generation, while mandatory green power offerings and greater imported power had positive and significant impacts.

Shrimali and Kniefel (2011) consider the impact of RPS, government green power purchasing, and financial incentives along with resource, economic, and political measures on wind, biomass, geothermal, and solar generation capacity. They used a fixed-effects model with State-specific time-trends for State-level data from 1991-2007 and found that RPS impact varied by type of renewable and was negative for combined renewables. It was positive for solar and geothermal and negative for wind and biomass. They also found that clean energy funds have a significant impact on the share of renewable energy, while previous literature showed that a related policy, public benefit funds, was not significant.

Delmas and Montes-Sancho (2011) focused on determinants at the utility rather than the State level. They found that the RPS has a negative influence on utilities' decision to invest in renewable capacity and that investor-owned utilities respond more positively to RPS mandates than publicly owned utilities. They consider the possibility that renewable capacity expansion may be due to the natural, social, and policy context in the State rather than due to the RPS, resulting in "sample selection" bias. They employ a two-stage Heckman approach with a logit model predicting RPS adoption and then use the predicted RPS in a Tobit model of capacity.

Adoption of distributed generation for residential and small commercial entities is likely to differ from utility-scale generation. For example, renewable energy technologies adopted by farmers usually represent only a small part of the farm business and produce electricity mainly for consumption on the farm, in contrast to renewable energy technologies adopted by utilities whose main product is electricity for sale to the public in the marketplace.

Sawyer et al. (1984) performed a State-level analysis for distributed generation; specifically, they used a statistical approach to examining how adoption rates for residential solar installations have varied across States. They conducted bivariate statistical correlation tests of 11 independent variables with solar adoption rates. They also found that actual adoption was low even where it was expected to be economically feasible. They attributed the low adoption rates to consumers being more concerned with time to pay back the investment rather than the overall life-cycle cost criterion that had been used in the projections. Anticipating Delmas and Montes-Sancho's concern about causation and sample selection bias, Sawyer et al. included an index of regional differences in cultural attitudes toward adoption of policy innovations and alteration of established patterns.

At the household level in the residential sector, economic variables shown to impact solar hot water adoption choices have included solar radiation availability (Mills and Schleich

2009), electricity rates (Fujii and Mak, 1984; Durham et al., 1988), and State tax credits (Durham et al. 1988). Demographic variables that positively related to energy-conserving investments are income, education, age, and household size (Labay and Kinnear 1981, Fujii and Mak 1984, Dillman et al. 1984, Durham et al. 1988, Long 1993; Walsh 1989, Sardianou 2007, O'Doherty et al. 2008, Mills and Schleich 2009, Willis et al. 2011). However results are not homogeneous. For example, Durham et al. (1988) find no significant impact from income and solar radiation availability.

No regression analyses have come to light that look specifically at renewable electricity adoption on farms, but two studies have used non-statistical approaches – in particular, simulation benefit-cost models have been used to analyze the economic feasibility of adopting the technology from the perspective of the individual farm operation. Solar photovoltaic technology has been evaluated for crop irrigation (Katzman and Matlin 1978) and to run fans and lighting in poultry barns (Bazen and Brown 2009).

Adoption of sustainable agriculture practices at the farm level involving reduced tillage, fertilizer, and chemicals has been studied more than adoption of renewable energy technologies, and those studies may offer insights about what influences the latter. Knowler and Bradshaw (2007) reviewed 55 such studies conducted in the United States over 25 years. They found that education, farm size, additional information, labor availability, networking (with agency, business, or other local individuals), and willingness to take risks were positively related to adoption. Age tended to be negatively related, but that depended on the type of practice studied. They found generally a great deal of discrepancy in the findings from study to study for the variables evaluated.

In addition to the above regression analyses, crosstabs, multivariate nominal scale analysis, and multiple discriminant function analysis have also been used to test various hypotheses about consumer decisions to adopt solar energy systems in Maine (Labay and Kinnear 1981). In that approach, perceived attributes of the product are found to explain adoption better than commonly used respondent personal characteristics (Ostlund 1974). Factor analysis has been used to explain technologies as diverse as hybrid corn, tractors, and beta-blockers (Skinner and Staiger, 2007). The advantage of factor analysis is that a large number of factors plausibly associated with technology diffusion are assumed to be linear combinations of a few unobserved factors (representing barriers to adoption) that are estimated.

Solar and Wind Electricity on U.S. Farms

Commercial wind and solar installations are often installed on or close to agricultural land, and many States with large agricultural sectors are leaders in renewable energy installations. This report focuses specifically on smaller scale distributed generation in agriculture.

Wind and solar applications can help farming operations stabilize electricity and energy expenditures and decrease carbon emissions. Further, off-grid wind and solar systems can provide the producer with an energy source where electricity transmission is difficult or impossible. Additionally, it can substitute fuel and gas use for generators on the farm, reducing transportation and maintenance costs as well as environmental concerns (Xiarchos and Vick 2011). However, renewable energy adoption remains rare on U.S. farming operations: the adoption rate is less than 1 percent (National Agricultural Statistics Service 2011).

The 2009 On-Farm Renewable Energy Production Survey (OFREPS), conducted as an add-on survey for operations who responded that they had produced some form of renewable energy on the 2007 Census of Agriculture (National Agricultural Statistics Service, 2009a), provides the first national observation on farm renewable energy generation (National Agricultural Statistics Service 2011).[7] Data portrayed include the type, size, cost, incentives, and estimated savings of renewable energy production. In 2009, 8,569 farms were reported to produce renewable energy from solar, wind, or methane digesters. We focus on renewable electricity from wind and solar. Solar energy is the most prevalent, generated on 7,968 of the farms in the survey (93 percent of all farms with renewable energy generation). The prominence of solar technology as a renewable energy source on farms is not surprising due to its many agricultural applications, the most important of which are water pumping for irrigation, electric fences, building lighting, and livestock watering, in descending order (Food and Agriculture Organization, 2000). The U.S. Department of Agriculture (USDA), National Agricultural Statistics Service (NASS) showcases the role of solar energy in irrigation in its *Farm and Ranch Land Irrigation Survey (*National Agricultural Statistics Service 2004, 2009b).

Solar PV systems are installed in 7,236 farms across the United States and are distributed in all the States. Top States for PV are California, Texas, Colorado, and Oregon. California leads the Nation with 25 percent of all farms reporting adoption of a PV system, while half of the operations generating on-farm solar PV are concentrated in the western parts of the United States. The number of farms using solar energy ranges widely from just 4 farms in Delaware to 1,906 operations in California, with an average of 159 and a median of 86 farms per State. In terms of capacity, the concentration of solar energy production is more pronounced. California represents almost 64 percent of PV

[7] Since the sample was drawn from the 2007 census questionnaire, farmers who installed renewable energy systems for the first time in 2008 and 2009 will not be captured.

capacity in agriculture, followed by New Jersey with 6 percent; the Western States hold 74 percent, and the top 10 States, 83 percent (table 1). Capacity is calculated based on State average system capacities. The average system capacity is 4.5 kilowatt (kW) for the United States; however the State variation is significant and ranges from 0.4 kW in Kansas and 15.5 kW in Delaware. New Jersey and California also have average capacity over 10 kW. The average capacity in the rest of the States ranges from about 0.5 kW to 4.5 kW, with a median of 1.35 kW.

For the analysis, we focus on farms adopting PV installations normalized by total number of farms in each State forming State adoption rates. Adoption rates for solar PV are presented in figure 2.

Table 1. Farms With Solar Photovoltaic (PV) by State

FARMS			CAPACITY				
State Rank	Count	Percent	State Rank	kW	Percent	kW*	Farms
California	1,825	25	California	20,493	63.7	11.23	1,825
Texas	541	7	New Jersey	1,943	6.0	14.08	138
Hawaii	469	6	Oregon	883	2.7	3.00	294
Colorado	445	6	Hawaii	840	2.6	1.79	469
Oregon	294	4	Colorado	736	2.3	1.65	445
Top ten	4,639	64	Top Ten	26,789	83.2	4.08	4,469
Western	3,739	52	Western	23,757	73.8	2.39	3,739
U.S.	7,236	100	U.S.	32,193	100.0	4.45	7,236

Only includes positive reported data and is confined to USDA National Agricultural Statistics Service disclosure limitations
*State average per farm

Small wind is the second most prevalent renewable fuel source; 17 percent of farms reporting renewable energy generation have wind-generating capacity (installed in 1,420 farms across the United States). The States with the largest amount of on-farm wind production are California, Texas, Colorado, and Minnesota. California leads the Nation with 9.5 percent, and about half of the operations with small wind are concentrated in the top 10 States, which show no district geographic pattern. The number of farms using small-wind energy ranges from zero farms in Delaware to 134 operations in California, with an average of 29 and a median of 21 farms per State. The concentration of small wind is more pronounced in terms of capacity. Minnesota represents about 22 percent of small-wind capacity in agriculture, followed by Washington with 12 percent. The top 10 States hold 66 percent (table 2). The average installed generating capacity of small-wind turbines is 6 kW, greater than the average solar capacity—4.5 kW per farm. The average is 4 and median is 3 kW per farm.

For the analysis, we focus on farms' small-wind installations normalized by total number of farms in each State forming State adoption rates. Adoption rates for small wind are presented in figure 2.

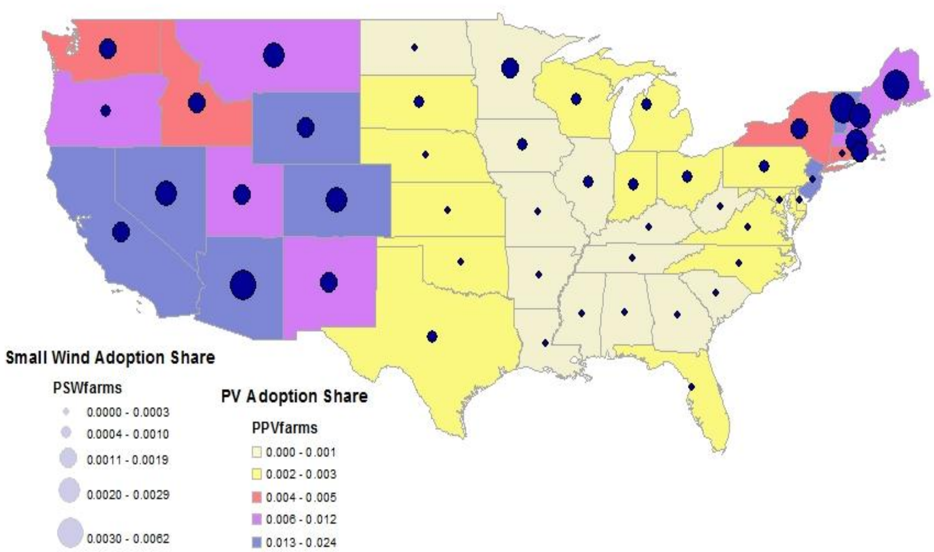
Table 2. Farms with Small Wind by State

FARMS			CAPACITY					
State Rank	Count	Percent	State Rank	kW	Percent	kW*	Turbines	Farms
California	134	9.53	Minnesota	2,880	26.22	20	144	99
Texas	102	7.25	Washington	1,273	11.59	19	67	50
Minnesota	99	7.04	Texas	592	5.39	4	148	102
Colorado	98	6.97	California	480	4.37	3	160	134
Arizona	63	4.48	Wisconsin	472	4.3	8	59	46
Montana	63	4.48	Colorado	441	4.01	3	147	98
Top 10	762	54.2	Top 10	7,291	66.37	8	946	711
U.S.	1,406	100	U.S.	10,986	100	6	1,831	1,406

Only includes positive reported data and is confined to USDA National Agricultural Statistics Service disclosure limitations

*State average per turbine

Figure 2. State Adoption Shares for Photovoltaic Solar and Small Wind.



Only includes positive reported data and is confined to USDA National Agricultural Statistics Service disclosure limitations.

The average installation cost per U.S. farm for solar PV was $31,947, corresponding to a size of 4.5 kW (7.1 $/W). The average installation cost per turbine for small wind was $12,972, corresponding to 6 kW (2.2 $/W). For solar PV systems smaller than 1kW, the cost to farmers averaged $8,000, while it was $18,000 for 1-5kW systems and $98,000 for 10-16kW systems. For small wind, the cost for turbines averaged $3,000 for systems smaller than 1kW, $6,000 for those between 1 and 5kW, and $27,000 for those between 5 and 20kW. Farmers spend, on average, less than $10,000 for installing solar PV systems in 17 States. The average expense was $10,000-$20,000 in 20 States, and $20,000-$40,000 in 10 States; only in 3 States the average expense for solar energy was higher than $40,000. Farmers spend, on average, less than $5,000 per turbine installed in 13

States. The average expense was $5,000-10,000 in 10 States, $10,000-$20,000 in 12 States, and $20,000-$50,000 in 6 States.

Table 3 shows the States with the highest and lowest installation costs, and the corresponding average residential electricity prices. There does not seem to be much correlation between State-level electricity prices and installation costs for small wind(r=0.02); correlation is more substantial in the case of solar PV (r=0.32). State-level electricity prices will affect the period of time needed for a farmer to recoup the initial investment in the renewable system. While the average installation costs are higher in New Jersey and Delaware relative to Nebraska and Indiana, for example, electricity prices are also much higher, indicating that over the life of the system, potential savings could be much higher. The payback period (time to recover initial installation costs) and potential lifetime savings are two metrics that a farmer may consider in addition to installation costs when deciding to invest in a renewable system.

Farmers that produced renewable energy on-farm reported savings on their utility bills for 2009 in nearly every State.[8] The savings were especially noticeable in New York, with annual savings over $5,000; Rhode Island and California with annual savings over $4,000; as well as South Carolina, Vermont, New Jersey, and Arizona with annual savings above the national average of $2,400. The median utility savings was $1,250; 13 States saved less than $1,000 in utility bills, 21 between $1,000-2,000, and 15 over $2,000.

The period of time needed for a farmer to recoup the initial investment in the renewable system will also be influenced by the financial support received. Farmers received financial support for installing renewable electricity from a number of sources such as Federal, State, and local government, as well as utilities. The average financial support received for solar PV was 44 percent of the project cost, slightly lower than the support for small wind (49 percent).

[8] Includes farmers that reported wind turbines, solar panels, and/or methane digesters.

Table 3. Lowest and Highest Average Installation Cost by State

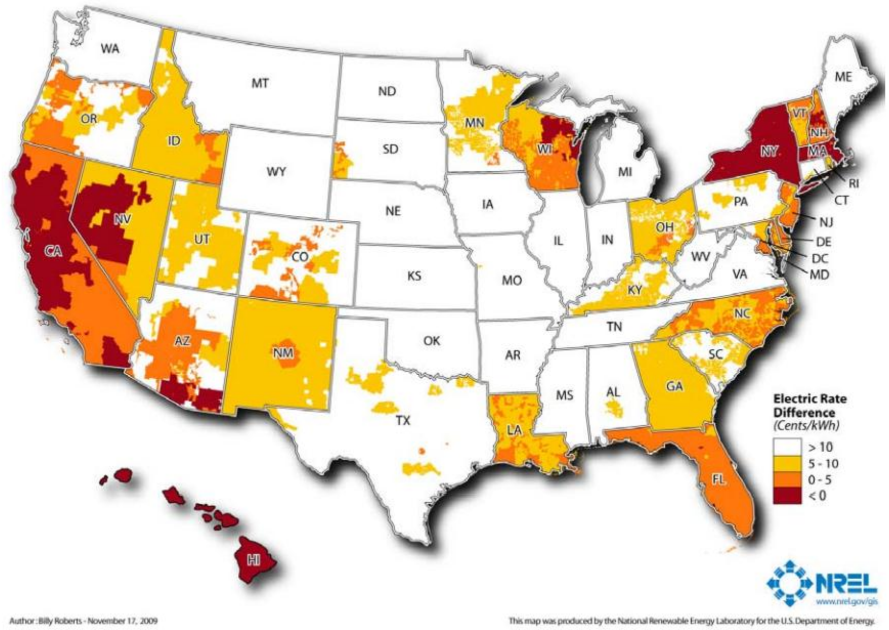
State	Installation Cost($)*	kW*	Electricity Price*** (c/kWh)	State	Installation Cost($)**	kW**	Electricity Price*** (c/kWh)
Solar PV				Small Wind			
Highest Five States							
New Jersey	112,855	14.08	15.66	New Jersey	47,518	8	15.66
Delaware	101,250	15.5	13.93	West Virginia	44,400	5	7.06
California	78,910	11.23	13.81	Massachusetts	43,218	7	17.68
Illinois	39,018	4.58	11.07	Minnesota	37,647	20	9.74
Connecticut	29,571	4.17	19.55	Iowa	23,840	8	9.49
Lowest Five States							
Kansas	4,607	0.41	8.88	Nevada	1,455	1	11.93
Oklahoma	4,612	0.43	9.09	Nebraska	1,563	1	7.87
North Dakota	5,048	0.43	7.51	Hawaii	1,799	1	32.5
Indiana	5,262	0.54	8.87	Utah	2,562	1	8.26
Nebraska	5,632	0.74	7.87	Arizona	2,768	1	10.27

Only includes positive reported data and is confined to USDA National Agricultural Statistics Service disclosure limitations
*Per farm
**Per turbine
*** Average residential electricity price

The OFREPS Survey is not sufficiently detailed to evaluate small-wind and solar-PV system return by State in this paper. The length of the payback period for solar PV and small wind depends on the panel type or the turbine, the quality of solar or wind resource at the installation site, grid-connection, prevailing electricity rates, and available financing and incentives. Depending on these and other factors, payback can range 6 to 30 years[9]. This paper, however, evaluates the factors that Denholm et al. (2009) and Edwards et al. (2004) identify to directly impact the return for solar-PV and small-wind installations respectively: energy prices, resource potential, and incentives that directly impact the return for renewable energy installations. Denholm et al. (2009) characteristically show in figure 3 that residential PV is close to breakeven cost in areas where there is a combination of high electricity prices and good solar resources (like California) or a combination of high electricity prices and incentives (like New York or Massachusetts). Similarly, Edwards et al. (2004) show that the economics of residential small-wind systems, as measured by breakeven cost and simple payback, depend on wind-resource class, electricity prices, and incentives.

[9] Sources include a. Solarbuzz http://www.solarbuzz.com/going-solar/using/economic-payback, and b. AWEA http://www.awea.org/learnabout/publications/upload/Small_Wind_FAQ_Factsheet.pdf. For specific case studies and/or scenarios, payback can be determined through discounted cash flow analysis or calculators available on the Web.

Figure 3. Increase in Electricity Price Required for Residential PV Breakeven at $8/Watt.



Source : Denholm et al., 2009

Factors Influencing Solar and Wind System Adoption on Farms

A range of potential factors that may account for State variations in renewable electricity adoption rates on farms is identified and evaluated.[10] Descriptive statistics and correlation analysis are presented.[11] Bivariate statistical correlation tests are performed, and significance is denoted as *** at the 0.01 level, and ** at the 0.05 level and * at the 0.10 level. A multivariate specification is constructed in the next section, following Menz and Vachon (2006) and Adelaja and Hailu (2008), to account for policy and institutional influences while controlling for structural and economic factors in the States (Adelaja and Hailu 2008, Yin and Powers, 2010, Shrimali and Kniefel 2011).[12] Even though the rigor of this analysis is restricted because some of the State characteristics do not necessarily represent the specific characteristics of the solar adopters, the analysis is pursued in order to understand adoption at the aggregate State level and to identify policy choices that can have an impact in renewable electricity technology adoption in the agricultural sector while accounting for other influences. This paper may also guide further analysis of farmer adoption behavior at the microdata level and serve as a background for future interpretations.[13]

Economic Factors

The influence of economic factors on renewable energy adoption has been examined on the residential (Mills and Schleich 2009, Fujii and Mak, 1984; Durham et al., 1988) and State (Adelaja and Hailu 2008) level. We focus on energy prices and resource potential that directly impact the return for renewable energy installations.

The cost of energy can be an important determinant for the diffusion of solar and wind energy. The State average electricity and diesel prices (*p.electricity* and *p.diesel*) approximate avoided energy costs when renewable electricity is produced on-farm. The electricity prices represent prices for residential customers in 2008 (U.S. Energy Information Administration, 2012a). Diesel prices are computed by subtracting State taxes from 2008 average regional on-highway (No2) diesel fuel prices (U.S. Energy Information Administration 2012b; U.S. Energy Information Administration 2009b).

The Pearson's correlation coefficient for the adoption share of PV (*PVAS*) is 0.48*** with diesel prices and 0.35** with electricity prices.[14] The Pearson's correlation for the adoption share of wind (*SWAS*) is 0.45*** with diesel and 0.35** with electricity prices.

[10] Variable abbreviations are summarized in table 13 of the appendix.
[11] Descriptive statistics are presented in table 14 of the appendix for select variables.
[12] Preliminary correlation analysis provides the basis for variable selection in the multivariate analysis because of limitations imposed by the small number of observations (Evans and Olson, 2003).
[13] Results can guide attention to variables of interest and be compared to future analysis; inferences about individual adoption impacts, however, are not recommended because of the potential of ecological inference fallacy (Robinson, 1950).
[14] Pearson's correlation coefficient is a measure of the strength of linear dependence between two variables that ranges from +1 to -1.

Solar and wind energy can directly replace electricity for on-grid applications and fossil-based fuels for off-grid applications. Most of the early adoption of PV on farms was for off-grid applications like water pumping; however, in the last decade, most PV additions have been on-grid.

State average electricity and diesel prices are highly correlated ($r = 0.73$), and consequently, only one is used in the multivariate analysis. Electricity prices (*p.electricity*) vary widely across States, ranging from $6.99/kWh in Idaho and $19.55/kWh in Connecticut. There is less variation in diesel prices (*p.diesel*); the coefficient of variation is 2.8 percent for diesel prices compared to 28.7 percent for electricity prices. So, it seems likely that even though electricity prices are less closely correlated with adoption than are diesel fuel prices, the wider variation in electricity prices makes them a better measure to reflect State-level differences in energy costs.

The economics of a renewable energy installation are also dependent on the resource potential available for energy production. The more potential there is for energy production, the faster the payback period is for the initial investment in the renewable system and the larger potential savings over the life of the system. Therefore, consumers' adoption behavior might likely be influenced by how "sunny" or "windy" their State is. We calculate the State resource potential for both wind and solar. The State annual average for daily solar resource denoted as *PV resource* was calculated in ArcGIS from low resolution data (surface cells of approximately 40 km by 40 km in size) developed by the National Renewable Energy Laboratory's (NREL's) Climatological Solar Radiation Model (National Renewable Energy Laboratory 2009). Arizona has the highest average State annual solar resource potential at 6.2 kWh/m2/day, and Michigan the lowest at 4.2 kWh/m2/day. The *wind resource* potential was calculated as an integer from one through five designating the average State wind classification based on wind-power density at 50 meters. The State averages were calculated in ArcGIS based on low-resolution data (25-kilometer grid cell resolution) from the national wind-resource assessment of the United States, first created for the U.S. Department of Energy by the Pacific Northwest Laboratory (National Renewable Energy Laboratory 2003). Mississippi, with an average classification of one, has the lowest State average, while Maine, North Dakota, and South Dakota have the highest, with an average classification of 5. The correlation of the PV-adoption share is 0.28* with solar resource, while the correlation of the wind-adoption share with the wind resource of 0.21 is non-significant.

Institutional Factors

The Rural Electrification Act of 1936 led to the formation of numerous cooperatives tending to rural electrification. As a consequence, farms are often served by electric cooperatives which are member-owned, private, independent, and non-profit electric utilities. The percentage of electric customers served by an electric cooperative (*% coop*) is included as an indicator of the prevalence of cooperatives in the electricity generation for each State, based on data available from the U.S. Energy Information Administration (U.S. Energy Information Administration 2012c). Electric cooperatives have distinct characteristics that can impact renewable energy adoption by farms. For example, the high cost of maintaining the infrastructure needed to cover large rural areas can cause prices for electric cooperatives to be higher. Indicatively, in Kentucky, electric cooperatives serve an average of eight consumers per mile of electric line, while investor-owned utilities (IOU) and municipal utilities serve 25 and 60 consumers per mile of electric line respectively (KAEC). Additionally, electric cooperatives, unlike IOUs, are not required by the Public Utility Regulatory Policies Act of 1978 (PURPA) to interconnect with and purchase power at avoided cost from customers with excess onsite generation. Similarly, many States with net metering, interconnection, and RPS exclude cooperatives from the regulation. Not surprisingly, the adoption share on farms is negatively correlated with the share of customers in the State that purchase electricity from electric cooperatives (r=-0.35** for PV adoption and r=-0.28* for wind adoption).

Policy Factors

Renewable energy policies have been important to the growth of renewable electricity production in the last decade. However, policies promoting renewable electricity development vary widely from State to State in formulation and effectiveness. Menz and Vachon (2006), Adelaja and Hailu (2008), Yin and Powers (2010), and Shrimali and Kniefel (2011) examined policies expected to impact State-level adoption at the utility-scale. Our examination is unique as it focuses on policies that can impact State-level adoption of distributed generation specifically in agriculture. Table 4 shows Pearson's correlation for the different policy instruments promoting distributed generation with solar PV and small-wind adoption rates in agriculture. Table 8 provides a view of the geographic distribution of such State policies.

RPS

Renewable Portfolio Standards (RPS) require a minimum amount of renewable electricity sales, or generating capacity, that electricity utilities must achieve according to a specified schedule of dates and mandates. By December 2009, 29 States and the District of Columbia had established an RPS.[15] The specified target amount and date to meet the requirements varied by State. Some States also provided specific solar and/or distributed generation (DG) "set asides." A "set-aside," also called a "carve-out," is a provision within an RPS that requires utilities to use a specific renewable resource to meet a certain percentage of their RPS. While RPS policies are designed to encourage utility-scale investments, those set-aside provisions provide incentives specifically for DG, such as solar and small-wind. Sixteen States and the District of Columbia have such set-asides implemented (Database of State Incentives for Renewables & Efficiency, DSIRE).

The RPS variables presented in the study are based on our analysis of DSIRE's Quantitative RPS Data Project (2009) for December 2009. RPS targets represent a percentage of retail electricity sales covered by the RPS at the final target date in each State. We estimate the RPS target for new renewable generation (*nr rps target*) by excluding traditional sources like biomass and hydro from our interpretation of the RPS tiers for each State. Similarly, we identify solar and distributed generation RPS set-aside

[15] Two States express their target in terms of installed capacity, while five additional States set a non-binding renewable energy goal. Those are excluded from the analysis.

targets (*sdg rps target*). We further identify States that exempt cooperatives from the RPS (*coop exemption*) and States that have a separate RPS for cooperatives (*coop _ rps*) as well as the respective targets that the cooperatives face (*coop rps target*). New renewable RPS targets (*nr rps target*) vary from zero to 33 percent of electricity sales, while solar/DG RPS targets (*sdg rps target*) only reach 5 percent. When a separate target is granted to cooperatives, it is much lower. Correlations with the different RPS indices are large and significant for solar adoption rates (maximum of 0.54 for *coop new RPS target*); they are much smaller for small-wind adoption rates and only significant for c*oop new RPS target* and *coop exemption*. As expected, the adoption rates are negatively correlated with *coop exemptions*. We also find that there is a statistically significant difference in the mean adoption rate of States with a *coop exemption* relative to those without one (table 5). The overall and cooperative specific targets are highly correlated both for new renewables (r=0.79) and solar/DG(r=99), and only one of each is used in the analysis.

Table 4. Correlation Analysis for Policy Variables With Solar-PV and Small Wind Adoption Rates

		Correlation with	
	Share	PVAS	SWAS
RPS			
NR RPS Target	NA	0.47***	0.23
Coop Exemption	0.31	-0.39**	-0.35*
Coop NR RPS Target	NA	0.54***	0.32**
SDG RPS Target	NA	0.33**	0.22
Coop SDG RPS Target	NA	0.34**	0.23
Net Metering			
Net Metering	0.83	0.28*	0.24
Effective Net Metering	0.54	0.46***	0.35**
NM P. Excess Electricity	NA	0.27*	0.30**
Cooperative Net Metering	0.54	0.21	0.25
Effective Coop Net Metering	0.40***	0.39**	0.36
Interconnection			
Interconnection	0.75	0.21	0.17
Effective Interconnection	0.29	0.47***	0.37**
Coop Interconnection	0.4	0.28*	0.28*
Effective Coop Interconnection	0.17	0.43***	0.47***
Financial Incentives			
Incentive	0.56	0.1	0.09
ITC rate, %	NA	-0.02	0.01
ITC	0.23	0.03	0.09
ITC Years	NA	0.0008	-0.04
PI rate, $/kWh	NA	0.2	-0.09
PI	0.17	0.22	-0.07
PI Years	NA	0.08	0.22
DP	0.4	0.17	0.22
DP Years	NA	0.17	-0.06
REAP #	NA	0.02	0.09
REAP $	NA	0.07	0.07

PVAS: Solar-PV adoption share. SWAS: Small-wind adoption share. Independent variable abbreviations summarized in Table 13 of the appendix.

Table 5. Test of Means of Solar-Photovoltaic (PV) and Small-Wind Adoption Rates for renewable Portfolio Standard (RPS)

		N	Mean	SD	z	p
Solar-PV Adoption Share(PVAS)						
Coop Exemption	0	22	0.0077	0.0065	1.992**	0.0464
	1	10	0.0028	0.0024		
Small-Wind Adoption Share (SWAS)						
Coop Exemption	0	21	0.0014832	0.0012	1.775*	0.0759
	1	10	0.0007	0.0007		

z and p are based on the Wilcoxon-Mann-Whitney non-parametric mean equality test.
***, **, * means are statistically different at the p>0.01, p>0.05 and p>0.10 level of confidence.

Net metering

Net-metering policies are aimed at small-scale distributed generation installations. Those policies allow utility customers with renewable energy systems to be compensated for electricity generated in excess of what they consume. Consequently, net metering can have positive financial implications for renewable energy adoption (Xiarchos and Vick 2011). The specific rules, however, vary significantly in design from State to State: for example, in terms of policy coverage, compensation rate per excess kWh generated (retail, avoided cost, or other), carryover and rollover timeframe, unidirectional or bidirectional meter use, subscriber and power limits (*Freeing the Grid*, DSIRE). Due to that variation, *Freeing the Grid* grades the effectiveness of net-metering legislation in each State (Rose 2008). Of the 41 States and the District of Columbia with net-metering policies in 2008, only 26 States were considered by *Freeing the Grid* to have "effective" net-metering policies (that is, received a grade of A, B, or C) based on their scoring methodology. Additionally, 14 States excluded electric cooperatives (the electric utilities that most often service farmers and ranchers) from net-metering requirements in 2008 (Xiarchos and Vick 2011).[16] The norm in net metering is a single bi-directional meter; however, it is possible that the electricity provider requires two meters: one that measures the flow of electricity from the grid and the other into the grid. For such a purchase-and-sale arrangement, the customer is required to receive only the utility's avoided cost for the excess electricity, which is a much lower price than the retail rate.[17] In 2008, only 29

[16]Additionally Delaware only requires net metering from cooperatives that competed outside their service territories.

[17]PURPA requires power providers to purchase excess power from grid-connected small renewable energy systems at a rate equal to what it costs the power provider to produce the power itself. Alternatively, the utility may offer a premium price above the utility's avoided cost.

States and the District of Columbia offered retail electricity price for the excess electricity generated.

According to the U.S. Energy Information Administration (2009a, 2010, 2011), the number of renewable electricity customers in net-metering programs has been steadily increasing: from 4,472 customers in 2002 to 48,886 customers in 2007, up to 96,506 customers in 2009. The majority of those customers (over 90 percent) are residential.[18]

Five indicators for net metering are examined: having a *net metering* regulation, having an *effective net metering* regulation, and having the regulation apply to electric cooperatives in the State (*coop net metering and coop effective net metering*) as well as the excess electricity price received in each State based on the net-metering rules (*nm p. excess electricity*). Net-metering indicators have lower correlations than effective net-metering indicators. Low correlation is also found for the estimate of the price received for excess electricity based on the net-metering rules of each State. Correlation is highest for *effective net metering* (r=0.46) and *effective coop net metering* (r=0.39). Focusing on those net metering indicators, we find that there is a statistically significant difference in the mean adoption rate of States with effective net-metering rules relative to those without effective net-metering rules for PV adoption (table 6). The statistical significance is highest for effective net metering. For effective cooperative net metering, Wilcoxon's rank-sum test of means is statistically significant only at the p>0.10 level of confidence, while for small wind, Wilcoxon's rank-sum test of means for adoption rates is statistically significant only for effective net metering at the 10-percent significance level. Another observation is that the correlation for cooperative indicators does not differ substantially from the respective general State indicators.[19] Due to the high correlation of the cooperative and the general State effective net-metering indicators (r=0.74), only the general State effective net metering is evaluated in the multivariate analysis.

[18] Some farms are included in the Energy Information Administration (EIA) "residential" category, while other farms are classified as commercial customers depending on the utility schedule they qualify for.
[19] Wilcoxon's rank-sum test of means for States with (effective) interconnection by (effective) coop interconnection further supports that the mean adoption rates of States with (effective) net metering does not differ significantly for States that exclude electric cooperatives from the regulation (not shown but available upon request).

Table 6. Test of Means of Solar-Photovoltaic (PV) and Small-Wind Adoption Rates for Net Metering

		N	Mean	SD	z	p
Solar-PV Adoption Share(PVAS)						
Effective Net Metering	0	22	0.0024	0.0025	-2.607***	0.0091
	1	26	0.0077	0.0067		
Effective Coop Net Metering	0	34	0.0035	0.0042	-1.929*	0.0537
	1	14	0.0094	0.0071		
Small-Wind Adoption Share(SWAS)						
Effective Net Metering	0	21	0.0005806	0.0006	-1.819*	0.0689
	1	25	0.0015	0.0016		
Effective Coop Net Metering	0	28	0.0007	0.0007	-1.418	0.1562
	1	18	0.0016	0.0018		

z and p are based on the Wilcoxon-Mann-Whitney non-parametric mean equality test.
***, **, * means are statistically different at the p>0.01, p>0.05 and p>0.10 level of confidence.

Interconnection

Interconnection standards stipulate the technical specifications and procedures by which the renewable energy systems will connect to the distribution grid. They are essential for ensuring the safety and stability of the distribution system, and they reduce transaction costs and uncertainties for customers interested in installing distributed generation systems and their utility. Rules again vary considerably by State, and according to the scoring methodology used in *Freeing the Grid*, only 14 of the 37 States and the District of Columbia that implemented interconnection standards were considered to be "effective"—that is, received a grade of A, B, or C—and met the requirements for satisfactorily having removed interconnection market barriers for renewable energy development (Rose 2008). Additionally, the electric cooperatives that most often service farmers were not subject to interconnection standards in 15 States in 2008 (Xiarchos and Vick 2011). We examine four indicators: *interconnection*, *effective interconnection*, *coop interconnection*, and *effective coop interconnection.*

Similarly to net metering, correlation is high only for effective interconnection and effective cooperative interconnection. Focusing on the effective interconnection indicators, we find that both for solar and small wind there is a statistically significant difference in the mean adoption rate of States with effective interconnection rules relative to those without effective interconnection rules (table 7). Additionally, the correlation for cooperative indicators does not differ substantially from each respective general State indicator.[20] Due to the high correlation of the cooperative and the general effective State interconnection indicator (r=0.74), only one is examined in the model representation.

Table 7. Test of Means of Solar-Photovoltaic (PV) and Small-Wind Adoption Rates for Interconnection

		N	Mean	SD	z	p
Solar-PV Adoption Share (PVAS)						
Effective Intercon-nection	0	29	0.0034	0.0040	-3.153***	0.0016
	1	19	0.0080	0.0070		
Effective Coop Intercon-nection	0	40	0.0042	0.0047	-2.656***	0.0079
	1	8	0.0108	0.0078		
Small-Wind Adoption Share (SWAS)						
Effective Intercon-nection	0	32	0.0008	0.0009	-2.483**	0.0130
	1	14	0.0018	0.0017		
Effective Coop Intercon-nection	0	38	0.0008	0.0009	-2.318**	0.0204
	1	8	0.0024	0.0020		

z and p are based on the Wilcoxon-Mann-Whitney non-parametric mean equality test.
***, **, * means are statistically different at the p>0.01, p>0.05 and p>0.10 level of confidence.

Financial Incentives

Tax incentives, rebates, and grants are offered by States to encourage the use of renewable electricity by making its installation more cost effective. Rebates and grants are direct payments: they offer a payment or discount that reduces the cost of renewable electricity installations. Installation tax credits are corporate and personal (income) tax credits expressed in terms of percent of expenses for renewable electricity installations. However, tax credits with low limits of payment act more like rebates and are estimated in the report as such.[21] Lastly, production incentives (or performance-based incentives) provide payment per generated kilowatt-hours (kWh). Payments, like feed in tariffs, are one form of production incentive (as in Washington State); renewable energy credits

[20] Wilcoxon's rank-sum test of means for States with (effective) interconnection by (effective) coop interconnection also shows that the mean adoption rates of States with (effective) net metering does not differ significantly for States that exclude electric cooperatives from the regulation (not shown but available upon request).

(RECs) and solar RECs (SRECs) are another (examples include California and Pennsylvania). Even a tax credit can be a performance-based incentive, like in Nebraska, where the tax credit offered is based on generated kWhs.

Twenty-seven States were identified to have some State incentive (*incentive*) that supported small-scale renewable distributed generation in 2008: 11 had tax credits (*ITC*); 19 had grant and rebate programs (*DP)*; and 8 had production incentives (*PI*). Loan programs can also provide financing for the purchase of renewable energy equipment, but such programs are not identified for our analysis. Database of State Incentives for Renewables and Efficiency (DSIRE), individual State programs, and REC markets were consulted to extract the financial variables examined. We include policy dummy variables and, when quantitatively comparable, we also include the incentive rates as well as the years since the policy adoption as measures of policy stringency. A binary variable is included for having some incentive (*incentive*) and for each policy separately: *ITC, PI*, and *DP*. For the investment tax credit and the production incentive, we also have each State's rate (*ITC rate* and *PI rate*) and the years from adoption (*ITC years* and *PI years*). For direct payments, incentives are not easily compatible, so we only include the years since policy adoption (*DP years*). We find that correlations with renewable electricity adoption rates are small and insignificant, not only for the binary variables but also for the incentive rates and years since enactment, which are examined as measures of policy stringency. The results are somewhat surprising provided the high upfront capital cost of renewable energy installations and the potential for those policies to increase cost effectiveness.

Rural Development's Renewable Energy Systems and Energy Efficiency Improvement Program, renamed Rural Energy for America (REAP) in the 2008 Farm Bill, has also provided some financial support to solar and small-wind installations. Most of the awards, however, have been for energy efficiency; for example, 74 percent in 2008. From 2001 to 2009, USDA's Rural Development funded 550 solar and small-wind projects with a total of over $17.5 million in funds. However, through 2009, awards were geographically concentrated to only a few States and did not focus on smaller systems (Xiarchos and Vick 2011). Consequently, State adoption rates for solar and small-wind are not expected to be highly correlated with the number of REAP awards in the State (*REAP #)*, or the dollar amount of awards (*REAP $*). Program changes after 2009 should make them a more influential factor (Xiarchos and Vick 2011), provided continuation of program funding in the coming years.

[21] For the purposes of this study, we placed tax credits with a limit of $2,000 or less in the "rebates" category. Tax credits with a limit of more than $2,000 are shown in the "tax credits" category.

Table 8. Select Policy Variables for the U.S. States.

State	Net Metering	Interconnection	Incentive	RPS	S DG RPS
Alaska					
Alabama					
Arkansas	Effective	Yes			
Arizona	Effective	Effective	ITC, DP	Yes	Yes
California	Effective	Effective	PI	Yes	
Colorado	Effective	Effective		Yes	Yes
Connecticut	Effective	Yes	DP	Yes	Yes
District of Columbia	Effective	Effective		Yes	Yes
Delaware	Effective	Yes	DP	Yes	Yes
Florida	Effective, Exempt	Exempt			
Georgia	Yes	Yes			
Hawaii	Yes	Yes		Yes	
Iowa	Effective, Exempt	Exempt	PI	Exempt	
Idaho					
Illinois	Exempt	Effective, Exempt	DP	Exempt	Yes
Indiana	Exempt	Exempt	DP		
Kansas			ITC	Exempt	
Kentucky	Effective				
Louisiana	Effective	Yes			
Massachusetts	Effective	Effective	DP	Yes	
Maryland	Effective	Effective	PI, DP	Yes	Yes
Maine	Effective			Yes	
Michigan		Yes	PI	Yes	
Minnesota	Yes	Yes		Yes	Yes
Missouri	Effective	Yes		Exempt	Yes
Mississippi					
Montana	Effective, Exempt	Exempt	ITC	Exempt	Yes
North Carolina	Exempt	Effective, Exempt	ITC	Yes	Yes
North Dakota	Exempt		ITC	Voluntary	
Nebraska			PI		
New Hampshire	Effective	Yes		Yes	Yes
New Jersey	Effective, Exempt	Effective, Exempt	PI	Yes	Yes
New Mexico	Effective	Yes		Yes	Yes
Nevada	Effective, Exempt	Effective	PI, DP	Yes	Yes
New York	Effective, Exempt	Effective, Exempt	ITC, DP	Exempt	Yes
Ohio	Effective	Exemption	DP	Exempt	Yes
Oklahoma	Yes				
Oregon	Effective	Effective, Exempt	ITC, DP	Yes	
Pennsylvania	Effective, Exempt	Effective, Exempt	PI, DP	Exempt	Yes
Rhode Island	Exempt		ITC	Yes	
South Carolina	Yes	Exempt	ITC		
South Dakota				Voluntary	
Tennessee			ITC, DP		
Texas	Yes	Exempt		Exempt	Yes
Utah	Exempt	Exempt	ITC, DP	Voluntary	
Virginia	Effective	Yes		Voluntary	
Vermont	Effective	Effective	DP	Voluntary	
Washington	Yes	Effective	PI,DP	Yes	
Wisconsin	Exempt	Exempt	DP	Yes	
West Virginia	Yes	Yes	DP		
Wyoming	Effective	Yes			

Exempt: Cooperatives are exempt from the policy
Source: USDA Office of Energy Policy and New Uses (OEPNU), Database of State Incentives for Renewables and Efficiency (DSIRE), Rose (2008), and Xiarchos and Vick (2011).

State Agricultural Characteristics

Adelaja and Hailu 2008, Yin and Powers 2010, and Shrimali and Kniefel 2011 account for economic, political, and demographic characteristics. Our analysis focuses in agriculture, so in addition to such characteristics, we also account for differences in the agricultural sector of the States. Structural characteristics of the agricultural sector should have an effect in the resulting renewable electricity adoption rates at the State level. In this section, we investigate which structural characteristics of the agricultural sector to include in the multivariate analysis as control variables. Even though most of the variables can serve as proxies to individual farmer characteristics at the aggregate level, they are analyzed for representing State conditions that increase the adoption probability for all farmers in the State. For example, organic acres can indicate a predisposition in the State's agricultural sector for addressing environmental concerns. Another example is share of cattle operations; since a predominant use of renewable energy systems in agriculture has historically been for water pumping, "ranching" States with many cattle operations can be expected to have larger adoption rates. All variables are normalized (as averages by operation or shares in the agricultural sector of the State) and are extracted from the 2007 Census of Agriculture (National Agricultural Statistics Service 2009a).

Correlation analysis for State agricultural characteristics with solar-PV and small-wind adoption rates are presented in table 9. We distinguish financial State variables like energy expenses by operation (*fuel expense* and *electricity expense*[22]) and electricity used by operation (*electricity used*), derived by dividing electricity expense by the 2008 State electricity price average,[23] and average funding share supporting renewable energy by operation[24] (*funding*). Wealth and investment effects are examined through the financial State variables of average profitability by operation (*net cash income*), average land owned (*land value*), and machinery value by operation (*machine value*). Agricultural production mix variables like the share of cattle and fruit operations in the State (*fruit, cattle*) as well as organic and conservation acres by operation (*organic* and *conservation*) are also evaluated. Solar and wind systems are often used for water pumping associated with cattle and small fruit operations (Xiarchos and Vick 2011) and are potentially adopted by farmers that are concerned with the environment and practice organic or conservation practices, so such State characteristics can have an effect on State adoption rates. Last, we examine farmer constituent variables like the State average for acre size of an operation (*size*), the share of operations in the State that are connected to the Internet (*internet*), and the agricultural sector's investment in the land expressed as the share of operations with full tenure of the land it operates (*tenure*).

From the financial variables, electricity used, utility, and land value have significant correlations. The average funding share for renewable energy installations reported in

---

[22] The variable "utility expense" is used as a proxy for electricity expense, although the utility expense would also include other utilities such as phones (National Agricultural Statistics Service 2009a).
[23] Electricity prices used are for residential customers in 2008 and come from the U.S. Energy Information Administration (2012a).
[24] The funding share for supporting renewable energy is extracted from the OFREPS (National Agricultural Statistics Service 2011).

NASS is not correlated with adoption share; this result is in line with the insignificant correlation for financial policy instruments. Average farm income (representing wealth and profitability in the State's agricultural sector), and machine value (representing wealth as well as capital investment in the State's agricultural sector) are not correlated with adoption shares. Average land value, another indicator for wealth, holds a significant correlation to solar-adoption shares, but not to wind-adoption shares. Fuel costs are uncorrelated, while electricity cost and electricity use are highly correlated with adoption rates. Electricity cost and electricity use are highly correlated (r = 0.92) and consequently only one is used in the multivariate analysis.

The product mix also seems significant. States with a lot of organic production are significantly correlated with solar and wind adoption rates. The share of cattle operations in the State is significantly correlated with wind adoption rates, while the share of fruit operations holds a significant relationship specifically with solar adoption rates. Internet connection share has a significant correlation with adoption shares, and tenure share has a significant correlation with the solar PV adoption share. Wind adoption rates are correlated with less variables (only about half) than solar adoption rates.

Table 9. Correlation Analysis for State Agricultural Characteristics With Solar-PV and Small-Wind Adoption Rates

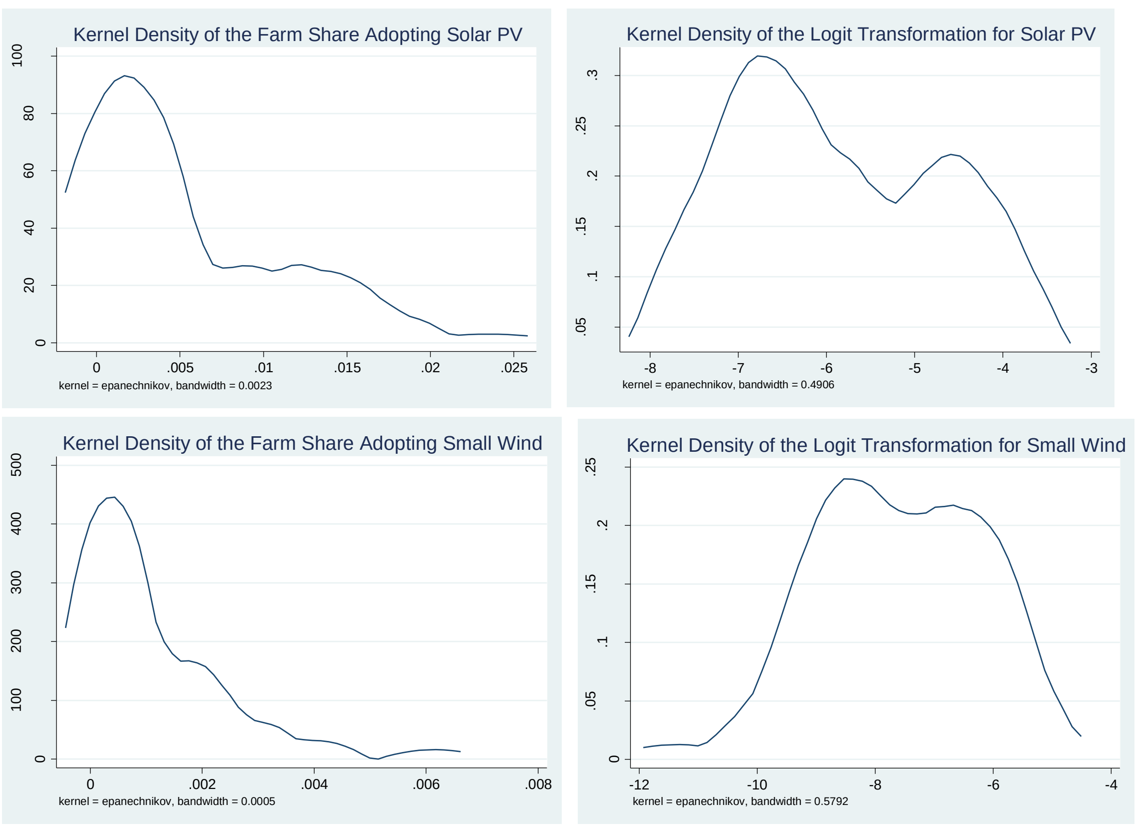
	PVAS	SWAS
Financial		
Fuel Expense	0.23	0.06
Electricity Expense	0.62***	0.3**
Electricity Used	0.48***	0.23
Land Value	0.36***	0.1
Machine Value	-0.13	-0.11
Net Cash Income	-0.02	-0.11
Funding Share	-0.01	-0.09
Product Mix		
Conservation Acres	0.02	0.03
Organic Acres	0.6***	0.68***
Fruit	0.55***	0.21
Cattle	-0.23	-0.33**
Constituent		
Internet	-0.33**	-0.38***
Tenure	0.41***	0.23
Size	0.22	0.09

PVAS: Solar-PV adoption share. SWAS: Small-wind adoption share.
Independent variable abbreviations summarized in Table 13 of the appendix.

Modeling Aggregate Renewable Electricity Adoption

The proportion of farms that adopt renewable electricity in a State is bounded between 0 and 1. The logit transformation of data such as the proportion of adopters removes the upper and lower boundaries of the scale and spreads out the tails of the distribution.[25] The logit transformation is recommended for proportions close to zero, as in the case of renewable electricity adoption on the farm, which is an extremely rare event. For example, the proportion of farms that have installed solar systems averages 0.005, with a range of 0.0004 in Iowa to 0.023 in California. The transformation of the renewable electricity adoption shares "stretches out" the proportions that are close to 0 and 1 and "compresses" proportions closer to 0.5, thus "normalizing" the data (figure 4).

Figure 4. Kernel Density Plots for the Share of Farms with Solar Photovoltaic (PV) and Small-Wind Installations Before and After the Logit Transformation[26]



[25] The zero wind-adoption observations in Delaware and South Carolina are treated as missing observations.
[26] A kernel density estimation is an alternative to a histogram that shows a visual impression of the probability density function of a variable, which in comparison to the discreteness of histograms is endowed with smoothness or continuity.

The model becomes:

$$z = \ln\left(\frac{y}{1-y}\right) = x'\beta + \varepsilon, \ \ \varepsilon \sim N(0, \sigma)$$

Aitchison (1986) calls the above transformation the additive logratio transformation and shows that *z* will follow a normal distribution, $N(\mu, \sigma^2)$, if y follows an additive logistic normal distribution. Aitchison (1986) proposes testing the appropriateness of the model (if *y* is distributed as an additive logistic normal distribution) by testing if *z* is normally distributed.

The model is fitted with ordinary least squares (OLS), and its formulation is influenced from the technology adoption literature. Due to the small number of observations, the empirical analysis needs to be parsimonious (Evans and Olson, 2003): the determinants are selected based on the preliminary correlation analysis in the previous section and a stepwise regression procedure. Results are presented in Table 10 and 11. Model 1 includes factors of interest, while Model 2 includes only those factors that are found to be significant. The variance inflation factors (VIFs) suggest that multicollinearity does not pose a problem. The model residuals are normally distributed as supported by the Shapiro-Wilk, Shapiro-Francia, and Skewness/Kurtosis tests in table 12 at the 1-percent marginal significance level. Consequently, our data support the distributional assumptions underlying the logit transformation regression model. We use robust standard errors, which Kieschnick and McCullough (2003) identify are more trustworthy for inferring significance with the logit transformation model. The logic transformation is worth exploring according to Smithson and Verkuilen (2006); it serves our rare event analysis well, while our data support that modeling approach. However, due to increased support for using the beta distribution for proportions (Kieschnick and McCullough 2003, Smithson and Verkuilen (2006), we also run the beta regression and show its results in tables 10 and 11. The beta regression assumes the dependent variable follows a beta distribution with two parameters μ and φ:

$$f(y;\mu,\varphi) = \frac{\Gamma(\varphi)}{\Gamma(\mu\varphi)\Gamma(1-\mu)\varphi)} y^{\mu\varphi-1}(1-y)^{(1-\mu)\varphi-1}, \quad 0 < \mu < 1 \ and \ \varphi > 0$$

where $E(y) = \mu \ and \ var(y) = \sigma^2 = \frac{\mu(1-\mu)}{\varphi+1}; \quad \mu = \frac{\omega}{\omega+\tau} \ and \ \varphi = \omega + \tau$

The parameters ω and τ are shape parameters (ω pulls the density towards 0 and and τ toward 1), that are parameterized into a location (mean) μ and a precision φ parameter. The parameter φ represents dispersion because variance increases as φ decreases: $\sigma = \mu(1-\mu)/\varphi+1$. However, φ is not the sole determinant of dispersion; variance is a function of both the mean and parameter φ, since the dispersion of a bounded random variable depends partially on location. Still, the location parameter μ and the precision parameter φ place no restrictions on each other and can be modeled separately (Smithson and Verkuilen, 2006). We run the beta regression on the formulation of variables appointed from the stepwise logit transformation model, and in accordance to Smithson and Verkuilen (2006), examine impacts of the variables both on the location (μ) and the dispersion (φ)[27] of adoption rates. Explicitly modeling dispersion on explanatory variables increases the Chi-square for both solar and wind adoption rates. The variables in the dispersion submodel that maximize the Chi-square are land value for solar

[27] The precision factor expressing variance.

adoption rates and land value and tenure for wind adoption rates. Slight differences in the mean results are noted. The beta models pick up significance for some additional variables to those found significant by the logic transformation regression.

PV adoption rates are positively influenced by economic factors in the State. Higher electricity prices correspond to higher State adoption rates. Furthermore, solar potential also accounts for variation in PV adoption rates. Higher radiation is positively related to increased State-level adoption. Institutional influences also systematically account for adoption variation. The percentage of State electric customers served by an electric cooperative is negatively related to PV adoption rates. In terms of policies supporting renewable electricity, only the solar and distributed generation target has a significant effect on adoption rates. Correlation analysis already showed a lack of connection between financial policy instruments and adoption rates, regression analysis further shows no statistically significant relationship for net-metering and interconnection policies with State-level adoption shares. Land ownership, Internet connectivity, and organic practices in agriculture at the State level are also found to have a significant relationship to adoption rates. The beta regression also picks up a negative relationship between adoption rates and electricity used in the farm sector.

The picture is similar for small-wind adoption rates. Share of customers served by electric cooperatives, organic practices, and Internet connectivity in the State have a systematic link to adoption shares for small wind, while net-metering and interconnection policies do not. The beta regression further shows a significant systematic positive relationship with electricity prices. However, some differences arise: adoption rates are not related to the intensity of the wind resource at the State level or land ownership; the beta regression also picks up that small-wind adoption rates are systematically related to the RPS for new renewables in addition to the solar and distributed generation target.

Table 10. Modeling Results for Solar-Photovoltaic (PV) Adoption Rates

PVAS	Logit Transformation Regression		Beta Regression	
	Model 1	Model 2	Model 1	Model 2
			Location Submodel (μ)	
Electricity Price	0.06* (0.03)	0.06** (0.02)	0.04* 0.02	0.04** 0.02
PV Resource	0.54*** (0.19)	0.44*** (0.15)	0.46*** 0.13	0.45*** 0.13
% Coop	-0.02*** (0.01)	-0.02*** (0.01)	-0.01** 0.01	-0.01** 0.01
SDG RPS Target	17.89* (9.32)	20.54** (7.98)	31.79*** 7.30	28.18*** 4.71
Organic	0.28*** (0.05)	0.26*** (0.03)	0.21*** 0.03	0.21*** 0.02
Internet	4.86** (1.88)	5.41*** (1.06)	7.50*** 1.35	6.93*** 0.85
Tenure	5.80*** (1.34)	5.26*** (1.02)	5.12*** 1.26	4.97*** 0.96
Effective Net Metering	-0.16 (0.22)		0.01 0.12	
Effective Interconnection	0.09 (0.24)		-0.16 0.14	
NR RPS Target	0.62 (1.64)		-0.23 1.04	
Electricity Used	-0.0004 (0.0006)		-9E-04** (4E-04)	-8E-04** 0.0004
Fruit	0.70 (1.34)		0.22 0.84	
Land Value	3.40E-08 (2.86E-07)		3.9E-07* (2.2E-07)	4E-07* 2E-07
Constant	-16. 54*** (1.90)	-15.79*** (1.29)	-16.77 1.16	-16.29*** 0.96
			Dispersion Submodel (*lnφ*)	
Land Value			-2.7E-06***	-3E-06***
			(8.3E-07)	8E-07
Constant			9.97***	9.87***
			0.74	0.68
N	48	48	48	48
R^2	0.86	0.85	-	-
F	(13,34)=34.09	(7, 40)=57.89	-	-
Wald X^2			(13)=531.92	(9)= 516.45
Prob > F	0.00	0.00	0.00	0.00
Mean VIF	2.4	1.56	-	-
Max VIF	3.62	1.89	-	-

*,**,*** significant at 1, 5, and 10 percent respectively. Robust standard errors in parenthesis.
Variable abbreviations summarized in Table 13 of the appendix. PVAS: Solar-PV adoption share.

Table 11. Modeling Results for Small-Wind Adoption Rates

SWAS	Logit Transformation Regression		Beta Regression	
	Model 1	Model 2	Model 1	Model 2
			Location Submodel (μ)	
Coop New RPS Target	2.31 (2.19)		3.74*** (1.44)	4.79*** (0.99)
SDG RPS Target	35.45* (19.79)	39.70** (16.23)	19.55** (9.81)	17.58** (7.95)
% Coop	-0.03** (0.01)	-0.03*** (0.01)	-0.02** (0.01)	-0.02*** (0.01)
Organic	0.37*** (0.06)	0.31*** (0.05)	0.29*** (0.02)	0.27*** (0.02)
Internet	4.81* (2.73)	5.47** (2.10)	5.50*** (1.65)	4.86*** (1.22)
Wind Resource	-0.03 (0.19)		-0.01 (0.09)	
Electricity Price	0.01 (0.05)		0.05(*) (0.03)	0.04** (0.02)
Tenure	2.27 (2.80)		2.28 (2.26)	
Effective Net Metering	-0.41 (0.30)		-0.14 (0.20)	
Effective Coop Interconnection	-0.05 (0.27)		-0.08 (0.16)	
Electricity Used	-0.18 (1.49)		0.29 (0.98)	
Cattle	-0.0005 (0.0007)		0.00 (0.00)	
Constant	-12.12*** (2.34)	-11.09*** (1.21)	-13.19*** (1.54)	-11.15*** (0.68)
			Dispersion Submodel ($ln\varphi$)	
Land Value			-3.8E-06***	-4.5E-06
			(1.1E-05)	(7.6E-07)
Tenure			-8.21*	-5.58
			(4.44)	(2.22)**
Constant			17.64***	16.36
			(2.75)	(1.80)*
N	46	46	46	46
R^2	0.72	0.68	-	-
F	(12,33)=15.00	(4,41)=39.40	-	-
Wald X^2	-	-	(12)= 730.59	(6)= 748.22
Prob > F or or X^2	0	0	0	0
Mean VIF	2.2	1.37	-	-
Max VIF	3.3	1.7	-	-

*,**,*** significant at 1, 5, and 10 percent respectively. Robust standard errors in parenthesis.
Variable abbreviations summarized in Table 13 of the appendix. SWAS: Small-wind adoption share.

Table 12. Normality Test for 2005 Logit Transformation Regression Models

		PVAS		SWAS	
	Statistic	Test	P value	Test	P value
Skewness/Kurtosis test	X^2	1.41	0.493	4.30	0.12
Shapiro-Wilk	W	0.98	0.62	0.96401	0.16
Shapiro-Francia	W'	0.99	0.84	0.96346	0.14

PVAS: Solar-PV adoption share. SWAS: Small-wind adoption share

Summary and Concluding Remarks

Adoption of solar and wind systems for generating on-farm electricity is not widespread, but installations on the farm have increased greatly, especially since 2005 following a trend of increased policy attention and investment in renewable energy. In 2009, policy support intensified as the American Recovery and Reinvestment Act of 2009 (ARRA) provided new incentives for the adoption of renewable energy systems, while an accruing number of States continue to adopt incentives to promote renewable energy installations.

Though technology adoption is ultimately an individual farm-level choice determined by specific farm-level characteristics, analyzing State-level variables can explain underlying State variation in adoption rates, evaluate policy effectiveness, and even inform model formulation of microlevel analysis. Our results suggest that some agricultural characteristics are found to relate to higher adoption rates: States with more organic acres per farm and more Internet connectivity have higher renewable electricity adoption rates. Higher energy price and solar resource have a significant and positive relationship with solar electricity adoption rates. For wind, economic influences do not appear to exhibit as strong of a systematic relationship with State adoption rates, with the exception of electricity price based on the beta regression. There are distinctions between wind and solar energy, but the differences are not dramatic. For example, tenure is significantly related to solar energy adoption but not wind adoption. Furthermore, wind energy adoption is influenced by both new renewable RPS target and solar/DG RPS target, while solar energy adoption is influenced by the solar/DG RPS target.

Electric cooperative prevalence in the State is found to have a negative relationship to renewable electricity adoption share, which underlines the importance of policy formulation. Out of the list of policy variables we considered, the RPS is actually the only policy variable to show a large and systematic effect on State adoption rates. Our results agree with Menz and Vachon (2006), Adelaja and Hailu (2008), and Yin and Powers (2010), who found the RPS to be important for renewable electricity adoption; however, their results applied to utility-scale renewable electricity adoption, while this is the first study to show an impact at the distributed-generation scale. While both wind and solar adoption rates have a significant relationship to the solar/DG RPS, only wind is also significantly related to the new RPS standard. Our study does not find a systematic relationship for other State policy instruments, at least in the form captured by our policy variables. Financial policy instruments like rebates, grants, investment tax credits, and production incentives do not appear to be correlated to State adoption rates for solar and wind systems. Multivariate analysis further showed that effective (coop) net-metering and interconnection fail to reveal a systematic relationship with renewable electricity adoption rates on farms.

While Yin and Powers (2010) showed that net metering and interconnection were not effective in increasing renewable generation, their analysis focused on utility capacity, and we expected that effective net metering might have an impact on distributed generation. Performance-based incentives, similarly to net metering, increase the positive flow of revenues from the renewable electricity system and reduce its payback period. Tax credits and direct payments, on the other hand, have the potential to reduce the high upfront capital cost of renewable energy installations that are considered impediments to adoption. For installation tax credits, the results further contradict the recent experience with the Federal investment tax credit, which increased to 30 percent under the Energy Policy Act of 2005 and resulted in a tripling of renewable energy installations between 2005 and 2008 (Sherwood 2010, 2009).

The incentives provided at the State level might indeed not influence adoption rates; adoption decisions might instead be determined by farmer characteristics. It is also possible that the effective incentives at the farm level are not sufficiently large to induce a significant impact. Alternatively, incentive dummies and stringency averages might not be adequately capturing the prices and incentives farms face. For example, the form of the direct payments and benefits offered vary substantially from State to State, making a comparable quantitative representation difficult. Furthermore, the dataset excludes any incentives provided at the utility or local level, which could play a significant role in adoption choices. Future examination at a more disaggregate level might provide more insights.

The lack of systematic impact of those policies on solar and wind system adoption seems to apply specifically to the agricultural sector, due to the smaller size bounds of renewable electricity installations used by farmers until 2009 as well as to institutional limitations. The negative relationship that the cooperative prevalence in electricity distribution has with solar-PV and small-wind adoption suggests that the institutional settings for rural energy policies are important determinants in the success of those policies. It also suggests that USDA’s Rural Development Utilities Programs, which helps rural utilities expand and keep their technology up to date while promoting rural infrastructure development, is in a unique position to work with electric cooperatives to promote distributed generation of renewable energy while increasing green job opportunities (Rural Development a, b).

The study is the first to examine the role of electric cooperatives on solar and wind system adoption on farms. It contributes to the literature of policy impacts on States’ renewable energy investment by providing insights on the effect of policies geared towards distributed generation, specifically on renewable electricity production in agriculture. Future work that could better categorize the different State policies might provide better insights on the role of financial policy instruments in promoting small-wind and solar installations in commercial, residential, as well as farm settings. The results of this study can assist States as they further refine and focus their policies to promote renewable electricity most effectively with limited budget resources. A more detailed examination of farm-level data from OFREPS in combination with the policy, institutional, and economic State-level variables identified in this report can provide a fuller and more realistic interpretation of the determinants of adoption of solar and wind energy generation.

References

Adelaja, S.J., and Y.G. Hailu. 2008. *Effects of Renewable Portfolio Standards and Other State Policies on Wind Industry Development in the US*. Mimeo, Michigan State University.

Aitchison, J. 1986. *The Statistical Analysis of Compositional Data*. Chapman and Hall, New York, NY.

Bazen, E. and M. Brown. 2009. Feasibility of Solar Technology (Photovoltaic) Adoption: A Case Study on Tennessee's Poultry Industry. *Renewable Energy* 34(3).

Database of State Incentives for Renewables & Efficiency. Available at: www.dsireusa.org. Accessed on April 11, 2011.

Database of State Incentives for Renewables & Efficiency Quantitative RPS Data Project. 2009. December 2009 Archive. Available at: http://www.dsireusa.org/rpsdata/index.cfm.

Delmas, M. and M. Montes-Sancho. 2011. U.S. State Policies for Renewable Energy: Context and Effectiveness. *Energy Policy*. 39(5)

Denholm, P. Margolis, R.M., Ong, S. and B. Roberts. 2009. Breakeven Cost for Residential Photovoltaics in the United States: Key Drivers and Sensitivities. NREL TP-6A2-46909. National Renewable Energy Laboratory (NREL), Department of Energy (DOE). http://www.nrel.gov/docs/fy10osti/46909.pdf (Accessed September 10, 2010)

Dillman, D.A., Roosa, E.A. and J.J. Dillman. 1983. Lifestyle and Home Energy Conservation in the United States: The Poor Accept Life-style Cutbacks While the Wealthy Invest in Conservation. Journal of *Economic Psychology* 3 (Sep).

Durham, C., Colby, B. and M. Longstreth. 1988. The Impact of State Tax Credits and Energy Prices on Adoption of Solar Energy Systems. *Land Economics* 64 (4).

Edwards, J.L., Wiser, R.H., Bolinger, M., and T. Forsyth. 2004. Building a Market for Small Wind: The Break-Even Turnkey Cost of Residential Wind Systems in the United States. Ernest Orlando LBNL-54865. Lawrence Berkeley National Laboratory (LBNL). http://emp.lbl.gov/sites/all/files/REPORT%20lbnl%20-%2054865.pdf (Access march 15, 2013)

Evans, J.R. and D.L. Olson. 2003. *Statistics, Data Analysis, and Decision Modeling*. Prentice-Hall, Upper Saddle River, NJ.

Food and Agriculture Organization. 2000. Solar Photovoltaics for Sustainable Agriculture and Rural Development. Environment and Natural Resources Working Paper No. 2. Rome, Italy: Food and Agriculture Organization. Available at: http://www.fao.org/sd/EGdirect/EGre0057.htm (Accessed September 14, 2012).

Freeing the Grid. Available at: http://www.gracelinks.org/1179/freeing-the-grid. Accessed on January 11, 2013.

Fujii, E.T., and J. Mak. 1984. A Model of Household Electricity Conservation Behavior, *Land Economics* 60.

KAEC. http://www.kaec.org/faq.htm. Accessed on July 1, 2012.

Katzman, M.T., and R.W. Matlin. 1978. Economics of Adopting Solar Energy Systems for Crop Irrigation. *American Journal of Agricultural Economics* 60.

Kieschnick, R., and McCullough B.D. 2003. Regression Analysis of Variates Observed on (0, 1): Percentages, Proportions, and Fractions. *Statistical Modeling* 3

Knowler, D. and B. Bradshaw. 2007. Farmers' Adoption of Conservation Agriculture: A Review and Sybthesis of Recent Research. *Food Policy* 32.

Labay, D. and T. Kinnear. 1981. Exploring the Consumer Decision Process in the Adoption of Solar Energy Systems. *Journal of Consumer Research* 8 (Dec).

Long, J. 1993. An Econometric Analysis of Residential Expenditures on Energy Conservation and Renewable Energy Sources. *Energy Economics* 15.

Menz, F.C., and S. Vachon. 2006. The effectiveness of different policy regimes for promoting wind power: Experiences from the States. *Energy Policy* 34.

Mills, B.F. and J. Schleich. 2009. Profits or Preferences? Assessing the Adoption of Residential Solar Thermal Technologies. *Energy Policy* 37.

National Agricultural Statistics Service. 2011. *On-Farm Renewable Energy Production Survey 2009.* Washington, DC: U.S. Department of Agriculture.

National Agricultural Statistics Service. 2009a. *Census of Agriculture 2007*. Washington, DC: U.S. Department of Agriculture.

National Agricultural Statistics Service. 2009b. *Farm and Ranch Land Irrigation Survey 2008.* Washington, DC: U.S. Department of Agriculture.

National Agricultural Statistics Service. 2004. *Farm and Ranch Land Irrigation Survey 2003.* Washington, DC: U.S. Department of Agriculture.

National Renewable Energy Laboratory. 2009. *Lower 48 PV Low Resolution.* U.S. Department of Energy. Available at: http://www.nrel.gov/gis/data_solar.html. Accessed on April 11, 2012.

National Renewable Energy Laboratory. 2003. *Lower 48 Wind Low Resolution.* U.S. Department of Energy. Available at: http://www.nrel.gov/gis/data_wind.html. Accessed on April 11, 2012.

O'Doherty, J., Lyons, S. and R. Tol. 2008. Energy-using Appliances and Energy-saving Features: Determinants of Ownership in Ireland. *Applied Energy* 85 (7).

Ostlund, L.E. "Perceived Innovation Attributes as Predictors of Innovativeness." *Journal of Consumer Research* 1(1974): 23-29.

Robinson, W.S. 1950. Ecological Correlations and the Behavior of Individuals. *American Sociological Review* 15(3: Jun)

Rose, J. 2008. *Freeing the Grid 2008: The Best and Worst Practices in State Net Metering Policies and Interconnection Procedures.* Network for New Energy Choices.

Rural Development. U.S. Department of Agriculture. Available at:
a. http://www.rurdev.usda.gov/utilities_LP.html , and
b. http://www.rurdev.usda.gov/UEP_HomePage.html. Accessed on April 11, 2013.

U.S. Energy Information Administration. 2013. Monthly Energy Review. February 2013. Avaialable at: http://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf. Accessed on March 10, 2013.

U.S. Energy Information Administration. 2012. Electric Power Monthly. March 2012. Available at: http://www.eia.gov/electricity/monthly/current_year/march2012.pdf. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2012a. *Electric Sales, Revenue, and Average Price. Form EIA-861. Annual Electric Power Industry Report 2008*. Available at: http://www.eia.gov/electricity/sales_revenue_price/. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2012b. *Gasoline and Diesel Fuel Update.* Full History Dataset. Washington DC: U.S. Department of Energy.

U.S. Energy Information Administration. 2012c. *Form EIA-861 data files. Annual Electric Power Industry Report 2008.* Available at: http://www.eia.gov/electricity/data/eia861/index.html. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2011. *Annual Energy Review 2009.* Washington, DC. Available at: http://www.eia.gov/electricity/annual/. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2010. *Annual Energy Review 2008.* Washington, DC. Available at: http://www.eia.gov/electricity/annual/. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2009b. *Annual Energy Review 2007.* Washington, DC. Available at: http://www.eia.gov/electricity/annual/. Accessed on July 10, 2012.

U.S. Energy Information Administration. 2009a. *Petroleum Marketing Annual 2008. Explanatory Notes.* Washington DC: U.S. Department of Energy.

Sardianou, E. 2007. Estimating Energy Conservation Patterns of Greek Households. *Energy Policy* 35.

Sawyer, S.W., A. Sorrentino, and R. M. Wirtshafter. 1984. Solar Energy Adoption Patterns in the United States. *Energy Systems and Policy* 8(2)

Sherwood, L. 2010. *U.S. Solar Market Trends 2009*. InterState Renewable Energy Council.

Sherwood, L. 2009. *U.S. Solar Market Trends 2008*. InterState Renewable Energy Council.

Shrimali, G., and J. Kniefel. "Are government policies effective in promoting deployment of renewable electricity resources?" *Energy Policy* 39(2011): 4726–4741.

Skinner, J., and D. Staiger. 2007. Technology Adoption from Hybrid Corn to Beta-Blockers, ed. C.M. Hulten, University of Chicago Press and National Bureau of Economic Research (NBER).

Smithson, M. and J. Verkuilen. 2006. A Better Lemon Squeezer? Maximum Likelihood Regression with Beta-Distributed Dependent Variables. *Psychological Methods* 11(1)

Walsh, M. 1989. Energy Tax Credits and Housing Improvement. *Energy Economics* 11.

Willis, K., Scarpa, R., Gilroy, R., and N. Hamza. 2011. Renewable Energy Adoption in an Ageing Population: Heterogeneity in Preferences for Micro-generation Technology Adoption. *Energy Policy* 39.

Xiarchos, I., and B. Vick. 2011. *Solar Energy Use in U.S. Agriculture: Overview and Policy Issues.* Washington, DC: U.S. Department of Agriculture, Office of the Chief Economist, Office of Energy Policy and New Uses.

Yin, H., and N. Powers. Do State Renewable Portfolio Standards Promote In-State Renewable Generation? *Energy Policy* 38(2010): 1140–1149.

Appendix

Table 13. Variable Abbreviations

Diesel Price	Diesel Price per Gallon
Electricity Price	Average Residential Retail Electric Price per Kilowatt Hour
PV Resource	Solar potential, (4.2-6.2)
Wind Resource	Wind classification, (1-5)
% Coop	Percentage of Customers Served by Electric Cooperatives
NR RPS Target	Renewable Portfolio Standard Target for New Renewables
Coop Exemption	Cooperative exemption from Renewable Portfolio Standard
Coop NR RPS Target	Cooperative Specific Renewable Portfolio Standard Target for New Renewables
SDG RPS Target	Renewable Portfolio Standard Target for Solar/Distributed Generation
Coop SDG RPS Target	Cooperative Specific Renewable Portfolio Standard Target for Solar/Distributed Generation
Net Metering	Net Metering Policy, (0,1)
Effective Net Metering	Effective Net Metering Policy, (0,1)
NM P. Excess Electricity	Net Metering Price for Excess Electricity per Kilowatt Hour
Cooperative Net Metering	Net Metering Policy for Cooperatives, (0,1)
Effective Coop Net Metering	Effective Net Metering Policy for Cooperatives, (0,1)
Interconnection	Interconnection Policy, (0,1)
Effective Interconnection	Effective Interconnection Policy, (0,1)
Coop Interconnection	Interconnection Policy for Cooperatives, (0,1)
Effective Coop Interconnection	Effective Interconnection Policy for Cooperatives, (0,1)
Incentive	Financial Incentive, (0,1)
ITC	Investment Tax Credit, (0,1)
PI	Production Incentive, (0,1)
DP	Grant and Rebate Program, (0,1)
ITC rate, %	Investment Tax Credit Rate, Percent
PI rate, $/kWh	Production Incentive Rate per Kilowatt Hour
ITC Years	Investment Tax Credit, Years since Enactment
PI Years	Production incentive, Years since Enactment
DP Years	Grant and Rebate Program, Years since Enactment
REAP #	Number of Projects funded by Rural Energy for America Program
REAP $	Dollars distributed to projects funded by Rural Energy for America Program
Fuel Expense	Fuel Expense by Operation
Electricity Expense	Electricity Expense by Operation
Electricity Used	Electricity Used by Operation
Funding Share	Funding Share Supporting the Cost of Photovoltaic and Small-Wind Installations
Net Cash Income	Net Cash Income by Operation
Land Value	Land Value by Operation
Machinery Value	Machinery Value by Operation
Organic	Organic Acres by Operation
Conservation	Conservation Acres by Operation
Fruit	Share of Fruit Operations in State
Cattle	Share of Cattle Operations in State
Tenure	Share of Operations Tenure with Full Tenure of Operated Land
Internet	Share of Operations Connected to the Internet

Table 14. Descriptive Statistics

Variable	Mean	Std. Dev.	CV	Min	Max
Diesel Price	$3.61	0.1	0.03	$3.43	$3.85
Electricity Price	$11.00	3.19	0.29	$6.99	$19.55
PV Resource	4.92	0.52	0.1	4.2	6.23
ACV_Score	56.65	25.47	0.45	9	96
% Coop	15.72	13.01	0.83	0	48.64
New Renewable Target	0.09	0.09	0.11	0	0.33
Solar/DG Target	0.005	0.01	2.27	0	0.05
NM P. Excess Electricity	0.08	0.058	0.648	0	0.19
ITC rate, %	0.06	0.11	2.086	0	0.4
PI rate, $/kWh	0.02	0.06	3.55	0	0.3
ITC Years	9.18	10.66	1.16	31	1
PI Years	1.88	0.646	0.34	3	1
DP Years	7.68	7.636	0.99	29	1
REAP #	10.92	15.036	1.38	0	61
REAP $	350,151	481,090	1.37	0	2,341,720
Electricity Expense	2,942.59	2,434.41	0.83	452.96	15,198.09
Electricity Used	280.55	221.28	0.79	64.16	1,100.51
Land Value	847,956.2	386,596.8	0.46	364,807	2,073,605
Organic	1.7	2.22	1.31	0.03	9.64
Fruit	0.05	0.07	1.58	0	0.46
Cattle	0.26	0.14	0.55	0.06	0.53
Tenure	0.7	0.08	0.12	0.5	0.89
Internet	0.59	0.08	0.13	0.4	0.74

Variable abbreviations summarized in Table 13 of the appendix.