Renewable Energy 55 (2013) 322–330

Contents lists available at SciVerse ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Why are Californian farmers adopting more (and larger) renewable energy operations?☆,☆☆

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ARTICLE INFO

Article history:
Received 2 June 2012
Accepted 30 October 2012
Available online 4 February 2013

Keywords:
Renewable energy
Double hurdle
Agriculture
Technology adoption

ABSTRACT

The paper examines the renewable energy adoption and system size determinants for Californian farmers. We utilize a double-hurdle methodology where system size is determined through a heteroskedastic ordered binary variable model for four size categories. Our results for system size show that determinants of technology adoption differ from size determinants. For example, environmental practices, Internet connection, and electricity price influence adoption, while, total value of production and acre value impact the size of the installed system. Surprisingly, the price of electricity bears no impact on the size category chosen. Renewable energy adoption and system size have been increasing over time, thus our insights about the interplay of the determinants for adoption and size choice, will assist policy formation.

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1. Introduction

Rising, and volatile energy prices, coupled with federal and state policies targeted towards reducing fossil-fuel consumption have helped lead to an increase of electricity generated from renewable sources in the US. Wind and solar based electricity have particularly increased (by 555% from 2000 to 2009) as resources are relatively abundant throughout the US (compared to e.g., geothermal, hydro) and installation costs have decreased. Similarly, the Nation's farm operators are increasingly investing in on-farm renewable energy generation. For example, the majority of both wind turbines (80%) and solar panels (89%) were installed after 2000 and more than half of all installations were after 2005 [1]. Environmental stewardship, favorable policies for renewable energy, and cost reduction opportunities have also helped grow renewable energy production by agricultural producers. Despite the rapid buildup in total and on-farm renewable energy production, literature targeting better understanding of the adoption decision is scarce. This work uses micro-level data from the state with the largest amount of farms adopting renewable energy production (California) to examine both the adoption and size decision for farmers.

The recent increase in renewable energy production has spawned a wealth of research investigating the adoption decision at highly aggregate levels (e.g., [2–4],); however, little has been said regarding the potential for the agriculture sector to contribute. Electricity is a critical input in farming, thus the recent increases in energy prices are making on-farm generation more attractive [5]. Many states with large agricultural sectors are leaders in renewable energy installations (Fig. 1) and since approximately 40% of land is in agriculture [6] the agriculture sector can be an important contributor to total renewable energy production.[3] By examining the characteristics of agricultural producers who choose to adopt renewable energy this work lends insight into individual adoption and size determinants. In terms of system size, agricultural producers are adopting renewable energy operations at opposite ends, and in between, the capacity spectrum; thus another focus of this work is to better understand why producers choose different capacity amounts.

☆ The views expressed here are solely the authors' and do not necessarily reflect USDA, ERS, OEPNU, or OCE.

☆☆ Data used are from the National Agricultural Statistics Service and made available to the Economic Research Service for the purposes of this paper.

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[3] There is an increasing number of agriculture land-owners leasing their land for large-scale commercial renewable energy production; however, that topic is not pursued here since the land-owners would not likely be the ones deciding the type and size of the renewable energy operation.

0960-1481/$ – see front matter Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.renene.2012.10.057

Fig. 1. States by size of agricultural sector and highest ranked states in renewable energy capacity excluding hydro (2009). Source: DOE, BEA 2010

California is a natural investigation arena for on-farm renewable energy adoption since it accounts for 23% of all farms reporting renewable energy production [1]. Further, California not only has much more renewable energy generating farms than the next state (Texas: 7%), it also houses much larger installations than average. The average farm in California with solar and/or wind technology has a generating capacity of 11 kilowatts (kw), versus 6.5 kw for all farms in the US.

1.1. Renewable energy in agriculture

Agricultural producers have been early adopters of some renewable energy technologies due partly to their convenient application for small and remote power needs. These applications might include electric fencing and water pumping. Other on-farm applications include larger installations such as wind turbines and solar panels for electricity production to offset commercial electricity purchases. Electricity is also produced on-farm by methane digesters; however, this technology is limited to livestock operations.

This paper focuses on farm operated wind and solar installations, excluding methane digesters (since along with being limited to livestock producers, they are also very large investments, typically installed by the largest operators). Though off-grid applications represented the majority of renewable energy use throughout the 1990s, in the last decade improved infrastructure, such as interconnection and net metering, has increased system sizes and led to the present growth of renewable energy production at the farm level.

Electricity represents around 18% of total energy consumed on-farm [8]; thus generating a share of electricity on-farm could reduce electricity expenditures and also insulate the producer from energy price fluctuations. In [9], a California producer stated that he utilizes his farms solar-generated renewable energy when commercial utility rates are the highest. Further, a renewable energy operation could provide the producer a dedicated energy supply in instances where electricity generation is difficult or impossible. It can also substitute for fuel and gas use, reducing transportation and maintenance costs as well as environmental concerns [7]. Renewable energy production can also be profitable, or help to reduce costs in the long run. There are large up-front capital costs; but once the amortized amount is paid for, the renewable energy fuel is free or negligible.

1.2. California

California is an important state for both commercial and farm-generated renewable energy. It is the second largest producer of renewable energy in the United States and the top state for electricity generated from geothermal, biomass, and solar sources [10]. It is the third highest ranking state after Texas and Iowa in wind installations. There are several reasons for the large production of renewable energy in California. California's residential electricity rate was 15.4 cents per kilowatthour in 2011, placing its electricity cost in the ten highest ranked states. In terms of resources, solar radiation in California is very high, averaging 5.91 kWh/m^2/day, in comparison to a 4.92 kWh/m^2/day US state average.[4] The wind resource in California is more varied (ranges from class 1 to class 6) with an average of class 3 for the state which is also the US State average.[5] California's renewable energy growth has also been supported by favorable policies. California has one of the most ambitious renewable portfolio standard (RPS) goals set at 33% by 2030, a feed-in-tariff since 2006, and state supported rebates for both photovoltaic (PV) and wind energy installations. In 2008 California accounted for 55% of all net metering customers in the United States [11]. Freeing the Grid graded California's net metering policy very high and deemed that its interconnection policy has been effective in promoting on grid renewable energy installations.

For agriculture, California is the highest ranking state in cash farm receipts accounting for 16% of national receipts for agricultural commodities, and 7% of US livestock revenue. With 25,400,000 dedicated acres, 81,700 farms, and 15 percent of US irrigated lands the state produces a large variety of agricultural products. It leads the US in milk production, generates nearly half of US grown fruits, nuts and vegetables, and is home to some of the most productive and valued land in the nation. In terms of revenue generated, California's top agricultural products are dairy products, grapes, almonds greenhouse and nursery products, cattle and calves, strawberries, lettuce, tomatoes, pistachios, walnuts and flowers [12].

A simple comparison with total US farms provides some interesting insights into California agriculture production. On average California farms are smaller than the US average (313 versus 418 acres), have been in operation 2 years less than the US average, and hold more capital in machinery and equipment ($108,145 per farm versus a US average of $88,357). A larger percent of farmers hold full tenure of their farm, but a smaller percent resides on the farm. There are more organic farms in California than the US average (4% compared to 0.9), but about the same share of farmers in California and the US practice conservation methods (approximately 22%). The share of energy expenses relative to total farm expenses is

[4] Based on ArcGIS analysis of low resolution data developed from the NREL's Climatological Solar Radiation (CSR). Based on monthly average and annual average daily total solar resource averaged over surface cells of approximately 40 km by 40 km in size. Last updated in April 2009. Avialable at: http://www.nrel.gov/gis/data_solar.html.

[5] Based on ArcGIS analysis of low resolution annual average wind resource potential for the United States produced by NREL. Represents wind power class at 50-m height above surface at a 25-km grid cell resolution. Last updated in April 2011. Available at: http://www.nrel.gov/gis/data_wind.html.

the same in California as in the US (11%); however electricity in California represents a greater share of total energy expenses (61% versus 47% for the US average). For irrigated farms 78 percent of energy expenses are for electricity compared to 58% for the US average.

2. Data

This work utilizes primary data from the 2009 On-Farm Renewable Energy Production Survey (OFREPS), the first national survey of farm operators with renewable energy operations [1]. It was conducted as an add-on survey in 2010 for those who responded that they had produced some form of renewable energy in the 2007 Census of Agriculture. Responses to this follow up survey provide data on the type, size, cost, incentives and estimated savings of renewable energy production. By combining the OFREPS survey with characteristics of farmers and their operations from the 2007 Census and other important variables (Table 1), this paper is able to examine attributes that explain why individuals are adopting renewable energy operations and evaluate how the system sizes are chosen.

Nationally the number of farms that responded they produced renewable energy in the OFRES was 8569. Solar energy production was the most prevalent form of renewable energy with an estimated 7968 farms, or 93% of all farms with renewable energy generation.

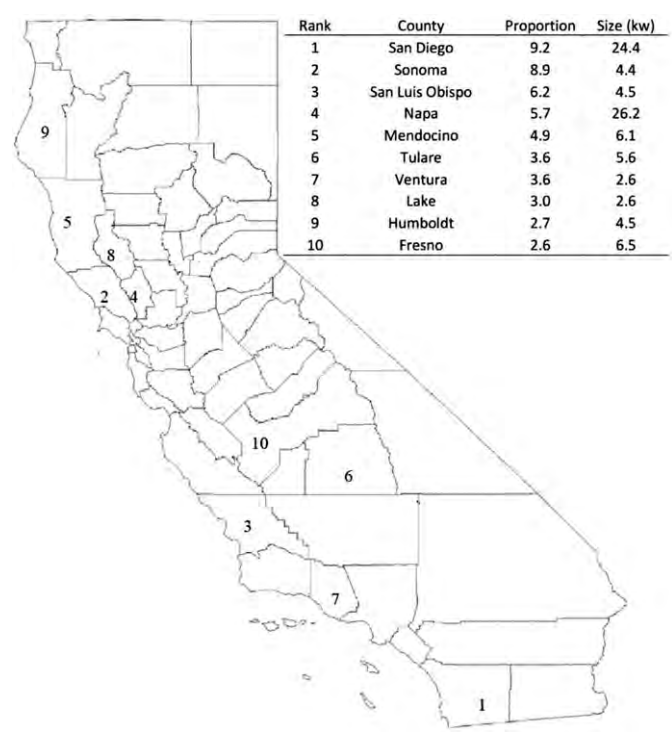
Table 1
Variables utilized in the econometric models.

Variable	Description	Source
Exogenous variables		
P kwh	Average retail electric price in the county	EIA, 2008
Farmer characteristics		
Internet	Indicator: operator has Internet access	Census, 2007
Residence	Indicator: operator residence on farm	Census, 2007
Age	Age of primary operator	Census, 2007
Year	Years operator has been on this operation	Census, 2007
Primary occupation	Indicator: farming is primary occupation	Census, 2007
Household income	Indicator: household income of principal operator	Census, 2007
Income share	Income percent from farm	Census, 2007
Farm operation attributes		
Acres owned	Acres owned by operator (in 100 s)	Census, 2007
Size	Acres in the operation (in 100 s)	Census, 2007
Acre value	Value of acres owned ($)	Census, 2007
Livestock	Indicator: farm is primarily livestock operation	Census, 2007
Fruit	Vegetables, fruit, nuts and other crops	Census, 2007
Hired manager	Indicator: if a manager is present	Census, 2007
TVP	Total value of production	Census, 2007
Organic	Indicator: organic farming operation	Census, 2007
Support	Received federal/state/local support	NASS, 2011
Tenure	Indicator: if 70% of the farmland is owned by the operation	Census, 2007
Conservation	Indicator: conservation practices used	Census, 2007
Machine value	Value of machinery owned by farm	Census, 2007
Electricity	Electricity used: utilities/ average retail	EIA, 2008/Census 2007

This result is expected since solar technologies tend themselves to a plethora of farm applications, especially in remote locations where a small amount of electricity has high value or where commercially-supplied electricity is prohibitively expensive. Specifically for off-grid applications, solar is estimated to be on average 20–90% less expensive than the competing energy alternative [7]. Wind is the second most prevalent on farm renewable fuel source, representing 17% of farms with renewable energy generation.

California has the majority of on-farm renewable electricity generation and operations are spread throughout the state. Indeed, out of the 56 counties, all but 3 have on-farm renewable energy production. Although San Diego has the highest number of operations, Napa has the operations with the largest size capacity on average. Fig. 2 maps the ten counties in California with the most renewable energy operations. These counties house 50% of the total number of farms with renewable energy operations. In terms of installed capacity, the concentration is higher but has declined over time: the top ten counties which accounted for 60% of installed panels prior to 2000 were down to 52% in 2005–2009. Additionally while some counties like San Diego, Mendocino, Sonoma, San Luis and Obispo have always ranked high in panel installations, the importance of other counties has changed over time: counties like Riverside, San Joaquin, and Stanislaus did not become important until later, while counties like Monterey and Trinity did not continue having many installations after 2000.

Though the size of the renewable energy systems installed on farms varies considerably, installations fall into three major categories: off-grid applications, small on-grid systems, and on-grid systems for larger commercial needs. Based on the distribution of the dataset and the size needs depending on the farm applications we distinguish four size categories: systems kW < 1 often represent off-grid installations serving small needs around the farm (example small irrigation and battery chargers); systems sized between $1 >$ kW ≤ 5 are typical for small on-grid needs like residential roof



Rank	County	Proportion	Size (kw)
1	San Diego	9.2	24.4
2	Sonoma	8.9	4.4
3	San Luis Obispo	6.2	4.5
4	Napa	5.7	26.2
5	Mendocino	4.9	6.1
6	Tulare	3.6	5.6
7	Ventura	3.6	2.6
8	Lake	3.0	2.6
9	Humboldt	2.7	4.5
10	Fresno	2.6	6.5

Fig. 2. Top ranked counties in California for renewable energy operations with average system size. Source: NASS (2011)

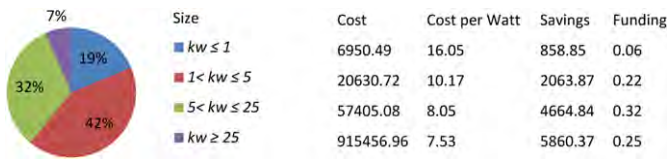


Fig. 3. Share of on Farm renewable energy systems by category. Source: NASS (2011)

mounted systems [7]; larger systems between $5 > kW \leq 25$ are used for small commercial needs; systems with $kW > 25$ represent large commercial installations.[6] Fig. 3 shows the shares of installations in each category for California.

Table 2 showcases the farmer and farm characteristics by system size to highlight the differences for the four categories. The table indicates that machine value, total value of production (TVP), and energy used are lower in farms with renewable energy. These values increase by ordered size category; and for large installations they are more than double the average for all California farms. With the exception of large commercial systems, farm income as a percent of total farmer remuneration is lower for farms with renewable energy installations. Value of acres owned is also larger for farms with installed renewable energy with the exception of off grid systems.

Fig. 4 shows that farms with renewable energy production are characteristically different than the average California farm and a distinct pattern emerges for the different size categories. A higher share of California farms with renewable energy on-farm is connected to the internet, is organic and practices conservation methods. While more farmers that produce on farm renewable energy are retired, they do not report farming as their primary occupation, and seem more vested on their farmland by residing on-farm, managing the operation themselves, and owning a high percent of the land they operate. In terms of size, operations with large commercial renewable energy systems show identical characteristics with the average California farm and differ notably from other farms with renewable energy systems. Off-grid systems typically are operated by a higher share of organic farmers and respondents who report farming as their primary occupation; a lower share of farmers with off-grid systems reside on farm, are retired and hold high tenure on their farm. More farmers with small commercial systems practice conservation methods and are connected to the Internet relative to other operations; while generally farmers with small grid connected renewable energy installations are retired, live on the farm and own most of the land in their operation. In terms of farm type there are more cattle farms but less fruit farms with renewable energy installations relative to all farms in California.

Fig. 5 provides more detail for the presence of renewable energy and different system size by farm type. A majority of on-farm renewable energy operations in California are utilized by fruit farmers. Cattle and other animal operations also stand out. As expected cattle operations host a large share of the small off-grid systems for their remote benefits. For other animal operations, however, the majority is small residential and commercial systems. The biggest share of large commercial systems is in fruit operations. A very small share of fruit operations has off-grid systems; the majority of fruit farms host small and large commercial systems. Horse operations also have a substantial amount of small commercial systems. Nurseries and greenhouses house small residential and commercial size systems, while vegetable operations have mostly small renewable energy installations, both on- and off-grid. Cow milk and dairy product operations have small on- and off-grid installations while sheep and goat product farms have small residential and commercial size systems.

[6] A similar breakdown can be found in NREL's open PV project: http://openpv.nrel.gov/visualization/index.php. Our breakdown is distinguished from NREL's in a couple of respects. We separate out systems of $kW < 1$ to approximate off grid installations, and combine systems between 5 and 25 kW into one category for ease of examination.

Table 2
California Farm characteristics with detail for different size categories.

Average	All farms	RE on Farm	Renewable energy on farms by size			
			$kw \leq 1$	$1 < kw \leq 5$	$5 < kw \leq 25$	$kw > 25$
Machine value ($1000)	148.1	102.2	59.3	64.7	129.8	310.3
TVP ($1000)	659.3	332.6	78.3	88.4	204.3	1669.7
Farm income (%)	26.8	21.3	22.5	19.5	19.6	40.6
Size (Acres)	456.5	1011.7	1008.8	2067.4	306.5	355.4
Year farming	20.6	17.8	21.4	17.0	15.6	24.4
Acre value ($1000)	64.4	72.3	19.7	72.2	94.1	75.8
Energy used ($/year)	1787.3	893.0	316.9	398.3	1050.0	3079.7
Price ($/kw h)	13.8	13.9	13.8	13.9	14.1	14.0

Source: NASS (2007, 2011).

3. Literature review

The technology adoption literature guides us in formulating the empirical methodology of the paper. In the absence of specific studies examining on-farm renewable energy adoption, determinants of adopting conservation practices in agriculture and energy conserving technologies in the residential sector are hypothesized to also underlie renewable energy adoption on the farm.

Factors influencing sustainable agricultural production are grouped into farmer characteristics which includes attitudes/awareness like age, education, income, farming experience, and tenure; farm operation characteristics like farm ownership, type, size, profitability, labor and capital; farm biophysical characteristics which could include soil erosion, slope, rainfall, or available sun radiation; and exogenous variables like regional policies and input prices [13–15]. There is no coherency on the significance or the sign of the different adoption influences but [13] found that educational level, farm size, income, labor, access to information, positive environmental attitudes and utilization of social networks emerge as variables that are more often positively rather than negatively associated with adoption. Capital is found to positively influence adoption more often than not, but the predominance of studies show insignificant coefficients. The results are inconclusive for experience, farm tenure and ownership.

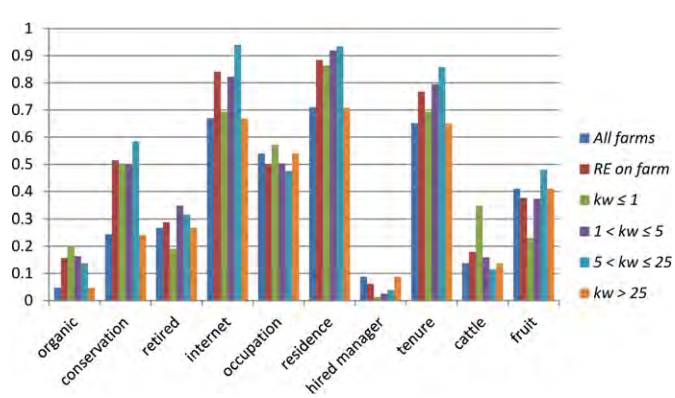


Fig. 4. California Farmer characteristic shares with detail for different size categories. Source: NASS (2011)

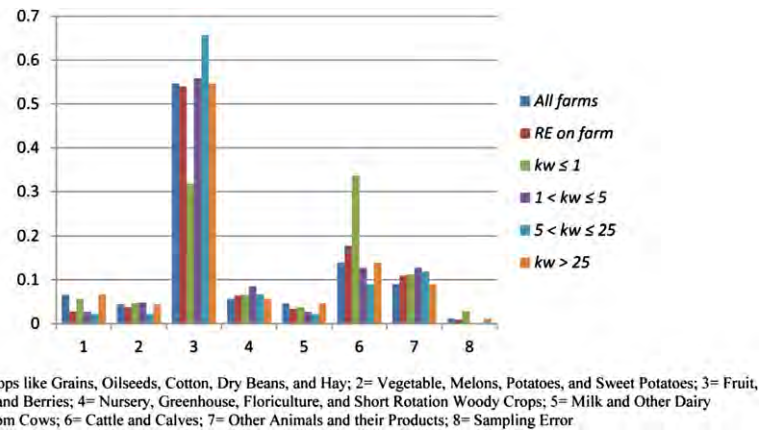


Fig. 5. Farm types in California for all farms, farms with renewable energy, and by system size. Note:1 = Crops like Grains, Oilseeds, Cotton, Dry Beans, and Hay; 2 = Vegetable, Melons, Potatoes, and Sweet Potatoes; 3 = fruit, Tree Nuts, and Berries; 4 = Nursery, Greenhouse, Floriculture, and Short Rotation Woody Crops; 5 = Milk and Other Dairy Products from Cows; 6 = Cattle and Calves; 7 = Other Animals and their Products; 8 = Sampling Error. Source: NASS (2011)

In the residential sector, economic variables shown to impact solar hot water adoption include solar radiation availability [16,17], electricity rates [18,19], and state tax credits [19]. Demographic variables that positively related to energy conserving investments are income, education, age, and household size [17–22]. However results are not homogeneous. For example [19], find no significant impact from income and solar radiation availability. Policies variables have been shown to play an important role in increasing utility scale capacity of renewables. Findings have varied, but to different degrees [3,4,23], show that policies such as an RPS, public benefit funds, and green power options have lead to statewide renewable energy investments. In the absence of studies examining on-farm renewable energy adoption, conservation practice adoption in agriculture and energy conservation in the residential sector are hypothesized to be determinants underlying renewable energy adoption on the farm.

The few studies that have examined on-farm renewable energy adoption have done so examining economic feasibility through simulation models. Probably the first such work was by [24] who considered the potential of adopting solar PV technology specifically for irrigation. Though the use of PV systems for irrigation has great potential, their prediction of wide-scale use by 2000 did not occur. Ref. [5] also considered the economics of PV technology, this time for the Tennessee poultry industry. They use a simulation benefit-cost model for 5 poultry-producing counties, with data for renewable energy production costs/benefits gathered from outside sources. They conclude that the variables with the largest impact on the Net Present Value calculation are: the percent of grant funding (35%), and the percent of the federal tax credit (15%).

4. Methodology

This study examines the determinants of adopting renewable energy on-farm as well as the factors that influence farmers to choose their size of renewable energy operation. Methodology analyzing technology adoption is rooted in the work of the expected utility framework.[7] Farmers make many choices (e.g., off-farm versus on-farm work, planting decisions) one of which is to adopt any new technology (assuming that they are aware of the new technology). A farmer will adopt the new technology if the expected utility with the new technology is greater than the expected utility with the traditional utility.

$$\text{Let } y_i = \beta X_i + \varepsilon_i \tag{1}$$

Where y is the adoption intensity, expressed in the paper as the kw size of their renewable energy operation, X_i is a vector of explanatory variables that may influence the adoption decision and β are the parameters to be estimated for those variables, and ε_i denotes the standard error term capturing unobserved behavior.

Equation (1) provides two pieces of information, *whether* farmer i adopted renewable energy and *how much* was adopted. To effectively use both pieces of information, we need a suitable modeling framework. We utilize a two-stage modeling technique first advanced by [25] commonly known as the 'double-hurdle model.[8] The general notion of the double-hurdle model and its counterpart (the Heckit model [26]) is that there are two parts to the question: if an observation occurred (a binary-choice); and if that observation occurred, what was the result (in a continuous sense). The benefit of these two models is that the two-stage process allows outcomes from the two stages to be determined by separate processes. Both models have received particular usage in the medical literature where the nature of health expenditures and habits (many observations with zero occurrences) is conducive for such modeling. Both models feature the two-stage modeling decision; however, the Heckit model is favored when sample-selection bias is an issue. Sample-selection bias is not an issue, since we are using the entire Census population of California farms, thus the Cragg double-hurdle model is optimal.

The first stage binary-choice model is used to examine if there are characteristics which significantly increase the likelihood of operations adopting renewable energy. The model is specified as:

$$y_i = \beta X_i + \varepsilon_i \quad \begin{cases} 1 & if \;\; yi > 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

[7] Expected utility is a more appropriate framework than profit maximizing or cost minimizing due to the nature of our technology. This is because farmers are likely adopting the technology for a variety of reasons, some which might not generate profits relative to the standard technology (e.g., early adopters, environmental stewardship, or a dedicated energy source).

[8] Another alternative would be to use a tobit model; however, a key limitation to the model is that the probability of a positive value and the actual value, given that it is positive, are determined by the same underlying process (i.e., the same parameters).

Vector X_i of explanatory variables utilizes those listed in Table 1 and can be broken down to:

- Exogenous variables representing those factors which are out of the farmers' control (e.g., electricity prices)
- Farmer characteristics (e.g., how long the farmer has been farming, if the farmer lives on-farm; if farming is the main occupation for the farmer)
- Farm characteristics (e.g., acres owned by the operation; value of machinery, farm type, e.g., primarily row crop).

The second-stage of the double-hurdle model focuses on those who 'participated' in the first-stage Equation (2). Typically, the second-stage component is estimated using a linear regression estimator; however, as noted in [27] an ordered binary model can be applied when the dependent variable is given quantitative meaning but we wish to acknowledge the discrete, ordered nature of the response. As described earlier, installations of renewable energy can fall into four categories: off-grid applications, small on-grid systems, small commercial systems and systems for larger commercial needs. An ordered binary variable model is estimated for these categories (Equation (3)):

$$y_i^* = \beta X_i + \varepsilon_i, \quad \varepsilon_i \sim \text{Normal}(0, \pi/3),$$

where y* adoption intensity with exact cutpoints unknown

$$\begin{aligned} y &= 1, \text{ if off grid} \\ y &= 2, \text{ if small residential} \\ y &= 3, \text{ if small commercial} \\ y &= 4, \text{ if large commercial} \end{aligned} \tag{3}$$

The ordered model can be extended to the heteroskedastic case by taking the variance of $\varepsilon_i$to be $1/3\pi^2\exp(z_i'\gamma)^2$ (with z_i a vector of explanatory variables) so that $\varepsilon/\exp(z_i'\gamma)$is now a homoskedastic error term [28,29]. This heterogeneous choice model is applicable when the parallel regression assumption is violated i.e., that the βs are the same for all j categories [29,30].[9] To test the assumption, $J-1$ binary regressions are estimated and the hypothesis that $\beta_1 = \beta_2 = \ldots = \beta_{j-1} = \beta$ is evaluated [31].

The ordered binary model is based on an interval regression model for the size ranges specified earlier to approximate our four categories (Equation (4))

$$y_i = \beta X_i + \varepsilon_i, \quad \varepsilon_i \sim \text{Normal}\left(0, \sigma^2\right),$$

where y is system size

$$\begin{aligned} y &\le 1 \text{ kw, off grid} \\ 1 \le y &\le 5, \text{ small residential} \\ 5 \le y &\le 25, \text{ small commercial} \\ y &\le 25 \text{ kw, large commercial} \end{aligned} \tag{4}$$

We interpret the ordered model (Equation (3)) as the main estimation tool and use interval regression (Equation (4)) to verify the robustness of the results. Since we wish to acknowledge the discrete ordered nature of the choice and model qualitatively the ordered responses, how these are assigned becomes irrelevant for estimating the probabilities of the choice. Interval regression gives quantitative meaning to y and calculates the effect that the explanatory variables have on the conditional mean. We focus on the ordered model because it gives a more worthwhile emphasis on how regressors influence the conditional probability distribution of the size category choice [32]. The model is estimated using maximum likelihood estimation procedures in STATA.

5. Results

Renewable energy adoption on the farm is determined by a combination of factors (first two columns of Table 3). The probability of adoption increases when a farm is connected to the Internet, faces higher electricity prices, and has demonstrated interest in environmental practices: organic or conservation techniques. The probability for adoption also increases when the farmer has vested interest in his land by residing on the farm or holding tenure for the acres operated. Contrarily, the probability of adoption decreases for farmers who have been farming longer. Additionally, the higher the household income share coming from the operation the lower the probability of adoption. A cattle farm has a higher probability for adopting renewable energy, while the probability of adoption decreases for fruit operations.

The results for the size choice as represented through the interval regression and the ordered logit are shown in the last three columns of Table 3. The coefficients of the interval regression and the ordered logit are very similar in magnitude, sign and z statistics. For the interval regression, the size intervals are expressed in logarithmic terms and the coefficients interpreted as in ordinary least squares (OLS). Operations that are connected to the Internet and have a hired manager install larger systems. The availability of outside funding has a large positive impact on system size. TVP, acre value owned, and if the farm practices conservation techniques have positive coefficients; but the coefficient for organic operations is negative. The interval regression and ordered logit also find that older operations and farmers residing on farm and with farming as their primary occupation tend to adopt smaller systems. Fruit farms are shown to install larger systems while cattle farms install smaller systems, as represented by the sign of the coefficient.

The ordered logit results rely on the parallel regression assumption, which assumes that the relationship between each pair of outcomes groups is the same. The Brant test [31,34] presented in Table 4 reveals that the parallel regression assumption is violated, and the violation is sourced in the explanatory variables of conservation, retirement, year, residence and funding. Consequently these variables are used to explain the variance of the heteroskedastic model. According to Ref. [34] an alternative specification to the heterogeneous choice model we adopt is the generalized ordered logit which allows the βs to differ across categories; however this specification does not fit our dataset. The results of the heteroskedastic model are very similar to the ordered model, while providing a better fit and coefficients that are closer to the interval regression. However, when heteroskedasticity is accounted for primary occupation, residence, fruit, and cattle drop out as significant factors in influencing system size. Furthermore we find that older farms and farms that use conservation practices have higher residual variability in their choice of size category for their installation. Contrarily, farmers that are retired, reside on farm, or have received funding show lower residual variability in the size category choices they make.

Comparing the results of the technology adoption choice to the heteroskedastic-ordered logit, it is evident that the determinants influencing the technology adoption are different than those that influence the size of the renewable energy system chosen. For example farm size and tenure increase the probability of adoption but have no impact on the size category chosen. Organic operations with higher probability of adoption, adopt smaller systems sizes.

[9] The underlying issue is first introduced by [33] who argues that in binary models differences in the degree of residual variation across groups can produce apparent differences in slope coefficients that are not indicative of true differences. Ref. [30] shows that the heterogeneous choice models provide a superior means for dealing with such problems by extending the specification to both binary and ordinal dependent variables and allowing a much more flexible specification of the variance equation.

Table 3
Technology and size adoption choice: model results.

Variable	Technology adoption choice			Size choice	
	Logit		Interval regression	Ordered logit homoskedastic	Ordered logit heteroskedastic
	Coefficients	AMEs	Coefficients	Coefficients	Coefficients
Conservation[a]	1.165***	0.030***	0.190*	0.303*	0.276**
Machine value	3.05E-08	6.63E-10	−3.36E-07	−5.27E-07	6.09E-08
Retirement[a]	0.033	0.001	0.107	0.225	0.191
TVP	−1.11E-08	−2.42E-10	4.32E-07***	1.03E-06***	9.89E-07**
Income share	−0.004***	−1.00E-04***	0.002	0.003	0.002
Size	1.34E-05**	1.43E-07**	1.00E-06	1.60E-06	3.71E-07
Year	−0.011***	−2.00E-04***	−0.011***	−0.023***	−0.017**
Internet[a]	0.688***	0.013***	0.640***	1.003***	0.796***
Acre value	1.78E-07	−3.86E-09	1.40E-06***	2.43E-06***	1.93E-06***
Organic[a]	1.150***	0.039***	−0.212*	−0.397*	−0.353**
Electricity	−1.40E-05	−2.97E-07	−1.46E-05	−4.89E-05	−1.00E-04
Fruit[a]	−0.204***	−0.004***	0.218**	0.370**	0.125
Cattle[a]	0.608***	0.016***	−0.392***	−0.577**	−0.305
Primary occupation[a]	0.010	−2.00E-04	−0.196*	−0.310(*)	−0.197
Residence[a]	1.034***	0.017***	−0.409***	−0.679**	−0.428
P kwh	0.117***	0.003***	0.012	0.019	0.028
Tenure[a]	0.280***	0.006***	0.179	0.327	0.221
Hired manager[a]	0.037	0.001	0.792***	1.508***	0.991**
Funding			0.967***	1.645***	1.142***
Cut 1				−0.322	0.023
Cut 2				2.268	1.989**
Cut 3				5.285	4.241***
Constant	−7.21***		0.167		
lnsigma			0.021		
Conservation					0.187*
Retirement					−0.339**
Year					0.016***
Residence					−0.529***
Funding					−0.228*
Sigma			1.022		
LR chi^2	(18) 802.31		(19) 251.44	(19) 250.37	(24) 288.68
Prob > chi^2	0		0	0	0
Loglikelihood	−3899.46		−543.328	−538.824	−519.668
Pseudo R2	0.093			0.189	0.217

Note: standard errors available upon request.
Significance is denoted as ***, **, * at the 0.01, 0.05, and 0.10 level respectively.
[a] Dummy variable; AMEs, dy/dx are for discrete change from 0 to 1.

Table 4
Parallel regression assumption.

Variables	Brant test		Coefficients of $J-1$ binary regressions		
	Chi^2	Probability	$y > 1$	$y > 2$	$y > 3$
All	74.820	0.000			
Conservation	6.610	0.037	−0.216	0.427	1.381
Machine value	3.300	0.192	−2.240E-07	−7.120E-07	−4.070E-06
Retirement	9.360	0.009	1.018	0.113	−1.997
TVP	3.820	0.148	5.110E-07	8.300E-07	2.010E-06
Income share	0.150	0.927	0.004	0.002	−3.490E-05
Size	2.460	0.293	0.000	−1.000E-04	−3.000E-04
Year	9.410	0.009	−0.035	−0.018	0.040
Internet	1.240	0.537	0.914	1.343	0.622
Acre value	6.340	0.042	9.920E-06	2.770E-06	−7.200E-07
Organic	1.940	0.379	−0.616	−0.474	0.239
Electricity	3.230	0.199	5.000E-04	1.000E-04	−1.000E-04
Fruit	1.700	0.428	0.423	0.140	0.829
Cattle	1.040	0.595	−0.680	−0.255	−0.415
Primary occupation	3.370	0.185	−0.324	−0.195	−1.270
Residence	10.240	0.006	0.089	−0.305	−1.893
P kwh	0.280	0.867	−0.020	0.040	−0.028
Tenure	4.610	0.100	0.834	0.353	−0.601
Hired Manager	0.540	0.763	0.520	1.379	1.333
Funding	7.860	0.020	2.499	1.454	0.888
Constant	–	–	−0.298	−3.174	−3.315

Note: standard errors available upon request.
Significance is denoted as ***, **, * at the 0.01, 0.05, and 0.10 level respectively.

The price of electricity is not a significant consideration when the system size is chosen but influences the decision of adopting the renewable energy technology. Additionally, factors like TVP, acre value, the presence of a hired manager, and whether farming is the operator's primary occupation (which have no impact on the choice of adopting renewable energy) are influential determinants for the size of the installed system.

To decipher what variables influence the adoption probability of each size category we examine the average marginal effects of the heteroskedastic ordered logit model. Table 5 provides details on the specific variables affecting the probability of adopting an off grid, small residential, small commercial or large commercial system respectively. There seems to be a very distinct divide between commercial and non-commercial systems. For example, being organic increases the probability of adoption of a small off-grid and residential system, but decreases the probability of adopting a commercial sized system. Similarly, higher TVP and acre value increase the probability of adopting a commercial system, and decrease the probability of adopting a small system.

Farmers operating longer have an increased probability of adopting an off-grid system and a decreased probability of adopting a small commercial system. Retired farmers have a decreased probability of owning an off-grid system or large commercial system, and a statistically positive probability of owning a small commercial system. Conservation practices increase the probability of installing a commercially sized system, and decrease the probability of adopting a residential system (there is no significant effect

Table 5
Marginal effects per size category.

Variable	Heteroskedastic ordered logit: average marginal effects			
	Off grid	Small residential	Commercial	Large commercial
Conservation[a]	−0.018	−0.064**	0.054**	0.029***
Machine value	−8.86E-09	−6.48E-09	1.24E-08	2.89E-09
Retirement[a]	−0.067***	0.038	0.048*	−0.018*
TVP	−1.44E-07***	−1.05E-07***	2.02E-07***	4.69E-08***
Income Share	−2.00E-04	−2.00E-04	4.00E-04	1.00E-04
Size	−5.39E-08	−3.94E-08	7.57E-08	1.76E-08
Year	0.004***	−0.001	−0.004***	0.001
Internet[a]	−0.138***	−0.053***	0.163***	0.027***
Acrevalue	−2.80E-07***	−2.05E-07***	3.94E-07***	9.14E-08***
Organic[a]	0.055**	0.033**	−0.073**	−0.015**
Electricity	1.66E-05	1.22E-05	−2.34E-05	−5.42E-06
Fruit[a]	−0.018	−0.014	0.026	0.006
Cattle[a]	0.047*	0.030*	−0.064*	−0.013*
Primary Occupation[a]	0.029	0.021	−0.040	−0.009
Residence[a]	−0.017	0.133***	−0.013	−0.103**
P kwh	−0.004	−0.003	0.006	0.001
Tenure[a]	−0.033	−0.022	0.046	0.010
Hired Manager[a]	−0.107***	−0.137**	0.165***	0.079
Funding[a]	−0.204***	−0.079**	0.256***	0.027**

Note: standard errors available upon request.
Significance is denoted as ***, **, * at the 0.01, 0.05, and 0.10 level respectively.
[a] dy/dx is for discrete change of dummy variable from 0 to 1.

on the adoption of an off-grid system). Internet connection (which might be related to grid connection) is an important determinant for the adoption of off-grid and small commercial systems; having connection decreases the probability of adopting an off-grid system by 14% and increases the probability of adopting a small commercial system by 16%. The impact on residential and large commercial systems is statistically significant but 3 and 8 times smaller respectively. The probability of installing a small commercial system is considerably influenced from having a hired manager (16%) and having received financial support for the project (25%). Funding availability also significantly reduces the probability of installing an off grid system (20%); which likely is aligned to the fact that renewable energy is an economically viable solution for small off-grid needs [7], thus the availability of funding is less important. The influence on residential and large commercial systems is much lower (−8 and 3% respectively). Having a hired manager also has a sizable negative impact on adopting an off grid or residential system, but has no impact on the adoption of a large commercial system.

While residing on the farm was found to be insignificant in determining system size in the heteroskedastic-ordered choice model, the average marginal effects reveal that it has a positive and statistically significant impact on the adoption of residential systems, and a negative statistically significant impact on the adoption of large commercial systems. Similarly being a cattle farm increases the probability of installing of an off grid and residential system by 5 and 3% respectively, and reduces the probability of installing a commercial system even though its coefficient was statistically insignificant in the ordered model. In accordance to the ordered logit results, the average marginal effect results show that fruit and primary occupation remain insignificant in determining the type of system installed.

6. Implications and concluding remarks

The results of this study provide insights about the state with the most on-farm renewable energy installations in the US. In line with other studies examining sustainable agriculture, environmental practices, size, Internet connection, tenure and residence on farm positively influence renewable energy adoption. However, age and income share are found to have a negative influence on adoption. Electricity prices are also found to influence adoption as suggested by [18,19].

The study further underlines the importance of evaluating the choice of the size adopted in addition to the technology adoption choice. Economic factors like TVP, acre value, the presence of a hired manager, and whether farming is the operator's primary occupation are influential determinants for the size of the installed system. Surprisingly the price of electricity bears no impact on system size. Additionally, the adoption of different system sizes is influenced by distinct characteristics. For example, conservation practices increase the probability of adopting a commercial size system while organic operations have a higher probability of adopting small and off grid systems. Operation type shows an interesting interaction: larger systems are installed on fruit operations, but the probability of adoption is low. Cattle and organic operations with higher probability of adoption, adopt small systems sizes.

Renewable energy system size has increased over time [7]; thus understanding the interplay of the determinants for adoption and size choice, will assist with policy formation and targeting. Further research on the influence of resource availability and installation costs introduced by [16,17,19] would add further insight on the economic incentives for renewable energy adoption.

Acknowledgments

The authors would like to express their gratitude towards the National Agricultural Statistical Service and Bob Dubman for providing the data used in this paper.

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