energies

Article

Adoption Model Choice Affects the Optimal Subsidy for Residential Solar

Tiruwork B. Tibebu [1], Eric Hittinger [2], Qing Miao [2] and Eric Williams [3,*]

[1] Department of Environmental Science, American University, Washington, DC 20016, USA; tibebu@american.edu
[2] Department of Public Policy, Rochester Institute of Technology, Rochester, NY 14623, USA; eshgpt@rit.edu (E.H.); qxmgla@rit.edu (Q.M.)
[3] Golisano Institute for Sustainability, Rochester Institute of Technology, Rochester, NY 14623, USA
* Correspondence: exwgis@rit.edu

Abstract: Understanding the adoption patterns of clean energy is crucial for designing government subsidies that promote the use of these technologies. Existing work has examined a variety of adoption models to explain and predict how economic factors and other technology and demographic attributes influence adoption, helping to understand the cost-effectiveness of government policies. This study explores the impact of adoption modeling choices on optimal subsidy design within a single techno–economic framework for residential solar PV technology. We applied identical datasets to multiple adoption models and evaluated which model forms appear feasible and how using different choices affects policy decisions. We consider three existing functional forms for rooftop solar adoption: an error function, a mixed log-linear regression, and a logit demand function. The explanatory variables used are a combination of net present value (NPV), socio-demographic, and prior adoption. We compare how the choice of model form and explanatory variables affect optimal subsidy choices. Among the feasible model forms, there exist justified subsidies for residential solar, though the detailed schedule varies. Optimal subsidy schedules are highly dependent on the social cost of carbon and the learning rate. A learning rate of 10% and a social carbon cost of USD 50/ton suggest an optimal subsidy starting at USD 46/kW, while the initial subsidy is 10× higher (USD 540/kW) with a learning rate of 15% and social carbon cost of USD 70/ton. This work illustrates the importance of understanding the true drivers of adoption when developing clean energy policies.

Keywords: optimal subsidy; adoption models; modeling uncertainty; techno–economic framework; residential solar PV

Citation: Tibebu, T.B.; Hittinger, E.; Miao, Q.; Williams, E. Adoption Model Choice Affects the Optimal Subsidy for Residential Solar. *Energies* **2024**, *17*, 728. https://doi.org/10.3390/en17030728

Academic Editor: Jay Zarnikau

Received: 4 December 2023
Revised: 15 January 2024
Accepted: 23 January 2024
Published: 3 February 2024

1. Introduction

1.1. Motivation

The residential sector accounts for about a third of the total electricity sales in the US [1]. Electricity use in this sector constituted 43% of US electricity consumption in 2021 [2]. About 38% of CO_2 emissions from the electric power sector come from the residential sector [3]. Rooftop (or "residential") solar is one approach to decarbonizing the residential sector.

Despite considerable cost reductions in recent decades, residential solar is often too expensive to be economically attractive in many parts of the world. Studies have shown that subsidies are required in all US states, except Hawaii, to achieve economic parity for consumers, while only six states achieve this parity through the use of subsidies [4]. A study by Tibebu et al. also shows that with no subsidy, the net present value (NPV) of adopting solar is positive in only five states (HI, CA, RI, CT, and MA), where there is high electricity prices and/or high insolation potential [5]. Whether NPV is positive or negative, subsidies can be a way to improve the attractiveness of residential solar. Previous work has shown that adoption of residential solar increases with increased NPV [6], meaning that subsidy should increase adoption rates regardless of the starting NPV.

Many governments subsidize rooftop solar. For example, the US federal government has long granted an income tax reduction for residential solar purchases [7], and the 2022 US Inflation Reduction Act creates and expands federal government subsidies for a variety of technologies, including residential solar [8].

1.2. Background

Given the prevalence of government subsidies for residential solar, it is important to characterize their benefits and costs in order to better manage them. Technology subsidies have direct and indirect benefits. Direct benefits arise from emissions reductions resulting from additional adoption stimulated at the time of the subsidy. Indirect benefits come from direct adoption, leading to technological progress and lower prices for customers in the future.

A benefit–cost analysis of residential solar subsidies has been examined in the previous literature. Van Bentham and collaborators combined adoption, technological progress and benefit modeling to find optimal solar subsidies in California [9]. Newbery investigated how multiple technology attributes (learning rate, technology capacity factor, and social cost of CO_2) affect renewable energy subsidies [10]. In our prior work, we found that an appropriate schedule of solar subsidies is justified (i.e., benefits exceed costs) and that allowing subsidies to vary between sub-regions (US states) improves their effectiveness [5]. We later found that different technologies have different structures in terms of optimal subsidy, e.g., utility wind delivers environmental benefits (i.e., emission reductions) that exceed costs even when they do not lead to cost reductions. However, subsidies for residential solar need to drive future cost reductions to be justified, leading to the eventual phase-out of the subsidy as an optimal strategy [11].

1.3. Research Gap

As with other energy system models that quantify the future of a complex techno–economic–social system, models that evaluate solar subsidies are uncertain. Uncertainty leads to less robust recommendations for policy. There are many previous examples where energy system model forecasts deviated significantly from real-world behavior. For example, the World Energy Outlook model from the International Energy Agency has consistently and drastically underpredicted solar power capacity additions [12]. In 2000, the Annual Energy Outlook "projections" from the Energy Information Administration (EIA) reported US wind capacity in 2020 as 6 GW for the "Reference case" and 18 GW for the "High renewables case" [13]. The actual wind capacity in 2020 was 118 GW, over five times higher than even the optimistic case for renewables [14]. There is also a lack of consensus among model results in which different models produce disparate results for policy-related outcomes. For example, estimates of the cost to mitigate 25% of US carbon emissions vary from USD 40/ton to USD 300/ton, depending on the model [15].

It is thus important to better characterize uncertainty in energy system models. The general theory categorizes uncertainty into three epistemic types: parametric, model and scenario [16]. Parametric uncertainty arises from the numerical values of the input data, model uncertainty arises from questions of appropriate model form, and scenario uncertainty arises from the basic assumptions under which the model is constructed [17,18]. Nearly all work to characterize uncertainty in energy system models focuses on parametric uncertainty. "Scenario analysis" is the study of parameter uncertainty conducted by choosing a set of parameter values and recalculating outputs for these different values. Note that this type of "scenario analysis" uses the word "scenario" differently from the previous division of epistemology info types. Often, three values are explored—low, baseline and high—where the baseline values are considered most likely, along with "plausible" lower and upper values. Scenario analysis is used in energy system modeling to study the effect of different parameter values on future energy technology portfolios [19] and climate policies [20]. An alternative approach to parametric uncertainty involves using probabilistic distributions to characterize uncertainties in input parameters and then applying Monte Carlo analysis to find the distribution of the modeling outputs [21].

While the characterization of parametric uncertainty is common, the treatment of modeling uncertainty in energy systems is rare. Typically, there are many modeling choices and assumptions to be made when selecting what driving factors to account for, how to model them, and how the factors combine to estimate a change in the system. For example, predicting the adoption of a technology under some price and other conditions is part of many energy system models. There are many different adoption model forms, e.g., Bass diffusion [22], discrete choice [23], and error function [6]. Within these forms, different driving variables can be included or excluded based on data availability and analyst preference. Models are often calibrated and tested against historical data, but this process rarely identifies a single modeling approach as unilaterally preferable. Analysts often choose a modeling form without clarifying why this choice is best, and we as a community should perhaps apply a level of rigor closer to that used when selecting parameter values.

There is a research gap in studying and recommending how to choose adoption models. This gap applies to energy system modeling in general, not just assessing technology subsidies, which is the focus of our work. There have been prior efforts to address modeling choices, and we have divided them into three types. In the first, a set of integrated energy system models developed by different research groups is selected, and the outputs are compared and contrasted [24,25]. Often, the same parametric inputs are chosen to clarify how differences in the models, as opposed to differences in the inputs, change the results. While this approach clarifies the degree of consensus among analysts in a modeling domain, it does not address the question of which model is more "realistic" or "preferable". A second stream of work builds a theoretical model of an energy system and explores how different assumptions affect the relationships [26,27]. For example, Goulder and Mathai [26] developed models of optimal technology subsidies, exploring how answers change if technological change is driven by research and development expenditures versus "learning by doing". This provides theoretical insight, but application is limited because the models are not based on the empirical data, so there is no means to validate the framework. A third approach compares and contrasts results from multiple modeling choices, calibrating them with the same empirical data [28,29]. For example, Dong et al. compared forecasts of California's adoption of residential solar using the model they developed, dBase, with others, such as the Bass diffusion model [28]. A limitation of this approach is that it is not clear if there are empirically preferred approaches and how modeling choice affects policy decisions.

We argued above that prior approaches to characterizing modeling uncertainty have significant limitations. Here, we propose a generally applicable approach that will yield new insights: considering an empirically grounded integrated energy system model informing a policy decision; in this case, determining optimal subsidies for residential solar in the US. Next, choose an element of the modeling framework— in this case the adoption model for solar adoption —and analyze multiple choices of functional form and explanatory variables. That is, using a common modeling framework and set of calibration data, evaluate different modeling approaches for the same phenomenon. This model evaluation has three elements. The first is whether the results are consistent with basic theory: check if the form of the model matches the expected trends in terms of adoption (example: is adoption always non-negative?) and includes, in some way, variables that are known to be important. The second element is conventional statistical argumentation to compare the goodness-of-fit or statistical significance of different model forms and variable choices against historical data. The third element of analysis is testing models with plausible boundary conditions for which analysts have reasonably certain expectations. In our example, if solar panels suddenly became much more expensive, there should be a noticeable reduction in adoption. Models that contradict these expectations can be rejected as unrealistic. Combining these three elements, modeling choices are down-selected to a subset that yields reasonable results. The next step is to use the remaining "feasible" choices of the modeling elements to determine the range of decision outcomes that emerge. The robustness of the resulting decisions is considered, given the range of outcomes arising from model choice and parameter uncertainty.

We explore the above approach to assessing and mitigating modeling uncertainty with a case study using a model that finds optimal government subsidies for residential solar in the US. The integrated model combines elements of adoption, technological progress and monetized emissions benefits, determining the optimal subsidy by maximizing emissions benefits less than subsidy expenditures. We analyze the different choices of regression-based adoption models with three different functional forms (error function, mixed log-linear regression, and logit demand function) and combinations of three sets of explanatory variables (net present value (NPV), socio-demographic, and prior adoption). The models are calibrated with county-level residential PV price, adoption, and socio-demographic data from three states, namely Arizona, California, and Massachusetts. We first compare the different adoption model choices from a theoretical and statistical perspective and then apply boundary testing as described above. From this, a subset of models is used to find the different values of optimal subsidies, considering variations in two uncertain parameters: the social cost of carbon (SCC) and learning rate (LR). We then examine and discuss the robustness of subsidy decisions considering adoption modeling choices and parameter uncertainty.

1.4. Contributions

In the analysis of rooftop solar subsidies, previous work has not evaluated modeling choices and how those choices affect the conclusions regarding how to set the subsidy. We will screen adoption modeling choices to potentially reject those that might otherwise be used but are likely to lead to erroneous results. The remaining "feasible" options provide information on what range of subsidies are expected to deliver net benefits.

More generally, we open up an important line of inquiry into characterizing uncertainty for energy system models. In this study, we show that it is crucial to account for uncertainties in both parameters and modeling choices when analyzing practical policy decisions. The approach methodically explores and evaluates modeling choices and their effect on specific decision outcomes (in this case, subsidy amount and schedule).

To clarify the differences in prior work, we note that one body of literature described above [24,26–29] compares the outcomes among integrated models developed by different groups. Our work is not concerned with measuring consensus among modelers but rather with quantifying preferable sub-model choices and how decisions are affected by model selection. This is related to the approach of Cohen et al., who constructed a theoretical understanding of how the presence or absence of uncertainty in the demand function affects subsidy decisions [27]. In contrast, we focused on empirical models, i.e., those calibrated with historical data and that are used to predict numerical results. A study by Dong et al. [28] compared the forecasts of different solar diffusion models, but they did not evaluate the preferability of models or how the choices affect policy decisions. While our work is focused on a case study of optimal solar subsidy, it offers broader insights into subsidy design in the US and a general approach to assess and mitigate modeling uncertainty.

The remainder of this paper proceeds as follows. In Section 2, we introduce the integrated framework used in this study, followed by a specific focus on the components of the adoption model. We present three different adoption model formulations and calibrate the parameters of these models with identical datasets. In Section 3, the results from the adoption model fitting are evaluated from both theoretical and statistical perspectives. Section 3 also establishes the role of adoption models in estimating the optimal subsidies for residential solar under different technological learning and social costs of carbon conditions. The discussions and conclusions of this study are discussed in Sections 4 and 5.

2. Methods

In this section, we first summarize an integrated model that determines optimal subsidies for clean energy technology, combining elements of adoption, technological progress, and benefit–cost analysis of emissions reductions. We then develop different adoption models for rooftop solar photovoltaics, with three functional forms and three different sets of explanatory variables (9 combinations). These adoption models are then used to explore the effects of functional formulations and parameter choices on optimal subsidy design.

2.1. Techno–Economic Framework

In this study, we apply a techno–economic framework developed by Tibebu et al. [5] that is used to analyze US state-level residential solar PV subsidies. Conceptually, the idea is that clean energy subsidies are justified for two reasons: first, the subsidy drives consumer adoption of clean energy technology, thereby reducing the use of fossil fuels and emissions (known as direct environmental benefits). Second, because of the direct adoption, the subsidy induces technological progress and learning by doing in the industry, which leads to cost reductions and performance improvements in terms of the technology for future consumers (known as indirect technological progress benefits). The integrated modeling framework enables the measurement of these two motivations to subsidize. Three separate models quantify consumer adoption, technological progress, and benefits and costs of emissions reductions. The adoption model predicts residential solar purchases in a region based on economic and demographic variables [6,30,31]. The technological progress model forecasts cost reductions as a function of adoption using an experience curve model [32]. Using emissions factors [33], the benefit–cost model estimates emission reductions in CO_2 and criteria pollutants (PM, SO_X, and NO_X) attributable to solar adoption and then uses the social cost of carbon [34] and the EASIUR model [35] to monetize the health benefits in terms of emission reductions. The three models are connected, and the effects of any schedule of solar subsidies can be calculated, including the resulting adoption, price reductions, and monetized emission benefits from 2020 to 2050. Optimization is then carried out to find the subsidy schedule that minimizes net social benefit, which is defined as the total emissions benefits less than government subsidy costs. The structure of the model is summarized in Figure 1. In previous work, we used this framework to analyze the effects of different adoption model formulations on the optimal subsidy design for residential solar PV [5,11].

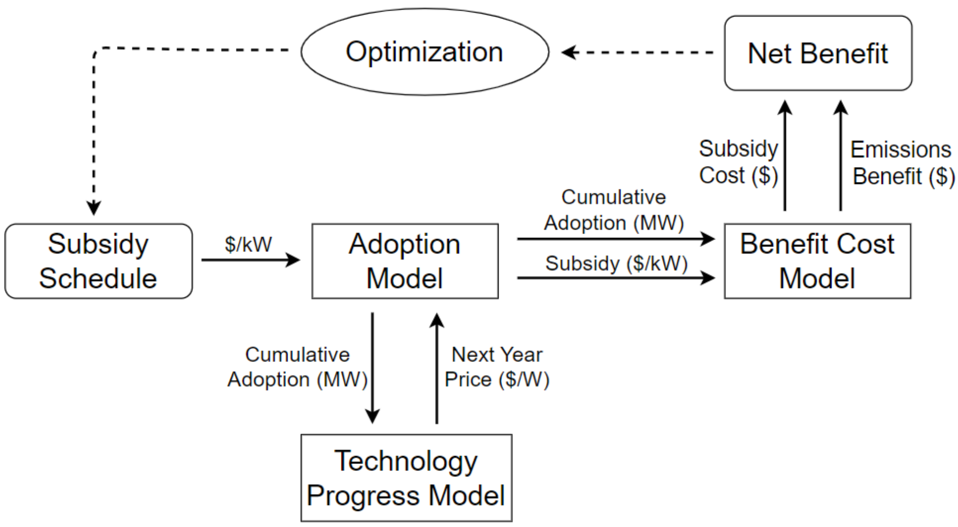

Figure 1. The integrated model consists of adoption, technological progress, and benefit–cost models to analyze optimal subsidy schedule for clean energy technologies. (Tibebu et al. [5]).

2.2. Adoption Models

A variety of diffusion models to predict residential solar adoption have been developed in the existing literature. These studies applied different mathematical structures to the diffusion process, including linear functions with log variants, nonlinear functions, and discrete choice models [5,9,23]. Different explanatory variables have been used, including economic (e.g., price, subsidy, net present value [6]), socio-demographic variables [30], user perceptions [36], and cumulative historical installations [31]). System dynamics models have also included the interaction among different PV market factors, such as national energy mix, economic status, and environmental goals [37]. In our study, the selection of the models is based on multiple factors like integration into a comprehensive framework, data availability, and ability to empirically validate model parameters. We consider models that are capable of generating long-term time series of the adoption rates for multiple regions. Our choice also includes non-economic variables such as socio-demographic characteristics and prior adoption to account for their influence on consumer behaviors.

Our goal is to try different combinations of functional form and explanatory variables for diffusion to compare modeling approaches in a systematic way. First, we explore whether certain choices appear more robust. We expect that conventional statistical argumentation will not indicate a single model form as unilaterally preferable, so we also analyzed how different adoption models affect the final decision (subsidy schedule). We selected three functional forms of diffusion models and three sets of explanatory variables (9 combinations) selected from the literature (Table 1) and calibrated the models using a common set of time series county-level data in the US. The first functional form is the integral of a Gaussian distribution, resulting in an "error function" form. The theoretical underpinning of the model is the idea that as the NPV of solar adoption increases, additional customers ought to follow a Gaussian distribution. Empirically, this model has been shown to fit historical data well for three US states (AZ, CA, and MA) and two countries (Japan and Germany) [6]. The second functional form is a mixed log-linear approach, chosen to reflect common modeling choices in multivariable regression approaches [30,38]. The third form is based on a logit function, frequently used in decision modeling [31]. We consider three sets of explanatory variables for each adoption model. The first case only uses a single economic variable, the net present value (NPV) of a rooftop system for a consumer, as the singular driver of technology adoption. The second case uses NPV and multiple socio-demographic variables, including per capita personal income, unemployment rate, and population density at the county level. The third case uses NPV and cumulative prior adoption in a county as variables. In the literature, previous adoption is considered an indicator of consumer awareness and installation experience, which grows over time and enhances adoption separately from economic considerations [31].

Table 1. Three functional forms and choices of explanatory variables were chosen to model rooftop solar adoption (NPV = net present value; Socio = socio-demographic variables; ERF = error function; MLL = mixed log-linear; Adopt = prior adoption).

Functional Forms	Model Framing	Explanatory Variable		
		NPV	NPV and Socio-Demographic	NPV and Previous Cumulative Adoption
Error function (ERF)	Adoption is modeled as an integral of a Gaussian distribution	ERF_NPV	ERF_NPV+Socio	ERF_NPV+Adopt
Mixed log-linear (MLL)	Adoption is modeled by logarithmically transformed regression model	MLL_NPV	MLL_NPV+Socio	MLL_NPV+Adopt
Logit	Probability of adoption is modeled as integral of extreme value distribution	LOGIT_NPV	LOGIT_NPV+Socio	LOGIT_NPV+Adopt

2.2.1. Data

We report the sources and descriptive statistics of the data used to calibrate the adoption models in Table 2. The geographic level chosen was a US county because it was possible to collect sufficient annual data for all variable choices for regression: 48 counties over 9–14 years in Arizona, California, and Massachusetts (655 observations total). We collected and compiled data from multiple government agencies and national research institution reports. Annual adoption and the price of residential solar PV systems were obtained from project-level datasets collected by the Lawrence Berkeley National Laboratory (LBNL) from state agencies and utilities [35]. State-level retail electricity prices were gathered from utilities by the EIA [38]. We collected socio-demographic data, such as population, income, population density, and unemployment rate, from the Census Bureau, Bureau of Economic Analysis, and Bureau of Labor Statistics databases [36,37,39]. The NPV of purchasing a rooftop solar system is calculated from the economic and solar insolation data, assuming a lifetime of 20 years and a lending rate varying across years between 3.3% and 8.1%. To forecast future income and population, we used annual data from 2000 to 2019 and performed a simple linear regression to project the values. For unemployment projections, we used the mean of the unemployment rate from 2000 to 2019, as these rates did not show any long-term trend over the years, but the mean varied between counties.

Table 2. Descriptive statistics of the variables were used to fit the adoption models for all 655 observations—48 counties in Arizona, California and Massachusetts; 10–15 years of data. (NPV = net present value; MW = megawatt; PV = photovoltaic; Std. Dev = standard deviation).

Variable	Unit	Mean	Std. Dev	Min	Max	Data Source
Annual adoption	MW/million free detached houses	69	82	0.14	442	[39,40]
Annual adoption	Watt/capita	10.6	0.0118	0.04	62.3	[39,41]
PV system price	USD/W	5.7	1.6	3.2	9.3	[39]
Electricity price	cents/kWh	16.5	3.3	8.8	25.8	[42]
NPV	USD/kW	236	1918	−5636	3305	
Income	USD/capita	57,191	20,200	27,730	143,504	[41]
Unemployment	%	7.5	3.9	2.3	27.5	[43]
Population density	Population/mile sq.	1222	3066	24.1	18,880	[41,44]
Prior adoption	Share of households with PV	1.2	1.4	0.004	7.8	
Number of observations		655				

The details of the three adoption models are discussed below.

2.2.2. Error Function Model

The first adoption model used in this study is derived from a residential solar diffusion model developed by Williams et al. [6]. This model exclusively uses an economic factor—the net present value (NPV) of adopting a rooftop solar system over a 20-year period—calculated using government incentives, electricity price, and solar energy potential. The "error function" is the integral of a normal distribution and is used to model adoption (Equation (1)). Conceptually, this model assumes that the profitability required to convince different consumers to adopt a rooftop solar system follows a normal distribution, with some consumers willing to adopt even when they lose money and other consumers still unwilling to adopt at high payback.

$$Annual\ adoption_t \left(\frac{MW}{million\ free\ detached\ houses} \right) = k \times \left(1 + \mathrm{erf}\left(\frac{NPV_t - \alpha_1}{\alpha_2} \right) \right) \quad (1)$$

where t is a year, and α_1 and α_2 are empirically determined parameters. k is a variable that reflects the maximum feasible adoption in one year, set at 2000 MW/million households. $Number\ of free\ detached\ houses_t$ is the difference between the total number of detached houses in a county and the number of households that have already adopted solar PV. NPV_t is the average net present value of a rooftop solar in a region for year

t. In addition to the adoption variables shown in Equation (1), we also considered two alternative cases, including additional variables. We employed a multi-variable extension of this model that includes NPV and socio-demographic variables (Equation (2)):

$$Annual\ adoption_t\left(\frac{MW}{million\ free\ detached\ houses}\right) = k \times \left(1 + \text{erf}\left(\frac{NPV_t - (\beta_1 income_t + \beta_2\ unemployment_t + \beta_3\ popn\_density_t + \beta_4)}{\beta_5\ income_t + \beta_6\ unemployment_t + \beta_7\ popn\_density_t + \beta_8}\right)\right) \quad (2)$$

We also considered a model that includes NPV and "consumer awareness", the latter measured through prior adoption, represented by the cumulative quantity of prior PV adoption normalized to the total market size (Equations (3) and (4)).

$$Prior\ adoption_t = \frac{\sum_{j=starting\ year}^{t-1} Number\ of\ households\ with\ PV_t}{Total\ households} \quad (3)$$

$$Annual\ adoption_t\left(\frac{MW}{million\ free\ detached\ houses}\right) = k \times \left(1 + \text{erf}\left(\frac{NPV_t - (\gamma_1 \log(Prior\ adoption\ _t) + \gamma_2)}{\gamma_3 \log(Prior\ adoption\ _t) + \gamma_4}\right)\right) \quad (4)$$

A nonlinear least squares method was applied to estimate the values of the parameters, and the results are given in Table 3. Note that the first model (Equation (1)) has two regression parameters (α_1 and α_2), the second has eight (β_{1-8}), and the third has four (γ_{1-4}). Table 3 shows the results of the nonlinear regression parameter fitting from the historical data.

Table 3. Estimated values of model parameters for error function (ERF) adoption model using least squares method (nonlinear). NPV = net present value; MW = megawatt; ERF = error function; Socio = socio-demographic variables; Adopt = prior adoption. (see Equations (2)–(4) for model definitions).

Dependent Variable: Annual Adoption in MW/Million Free Detached Houses			
	Models		
	ERF_NPV	**ERF_NPV+Socio**	**ERF_NPV+Adopt**
Numerator:			
Income (β_1)		966	
Unemployment (β_2)		−197	
Population density (β_3)		−166	
Prior adoption (γ_1)			−12,200
Constant (α_1, β_4, γ_2)	8074	2	5890
Denominator:			
Income (β_5)		665	
Unemployment (β_6)		−150	
Population density (β_7)		−245	
Prior adoption (γ_1)			−4900
Constant (α_2, β_8, γ_4)	4679	5	7790
Number of observations	655	655	655

2.2.3. Log-Linear Regression Model

The second diffusion model takes the form of a mixed log-linear regression to predict adoption. This type of model has been extensively used to analyze the adoption of clean energy technologies [30,38]. The first model (Equation (4)) only uses NPV as the main predictor variable (Equation (5)):

$$\log\left(Annual\ adoption_t\right) = \beta_1 \times NPV_t + \beta_o + \varepsilon \quad (5)$$

where t again refers to year. Taking the logarithm ensures that $Annual\ adoption_t$ will be positive, an approach commonly applied for non-negative quantities. The second model (Equation (6)) includes the socio-demographic explanatory variables:

$$\log\left(Annual\ adoption_t\right) = \beta_1 \times NPV_t + \beta_2 \times log(income_t) + \beta_3 \times unemployment_t + \beta_4 \times log(population\ density_t) + \beta_o + \varepsilon \quad (6)$$

The third log-linear model considers NPV and prior adoption as explanatory variables:

$$\log\left(Annual\ adoption_t\right) = \beta_1 \times NPV_t + \beta_2 \times log(prior\ adoption_t) + \beta_o + \varepsilon \quad (7)$$

where β_i and ε represent empirically fitted coefficients and the error term, respectively. For convenience, we use β to denote regression variables for all three forms. Note that this means, e.g., that β_1 for Equation (5) is not the same as β_1 in Equations (6) and (7).

The economic and socio-demographic explanatory variables that we chose for inclusion in our study are those consistently found to be significant PV adoption predictors in earlier analyses [38,45]: income, unemployment rate, and population density.

Table 4 shows the regression results for the three cases. The R^2 for the first model that consists of only the NPV variable is 0.58. This indicates that this variable can explain around half of the variation in terms of adoption. Adding socio-demographic variables in the second model increased the adjusted R^2 to 0.64. The second model shows that unemployment and population density coefficients are negative. This result implies that areas with high unemployment and population density tend to have lower adoption rates, which is expected. The model with NPV and the share of the previous years' adoption as explanatory variables has the highest adjusted R^2 value (0.83). The relevance and interpretation of this will be discussed in depth later, but the high value is thought to be due to the high correlation between the NPV and prior adoption rates. Note that the coefficient for NPV is very different (though similarly significant) for the model that uses prior adoption compared to the other two models.

Table 4. Estimated values for parameters of mixed log-linear (MLL) adoption model using least squares regression, see Equations (5)–(7) for model definitions. Values in parentheses are standard errors. (NPV = net present value; Socio = socio-demographic variables; Adopt = prior adoption).

Dependent Variable: Annual Adoption in Watt/Capita (Log)			
	Models		
	MLL_NPV	**MLL_NPV+Socio**	**MLL_NPV+Adopt**
NPV (β_1)	0.000568 *** (0.000019)	0.000544 *** (0.000018)	0.000130 *** (0.000019)
Income		0.604 *** (0.169)	
Unemployment		−0.05 *** (0.0106)	
Population density		−0.288 *** (0.0329)	
Prior adoption			1.3 *** (0.0425)
Constant	1.48 *** (0.0365)	−3.03 * (1.77)	4.05 *** (0.0875)
Number of observations	655	655	655
R^2	0.58	0.638	0.827
Adjusted R^2	0.579	0.636	0.826
Residual std. error	0.928	0.863	0.597
F Statistic	901 ***	287 ***	1554 ***

Note: * $p < 0.1$; *** $p < 0.01$.

2.2.4. Logit Demand Function Model

For the third model, we employed an adoption model developed by Lobel and Perakis [31]. In our notation, the number of households adopting rooftop solar in a region in year t follows a logit function (Equation (8)).

$$Number\ of\ households\ adopting_t = Number\ of\ free\ detached\ houses_t \times \left(\frac{e^{V(t)}}{1+e^{V(t)}}\right). \quad (8)$$

$$V(t) = \beta_1 \times NPV_t + \beta_2 \times log(Prior\ Adoption_t) + \beta_0 + \varepsilon \quad (9)$$

where

$$Prior\ adoption_t = \frac{\sum_{j=starting\ year}^{t-1} Number\ of\ households\ with\ PV_t}{Total\ households}$$

β_i represents empirically determined demand parameters, and ε is the error term referring to the demand shock that is not captured by the data. In our application, only the deterministic components are considered, and ε is set to zero. From Equations (8) and (9), the demand function can be written as follows:

$$Number\ of\ households\ adopting_t = Number\ of\ free\ detached\ houses_t \times \left(\frac{e^{\beta_1 \times NPV_t + \beta_2 \times log(Prior\ Adoption_t) + \beta_0}}{1+e^{\beta_1 \times NPV_t + \beta_2 \times log(Prior\ Adoption_t) + \beta_0}}\right) \quad (10)$$

Rearranging Equation (10) yields a linear function that can be used to determine the parameters of the demand model (Equation (11)).

$$\ln\left(\frac{Number\ of\ households\ adopting_t}{Number\ of\ free\ detached\ houses_t - Number\ of\ households\ adopting_t}\right) = \beta_1 \times NPV_t + \beta_2 \times log(Prior\ Adoption_t) + \beta_0 \quad (11)$$

The annual adoption in year t is determined by multiplying the demand function (Equation (10)) with the average size of rooftop solar installation and is shown in Equation (12).

$$Annual\ adoption_t\left(\frac{MW}{million\ free\ detached\ houses}\right) = Average\ rooftop\ solar\ size\ (W) \times \left(\frac{e^{\beta_1 * NPV_t + \beta_2 * log(Prior\ Adoption_t) + \beta_0}}{1+e^{\beta_1 * NPV_t + \beta_2 * log(Prior\ Adoption_t) + \beta_0}}\right) \quad (12)$$

A second model considers that NPV is the only determinant of utility:

$$Number\ of\ households\ adopting_t = Number\ of\ free\ detached\ houses_t \times \left(\frac{e^{\beta_1 \times NPV_t + \beta_0}}{1+e^{\beta_1 \times NPV_t + \beta_0}}\right) \quad (13)$$

A third model considers that utility is a function of NPV and socio-demographic variables:

$$Number\ of\ households\ adopting_t = Number\ of\ free\ detached\ houses_t \times \left(\frac{e^{\beta_1 \times NPV_t + \beta_2 \times log(income_t) + \beta_3 \times unemployment_t + \beta_4 \times log(population\ density_t) + \beta_0}}{1+e^{\beta_1 \times NPV_t + \beta_2 \times log(income_t) + \beta_3 \times unemployment_t + \beta_4 \times log(population\ density_t) + \beta_0}}\right) \quad (14)$$

We use β to denote the regression parameters in all three models. Note that this means that β_1 will be different for Equations (10), (13), and (14).

Table 5 shows the regression results for the three cases of the logit model. Adding socio-demographic variables did little to increase the statistical fit view through the lens of R-squared (0.558 to 0.572). Including prior cumulative adoption increased R-squared more substantially (to 0.869) and significantly reduced the coefficient associated with NPV. See Section 3.1 for further discussion of this change.

Table 5. Estimated values for parameters for log adoption model using logistic (LOGIT) regression, see Equations (10), (13) and (14) for model definitions. Values in parentheses are standard errors. (NPV = net present value; Socio = socio-demographic variables).

	LOGIT_NPV+Prior Adoption	LOGIT_NPV	LOGIT_NPV+Socio
NPV (β_1)	0.000064 *** (0.000016)	0.00055 *** (0.000019)	0.000535 *** (0.000019)
Income			0.459 ** (−0.181)
Unemployment			−0.0297 *** (−0.0114)
Population density			−0.118 *** (−0.0352)
Prior adoption	1.44 *** (−0.036)		
Constant	−2.41 *** (0.0749)	−5.26 *** (0.037)	−9.35 *** (1.89)
Number of Observations	655	655	655
R^2	0.869	0.558	0.575
Adjusted R^2	0.869	0.557	0.572
Residual Std. Error	0.511	0.94	0.92
F Statistic	2171 ***	823 ***	220 ***

Note: ** $p < 0.05$; *** $p < 0.01$.

3. Results

3.1. Evaluation of Adoption Models

In this section, we evaluate the developed adoption curves from different perspectives: theory, statistical reasoning, and expectation testing. Combining these, we discuss model and variable preferability.

Theory: By theory, we mean clarifying the goals of the model, expectations about the effect of explanatory variables on adoption, and commentary on how the measured quantities reflect intention. The goal of these models is to explain and predict with reasonable accuracy the adoption of residential solar PV while including a dependent variable that measures the effect of government subsidies (which is required when studying optimal subsidy design and justified by empirical analysis). There are many factors that contribute to the economic value of a PV system (e.g., capital costs, electricity costs, and solar insolation), and we assume that the total economic value proposition, measured via NPV, is the most effective metric for measuring a consumer's economic preferences. We expect that many consumers do not actually calculate NPV but are attentive to some similar quantity (e.g., payback time) presented to them by the installer or other source. Factors other than NPV presumably also affect purchase decisions, e.g., wealthier households will have more savings and better credit and so are expected to adopt more. This leads to the inclusion of socio-demographic variables: income, unemployment, and population density. It is expected that lower population density leads to higher adoption due to a greater share of large, detached houses suitable for rooftop solar. Finally, a greater scale of the local solar industry presumably enhances the degree to which solar is marketed and thus sold to consumers. Industry experience/scale and network effect on diffusion are measured using cumulative prior adoption [31,46]. Note that cumulative prior adoption does not directly measure industry experience/scale but represents the totality of conditions that led to adoption, including economic factors. Because favorable (or unfavorable) economic and demographic conditions tend to persist over time (e.g., high insolation, income levels, and electricity prices), the degree to which prior cumulative adoption reflects industry scale/experience versus other persistent conditions that favor/disfavor solar is not clear.

Statistical reasoning: One approach is to compare the total square error (TSE) in the prediction model of adoption versus actual historical adoption. TSE is used instead of

R-squared because the error function and logit models are nonlinear. Table 6 shows the TSE for the nine combinations of three functional forms and three sets of explanatory variables. The error function/previous cumulative adoption model has the lowest TSE (1068), followed by the logit model/previous cumulative adoption and error function/NPV+socio-demographic and error function/NPV. Note that adding socio-demographic variables results in only a small reduction in TSE.

Table 6. Total squared error (TSE) of the adoption models fitted using historical county data. (NPV = net present value).

Functional Forms	Explanatory Variable		
	NPV	**NPV and Socio-Demographic**	**NPV and Previous Cumulative Adoption**
Error function	1400	1340	1070
Mixed log-linear	1590	1480	1600
Logit	1720	1720	1250

A second statistical approach is to check the correlations between the independent variables. Given the objective of the model to predict adoption given interventions that change NPV (subsidy), it is important to ensure that no other independent variable is strongly correlated with NPV. Such a correlation would affect regression results that define the effect of changing NPV on adoption. Table 7 shows the correlation matrix between the different explanatory variables. NPV and prior cumulative adoption have the highest correlation, 0.82, followed by income and population density, which is about 0.7. The high correlation between prior cumulative adoption and NPV suggests that a model including both variables may misattribute their effects, forcing the analyst to consider which of the two is truly driving adoption.

Table 7. Correlation matrix between the different input variables. (NPV = net present value).

	NPV	**Income**	**Unemployment**	**Population Density**	**Prior Cumulative Adoption**
NPV	1				
Income	0.17	1			
Unemployment	−0.24	−0.60	1		
Population density	−0.01	0.69	−0.32	1	
Prior cumulative adoption	0.82	0.22	−0.32	−0.02	1

Expectation/hypothesis testing: By expectation testing, we mean testing the model's forecasting power with different values of NPV and judging if the outcomes make sense. Table 8 shows all of the model results for California in terms of adoption in 2021 for select sample values of NPV. The idea is to test what each adoption model predicts in cases where the subsidy is removed or increased or where prices change due to supply chain issues. It is plausible that NPV could fall sharply or even become negative if a government's subsidy policy changed. History suggests that the consumer base that purchases rooftop solar with negative NPV is a relatively small submarket of environmentally conscious consumers [47]. Given this history, we expect that adoption in 2021 would be much lower if NPV turns substantially negative relative to our estimated positive value of USD 949/kW. Table 8 shows the results. Most of the nine models suggest that adoption decreases steadily with lower NPV, with very low adoption rates when NPV = −USD 1000/W. However, models with prior cumulative adoption as a variable show very small changes in adoption as homeowner benefits go from substantially positive (+1500 USD/kW) to negative NPV (−USD 1000 USD/kW). We find this to be unrealistic, and it suggests that the high correlation between NPV and prior cumulative adoption has artificially suppressed the dependency of adoption on NPV. In short, we propose that cumulative prior adoption is a good predictor of future adoption mainly because it is a good predictor of NPV and that consumers are mainly adopting because of low NPV rather than other factors relating to prior adoption.

Table 8. 2021 Adoption (MW) of rooftop solar in California for different values of net present value for 9 model combinations. Note that any model with Prior Adoption as variable indicates high adoption rate even with negative NPV. (NPV = net present value; ERF = error function; Socio = socio-demographic; MLL = mixed log-linear).

NPV, USD/kW	ERF_NPV	ERF_NPV+Socio	ERF_NPV+Prior Adoption
1500	534	554	1066
949	356	373	924
500	251	265	819
0	167	178	715
(1000)	69	75	539
NPV, USD/kW	**MLL_NPV**	**MLL_NPV+Socio**	**MLL_NPV+Prior Adoption**
1500	416	475	1050
949	305	352	977
500	236	276	922
0	178	210	864
(1000)	101	122	758
NPV, USD/kW	**LOGIT_NPV**	**LOGIT_NPV+Socio**	**LOGIT_NPV+Prior Adoption**
1500	333	360	911
949	247	269	880
500	193	212	855
0	147	163	829
(1000)	85	95	779

We conclude that prior cumulative adoption should be rejected as an explanatory variable for our purposes despite the better TSE results; it is incompatible with the objective of an adoption model that reasonably captures the effect of changes to NPV, which is needed to assess the benefits of subsidy. The high correlation between prior cumulative adoption and NPV suggests that this regression coefficient might not appropriately reflect exogenous changes in NPV only. Prior adoption is a good predictor variable for current adoption in the absence of NPV data, but causality becomes confused when both are included due to their covariance. The expectation analysis (Table 8) shows that adoption models using prior cumulative adoption have, we argue, an unrealistically weak dependence on NPV, suggesting that consumers are generally indifferent to gaining or losing USD 1000.

The next best model in terms of TSE is the error function model using NPV+socio-demographic variables, but the fit for the error function model with NPV only is almost the same. Even though we propose that the models using NPV+prior adoption do not give reasonable results, we continue to use all nine models in the following results because both demographic variables and prior cumulative adoption are used in the literature as explanatory variables, and it is important to understand how that modeling choice affects subsidy decisions.

3.2. Optimal Subsidy

The adoption models described above are used in the techno–economic framework to estimate optimal national subsidies for residential solar. The techno–economic framework integrates adoption, technological progress, and benefit–cost models to determine the optimal subsidy that maximizes national net benefit, i.e., the benefits resulting from emissions reductions and technological progress minus the cost of the subsidy. Different annual schedules of national subsidies (USD/W) are considered, and a generalized reduced gradient nonlinear method is used to find the one that minimizes emissions benefits less than government expenditures. Figure 2 shows the optimal subsidy results for different cases of learning rate and the social cost of carbon. For the base case learning rate of 15% and a carbon cost of USD 45/ton, the error function models with NPV and NPV+Socio-demographic variables yield non-zero subsidies, while the other seven models suggest that the optimal subsidy is zero, i.e., the benefits do not justify the costs (Figure 2a). For the models that use previous cumulative adoption as an explanatory variable, this is not surprising given their assumed irrelevance in terms of NPV: if you assume that adoption does not depend on the economics of solar, then offering a subsidy will have little effect on adoption and is thus a waste of government funds. Figure 2b–d show optimal subsidies for higher values of learning rate and/or the social cost of carbon. Higher values lead to more modeling scenarios yielding non-zero subsidies. Note that the precise schedule of subsidy is sensitive to both model and parameter value choices but in different ways.

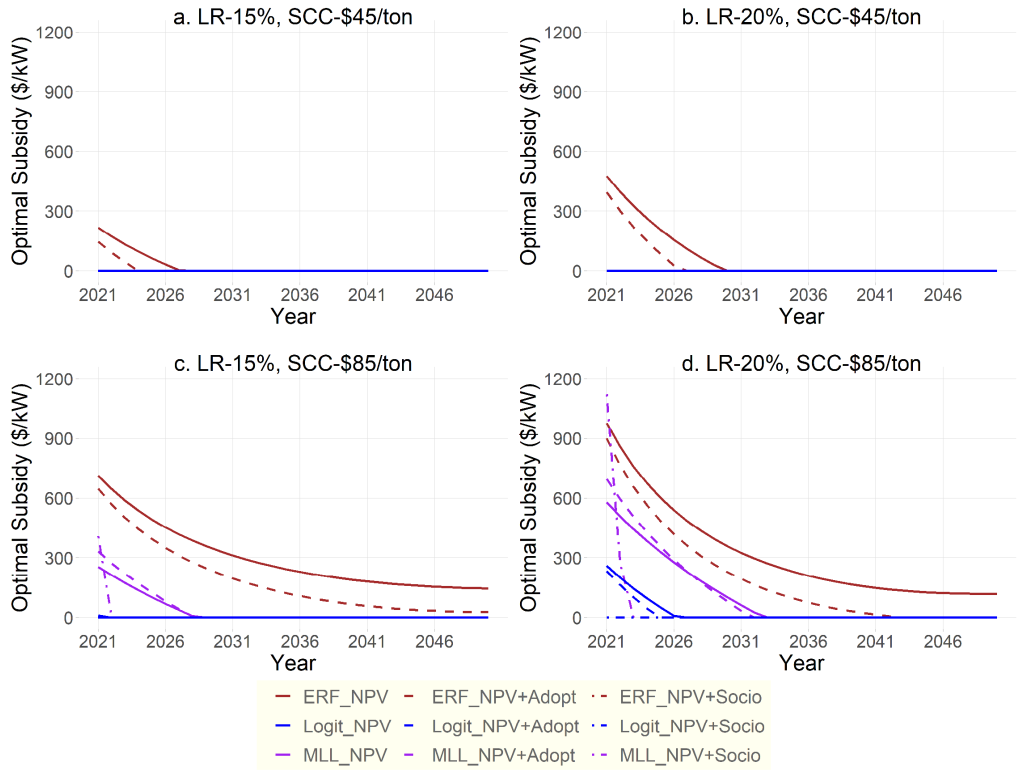

Figure 2. Optimal subsidy schedule for four combinations of learning rate (LR) and social cost of carbon (SCC) for all nine adoption models considered. A model does not appear on a graph when the optimal subsidy is zero (i.e., is it socially preferable not to subsidize). As the values of LR and SCC increase, optimal subsidy and number of models that indicate that a subsidy is justified also increase. (ERF = error function; MLL= mixed log-linear; NPV = net present value; Socio = socio-demographic; Adopt = prior adoption).

There are several general features of importance shown in Figure 2: First, justifying residential solar subsidies requires a reasonably high learning rate, i.e., both direct benefits from stimulating adoption and indirect future benefits from inducing cost reductions are needed. The social cost of carbon is an important but uncertain input parameter [48]. Note that the value prescribed by the US government in benefit–cost analysis has varied from USD 43/ton during the Obama administration to USD 3–5/ton under Trump and USD 53/ton during the early Biden presidency [49]. However, many argue that the real social costs are notably higher, e.g., USD 100/ton or more [50]. Second, in all cases where a rooftop solar subsidy is justified, the optimal subsidy schedule declines over time, usually with a finite duration. This was not a model assumption: subsidy schedule was free to take any value in any year and thus follow any type of trend. We also ran another version of the model omitting benefits from reduced emissions of criteria pollutants (PM, SO_x, and NO_x) and found that subsidy was zero except at the highest SCC cases. Thus, accounting for non-carbon emission benefits is key in justifying solar subsidie.

Figure 3 shows the first-year (2021 only) optimal subsidy level for many combinations of learning rates and social costs of carbon. Across the nine models, the optimal subsidy is zero for lower values of learning rate and carbon cost, with a threshold combination of both that leads to a non-zero subsidy. Unsurprisingly, the figure shows that the optimal subsidies are either mostly zero or always zero when the prior cumulative adoption variable is used in the error function and logit demand function adoption models. This is because those models implicitly believe that rooftop solar adoption is naturally high and rising and that the private economics of rooftop solar is unimportant, suggesting that the use of subsidies has little effect. For the mixed log-linear model with a prior cumulative adoption variable, a high subsidy value is offered in the early period to stimulate adoption, which could, in turn, drive adoption in later years. The optimal subsidy obtained with a given adoption model is similar to the single variable with NPV and the multi-variable models with NPV and socio-demographic variables. This indicates that the choice of adoption model may impact the optimal subsidy estimates more than the choice/inclusion of socio-demographic variables, or at least those considered in this study.

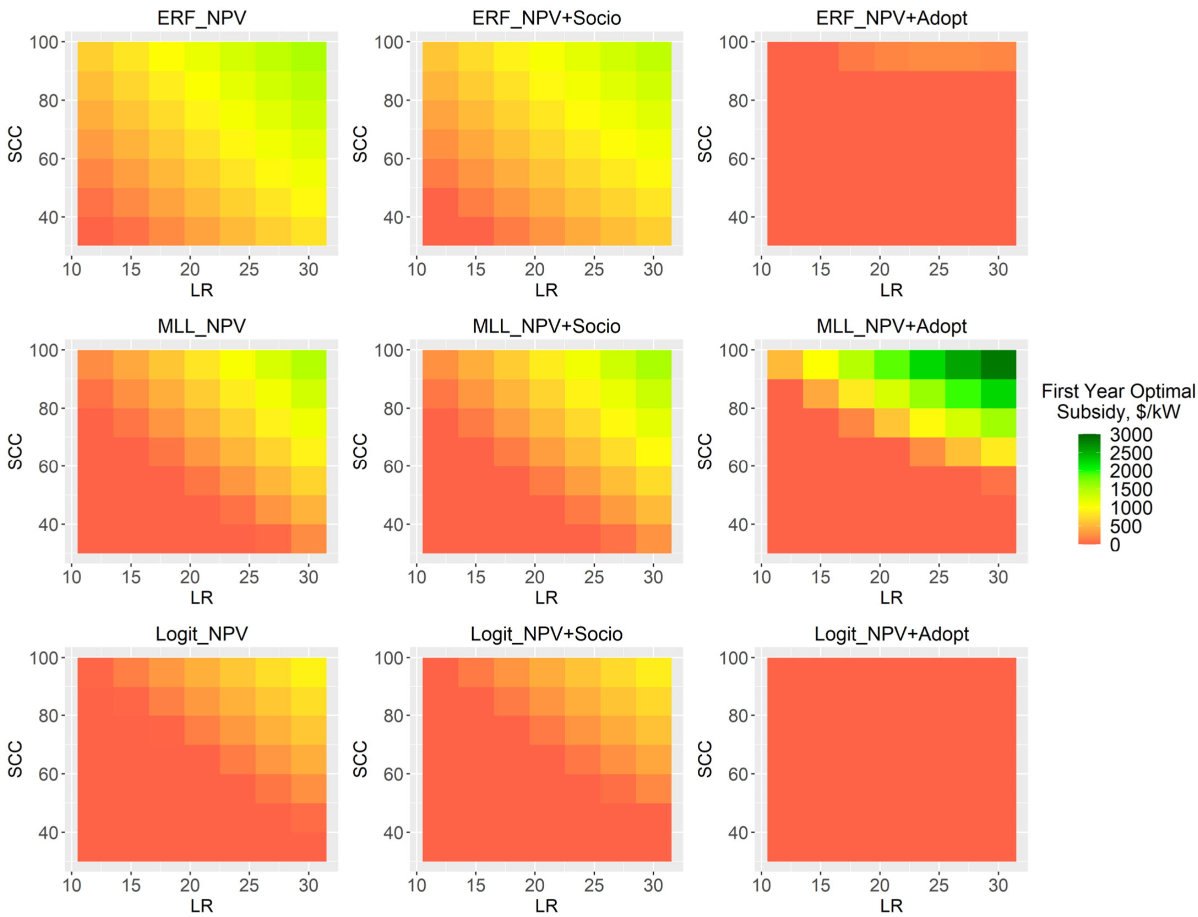

Figure 3. First-year optimal subsidy determined using the different adoption models for different values of learning rate (LR, %) and the social cost of carbon (SCC, USD/ton). While the three adoption models (error function, mixed log-linear, and logit) differ, adding socio-demographic variables to the NPV variable has only a small effect on optimal subsidy levels. Only the left two columns are considered “feasible” models, because adoption models that include prior adoption (right column) are problematic for reasons discussed in Section 3, and generally propose zero or very large subsidy of rooftop solar. (ERF = error function; MLL = mixed log-linear; NPV = net present value; Socio = socio-demographic; Adopt = prior adoption).

4. Discussion

Energy system modeling needs to treat both parameter uncertainty and modeling choices: This analysis demonstrates the need to analyze different model choices in energy system modeling. The current norm for uncertainty analysis, when carried out, only considers parameter uncertainty. The few prior examples that address modeling uncertainty compare how outcomes differ by choices of modeling groups [21], but connecting the different results to specific choices in sub-models is not evaluated. However, Figures 2 and 3 demonstrate that the final decision outcome of the model—subsidy schedule, in this case—varies considerably under different sub-models and parameter choices. Even though the paper by Dong et al. [28] considers different adoption models, their study has a much narrower focus and lacks an analysis of the policy implications particularly related to the design of clean energy subsidies. The research conducted by Goulder and Mathai [26] shows that carbon taxes and CO_2 abatement vary under two forms of technological progress models, but their study is not empirically validated. Given the many possible options for sub-models within an energy system model, it is thus important to evaluate these choices as well as parameter uncertainty. This work is intended as a proof-of-concept: We investigated the effect of one sub-model choice (adoption) in a larger modeling system. Future practice in energy system modeling should include evaluations and comparisons of multiple sub-models.

Evaluation of models should combine statistical argumentation with theory/ expectations: Models using prior cumulative adoption as an explanatory variable showed the best statistical fit through the lens of R-squared and total square error metrics, which may also explain why this modeling approach has been used by other researchers. However, the analysis in Section 3.2 combining statistical measures with theory and expectation for the model (the predicted effect of NPV changes on adoption) led us to reject prior cumulative adoption as a useful explanatory variable for our application. Including prior adoption in the model led to the erroneous conclusion that rooftop solar subsidies in the US are never justified because the resulting adoption model suggests that consumers are largely indifferent to the price of rooftop solar (Table 8). This is an example with general implications, showing that the form of the model needs to be appropriate for the analysis at hand.

The systems model, when considering both model and parameter uncertainty, does not narrow the optimal subsidy to a specific schedule, but suggests that policy makers pay close attention to cost reductions and the scope of environmental benefits expected: One might hope that a model predicting optimal subsidies would yield a narrow scope of schedules that a policy maker could use directly. However, the optimal subsidy schedule changes substantially across different choices in terms of adoption models and the values of learning rate/social cost of carbon. In addition to the factors considered, there are also other sub-model choices in terms of cost reductions, emissions benefits, and other parameters that could differ from the base case. This is not a deficiency in the model but a simple acknowledgment that there is substantial uncertainty in predicting optimal multi-decade policy decisions for an energy system.

It is also important to emphasize that optimization is far from the only factor that policy makers use in deciding subsidy policies. For example, there are typically politically driven goals, such as targets concerning the adoption of a certain technology by a certain year. Furthermore, subsidy schedules are not set in stone decades in advance; they can be and are often adjusted. This said, there are common features in terms of the optimal subsidy in all of the cases considered. First, the model indicates that a rooftop solar subsidy needs to induce substantial cost reductions through some form of technological progress to be justified. This indicates that policy makers should pay close attention to cost trends to justify rooftop solar subsidies, even during the adjustment process. Second, the scope of environmental benefits included substantially affects the justification of subsidy. While arguments for renewable energy subsidies often focus on carbon reductions, emissions benefits from reducing criteria pollutants are of a similar magnitude. Third, even across a wide range of model and parametric choices, the optimal subsidy schedule for rooftop solar declines over time, suggesting a general trend for rooftop solar subsidy to follow.

Lastly, it is important to acknowledge the limitations of the integrated techno–economic frameworks and their sub-models. The technological progress model implements a one-factor experience curve equation. This model ignores other factors, such as R&D and emerging technologies, which may contribute to technological progress and cost reduction. The benefit–cost model applies carbon price and emission factor using estimates that are uncertain due to the future grid–energy mix. In addition to these limitations, our study singles out residential solar PV and does not account for the interactions with other components, such as transmission and distribution (T and D) in the power system, considering that such a systematic view may influence future electricity prices, emissions estimates, and cost estimates as additional T and D expenses are incurred to integrate the growing residential solar PV market.

5. Conclusions

In this work, we have shown how a practical policy decision—the design of an optimal rooftop solar subsidy—is affected by different choices about the modeling of consumer adoption and examined the results under different technological learning and social carbon cost assumptions. While we do not take a position on which model is correct, it is notable that all nine scenarios (three model structure times and three sets of input variables) used the same data sources, the same benefit–cost model, and the same technological progress model, resulting in considerably different conclusions. The basic finding of the work is that different plausible adoption models can lead to drastically different practical conclusions varying from "residential solar should never be subsidized" to "residential solar subsidies should be several times higher than they are today". This finding has broader implications in both analysis and policy design. While many analysts pay attention to parametric uncertainty by considering different values for things like installation cost and learning rate, there is much less attention given to model structure uncertainty, which can affect the conclusions to a similar degree. Our findings suggest that studies on renewable energy policy should incorporate multiple perspectives of analytical and modeling inputs. For policy implementation, this work illustrates that the prudent choice of subsidy for rooftop solar is strongly dependent on one's belief about how the adoption of the technology works, which can be further studied. Future research could use this work as a basis to explore and identify systematic ways to evaluate the effectiveness of technology adoption models and their application in policy design.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en17030728/s1, Figure S1. US annual adoption starting from 2012 under the Federal Tax Credit (30% until 2020, 26% for 2020–2022, 22% for 2023, and zero afterwards) and learning rate of 15% predicted by the nine different adoption models. Figure S2. Forecasted annual adoption for all of the US with and without planned FTC (30% until 2020, 26% for 2020–2022, 22% for 2023, and zero afterwards). Learning rate for rooftop solar is 15%. The gap between the two lines represents the subsidy-induced adoption, which can continue after subsidies are removed due to the technological progress effect that the subsidy had on future solar costs. The Excel file contains details of data for 8 variables used in calibrating regression models with 665 data points each for different counties and years.

Author Contributions: T.B.T.: conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, writing—review and editing, visualization; E.H.: conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, writing—review and editing, visualization; Q.M.: conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, writing—review and editing, visualization; E.W.: conceptualization, methodology, data curation, formal analysis, investigation, writing—original draft, writing—review and editing, visualization. All authors have read and agreed to the published version of the manuscript.

Funding: This material is based upon work supported by the Directorate for Social, Behavioral and Economic Sciences of the National Science Foundation under Award No. 1829343.

Data Availability Statement: Data are contained within the article and Supplementary Materials.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. EIA. Annual Energy Outlook 2023. U.S. Energy Information Administration—EIA 2023. Available online: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=8-AEO2023&cases=ref2023&sourcekey=0 (accessed on 18 December 2023).
2. EIA. Use of Energy in Homes—U.S. Energy Information Administration (EIA) 2021. Available online: https://www.eia.gov/energyexplained/use-of-energy/homes.php (accessed on 18 December 2023).
3. EIA. Where Greenhouse Gases Come from—U.S. Energy Information Administration (EIA) 2023. Available online: https://www.eia.gov/energyexplained/energy-and-the-environment/where-greenhouse-gases-come-from.php (accessed on 18 December 2023).
4. Hagerman, S.; Jaramillo, P.; Morgan, M.G. Is rooftop solar PV at socket parity without subsidies? *Energy Policy* **2016**, *89*, 84–94. [CrossRef]
5. Tibebu, T.B.; Hittinger, E.; Miao, Q.; Williams, E. What is the optimal subsidy for residential solar? *Energy Policy* **2021**, *155*, 112326. [CrossRef]
6. Williams, E.; Carvalho, R.; Hittinger, E.; Ronnenberg, M. Empirical development of parsimonious model for international diffusion of residential solar. *Renew. Energy* **2020**, *150*, 570–577. [CrossRef]
7. Cunningham, L.J. *Renewable Energy and Energy Efficiency Incentives: A Summary of Federal Programs*; Congressional Research Service: Washington, DC, USA, 2016.
8. US Congress. Inflation Reduction Act of 2022. HR5376—Inflation Reduction Act of 2022. 2022. Available online: http://www.congress.gov/bill/117th-congress/house-bill/5376/text (accessed on 4 July 2023).
9. van Benthem, A.; Gillingham, K.; Sweeney, J. Learning-by-Doing and the Optimal Solar Policy in California. *Energy J.* **2008**, *29*, 131–152. [CrossRef]
10. Newbery, D. Evaluating the case for supporting renewable electricity. *Energy Policy* **2018**, *120*, 684–696. [CrossRef]
11. Tibebu, T.B.; Hittinger, E.; Miao, Q.; Williams, E. Roles of diffusion patterns, technological progress, and environmental benefits in determining optimal renewable subsidies in the US. *Technol. Forecast. Soc. Change* **2022**, *182*, 121840. [CrossRef]
12. Hoekstra, A. Photovoltaic Growth: Reality Versus Projections of the International Energy Agency—With 2018 Update (by Auke Hoekstra). Steinbuch 2018. Available online: https://maartensteinbuch.com/2017/06/12/photovoltaic-growth-reality-versus-projections-of-the-international-energy-agency/ (accessed on 1 October 2022).
13. EIA. *Annual Energy Outlook 2000*; Energy Information Administration: Washington, DC, USA, 1999.
14. EIA. The United States Installed More Wind Turbine Capacity in 2020 than in Any Other Year. Today in Energy 2021. Available online: https://www.eia.gov/todayinenergy/detail.php?id=46976 (accessed on 2 October 2022).
15. Moore, F.C.; Diaz, D.B. Temperature impacts on economic growth warrant stringent mitigation policy. *Nat. Clim. Change* **2015**, *5*, 127–131. [CrossRef]
16. Morgan, M.G.; Henrion, M.; Small, M. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*; Cambridge University Press: Cambridge, UK, 1990.
17. Pizer, W.A. The optimal choice of climate change policy in the presence of uncertainty. *Resour. Energy Econ.* **1999**, *21*, 255–287. [CrossRef]
18. Paltsev, S. Energy scenarios: The value and limits of scenario analysis. *WIREs Energy Environ.* **2017**, *6*, e242. [CrossRef]
19. Olaleye, O.; Baker, E. Large scale scenario analysis of future low carbon energy options. *Energy Econ.* **2015**, *49*, 203–216. [CrossRef]
20. Clarke, L.; Edmonds, J.; Krey, V.; Richels, R.; Rose, S.; Tavoni, M. International climate policy architectures: Overview of the EMF 22 International Scenarios. *Energy Econ.* **2009**, *31*, S64–S81. [CrossRef]
21. Gillingham, K.; Nordhaus, W.D.; Anthoff, D.; Blanford, G.; Bosetti, V.; Christensen, P.; McJeon, H.; Reilly, J.; Sztorc, P. *Modeling Uncertainty in Climate Change: A Multi-Model Comparison*; National Bureau of Economic Research: Cambridge, MA, USA, 2015. [CrossRef]
22. Bass, F.M. A New Product Growth for Model Consumer Durables. *Manag. Sci.* **1969**, *15*, 215–227. [CrossRef]
23. El Zarwi, F.; Vij, A.; Walker, J.L. A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 207–223. [CrossRef]
24. Bistline, J.E.T.; Brown, M.; Siddiqui, S.A.; Vaillancourt, K. Electric sector impacts of renewable policy coordination: A multi-model study of the North American energy system. *Energy Policy* **2020**, *145*, 111707. [CrossRef]
25. Bistline, J.; Blanford, G.; Brown, M.; Burtraw, D.; Domeshek, M.; Farbes, J.; Fawcett, A.; Hamilton, A.; Jenkins, J.; Jones, R.; et al. Emissions and energy impacts of the Inflation Reduction Act. *Science* **2023**, *380*, 1324–1327. [CrossRef] [PubMed]
26. Goulder, L.H.; Mathai, K. Optimal CO_2 Abatement in the Presence of Induced Technological Change. *J. Environ. Econ. Manag.* **2000**, *39*, 1–38. [CrossRef]
27. Cohen, M.C.; Lobel, R.; Perakis, G. The Impact of Demand Uncertainty on Consumer Subsidies for Green Technology Adoption. *Manag. Sci.* **2016**, *62*, 1235–1258. [CrossRef]

28. Dong, C.; Sigrin, B.; Brinkman, G. Forecasting residential solar photovoltaic deployment in California. *Technol. Forecast. Soc. Chang.* **2017**, *117*, 251–265. [CrossRef]
29. Kobos, P.H. *The Implications of Renewable Energy Research and Development: Policy Scenario Analysis with Experience and Learning Effects*; Rensselaer Polytechnic Institute: Troy, NY, USA, 2002.
30. Davidson, C.; Drury, E.; Lopez, A.; Elmore, R.; Margolis, R. Modeling photovoltaic diffusion: An analysis of geospatial datasets. *Environ. Res. Lett.* **2014**, *9*, 074009. [CrossRef]
31. Lobel, R.; Perakis, G. *Consumer Choice Model for Forecasting Demand and Designing Incentives for Solar Technology*; MIT Sloan Research Paper: Cambridge, MA, USA, 2011. [CrossRef]
32. Arrow, K.J. The Economic Implications of Learning by Doing. *Rev. Econ. Stud.* **1962**, *29*, 155–173. [CrossRef]
33. Azevedo, I.; Donti, P.; Horner, N.; Schivley, G.; Siler-Evans, K.; Vaishnav, P. Electricity Marginal Factors Estimates 2020. Available online: https://cedm.shinyapps.io/MarginalFactors/ (accessed on 4 July 2023).
34. Interagency Working Group on Social Cost of Greenhouse Gases, US Government. Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis. 2016. Available online: https://www.epa.gov/sites/default/files/2016-12/documents/sc_co2_tsd_august_2016.pdf (accessed on 5 July 2023).
35. Heo, J.; Adams, P. The Estimating Air Pollution Social Impact Using Regression (EASIUR) Model 2015. Available online: https://barney.ce.cmu.edu/~jinhyok/easiur/ (accessed on 4 July 2023).
36. Zhai, P.; Williams, E.D. Analyzing consumer acceptance of photovoltaics (PV) using fuzzy logic model. *Renew. Energy* **2012**, *41*, 350–357. [CrossRef]
37. Jeon, C.; Lee, J.; Shin, J. Optimal subsidy estimation method using system dynamics and the real option model: Photovoltaic technology case. *Appl. Energy* **2015**, *142*, 33–43. [CrossRef]
38. Drury, E.; Miller, M.; Macal, C.M.; Graziano, D.J.; Heimiller, D.; Ozik, J.; Iv, T.D.P. The transformation of southern California's residential photovoltaics market through third-party ownership. *Energy Policy* **2012**, *42*, 681–690. [CrossRef]
39. Barbose, G.; Darghouth, N.; O'Shaughnessy, E.; Forrester, S. Tracking the Sun: Pricing and Design Trends for Distributed Photovoltaic Systems in the United States, 2021 Edition 2021. Available online: https://emp.lbl.gov/publications/tracking-sun-pricing-and-design-0 (accessed on 7 July 2023).
40. Census Bureau. Historical Census of Housing Tables: Units in Structure n.d. Available online: https://www.census.gov/data/tables/time-series/dec/coh-units.html (accessed on 7 July 2023).
41. BEA. BEA Data | U.S. Bureau of Economic Analysis (BEA) 2021. Available online: https://www.bea.gov/data (accessed on 7 July 2023).
42. EIA. Electric Sales, Revenue, and Average Price—Energy Information Administration 2021. Available online: https://www.eia.gov/electricity/sales_revenue_price/ (accessed on 7 July 2023).
43. U.S. Bureau of Labor Statistics. Databases, Tables & Calculators by Subject 2021. Available online: https://www.bls.gov/data/ (accessed on 7 July 2023).
44. U.S. Census Bureau. Data. Census Website 2021. Available online: https://data.census.gov/profile?q=United%20States&g=010XX00US (accessed on 7 July 2023).
45. Dharshing, S. Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy Res. Soc. Sci.* **2017**, *23*, 113–124. [CrossRef]
46. Rubin, E.S.; Azevedo, I.M.L.; Jaramillo, P.; Yeh, S. A review of learning rates for electricity supply technologies. *Energy Policy* **2015**, *86*, 198–218. [CrossRef]
47. Sigrin, B.; Pless, J.; Drury, E. Diffusion into new markets: Evolving customer segments in the solar photovoltaics market. *Environ. Res. Lett.* **2015**, *10*, 084001. [CrossRef]
48. Anthoff, D.; Tol, R.S.J. The uncertainty about the social cost of carbon: A decomposition analysis using fund. *Clim. Chang.* **2013**, *117*, 515–530. [CrossRef]
49. Stanford University. Stanford Explainer: Social Cost of Carbon. Stanford News 2021. Available online: https://news.stanford.edu/2021/06/07/professors-explain-social-cost-carbon/ (accessed on 7 July 2023).
50. Hope, C. The Social Cost of CO_2 from the Page09 Model. *Econ. Discuss. Pap.* **2011**, 1–30. [CrossRef]