8-25-2022

Integrated Framework for Analyzing Clean Energy Technology Subsidies

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Integrated Framework for Analyzing Clean Energy Technology Subsidies

by

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Sustainability

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Rochester Institute of Technology
Rochester, NY

August 25, 2022

CERTIFICATE OF APPROVAL

Golisano Institute for Sustainability

Rochester Institute of Technology

Rochester, New York

Ph.D. Degree Dissertation

The Ph.D. Degree Dissertation of Tiruwork Berhanu Tibebu has been examined and approved by the dissertation committee as satisfactory for the dissertation requirement for the Ph.D. degree in Sustainability.

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ABSTRACT

Renewable energy technologies can significantly reduce fossil fuel consumption and greenhouse gas emissions associated with the energy sector. In US, both federal and state governments have implemented numerous policies and programs to support these technologies. But these policies require a substantial amount of public spending. In this study, an integrated model to identify optimal subsidy schedules for clean energy technologies that maximize social benefits less subsidy costs is developed. The national flexible optimal subsidy schedule for residential solar PV begins at $585/kW and declines to zero in 14 years. An alternative analytical model is also presented to analyze technological features affecting subsidy design. Three important factors determining the social benefits of subsidizing the use of clean energy technology are examined: the price sensitivity of adoption, induced cost reductions through learning, and environmental benefits. Results show that optimal subsidy schedules for utility wind are roughly constant over time. In contrast, optimal residential solar subsidies either decline over time or are not desirable (subsidy of zero). The results imply that the optimal subsidy for utility wind is justified mainly through the direct environmental benefits, unlike residential solar PV, in which indirect technological progress benefits primarily justify the subsidy. The effects of multiple adoption modeling and parameter choice alternatives on optimal subsidy design are also explored. The study considers three different model structures for rooftop solar adoption consisting of a combination of single and multiple explanatory variables. Results show that the scale of sensitivity of optimal subsidy designs to technology learning rate assumptions depends on the model choice. This dissertation shows that analytical inputs can be instrumental in informing policymakers deciding on subsidy schedules promoting renewable technologies. These tools can integrate environmental benefits and the complex interaction between the subsidy, diffusion patterns, and technology cost trajectories to ensure socially optimal policy designs.

Acknowledgments

I am deeply grateful to my Ph.D. advisors: Dr. Eric Hittinger, Dr. Qing Miao, and Dr. Eric Williams. Thank you for giving me the opportunity to be part of your research team. I am always indebted for the continuous advice, support, and encouragement throughout my Ph.D. study. Your guidance and valuable comments have immensely helped me find my way as a researcher. I would also like to express my gratitude for financially assisting me with my study here and the funding for attending conferences. Words cannot fully describe the kindness and support you showed me throughout the years. Thank you, and I will always look up to you as a researcher and as a person.

I want to express my profound appreciation to my research committee member, Dr. Nathan Williams, for being an integral part of my Ph.D. journey. Thank you for sharing your knowledge and expertise. Your insightful comments, feedback, and questions have been an exceptional input to my dissertation work.

I am extremely grateful to Dr. Callie Babbitt. Thank you for the guidance, career advice, and teaching me the fundamentals of effective scientific communications. I would also like to thank all GIS faculty members for educating me about the foundations of sustainability that led me to this stage. I extend my heartfelt appreciation to GIS staff assistant Angelique Armstrong for the continuous follow-ups and administrative paperwork and for helping me run things smoothly. Many thanks to fellow students for making my time at GIS enjoyable.

I could not have undertaken this journey without my family's constant moral support, encouragement, and unconditional love. Thank you for being there all the time. My parents, Berhanu Tibebu and Asselefech Desalegn, my sisters Tigist and Kidist, my brother Yohannes, Biruk Tibebu, Medrek W/Meskel, and Berhanu Desta, I cannot thank you all enough.

I want to thank my dear friend Tigist Mussa whom I have learned a lot from, and special friends I met at RIT, Anupama Garani, Ajeeta Khatri, and Ruiwen Fan, for the amazing experience. You have made my study and life in Rochester a wonderful time. My warmest appreciation also goes to Haimanot Yohannes and Wondwossen Teferi. Thank you for all the support and for making me feel at home.

Finally, I give glory and thanks to God. Glory to our Lady St. Mary. Thank you, Lord, for everything.

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Chapter 1: Introduction

1.1 Background

In the US, 63% of electricity generation in 2018 came from fossil fuel sources such as coal and natural gas (US EIA, 2020a). The high share of fossil fuel sources in the energy grid mix has led the power sector to be one of the most emissions-intensive sectors in the country and contributed 27% of total greenhouse gas emissions in the same year (US EPA, 2018a). Combustion of fossil fuels results in greenhouse gas emissions that can have both short- and long-term effects on the environment. It can also have a negative impact on human health as a result of air pollution and air quality reduction.

Various policy tools can be employed to achieve environmental emissions reductions. These mechanisms can be administrative: laws that restrict or ban the emission of harmful substances, or informative: labeling environmentally friendly products (Palm and Larsson, 2007). From an economic point of view, direct pricing of emissions (tax and tradable permits) is the most efficient instrument to reduce environmental emissions. But policymakers do not usually implement such mechanisms as they can have a considerable economic restraint on the firmly established sectors (Fischer and Newell, 2005). As a result, subsidies to emerging clean technologies are regarded as the second-best option to overcome the challenges of environmental emissions (Metcalf, 2007).

Renewable energy sources are considered the primary option to reduce fossil fuel consumption and address the consequences of emissions from conventional power plants. Clean energy technologies mainly use renewable sources such as solar and wind to generate electricity and have zero operational emissions. Both federal and state governments have employed different incentives to promote the adoption of such technologies. The two main types of incentive programs the federal government offers are investment and production tax credits for renewable energy projects. In addition, various forms of grants and loan programs are also enacted by the federal government (US EIA, 2018). State governments have also adopted several strategies to increase the share of renewable energy generation in their electricity system. 29 states and Washington, DC, have implemented renewable portfolio standards (RPS) policies to achieve a targeted percentage of renewable electricity sales (Barbose, 2019). New York state's 2015 clean energy standard sets a goal to meet 50% of the load using electricity generated from renewable resources by 2030 (N.C. Clean Energy Technology Center, 2020). California and Massachusetts also expect to meet 60% and 40% of their electricity demand from clean energy within a similar time frame (Barbose, 2019). RPS goals are promoted through a renewable purchase requirement imposed on utilities and load serving entities. The load serving entities mainly meet this requirement by operating their own renewable energy facility or purchasing renewable energy credits (RECs) from private facilities that generate electricity from eligible resources (Wiser et al., 1998). State governments have also implemented a net metering policy that allows grid connected customers to receive credits for excess renewable energy electricity generated and fed into the grid (Stokes and Breetz, 2018).

Over the years, renewable energy capacity has grown in the US energy mix. The total renewable energy nameplate capacity (excluding hydropower) in the US reached about 160 GW in 2019, up from 16 GW in 2000. The electricity generated from renewables (excluding hydropower) has also increased from a share of 2.1% in 2000 to 10.7% in 2019. Several factors drive this increased adoption of renewables in the US, to name a few: technology cost decline, emissions regulations, and incentive policies. The evaluation of the efficiency and effectiveness of various policies in driving RE adoption and electricity generation has been a focus point of many empirical studies. Tax incentives, rebates, and grants are found to be effective in promoting renewable energy capacity (Hitaj, 2013; Kilinc-Ata, 2016; Sarzynski et al., 2012). RPS policy implementation is also effective in stimulating RE investment and deployment but did not significantly increase the share of RE generation (Carley, 2009).

Both federal and state governments have spent substantial financial investments to implement renewable energy policies. The 2009 American Recovery Act allocated more than $25 billion for supporting renewable power generation (Aldy, 2013). Federal government spending on subsidies related to renewables was about $6.7 billion in 2016, 93% of which was through tax-related support and direct expenditure (US EIA, 2018). State government’s renewable energy funding noticeably emerged in the late 1990s with as high as a $135 million annual funding program in California for a duration of 13 years (Bolinger et al., 2001). CA also has a statewide budget of $3.3 billion to promote solar power in the state (CPUC, 2020). As a result of such large public spending, it is crucial to evaluate the efficiency of government policies from environmental, economic, and technological perspectives.

1.2 Literature review

There is a significant body of literature that estimates the near-term environmental effects of clean energy subsidies. Prior work on the direct costs and benefits of subsidies is detailed and covers a variety of technologies. Michalek et al. (2011) use life-cycle assessment and environmental risk modeling to compare emissions damage reduction from the adoption of EVs with the environmental externalities and oil cost of conventional vehicles in the US. Their work shows that the direct social benefits of owning and operating EVs with large battery packs are far less than the cost of EV subsidies. Sexton et al. (2018) investigate the effectiveness of state and federal subsidies for rooftop solar and calculate direct pollution avoidance benefits, showing that subsidy levels and resulting environmental benefits are uncorrelated. The authors identify states with generous subsidies that exceed avoided environmental damages and other states with subsidies lower than environmental benefits. Hughes and Podolefsky (2015) estimate the economic cost of rebate programs for residential solar photovoltaic installations in California and compare that with monetized benefits from reduced electricity generation and CO_2 emissions savings. They find that the benefits are moderate compared to other efficiency programs, such as utility-based demand-side management (Gillingham et al. 2006). Frondel et al. (2010) examine the renewable energy policy in Germany by comparing the cost of government investment in renewable energy promotion with its benefits in terms of climate impact, job creation, and technological innovation. They conclude that the cost of government support is higher than the benefits.

While these studies provide a detailed examination of the environmental benefits directly resulting from adoption, they do not incorporate the potential impact of subsidy policy on technological learning and consequent long-term effects on adoption. Prior literature on optimal subsidy has considered the learning effect for several different policy objectives, such as attaining an increased share of clean energy generation (Kim and Lee, 2012; Dong, 2014), achieving a target adoption rate (Hsu, 2012; Jeon et al., 2015; Lobel and Perakis, 2011), or improving performance through R&D investment (Shrimali and Baker, 2012). From a social welfare perspective, van Benthem et al. (2008) developed a model to assess the economic efficiency of subsidies that correct environmental externalities and induce learning-by-doing. The model is applied to evaluate the residential PV subsidy in California, which shows that, in the case of the California Solar Initiative (CSI) program, the subsidy is economically justified only if spillover benefits from learning is taken into account. Wand and Leuthold (2011) take a similar approach to evaluate the social net benefit of feed-in tariffs for residential solar PV installations in Germany. They show that an optimal solar PV feed-in tariff varies under different scenarios of solar cell technology and economic growth.

1.3 Knowledge gap

Given the body of literature discussed above, there are critical knowledge gaps to fill when investigating the design of efficient policies that support clean energy technologies. The first area is practical application: there is a lack of work connecting system modeling to practical decisions faced by policymakers. What is the appropriate extent and duration of a subsidy? Van Bentham et al. (2008) conclude that California policymakers made the "right" choice from 2006-2016. Lobel and Parekis (2011) argue that Germany should have larger upfront subsidies that declined more quickly. Jeon et al. (2015) develop a systems dynamics model and find separate allocations for research and development versus adoption subsidies. These are informative results, but clearly more work is needed to corroborate as well as assess other decision attributes important to policymakers. In addition to this, an important question relates to the appropriate geographic unit over which to implement a subsidy: should the solar subsidy in

California and Maine be identical? Currently, in the US, the federal subsidy for solar is equivalent nationwide, though individual states often supplement this with their own programs. However, the financial benefits of solar panels vary widely by location, i.e. NPV of adoption is higher in states with higher solar insolation and electricity prices. The public benefits of solar panels, specifically emissions reductions in carbon and other pollutants, depend on the electricity system in which they reside, which also varies by state. It is thus important to consider how heterogeneity between areas affects the appropriate geographic unit and values for subsidies. A second priority is to examine the arguments and justifications for subsidizing different clean energy technologies. E.g., how do residential solar subsidies compare with utility solar or wind? One approach is to identify how technological characteristics such as diffusion patterns, technological progress, and environmental benefits affect and drive the subsidies for these technologies. The third point is considering the impact of model and parameter uncertainties on policy design. Most prior authors recognized that subsidy outcomes are sensitive to uncertain parameter values such as learning rates, future electricity prices, and externality costs. While uncertainty in forecasting complex energy systems will not be resolved anytime soon, it is important to progressively improve modeling of each component and better characterize how qualitative outcomes depend on both model structure and parameter selection assumptions.

1.4 Research goals and novel contributions

Governments justify implementing renewable energy subsidies on the grounds of public-good argument through environmental benefits and technology development. But it is not clear how both federal and state governments set and decide on the levels and durations of these policies. This dissertation addresses this matter by developing a comprehensive assessment and modeling approach to design optimal policies from society's perspective. The main goal of this study is to inform policymakers by providing quantitative analysis and analytical tools accounting for different factors that play a role in designing efficient policies. These include consumer demand growth rate, technology attributes, and geographic heterogeneity.

This research develops an integrated framework to analyze clean energy technology subsidies. The model can easily be adapted to evaluate other forms of policies and can flexibly be applied to different types of emerging technologies at the desired geographic aggregations and timeframes. In addition, the topics covered using the framework are directly related to the field of sustainability. From society's perspective, it studies how governments can promote clean energy technologies by directly targeting end-use consumers and delivering social benefits. From an environmental standpoint, the research constitutes an analysis of emissions reduction potential of government policies. It uses geographically resolved dispatch level metrics to evaluate emission reductions and damages avoided from greenhouse gases (CO_2)

and criteria pollutants (NO_x, SO_2, and PM). Economic-wise, benefit-cost analysis is performed to design optimal policies that maximize net benefits. The contribution of this dissertation lies in the comprehensive analysis of government policies integrating these three components, accounting for the cross-over interaction with technological progress, and evaluation under different technology diffusion modeling alternatives.

The main research question of this dissertation is:

> *How can government policies be informed for socially optimal benefits by combining environmental and technological benefits and accounting for techno-economic characteristics and uncertainties in different model components?*

This study explores the design of a socially optimal government subsidy schedule for renewable energy technologies and covers the following three specific research areas.

Research Question 1: What is the optimal subsidy for residential solar?

> In Chapter 2, this research develops an integrated framework that comprehensively accounts for current and future expected benefits and costs of clean energy technology policies. The study implements improved adoption and emissions valuation models by accounting for state and consumer heterogeneity.

Research Question 2: What are the roles of diffusion patterns, technological progress, and environmental benefits in determining renewable subsidies?

> Chapter 3 uses the integrated framework to quantify the effect of adoption, technology cost reductions, and environmental benefits on optimal subsidy plans. The study presents a case study of optimal subsidy design for residential solar PV and utility-scale wind.

Research Question 3: What are the effects of technology diffusion model uncertainties on optimal subsidy design?

> In Chapter 4, we consider three different adoption models with three different combinations of explanatory variables. The study uses an inter-model comparison to analyze the effect of varying modeling alternatives on optimal subsidies for residential solar PV.

Chapter 2: What is the optimal subsidy for residential solar?

2.1 Introduction

In 2019, CO_2 emissions from the electric power sector was about 1,600 million metric tons (US EIA, 2020b), of which, 38% was from the residential sector. This makes the residential sector to be the highest electricity related end-use CO_2 emissions generator (US EIA, 2020c). To address such environmental emissions, federal and state governments have implemented various policies to support clean energy technologies. These policies target both supply-side and demand-side deployments using subsidies, emissions taxes, performance standards, cap and trade, technology quotas, or outright banning of undesirable technologies or materials (Goulder and Parry, 2008). Among these different policy instruments, this work focuses on subsidies, which are regarded as an important policy approach to driving adoption of clean energy technologies, especially those that are less mature (Carley, 2009; Kilinc-Ata, 2016; Polzin et al., 2015). A subsidy is an attractive policy instrument because it provides a direct financial incentive which lowers the cost of adopting the technology (Abolhosseini and Heshmati, 2014) and is generally preferred by technology investors over other policy tools (Bürer and Wüstenhagen, 2009; Kasemir et al., 2000).

Two main conceptual arguments are used to justify clean energy subsidies. The first is that the subsidy directly drives consumer adoption of clean energy technologies, reducing the use of fossil fuels and yielding environmental benefits in the form of reduced emissions. The second justification for energy technology subsidies argues that the government can play an important role in stimulating market development and continued improvements of socially desirable technologies. By changing the relative price of adopting clean energy technologies, the subsidy can create a market for these technologies, drive post-adoption innovation (Nemet, 2009), and enable learning by doing (Arrow, 1962). The induced technological learning may lead to a substantial amount of cost-reduction or performance-enhancing improvement in existing technologies, thereby activating broader adoption.

The two conceptual arguments for economic justification of renewable policies are incomplete on their own: the first (direct environmental benefit) neglects an explicit role for government in supporting promising emerging technologies and innovations, while the latter (indirect innovation benefit) ignores the fact that some technologies may take too long to be competitive or have too little environmental benefit to justify current production subsidies. Considering only one of the two justifications can result in underestimation of the total benefit of the subsidy.

2.2 Literature Review

To date, only a handful of studies have attempted to estimate the optimal government subsidy of residential solar, considering different types of subsidies, e.g., a one-time investment subsidy offered at the time of initial installation vs. an operational subsidy like Feed-in-Tariff (FIT) that pays above-market prices for solar-generated power. Van Bentham et al. (2008) provide the first benefit-cost analysis of solar investment subsidies accounting for the interaction of technological progress and diffusion. The authors study residential solar subsidies in California using an experience curve to describe cost reductions, developing a simple adoption model that depends on Net Present Value (NPV) and monetizing benefits from carbon and criteria pollutant emission reductions. Their results indicate that the existing California Solar Initiative (CSI) program was similar to the optimal subsidy in maximizing public benefits. Wand and Leuthold (2011) study the FIT policy in Germany using a similar model, finding that public benefits of optimal subsidy varied by design and extent depending on scenarios for driving variables such as electricity prices, cost of environmental externality, and PV market growth rates. Lobel and Parekis (2011) also analyze solar FIT schedules in Germany, finding that optimal schedules started with higher subsidy and declined faster than the implemented national subsidy. Studies after these varied in aspects of model and geography. Alternate optimization objectives were considered, maximizing adoption with fixed budget (Dong, 2014; Jeon et al., 2015) and minimizing subsidy expenditures to achieve different goals.

This chapter follows on the above literature to design optimal subsidy schedule for residential solar PV in the US. The study conducts the analysis at the state level and estimates state-specific adoption of solar panels, and environmental benefits using the marginal emissions factors that account for heterogeneity in electricity systems. We aggregate the state-specific benefits at the national level and estimate a uniform federal optimal subsidy that maximizes total nation-wide net social benefits. We also examine the distribution of these benefits across states under a homogeneous national-level subsidy schedule. We further estimate a state-by-state optimal subsidy schedule that yields greater national benefits. The model accounts for observed adoption patterns of homeowners, technological progress via an experience curve, and a sophisticated locationally-resolved evaluation of emissions reductions.

This work contributes to methods and applications of modeling optimal subsidies. For methodological contribution, we draw on developments in modeling of solar diffusion, electricity system emissions, and valuation of pollution damages to develop an improved model linking adoption, technological progress, and subsidy design. First, for diffusion, we use the model recently developed by (Williams et al., 2020) that explains PV diffusion as a function of NPV as experienced by consumers. While qualitatively similar to the diffusion modeling in Van Bentham et al. (2008) and Wand and

Leuthold (2011), the model has a different functional form and definition of variables and has been shown to be empirically robust with same parameter values in five different regions (California, Massachusetts, Arizona, Germany and Japan) (Williams et al., 2020). Second, there is increasing recognition that emissions reductions due to a demand shift, such as from solar panels, are better described via marginal as opposed to average emissions (Siler-Evans et al., 2013). The core issue is that average emission factors assume that the operation of all power plants changes when a demand change is introduced to the grid, while marginal emissions account for observed changes in generation mix, generally for the power plant at the margin (Hawkes, 2014). Third, there has been an evolution in risk assessment valuations of criteria air pollutants such as SO_2, NO_X, and particulate matter (PM). Improved knowledge and modeling of chemical transformations of pollutants enables more accurate estimates of concentrations (Azevedo et al., 2019). Also, recognition of locational variations in pollutant damages has led to more geographically resolved models of social costs (ibid), which we integrate into this work. In the application of optimal subsidy modeling to policy, our primary goal is to explore the effect of different geographical aggregations on benefits and costs, in particular to compare a nationwide subsidy versus one that varies state-by-state in the US.

2.3 Methods

This study conducts a benefit-cost model of residential solar in the US, with a time horizon of 2018-2047. We conduct the analysis at the state level and estimate state-specific adoption of solar panels, and environmental benefits using the marginal emissions factors that account for heterogeneity in electricity systems. We aggregate the state-specific benefits at the national level and estimate a uniform federal optimal subsidy that maximizes total nation-wide net social benefits. We also examine the distribution of these benefits across states under a homogeneous national-level subsidy schedule. We further estimate a state-by-state optimal subsidy schedule that yields greater national benefits. The model accounts for observed adoption patterns of homeowners, technological progress via an experience curve, and a sophisticated locationally-resolved evaluation of emissions reductions.

The integrated model developed in this research constitutes three modules: adoption, technology progress, and benefit-cost analysis (Figure 1). The model is applied to assess the interaction between subsidy, adoption, technological progress, and social benefits over time. Specifically, we expect that adding a subsidy leads to increased immediate solar PV adoption, which then drives technological learning and cost reductions of the technology. The technological progress resulting from initial "induced adoption" will in turn increase PV adoption in the following years. We estimate the benefits as monetized emissions reductions from total induced technology adoption, which includes those directly stimulated by the subsidy and the follow-on adoption driven by the technology price reductions. From the government's perspective, we calculate the net benefit nationwide as the total emission reduction benefits minus the government's expenditure on subsidies, both discounted to present value. Using this analytical framework, we compare and evaluate the effects of different subsidy schedules relative to results under a "no-subsidy" case, where adoption and technology progress still occur but are not stimulated by government subsidy.

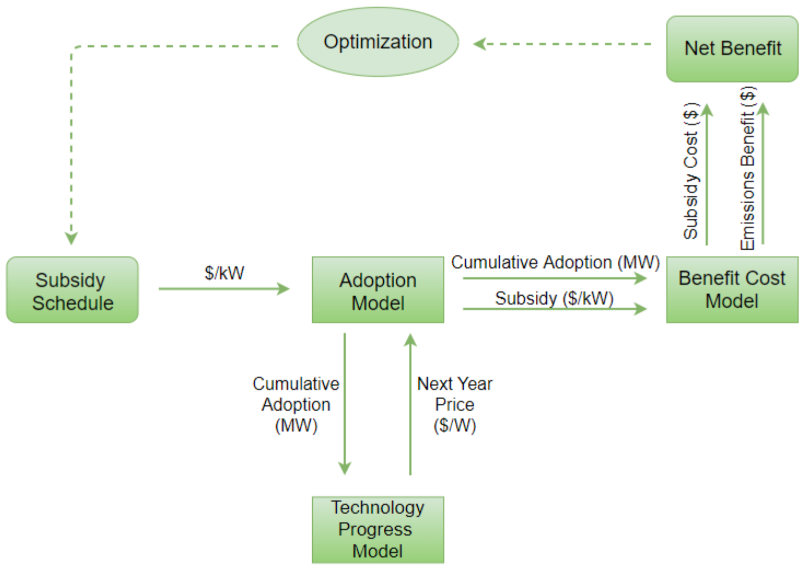


Figure 1. Summary of integrated model combining adoption, technological progress and benefit-cost analysis. A simple optimization routine is applied to this model to identify the subsidy schedule that maximizes discounted net benefits.

The three models that constitute the integrated framework are discussed below.

2.3.1 Adoption Model

Various models have been developed to predict the adoption rate or purchase decision of a consumer as a function of time, economic cost and benefit, demographics, and environmental attitudes. These include Bass diffusion modeling (Guidolin and Mortarino, 2010), discrete choice models (Islam, 2014), and agent-based models (Macal et al., 2014; Noll et al., 2014; Rai et al., 2016; Zhang et al., 2016). For this study, with the goal of integrating the adoption model into a larger framework, we use a parsimonious model with minimal regressors that are reducible to plausible assumptions about fundamental system interactions. This adoption module uses a technology diffusion model developed in Williams et al., (2020). The model is constructed for residential solar PV diffusion and uses regression parameters whose values have straightforward interpretations in terms of the system's dynamics. It starts with one explanatory variable, Net Present Value (NPV) as experienced by residents in a particular region, to explain the rate of adoption. The NPV of a residential PV system can be written as:

$$NPV_k^j\left(\frac{\$}{kW}\right) = (-I^j + S^j) + \sum_{i=1}^{N} \frac{E_k * P_k}{(1+int)^i}\frac{1}{CAP} \tag{1}$$

where j is a year in a US state k. I^j is the investment cost ($/kW) of the PV system, S^j is the subsidy investment ($/kW), e.g. a 30% federal tax rebate in the US. The subsidy, S^j we consider in this study is a capital subsidy that offsets the initial upfront cost of PV installation. The choice of this type of subsidy is based on the current/historical US federal government investment tax credit support for roof-top solar. There are other subsidy mechanisms, such as Feed-in-Tariffs (FIT), used e.g. in Germany and Japan. Empirical evidence from the diffusion model (Williams et al 2020) suggests that to a first approximation, effects of adoption by government support can be modeled by its effect on Net Present Value and is not tied to any specific form. E_k (in kWh) is the annual electricity production based on solar resources and P_k ($/kWh) is the average price of selling electricity to the grid in state k. P_k corresponds to the retail electricity price in each state. The formula assumes net metering, pervasive in the US, in which residential PV systems earn the retail price for all electricity generated. CAP is the nominal capacity of the PV system, taken as 5 kW (US EIA, 2017a), int is the real discount rate with default value of 3% and N is the expected lifetime of a solar PV system which is considered to be 20 years. All monetary values are adjusted in real 2018 dollars.

Based on the approach in Williams et al. (2020), we assume that the annual residential solar installation, normalized to the number of detached homes without PV, follows a normal distribution as a function of NPV. For a given NPV, the number of consumers who will purchase is the integral of a normal distribution (Equation 2).

$$Adoption_k^j\left(\frac{MW}{million\ houses}\right)(NPV) = \alpha \int_{-\infty}^{NPV} dx\, e^{-\left(\frac{x-\mu}{\sigma}\right)^2} = K\left(1 + \mathrm{erf}\left(\frac{NPV-\mu}{\sigma}\right)\right) \tag{2}$$

where erf(x) is the error function, μ is the peak customer acquisition value and σ is the spread in this value. The values of μ and σ, determined in the original model empirically from observed price/adoption data, are 7,100 $/kW and 4,110 $/kW, respectively. K is a constant fixed at 2,000 kW/million free households. Williams et al. (2020) test the model using 47 data points for annual adoption and NPV in five regions (three US states: Arizona, California, and Massachusetts and two countries: Germany and Japan) from 2005-2016. The model fit to data is surprisingly tight considering its simplicity: The Root-Mean-Square-Error in adoption rate is 17 MW/million households and the average value of adoption rate in the dataset is 41 MW/million households.

We use the adoption model outlined above along with data on state-level total cumulative PV adoption and number of households with solar PV installations in 2017 to project annual adoptions starting from 2018 given a certain federal subsidy. The data are collected from the US Energy Information Administration (EIA) (US EIA, 2017b). We also use the average electricity price in state k, P_k obtained from EIA's electric power monthly report (US EIA, 2018) and annual electricity production, E_k using the PVWatts® model from the National Renewable Energy Laboratory (NREL). We use the total number of households that have already installed PV at the initial year of the analysis and total number of detached houses in a given state, obtained from the US Census Bureau (2011), to determine the total number of potential free households installing PV in the next year. A state's annual adoption is determined by multiplying the results of Equation 5 with the estimated number of potential free households. The model then estimates the total number of households installing PV annually by taking the ratio of annual adoption and the average household PV system size, which in turn is used to determine the remaining number of detached households that are yet to install PV. The results of annual state-level adoption are summed up to determine national level annual adoption which in turn is used to estimate national cumulative adoption (P^j). Cumulative adoption is used as an input for the technology model to determine the cost of installing PV technology. The following variables are used to estimate the state-level annual adoption (MW).

$hh\ with\ PV_k^j\,(million\ houses)$ – is the number of detached households with PV

$hh\ without\ PV_k^j\ (million\ houses)$ – is the number of free detached households without PV

$$Annual\ Adoption_k^j\ (MW) = \ Adoption_k^j\left(\frac{MW}{million\ houses}\right)(NPV) * hh\ without\ PV_k^{j-1},\ \ 1 < j < 30 \qquad (3)$$

The analysis uses data for 2017 as the base or initial year ($j = 0$) and estimates the adoption starting from 2018 ($j = 1$) to 2047 ($j = 30$).

For $j > 0$, the model estimates the number of households installing PV annually by dividing the annual adoption (Equation 3) with the PV system size of 5 kW (5000W). This in turn is used to determine the remaining number of detached households that are yet to install PV.

$$\begin{matrix} hh\ with\ PV_k^j \\ (million\ houses) \end{matrix} = \frac{Annual\ Adoption_k^j\ (MW)}{5000\ W}, \qquad where\ 1 < j < 30 \qquad (4)$$

$$\begin{matrix} hh\ without\ PV_k^j \\ (million\ houses) \end{matrix} = \begin{matrix} hh\ without\ PV_k^{j-1} \\ (million\ houses) \end{matrix} - \begin{matrix} hh\ with\ PV_k^j \\ (million\ houses) \end{matrix},\ \ where\ \ 1 < j < 30 \qquad (5)$$

2.3.2 Technological Progress Model

The technological progress model is based on a modification of the one-factor experience curve. Developed first to describe cost reductions in aircraft manufacturing (Wright, 1936), the experience curve is an empirically observed power law decay of some characteristic of industrial processes and cumulative experience implementing that process (Teplitz and Carlson, 1991; Yelle, 1979). In the energy domain, the experience curve takes the form:

$$C^j\left(\frac{\$}{W}\right) = C^0\left(\frac{P^{j-1}}{P^0}\right)^{-\alpha} \qquad (6)$$

where P^j is a measure of cumulative adoption of a technology (e.g., the total watt capacity of solar cells produced), C^j is the technology price per energy unit (e.g., \$/W_p or \$/kWh), C^0 and P^0 are initial cost and production values, and α is a (positive) empirical constant, known as the learning coefficient. α is related to the fractional reduction in costs for every doubling of production, known as the Learning Rate, given by the equation $LR = 1\text{-}2^{-\alpha}$. Despite its simplicity, the above equation fits empirical data quite well. Nagy et al. (2013) showed that R-squared exceeds 90% for a majority of 62 technologies. While there are more complex models that separate learning into separate factors such as learning-by-doing, learning-by-research, materials and other factors (Nemet, 2006; Pillai, 2015), understanding such distinctions is not the purpose here, so the empirically robust single factor curve above is used.

The technological progress model uses time series data from Solar Energy Industries Association (SEIA) and International Energy Agency (IEA) reports on production and cost of residential PV in the US. Using these data, we estimated a technology learning rate (LR) of 15% (IEA, 2017; SEIA, 2017). Initial cost, C^0, and cumulative production, P^0, are taken as 3.84 \$/W (real \$2018) and 10,318 MW, representing the state of US residential solar at the end of 2017. Technology price projections are made starting from 2018 using Equation 6.

The technological progress model assumes learning and technological cost reductions at the national scale and uses the estimate of the national cumulative adoption. The state-level annual adoption are aggregated to determine the national annual adoption.

$$National\ Annual\ Adoption^j\ (MW) = \sum_{k=1}^{51} Annual\ Adoption_k^j\ (MW) \qquad (7)$$

The national cumulative adoption of the technology in a year j is given by Equation (8).

$$P^{j} = P^{0} + \sum_{i=1}^{j} National\ Annual\ Adoption^{i}\ (MW), \quad j > 0 \qquad (8)$$

The adoption and the technological progress models are interdependent and are run iteratively: set a subsidy level, calculate expected adoption in the first period, use that adoption to estimate technological progress and resulting price in the second period, which dictates adoption in the second period, etc.

We tested state-level experience curves that separated module and balance-of-system costs but found that there was insufficient data to support that approach. Thus, the technology progress model has US residential PV adoption following a single national experience curve. Note that PV adoption at commercial and utility scales as well as elsewhere in the world has spillover effects affecting US residential solar prices. We assume that US residential adoption more or less tracks global adoption in all markets and have verified that this assumption is reasonable in historical behavior of solar markets. We consider our assumption to be a reasonable approximation after looking at the historical data on both US residential and global PV adoption. The global solar installation trend over time is compared with the US residential adoption using different starting years. If the initial year is set to be 2004, the US is adopting residential PV much faster than the rest of the world implying that the US observes a smaller effect of learning rate as the global installation is not contributing enough to the cost reduction. On the other hand, for the most recent years like 2010, the two growth rates roughly come closer to each other. The spillover effect from the global PV adoption as well as US commercial and utility scale PV installation is observed to progressively reduce over the years. We find the later trend to be more relevant for a model projecting future adoption rates, hence, a single learning rate is employed.

2.3.3 Benefit-Cost Model

The emissions model is based on the established literature regarding the current and expected future environmental benefits of emerging clean energy technologies. This includes several studies looking at the environmental benefits from the adoption of wind, solar, and electric vehicles (Cullen, 2013; Nugent and Sovacool, 2014; Siler-Evans et al., 2013; Sioshansi and Denholm, 2009). This body of literature uses different approaches depending on the technology studied but tends to follow a common process: study the effect of adoption on electricity system dispatch, estimate resulting upstream and downstream emissions changes, and run a physical environmental risk analysis (fate/transport, exposure, and dose/response).

Assessment of emissions reductions is determined using marginal emissions factors linked to estimated damages from specific power plants. Marginal emission factors (MEFs) are quantities that reflect the emission intensity of those conventional power generators that are displaced in response to a given intervention (Siler-Evans et al., 2012). MEFs are reliable measurements (Siler-Evans et al., 2013) used when assessing the avoided emissions attributed to the displaced conventional electric power generator as a result of the adoption of clean energy technology. This research employs MEFs generated by Azevedo et al., (2019). Their model is based on regression analysis of hourly generation and emission data to estimate regional MEFs for CO_2, NO_x, SO_2 and PM2.5 for the US electricity system. The emission model further estimates the avoided damage from reductions of CO_2, NO_x, SO_2 and PM2.5 emissions based on existing literature and models (Heo and Adams, 2015) that estimate social costs and marginal damage factors (MDFs) of emissions (Azevedo et al., 2019).

The data for the marginal emission and damage factors are disaggregated into 22 eGRID regions. Since our analysis is done at the state level, the particular eGRID region a state belongs to is determined using the US Environmental Protection Agency (EPA) Power Profiler tool (US EPA, 2018b). The eGRID region that covers the highest number of zip code areas in a given state is taken as the representative region for that state. Averages of the hourly marginal emissions data between 9 am – 3 pm for the year 2016 are used to estimate the total emissions avoided in each state. The 2016 average marginal damage data is used in our base case analysis for pollutants and a social cost of $45/ton (ton = metric ton) is used for determining CO_2 emissions damage. Though marginal emissions factors have been more consistent than average emissions factors as the grid composition have shifted, cleaner future grids may have lower MEFs than today.

The Benefit-Cost model starts with estimating the discounted environmental benefit of a 1MW solar PV system over a lifetime of N = 20 years ($EB20$). This is performed for each state using state-specific capacity factors. The energy generation from 1MW of solar PV system is given by:

$$Generation_k\ (MWh) = 1MW * CF_k * 8760\ h \tag{9}$$

where CF_k – is the capacity factor in state k. We assume that the annual energy generated from the solar PV degrade at 0.5%/year. We used 0.5% after looking at the degradation rate of five current PV modules available in the US market whose production is expected to increase in the coming years (Feldmand and Margolis, 2018). Hence,

$$Annual\ Genration\ {}_k^j(MWh) = Generation_k * (1 - R_d)^{j-1} \tag{10}$$

where R_d – is the degradation rate. Marginal emissions and damage factors are employed to estimate the amount of emissions and damages that can be avoided as a result of the estimated annual generation. The damage that can be avoided from CO_2 emissions reductions is estimated using CO_2 marginal emissions factors (MEF) and a social cost of carbon of \$45/ton (Equation 11 and Equation 12).

$$voided\ CO_2\ Emissions_k^j\ (ton) = \ Annual\ Genration\ _k^j\ (MWh) * \ MEF_{CO_2,k}\left(\frac{ton}{MWh}\right) \tag{11}$$

$$Avoided\ CO_2\ Damage_k^j\ (\$) = Avoided\ CO_2\ Emissions_k^j\ (ton) * 45\left(\frac{\$}{ton}\right) \tag{12}$$

For criteria pollutants (NO_x, SO_2 and PM), we used the respective marginal damage factors (MDF) to estimate the resulting avoided damage (Equation 13).

$$\begin{aligned} &Avoided\ Criteria\ Pollutants\ Damage_k^j\ (\$) \\ &\quad = Annual\ Generation_k^j\ (MWh) * \left(MDF_{NO_x,k} + MDF_{SO_2,k} + MDF_{PM,k}\right)\left(\frac{\$}{MWh}\right) \end{aligned} \tag{13}$$

Equation 12 and 13 are summed up to estimate the annual damage that can be avoided from 1MW of solar PV installation accounting for both CO_2 and criteria pollutants emissions reduction.

$$Avoided\ Damage_k^j\ \left(\frac{\$}{MW}\right) = Avoided\ CO_2\ Damage_k^j + \ Avoided\ Criteria\ Pollutants\ Damage_k^j \tag{14}$$

By using Equation 14, we estimate the discounted benefit from 1MW solar PV system over a lifetime of N = 20 years as:

$$Env.Benefits_k\ \left(\frac{\$}{MW}\right) = \sum_{j=1}^{20} \frac{Avoided\ Damage_k^j}{(1+DR)^j} \tag{15}$$

where DR – is the discount rate. Based on the discounted 20-year benefit of a 1 MW solar PV, we can estimate the discounted benefit resulting from any given annual adoption. For $Annual\ Adoption_k^j\ (MW)$ in a given year j and state k, the annual discounted benefit is given by:

$$Discounted\ Annual\ Benefit_k^j(\$) = \ Annual\ Adoption_k^j\ (MW) * \frac{Env.Benefits_k\ \left(\frac{\$}{MW}\right)}{(1+DR)^j} \tag{16}$$

We considered the benefit from residential solar PV installations to last over 30 years ($1 < j < 30$), hence, the cumulative discounted benefit is estimated by aggregating the annual values estimated in Equation 16.

$$Discounted\ 30\text{-}year\ Benefit_k(\$) = \sum_{j=1}^{30} Discounted\ Annual\ Benefit_k^j(\$) \tag{17}$$

The model estimates the benefit resulting from a given subsidy schedule relative to the discounted benefit of a no-subsidy counterfactual case where S^j = 0.

$$Benefits_k(\$) = \begin{pmatrix} Discounted\ 30\text{-}year\ Benefit_k \\ with\ subsidy\ (S^j) \end{pmatrix} - \begin{pmatrix} Discounted\ 30\text{-}year\ Benefit_k \\ without\ subsidy\ (S^j = 0) \end{pmatrix} \tag{18}$$

The discounted annual government cost as a result of subsidy, S^j in year j is given by:

$$Discounted\ Annual\ Gov.Cost_k^j\ (\$) = \frac{S^j *\ Annual\ Adoption_k^j}{(1 + DR)^j} \tag{19}$$

Hence, the cumulative government cost is estimated by:

$$Costs_k(\$) = \sum_{j=1}^{30} Discounted\ Annual\ Gov.Cost_k^j \tag{20}$$

The net benefit in a given state k is:

$$Net\ Benefit_k(\$) = \ Benefits_k(\$) - Costs_k(\$) \tag{21}$$

The national net benefit is the sum of the state-level net benefits for each of 50 states plus Washington, DC.

$$National\ Net\ Benefit\ (\$) = \sum_{k=1}^{51} Net\ Benefit_k(\$) \tag{22}$$

Similarly, the total government cost at the national level is given by:

$$National\ Govenment\ Cost\ (\$) = \sum_{k=1}^{51} Costs_k(\$) \tag{23}$$

2.3.4 Optimizing subsidies to maximize benefits

The subsidy considered is an initial capital cost subsidy ($/kW), with the same amount paid to any consumer in an area. The adoption model from 2.3.1 aggregates all consumers in a region, i.e. it does not distinguish between different incomes or demographic characteristics. Early adopters are expected to mainly be high- and medium-income households – income-differentiated subsidies to encourage adoption by lower income households are not treated here. We allow subsidies to have a variable schedule and use cost-benefit analysis to find the unique schedule that results in the highest net benefits.

National Flexible Subsidy: In this case the capital subsidy is constant over the US (like the Federal Tax Credit and flexible in the sense that it can freely vary in value each year. The decision variables for optimization are values of the subsidy in each year, S^j ($j = 1 \dots 30$). The optimization model is formulated as:

Decision variables:

$$S^j \left(\frac{\$}{kW}\right), \qquad for \;\; 1 \leq j \leq 30$$

Objective function:

$$\max \left(National\ Net\ Benefit\right) = \max \left(\sum_{k=1}^{51} Net\ Benefit_k\right) \qquad (24)$$

State-by-state Flexible Subsidy: In this case the capital subsidy can vary by year and by state. The subsidy decision variable is a 51x30 matrix, S_k^j, where the index k indicates state and j the year of the subsidy.

Decision variables:

$$S_k^j \left(\frac{\$}{kW}\right), \qquad for \;\; \begin{matrix} 1 \leq j \leq 30 \\ 1 \leq k \leq 51 \end{matrix}$$

In this case, the set of 51 different subsidy schedules (including Washington, DC) are jointly optimized to maximize the national net benefit same as $Eq. (24)$:

We implement the optimization model with Excel Solver and using a nonlinear Generalized Reduced Gradient (GRG) algorithm. For nonlinear optimization, Baker (2015) discusses that the solutions from Solver are local optimum and that there is no guarantee for the results to be global optimum solutions. But having additional information on the characteristics of objective function (the net benefit in this case) may help to understand the solution better. While assessing the functionality of the integrated framework and estimating the net benefit resulting from different fixed and declining subsidy schedules, it is observed that the graph of the objective function against the decision variables has a similar shape to a concave function. This may suggest that the local maximum identified can be considered as the best solution. This optimization method has also a Multistart option for global optimization, which applies

Continuous Branch and Bound methods. In this case, the optimization automatically chooses different starting points for the decision variable selecting the best solution from different locally optimal solutions. We did the analysis both with and without this option and the two converge to the same answer. The optimal state-by-state flexible subsidy that is different across US states is implemented using Microsoft Excel OpenSolver Add-in. We used a nonlinear solver model known as COIN-OR Bonmin. This tool finds globally optimal solutions to convex nonlinear problems in continuous and discrete variables and may be applied heuristically to nonconvex problems. We ran the optimization model using different initial values and have obtained the same result each time.

2.3.5 Direct and indirect benefits

We define total benefits from a subsidy as the difference between the discounted 30-year benefit from reduced CO_2 and criteria pollutant emissions with subsidy and the discounted 30-year benefit from reduced CO_2 and criteria pollutant emissions with no subsidy. The benefit can be conceptually divided into two components: direct benefit and indirect benefit. Direct benefits are those that come from the additional solar panels that are adopted because of a policy, while indirect benefits are the effects that this policy has on future adoption through technological progress. These are reasonably distinct conceptually, but difficult to precisely separate mathematically. The approach we used tries to break down the two components by employing a simple adjustment to the integrated framework. When estimating the direct benefit, we assumed that the subsidy has no effect on the technology price reduction. Instead of running the adoption and technological progress models iteratively, an exogenous technological price that would follow the same trajectory as the counterfactual "no subsidy" case is used. The direct benefit is the discounted emissions reduction benefits resulting from subsidy induced adoption while disregarding the effect of the subsidy on technology progress. The indirect benefit is associated with the additional PV adoption driven by the subsidy-induced technological progress in the form of cost reductions (technology progress benefits through learning and innovation that is attributed to the government intervention).

We use the following quantitative separation of direct versus indirect benefits yielded by the optimal subsidy schedule. First, the learning curve is used with no subsides to develop a counterfactual trajectory of PV cost reductions without subsidy, denoted by ${C_o}^j \left(\frac{\$}{W}\right)$, with j being an index for year. Given $S^j \left(\frac{\$}{kW}\right)$, a schedule of PV subsidies, the resulting PV cost reductions become more rapid, denoted by $C^j \left(\frac{\$}{W}\right)$. PV adoption directly induced by the subsidy is:

$$Direct\ Induced\ Adoption = Adoption\left(S^j, {C_0}^j\right) - Adoption\left(S^j = 0, {C_0}^j\right), \qquad (25)$$

The indirect adoption induced is that due to the PV cost reductions resulting from the subsidy:

$$Indirect\ Induced\ Adoption = Adoption\left(S^j, C^j\right) - Adoption\left(S^j, {C_0}^j\right) \qquad (26)$$

The total induced adoption is the sum of equations (25) and (26), which is used in assessing net benefits.

2.3.6 Carbon abatement cost

Estimating the abatement costs of a subsidy provides a useful metric that can be compared with other mitigation options. We calculate public carbon abatement costs in terms of the subsidy expenditure by the government per mass of reduction. Note that is distinct from the usual definition of abatement cost, which assessing total costs, both public and private. From the perspective of government and allocation of public budgets, it is useful to know the public expenditures needed to mitigate carbon. This leads to the definition:

$$Carbon\ abatement\ cost\ (no\ criteria\ benefits)\left(\frac{\$}{ton}\right) = \frac{Government\ subsidy\ cost\ (\$)}{Total\ CO_2\ reduction\ (tons)} \qquad (27)$$

The denominator embodies the CO_2 reductions specifically attributable to the subsidy, as modeled by its effect on consumer adoption. Solar panels and other technology interventions lead to co-benefits in emission reductions in addition to carbon. The carbon mitigation cost accounting for co-benefits is defined as:

$$Carbon\ abatement\ cost\ (w/\ criteria\ benefits)\left(\frac{\$}{ton}\right) = \frac{Government\ subsidy\ cost\ (\$) - Criteria\ \ pollution\ benefits\ (\$)}{Total\ CO_2\ reduction\ (tons)} \qquad (28)$$

There are many prior analyses of total carbon mitigation cost for solar and other technology interventions (e.g. Das et al., 2020; Marcantonini and Ellerman, 2013), to our knowledge this is the first work to assess public mitigation costs as mediated through subsidy stimulated adoption.

2.4 Results and Discussions

2.4.1 Optimal national flexible subsidy starting in 2018

Figure 2 shows results for the optimal national flexible subsidy over the 30-year analysis period from 2018 through 2047. For comparison purposes, we also plot expected schedule for planned/historical US federal tax credits (FTC) that phase out between 2019 and 2022: a 30% tax credit for 2018-2019, 26% for 2020, 24% for 2021 and zero tax credit afterwards. The optimal national flexible subsidy starts at $585/kW and declines nonlinearly to zero after 14 years. The optimal flexible subsidy declines over time because it accounts for technological progress and the resulting cost competitiveness of the technology, reducing the possibility of providing incentives to "free riders" - consumers who would have purchased solar even without a subsidy. The table in Figure 2 shows outcomes from different subsidy schedules. First note that the model predicts substantial adoption of residential solar even without subsidy: 19% of detached households by 2047. This is partly because residential solar is economically attractive in some states (particularly Hawaii and California) and adoption in these states lowers prices for consumers in other states. This is also because the diffusion model assumes slow, but continuing, rates of residential solar even with low NPV. The planned FTC subsidy starts much higher than the optimal subsidy, and ends much sooner. The model thus suggests that at current prices a more modest subsidy than FTC would still encourage adoption, but that subsidy should continue longer due to persistent social benefits.

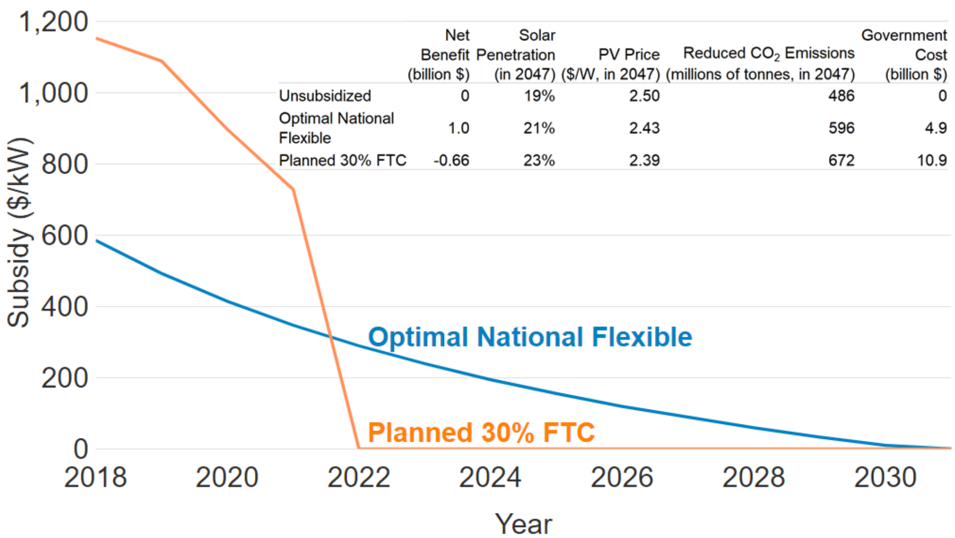


Figure 2. Schedules for optimal national flexible subsidy and planned/historical 30% Federal Tax Credit (FTC). These results assume real discount rate of 3%, learning rate of 15% and social cost of carbon of $45/ton. The net benefit is higher and government cost is lower for the optimal schedule compared to planned FTC ($1.0 billion net benefit and $4.9 billion cost versus -$0.66 billion net benefit and $10.9 billion cost).

Results are sensitive to the values of discount rate, learning rate, and the social cost of carbon. We conduct a variety of sensitivity analyses. Starting from base values of 3% for societal discount rate, 15% for learning rate and a social cost of carbon of $45/ton, we allow varying individual parameters to find the threshold value that results in negative net benefits. Results indicate that net benefits from subsidizing residential solar fall below zero if the discount rate is above 5%, the solar learning rate is below 6%, or the social cost of carbon is below $30/ton.

2.4.2 Retrospective early technology subsidy starting in 2012

Our model suggests that the government should subsidize clean energy technology in its early stage to maximize the technological learning benefits and gradually reduce the subsidy as the technology matures. To further examine this argument, we analyze an alternative retrospective case in which the analysis starts in 2012. Residential solar saw dramatic cost reductions from 2012 to 2018, so 2012 can serve as a baseline for the "earlier stage". The optimal national flexible subsidy is compared with a perpetual 30% FTC for rooftop solar systems. According to the results in Figure 3, our model suggests relatively high subsidies in the first few years, but aggressively reduces the subsidy over time in both absolute and percentage terms. While the results suggest that the perpetual 30% tax credit is too high today (about double the optimal national flexible subsidy in 2018), it was lower than optimal for the years up to 2014. This demonstrates the importance of subsidizing more at the early stage of technology adoption and decreasing the support over time as the technology becomes more cost competitive. It also suggests that if the government provided a more generous subsidy at the very early stage of technology development, it would have led to greater cost reductions at a faster pace and reduced the need for future subsidies that are increasingly accessed by free riders.

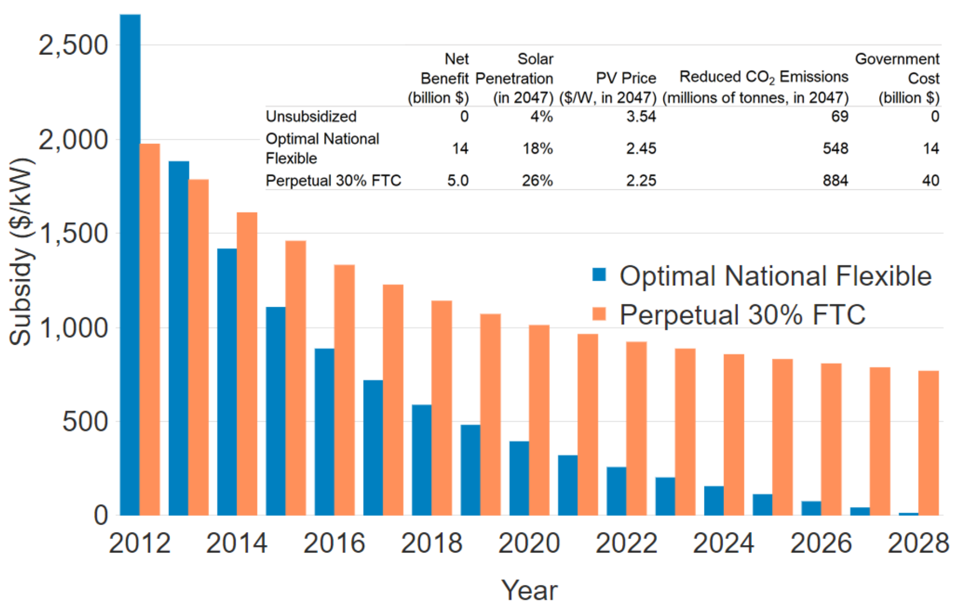


Figure 3. Optimal national flexible subsidy compared with a perpetual Federal Tax Credit (FTC) of 30% starting in the year 2012. This comparison shows that government subsidies for solar can be most beneficial when they are high at the early stage of adoption to get more learning benefits with fewer free riders, and then reduced over time as the technology becomes relatively mature. The results agree with the base case results suggesting that the 30% FTC is currently higher than optimal, but also show that the same 30% credit was too low for years before 2014.

2.4.3 Direct vs. Indirect benefits

In the introduction we distinguished between the direct environmental benefits of a subsidy, those due to stimulated adoption, versus indirect benefits, adoption due to future cost reductions driven by the subsidy. The direct benefit is the discounted emissions reduction benefits resulting from subsidy-induced adoption while disregarding the effect of the subsidy on technology progress. To calculate this, we assume that the technology price would follow the same trajectory as the counterfactual no-subsidy case, meaning that the effects of the subsidy are limited to offset emissions from direct adoption. The indirect benefit is associated with the additional PV adoption driven by the subsidy-induced technological progress in the form of cost reductions (technology progress benefits through learning and innovation that is attributed to the government intervention). We estimated direct and indirect benefits for the optimal national flexible subsidy. For the optimal national flexible subsidy schedule starting in 2018, 46% of benefits are attributed to the direct environmental benefit and 54% for the indirect technology innovation benefit (Figure 4). The total discounted benefit is $6 billion over the 30-year analysis period, with subsidy cost of $4.9 billion and the net benefit is $1.8 billion as indicated in Table 1. This demonstrates the importance of accounting for both direct and indirect benefits when justifying subsidy support. For the optimal national flexible subsidy schedule starting in 2012, we estimate that the indirect technology benefit accounts for 94% of the net benefits. The larger share for indirect benefits in 2012 versus 2018 is because that earlier subsidy leads to more significant long-term price reductions. This result asserts that the main justification for subsidizing early technology adoption is the long-term indirect technological progress and not the environmental benefits of immediate adoption. From another perspective, note that sensitivity analysis shows that solar subsidies are not justified if the learning rate falls below 6%. This indicates that neglecting technological progress when assessing the benefits of a subsidy can lead to qualitatively different results.

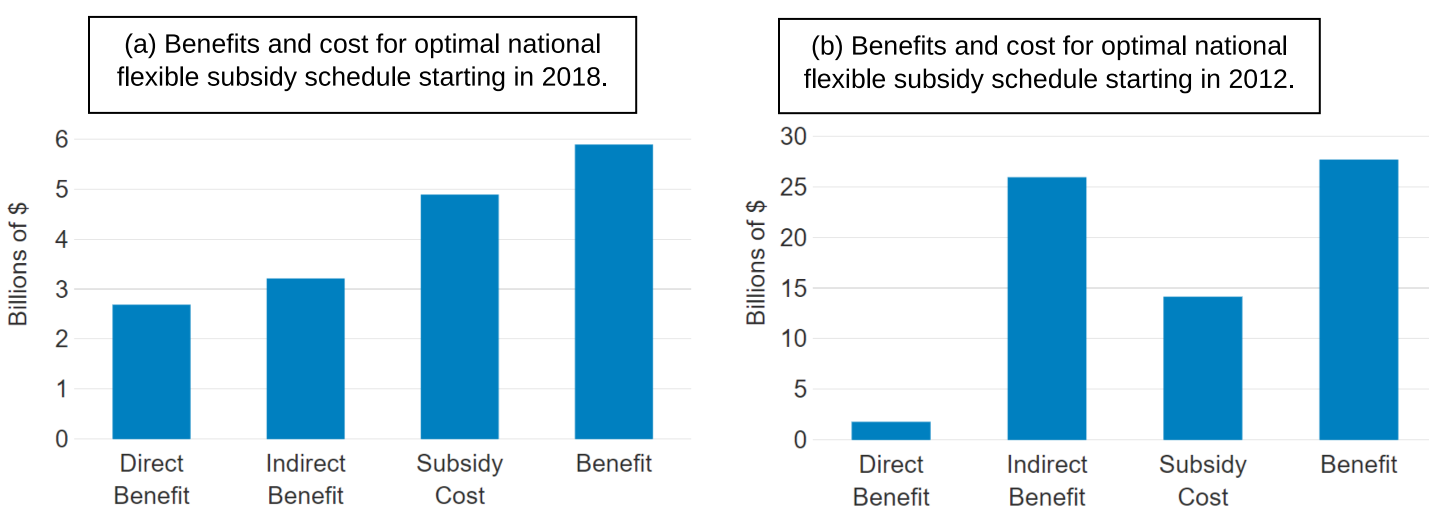


Figure 4. Direct and indirect benefits for the optimal national flexible subsidy schedule starting in 2018 (a) and early technology subsidy schedule starting in 2012 (b). This figure demonstrates the importance of both the direct environmental benefits and technological progress benefits when evaluating the economic justification of a subsidy schedule.

2.4.4 State-by-state heterogeneity and state-flexible subsidy

There is significant heterogeneity between states in economic and environmental benefits of residential solar, driven by differences in electricity prices, solar insolation and grid composition. We first clarify these differences by showing state-by-state results for our baseline optimal national flexible subsidy in Figure 5(a,b). This figure shows large differences by state. The highest per capita net benefit occurs in Wisconsin ($18/person), followed by New Jersey and Indiana ($16/person). In contrast, Hawaii (-$97/person), California (-$16/person), Connecticut (-$10/person) and Massachusetts (-$9/person) all show negative net benefits. Negative social net benefits occur in Hawaii, California and New England states because 1) adoption stimulated by a subsidy is low because PV economics are already favorable, and/or 2) lower grid emissions in these states leads to lower environmental benefits from solar. Due to higher solar resources and higher electricity prices, the NPV in 2018 of a rooftop solar system in California is estimated at $1,140/kW, compared to $896/kW in Massachusetts and -$900/kW in Ohio. Better economic conditions imply less need for (and thus lower benefits from) a subsidy. To provide an example of grid emissions differences, the marginal CO_2 emission factor in Ohio is 727 kg/MWh versus 422 kg/MWh in California. Differences are even larger for damages from criteria pollutants.

All prior results (including Figure 5a-b) assume a federal subsidy equal across the US, with the national net benefit determined by summing up net benefits obtained in each US state. Alternatively, subsidies could be allowed to vary by state, representing a scenario where a federal decisionmaker is attempting to maximize long-term benefits of the policy for the country as a whole by setting federal subsidy levels that differ by state. We analyze the case in which flexible subsidy schedules in each state are optimized to maximize net national benefits, a state-by-state flexible subsidy. While current federal subsidy policies are typically uniform across the country, there is precedent for the principle of state variability, e.g. DOE appliance efficiency standards are different by region (DOE, 2016). Following this idea, we redo the optimization modeling allowing subsidy levels to vary independently in 51 different regions (50 states plus Washington, DC). Results for state-level net benefits and subsidy costs for homogenous Federal support versus re-optimized state-by-state subsidies are compared in Figure 5 and Table 1. A state-by-state flexible subsidy has a notable increase in national net benefits: $2.8 versus $1.0 billion for a national flexible subsidy. Solar penetration also increases from 21% in 2047 for the national flexible subsidy to 24% for a state-by-state flexible one, and emissions benefits are higher as well.

Figure 5(c) shows net benefits by state for the optimal state-by-state flexible subsidy. All states have a positive net benefit, highest in Rhode Island and Connecticut ($18/person) followed by Indiana and Wisconsin ($16/person) and lowest in Washington ($2/person). The highest per capita net benefits occur in the Midwest mainly due to larger reductions in coal consumption and in criteria pollutants (especially SO_2). Figure 5 shows state-by-state subsidy levels in the first year (2018). The subsidy starts as high as $1,250/kW in Missouri and Indiana but has more moderate values of $450/kW - $620/kW in Florida, Nevada, Arizona, and New Mexico (Figure 6). The optimization results propose low subsidies in California ($91/kW in 2018) and no subsidy for Hawaii.

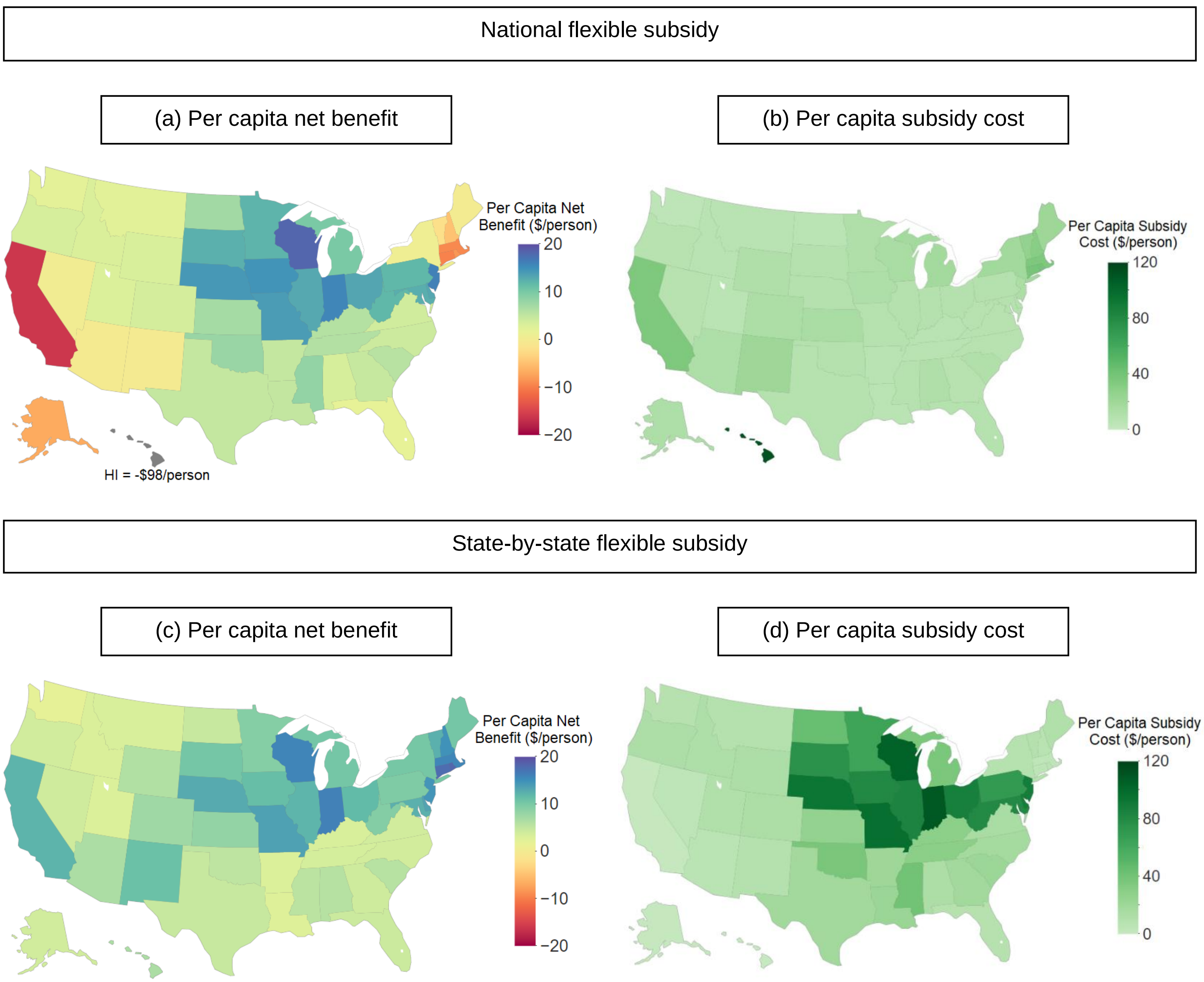


Figure 5. State level results for optimal subsidies.: (a) National flexible subsidy, net benefit per capita, (b) National flexible subsidy, subsidy cost per capita, (c) State-by-state flexible subsidy, net benefit per capita, (d) State-by-state flexible subsidy, subsidy cost per capita. For both national and state-by-state subsidies, the objective is to maximize national net benefits. The differences between states are due to variations in NPV for residential solar PV resulting from different insolation and electricity prices and the current electricity generation mix, affecting both the displaced emissions and monetized benefits. For optimal national flexible subsidy schedule, government expenditure is high in states such as California and Hawaii but results in a negative net benefit due to overpaying free riders. For the state-by-state flexible subsidy schedule, all states have positive net benefits. In this case, government investment is focused on Midwestern states relative to other regions, mainly due to larger benefits from displacing coal power.

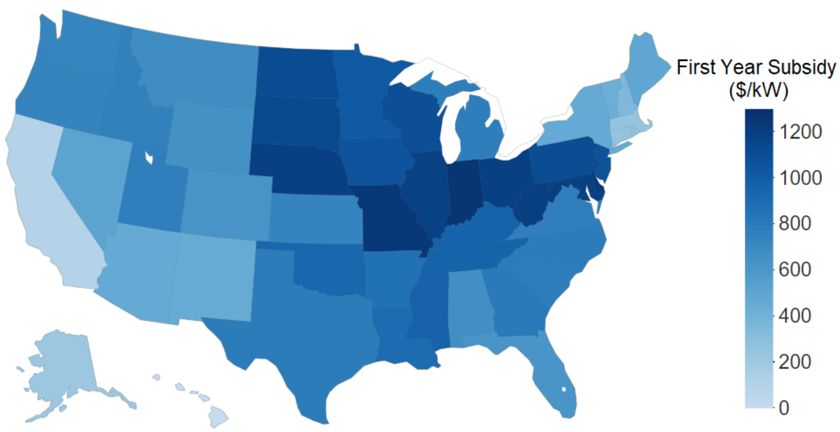


Figure 6. Optimal first-year subsidy level for a state-by-state flexible subsidy schedule. The subsidy starts as high as $1,250/kW for some states in the Midwest while it offers little to no subsidy for states like California and Hawaii.

2.4.5 Carbon Abatement Cost

The carbon abatement cost of subsidies is a useful measure to compare subsidies with other mitigation options. Table 1 summarizes our results obtained for different subsidy schedules, including both definitions of carbon abatement costs (including and excluding criteria pollutant benefits, equations 27 and 28). Section 2.4.4 has definitions and formula, recall that we assess public (government) expenditures to mitigate. This is distinct from the total costs (public + private) of mitigation. When excluding criteria pollutant benefits, the CO_2 mitigation costs of optimal subsidies is $45/ton (national flexible and $49/ton (state-by-state flexible). Mitigation costs are higher with FTC subsidies at $59/ton (phased out) and $69/ton (perpetual). However, carbon mitigation benefits are much lower if criteria pollution co-benefits are permitted: $21/ton for nationally flexible subsidy and $17/ton for state-by-state flexible. Indeed, running the model with only carbon benefits (not shown) leads to much lower optimal subsidies. Our measure of public mitigation costs is not directly comparable to total mitigation costs, the latter is the typical measure and has been characterized elsewhere, e.g. (Das et al 2020). Future work to characterize public mitigation cost for other technologies would inform government decisions on allocation of technology promotion subsidies.

A primary theme of this work is that estimates of subsidy benefits should include indirect technological progress benefits. To understand this effect, we calculate the CO_2 mitigation cost of the optimal national flexible subsidy schedule with no technological progress (learning rate of zero). The result with zero learning rate is $81/ton of carbon reduced (versus $45/ton with learning rate = 15%), showing that technological progress plays a large role in reducing estimated mitigation costs of the subsidy program.

Table 1. Summary results for different subsidy schedules for residential solar. In the no-subsidy case, adoption and technological progress still occur, leading to emission reductions. Net benefits refers to benefits of the subsidy (thus zero for no-subsidy) and are estimated over 30 years at 3% real discount rate and learning rate of 15%. All financial results are in real 2018 dollars. (FTC = Federal Tax Credit). CO_2 Mitigation Cost is the government expenditures spent on subsidies per ton of CO_2 reduced through stimulated adoption.

	Net Benefit (billion $)	Solar Penetration (in 2047)	PV Price ($/W, in 2047)	Reduced CO_2 Emissions (millions of tons, in 2047)	Government Cost (billion $)	CO_2 Mitigation Cost – No Criteria Pollutant benefits ($/ton)	CO_2 Mitigation Cost – w/ Criteria Pollutant benefits ($/ton)
Unsubsidized	0	19%	2.50	486	0	0	0
Optimal National Flexible)	1.0	21%	2.43	596	4.9	44.5	21.0
Optimal State-by-State Flexible)	2.8	24%	2.37	704	10.6	48.6	17.1
Planned 30% FTC (ends 2022)	-0.66	23%	2.39	672	10.9	58.6	26.2
“Perpetual” 30% FTC (ends 2031)	-10.0	30%	2.24	1,051	38.8	68.6	38.3

2.4.6 Sensitivity analysis: discount rates

We conduct additional sensitivity analysis to examine how the results vary under different assumptions of discount rate (Figure 7). The model optimized at a 5% discount rate (not shown) resulted in a maximum net benefit of $107 million. This is nine times lower than the base case analysis done with a 3% discount rate. For this case, the subsidy gives out $278/kW at the initial stage of the support, which reduces to $5/kW after 12 years. Figure 7 shows the net benefits of our baseline optimal national flexible subsidy schedule if the discount rate is different than the one assumed. The general trend is expected: higher discount rates result in lower net benefits from investing in rooftop solar adoption. However, sensitivity analysis shows that a discount rate of 1% induces lower net benefit than 2%. This is because these low rates stimulate relatively more natural, non-subsidized adoption (because it essentially lowers the experiences cost of rooftop solar), resulting in higher government spending and transfers to free riders.

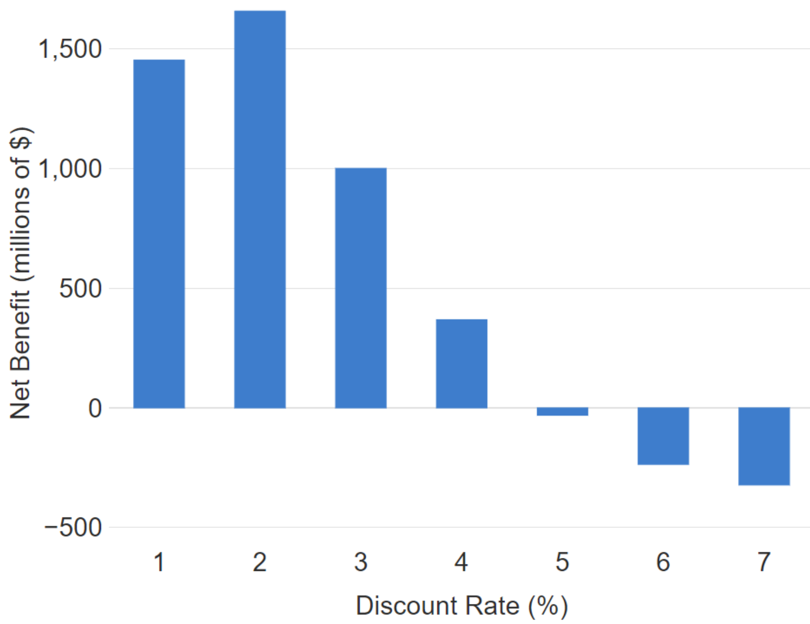


Figure 7. Sensitivity analysis results showing the net benefit of the optimal national flexible subsidy for different discount rates. The results are optimized for the base case analysis (3% discount rate).

2.5 Conclusions and Recommendations

In this research, we present a framework for identifying the optimal government subsidy for emerging clean energy technologies by modeling dynamic interactions among subsidies, consumer adoption, technology progress, and environmental benefits. Our results indicate that subsidizing residential solar in the US delivers net benefits to society (in base case model) and demonstrates the importance of accounting for technological progress when estimating net benefits. In particular, we show that the indirect benefits resulting from subsidy-induced technological improvement are comparable to or larger than the direct environmental benefits associated with the immediate subsidy-induced solar adoption. This means that the total benefits of the solar subsidy would be significantly underestimated if the technological learning effect is not accounted for. This holistic approach has distinguished our study from prior research that focused on the direct environmental benefits of clean energy subsidies. Our dynamic model shows that government subsidy is particularly important in a technology's early development stage because of its effect on technological progress and cost reduction. Meanwhile, the need for subsidy decreases as the technology becomes competitive enough to attract consumers at unsubsidized prices. Incorporating this dynamic technological progress perspective justifies a declining subsidy schedule, as quantified above. To compare our results with prior work, van Benthem et al. (2008)

determine an optimal subsidy for residential solar in California, with maximal positive net benefit resulting from subsidy of $3.2/W starting in 2006, falling to $0.78/W in 2016. These results are quantitatively similar to the values that we found for a federal subsidy and both analyses indicate a qualitative trend of initially high subsidy that falls to zero. Important for policy considerations, our identified optimal national flexible subsidy starting from 2018 is lower than the subsidy level of the 30% federal tax credit, which suggests that the current policy might be over-subsidizing solar.

It is worth noting that this and other studies model technological progress using a learning rate, which quantifies the degree to which adoption drives cost reductions. We find that, for learning rates below 6% (for a national subsidy and 3% discount rate), cost reductions are too slow to justify any solar subsidy. However, nearly all estimates of solar learning rates exceed 7% (Rubin et al., 2015) and we use a typical value of 15%. Given these results, future assessments of subsidies and other public sector interventions for technologies such as electric vehicles, wind power, and energy storage should account for technological progress as well. This is particularly important for less mature technologies – we found that indirect benefits accounted for more than 90% of the overall social benefit of a rooftop solar subsidy in 2012.

Our model also illustrates the geographic heterogeneity in the welfare effect of technology subsidy. We show that a homogenous national subsidy (with flexible schedules) leads to substantially different benefits and costs across states, due to heterogeneity in climate and insolation, electricity prices, energy portfolio, and benefits of increased renewable generation. We also estimate the optimal subsidy that varies state-by-state, which allows all states to achieve positive net benefits and thus allows more efficiency gains. Specifically, the total national net benefits increase from $1.0 billion for a homogenous national subsidy to $2.8 billion for a state-by-state subsidy. Certainly, a Federal subsidy that offered different levels of support by state would be politically challenging, though there are a few points of precedence in Federal rulemaking, such as the regional differentiation in DOE efficiency standards (DOE, 2016) and the state-by-state emissions reduction targets in the proposed Clean Power Plan (US EPA, 2015). Furthermore, individual states often supplement the FTC. Our results inform, at least qualitatively, the beneficial degree of such state-level supplements. It is notable that current state support has the opposite pattern than the optimal identified in this work, primarily for political reasons: our work suggests that an optimal subsidy would be focused on the Midwest with lower support in California, New England, and Hawaii, while actual state policy produces the inverse.

While the US market was the focus of this study, the integrated model can be broadly applied to other nations or regions to assess the costs and benefits of their government subsidies. Our adoption model (derived from a global analysis using data that includes Germany and Japan) and the technological progress model can be modified by taking the historical PV adoption rate, electricity price, and annual solar energy production in other countries of interest. The benefit-cost model can be adjusted accordingly by using other countries' marginal emissions and damage factors depending on their electric power systems. In addition to PV, our model can also be applied to other relevant clean energy technologies including utility scale solar and wind and electric vehicles, or even other industries where technological adoption has different types of benefits. Alternately, the sophistication of the model could be enhanced by adding decision-making under uncertainty (through Monte Carlo analysis, for example), integrating different types of solar technologies, or including categories of benefits or costs neglected here.

Chapter 3: Roles of diffusion patterns, technological progress and environmental benefits in determining renewable subsidies

3.1 Introduction

Burning fossil fuels such as coal and natural gas for electricity generation emits greenhouse gases and pollutants that are a health risk to humans and cause long-term environmental damage. To overcome these and other negative effects, federal and state governments adopt a variety of programs to promote the use of clean energy technologies, including subsidies for the installation of or production from renewable generation. Clean energy technology subsidies can also have a wide range of social benefits which include advancing innovation in new and early-stage technologies, enhancing energy security, and promoting economic growth through creation of green jobs. However, clean energy subsidies are associated with substantial public spending.

A government report shows that the total tax-related credits for solar and wind power are estimated to be about $12.3 billion and $23.7 billion, respectively, for the years between 2016-2020 (Joint Committee on Taxation, 2017). While subsidies continue to be an important mechanism to promote clean energy development and deployment, it is not always clear how federal and state governments design subsidies in order to balance these costs and benefits. Large renewable energy support plans should attempt to implement efficient subsidies that maximize the long-term net benefits to society and considering analytical inputs can be helpful to ensure the cost-effectiveness of the decision making.

There are two primary conceptual justifications for subsidy of clean energy technologies. The first perspective is that a subsidy prompts immediate consumer adoption of the technology, which yields direct social benefits in the form of reduced emissions. In other words, the subsidy is meant to stand in for the environmental benefits that result from offsetting fossil fuel externalities, lowering total social costs. This direct environmental benefit perspective is well-studied and results often show that the subsidy cost exceeds societal benefits (Michalek et al., 2011; S. E. Sexton et al., 2018) or estimate a high carbon mitigation cost (Hughes and Podolefsky, 2015; Macintosh and Wilkinson, 2011). This perspective implicitly assumes that the technology is stagnant, evaluating it with respect to a temporal snapshot of costs and benefits.

A second perspective is that the subsidy promotes adoption over time, leading to the development of new markets and stimulating technological progress. These post-adoption innovations enable further cost reduction or performance improvement in these technologies (Herron and Williams, 2013; Tsuchiya, 1989) and deliver benefits to society over the long-term. Previous studies identify that diffusion of various clean energy technologies can be driven by directly incentivizing and as a result lowering the cost of adopting these technologies (Nicolini and Tavoni, 2017; Sarzynski et al., 2012). This idea can be embedded in a benefit-cost model to find an optimal level of public support, i.e. the subsidy that maximizes benefits less costs. (van Benthem et al., 2008) evaluated optimal subsidy trajectory for residential solar PV in California accounting for monetized environmental and consumer benefits and learning-by-doing externalities that are compared against the total subsidy cost. (Wand and Leuthold, 2011) carried out a similar analysis for residential PV systems in Germany and examined the variability of net social benefit results under different scenarios.

3.2 Literature Review

In Chapter 2 we have shown how optimal subsidies can vary under different levels of learning rate and social cost of carbon employed to estimate environmental benefits. Other studies also explore how the optimal subsidy and the resulting net benefits vary under different conditions related to technological attributes such as learning rate. For example, (van Benthem et al., 2008) found that below some critical value of learning rates, public subsidies are no longer justified from a benefit-cost perspective. (Matteson and Williams, 2015) showed that subsidy spending to reach price parity is much higher when lower learning rates are assumed. In another case, (Newbery, 2018) investigated how multiple technology attributes (learning rate, technology capacity factor and social cost of CO_2) affect renewable energy subsidies. The analytical framework presented in (Newbery, 2018) assumes that technologies have a maximum growth rate and saturation level, and that the optimal subsidy will grow the technology at this pace until saturation.

While these studies carry out different analyses and identify technology characteristics that may affect optimal subsidies, none of them conduct an integrated assessment to determine why optimal subsidies for different technologies are sensitive to these factors. The modeling framework by (Newbery, 2018) does not include a diffusion model and assumes that an optimal subsidy drives the maximum rate of adoption until saturation. In contrast, this work uses empirically-calibrated diffusion models and determines optimal subsidy explicitly by maximizing public benefits less costs. This work contributes to the existing energy subsidy literature as the first study which explores and compares the effects of various technology attributes on optimal subsidy patterns, when integrating adoption and marginal emissions models. As a case study, this chapter takes a comparative approach to address the questions of why and how policy support should vary for different technologies. This study undertakes a case study comparing utility wind and residential solar to clarify how differences in three key attributes of a technology affect its optimal subsidy schedule: environmental benefits, price sensitivity of diffusion, and pace of cost reductions. These technology attributes are considered to be vital components when justifying the economic efficiency of clean energy subsidies (Newell et al., 2019) and have been integrated into government policy design and analysis studies (van Benthem et al., 2008; Wand and Leuthold, 2011).

The first attribute, environmental benefits, comes from reducing use of fossil generators, the largest impacts of which come from greenhouse gas and criteria air pollutant emissions (e.g. SO_2, NO_x $PM_{2.5}$). Specifically, the benefits of a renewable energy technology arise from the change in emissions of the grid that technology is embedded in and thus should vary by region depending on local energy grid mix. Higher environmental benefits can be gained if the renewable technology is integrated in a grid that is composed of emissions-intensive generators such as coal and natural gas or is more effective at displacing emissions from these sources.

The second attribute relates to the rate of technology diffusion. Diffusion models are used to explain and predict how subsidy and other technology attributes influence adoption. The price sensitivity of diffusion represents the increase in adoption level in response to a subsidy and is measured in W/$. The price sensitivity is expected to vary by technology, given that different consumer classes have different preferences towards technology and value their attributes differently.

The third technology element is cost reduction over time, i.e. at what pace does the technology become less expensive given adoption and other factors? In this regard, experience curve models applying learning rates are a common choice to measure cost reductions resulting from subsidy interventions. The experience accumulated from learning among different technologies depends on the different level of maturity, rate of adoption, and observed cost reduction. This variation can affect the amount of investment and policy measures required to bring down the cost of emerging technologies (Neij, 1997; Neij et al., 2003).

This chapter uses two models to compare the optimal subsidy design for industrial wind and residential solar generation. The first model applies the integrated framework developed in Chapter 2. This model, referred to as "model-with-learning", uses a techno-economic framework that integrates sub-models of adoption, technological progress, and emissions benefits to analyze the costs and benefits of long-term subsidy support. The second model applies a simplified algebraically-solvable framework, without accounting for technological learning, to establish a direct mathematical relationship between the environmental benefits and adoption and subsidy design output. This model provides a simple functional relationship constituting environmental benefits and price sensitivity of adoption to determine the optimal subsidy of a technology under constant technology price. The two models are quantified using data disaggregated into 13 US regions as described in the EIA's "Hourly Electric Grid Monitor" data report across the contiguous US (EIA, 2021a). The results from these two technologies are used to better understand the determinants of optimal energy subsidy. The analysis applies the same models to the two technologies but comes to different conclusions about the nature of government support, which is explained and discussed in this chapter.

3.3 Methods: Model-with-learning

In this section, we apply the techno-economic model developed in Chapter 1 for determining the socially optimal government subsidy schedule for a clean energy technology (Figure 1). The integrated framework combines three independent models: adoption, technology progress, and environmental benefits. The three models are interlinked to one another in such a way that the environmental benefits are estimated from both the adoption induced by the subsidy and the stimulated adoption through technology cost reduction over a long-term period. The optimization uses a social planner perspective that views government support (subsidies) as a means to achieve social benefits (emissions reductions). The objective of the government is to maximize the national net present value defined as the monetized and discounted emissions benefits minus subsidy cost. This framing thus takes the perspective that the government is using subsidy to “purchase” emissions reductions now and in the future, including the indirect effect of technological progress on later adoption. However, this model does not attempt to account for the economic benefit (or net cost) to the consumer or allocative efficiency between social groups when identifying the optimal subsidy.

The model is applied to residential solar and utility wind in 13 grid regions in the continental US. EIA uses these regions to report hourly operating data of the electric power grid (EIA, 2021a). The geographical map and the labels used to represent these regions are shown in Figure 8 and Table 2. The geographic variability of wind and solar production and electricity prices calls for a degree of regional specificity. The 13 regions are domains over which electricity is traded, thus reflecting differences in wholesale prices, and partly accounts for variability in renewable resource availability.

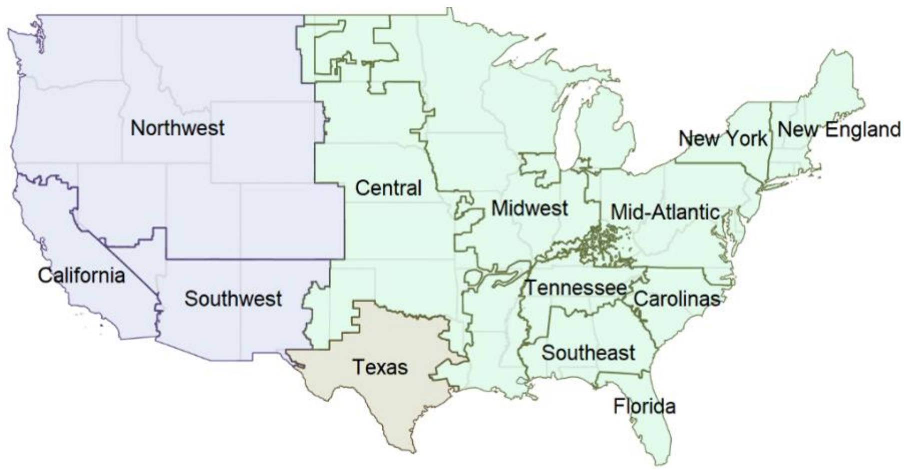


Figure 8. Geographical scope of optimal subsidy analysis consisting 13 ISO regions. (EIA, 2021a).

Table 2. Names used to represent the 13 regions on EIA's "Hourly Electric Grid Monitor" website (EIA, 2021a) and this study.

EIA	This study
California	CAISO (California Independent System Operator)
Carolinas	Carolinas
Central	SWPP (Southwest Power Pool)
Florida	FL (Florida)
Mid-Atlantic	PJM (Pennsylvania, New Jersey, Maryland)
Midwest	MISO (Midcontinent Independent System Operator)
New-England	NEISO (New England Independent System Operator)
New York	NYISO (New York Independent System Operator)
Northwest	NW (North West)
Southeast	SOCO (Southern Company)
Southwest	SW (South West)
Tennessee	TVA (Tennessee Valley Authority)
Texas	ERCOT (Electric Reliability Council of Texas)

3.3.1 Adoption model

There is a large body of literature that creates and evaluates adoption models for clean energy technologies. Adoption models often use an S-shaped curve to fit technology diffusion over time and may take on different forms such as Bass, Logistic and Gompertz (Dalla Valle and Furlan, 2011). These models are applied for long-term forecasting (Dong et al., 2017), comparing technology diffusion between regions (Dalla Valle and Furlan, 2007; Panse and Kathuria, 2015), and studying adoption among different sectors (Wang et al., 2017). Other adoption research has used consumer choice models to study the relationship between various technology attributes and consumer adoption (Islam, 2014), or agent-based models to assess the interaction between consumers, technology manufacturers, and the government under a multiple decision-making environment (Zhang et al., 2011). But these adoption models are often relatively complex and difficult to integrate into analysis of current and future policies (Gnann et al., 2018; Rao and Kishore, 2010). As a result, the direct application of these models in energy systems modeling and proposed policy directives has been limited. For that type of analysis, a simpler model that captures overall trends in adoption is most useful, even if it lacks high-resolution diffusion data.

The adoption model selected for this study follows the approach developed by (Williams et. al., 2020) to determine the rate of annual residential solar adoption as a function of Net Present Value (NPV) of the system. In that work, the parameters of the residential solar model are determined empirically from five different regions. The model can directly take in policy measures such as subsidies in the NPV estimation. In this analysis, the residential solar adoption model is directly taken from an earlier study (Williams et. al., 2020) and the same approach is applied to estimating the adoption model for utility-scale wind generation. The details of the modified diffusion model for wind power are provided in the following section.

3.3.1.1 Wind adoption model

To estimate the adoption rate of utility-scale wind power, we modify a diffusion model developed by (Williams et al., 2020) that effectively reproduced the adoption pattern of residential solar PV using one explanatory variable: the NPV as experienced by the homeowner. Specifically, the same model is estimated using annual wind adoption and other observed cost and policy data from four states in the US (California, New York, Pennsylvania, and Texas) and two European countries (Denmark and Germany) within the time frame of 2002-2018. There are two main reasons for the selection of these regions. First is data availability. Publicly available and open-source data is used (with sources described in Table 3) for estimating the NPV and capacity of wind adoption in the regions considered. Second, the observed adoption of wind in these regions is high on average but varies over time, giving greater variation to calibrate the model.

The NPV of adopting a wind power plant in a given region is estimated as:

$$NPV\left(\frac{\$}{MW}\right) = (-C_{total}) + \sum_{i=1}^{N} \frac{E * R}{(1+int)^{i}} \frac{1}{CAP} \qquad (29)$$

where,

C_{total}: capital cost of wind power plant ($)

E: electricity produced by the wind power plant in a year (MWh)

R: revenue from wind electricity generation ($/MWh), mechanism varies by region

int: wind power weighted average cost of capital (%)

CAP: capacity of power plant

N: lifetime of wind power system (20 years)

R ($/MWh) accounts for the revenue that wind projects receive from electricity generation. It constitutes the market or contract price of wind energy and all applicable policy incentives. There are a variety of subsidy mechanisms at the US state and federal level, compensating producers differently, often proportional to electricity generated. State-level Renewable Portfolio Standards (RPS) to promote wind energy, usually achieved through a renewable purchase requirement, are imposed on load-serving entities. The load-serving entities can meet this requirement either by operating their own renewable energy facility or by purchasing renewable energy credits (RECs) from independent facilities that generate electricity from eligible resources (Wiser et al., 1998). For wind power generators, this either results in a renewable energy credit market, which effectively plays the same role as a production incentive, or a contracted bundled power purchase agreement (PPA) (market price including RECs). Hence, the value of R in Eq. 2 includes the federal production tax credit (PTC), market value of wind, and the value of renewable energy credits (RECs) implemented in Texas, Pennsylvania, and New York. For California, project NPVs are estimated using federal PTC and PPAs signed between wind developers and the utilities. This data is collected and reported by the states and LBNL. For Germany, R represents feed-in-tariffs (FITs) and for Denmark R is the sum of FITs and electricity market prices (IEA, 2015). The data sources used to estimate R are provided in Table 3.

The adoption model uses regression-produced parameters that are identical in the six regions considered, assuming that NPV is the sole determinant of adoption. Differences between areas are only accounted via region-specific data influencing NPV, such as subsidy level, resource availability, and capacity factor. The normalized annual wind power adoption is formulated to follow a normal distribution as a function of the NPV. The functional form of the adoption model is given by:

$$Adoption\ \left(\frac{MW}{TWh}\right) = \frac{Annual\ wind\ power\ adoption\ (MW)}{Remaining\ generation\ (TWh)} = k\left(1 + \mathrm{erf}\left(\frac{NPV - \mu}{\sigma}\right)\right) \qquad (30)$$

where, erf(x) is the error function. μ and σ, determined empirically, are the NPV that results in peak increase in wind adoption and the spread in adopter preferences, respectively. As indicated in equation (30), the annual wind adoption is divided by the remaining electricity generation of each region to account for the different sizes of the electricity grids considered. The remaining generation in a given year is estimated as the total electricity generation in the grid minus cumulative wind power generation. k defines the maximum achievable adoption (max adoption = 2k) and is fixed at one half of the maximum annual wind capacity per TWh of generation. The value of k, estimated by assuming a 35% capacity factor and a lifetime of 20 years for wind, is 8.2 MW/TWh. Applying non-linear least square regression, the value of μ is estimated to be \$1,589/kW and that of σ is found to be \$1,690/kW with a total square error of 561 MW/remaining TWh. The empirically-fitted adoption model using these values is shown in Fig. 9. The empirical fit of the model form is better for residential solar than for utility wind, for several reasons. There is “lumpiness” in utility wind adoption, i.e. larger projects add a discrete block to capacity in a given year. Also, wind projects experience stochastic delays based on time needed for permitting, local approvals, and extension of transmission and distribution. In contrast, residential solar in a state is the accumulation of thousands of small projects, implemented over a time scale of months rather than years. It is thus not surprising that utility wind adoption does not smoothly follow economic conditions in a given year.

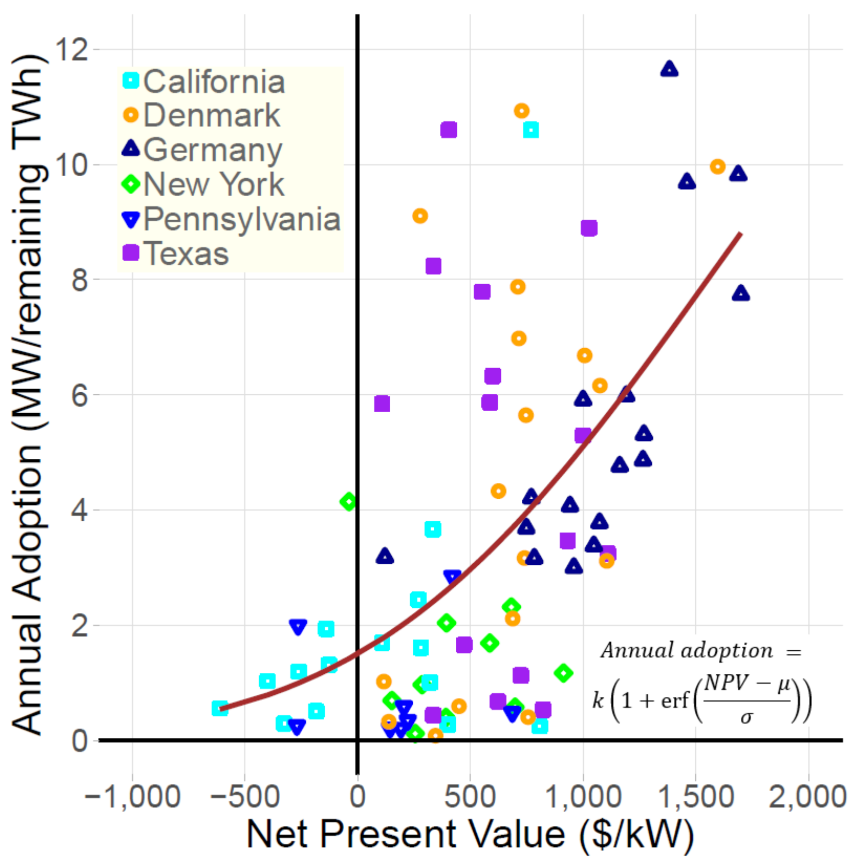


Figure 9. Adoption model for utility-scale wind generation using the NPV (\$/MW) as the explanatory variable. The model is developed by empirically analyzing wind diffusion data from six regions, with

data from 2002 to 2018. The adoption curve is fitted using the error function with two regression parameters μ and σ with values of $1,589/kW and $1,690/kW, respectively, and the value of k is set at 8.2 MW/TWh.

Table 3. Wind adoption model data sources.

Region	Wind Installed Cost	Capacity Factor	Electricity Price	PTC	REC	PPA	FIT	Annual Installation	Total Generation	Interest Rate
NY	(Berkeley Lab, 2019)	(Berkeley Lab 2020, Berkeley Lab, 2018)	(NYISO, 2003)	(IRS, 2002)	(NYSERDA, 2017)			(Berkeley Lab, 2019)	(EIA, 2019)	(IEA, 2018)
CA	(Berkeley Lab, 2019)	(Berkeley Lab 2020, Berkeley Lab, 2018)		(IRS, 2002)		(Wiser et al., 2020)		(Berkeley Lab, 2019)	(EIA, 2019)	(IEA, 2018)
TX	(Berkeley Lab, 2019)	(Berkeley Lab 2020, Berkeley Lab, 2018)	(Potomac Economics, 2002)	(IRS, 2002)	(Wiser and Bolinger, 2008; Wiser and Bollinger, 2019)			(Berkeley Lab, 2019)	(EIA, 2019)	(IEA, 2018)
PA	(Berkeley Lab, 2019)	(Berkeley Lab 2020, Berkeley Lab, 2018)	(Monitoring Analytics, 2003)	(IRS, 2002)	(PAPUC, 2007)			(Berkeley Lab, 2019)	(EIA, 2019)	(IEA, 2018)
Denmark	(IRENA, 2019)	(IRENA, 2019)	(Nord Pool, 2020)				(Albizu et al., 2018)	(IEA, 2019; IRENA-GWEC, 2013)	(OECD, 2021)	(IEA, 2018)
Germany	(IRENA, 2019)	(IRENA, 2019)					(Federal Network Agency, 2018; Hitaj et al., 2014)	(German Wind Energy Association, 2020)	(OECD, 2021)	(IEA, 2018)

3.3.1.2 Comparing utility-scale wind and residential solar adoption curves

In the framework, the effectiveness of a subsidy is reflected by the additional adoption resulting from an increase in subsidy, expressed in Watts adopted per $ of subsidy spent. This adoption price sensitivity is different for wind and solar for two reasons. First, the underlying adoption curves are different, i.e. different numerical values for μ and σ. μ = $1,589/kW for utility wind and $7,101/kW for residential solar, σ = $1,690/kW for utility wind and $4,110/kW for residential solar. Second, the sensitivity depends on where on the adoption curve the technology starts. For all grid regions except CAISO, unsubsidized wind has a higher NPV than unsubsidized residential solar.

To show how differences in the adoption curve affect subsidy effectiveness, Figure 10 displays the adoption curves for utility-scale wind and residential solar. Because of different scales and capacity factors that impede a comparison in absolute terms, we normalize the adoption from a given NPV by the adoption resulting at the NPV breakeven point (NPV = 0). In this adoption model, the slope changes with NPV, positively accelerating over the range of relevant NPV levels. Figure 9 shows that adoption of utility wind power is more sensitive to changes in NPV than for rooftop PV. Also, a closer look at the left side of the plot shows that residential solar adoption rate is higher than utility-scale wind in cases where NPV is negative, implying that homeowners are more willing to adopt the technology than wind developers when net losses are possible. These differences could be due to the two different groups of consumers: homeowners versus power plant developers. A homeowner's financial decision to invest in rooftop solar adoption may be focused on offsetting their residential retail electricity cost. But their decision can also be strongly influenced by consumer attitude towards the environmental benefits of green energy and indirectly by network effects (Bollinger and Gillingham, 2012; Crago and Chernyakhovskiy, 2016), potentially even outweighing the financial considerations. On the other hand, wind developers aim to sell the generated electricity into a market, which may be more directly based on financial considerations. Overall, the different patterns of adoption have further implications on the optimal subsidy design of the technology. The steepness of the adoption curve determines the amount of induced adoption resulting from a subsidy and thus the economic effectiveness of the subsidy, with a steeper adoption curve suggesting more sensitivity to subsidy.

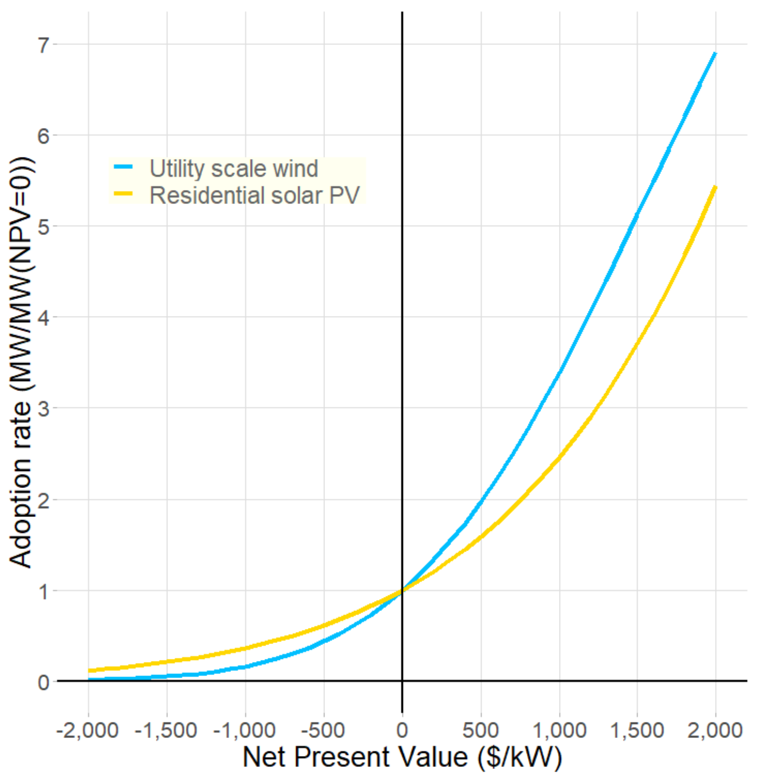


Figure 10. Normalized adoption curves for utility wind and residential solar PV. For both technologies, the adoption is normalized to the respective value of adoption when Net Present Value=0.

3.3.2 Technology progress model

The technological progress model applies a one-factor experience curve to forecast technology cost reductions. A one-factor experience curve gives the unit cost of production as:

$$C^j = C^0 \left(\frac{P^j}{P^0}\right)^{-\alpha} \tag{31}$$

In the equation above, P^j is cumulative adoption, C^0 and P^0 are initial cost and capacity values, and α is a constant learning coefficient. The fractional cost reduction for every doubling of production is defined as the learning rate, and is given by $LR = 1\text{-}2^{-\alpha}$. Two-factor experience curves that include learning from R&D support are also used to model technology cost reductions (Klaassen et al., 2005). However, their application is restricted mostly due to data availability limitations on public and private R&D expenditures. Studies have also modified the one-factor experience curve by disaggregating systems into different component costs, such as PV module and balance-of-system costs in solar PV technologies (Elshurafa et al., 2018). With the goal of analyzing the impact of learning on optimal subsidy design, we choose to use the empirically robust one-factor experience curve in our model. The technological progress model uses a learning rate of 9.8% for wind (Williams et al., 2017) and 15% for rooftop solar estimated using price data from (IEA, 2017) and cumulative adoption data from (SEIA, 2017).

3.3.3 Benefit-Cost model

The environmental benefit from clean energy technology adoption depends on the energy mix of the grid. In this research we apply marginal emissions and damage factors to measure the amount of emissions reductions and the resulting avoided health and climate damages. Marginal emissions factors are mainly determined by the type of generator displaced, and as a result tend to be relatively higher in coal-heavy areas like the Midwest than in other regions. The environmental benefits model is based on an emissions assessment model estimating environmental emissions reductions resulting from changes in output from conventional power plants (Azevedo et al., 2019). That study estimates the marginal emissions data from historical emissions and generation data and integrates it with emissions damage estimates from the EASIUR model (Heo and Adams, 2015). We estimate the present benefits by discounting the monetized emissions benefits from reduced CO_2 and criteria pollutants (SO_2, NO_x $PM_{2.5}$) as a result of the subsidy-induced adoption. In this paper, our goal is to optimize the net social benefit of a technology subsidy, which is measured as the discounted, monetized environmental benefits minus subsidy expenditure. This approach is different from other studies that use multi-objective optimization model and estimate separately the benefits and environmental costs of certain economic activities such as export trade (e.g., Wang et al., 2020).

3.4 Model-with-learning results

The integrated model shown in Figure 1 is used to analyze the optimal subsidy schedules for utility wind. This result is then compared with the optimal subsidies for residential PV estimated using a similar geographical resolution. The two technologies use the same framework but with different inputs, as described in Table 4, specifically using different parameters for diffusion, capacity factor, learning rates, and electricity prices for the two technologies. Project lifetime and emissions offset benefits per MWh are the same. In both cases, the model uses a non-linear optimization technique to determine an optimal subsidy schedule. The model applies no constraints on the level or temporal trend of the subsidy, which can be set to any level in each year.

Table 4. Optimal subsidy model data.

	Utility-scale wind	**Residential solar PV**
Installed price	(Wiser et al., 2020)	(Berkeley Lab, 2020b)
Learning rate	(Williams et al., 2017)	(IEA, 2017; SEIA, 2017)
Electricity price	(CAISO, 2018; ERCOT, 2018; MISO, 2018; NEISO, 2017; NYISO, 2018; PJM, 2017)	(EIA, 2020)
Capacity factor	(NREL, 2016a)	(NREL, 2016b)
Total generation	(EIA, 2019)	
Detached households		(US Census Bureau, 2011)
Marginal emissions factors	(Azevedo et al., 2019)	(Azevedo et al., 2019)
Marginal damage factors	(Azevedo et al., 2019)	(Azevedo et al., 2019)

This section presents two sets of results for optimal subsidy schedule: a homogeneous subsidy schedule in which the subsidy level is the same across the 13 regions (effectively a uniform Federal subsidy) and a heterogeneous subsidy schedule that offers different levels of subsidies for each region (representing either differentiated regional/state subsidies or the less likely case where a Federal subsidy varies by location). In both cases, the objective is to maximize the discounted national net benefit.

Fig. 11 shows the homogeneous optimal government subsidy schedule for utility wind and residential solar, respectively. For utility-scale wind power, the optimal subsidy ranges between \$34/MWh and \$38/MWh over the 30-year analysis period (Fig. 11a). On the other hand, our model for residential solar PV (Fig. 10b) suggests its optimal subsidy should start at \$25/MWh and decline to zero over 16 years. The qualitative difference between these two trends is surprising. The causes of the differing wind and solar results are discussed later (and motivates the creation of a "model-without-learning") but are related to the different techno-economic properties of the technologies.

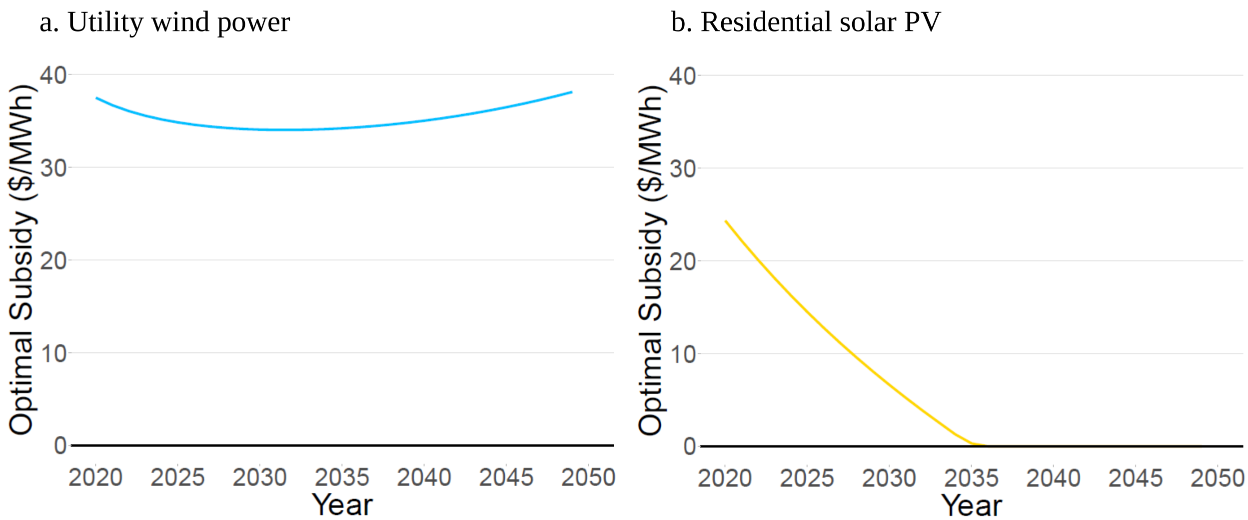


Figure 11. Uniform federal subsidy schedule that optimizes national net benefits, using the model-with-learning for (a) utility-scale wind power and (b) residential solar PV. The optimal subsidy for utility wind will be ongoing for the study period whereas the subsidy for solar PV is declining and becomes zero after 16 years.

Figure 12 displays the proposed optimal subsidy schedules that vary across the 13 regions, for utility wind and residential solar power, respectively. Note that the 13 regions have different electricity rates and renewable energy potential (capacity factor), both of which influence the NPV of adopting the technology. The existing electricity grid generation mix also varies across regions, governing the level of displaced emissions and monetized benefits. As a result, optimal support varies by region. The general trend of each subsidy remains similar to that of the homogeneous subsidy, but the level of the optimal subsidy varies for the regions.

The model suggests that wind generation should be subsidized at a higher level in MISO than in CAISO, the Southwest, or Florida. The reason for this finding is that the current electricity system is emissions-intensive in MISO and the wind potential is high. The subsidy level for wind power in Florida is the lowest mainly because of the unfavorable wind resource potential in the region (capacity factor = 21%) as compared with other regions such as MISO (capacity factor = 43%), along with a lower capability to offset emissions. The marginal CO_2 emissions factor in FL is 461 kg/MWh, lower than the 693 kg/MWh in MISO.

The regional-variable optimal subsidy for residential solar PV declines in all regions, offering the highest subsidy in MISO and no subsidy in CAISO. The indirect technological progress benefit plays a major role when accounting for the net benefit of subsidizing rooftop solar. Essentially, the model finds that technology progress will drive down the cost sufficiently for adoption, and the optimal subsidy schedule declines as the technology becomes more cost competitive.

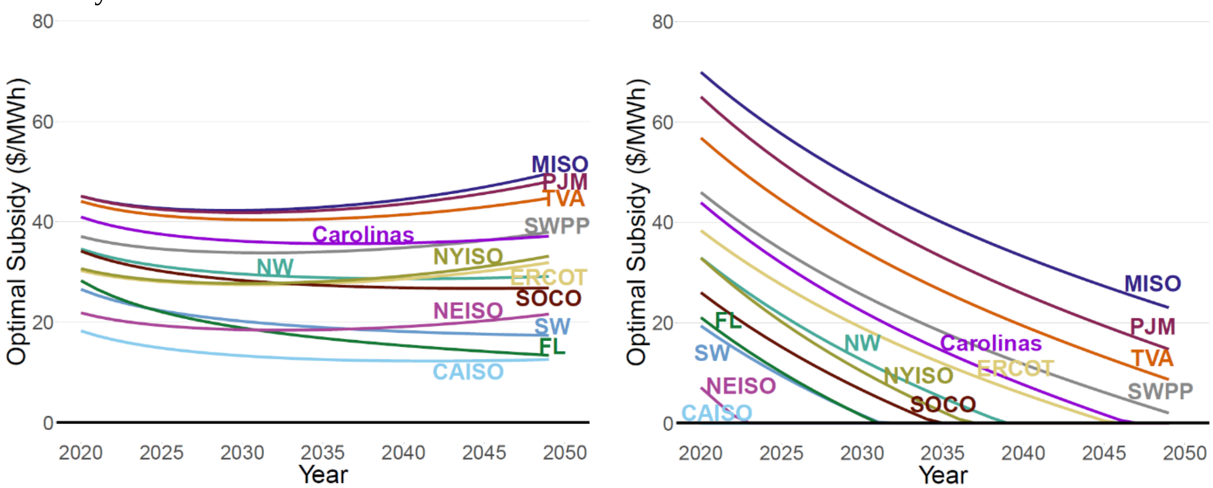


Figure 12. Subsidy schedules that vary by region that optimize national net benefits, using the model-with-learning, for (a) utility-scale wind power and (b) residential solar PV. The subsidy for wind is flat whereas solar subsidy declines over time in all regions. The optimal subsidy differs by region due to variation in electricity price, wind and solar energy potential, and energy grid mix. The geographical map and abbreviations used for these regions is given in Section 1 of the SI.

3.5 Methods: Model-without-learning

From Fig. 11 and Fig. 12, the optimal subsidies of utility scale wind and residential solar are quantitatively and qualitatively different. The subsidy schedule for utility-scale wind stays approximately the same over the time period, whereas the residential solar subsidy declines to zero. Identifying the cause(s) of the qualitative differences in subsidy schedules is difficult to explain because the model is comprised of three independent sub-models simultaneously interacting with one another. The subsidy determines the adoption through both short- and long-term technology cost reduction, hence, the adoption and the technology progress models cannot be easily isolated as possible causes. The model also applies a non-linear optimization that finds the optimal schedule numerically, accounting for direct and indirect benefits and costs. To further examine the technological factors that determine the optimal subsidy, we created a simpler model which captures the important features of the model above but simple enough for the optimal solution to be solved algebraically. This model-without-learning assumes technological progress to be zero in order to make it mathematically simple. Turning off the technological progress in both residential solar PV and utility scale wind technologies allows to account for only the direct adoption resulting from the subsidy and nullify the adoption stimulated by technological progress.

3.5.1 Benefit-cost analysis

This section begins by assuming the social benefits of clean energy subsidies come from the emission reduction of induced adoption of the technology, and hence, define the $Net\ Benefit, NB$ (\$) as the monetized emissions benefit from subsidy-stimulated adoption minus the subsidy cost.

$$Net\ Benefits\ = Stimulated\ Adoption * \ B - A(S) * \ S \qquad (32)$$

where,

$$Stimulated\ Adoption = A(S) - \ A(S = 0) \qquad (33)$$

$A(S)(MW)$ is the adoption with subsidy, $A(S = 0)(MW)$ is the adoption with no subsidy and $S\left(\frac{\$}{MW}\right)$ is the unit subsidy cost. In essence, the benefit of a subsidy comes only from the additional induced adoption while the cost of the subsidy must be paid to all adopters (including those who would adopt without subsidy). The benefits, $B\left(\frac{\$}{MW}\right)$ is the discounted environmental benefit of adopting a clean energy technology over a lifetime of 20 years and is given by:

$$Benefits\ = \sum_{i=1}^{20} \frac{Avoided\ Damage}{(1 + DR)^i} \qquad (34)$$

$Avoided\ damage$ is estimated from marginal emissions and damage factors of CO_2 and criteria pollutants and DR is the discount rate. Substituting Eq. 33 in Eq. 32 and rearranging, the net benefit can be written as:

$$Net\ Benefits = A(S) * (B - S) - A(S = 0) * B \qquad (35)$$

Here, we use a similar approach implemented by Chen and Song (2017) and Fischer and Newell (2005), and define the policymaker’s objective of determining a subsidy level that maximizes the net benefit. Thus, we find the first-order differential solution of Eq. 35.

$$\frac{\partial Net\ Benefits}{\partial S} = (B - S) * \frac{\partial A(S)}{\partial S} - A(S) = 0 \qquad (36)$$

The solution to Eq. 8 depends on the adoption curve and the parameters used for defining it. Since different clean energy technologies can have different adoption curves and adoption parameters, the optimal solutions vary for different technologies.

3.5.2 Model-without-learning for optimal subsidy level

An adoption model with an exponential curve (equation 9) is used to explain the functional relationship between a given subsidy level and the resulting adoption. This model is chosen because it has a similar shape as our preferred error function model in the range of realistic NPVs, has a higher R^2 (i.e., goodness of fit) value than other types of curves, and is easily differentiable. For the subsidy ranges we consider in this study, the exponential curve is a very good approximation of our preferred model.

$$A(S) = A(0)e^{a_1 S} \qquad (37)$$

where, a_1 is defined as the price sensitivity of adoption. The unit of a_1 is W/$ and related to the economic price elasticity of adoption as:

$$Elasticity = \frac{\partial\, A(s)/A(s)}{\partial\, S/S} = a_1 * S \qquad (38)$$

Substituting Eq. 37 into Eq. 36 and solving for the optimal solution gives a rather simple solution:

$$Optimal\ subsidy = B - \frac{1}{a_1} \qquad (39)$$

Eq. 39 gives the theoretical optimal subsidy level and defines a mathematical condition for when the subsidy is justified. For a clean energy technology with an adoption curve as defined in Eq. 37, the choice to subsidize a technology should occur when $B > \frac{1}{a_1}$. This criterion implies that to justify subsidizing a given technology at the current price, the environmental benefit (in $/MW) should be greater than the subsidy expenditure per stimulated adoption (also in $/MW). This is a logical, if somewhat simple, conclusion.

Table 5. Model with and without learning.

	Model-with-learning	Model-without-learning
Adoption model	$A(S) = k\left(1 + \mathrm{erf}\left(\frac{NPV_o + S - \mu}{\sigma}\right)\right)$	$A(S) = A(0)e^{a_1 S}$
Optimal subsidy	Numerically solved (non-linear optimization)	$S^* = B - \frac{1}{a_1}$

Federal subsidy type	Heterogeneous (varies over 13regions) or homogeneous (uniform federal)	Heterogeneous
Learning rate	15% (residential solar) and 9.8% (utility wind)	0%

3.6 Model-without-learning results

The optimal subsidy level determined by the model-without-learning considers two main factors: the benefit, B ($/MW) and the price sensitivity of adoption, a_1 (MW/$). The break-even line for subsidizing a technology is $B = 1/a_1$ (Eq. 39). Using the data we have collected for the wind and solar models with learning, we calculate and plot the values of $a_1$and B for each region. a_1 is determined by applying exponential regression curve fitting to the adoption model for each region. B is estimated using Eq. 34 considering each region's marginal emissions and damage data. When estimating the value of B in a particular region, marginal emissions and damage factors are the same for both wind and solar PV technologies, but differ by capacity factor. Since wind technology has a relatively higher capacity factor than solar PV, the monetized environmental emissions reduction benefit per MW of adoption is higher for wind than solar PV and has different geographic distribution. Moreover, as shown in Figure 9, the adoption curve for wind technology is determined to be steeper than solar, implying that the subsidy expenditure per stimulated adoption for wind is lower than for solar PV.

Figure 13 shows the values of price sensitivity of diffusion and benefit for residential solar and utility-scale wind power in the 13 regions. The optimal subsidy, equal to $B - 1/a_1$, is positive for wind in all regions. Meanwhile, optimal subsidy for rooftop solar lies below the break-even line for 9 regions out of 13.

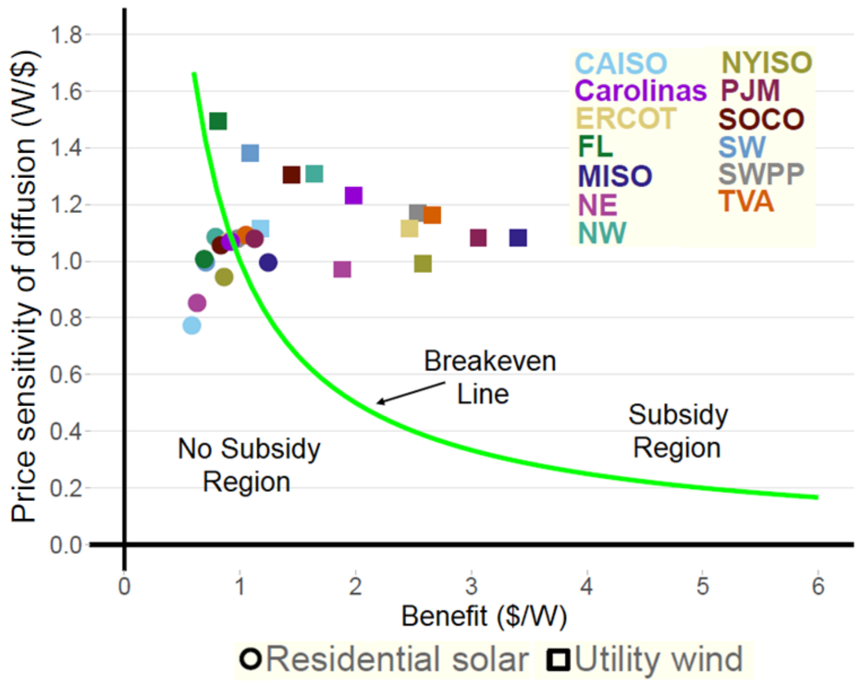


Figure 13. Technology attributes ($/Watt of environmental benefits on x-axis, Watt/$ sensitivity of diffusion to price on y-axis) in 13 grid regions in the US. The green line is derived using the model-without-learning model. It is the breakeven point above which a subsidy is theoretically justified. Note that this simpler model does not include technological progress, which is an important element justifying solar subsidies.

Figure 14 presents a comparison of the optimal subsidy estimates from the model-without-learning and the first-year subsidy level from the model-with-learning, for both technologies. For utility wind, the optimal subsidies obtained using this model, which assumes zero learning rate, are close to the estimates from the model incorporating learning rate. This suggests that technology progress plays a minor role in determining the optimal wind subsidy. Note that the model-with-learning often indicates lower subsidies than without. This is because technological progress would continue to lower costs, reducing the need for subsidy. In contrast, the optimal subsidy results for residential solar PV between from the two models often differ in sign, the model-without-learning indicating a negative subsidy (i.e. do not subsidize) with the model-with-learning showing a positive one. When accounting for technological progress, the optimal subsidy of residential solar has increased noticeably, suggesting that technological progress is a critical part of the argument in favor of subsidy.

a. Utility-scale wind

b. Residential solar PV

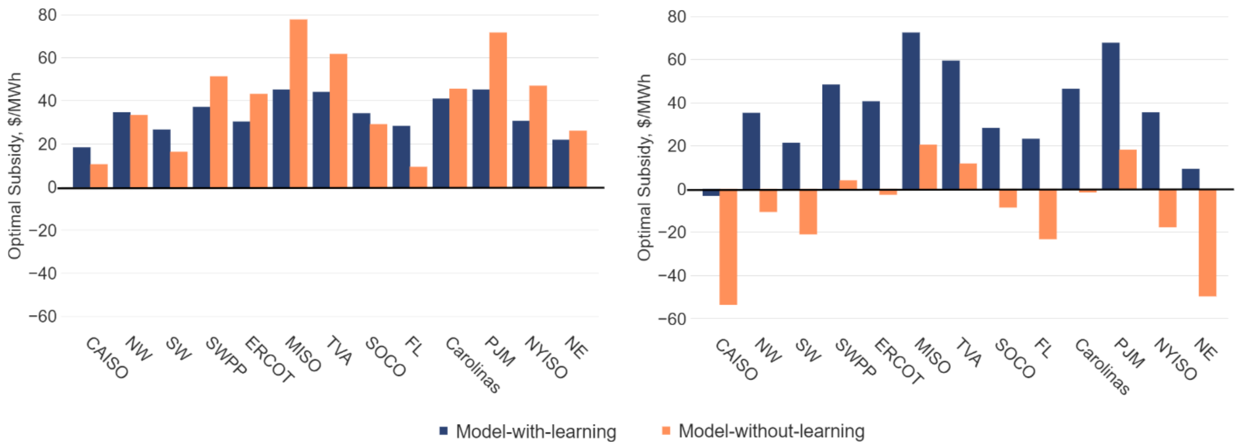


Figure 14. First-year optimal subsidy level for model-with-learning and model-without-learning in 13 grid regions for utility-scale wind (a) and residential solar (b). The main difference between the two models is that the model-without-learning assumes a zero learning rate for both technologies whereas the model-with-learning uses learning rates of 9.8% and 15% for wind and residential PV, respectively. For utility wind, optimal subsidy is less affected by learning but in the case of solar PV, the subsidy is much higher when learning is included.

3.7 Discussions: Linking technology attributes to subsidy structure

To better understand the drivers of differences in the optimal subsidies for wind and solar, the three sets of technology attributes identified as most relevant, which include cost reductions through technology progress, adoption sensitivity, and environmental benefits are further examined. Table 6 shows important input values and various output calculations for utility wind and residential solar. First, for cost reduction, the learning rate for solar (15%) is larger than wind (9.8%). The subsidy profiles in Figure 12 suggest that a higher learning rate leads to a steeper slope of subsidy reductions. This is because rapid cost reductions imply more frequent subsidy adjustment to avoid payments to consumers who would otherwise purchase at the lower price. Additionally, the results in Figure 13 show that the higher learning rate for solar makes it a critical part of the justification of subsidies for that technology, unlike wind energy. The results in Chapter 1 also demonstrate that residential solar provides the most benefits when subsidy starts at a high level and is phased out over time.

Second, the price sensitivity of adoption is determined from an empirical analysis of NPV and adoption for both technologies. Relative to residential solar, utility wind adoption accelerates faster for NPV above zero and falls more quickly when NPV is below zero, partly explained by utilities being more sensitive to price changes than private consumers. This means that a subsidy-induced shift in NPV has a stronger effect for wind than for solar, making subsidy a “stronger” influence on wind adoption and reducing concerns about “free riders” that are not influenced by the government support.

Third, environmental benefits for a given capacity of wind (0.8-3.4 $/W) are much higher than solar (0.6-1.2 $/W) in most regions. This is largely due to the higher capacity factor for wind compared to solar (21-49% versus 14-19%), which leads to higher generation, and thus benefits from a given quantity of wind capacity. However, environmental benefits are also influenced by the relationship between wind resource and grid emissions, both of which are geographically dependent (wind resource is strong in the central US, which is more heavily reliant on coal power). The larger environmental benefits for wind, combined with its stronger sensitivity of adoption, leads to a qualitatively different subsidy pattern: optimal wind subsidies persist over time, though with values that vary by region. As wind power is both more mature and has a lower learning rate, the optimal subsidies are roughly constant over time, rather than declining, as for residential solar. The model-without-learning shows the combinations of environmental benefits and diffusion sensitivity that justify an ongoing subsidy.

Table 6. Technology attributes of residential solar and utility wind and optimal subsidies (with and without technological progress). Range of values reflects results from 13 different grid regions.

Technology attribute	Utility wind	Residential solar
Capital cost in 2019 ($/W)	1.4	3.8
Capacity factor	21-49%	15-19%
Annual income (no subsidy) ($/yr-kW)	48-118	125-264
NPV in 2020 (no subsidy) ($/kW)	-783-170	-1,939-122
Emission benefits ($/W)	0.8-3.4	0.6-1.2
Learning rate	9.8%	15%
Diffusion sensitivity (W/$)	0.97-1.50	0.77-1.09
Optimal subsidy ($/MWh) – Model-with-learning	18-45, roughly constant	0 in 1 region; 7-70, declining to zero over 4-27 years in 12 regions
Optimal subsidy ($/MWh) – Model-without-learning	9-78	0-20

3.8 Sensitivity analysis: discount rates

Our base case analysis so far considers a discount rate of 3% for both residential solar PV and utility-scale wind technologies. In this section, we analyzed how optimal subsidies for residential solar and utility wind technologies vary when using different discount rates. Fig. 15 shows optimal subsidies for these two technologies for discount rates between 1% - 6%. For residential solar PV, optimal subsidies start as high as $47/MWh when the discount rate is 1%, but the first-year optimal subsidy level starts to decline when discount rates are increased. The results show that optimal subsidies for residential solar PV are not justified if discount rates are higher than 6%. On the other hand, optimal subsidies for utility-scale wind estimated using different discount rates remain relatively the same as the base case results. For residential solar PV technologies, the government subsidizes higher in the early stages to stimulate the long-term indirect technological cost reduction benefits. The use of higher discount rates accrues lower values of benefits today from future technological progress benefits, implying lower optimal subsidy. The subsidy for utility-scale wind is mainly justified by the short-term direct environmental benefits. In this case, both the government subsidy cost and emissions reductions benefit relatively occur in the same period and are uniform over time. Hence, the discount rate has less effect on the final result. But, in both cases, the arguments used to justify the subsidy and the qualitative difference observed between the optimal subsidies of these two technologies remain unchanged.

a. Residential Solar

b. Utility-scale wind

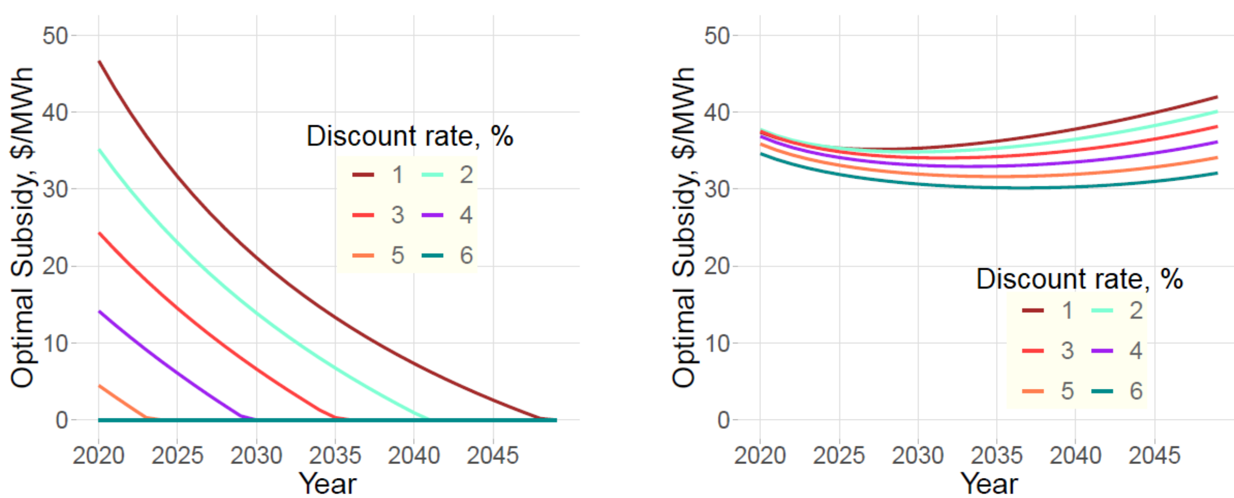


Figure 15. Uniform optimal subsidies for residential solar PV and utility-scale wind for discount rates ranging between 1% - 6%

3.9 Conclusions and Recommendations

This chapter employs two models (with and without technological learning) to understand the role of technology attributes in the optimal subsidy design for two important clean energy technologies. The model-with-learning applies an integrative approach to capture the dynamic interaction between the constituent elements of adoption, technology progress, and environmental benefits. The setup of the model makes it difficult to disentangle the relationships between these inputs and conclusions. Hence, this chapter develop a simpler, more analytically tractable model (model-without-learning) that neglects technological progress, which allows to solve for explicit relationships between technology attributes and the optimal subsidy. The model-with-learning indicates an ongoing subsidy for wind is justified in all 13 grid regions, while for residential solar the optimal subsidy schedule declines to zero over time. The model-without-learning clarifies how region-dependent environmental benefits and price sensitivity of adoption determine the optimal subsidy. Both models can have practical applications in clean energy policy design. Studies working on comprehensive analysis integrating both environmental and technological benefits of optimal subsidy designs may apply the model-with-learning method while the model-without-learning can be a better analytical tool when trying to uncover the determinants (different technological attributes) that drive optimal subsidies. The model-without-learning can also be used for policy designs of technologies at current price or constant cost assumptions.

The findings in this chapter have specific implications for the ongoing discussion about existing renewable energy policy. For utility wind, there is a recurring debate at the federal level whether to continue the Production Tax Credit. One argument to end subsidies is that cost reductions in wind have led to an industry that no longer needs them. It may be true that the wind industry does not require subsidy to continue, but the benefit-cost perspective indicates that subsidy continuation is still an efficient means of realizing public benefits in terms of emission reductions. This analysis highlights that wind power development does not actually require technology cost reductions to deliver net societal benefits. However, subsidy for this technology is justifiable and is less dependent on tuning the subsidy schedule to adjust for cost reductions.

What do these results suggest for policy design in the general sense? First, while government subsidies for clean energy technologies are well-known in economic theory, there has been limited research about the optimal subsidy design by technology over the long run (e.g., whether and how the subsidy levels should be adjusted compared to the past). This research introduces a new perspective that compares utility wind and residential solar with a similar adoption and subsidy modeling framework, and accounts for their distinctive technology attributes in their respective optimal subsidy schedules. The results demonstrate that two superficially similar clean energy technologies (in our case, both are intermittent renewable electricity sources transitioning to a mature industry) may call for different government support strategies with different justifications. Specifically, a prior analysis done in Chapter 1 demonstrated that residential solar provides the most benefits when subsidy starts at a high level and is phased out over time. But for utility wind, the story appears to be different: due to somewhat stronger environmental benefits and a customer base that is more sensitive to financial elements, a continual subsidy is preferred. This analysis also suggests that the arguments we use to support other clean energy technologies should be carefully considered: a "one size fits all" policy design is not appropriate. Instead, the details of optimal policy support depend on each technology's techno-economic characteristics.

Chapter 4: Informing optimal subsidy for residential solar: the role of technology adoption modeling uncertainties

4.1 Introduction

In the US, federal and state governments have employed different subsidy programs to promote clean energy technology adoption. The subsidies target different sectors, including technology manufacturers and end-use consumers. These policies are intended to reduce the environmental impacts of greenhouse gas emissions from fossil fuel consumption when generating electricity. The policies can also drive technology development and innovations in emerging technologies for broader adoption in the future. However, renewable energy subsidies require substantial financial investments and public spending. Hence, careful planning and design accounting for model and parameter uncertainties are essential to ensure long-term economic and social benefits.

Uncertainties pose a critical challenge to the robustness of energy system models forecasting long-term energy trends. Energy system models employ different techniques to predict future capacity additions and give prospects on the roles and performances of renewable energy technologies. These models rely on several parameters and system representations contributing to uncertainties. Parameters are input variables to the model and represent different driving factors, such as future technology price and innovation, economic growth and electricity demand, and policy choices. These inputs are forecasted and can significantly deviate from actual trajectories. Modeling errors also occur when reproducing real-world systems and decisions.

Studies have applied various techniques to integrate and analyze uncertainties in energy system models and policies. Scenario analysis is widely used to study the effect of uncertainty on future energy technology portfolios (Olaleye and Baker, 2015) and climate policies (Clarke et al., 2009). (Paltsev, 2017) discusses that scenario analysis can be helpful to qualitatively study the risks and benefits associated with various policies and investment decisions but points out that this analysis does not account for the complex nature of energy systems; as a result, it consistently underestimates the projections of clean energy adoption and generation. A different approach involves using probabilistic distribution to characterize uncertainties in model parameters. Pizer (1999) shows that accounting for uncertainty in various climate and economic parameters leads to higher optimal tax policy than the analysis done when employing an average value. A study by Marangoni et al. (2017) determines an optimal R&D portfolio program across four clean energy technologies by considering the uncertainty involved with future technology learning rates. This paper shows that applying a distribution of learning rate values in the portfolio analysis results in a higher R&D investment than the case where a single deterministic learning rate value is used. In contrast, the investment ranking across the technologies remains the same.

Another aspect of uncertainty analysis discussed less often in literature focuses on model uncertainty. This analysis involves investigating the effect of uncertainty that exists in the model or structure used to represent the real-world system under study (Morgan et al., 1990). Morgan et al. (1990) point out that model uncertainty can affect the outcome of the analysis considerably, whereas Gillingham et al. (2015) show the variance in climate model outcomes is mainly explained by parameter uncertainty than structural uncertainty. Studies have looked at the effect of model uncertainty through a systematic comparison of various energy models, and results show that model choices have a notable impact on future renewable energy projections (Blair et al., 2009; Luderer et al., 2017; Mai et al., 2018) and capacity expansion planning (Henry et al., 2021). Bistline et al. (2020) carried out multiple model-intercomparison under similar scenarios to determine renewable policy coordination impacts on energy system models across countries. Their study shows that model results may vary because of input assumptions, structural decisions framework, and spatial and temporal resolution differences. In addition to these studies in which the outcome of different models is compared, researchers have also explored results from multiple modeling alternatives within a single framework. A paper by (Goulder and Mathai, 2000) shows that optimal CO_2 abatement and carbon tax policies vary when different technical change models and policy optimization criteria are considered. A study by (Cohen et al., 2016) applies two different demand models, linear and non-linear, to determine the impact of demand uncertainty on optimal subsidy. This study considers different forms of demand models to show that policymakers will under-subsidize if demand uncertainty is ignored, regardless of the type of demand function. But they show that consumer benefits can be higher or lower with uncertainty, depending on the type of demand function used.

Studies have indicated serious concerns about the robustness of forecasts for electricity system models. For example, the World Energy Outlook model from the International Energy Agency has consistently and drastically underpredicted solar power capacity additions (Hoekstra 2018). In 2000, the Annual Energy Outlook "forecasts" from the Energy Information Administration (EIA) report U.S. wind capacity in 2020 as 6 GW for the "Reference case" and 18 GW for the "High renewables case" (EIA 2020). The actual Wind Capacity in 2020 was 118 GW, over five times higher than even the optimistic case for renewables. It is also observed that there is 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 U.S. carbon emissions vary from $40-$300/ton, depending on the model (Sanstead 2015). In these instances, it is unclear whether parameters, models or combinations of these two factors contributed to the uncertainty and deviations from actual trends.

Previous studies have developed different methods integrating several parameters and models to analyze optimal subsidy designs for clean energy technologies (Tibebu et al., 2021b; van Benthem et al., 2008). These models are essential to determine different technology characteristics affected by the policy. For instance, the models can be useful for predicting subsidy induced consumer adoption and long-term technology cost reductions. The models can also be applied to measure emissions reduction benefits resulting from the policies. But these models constitute uncertainties inherent to both parameter selection and model formulations which can have implications on the outcomes and policy recommendations. Research by Tibebu et al., (2022) used residential solar PV and utility-scale wind technologies to show that diffusion parameters are one of the determinant factors when justifying clean energy subsidies. This implies that any uncertainty in the parameters and diffusion pattern modeling would directly impact the policy design. Studies have indicated that different diffusion models disagree on the estimated adoption levels. Dong et al. (2017) used multiple diffusion models to forecast residential solar PV in California and determine the impact of different policy changes on PV adoption. Their results show that the baseline peak annual installation difference across the models is about 500 MW and indicate that top-down methods are not suitable for long-term impact analysis on adoption, but their study is not clear on where the difference in the results originated. This study aims to analyze how different modeling and parameter alternatives of a critical element, i.e., the diffusion model, affect practical policy decisions.

In this study, we analyze the role of adoption model uncertainties when designing clean energy subsidies. We determine the optimal subsidy that maximizes social net benefits for residential solar PV in the US using combinations of different adoption model functions and variables. Other studies have previously used the models and variables we selected to determine residential solar adoptions and analyze different policies. The models are calibrated with county-level residential PV price, adoption, and socio-demographic data from three states, namely Arizona, California, and Massachusetts. The goodness of fits of the models are compared using statistical measures but evaluating nonlinear regressions and correlations in some explanatory variables makes it challenging to select a single best model. We also performed a retrospective prediction to compare and validate model forecasts and accuracy.

This research contributes to the methodology and analysis of optimal government policy design tools by exploring the effects of uncertainties in model and parameter choices on subsidy schedules for clean energy technologies. Although the study by Dong et al. (2017) compared the forecasts of different diffusion models, they did not evaluate how the different outcomes may affect future policy decisions. In addition, the framework they considered either did not explicitly account for technological progress or is determined exogenously. Gillingham et al. (2015) consider combinations of modeling choices by different groups. Our result clarifies how important individual modeling choice affects decision outcomes. The paper by Cohen et al. (2016) considers two functional forms with only one parameter, i.e., price, in both cases. In this study, we show how consideration of additional explanatory variables and increased complexity would affect optimal subsidy design. Cohen et al. (2016) also point out that their analysis is carried out for a single-period model. Hence, further study is required to determine the effect of uncertainty on subsidy schedules accounting for the role of technological progress over time.

4.2 Methods

In this section, we consider three different adoption models with single and multiple explanatory variables. These models are then used to explore the effects of functional formulations and parameter choices on optimal policy design using a techno-economic framework.

4.2.1 Techno-economic framework

In this study, we apply a techno-economic framework developed by Tibebu et al. (2021) that is used to analyze state-level residential solar PV subsidies. The framework constitutes adoption, technology progress, and benefit-cost models. The adoption and technology progress models are run iteratively to synthesize technology diffusion induced directly by a government subsidy and indirectly by technology cost reductions. In this framework, the benefits of the government subsidy are justified using the direct environmental benefits from emissions reduction and the indirect technological progress benefits. The net benefit of the policy intervention is estimated using the benefit-cost model that compares the monetized public benefits from emissions reductions resulting from the subsidy-stimulated adoption and the government cost. The framework also implements an optimization tool to determine the optimal subsidy schedule that maximizes the national net benefit, i.e., the benefits minus the cost, from the government's perspective. We used this framework to analyze the effects of different adoption model formulations on the optimal subsidy design for residential solar PVs.

4.2.2 Adoption models

Research works on policy design for renewable technologies implemented different diffusion models to study the impacts of different policy instruments on renewable technology adoption. These studies applied different forms of mathematical formulations to model the diffusion process based on the economic attractiveness of the technology (Tibebu et al., 2021b; van Benthem et al., 2008). Other studies used system dynamics theories to account for the interaction among different PV market factors such as national energy mix, economic status, and environmental goals (Jeon et al., 2015). Statistical methods with multiple variables, including past cumulative installations, government incentives, and techno-economic and socio-demographic variables, are also used to model PV diffusion (Dong, 2014; Müller and Trutnevyte, 2020).

This study uses three diffusion models from the literature (Table 7). Different studies previously developed these three models to analyze the diffusion of clean energy technologies. In the first model, consumer adoption is formulated using an integral of Gaussian distribution resulting in an error functional form. The second diffusion model uses a mixed log-linear regression. The third model develops residential solar market purchase decisions considering that the probability of adoption for a given consumer is determined by integrating an extreme value distribution which gives a logit function demand model. We also consider three cases of each adoption model. The first case uses only the economic variable, the Net Present Value (NPV), as the primary driver of technology adoption. The second case includes a multi-variable model constituting economic and socio-demographic variables, including per capita personal incomes, unemployment rates, and population density at the county level. The third case applies financial and consumer awareness of the technology accounted through the share of previous technology adoption. These adoption models are integrated into a single techno-economic framework to determine the socially optimal subsidy for residential solar PV.

Table 7. Model names and theoretical framings for three adoption models with three different functional forms consisting of single and multi-variable explanatory variables.

Functional Forms	Model Framing	Explanatory Variable: NPV	Explanatory Variable: NPV and socio-demographic	Explanatory Variable: NPV and previous cumulative adoption
Error function	Adoption is modeled as an integral of a Gaussian distribution	ERF_NPV	ERF_NPV+Socio	ERF_NPV+Adopt
Mixed log-linear	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

We used different data to estimate the three adoption models (Table 8). All three adoption models are developed by using historical county-level residential solar PV adoption and price data from three states, namely Arizona, California, and Massachusetts. The economic factor, NPV, is the discounted financial benefit of adopting residential solar PV over a lifetime of 20 years. The NPV is estimated using residential solar PV price, incentives, and adoption data gathered from Berkeley Lab's Tracking the Sun report (Barbose et al., 2021). We compiled annual PV systems installed in 48 counties from the three states. The data time frame spans from 2005-2019 for most counties, while for others, the available start year falls between 2007-2010. We used NREL's PVWatts calculator to determine each county's annual solar energy production (NREL, 2016b). The residential electricity price of the utility with the largest number of PV customers in each county is obtained from EIA (EIA, 2021b). Socio-demographic data employed in our study, including income and unemployment rate, are collected from (BEA, 2021; US Bureau of Labor Statistics, 2021). We estimate population density by compiling population and land area data from (BEA, 2021; US Census Bureau, 2021). The demographic data are assumed to be exogenous when integrated into the techno-economic framework. We used annual data from 2000-2019 and performed a simple linear regression to project income and population. We used the mean of yearly rates for the unemployment rate from 2000-2019. The descriptive statistics of the variables used in the three adoption models are shown in Table 9.

Table 8. Data sources for residential solar PV adoption model fittings.

Variable	Data source
Residential solar PV price, incentives, and adoption	Barbose et al. (2021)
Solar insolation	NREL (2016b)
Electricity price	EIA (2021)
Income	BEA (2021)
Unemployment rate	US Bureau of Labor Statistics (2021)
Population	BEA (2021)
Land area	US Census Bureau (2021)

Table 9. Descriptive statistics of the variables used for fitting the adoption models.

Variable	Unit	Mean	Std.Dev	Min	Max
Annual Adoption	MW/million free detached houses	69	82	0.14	442
Annual Adoption	Watt/capita (log)	1.6	1.4	-3.1	4.1
NPV	$/kW	236	1,918	-5,636	3,305
Income	$/capita (log)	10.9	0.3	10.2	11.9
Unemployment	%	7.5	3.9	2.3	27.5
Population Density	Population/mile sq. (log)	5.9	1.4	3.2	9.8
Prior Adoption	Share of households with PV (log)	-1.9	0.8	-4.4	-0.5
Observations		655			

The details of the three adoption models are discussed below.

4.2.2.1 Error Function Model

The first adoption model used in this study is derived from a residential solar diffusion model developed by Williams et al. (2020). This model exclusively uses an economic factor – the Net Present Value (NPV) of adopting rooftop solar system over a 20-year period – consisting of government incentives, electricity price and solar energy potential. Adoption is formulated as the integral of a normal distribution that is mathematically modeled by using an error function (Equation 1).

$$Annual\ adopion\ \left(\frac{MW}{million\ free\ detached\ houses}\right) = k\left(1 + \text{erf}\left(\frac{NPV - \mu}{\sigma}\right)\right) \tag{40}$$

where, μ and σ are empirically determined parameters. In addition to the adoption variables shown in Eq. 1, we also consider two alternative cases consisting additional variables. We employ a multi-variable adoption model as a function of NPV and socio-demographic variables (Eq. 41) and NPV and previous years adoption (Eq. 42).

$$Annual\ adoption\ \left(\frac{MW}{million\ free\ detached\ houses}\right) = k\left(1 + \text{erf}\left(\frac{NPV - (\alpha_1 * income + \alpha_2 * unemployment + \alpha_3 * popn\_density + \alpha_4)}{\alpha_5 * income + \alpha_6 * unemployment + \alpha_7 * popn\_density + \alpha_8}\right)\right) \tag{41}$$

$$Annual\ adoption\ \left(\frac{MW}{million\ free\ detached\ houses}\right) = k\left(1 + \text{erf}\left(\frac{NPV - \left(\beta_1 * \log\left(\frac{x_{t-1}}{M_t}\right) + \beta_2\right)}{\beta_3 * \log\left(\frac{x_{t-1}}{M_t}\right) + \beta_4}\right)\right) \tag{42}$$

A non-linear least square method is applied to estimate the values of the parameters and the results are given in Table 10.

Table 10. Estimated values of the parameters using least square method.

	Dependent variable: Annual Adoption Watt/capita (log)			
		Models		
		ERF_NPV	ERF_NPV+Socio	ERF_NPV+Adopt
μ	Income		966	
	Unemployment		-197	
	Population Density	8074	-166	
	Prior Adoption			4.36E+21
	Constant		2	1.35E+21
σ	Income		665	
	Unemployment		-150	
	Population Density	4679	-245	
	Prior Adoption			2.26E+21
	Constant		5	-1.4E+15
	Observations	655	655	655

4.2.2.2 Regression Model

The second diffusion model implements a mixed log-linear regression to predict adoption. This type of model has been extensively used to analyze the adoption of clean energy technologies (Davidson et al., 2014; Drury et al., 2012). The first model (Eq. 43) uses only the NPV as the main predictor variable, while model 2 (Eq. 44) and model 3 (Eq. 45) incrementally include more variables to account for socio-demographic factors and past adoptions, respectively.

$$Annual\ adoption, \frac{W}{capita}(log) = \beta_1 * NPV + \beta_o + \varepsilon \quad (43)$$

$$Annual\ adoption, \frac{W}{capita}(log)$$
$$= \beta_1 * NPV + \beta_2 * log(income) + \beta_3 * unemployment + \beta_4 * log(population\ density)$$
$$+ \beta_o + \varepsilon \quad (44)$$

$$Annual\ adoption, \frac{W}{capita}(log) = \beta_1 * NPV + \beta_2 * log(prior\ adoption) + \beta_o + \varepsilon \quad (45)$$

where, β_i and ε represent the empirically fitted coefficients and the error term, respectively. The economic and socio-demographic explanatory variables we considered in our study, which include income, unemployment rate, and population density, are found to be significant PV adoption predictors in different studies (Dharshing, 2017; Drury et al., 2012; Müller and Trutnevyte, 2020).

We carried out ordinary least square regression to estimate the coefficients of the variables. Table 11 shows the results of the regression for the three cases. The R^2 for the first model consisting of only the NPV variable is 58%. This indicates that this variable can explain most of the data variation in the adoption. Adding socio-demographic variables in the second model has increased the adjusted R^2 to 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. The third model with NPV and share of previous years' adoption as explanatory variables have the highest adjusted R^2 value due to the correlation between the NPV and prior adoption rates. In this model, the coefficient of NPV is seen to vary significantly from the estimates obtained in models 1 and 2.

Table 11. Parameter coefficient estimates for predicting annual adoption using mixed log-linear regression.

Dependent variable: Annual Adoption Watt/capita (log)			
		Models	
	MLL_NPV	MLL_NPV+Socio	MLL_NPV+Adopt
NPV	0.000568***	0.000544***	0.000130***
	(0.000019)	(0.000018)	(0.000019)
Income		0.604265***	
		(0.169458)	
Unemployment		– 0.049573***	
		(0.01062)	
Population Density		– 0.287913***	
		(0.032915)	
Prior Adoption			1.295935***
			(0.042542)
Constant	1.477420***	– 3.033669*	4.045906***
	(0.036548)	(1.771840)	(0.087528)
Observations	655	655	655

R2	0.579755	0.638136	0.826580
Adjusted R2	0.579112	0.635909	0.826049
Residual Std. Error	0.928377	0.863468	0.596836
F Statistic	901***	287***	1,554***

Note: *p<0.1; **p<0.05; ***p<0.01

4.2.2.3 Logit demand function model

For the third model, we employ an adoption model developed by Lobel and Perakis (2011). The demand for solar panel at time t, q_t, is given by a logit demand model as shown in Eq. 46.

$$q_t = (M - x_{t-1}) * \left(\frac{e^{V(t)}}{1 + e^{V(t)}}\right) \qquad (46)$$

where, M is the total market size, x_{t-1} is the number of households that have already adopted solar PV, and $V(t)$ is the consumers' utility profile for adopting solar PV. The first term of Eq. 46 represents the number of remaining households who have not yet purchased solar PV at time t and the second term is the probability of adoption for these customers. The original demand model presented in Lobel and Perakis (2011) assumes that a consumer’s perceived utility and their decision to purchase solar panels is mainly influenced by the economic benefit (NPV) and the number of households that have already adopted solar PV (representing familiarity with the technology). The later component represents the effect of information spread and consumer awareness of the technology on diffusion patterns and is assumed to be proportional to the log of fraction of customers with PV (Eq. 47).

$$V(t) = a * NPV_t + b * log\left(\frac{x_{t-1}}{M}\right) + c + \varepsilon \qquad (47)$$

where, a, b, and c are empirically determined demand parameters. ε is the error term referring to the demand shock that is not captured by the data. In this model only deterministic components are considered and ε is set to zero. From Eq. 46 and 47, the demand function can be written as:

$$q_t = (M - x_{t-1}) * \left(\frac{e^{a*NPV_t + b*log\left(\frac{x_{t-1}}{M}\right)+c}}{1 + e^{a*NPV_t + b*log\left(\frac{x_{t-1}}{M}\right)+c}}\right) \qquad (48)$$

Rearranging Eq. 48 yields a linear function that can be used to determine the parameters of the demand model (Eq. 11).

$$\ln\left(\frac{q_t}{M_t - x_t}\right) = a * NPV_t + b * log\left(\frac{x_{t-1}}{M}\right) + c \qquad (49)$$

In addition to the model discussed above, we consider two modified models that include either the single NPV variable (Eq. 50) or multiple variables capturing socio-economic factors (Eq. 51). In the single variable model, we assume that consumer's utility is driven mainly by NPV whereas in the multi-variable model we account for additional socio-demographic factors.

$$q_t = (M - x_{t-1}) * \left(\frac{e^{\beta_1 * NPV_t + \beta_o}}{1 + e^{\beta_1 * NPV_t + \beta_o}} \right) \tag{50}$$

$$q_t = (M - x_{t-1}) * \left(\frac{e^{\beta_1 * NPV_t + \beta_2 * log(income) + \beta_3 * unemployment + \beta_4 * log(population\ density) + \beta_o}}{1 + e^{\beta_1 * NPV_t + \beta_2 * log(income) + \beta_3 * unemployment + \beta_4 * log(population\ density) + \beta_o}} \right) \tag{51}$$

Table 12. Parameter coefficient estimates for logit demand models.

	Dependent variable: $\ln\left(\frac{q_t}{M_t - x_t}\right)$		
	Models		
	(1)	(2)	(3)
NPV	0.000550*** (0.000019)	0.000535*** (0.000019)	0.000064*** (0.000016)
Income		0.459858** (-0.181206)	
Unemployment		-0.029721*** (-0.011356)	
Population density		-0.118731*** (-0.035196)	
Prior adoption			1.437034*** (-0.036427)
Constant	-5.260578*** (0.036997)	-9.346431*** (1.894669)	-2.412440*** (0.074947)
Observations	655	655	655
R2	0.557722	0.57505	0.869418
Adjusted R2	0.557045	0.572434	0.869018
Residual Std. Error	0.939796	0.923326	0.511046
F Statistic	823***	220***	2,171***

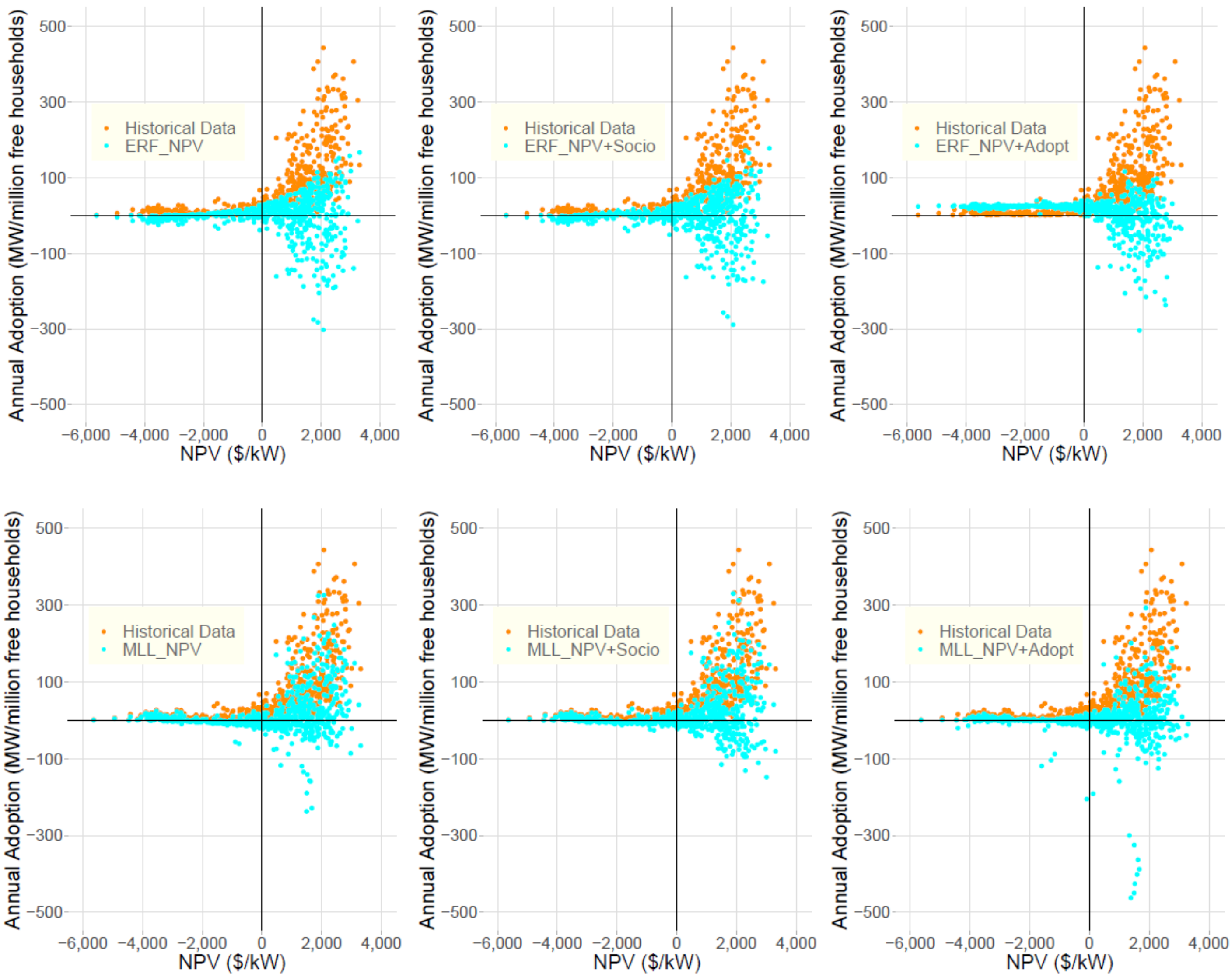
Note: *p<0.1; **p<0.05; ***p<0.01

4.2.3 Model Evaluation

We have compared the three models using the total squared error (TSE) and the residuals, which is the difference between the actual and the predicted values. But this metric may not be ideal for measuring the models' quality in forecasting adoption. Even though Table 13 shows that the error function and the logit models with NPV and prior adoption variables have the lowest TSE, these models overestimate the adoption level when forecasting (shown in the results section). It is also seen that the TSE of the error function and logit models do not change significantly when adding socio-demographic variables.

Table 13. Total squared error of the adoption models fitted using historical county data.

	Explanatory Variable		
Functional Forms	NPV	NPV and socio-demographic	NPV and previous cumulative adoption
Error function	1399	1342	1192
Mixed log-linear	1585	1481	1598
Logit	1716	1715	1247



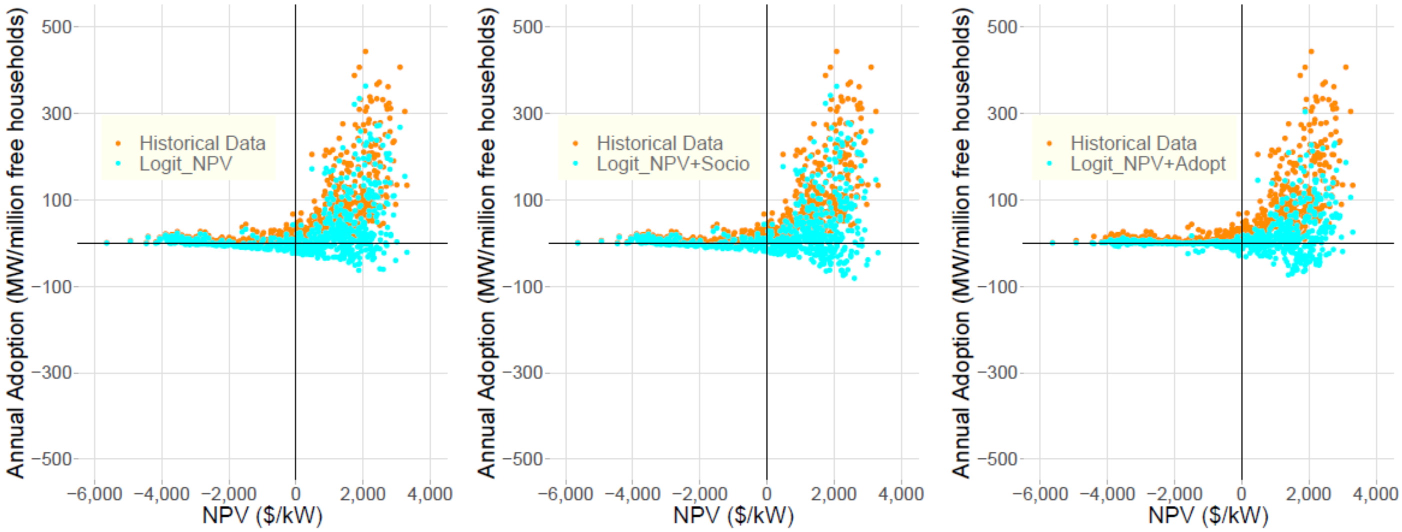


Figure 16. Historical data and residual plots for different adoption models. An error function, mixed log-linear regression and logit functions are used to model adoption trends.

Each model is fitted using a single (NPV) and multiple (NPV and socio-demographic or NPV and prior adoption) explanatory variables.

Table 14 shows the correlation matrix between the different explanatory variables. NPV and prior adoption have the highest correlation, 0.8, followed by income and population which is about 0.7.

Table 14. Correlation matrix.

	NPV	Income	Unemployment	Population density	Prior adoption
NPV	1				
Income	0.17	1			
Unemployment	-0.24	-0.60	1		
Population density	-0.01	0.69	-0.32	1	
Prior adoption	0.82	0.22	-0.32	-0.02	1

4.3 Results and Discussions

In this section we first compare the different adoption curves presented in the methods section. Then we show how these models affect the optimal subsidy design for residential solar PV.

4.3.1 Adoption Curves

We compared the different adoption models by plotting them on the same graph. Figure 17 shows the annual adoption predicted using the models as a function of the NPV. We plot the adoption as a function of the NPV mainly because government subsidy influences PV adoption by changing its relative price, or the NPV. Since our primary goal is to look at the relationship between adoption models and subsidy design, we are not plotting the diffusion curves against other variables.

Looking at only the single variable models (Figure 17-left), the error function model has the steepest slope than the mixed log-linear and logit models. This implies that subsidies can stimulate more adoption when employing the error function model than the others. Figure 17-right shows additional adoption curves fitted using the multi-variable models consisting of socio-demographic and prior adoption variables. Here, the adoption models consisting of prior adoption as an explanatory variable result in a higher adoption for low NPV values, subsequently driving future adoptions and restricting the need for government subsidies at the later stage.

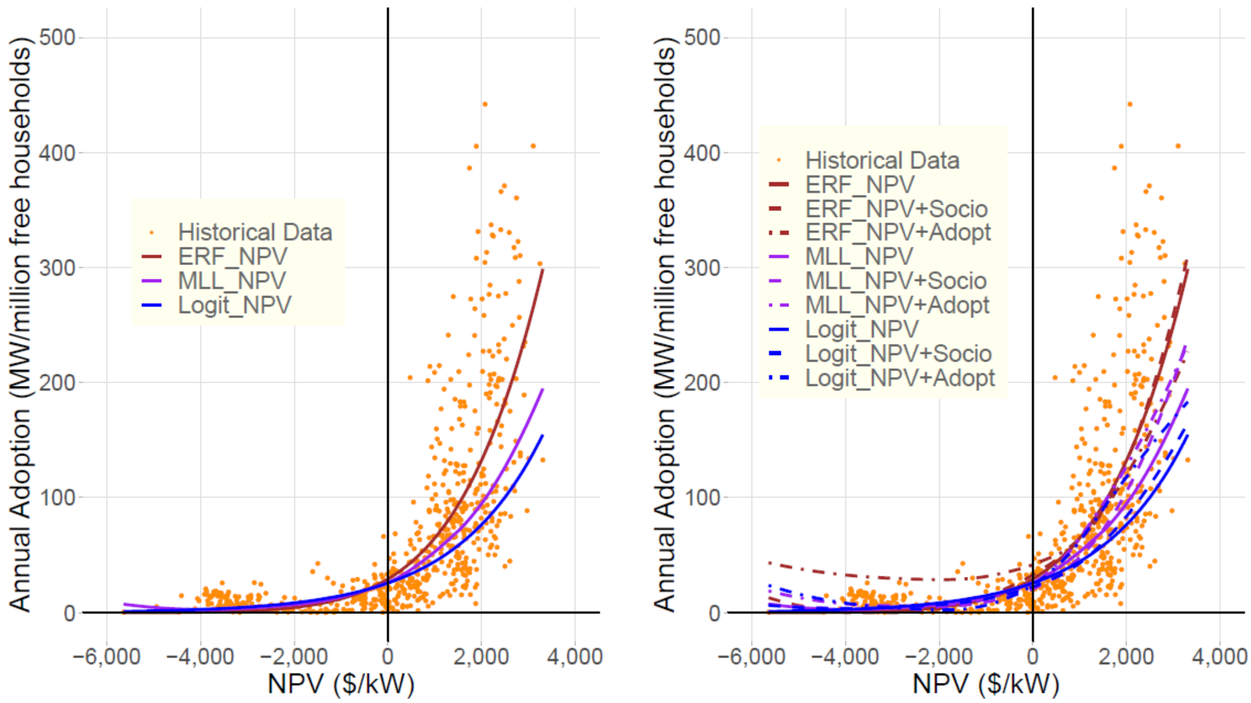


Figure 17. Adoption prediction comparison for the three models as a function of the NPV. Figure on the left is adoption curve for the single variable adoption models. Figure on the right is adoption curve for all three cases of the models. A smooth line curve is fitted for those models with scatter plots.

4.3.2 Forecasting Residential Solar PV Adoption

The three adoption models are integrated into the techno-economic framework to determine the residential solar PV adoption level resulting from a given subsidy. In this case, we performed a retrospective forecasting starting from 2012 by considering residential solar PV federal tax credit subsidy policy as planned by the government. This subsidy offers 30% of the investment as a federal tax credit (FTC) for systems installed before 2020. The credit is lowered to 26% for installations between 2020–

2022, to 22% for systems connected in 2023, and is expected to expire after 2024. Figure 18 shows the annual residential PV diffusion in the US predicted by the techno-economic framework using the different adoption models. The error function model consisting of the prior adoption variable forecasts the highest diffusion rate, with peak annual adoption reaching about 16 GW in 2024. The mixed log-linear and logit models with the same explanatory variables are also observed to predict a higher adoption rate than the rest of the models, even after the FTC expires.

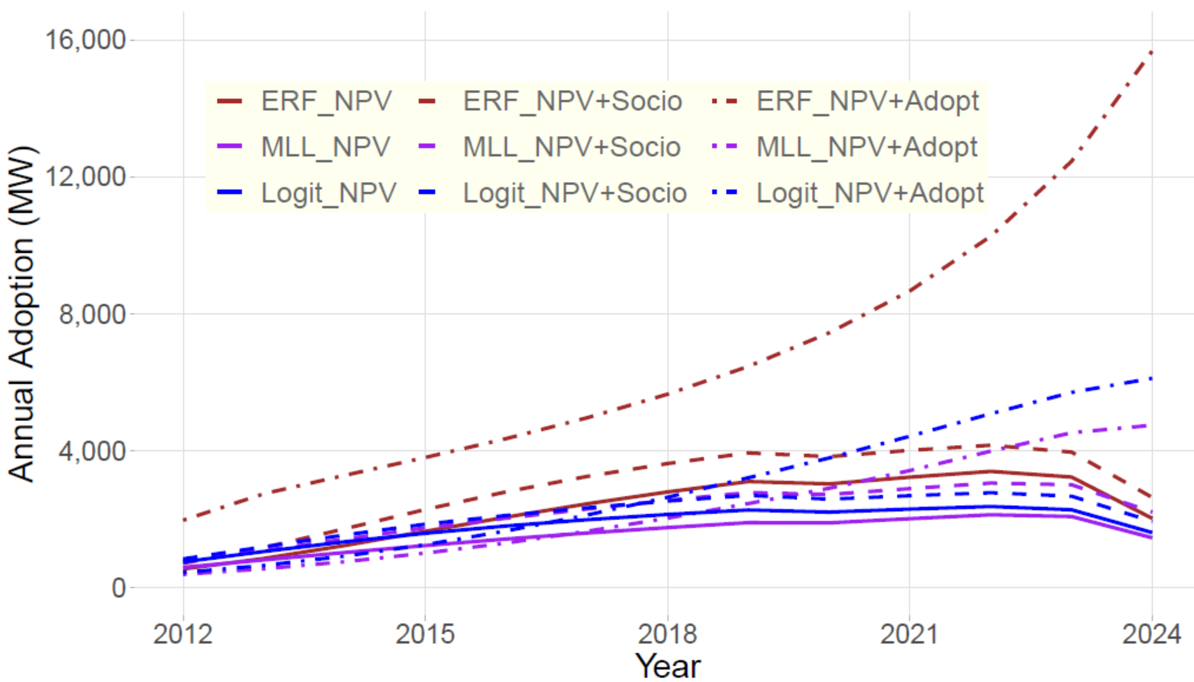


Figure 18. US annual adoption starting from 2012 with planned 30% FTC and learning rate of 15% predicted by the different adoption models.

Figure 19 shows the impacts of the 30% FTC subsidy on residential PV adoption for the different models. The figure shows US PV adoption predicted by each model with and without this subsidy. The gap between the two curves represents the stimulated adoption due to the subsidy. The subsidy induces more adoption for the error functions model with NPV and socio-demographic variables than the rest of the models. The no-subsidy adoption trends seem higher for the mixed log-linear and logit demand models than for the error function model.

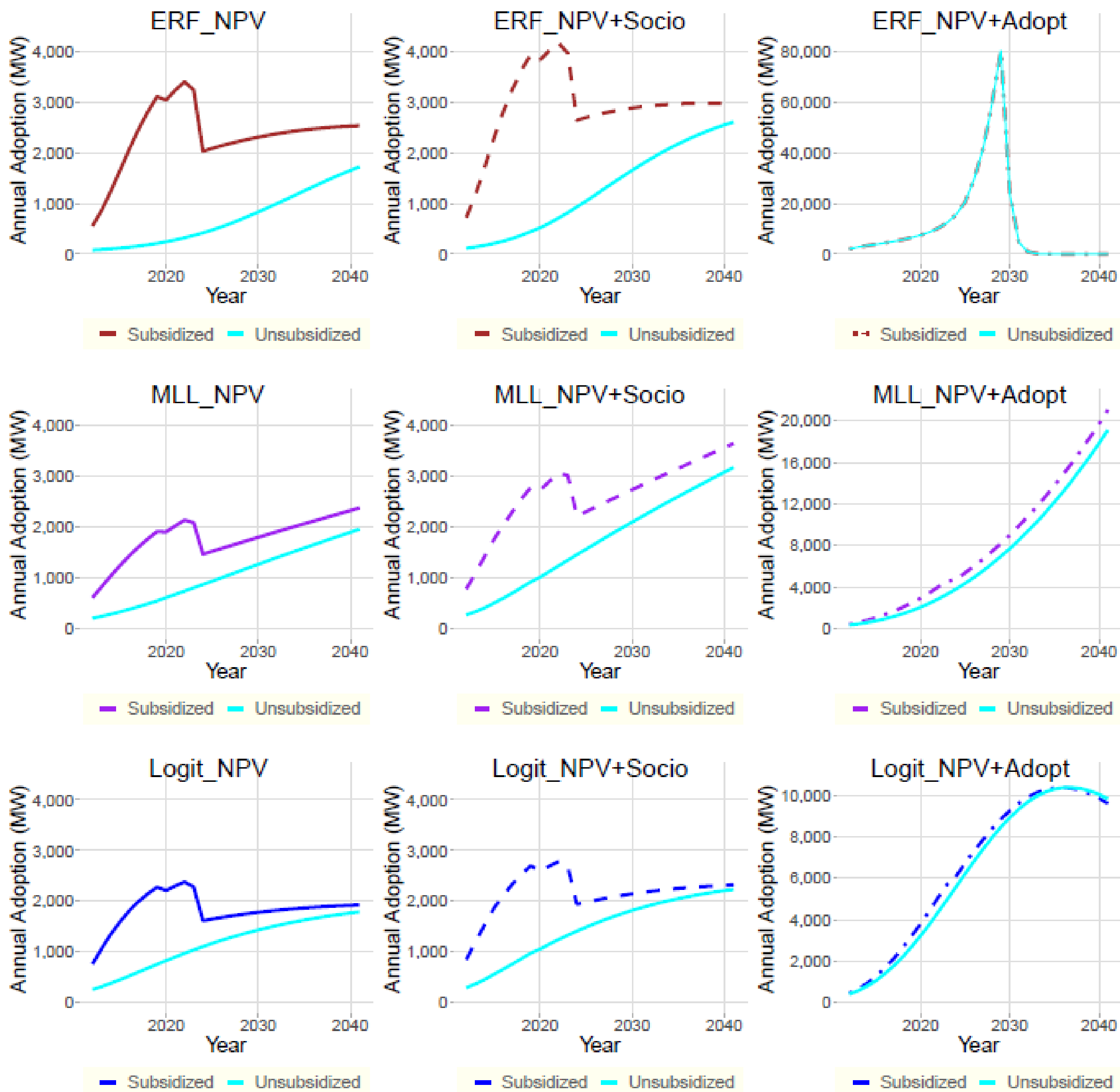


Figure 19. US annual adoption starting from 2012 with planned 30% FTC subsidy that expires in 2024 and no subsidy at LR of 15%.

4.3.3 Optimal Subsidy

The adoption models are also integrated into the techno-economic framework to estimate optimal subsidies for residential solar. The techno-economic framework applies adoption, technological progress, and benefit-cost model to determine the optimal subsidy that maximizes national net benefit, i.e., benefits resulting from emissions reductions and technological progress minus the subsidy cost. Fig. 20 shows the optimal subsidy results for different cases of learning rate and social cost of carbon. For the base case learning rate of 15% and carbon cost of $45/ton, optimal subsidy estimates are zero for all adoption models except the ERF_NPV and ERF_NPV+Socio (Fig. 20(a)). When the social cost of carbon is increased to $85/ton, the mixed log-linear models with NPV alone and NPV and socio-demographic variables result in optimal subsidies starting at $250/kW and $330/kW (Fig. 20(c)). For the techno-economic model with logit demand adoption models (Logit_NPV and Logit_NPV+Socio), subsidies stimulate adoption and result in net benefits when a higher learning rate and social cost of carbon are considered.

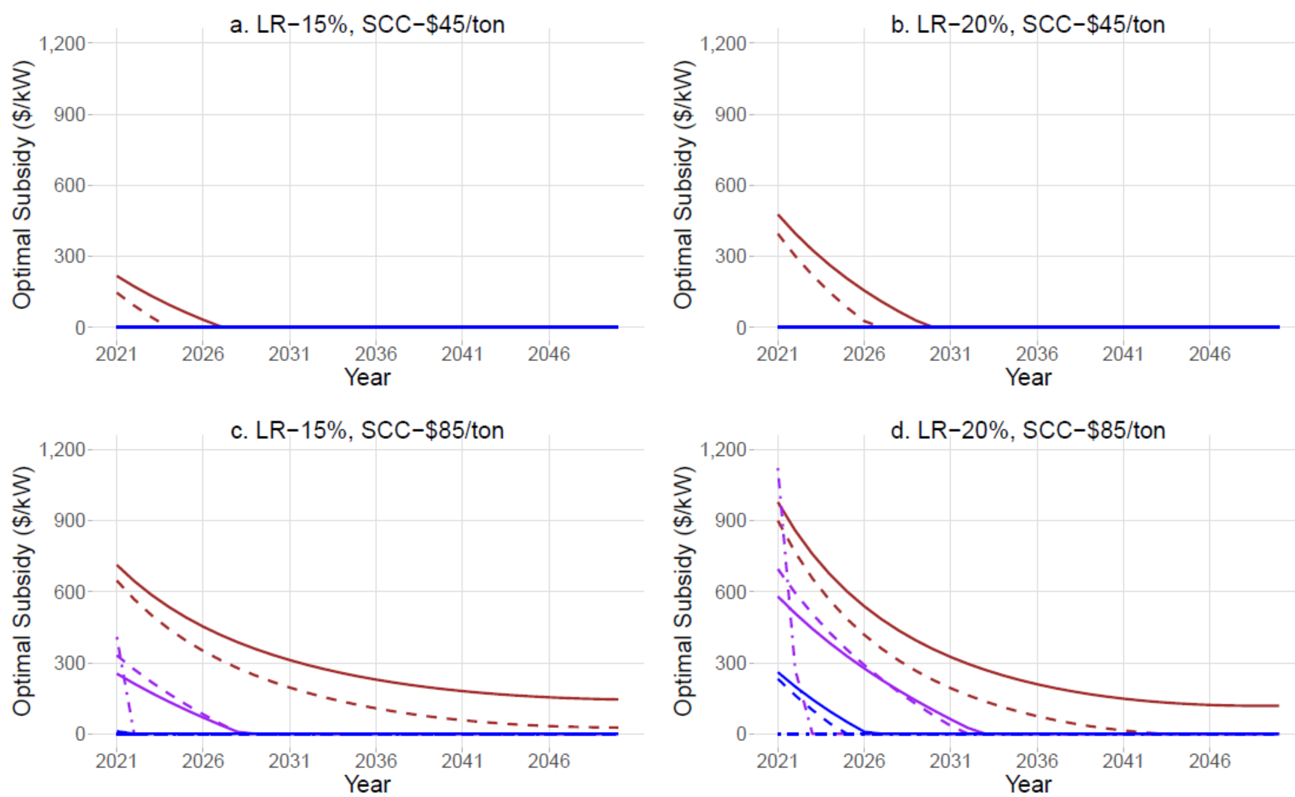


Figure 20. Optimal subsidy schedule for sample cases of learning rates and social costs of carbon. The results show that optimal subsidy schedule estimates vary considerably when different adoption models are used.

Figure 21 shows the first-year optimal subsidy level for different learning rates and social costs of carbon. The optimal subsidy is mostly zero for lower values of learning rate and carbon cost in all cases. The figure shows that the optimal subsidies are zero when the prior adoption variable is used in the error function and logit demand function adoption models. For the mixed log-linear model, a high subsidy value is offered in the early period to stimulate adoption, which could, in turn, drive adoption in the later years. The optimal subsidy obtained with a given adoption model is very close for the single variable with NPV and the multi-variable models with NPV and socio-demographic variables. This indicates that the model choice may impact the optimal subsidy schedule estimates more than adding socio-demographic variables considered in this study.

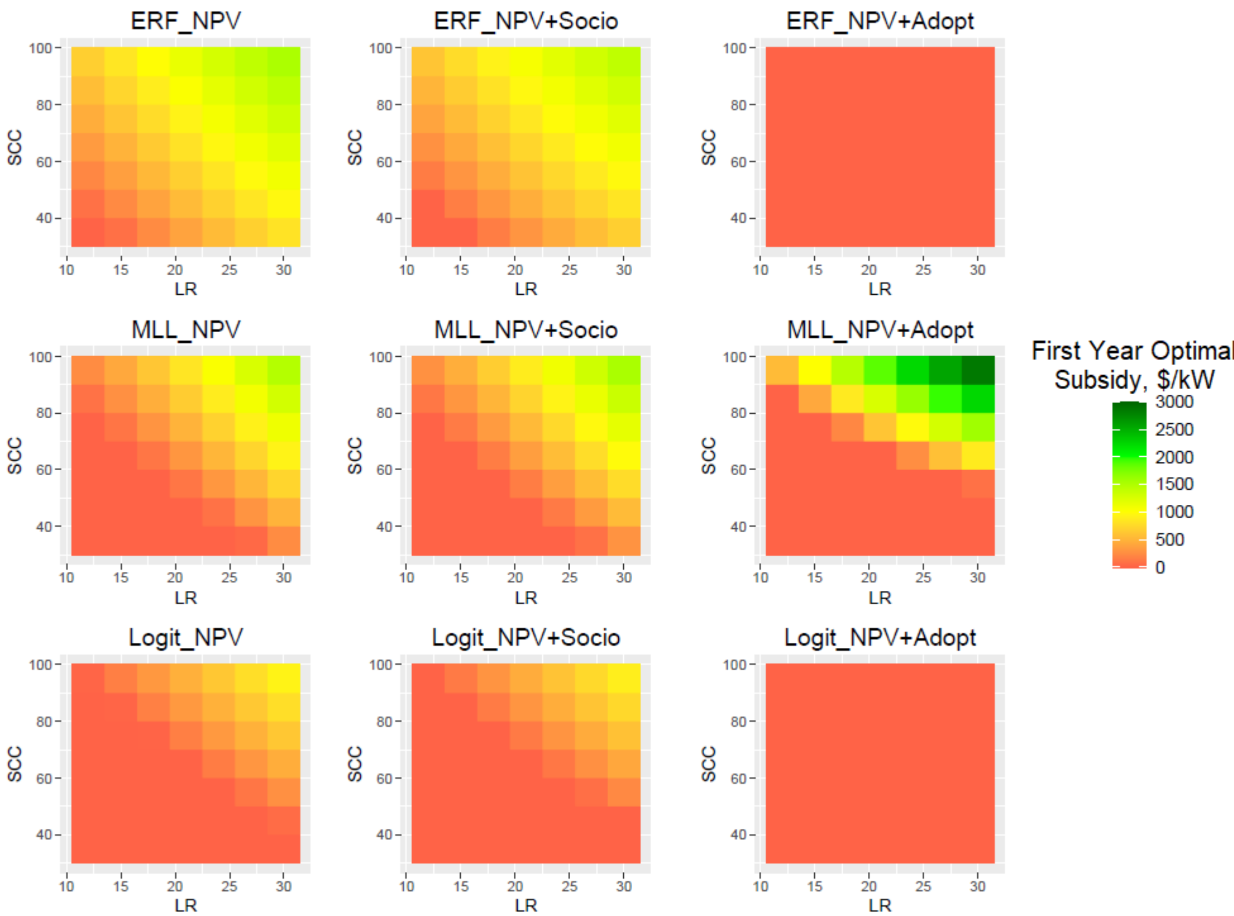


Figure 21. First year optimal subsidy determined using the different adoption models for different values of learning rate (%) and social cost of carbon ($/ton).

4.4 Sensitivity analysis: discount rates

The optimal subsidies estimated above apply a discount rate of 3%. We carried out a sensitivity analysis using discount rates ranging from 1%-5%. Fig. 22 shows the optimal subsidies for residential solar PVs for three adoption models employing single variable (NPV) and multi-variable (NPV+Socio) parameters at a learning rate of 20% and a social cost of carbon of $85/ton. Similar to the observation in Chapter 3, the first-year optimal subsidies are lowered for higher discount rate values, but the subsidy declines at almost the same rate as the base case value. Higher discount rates imply lower accrued benefits which are accounted through long-term technological progress and cost reductions.

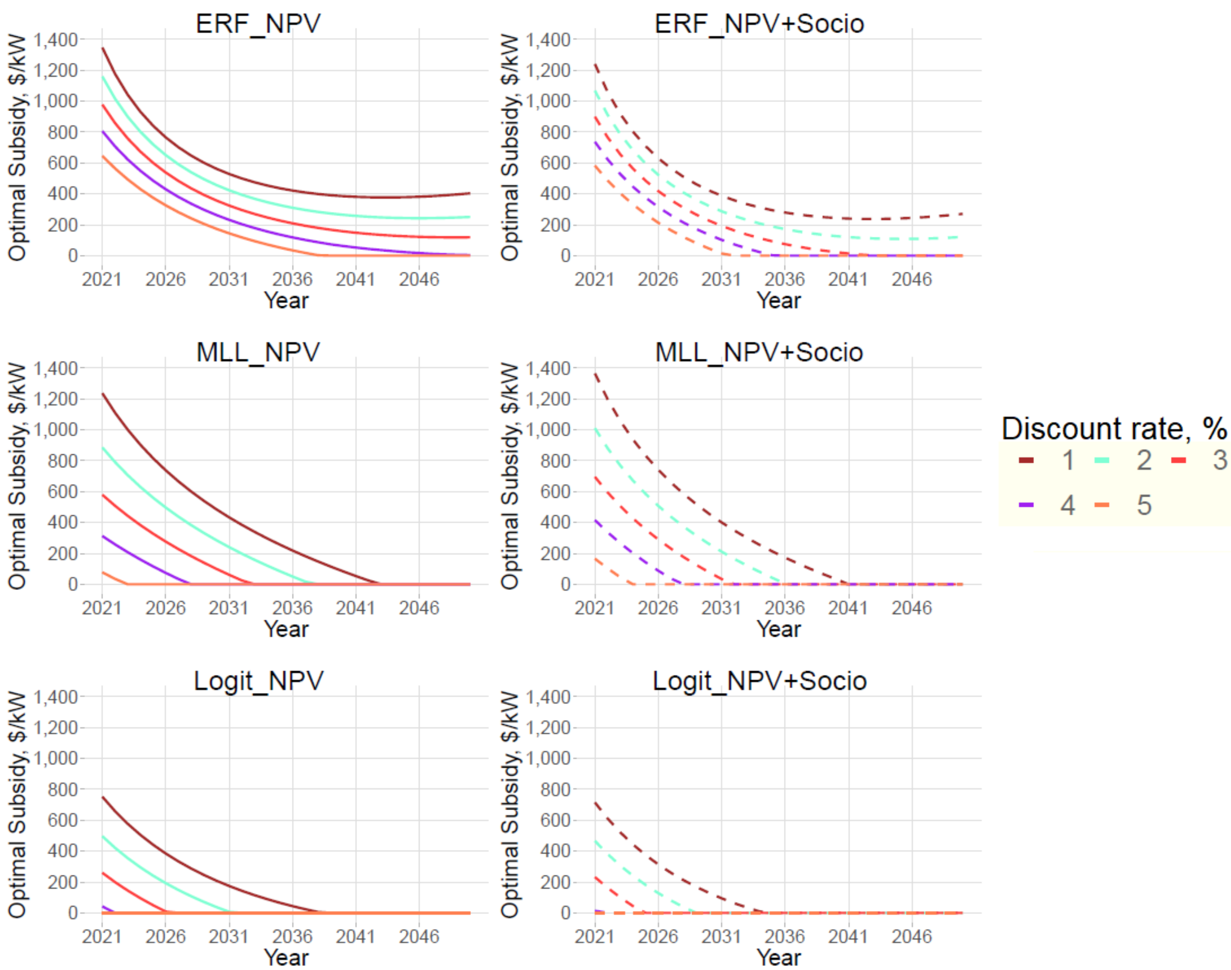


Figure 22. Optimal subsidy design using different discount rates at a learning rate of 15% and social cost of carbon of $45/ton.

4.5 Conclusions and Recommendations

This research studies the impacts of adoption model formulation and parameter choice on optimal subsidy design for residential solar PVs. We analyzed three adoption model functional forms with three combinations of explanatory variables within a single techno-economic framework. We show how policy decisions vary using these different models and examine the results under different technological learning and social carbon cost assumptions.

We have observed that adding socio-demographic variables to adoption models with NPV variables does not significantly change the optimal subsidy schedule. For instance, at a learning rate (LR) of 15% and social cost of carbon (SCC) of $45/ton, the optimal subsidy schedule starts at $217/kW and $146/kW for the error function model with a single variable model and multi-variable model consisting of socio-demographic variables, respectively. At this LR and SCC, differences in optimal subsidy are more notable across different model formulations using similar explanatory variables. We found that the optimal subsidies are zero for both single and multi-variable mixed log-linear and logit adoption models.

In the literature on energy system models and policy analysis frameworks, it is more common to see sensitivity analysis in which the studies evaluate and compare outcomes using different values of input variables. In regression-based studies, it is a standard practice to select different combinations of input parameters to test the robustness of estimated coefficients. But it is far less common to explore the effects of varying model formulations using similar input variables. In this study, we found that for the single variable models consisting of only the NPV, at SCC of $85/ton, lowering the learning rate from 20% to 15% has reduced the optimal first-year subsidy by 96% for the logit demand model. These values were 27% and 56% for the error function and mixed log-linear models, respectively. This shows that the impact of technology cost reduction assumption on optimal subsidy design depends on the model formulation assumptions. Optimal policy design can be more sensitive to learning rate changes when the logit demand function is used than the other models. A similar result is also observed for the multi-variable models consisting of NPV and socio-demographic variables.

Often, researchers address uncertainty by adding model complexity through accounting for additional factors thought to influence the outcomes. In our case, the single variable models employing the NPV resulted in a declining subsidy. But, adding previous adoption variables to account for consumer awareness of the technology had resulted in a qualitatively different outcome. In the case of the error function and logit demand models, results suggest that government subsidies are no longer needed for residential solar PVs at any sensible values of learning rate and carbon cost. On the other hand, for the mixed log-linear model, the optimal subsidy is only an early investment by the government. This shows that adding more variables can be problematic if the statistical significance of the NPV is masked due to multicollinearity issues. In this case, it is also important to point out that the need for government support depends on how strong its effect is on adoption. Results show that if the adoption curve is steeper as a function of the NPV (or subsidy), the subsidy can stimulate and induce more adoption compared to the no subsidy case, resulting in a higher net social benefit. But it would be hard to justify the subsidy if other factors such as socio-demographic or prior adoptions are the main driving factors for adoption.

Chapter 5: Conclusions

Governments have implemented different policies to promote the adoption of clean energy technologies that can be used to reduce greenhouse gas emissions from electricity generation. Among these policies, subsidies providing financial incentives to end-use consumers have become an important policy approach to driving the adoption of clean energy technologies. This dissertation investigates analytical methods to establish ideal government subsidy levels for future pathways that can result in clean and sustainable energy generation. This study also provides a structured tool to analyze and identify technology-specific attributes and modeling approaches that may affect socially optimal policy designs.

Chapter 2 develops an integrated framework that comprehensively analyzes the economic justifications of clean energy technology subsidies and determines subsidy schedules that maximize social benefits. The framework constitutes a model that accounts for adoption induced by a subsidy by extrapolation from empirical data. The framework also considers that the adoption can induce cost reductions by stimulating industry investments and learning. This is needed as many energy subsidies are justified through their potential to develop the industry over time. A benefit-cost model is included in the integrated framework to determine if the subsidy investment is in the public interest. We applied the framework for residential solar PV technologies in the US. We found that considering technological progress is a critical part of the justification of a public subsidy for these early-stage technologies. The results also show that the subsidy for emerging technologies ought to start high and be tapered off aggressively as prices fall. The study highlights that the effect of free riders and geographical heterogeneity limits the net benefits of high subsidy levels once a technology has become competitive enough to attract consumers at unsubsidized prices.

Chapter 3 presents a comparative assessment for optimal subsidies in residential solar PV and utility-scale wind technologies. While we find that the optimal government subsidy for residential solar PV should decline over time, relatively constant optimal subsidy schedules are observed for utility wind. This fundamental difference is analyzed through a simplified approach that provides analytical solutions to optimal subsidy design modeling. This approach and the integrated framework developed in Chapter 2 are used to identify three technological attributes that drive the qualitative differences observed in the policy design of the two technologies. These include environmental benefits, price sensitivity of diffusion, and technological cost reductions. The results show that environmental benefit is the primary justification for wind technology subsidies, whereas technological progress benefits are the main element when justifying subsidies for residential solar PVs. The fact that the subsidy targets two groups of consumers also has further implications for the optimal subsidy difference between these two technologies. Wind technology adaptors are more sensitive to price change and economic effectiveness induced by the subsidy than homeowners buying residential solar PV. The results of this chapter demonstrate that governments should carefully implement technology specific policies accounting for the differences in technological characteristics and justifications.

Chapter 4 evaluates the effects of uncertainties in adoption models on optimal policy design. We used three model structures: an error function, a mixed log-linear regression, and a logit function. These models are examined using a combination of single and multiple explanatory variables. The first case uses the Net Present Value (NPV) of adopting a rooftop solar system over a 20-year period consisting of government incentives, electricity cost, and solar energy potential. In addition to the economic gain, multi-variable models are also considered, allowing us to account for other factors that can drive adoption, including socio-demographic variables such as income, unemployment rate, population density, and consumer awareness quantified using prior adoption rates. The models are fitted using historical county-level data from three states, namely Arizona, California, and Massachusetts. Each adoption model is then integrated into the techno-economic framework developed in Chapter 2 to analyze the variation in optimal government policies. We have observed that adding socio-demographic variables did not significantly change the optimal subsidy design for all three model configurations, but high variation is observed across different models using similar variables. We also found that subsidies are not justified when using prior adoption variables. These results imply that optimal subsidy designs can be sensitive to adoption model structural formulation variable choices.

In our study, the technology progress model utilizes a national experience curve which is based on US cumulative PV adoption and installed price. This assumes that the US adoption follows a similar growth trend as the global adoption. Two alternative patterns of US versus rest-of-world adoption are possible. First, rest-of-world adoption could be entirely independent from the US. This case could be modeled through an exogenous forecast of global adoption. Second, adoption patterns among countries might asymmetrically interact, e.g. one nation might choose to wait for subsidy efforts elsewhere to bear fruit before investing in a technology. This case might be modeled with a game theory model. There are practical and theoretical difficulties with modeling both the independent rest-of-world and interacting policies cases. The independent rest-of-world case requires a plausible forecast of global adoption. The interacting policies case faces the practical challenge of formulating a plausible game theory representation of national subsidy decision-making processes. From a philosophical perspective, national policy-making address global and local environmental challenges ought not to be contingent on the actions of other nations.

This study applied a benefit-cost analysis to determine the social net benefits of subsidizing clean energy technologies. We estimated the monetized benefits from avoided emissions and damages from conventional power plants because of the adoption of clean energy technologies. These types of policies are analyzed over a long period and involve intergenerational discounting. For long-term public projects, in which the costs and benefits represent the consumption profile changes from society's perspective, consumption interest rates or social rate of time preference is considered to be the appropriate discount rate (Interagency Working Group on Social Cost of Greenhouse Gases, United States Government, 2021; US EPA, 2010). This value differs from the rates used for private individuals and firms investments which may account for capital return tax and investment risks (US EPA, 2010). In our base case analysis, we used a 3% discount rate to estimate the net benefits of subsidizing clean energy technologies. This rate is recommended for discounting intergenerational social projects and is determined using average consumption interest rates observed over 30 years (IWG, 2021). This value is lower than the rates used for private sectors, which are estimated using post-tax rates accounting for investment risks (Interagency Working Group on Social Cost of Greenhouse Gases, United States Government, 2010).

Governments apply different policies to promote the use of clean energy technologies. These policies are essential to reduce the negative externalities of fossil fuel consumption for electricity generation and address energy security issues. But it is often seen that decision-makers implement a one size fits all policy targeting different technologies. The results of this study show that the economic justifications and efficiency of these policies depend on the specific characteristics of the technology, such as diffusion patterns, technology cost reduction, and environmental benefits. The subsidy-driven dynamic interaction among these characteristics can vary for different technologies calling for the need to design technology specific policies.

In this study, we only consider one clean energy technology at a time when determining optimal subsidies. The integrated framework can be modified to carry out an alternative analysis that can optimize for multiple technologies. This type of analysis can inform the government on how to allocate a limited budget to different technologies while maximizing national net benefits. This dissertation also does not account for funding sources and does not put any constraint on government spending. The scope of our study is also limited to one type of demand-pull policy that directly affects the economics of technology adoption by homeowners or wind developers. But governments can also apply other mechanisms for promoting R&Ds in clean energy technologies.

5.1 Policy Implications

In the US, federal and state legislators have passed financial incentives and regulatory policies to support small and large-scale clean energy technologies such as wind, solar PVs, and electric vehicles. Although the subsidies for these technologies are established through a political process, it is unclear how the decisions are informed and what analytical tools are applied to identify efficient public spending. Policymakers deciding on subsidy schedules promoting renewable technologies should investigate the long-term costs and benefits to help inform that process. They should consider not only the environmental benefits but also the complex interaction between the subsidy, diffusion patterns, and technology cost trajectories.

The federal government implements a homogeneous subsidy that is equal across US states. But it is important to consider that the performance and outcomes of such types of subsidies depend on the geographical variations driven by renewable resource potential and the current energy grid mix. In this study, we observed that national net benefits could increase when geographically differentiated subsidies are applied for residential solar PV and utility-scale wind optimal incentive designs. These technologies can displace a massive amount of environmental emissions in the Midwest region, which results from a high proportion of coal-powered electricity generation. Optimal subsidies for these technologies are found to be higher in these regions than in others. But this finding may reverse if clean energy technologies, for e.g., electric vehicles and storage, have the potential to increase electricity generation from emissions-intensive power plants. Hence, analyzing the effects of subsidies of clean energy technologies accounting for geographical variation and the energy-grid mix is essential.

The federal government continues to allocate a considerable amount of budget to provide incentives for using residential clean energy technologies such as solar PV and electric vehicles. Policy mechanisms such as tax incentives can reduce the cost of adopting these technologies for consumers. But the government should also implement policies that specifically target low-income households, as the technologies are still inaccessible for these communities due to the high cost. At state level, New York has community solar programs for low- and moderate-income households and California offers solar incentives for single and multifamily low-income housings. Similar policies can be adapted at the federal level. In addition to this, it is also important to explore environmentally safe ways to handle renewable energy equipment after its lifetime. Solar PVs and wind turbines have an average lifetime of 20 years. The government should devise regulations for end-of-life management and policies that promote the development of infrastructure for recycling and remanufacturing of these technologies.

5.2 Limitations

There are a number of caveats to this work. First, the model carves out residential solar as a separate piece of the energy system, but the grid context will evolve, influencing important variables such as electricity prices and emissions factors. There are additional factors that we do not account for in this study. Lifecycle emissions and end of life recycling of PV modules and other solar PV system components are not evaluated in the benefit-cost model. Assessment of such factors requires a detailed material component and environmental policy framework analysis which we consider to be out of scope of this study. The benefit-cost analysis does not account for administrative and transaction costs of federal subsidies. But we re-run our base case model assuming an additional overhead cost of 1-5% of government spending and find results mostly unchanged. The optimal national flexibly subsidy schedule starts at \$575/kW and declines to \$2/kW in 13 years (for 1% transaction cost) and the subsidy starts at \$534/kW and declines to \$21/kW in 11 years (for 5% transaction cost) with net benefits of \$0.95M and \$0.78M, respectively. Both of these scenarios adding administrative and transaction costs are similar to our base case with starting subsidy of \$585/kW, declining to \$10/kW after 13 years.

The results of our analysis do not consider the effect of residential solar PV on the transmission and distribution systems. Other studies estimate that for low diffusion levels, grid connected distributed PV generation may result in avoided costs ranging between 0 – 0.2 ¢/kWh (Taylor et al., 2015), whereas high levels of adoption incur a distribution system upgrade cost of about 0 – 0.04 \$/W (Horowitz et al., 2018). We consider two scenarios, one in which PV reduces transmission and distribution costs at the midpoint of (Taylor et al 2015) and a second in which PV increases them, the midpoint of (Horowitz et al 2018). We rerun the model for each scenario. If PV reduces transmission and distribution costs by 0.1 ¢/kWh, the optimal national flexible subsidy schedule starts at \$562/kW in 2018 and declines to \$10/kW in 13 years, with a net benefit of \$1,580M. If PV induces an additional \$0.02/W in transmission and distribution costs, the optimal national flexible subsidy starts at \$603/kW and declines to \$9/kW in 13 years, with a net benefit of \$346M. In both cases the subsidy schedule does not change much, suggesting that using literature values for the effects of PV on transmission and distribution do not significantly affect model results. In addition, increased deployment of small-scale PV can affect wholesale power prices, result in curtailment, and require additional storage in the electricity system. Our model indicates that the share of total electricity from rooftop solar would reach to up to 17% in Hawaii and 15% in California, levels that are probably manageable with known technologies.

This work is based on the integration of different models, each with their own limitations. First, with regards to the overall scope of the model, note that the interaction of wind and solar with the rest of the electricity grid is mediated through an exogenous electricity price. Within the scope of covered factors, the diffusion model developed for utility scale wind does not fit the historical empirical data as closely as for residential solar (Williams et al., 2020). Second, our adoption model uses a single factor, i.e., the Net Present Value, to determine adoption level. But utility scale wind developments can be affected by other factors such as policy uncertainty and investor decisions, that are not fully accounted for in our model. The revenues from clean energy technologies may also vary in the future depending on changes in net metering policies and lower electricity prices for renewables. Lastly, the environmental benefit of clean energy technologies is estimated via a social cost of carbon (base case = $45/ton) and use of the EASUIR environmental risk model (Heo and Adams, 2015), though we note that the estimation of future carbon price and emissions factors are uncertain.

5.3 Future works

The integrated model developed in this study can be adopted to evaluate optimal policy directives for other technologies, such as electric vehicles. The analytical perspectives demonstrated in this work can be used by researchers to integrate the effects of consumer adoption and technological progress and estimates net benefits from subsidizing other emerging technologies. Further study is also required to analyze uncertainties in technological progress models. One area can be to compare one-factor and two-factor experience curves consisting of R&D investments. This type of study may require a systematic approach to overcome multi-collinearity issues and private research data limitations in the two-factor model.

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