Roles of diffusion patterns, technological progress, and environmental benefits in determining optimal renewable subsidies

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Abstract

In this paper we developed an integrated model to identify the optimal subsidy schedules for clean energy technologies that maximize social benefits less subsidy costs. We focus on three important factors in determining the social benefits of subsidizing the use of clean energy technology, which are the price (or cost) sensitivity of adoption, induced cost reductions through learning, and environmental benefits. We quantify how distinct profiles of these three factors result in qualitatively different optimal subsidy plans for utility wind and residential solar power in 13 electricity grid regions in the United States. Results show that optimal subsidy schedules for utility wind depend on the region, starting at $20-60/MWh, and are roughly constant over time. In contrast, residential solar subsidies either decline over time (starting from $8-70/MWh) or are not desirable (subsidy of zero). The subsidy profiles are dramatically different for three primary reasons: 1) The direct environmental benefits from emissions reductions for wind are larger than the subsidy expenditure, justifying an ongoing subsidy; 2) The price sensitivity of diffusion for utility wind is larger than for residential solar; 3) Faster cost reductions for residential solar suggest a temporary subsidy to unlock future markets.

Keywords: Optimal subsidy policy, clean energy technology, diffusion sensitivity, technological progress, environmental benefits

Highlights

- We study optimal subsidy design for utility wind and residential solar PV technologies.
- Optimal subsidy declines for residential PV, whereas it remains flat for utility wind.
- Higher price sensitivity of adoption and environmental benefits exceeding expenditure result in continuing subsidy for utility wind.
- Residential solar PV is mainly justified by future technology cost reductions.

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 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 benefits perspective is well-studied and results often show that the subsidy cost exceeds societal benefits (Michalek et al., 2011; 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; Nemet, 2009; Tsuchiya, 1989) and deliver benefits to society over the long-term. 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. Tibebu et al. (2021) developed a dynamic, analytical framework for estimating the optimal subsidy schedule for residential solar PV in the US that maximizes the net benefit from both the immediate subsidy-induced adoption and additional future adoption driven by technological learning and cost reduction due to the subsidy.

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, Tibebu et al. (2021) and 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 considered than high learning rates. Optimal subsidies are also shown to vary under different levels of social cost of carbon employed to estimate environmental benefits (Tibebu et al., 2021). 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.

In this work we undertake 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. 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 emission profile 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).

In this study, we develop two models to compare the optimal subsidy design for industrial wind and residential solar generation. The first 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. We quantify the two models using data disaggregated into 13 US regions as described in the EIA's "Hourly Electric Grid Monitor" data report across the contiguous US (EIA, 2021) (Figure S1). The results from these two technologies are used to better understand the determinants of optimal energy subsidy. Our analysis applies the same models to the two technologies but comes to different conclusions about the nature of government support, which we explain and discuss.

This work contributes to the existing energy subsidy literature as the first study which explores and compares the effects of various technology attributes (environmental benefit, price sensitivity of adoption, and learning rate) on optimal subsidy patterns integrating adoption and marginal emissions models. As a case study, this paper takes a comparative approach to addresses the questions of why and how policy support should vary for different technologies. Quantitative and qualitative differences are observed when estimating optimal subsidies for utility wind and residential solar PV, which are two of the most important emerging generation technologies. While prior research (e.g., Newbery, 2019) also investigates how technology attributes affect subsidy, their modeling framework does not include a diffusion model and assumes that an optimal subsidy drives the maximum rate of adoption until saturation. In contrast, our work uses empirically-calibrated diffusion models and determines optimal subsidy explicitly by maximizing public benefits less costs. The study also 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. We find that the optimal subsidy for utility wind is justified mainly through the direct environmental benefits, unlike residential solar PV in which the subsidy is primarily justified by indirect technological progress benefits. We also show how the optimal subsidy for the two technologies varies when technological progress is not accounted for.

The remainder of this paper proceeds as follows. Sections 2 and 3 present the methodology and the results from the techno-economic model. In the results section, we identify the differences in the qualitative form of optimal subsidy schedules for residential solar and utility-scale wind. To understand and explain these results, we create a simpler mathematical model and present corresponding results in Sections 4 and 5.

2. Methods: Model-with-learning

In this section, we present a techno-economic model for determining the socially optimal government subsidy schedule for a clean energy technology, applying it 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, 2021). The geographical map and the labels used to represent these regions is described in Section 1 of the SI. The geographic variability of wind and solar availability 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. The overall model is an integrated framework that synthesizes the two main economic justifications of clean energy technologies: direct environmental and indirect technological benefits. The model is based on one used to evaluate state-level residential solar PV subsidies in Tibebu et al. (2021). The integrated framework combines three independent models: adoption, technology progress, and environmental benefits (Figure 1). We discuss each of these models in turn.

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 (Alessandra and Claudia, 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 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 (Tibebu et al. 2021) and we apply the same approach to estimating the adoption model for utility-scale wind generation. We provide more details of the modified diffusion model for wind power in Section 2.1.1.

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:

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

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).

The benefit-cost model is based on an emissions assessment model estimating environmental emissions reductions resulting from the adoption of renewable energy technologies that displace conventional power plants (Azevedo et al., 2019). 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. 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.

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, we note that 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.

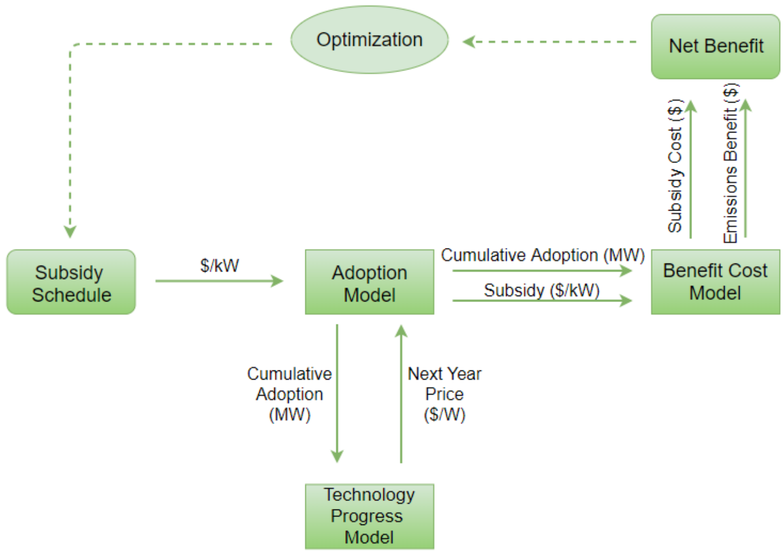

Figure 1. Model-with-learning for analyzing optimal subsidy schedule integrating adoption, technology progress, and benefit-cost models. The model accounts for both the short-term adoption stimulated by the subsidy and the indirectly induced adoption from technology cost reduction over the long-term.

2.1.1. 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, we estimate the same model 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. We used publicly available and open-source data (with sources described in Table 1) for estimating the NPV and wind adoption capacity 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:

$$NPV\left(\frac{\$}{MW}\right) = (-C_{total}) + \sum_{i=1}^{N} \frac{E * R}{(1+int)^i} \frac{1}{CAP} \qquad (2)$$

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 price 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 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 1.

The adoption model uses regression-produced parameters that are identical in the six regions considered, assuming that 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:

$$Adoption\left(\frac{MW}{TWh}\right) = \frac{Annual\ wind\ power\ adoption\ (MW)}{Remaining\ generation\ (TWh)} = k\left(1 + \mathrm{erf}\left(\frac{NPV - \mu}{\sigma}\right)\right) \qquad (3)$$

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 (3), 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. 2. The empirical fit of the model form is better for residential solar than for utility wind. Note that 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.

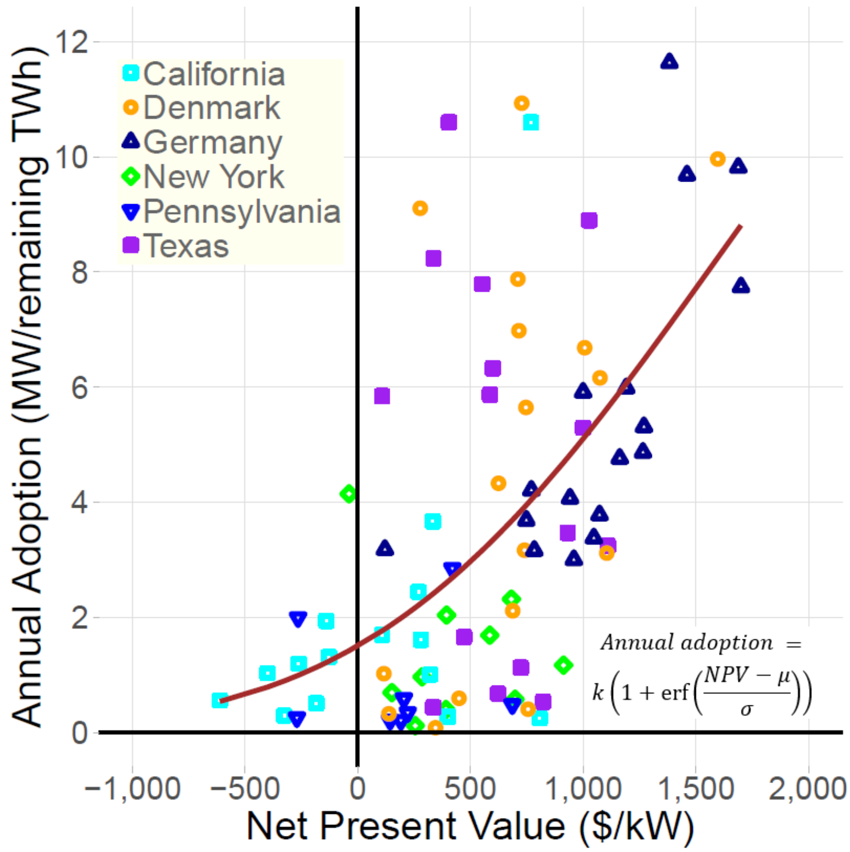

Figure 2. Adoption model for utility-scale wind generation using the NPV ($/MW) as the explanatory variable. The model is developed by empirically analyzing wind diffusion data from six regions, with data from 2002 to 2018. The adoption curve is fitted using the error function with two regression parameters 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 1. Wind adoption model data sources.

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

2.1.2. Comparing utility-scale wind and residential solar adoption curves

In the framework of our adoption model, 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 = $4,110/kW for residential solar and $1,690/kW for utility wind. 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 3 displays the adoption curves for utility-scale wind and residential solar, with adoption normalized to its value at zero Net Present Value. 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 3 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 invest in rooftop solar adoption is mainly to offset their residential retail electricity price. 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.

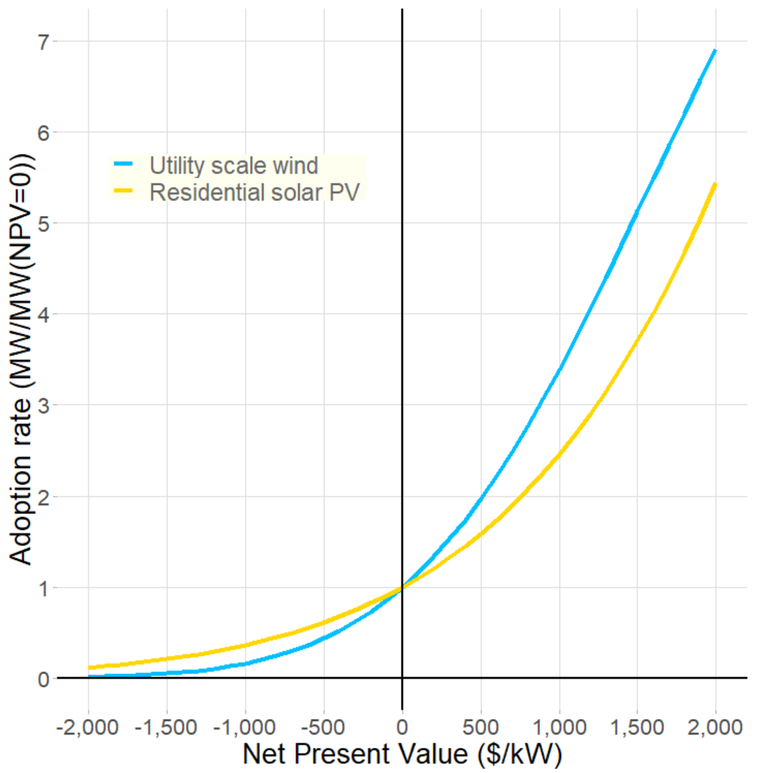

Figure 3. Normalized adoption curves for utility wind and residential solar PV. For both technologies, the adoption is normalized to the respective value of adoption when NPV=0.

3. Model-with-learning results

We use the integrated model shown in Figure 1 to analyze the optimal subsidy schedules for utility wind. We then compare the wind subsidy to the optimal subsidies for residential PV derived from Tibebu et al. (2021) with a minor change of the geographical resolution from state-level to 13 grid regions (to match the geographical unit of the wind analysis). The two technologies use the same framework but with different inputs, as described in Table 2, 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 (a subsidy that is free to vary over time).

Table 2: 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, 2021)	
Detached households		(US Census Bureau, 2011)
Marginal emissions factors	(Azevedo et al., 2019)	(Azevedo et al., 2019)

In this section, we present 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. 4 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. 4a). On the other hand, our model for residential solar PV (Fig. 4b) 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.

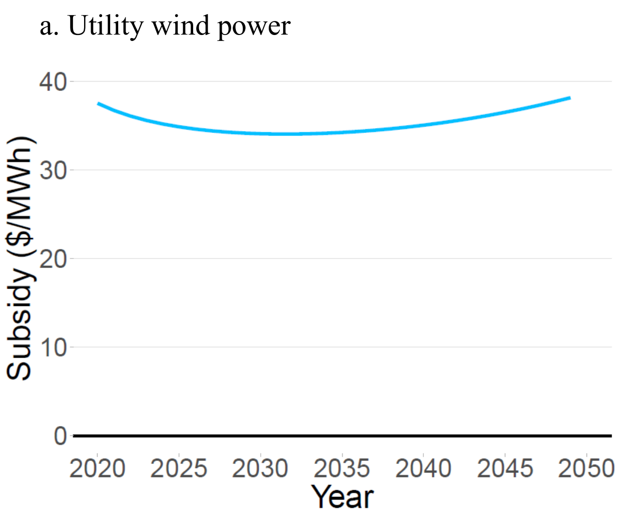

Figure 4. Uniform federal subsidy schedule that optimizes national net benefits, using the model-with-learning for (a) utility-scale wind power and (b) residential solar PV. The optimal subsidy for utility wind will be ongoing for the study period whereas the subsidy for solar PV is declining and becomes zero after 16 years.

Figure 5 displays our 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 different regions.

Our 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.

a. Utility scale wind

b. Residential solar PV

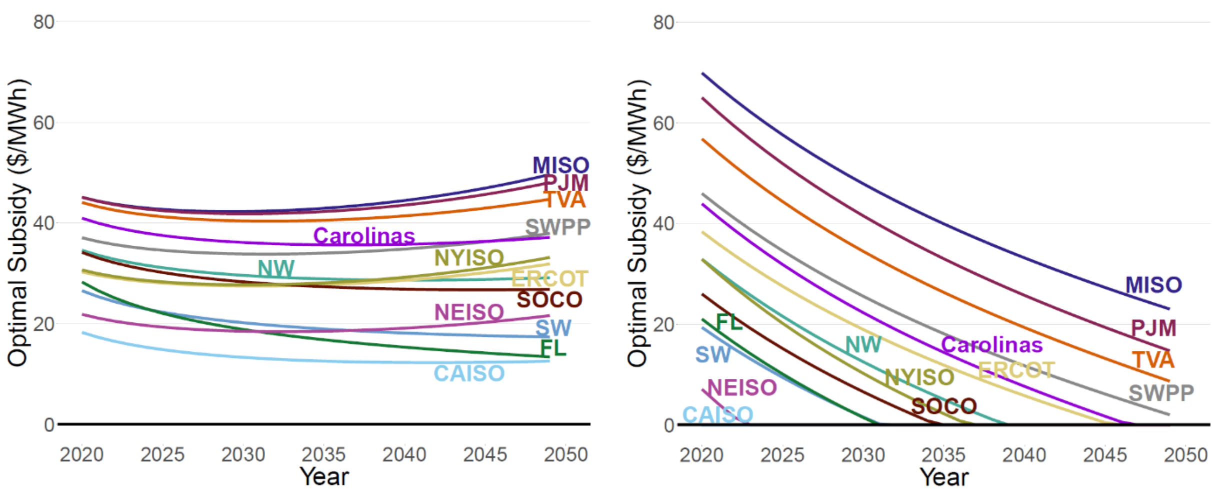

Figure 5. Subsidy schedules that vary by region that optimize national net benefits, using the model-with-learning, for (a) utility-scale wind power and (b) residential solar PV. The subsidy for wind is flat whereas solar subsidy declines over time in all regions. The optimal subsidy differs by region due to variation in electricity price, wind and solar energy potential, and energy grid mix.

4. Model-without-learning

From Fig. 4 and Fig. 5, 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 schedule declines to zero. Identifying the cause(s) of the qualitative differences in subsidy schedules is difficult to explain as 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. Specifically, unlike the previous model based on non-linear optimization, this model relies on a set of equations that can be solved mathematically for the optimal solution. 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 us to account for only the direct adoption resulting from the subsidy and nullify the adoption stimulated by technological progress. While we also address the problem by setting learning equal to zero in the model-with-learning (see SI, section 2), the set of equations below allows for a direct understanding of the relationships between inputs and outputs.

4.1. Benefit-cost analysis

We begin 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.

$$Net\ Benefits\ = Stimulated\ Adoption * \ B - A(S) * \ S \tag{4}$$

where,

$$Stimulated\ Adoption = A(S) - \ A(S = 0) \tag{5}$$

$A(S)(MW)$ 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 just 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:

$$Benefits\ = \sum_{i=1}^{20} \frac{Avoided\ Damage}{(1 + DR)^i} \tag{6}$$

$Avoided\ damage$ is estimated from marginal emissions and damage factors of CO_2 and criteria pollutants and DR is the discount rate. Substituting Eq. 5 in Eq. 4 and rearranging, the net benefit can be written as:

$$Net\ Benefits = A(S) * (B - S) - A(S = 0) * B \tag{7}$$

Here, we draw upon 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. 7.

$$\frac{\partial Net\ Benefits}{\partial S} = (B - S) * \frac{\partial A(S)}{\partial S} - A(S) = 0 \tag{8}$$

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.

4.2. Model-without-learning for optimal subsidy level

We specify a simpler adoption model with an exponential curve (equation 9) to explain the functional relationship between a given subsidy level and the resulting adoption. We choose this model 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 (see Section 3 of SI).

$$A(S) = A(0)e^{a_1 S} \qquad (9)$$

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:

$$Elasticity = \frac{\partial\, A(s)/A(s)}{\partial\, S/S} = a_1 * S \qquad (10)$$

Substituting Eq. 9 into Eq. 8 and solving for the optimal solution gives a rather simple solution:

$$Optimal\ subsidy = B - \frac{1}{a_1} \qquad (11)$$

Eq. 11 gives the estimate for the optimal subsidy level and defines a mathematical condition for when subsidy is justified. For a clean energy technology with an adoption curve as defined in Eq. 9, 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). As an additional verification, the model-without-learning is also implemented using the error function adoption model from Eq. 3 (presented in Section 2 of the SI) and the numerically solved results of that analysis is similar to the simpler result presented below.

Table 3: Model with and without learning.

	Model-with-learning	**Model-without-learning**
Adoption model	$A(S) = \bar{\alpha}\left(1 + \text{erf}\left(\frac{NPV_o + S - \mu}{\sigma}\right)\right)$	$A(S) = A(0)e^{a_1 S}$
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%

4.3. 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 $B = 1/a_1$ (Equation 11). 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 equation 6 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 we show in Figure 3, 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 7 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.

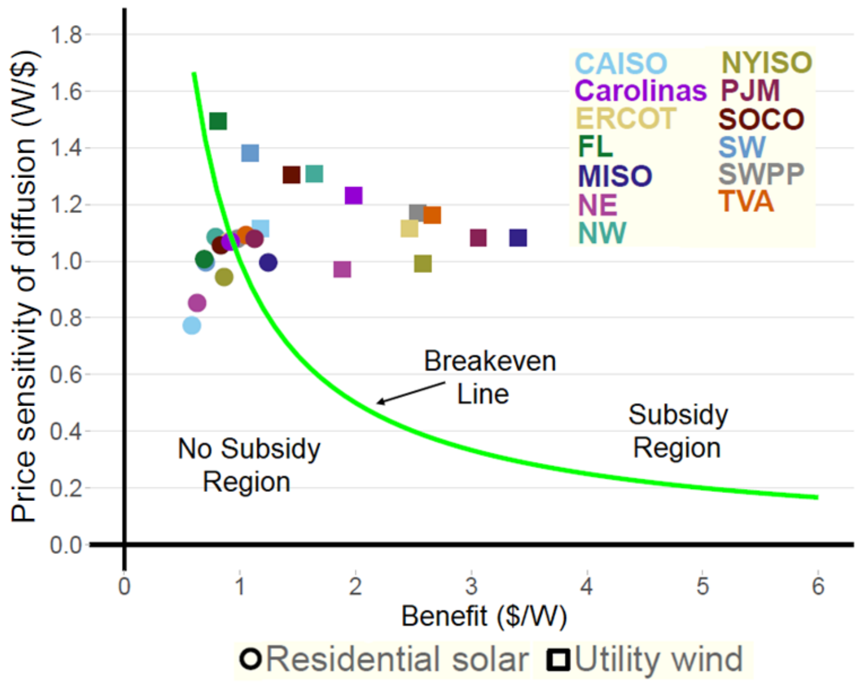

Figure 7. Analytical solutions of optimal subsidy schedule for wind and rooftop solar in 13 regions, using the model-without-learning. The optimal subsidy for residential solar is below the breakeven line for most regions, whereas the optimal subsidy for wind is above it for all regions. Note that this simpler model does not include technological progress, which is an important element justifying solar subsidies.

Figure 8 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. But the optimal subsidy results from the two models are noticeably different for residential solar PV. 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

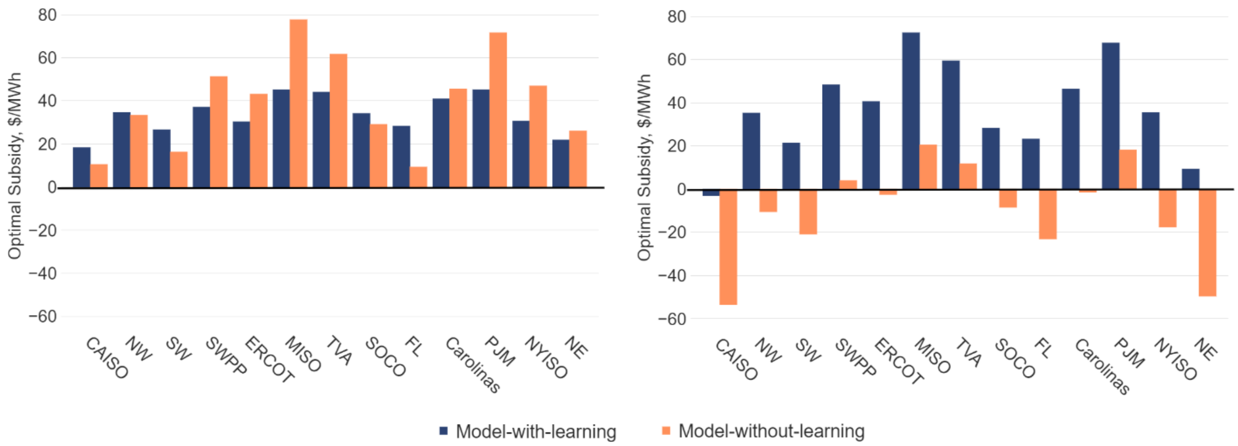

Figure 8. First-year optimal subsidy level for model-with-learning and model-without-learning in 13 regions for utility-scale wind (a) and residential solar (b). The main difference between the two models is that the model-without-learning assumes a zero learning rate for both technologies whereas the 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.

4.4 Linking technology attributes to subsidy structure

To better understand the drivers of differences in the optimal subsidies for wind and solar, we further examine the three sets of technology attributes we identify as most relevant, which include cost reductions through technology progress, adoption sensitivity, and environmental benefits. Table 4 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 5 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 8 show that the higher learning rate for solar makes it a critical part of the justification of subsidies for that technology, unlike wind energy. Previous work by (Tibebu et al., 2021) also demonstrated 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 4: 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

5. Caveats/Assumptions

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. We also explore a different form of adoption model using a more traditional ordinary least square/linear regression method, and for some regions, we obtained qualitatively different optimal subsidy results from the base case analysis (Section 4 of SI). Third, 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.

6. Conclusion

In this study we employ 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, we develop a simpler, more analytically tractable model (model-without-learning) that neglects technological progress, allowing us 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 schedule has subsidies decline to zero over time. The model-without-learning clarifies how region-dependent environmental benefits and price sensitivity of adoption determine the optimal subsidy.

Our research findings 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. For residential solar, both the Federal Tax Credit and most state programs have demonstrated some form of scaling down support over time. From this analysis we highlight 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). Our 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. Our 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 (Tibebu et al., 2021) 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.

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