What is the optimal subsidy for residential solar?

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Highlights

- We develop a benefit-cost analysis of subsidizing residential solar panels in the US.
- Our model integrates technological progress, diffusion, and emissions reductions and accounts for cross-state heterogeneity.
- Optimal subsidy schedule yields 250% more net benefit than existing federal tax credit with 55% less spending.
- Optimal subsidy schedules start higher, but fall rapidly to account for technological progress.
- Net benefits can be increased by allowing subsidy schedules to vary across states.

Abstract

How do we design clean energy subsidies to deliver greater benefits to society? Analytical answers to this question are scarce. Modeling should address both direct benefits from stimulating consumer adoption the year the subsidy is paid as well as indirect benefits from lowering future technology costs. We develop a benefit-cost analysis of residential solar subsidies in the US, disaggregated by state, accounting for technological progress, consumer adoption, and carbon and criteria emission reductions. We assess existing solar subsidies and also find the optimal subsidy schedule that maximizes net benefits starting in the year 2018. In the base case the optimal subsidy schedule begins at $585/kW and declines to zero in 14 years. The optimal subsidy starts higher and falls more quickly than the current federal tax credit, due to long-term benefits from early cost reductions and the need to reduce subsidies as a technology becomes cheaper. We also estimate state-by-state flexible subsidies which result in higher net benefits compared to a homogenous national subsidy ($2.8 billion versus $1.0 billion). Neglecting criteria pollution benefits, optimal subsidies that account for technological progress and consumer behavior mitigate carbon at a cost of $42-47/ton, comparable to utility solar.

Keywords: clean energy, subsidy, emission reduction, technology cost, public benefits, net benefits

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1. Introduction

1.1 Motivation

Governments have adopted a range of policies to support clean energy technologies with the goal of addressing both local and global pollution and improving energy security. 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). Providing subsidies may incur substantial government expenditures. For instance, the American Recovery Act of 2009, which included more than $90 billion of clean energy investments, was the largest energy bill in history (Aldy, 2013). In another case, the total cost of federal tax-related support for the energy sector was estimated around $8.8 billion in 2016, of which nearly 60 percent was attributed to tax incentives supporting renewables (US EIA, 2018). It is, therefore, imperative to provide a rationale for the environmental, technological and social benefits achieved from such large public spending and improve the methods that are used to evaluate the correct level of support.

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. This argument is related to the traditional economic theory that market forces will optimally allocate resources, but only if products are "correctly" priced. While taxing emissions is widely believed to be economically efficient, subsidizing zero-emissions alternatives is an approximate alternative. Subsidies can help address the environmental externalities of fossil fuel consumption, but assessing the correct level of subsidy is complicated by a variety of practical challenges: estimating the quantity and distribution of emissions reductions from adoption, choosing an appropriate value for the social cost of emissions, and correct treatment of time discounting and consumer heterogeneity.

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. From this perspective if, for example, electric vehicles (EVs) – an emerging clean technology – are more expensive than traditional vehicles, government subsidies can grow the market until technological progress allows EVs to become competitive with the incumbent. Once achieved, the developed technology can deliver long-term social benefits, presumably without further subsidy. This approach is based on the public good argument that government should encourage innovation and development of immature technologies that are not receiving sufficient investment in private markets (Popp et al., 2011). 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. This perspective (unlike the first) suggests that if the goal of the government is to foster an immature technology (distinct from mitigating externalities, discussed above), government support should decline to zero as the technology becomes more mature and competitive. Stimulating longer term cost reductions is often an explicit goal of a subsidy, thus a proper policy assessment should account for the interactions of subsidy, technological progress and diffusion.

1.2 Literature review

Many prior assessments of the benefits and costs of existing energy technology subsidies address direct, near-term benefits, i.e. does the adoption stimulated in a given year by the subsidy yield social benefits that exceed the subsidy costs? For example, Michalek et al. (2011) study electric vehicles in the US, using life-cycle assessment and environmental risk modeling to compare reductions in emission damages from adoption with the cost of federal subsidy. They found that subsidy costs far exceeded monetized externality benefits ($7,500 versus $440). For residential solar, Macintosh and Wilkinson (2011) analyze solar subsidies in Australia during the 2000s and find high carbon abatement costs of US$238-282/t$CO_2$, a figure higher than many estimates of the social cost of carbon. Hughes and Podolefsky (2015) compare the economic cost of subsidies in California from 2007-2012 with avoided electricity use and carbon emissions, finding costs of mitigating carbon of 130-196 $/ton CO_2. Sexton et al. (2018) perform a state by state analysis of state and federal subsidy expenditures for rooftop solar and direct benefits from avoided pollution, finding that subsidies had net benefits in some states and net costs in others.

Another set of literature examines the interaction of subsidies, diffusion and technological progress, considering how lowering technology costs influences long-term consumer adoption. The concept of interaction between the market willingness-to-pay and the technological progress curve is studied by Tsuchiya (1989). The author overlays expected cost reductions in photovoltaic panels as a function of adoption (i.e. an experience curve) with a hypothetical series of willingness-to-pay levels in different solar submarkets. Results indicate an initial period in which subsidies are required, followed by a crossover point beyond which market forces would drive adoption. Frondel et al. (2010) assess energy policy in Germany by comparing the cost of government investment with the benefits for renewable energy promotion (including residential solar), greenhouse gas reductions, job creation, and technological innovation. They conclude that the cost of government support is higher than benefits. Herron and Williams (2013) model interactions between adoption driven by economic benefits, accounting for geographical heterogeneity and technological progress for residential fuel cells in the US. They identify the crossover point as well as a saturation point beyond which no additional customers would be gained, and estimate an optimal subsidy as the minimum government expenditure needed to deliver benefits to pre-crossover consumers.

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 et al., 2014; Jeon et al., 2015) and minimizing subsidy expenditures to achieve different goals.

Given this body of literature, what are the critical questions for investigation of optimal subsidies? One area is uncertainty. Most prior authors recognized that subsidy outcomes are sensitive to uncertain parameter values such as learning rates, diffusion model parameters, 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 assumptions. A second 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. A third 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 fourth priority is comparison of optimal subsidy results for a given technology with other mitigation options. E.g. how do residential solar subsidies compare with utility solar or wind? One approach is to use comparable measures from technology assessments, such as carbon mitigation cost ($ per ton of CO_2 emissions reduced).

1.3 Research goal and scope

The goal of this work is to contribute 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 factors (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. We recognize that political considerations are major drivers of subsidy policy and the expediency of the current system. Results from energy system models will not upend politics, but a key role of modeling is to provide input on the benefits and costs of different approaches. To this end, we estimate an optimal flexible national schedule of solar subsidies and then allow subsidies to vary by state in order maximize net benefits to the nation. We also explore the sensitivity of results to different values of learning rate, discount rate, electricity price and social costs of carbon to identify qualitative trends that are robust under uncertainty. In addition, we identify the carbon mitigation cost, both including and excluding criteria pollutant benefits, in order to compare residential solar with other mitigation options.

To achieve the above, we construct a benefit-cost model of residential solar in the US, with a time horizon of 2018-2043. 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. Some categories of costs and benefits are not included in the model, including effects on wholesale power prices, transmission & distribution costs, and curtailment. However, we do refer to literature estimates of these costs and benefits and sum them up to compare against the costs and benefits included in our analysis.

2. Modeling and Data

The model developed in this research integrates three modules: adoption, technology progress, and benefit-cost analysis (Figure 1) 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. To clarify terminology used:

$$Benefits\ (\$) = \begin{pmatrix} Discounted\ 30year\ Benefit\ from \\ reduced\ CO_2\ and\ criteria\ pollutant \\ emissions\ \boldsymbol{with\ subsidy} \end{pmatrix} - \begin{pmatrix} Discounted\ 30year\ Benefit\ from \\ reduced\ CO_2\ and\ criteria\ pollutant \\ emissions\ \boldsymbol{with\ no\ subsidy} \end{pmatrix} \quad (1)$$

$$Costs(\$) = Discounted\ 30year\ government\ subsidy\ expenditures, \quad (2)$$

and

$$Net\ Benefits\ (\$) = Benefits\ (\$) - Costs\ (\$) = Eq.(1) - Eq.(2). \quad (3)$$

The model is implemented for the US, disaggregated by state. State averages are used for data such as retail electricity price, solar insolation, and emissions damages from criteria pollutants. The time frame for the base case analysis is 2018-2047. An alternative retrospective scenario is done for a subsidy schedule with the time frame of 2012-2041. The analysis of the various subsidy schedules, including the optimal flexible subsidy, assumes a federal subsidy that is equal across the US. An alternative case is also considered where different levels of subsidies are implemented in each state. In all cases, the national net benefit of a subsidy is determined by summing the net benefits obtained for each US state. The analysis and all results are in real 2018 dollars.

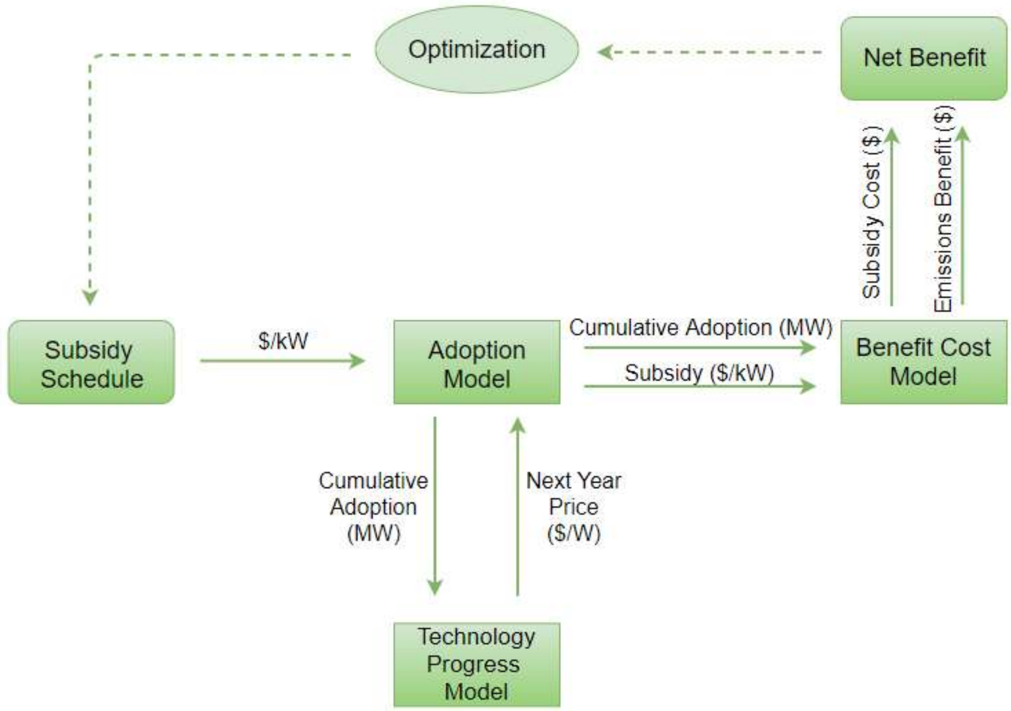


Figure 1: Summary of integrated model combining adoption, technological progress and benefit-cost analysis. A simple optimization routine is applied to this model to identify the subsidy schedule that maximizes discounted net benefits.

2.1. Integrated framework

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

2.1.1. 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:

$$NPV_k^j\left(\frac{\$}{kW}\right) = (-I^j + S^j) + \sum_{i=1}^{N} \frac{E_k * P_k}{(1+int)^i} \frac{1}{CAP} \tag{4}$$

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. 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 U.S., 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 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 5).

$$Adoption\left(\frac{MW}{million\ houses}\right)\left(NPV(\frac{\$}{kW})\right) = \alpha \int_{-\infty}^{NPV} dx\, e^{-\left(\frac{x-\mu}{\sigma}\right)^2} = \bar{\alpha}\left(1+\operatorname{erf}\left(\frac{NPV\,(\frac{\$}{kW}) - \mu}{\sigma}\right)\right) \tag{5}$$

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. $\bar{\alpha}$ is a constant fixed at 2,000 kW/million free households. Williams et al 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.

2.1.2. 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:

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

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 (Table S4 of the SI) 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.

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 (see Section 1.9 of SI).

2.1.3. 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, 2018). 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 is used for determining CO_2 emissions damage. Though marginal emissions factors have been more consistent than average emissions factors as the grid composition has shifted, cleaner future grids may have lower MEFs than today. Thus, we consider an alternative scenario of declining emissions factors, provided in Section 1.10 of the SI.

2.2. 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 2.1.1 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. 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.

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 (emissions benefits less subsidy costs) as laid out in equations (1) - (3). For the national flexible subsidy case, the decision variables for optimization are values of the subsidy in each year, S^j ($j = 1 \ldots 30$). The optimization model is formulated as:

Decision variables:

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

Objective function:

$$\max\left(National\ Net\ Benefit\right) = \max\left(\sum_{k=1}^{51} Net\ Benefit_k\right) \tag{7}$$

where k indicates state.

For the state-by-state flexible case, 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, *Objective function:*

$$\max\,(National\ Net\ Benefit) = \max\left(\sum_{k=1}^{51} Net\ Benefit_k\right) \qquad (8)$$

We implement the optimization model with Excel Solver and using a nonlinear Generalized Reduced Gradient (GRG) algorithm. This optimization method has 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. Details of the integrated framework and the constituent models are provided in Section 1.1 of the SI.

2.3. Direct and indirect benefits

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:

$$Direct\ Induced\ Adoption = Adoption\left(S^j, {C_0}^j\right) - Adoption\left(S^j = 0, {C_0}^j\right), \qquad (9)$$

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

$$Indirect\ Induced\ Adoption = Adoption\left(S^j, C^j\right) - Adoption\left(S^j, {C_0}^j\right) \qquad (10)$$

The total induced adoption is the sum of equations (9) and (10), which is used in assessing net benefits.

The $Benefits(\$)$ (defined in $Eq.(1)$) and the $Costs(\$)$ (defined in $Eq.(2)$) can be mathematically given as:

$$Benefits\ (\$) = \sum_{j=1}^{30} \frac{EB20\left(Adoption\left(S^j, {C_0}^j\right) - Adoption\left(S^j = 0, {C_0}^j\right)\right)}{(1+DR)^j} \qquad (11)$$

where,

$EB20$ (\$/MW) – is the discounted environmental benefit of adopting 1 MW of solar PV over its expected lifetime of 20 years and an assumed annual degradation rate of 0.5% for solar panels based on the estimates in Feldmand and Margolis (2018)

DR – is the discount rate

$$Government\ Susbsidy\ Costs(\$) = \sum_{j=1}^{30} \frac{S^j\left(Adoption\left(S^j, {C_0}^j\right)\right)}{(1+DR)^j} \qquad (12)$$

2.4. Carbon abatement cost

As discussed in the introduction, estimating the abatement costs of a subsidy provides a useful metric that can be compared with other mitigation options. We calculate carbon abatement costs, but note the complication that the benefit-cost analysis includes both carbon and criteria pollutant benefits. We thus consider two measures:

$$Carbon\ abatement\ cost\ (no\ criteria\ benefits)\left(\frac{\$}{ton}\right) = \frac{Government\ subsidy\ cost\ (\$)}{Total\ CO_2\ reduction\ (tons)} \tag{13}$$

$$Carbon\ abatement\ cost\ (w/\ criteria\ benefits)\left(\frac{\$}{ton}\right) = \frac{Government\ subsidy\ cost\ (\$) - Criteria\ \ pollution\ benefits\ (\$)}{Total\ CO_2\ reduction\ (tons)} \tag{14}$$

Many prior analyses of carbon mitigation costs do not consider criteria pollution co-benefits (e.g. Das et al., 2020; Marcantonini and Ellerman, 2013), and Equation 13 is most appropriate for comparison. The version in Equation 14 is useful to understand how accounting for criteria benefits reduces carbon abatement costs.

2.5. Assumptions

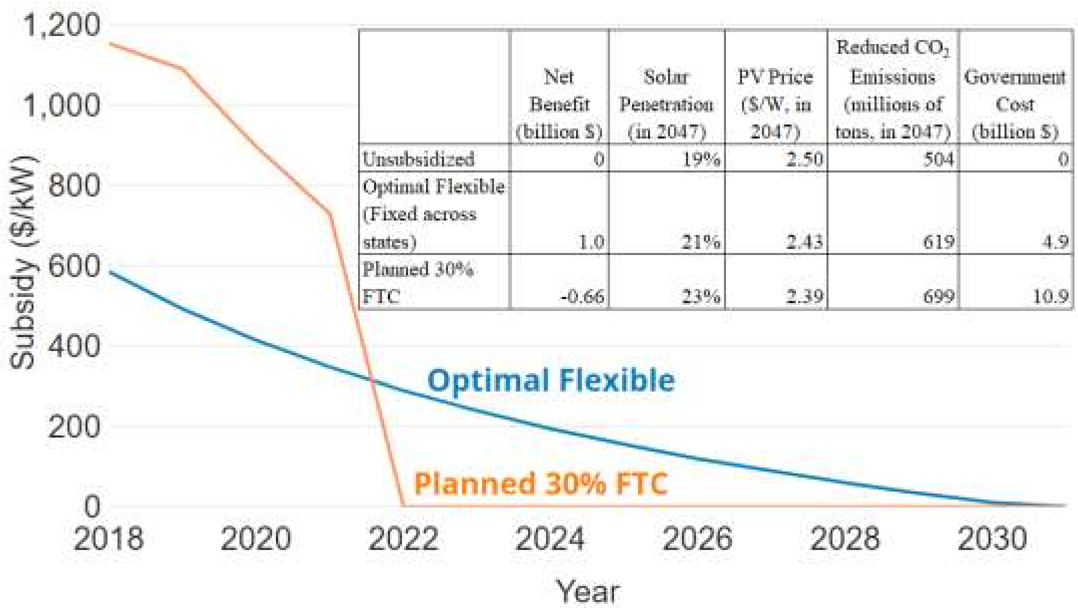
To summarize key assumptions of our model: benefits assessed are carbon emissions and criteria pollutant air emission reductions (PM, SO_2, NO_X). The former uses a social cost of carbon of $45/ton, and the latter is based on estimates by the EASUIR model (Azevedo et al., 2019). There is uncertainty in both of these estimates (Interagency Working Group on Social Cost of Greenhouse Gases US Government, 2016; Levy et al., 2009). Note that monetized carbon and criteria emissions are similar in magnitude, thus accounting for both is important in justifying a subsidy. There are benefits and costs not accounted for such as energy security, economics (e.g. domestic employment), and reduced extraction impacts. We assume that the real price of electricity displaced by residential solar does not change over time. This is reasonable from the perspective of retrospective forecasting: electricity prices in the US have more or less tracked inflation in the last two decades (US EIA, 2020). This said, electricity grids are undergoing significant changes. Increased regulation could increase prices earned by residential customers, while retraction of net metering policies could lower them. The net future outcome of these opposing drivers is unclear, so we argue that constant price is a reasonable neutral forecast for analyzing residential solar. Having said that, we also provide an alternative analysis where we consider declining emissions factors and electricity prices in Section 1.10 of the SI.

3. Results

3.1. Optimal flexible subsidy starting in 2018

An optimal subsidy schedule is a set of annual values, S^j($/kW), where j is an index for year, that maximize net benefits (emissions benefits less government cost), as described in Section 2. Figure 2 shows results for the optimal flexible subsidy over the 30-year analysis period from 2018 through 2047. For comparison purposes, we also plot expected schedule for planned/historic 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 flexible subsidy starts at $585/kW and declines nonlinearly to zero after 13 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.

We also analyzed different subsidy schedules including a constant subsidy and a subsidy that declines linearly. The main lesson from these results is that declining subsidies perform better. This is not surprising given that they should be adjusted to account for solar cost declines. Detailed results are in Section 1.2 and 1.3 of the SI.



	Net Benefit (billion $)	Solar Penetration (in 2047)	PV Price ($/W, in 2047)	Reduced CO_2 Emissions (millions of tons, in 2047)	Government Cost (billion $)
Unsubsidized	0	19%	2.50	504	0
Optimal Flexible (Fixed across states)	1.0	21%	2.43	619	4.9
Planned 30% FTC	-0.66	23%	2.39	699	10.9

Figure 2. National subsidy schedules for optimal flexible and planned/historical 30% Federal Tax Credit (FTC). These results assume 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 with results reported in Section 1.7 of the SI. In summary, 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 discount rate is above 5%, the solar learning rate is below 6%, or the social cost of carbon is below \$30/ton.

3.2. 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 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 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.

	Net Benefit (billion \$)	Solar Penetration (in 2047)	PV Price (\$/W, in 2047)	Reduced CO_2 Emissions (millions of tons, in 2047)	Government Cost (billion \$)
Unsubsidized	0	4%	3.54	71	0
Optimal Flexible (Fixed across states)	14	18%	2.45	569	14
Perpetual 30% FTC	5.0	26%	2.25	917	40

Figure 3. National optimal flexible subsidy compared with a perpetual national 30% tax credit 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.

3.3. 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 flexible subsidy. For the optimal flexible subsidy schedule starting in 2018, 46% of benefits are attributed to the direct environmental benefit and 54% for the indirect technology innovation benefit. 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 S1. This demonstrates the importance of accounting for both direct and indirect benefits when justifying subsidy support. For the optimal 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. Additional results are presented in Section 1.6 of the SI.

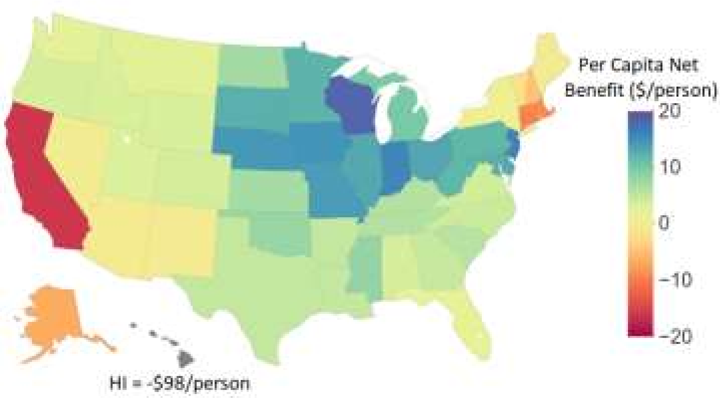
3.4. State-by-state heterogeneity and state-flexible subsidy

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 national optimal subsidy in Figure 4(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.

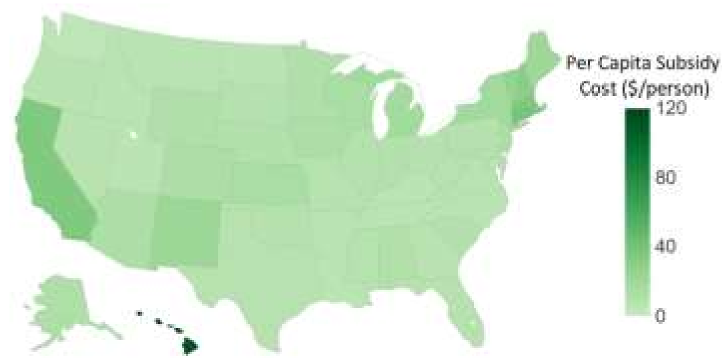
All prior results (including Figure 4a-b) assume a federal subsidy equal across the US, with the national net benefit determined by summing up net benefits obtained in each US state. Alternatively, subsidies could be allowed to vary by state, representing a scenario where a federal decisionmaker is attempting 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. 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 4 and Table 1. A state-by-state subsidy has a notable increase in national net benefits: \$2.8 versus \$1.0 billion for a national fixed subsidy. Solar penetration also increases from 21% in 2047 for the national subsidy to 24% for a state flexible one, and emissions benefits are higher as well.

Figure 4(c) shows net benefits by state for the state-specific 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 5). The optimization results propose low subsidies in California (\$91/kW in 2018) and no subsidy for Hawaii. Additional results on estimated per capita CO_2 and criteria pollutants benefits are provided in Section 1.8 of the SI.

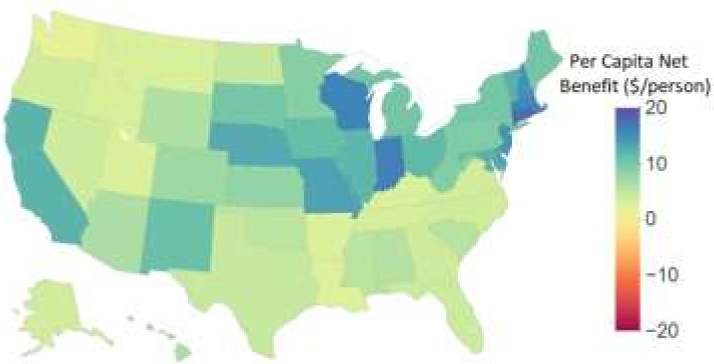
(a) Per capita net benefit for national homogeneous subsidy



(b) Per capita subsidy cost for national homogeneous subsidy



(c) Per capita net benefit for state varying subsidy



(d) Per capita subsidy cost for state varying subsidy

Figure 4. State-by-state results for optimal flexible subsidy: (a) National homogenous subsidy, net benefit per capita, (b) National homogenous subsidy, subsidy cost per capita, (c) State-varying subsidy, net benefit per capita, (d) State-varying subsidy, subsidy cost per capita. For both national homogenous and state-varying subsidies, the objective is to maximize national net benefits. The differences between states are due to variation 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 homogenous subsidy schedule, government expenditure is high in states like California and Hawaii but results in a negative net benefit due to overpaying free riders. For the varying subsidy schedule, all states have positive net benefits. In this case, government investment is focused on Midwestern states relative to other regions.

Figure 5. Optimal first-year subsidy level for a variable state-by-state subsidy schedule implementation. 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.

3.5. Carbon Abatement Cost

As discussed in the introduction and methods section, 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 13 and 14). When excluding criteria pollutant benefits, the CO_2 mitigation costs of optimal subsidies is $43/ton (national homogenous) and $47/ton (state-varying). Mitigation costs are higher with FTC subsidies at $56/ton (phased out) and $67/ton (perpetual). However, carbon mitigation benefits are much lower if criteria pollution co-benefits are permitted: $20/ton for nationally homogenous subsidy and $17/ton for state-varying. Indeed, running the model with only carbon benefits (not shown) leads to much lower optimal subsidies.

To compare these costs with other technologies, Das and collaborators estimated abatement costs for utility solar and wind, accounting both for technological progress and revenue decline (Das et al., 2020). Carbon abatement costs for utility solar run from $40-$60/ton depending on location and expected future prices. The government subsidy needed to ensure NPV>0 for solar developers is typically around half of these mitigation values. The carbon abatement costs for (unsubsidized) utility wind start negative (-7$/ton) for some favorable locations but are much higher for much of the U.S. and later in adoption (up to around +$45/ton). Thus, residential solar remains a relatively costly mitigation option, though technological progress and diffusion lower the difference substantially.

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 subsidy schedule with no technological progress (learning rate of zero). The result with zero learning rate is $771/ton of carbon reduced (versus $43/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).

	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	504	0	0	0
Optimal Flexible (Fixed across states)	1.0	21%	2.43	619	4.9	42.6	20.1
Optimal Flexible (Varying by state)	2.8	24%	2.37	731	10.6	46.7	17.1
Planned 30% FTC (ends 2022)	-0.66	23%	2.39	699	10.9	55.9	26.2
"Perpetual" 30% FTC (ends 2031)	-10.0	30%	2.24	1,095	38.8	65.6	38.3

4. Caveats

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. Sensitivity analysis in the supporting information explores alternative futures other than the base case. For example, the base case assumes marginal emissions rates are approximately fixed over 30 years across the US. Marginal emissions factors are much less sensitive to renewable additions than average factors but are more difficult to predict (Siler-Evans et al., 2012; Ryan et al., 2016). We redo the analysis using a scenario with reduced marginal emissions rates, shown in the SI, section 1.10, which naturally leads to lower subsidy levels. In forecasting technological progress, we assume that the rest of the world and other sectors (utility and commercial) adopt solar at a similar rate as US residential. As shown in Section 1.9 of SI, this trend held for the last 20 years, and is thus a plausible future scenario. Two alternative patterns of US versus rest-of-world adoption are possible: rest-of-world adoption could be entirely independent from the US, or adoption patterns among countries might strategically and asymmetrically interact. These both have practical and conceptual difficulties (discussed further in SI, section 1.9). We have also assumed that learning in installed costs for US residential solar occurs at the national level, after concluding that available data did not support state-differentiated technological progress. Also note that we treat electricity prices and insolation as uniform across each state. We undertook an alternative scenario that breaks California into three separate regions, finding results that are similar to the aggregated model (see Section 1.11 in the Supplemental Information). On the policy implementation level, while declining subsidies for emerging technologies are almost universal, there can be political complications in prudently setting subsidy levels that balance renewables adoption goals with policy cost. For example, Spain's generous and popular feed-in tariff structure was suddenly replaced in 2013 with a lower-paying system in order to control program costs. This caused financial issues for the solar industry, with years of lawsuits over lost revenues.

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 subsidy schedule that is fixed across states 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.

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 – 0.4 $/W (Horowitz et al., 2018). Incorporating the average values of these estimates in our model and optimizing for subsidy schedule that is fixed across states show that the optimal subsidy schedule starts at $562/kW in 2018 and declines to $16/kW in 12 years, resulting in a net benefit of $880M. These results show that residential solar PV should still be subsidized under these conditions and that there is social net benefit gain. In addition, other things to consider with regards to increased deployment of small-scale PV include impacts on wholesale power prices, curtailment, and integration of 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.

5. Conclusion and policy implications

In this research, we present a framework for identifying the optimal government subsidy for emerging clean energy technologies by modeling the 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 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 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 study models 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, because of heterogeneity in climate and insolation, electricity prices, energy portfolio, and benefits of increased renewable generation. We also estimate a set of state-specific optimal flexible subsidies 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. This 180% increase in net benefit is much higher than the magnitude obtained in a previous study by Holland et al., (2016) that estimates the gains from differentiating EV subsidies to be in the range of $10-$60M (0.5%-3.3%) without considering the effect of learning by doing. 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.

As with any energy system model dependent on an uncertain future, precise characterization is unlikely. However, we argue that certain qualitative features of this work are robust and relevant to future efforts. First, consideration of technological progress is a critical part of the justification of a public subsidy, especially for early-stage technologies. Second, subsidy (and other policy support) of an emerging technology ought to start high and be tapered off aggressively as prices fall. Third, the effect of free riders limits the net benefits of high subsidy levels once a technology has become competitive enough to attract consumers at unsubsidized prices. Finally, we hope that this work demonstrates an analytical perspective that can be used by researchers to integrate the effects of consumer adoption and technological progress into estimates of net benefits from other emerging technologies.

Resource Availability Additional results and description of the model, as mentioned throughout the text above, is available in a Supporting Information document. The model and data inputs used in this work are available as a separate Microsoft Excel file uploaded as part of the Supporting Information for this work.

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