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Technological diffusion trends suggest a more equitable future for rooftop solar in the United States

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Abstract

Equity has become central in the academic and regulatory discourse shaping the future of residential-scale clean energy technologies in the United States, particularly rooftop solar. Here, we develop a holistic perspective on these issues by analyzing rooftop solar adoption trends using two alternative forecasting methods: an inside-view forecast based on historical solar adoption data, and an outside-view forecast based on adoption data for other emerging consumer technologies. We show how rooftop solar, like other emerging consumer technologies, has become more equitably adopted over time. We show that solar diffusion patterns are largely consistent with those of other technologies. Both forecasting methods suggest that clean energy technologies should be expected to become more equitably adopted over time. Policy could accelerate this process by supporting low-income adoption without unduly curbing overall diffusion.

1. Introduction

Emerging consumer technologies such as rooftop photovoltaics (PV), electric vehicles (EVs), small-scale batteries, and smart thermostats could play key roles in decarbonization (Victoria *et al* 2021). The benefits of these emerging clean energy technologies have not yet been distributed equitably (Borenstein and Davis 2016). High-income households are adopting emerging clean energy technologies more frequently than low- and moderate-income (LMI) households (Muehlegger and Rapson 2018, Forrester *et al* 2022). For instance, the median income of a rooftop PV adopter in the United States in 2021 was about 75% higher than the national median income (Forrester *et al* 2022), and households earning less than \$100 000/year account for about 72% of conventional car buyers but only 44% of EV buyers in California (Muehlegger and Rapson 2018).

Inequitable adoption and its implications are shaping residential clean energy policymaking in the United States, particularly in the cases of rooftop PV and EVs (Rule 2015, Klass 2020). Equity-based arguments merit particular scrutiny in public policy discourse, given that stakeholders can appeal to equity as an effective strategy to drive policies that do not improve public welfare, including the welfare of those individuals ostensibly served by equity-based policies (Kaplow and Shavell 2001). Equity-based arguments have been used to support reforms to redistribute the benefits of these technologies (Klass 2020), including through measures that may curb overall deployment. One example are equity-based arguments for PV rate reforms (Rule 2015). Reforms are needed to mitigate regressive cross-subsidies under existing rate structures that shift costs from relatively affluent PV adopters onto less affluent non-adopters (Borenstein *et al* 2021). At the same time, these reforms can reduce the value of rooftop PV adoption and curb deployment (Rule 2015). Given the urgent need for decarbonization, the design of such reforms and their ability to promote equity should be closely evaluated. Do such reforms in fact drive more equitable outcomes? And do these gains in equity justify tradeoffs in the pace and scale of clean energy deployment?

Clean energy research has largely evaluated inequitable adoption based on the context-specific characteristics of specific technologies and markets, such as high up-front adoption costs and tax credits that favor high-income adoption (Borenstein 2017, Muehlegger and Rapson 2018, Lukanov and Krieger 2019, Sunter *et al* 2019, Hardman *et al* 2021, Sheldon

2022). These studies largely conclude that PV and EVs are inequitably deployed due to context-specific barriers to LMI adoption. Heeter *et al* (2021) is the only study, to our knowledge, to project LMI PV adoption trends into the future. That study projects LMI PV adoption to increase over time and explores how incentives could accelerate LMI adoption. The trajectory of LMI adoption of clean energy technologies is a key open question that could shape the appropriate policy responses to inequitable technology adoption. If these technologies become more equitable over time, then measures with near-term equity objectives that curb deployment could counter-productively decelerate transitions to more equitable adoption.

We explore how clean energy technology adoption equity could evolve by employing inside- and outside-view forecasting, using rooftop PV as a case study. Inside-view forecasts rely on context-specific information to project future trends. In our case, we use historical PV adoption patterns to project future trends in adoption equity. An inside view of clean energy technology adoption inequity can help develop targeted approaches catered to the nuances of specific clean energy technologies. However, inside views tend to over-emphasize contextual nuances and under-estimate the degree to which outcomes are similar across related contexts (Kahneman and Tversky 1979). Forecasters can correct inside-view biases—used here as a statistical term—by developing an outside view: an analysis of comparable reference cases as a basis for evaluation and projection. Reference cases are related contexts that sufficiently resemble the context in study. We explore adoption patterns in other emerging consumer technologies as reference cases for rooftop PV adoption. Outside views mitigate inside-view biases through regression toward the mean as proxied by the reference-case average (Kahneman and Tversky 1979). Effective forecasting requires synthesizing both views, leveraging context-specific information from inside views to make adjustments toward or away from the reference cases (Kahneman and Tversky 1979).

In this paper, we aim to build a holistic view of PV adoption inequity and its implications by exploring inside and outside views of the issues. Our research question is whether and how quickly clean energy technologies will become more equitably adopted. Our objective is not to dispute existing claims but rather to build a more complete and precise understanding of the issues. Our geographic focus is on the United States. Our primary insight is that rooftop PV may be relatively inequitable compared to other durable consumer technologies at similar levels of deployment, but that trends across technologies suggest that PV adoption will become substantially more equitable. We explore the implications of these insights for equity-based interventions such as subsidies and electricity rate reforms.

2. Method

Our analysis relies on three data sources. The first is rooftop PV diffusion data compiled by the Lawrence Berkeley National Laboratory (Barbose *et al* 2022). The PV data sample comprises records on 2252391 PV systems installed from 2000–2020 that could be matched to modeled household-level income estimates procured from Experian. See O'Shaughnessy *et al* (2021) for further discussion of the PV household-level income estimates. The second source comprises technology deployment data for reference-case technologies. We pulled these data from the U.S. Energy Information Administration's Residential Energy Consumption Surveys (RECS) and Bureau of Labor Statistics data compiled by Attanasio and Pistaferri (2016). These sources provide a long-term time series (1987–2020) on an array of consumer technologies, including domestic appliances (e.g. washing machines), home electronics (e.g. personal computers), and personal vehicles. While none of these technologies is perfectly comparable to rooftop PV, we shall show that common diffusion patterns among these disparate consumer technologies can provide useful insights into likely future PV diffusion patterns. The third source is the U.S. Census, which we use as a basis for estimating income levels in the broader population.

Technology adoption equity can be measured in numerous ways. We focus our analysis on the share of PV adopters earning less than the U.S. national median income, which we refer to as the LMI adoption share. The LMI adoption share is relatively intuitive in that the metric would equal 50% if adoption were randomly distributed across the population. We analyze cumulative LMI adoption shares given that our reference-case data are in cumulative terms. The RECS data are published in discrete income bins (e.g. \$15 000–\$25 000). To estimate LMI adoption shares in the RECS data, we estimated the proportions of households below and above the median income within those bins based on a lognormal income distribution. In every year, the number of households below the split is slightly overrepresented in the survey. We adjusted the number of households below the median such that the number of households below and above the median income has a 1:1 ratio.

Our objective is to forecast future PV LMI adoption shares as a function of historical PV LMI adoption shares (inside-view forecast) and in relation to the LMI adoption shares of reference-case technologies (outside-view forecast). We base our inside-view approach on the technological diffusion literature. Beginning with Bass (1969), that literature shows how diffusion tends to increase non-linearly over time, typically described by an S-curve parameterized by factors such as innovation, social contagion, individualism, and status competition (Easingwood et al 1983, Bass et al 1994, Agarwal and Bayus 2002). Income threshold diffusion models suggest that income inequality can drive S-shaped diffusion (Van den Bulte and Stremersch 2004). Under income threshold models, early adoption catalyzes technology cost reductions that bring prices within financial reach for more customers (Conceiação et al 2003, Torres Preto 2004, Hyytinen and Toivanen 2005, Vona and Patriarca 2011). As prices decline, emerging technologies then diffuse to LMI customers. Empirical evidence supports the premise of income thresholds for a variety of emerging technologies (Attanasio and Pistaferri 2016), including rooftop PV (Forrester et al 2022). We therefore assume that LMI adoption probabilities increase as a function of deployment. Given that the U.S. income distribution is roughly lognormal, we assume that the cumulative density function of LMI adoption shares is S-shaped with respect to cumulative deployment.

We project S-shaped LMI adoption shares through a simple logistic regression defined by three parameters: the maximum LMI adoption share value, the midpoint (q_0), and the slope of the curve (k). We assume the long-term maximum LMI adoption share to be 0.5, representing the point at which the technology is proportionately distributed with respect to income. We estimated the remaining two parameters through a logistic regression of the following form:

$$LMI_q = \frac{0.5}{1 + e^{-k(q-q_0)}} \tag{1}$$

Where LMI_q is the cumulative LMI adoption share at cumulative logged deployed capacity of q. We used sample means, medians, maxima, and minima as initial points for the warm start of the curve fitting. We use rooftop PV projections from Davis et al (2022) to map forecasted deployed capacity to specific years for visualization purposes.

The simple logistic regression in equation (1) suits our objective to create an illustrative inside-view forecast. The primary limitation of the model is that all parameters are estimated from historical trends in LMI adoption shares. Our model excludes factors such as innovation and social contagion that could shape LMI diffusion. We recognize that more complex diffusion models could yield more precise insights into adoption equity patterns. Another strategy would be to forecast LMI adoption shares through agent-based modeling (Rai and Robinson 2015); an approach used by Heeter et al (2021) to model LMI PV adoption under various policy scenarios. Still, visual inspections of the PV (see figure 1) and reference-case (see figure 4) data support the premise that LMI adoption shares follow an S-curve with respect to cumulative deployment. Future researchers could consider how alternative diffusion models could yield more precise projections for LMI adoption shares.

As a robustness check, we also forecast future PV LMI adoption shares as a direct function of time through an autoregressive time series model. The untransformed time series (depicted in figure 1) exhibits a clear upward trend, rendering the series un-stationary (Brockwell and Davis 2002). An augmented Dickey–Fuller test shows that the second difference of PV LMI adoption shares is stationary for specific subsamples of the data. We run an autoregressive model on the most recent subsample of data that yields stationary second differences, in this case 2000–2020. We forecast based on an autoregressive model using the forecast package in R (Hyndman and Khandakar 2008).

We build confidence intervals for the forecasted PV LMI adoption shares based on the method described in Lafond et al (2018), which allows for intervals to expand over time to reflect higher uncertainty for projections made further into the future. The confidence intervals are built on the following probability distribution:

$$LMI_t \sim N\left(\widehat{LMI}_t, \sigma^2\left[\tilde{t} + \frac{\tilde{t}^2}{T-1}\right]\right) \tag{2}$$

Where $\widehat{LMI}_t$ is the projected LMI adoption share in year t, σ is the standard forecasting error from equation (1) in the case of the S-curve model and the standard error of residual values in the case of the autoregressive model, $\tilde{t}$ is the number of years elapsed into the future from the base projection made in 2020 (e.g. for 2021 $\tilde{t} = 1$, for 2022 $\tilde{t} = 2$, etc), and T is the number of years used to make the projection. In the case of the S-curve model, we use rooftop PV projections from Davis et al (2022) to map forecasted deployed capacity to specific years.

We note two limitations before proceeding to the results. First, as noted, our inside-view forecasting approach is based purely on historical trends in LMI adoption shares. The forecasts should be interpreted as illustrative projections of future LMI adoption shares if current market and technological conditions persist into the future. Our forecasts do not account for potential changes in products (e.g. emergence of new financing options), policies (e.g. subsidies for LMI adoption), or technological trends in other demand-side resources (e.g. battery storage) that could affect LMI adoption shares. Second, our analysis takes a narrow view of a broader issue. We analyze the distribution of rooftop PV adoption, which is a component of distributive justice under emerging energy justice frameworks (Sovacool and Dworkin 2014). We do not, however, analyze adoption in terms of other tenets of energy justice such as procedural and restorative justice (Carley and Konisky 2020). For this reason we do not frame our results or our discussion in energy justice terms. We focus on the inside- and outside-view forecasts and the implications of the quantitative results.

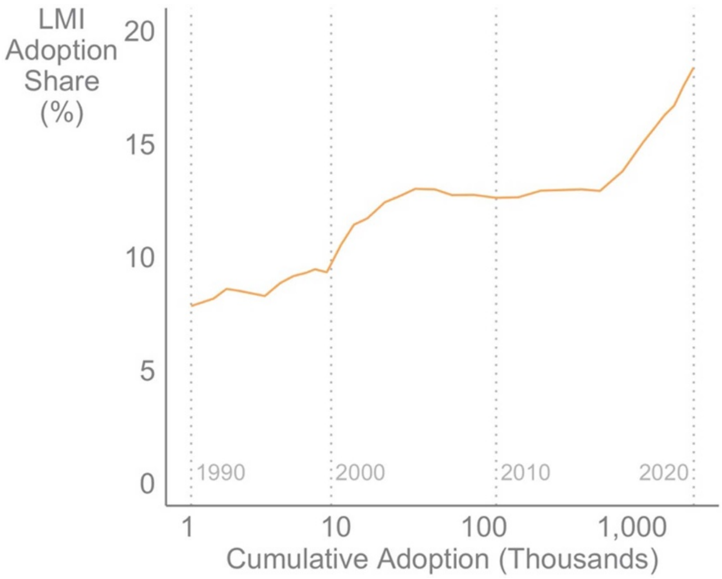

Figure 1. Rooftop PV LMI adoption shares by logged cumulative adoption.

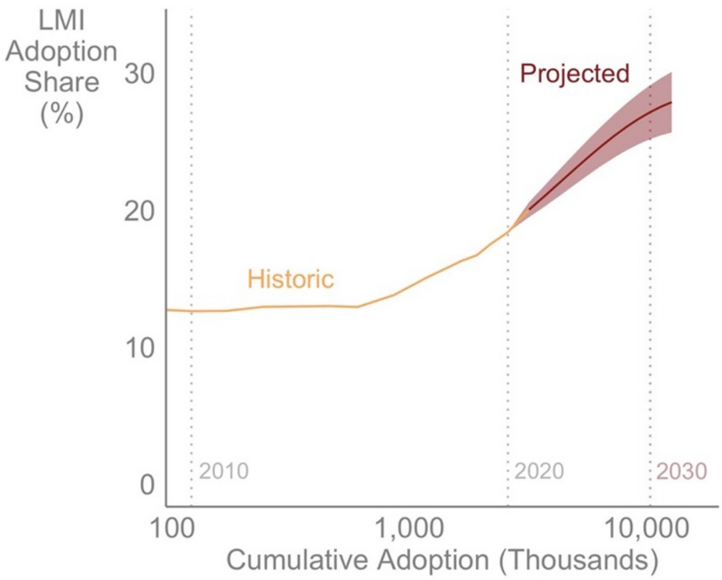

Figure 2. Inside-view forecast of future PV LMI adoption shares as a function of diffusion (S-curve model). Area represents 95% confidence intervals.

3. Results

As has been observed elsewhere, rooftop PV adoption is becoming more equitable over time (figure 1). The PV LMI adoption share grew from about 8% in 1990 to 18% in 2020, implying that LMI households remain about 32 points under-represented among PV adopters. Figure 2 depicts the forecasted PV LMI adoption shares as a function of diffusion—our preferred model—while figure 3 depicts the time series forecast. The diffusion model forecasts that LMI households will account for 27% (±2%) of PV adopters at a cumulative deployment level of 10 million systems (about 8% of U.S. households). The time series forecast suggests that LMI households will account for about 21% (±2%) of PV adopters by 2030.

Moving to the outside view, figure 4 depicts the LMI adoption shares of the reference-case technologies. All reference-case technologies become more equitable as they diffuse, consistent with the theoretical expectations of income threshold models (see Methods). Ideally, we could estimate a distributional average of reference-case LMI adoption shares at the same deployment levels as rooftop PV. However, whereas only around three million PV systems had been installed in the United States by 2020, we only have reference-case data at cumulative deployment

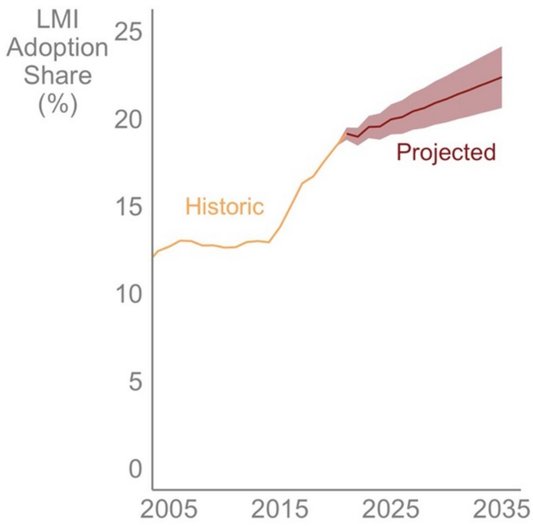

Figure 3. Inside-view forecast of future PV LMI adoption shares as a function of time (autoregressive model). Area represents 95% confidence intervals.

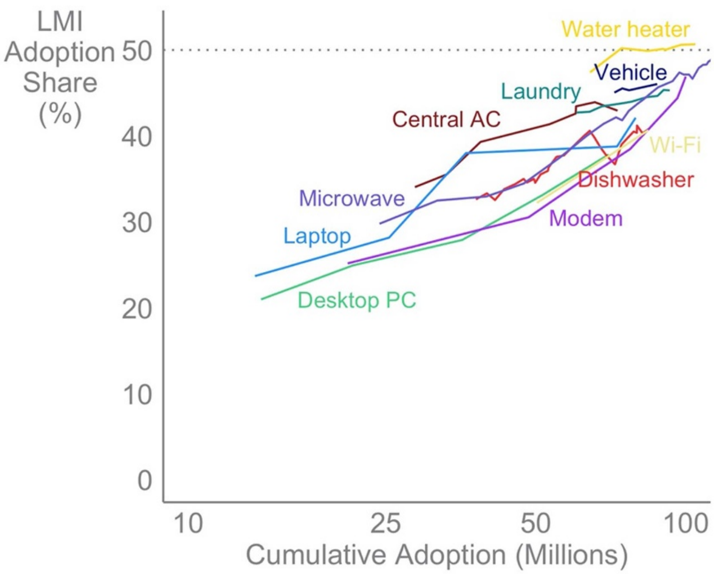

Figure 4. Technology LMI adoption shares by logged cumulative adoption.

levels above ten million cumulative adoptions. We address this gap by projecting reference-case LMI adoption shares backward, again assuming an S-curve relationship between LMI adoption shares and cumulative deployment. The reference-case technologies can be broadly grouped into two categories: consumer durables (e.g. vehicles, central air conditioning) and information technology or IT (e.g. computers, modems). Of the two categories, PV is more like the consumer durables in that it is a long-lived functional asset. However, as illustrated in figure 5, current PV LMI adoption shares are more like those of IT products at similar penetration levels. The projections suggest that PV LMI adoption shares are lower than the reference-case distributional average and substantially lower than the LMI adoption shares of other consumer durables at the same level of cumulative deployment. Like the IT products, the gap between PV and the distributional average is likely to narrow but not necessarily close over time as rooftop PV diffuses.

The inside- and outside-view forecasts converge over time (figure 6). While the inside-view projection is initially about 6 percentage points lower than the outside view, the gap narrows to just one point at a cumulative deployment level of ten million systems. A synthesis of both views suggests that PV LMI adoption shares will increase from around 18% today to 25%–29% at a cumulative adoption level of ten million systems, projected to occur around 2030. In absolute terms, our results suggest that around three million LMI households

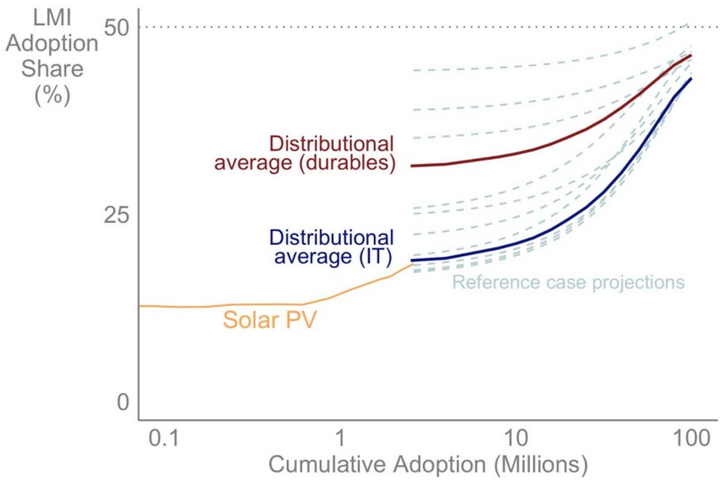

Figure 5. Observed and projected LMI adoption shares by logged cumulative adoption.

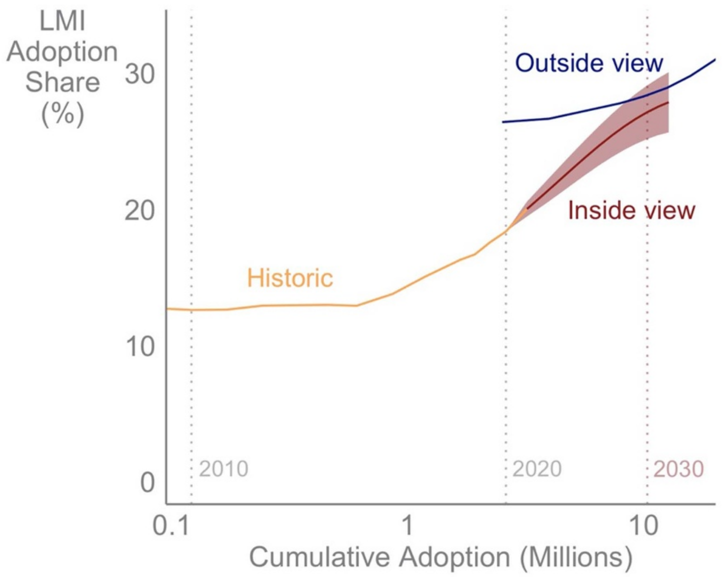

Figure 6. Forecasted rooftop PV LMI adoption shares under inside-view and outside-view projections. The outside view is based on the distributional average of all reference-case technologies. Area represents 95% confidence intervals. Inside-view forecast based on S-curve projection.

will have adopted by 2030, equating to around 20 gigawatts of capacity based on typical residential PV system sizes. That estimate concurs with an estimate from Heeter *et al* (2021), using agent-based modeling, that about 19 gigawatts of rooftop PV will be installed on single-family LMI households by 2030 in a business-as-usual scenario, though that study's definition of LMI varies slightly from our definition. Similarly, Heeter *et al's* results suggest that LMI adoption shares will reach about 28% in 2030[2]. Whether LMI adoption shares tend toward the higher end of that range depends on the comparability of rooftop PV with the reference cases. As noted, rooftop PV is arguably most comparable to consumer durables such as central air conditioners, laundry machines, and dishwashers, which are—like PV—long-lived assets primarily procured by homeowners rather than renters. LMI adoption shares for these long-lived assets appear to plateau at higher deployment levels (see figure 4). These plateaus may partly reflect the larger share of LMI renters who are less likely to own these appliances. PV LMI adoption shares may similarly plateau below 50% for the same reason: LMI renters and households in multifamily buildings face unique PV adoption barriers. For this reason rooftop PV may not become perfectly equitable (i.e. 50% LMI adoption share) even in the long term.

[2] Heeter *et al* defined LMI as households earning less than 120% of area median income. Precise numerical results were not available upon request from the authors of the Heeter *et al* study. These numerical approximations are based on figures 3 and 4 from the study.

4. Discussion

Inside- and outside-view forecasts of rooftop PV adoption both suggest that rooftop PV adoption will become substantially more equitable. While we focus on rooftop PV as a case study, the common trends across rooftop PV and all reference cases support the hypothesis that all emerging clean energy technologies will become more equitably adopted through diffusion.

One key implication of our results is that technological diffusion is the primary driver of increasing adoption equity. This conclusion is supported by the common trends in adoption equity exhibited across technologies as diverse as personal computers and vehicles. For instance, increasingly equitable adoption of information technologies (computers, modems, Wi-Fi) may be partly attributable to policies to reduce the 'digital divide' between high- and low-income technology users (Sanders and Scanlon 2021). Still, the similarities across technologies suggest the impacts of such policies are secondary to the impacts of diffusion. Put another way, targeted policies (e.g. subsidies for LMI adopters) may accelerate a transition toward LMI adoption that is primarily driven by technological diffusion. Policies to facilitate market processes that drive diffusion could similarly accelerate that transition. For instance, policies to improve access to financing could drive LMI diffusion given the key role that financing can play for LMI adoption (Drury *et al* 2012, O'Shaughnessy *et al* 2021), especially in developing countries (Dutt 2020).

Trends in rooftop PV deployment provide further support for the claim that technological diffusion is the primary driver of more equitable adoption. As PV diffuses and prices fall, more households can afford PV, increasing adoption and driving further price reductions. This process of learning and diffusion drove a 70% reduction in median U.S. residential PV installed prices from 2000 to 2020 (Barbose *et al* 2021). To compare the relative impacts of diffusion and targeted interventions for LMI adoption, consider the case of California. From 2006 to the end of 2021, California reserved around \$162 million in subsidies for income-qualifying households, meaning households earning less than 80% of area median income (CPUC 2022). By the end of 2021, California had distributed PV subsidies to around 9600 income-qualifying LMI households (CPUC 2022). The California LMI incentive is the largest such program in the United States, yet our data suggest that the program drove only around 4% of cumulative LMI adoption in the state, with about 220 000 LMI households having adopted PV without receiving the LMI incentive under using the program's LMI definition. Further analysis would be required to determine the precise role of diffusion and price reductions in driving LMI adoption, but these data support the hypothesis that most LMI rooftop PV adoption has been driven by diffusion and falling prices.

The above discussion is not meant as a critique of targeted equity-based interventions. Equity-based interventions can meet specific near-term objectives, such as the alleviation of issues associated with energy poverty and insecurity. Further, due to the design of electricity rate structures, inequitable adoption of clean energy technologies can result in significant and regressive cross-subsidies (Borenstein *et al* 2021). While cross-subsidies are ubiquitous in public policy (Brooks *et al* 2018), the extent and regressivity of cross-subsidization for rooftop PV could require policy interventions that would not be necessary for other emerging technologies. Regulators are obligated to address inequitable cross-subsidies to comply with legal principles that electricity rates be just and reasonable (Welton and Eisen 2019). Still, our results suggest that careful analysis is required to determine the appropriate balance of measures to achieve near-term equity objectives while also supporting the large-scale diffusion of emerging technologies. A balance of targeted incentives and measures to support conventional diffusion could achieve a broader set of near- and long-term equity objectives. An example of such analysis is a California proposal for new rate structures that would curb rooftop PV adoption. The proposed rule (California Public Utilities Commission Proceeding R.20-08-020) suggests that regulators sought to balance near-term equity concerns with longer-term diffusion needs. The proposal, for instance, reduces compensation for exported PV output to mitigate regressive cross-subsidies. At the same time, regulators designed the rule to ensure a minimum payback period deemed sufficient for California rooftop PV deployment and decarbonization goals. While stakeholders dispute whether the proposal achieves the right balance, the process suggests that regulators can explore ways to achieve near-term equity goals without unduly curbing the processes that lead to long-term LMI diffusion.

Our results could also motivate alternative perspectives on the equity implications of policies to support emerging technologies. Because of typical technological diffusion patterns, most policies to support the broad (i.e. income-agnostic) adoption of emerging technologies are inequitable in the near term. For instance, rooftop PV subsidies and cross-subsidies through utility rate structures are unequivocally near-term inequitable since these subsidies accrue disproportionately to high-income, early adopters (Borenstein and Davis 2016, Borenstein *et al* 2021). Similar arguments can be made for incentives for the adoption of other emerging technologies such as EVs, smart thermostats, and heat pumps. Yet, because technologies tend to diffuse from high- to lower-income adopters, the long-term equity implications of these policies are more ambiguous. A near-term inequitable incentive for technology adoption could lay the groundwork for the mass diffusion and cost reductions that make technologies economical for LMI households. For instance, early rooftop PV subsidy programs in relatively rich countries such as Germany, the United States, and Japan drove the cost reductions that make PV adoption an economically viable choice for LMI households around the world in 2022 (Nemet 2019). Thus, efforts to promote equitable technology adoption should consider both the near- and long-term implications of different policy measures.

Finally, it is worth recognizing important differences in the political contexts of technologies that emerged in the past and technologies that are emerging today. Emerging clean energy technologies are diffusing at a time of perceived growing social inequality and increasing demands on policymakers to address that inequality (Hauser and Norton 2017). Caution is merited when extending such demands to clean energy policy. Policies to ostensibly promote technology adoption equity could inefficiently advantage incumbent technologies that were not subjected to similar interventions. As already noted, equity-based clean energy interventions should be based on careful analysis of near-term equity gains (e.g. energy burden reduction) and technological diffusion as the key driver of long-term equity.

5. Conclusion

Inequitable adoption patterns have driven equity to the center of the regulatory discourse around emerging clean energy technologies, particularly rooftop PV and EVs. This discourse is based on a historical view of adoption trends rather than an informed view of expected future deployment trajectories. In this paper, we inform this discourse by using inside- and outside-view forecasting techniques to project future trends in rooftop PV adoption equity. We show that rooftop PV will likely become substantially more equitable over time, as do all the reference case technologies in our study. We estimate that the share of rooftop PV adopters earning less than the U.S. median income will grow from around 18% in 2020 to 25%–29% by 2030, consistent with deployment trends observed for other emerging technologies. That projection implies that around three million households earning less than the U.S. median income will have adopted rooftop PV by 2030, roughly the size of the entire U.S. rooftop PV market by the end of 2021. Policies that promote adoption at the margins could accelerate these trends. Conversely, policies that inadvertently curb adoption to promote near-term equity entail tradeoffs in long-term equity by decelerating these trends.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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