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Encouraging Voluntary Government Action via a Solar-Friendly Designation Program to Promote Solar Energy in the United States

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Sustainable development requires an accelerated transition toward renewable energy. In particular, substantially scaling up solar photovoltaics (PV) adoption is a crucial component of reducing the impacts of climate change and promoting sustainable development. However, it is challenging to convince local governments to take action. This study uses a combination of propensity score matching (PSM) and difference-in-differences (DID) models to assess the effectiveness of a voluntary environmental program (VEP) called SolSmart that targets local governments to engage in solar-friendly practices to promote the local solar PV market in the United States. Via specific designation requirements and technical assistance, SolSmart simplifies the process of acting on interest in being solar friendly, has a wide coverage of basic solar-friendly actions with flexible implementation, and motivates completion with multiple levels of designation. We find that a local government's participation in SolSmart is associated with an increased installed capacity of 18 to 19%/mo or with less statistical significance, an increased number of installations of 17%/mo in its jurisdiction. However, SolSmart has not shown a statistically significant impact on soft cost reductions to date. In evaluating the impact of the SolSmart program, this study improves our understanding of the causation between a VEP that encourages solar-friendly local government practices and multiple solar market outcomes. VEPs may be able to promote shifts toward sustainable development at the local level. Our findings have several implications for the design of VEPs that promote local sustainability.

voluntary environmental program | solar-friendly practices | technology adoption | solar photovoltaic | soft costs

Solar is a critical element of the energy technology portfolio for combating climate change and shifting toward sustainable development (1, 2). Historically, financial incentives have been the dominant policy instrument to promote the deployment of solar technologies through reducing barriers related to the high up-front costs of adoption. However, there is a growing awareness that solar adoption is also heavily influenced by the local regulatory and policy environment (3–6). Variation in local rules and regulations, such as local building codes and permitting processes, can lead to different levels of cost reductions and installation across local jurisdictions (7–12). Despite documented best practices, these actions are unevenly adopted by local governments, even when mandated by law (as is the case in California) (13). It remains a challenge to increase governments' awareness and motivate their adoption of these practices to build a solar-friendly marketplace.

To facilitate governments' sustainability actions, voluntary environmental programs (VEPs) have increased in popularity among local governments in the past decade (14–16). VEPs (e.g., WasteWi$e, Green Lights, and 33/50) emerged as a nonregulatory tool for the private sector and are widely used to encourage firms' voluntary green behaviors by providing certification (17–21). They have long been advocated as an alternative policy tool to mandatory regulations due to greater political traction and flexibility (22–27). Prior research has shown that VEPs for firms have been largely successful (22, 27, 28), and there has been a growing body of work on VEPs that encourage public agencies' sustainability actions (7, 24, 29–31). However, most work focuses on the motivations and strategies for public agencies to join and implement these VEPs (24, 29, 31). The present study aims to improve our understanding of the effectiveness of VEPs for public sector agencies in achieving sustainability goals.

This study represents a national examination of the impact of a VEP that targets local governments to engage in solar-friendly practices to expand the local solar photovoltaics (PV) market. In 2016, The Solar Foundation and the International City/County Management Association, with support from the US Department of Energy's Solar Energy Technologies Office, launched "SolSmart." In contrast to mandatory regulations imposed at the state or federal level, SolSmart, as a VEP, encourages local governments to adopt best practices to promote solar PV installations via national recognition and no-cost technical assistance. To achieve Bronze, Silver, or Gold SolSmart designation levels, local governments choose to accomplish required and optional actions from eight categories,

SOCIAL SCIENCES

SUSTAINABILITY SCIENCE

Significance

Due to market and system failures, policies and programs at the local level are needed to accelerate the renewable energy transition. A voluntary environmental program (VEP), such as SolSmart, can encourage local governments to adopt solar-friendly best practices. Unlike previous research, this study uses a national sample, more recent data, and a matched control group for difference-in-differences estimation to quantify the causal impact of a VEP in the public, rather than private, sector. We offer empirical evidence that SolSmart increased installed solar capacity and, with less statistical significance, the number of solar installations. The results inform the design of sustainability-focused VEPs and future research to understand the causal pathways between local governments' voluntary actions and solar market development.

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including 1) permitting; 2) planning, zoning, and development regulations; 3) inspection; 4) construction codes; 5) solar rights; 6) utility engagement; 7) community engagement; and 8) market development and finance (32). A more detailed description of SolSmart designation requirements can be found in *SI Appendix*.

From a theoretical perspective, SolSmart may encourage local governments to become solar friendly due to 1) reducing the information costs for communities to learn best practices (22, 28), 2) starting with a wide range of basic actions, 3) allowing flexible implementation, and 4) motivating completion via recognition. First, VEPs provide policy and administrative guidelines as well as technical assistance, which can save participants' time and resources to search for and adopt these best practices (22, 33), thus bridging the knowledge–action gap (34, 35). Second, many of the best practices provided in the SolSmart program guide establish a minimum threshold for being solar friendly. For example, some actions make the administrative process more transparent rather than more streamlined, such as posting an online checklist detailing the rooftop solar PV permitting process. Starting from these basic actions can get local governments' "foot in the door" and encourage them to subsequently adopt other recommended practices that may require more effort and investment (36–40). Third, existing inconsistencies in practices across jurisdictions suggest that local governments have preferences on the combination of best practices to adopt (13, 41). SolSmart allows local governments to choose any customized designation pathway based on their preferences as well as technical, bureaucratic, and financial capabilities. However, the flexible implementation of SolSmart also allows local governments to get credit for the best practices they have already completed, which may reduce the measurable effects of SolSmart on the solar market. Lastly, SolSmart motivates completion by offering recognition via Gold, Silver, and Bronze designation levels. This recognition allows local governments to benchmark their performance to others. This may provide an intrinsic reward in the form of praise, which is more effective than extrinsic rewards, such as financial incentives (42).

It is challenging to examine the effectiveness of using VEPs in the public sector due to potential endogeneity issues when measuring program effects and limited data availability (8, 22, 24, 25). This study evaluates the effect of SolSmart in terms of solar energy adoption and soft costs. Market expansion is the ultimate goal of this VEP, and reducing soft costs is critical for increasing solar adoption, as soft costs represent up to 70% of the installation cost for residential PV systems (10). To address the endogeneity issue, we use a combination of propensity score matching (PSM) and difference-in-differences (DID) models to capture the change in solar market development due to participation in SolSmart. These quasiexperimental techniques allow us to estimate this effect by comparing the changes in the outcome variables before and after designations between the SolSmart communities and the matched control group of non-SolSmart communities. In addition, this study leverages a unique dataset from the SolSmart program and merges it with several national solar market datasets to conduct a national evaluation of a VEP in the public sector.

Overall, we find that participation in SolSmart is associated with increased installed capacity and, with less statistical significance, higher numbers of installations, but there is no observable impact on soft cost reductions. Our findings suggest that SolSmart, as a VEP that offers detailed guidance, technical assistance, and flexibility for participants to adopt a wide range of best practices, has achieved its intended outcome to promote solar adoption in the local communities. In addition, we compare the statistical results with perceived impacts as reported by local government and solar installer survey respondents, which are largely consistent. Our findings have implications for the design of VEPs more broadly to engage local governments to promote sustainability initiatives.

Results

We used a combination of PSM and DID approaches to estimate the effect of SolSmart in terms of solar energy adoption and soft costs. Using PSM, we performed exact one-to-one matching across 15 key characteristics that describe communities' demographic, solar PV market, and environmental attributes to identify the most similar non-SolSmart community for every SolSmart community. Given the risk of selection bias, where communities that chose to participate in SolSmart are more committed to solar and would see solar growth regardless of participation, we report two matching processes to evaluate the robustness of the results. Most (14 of 15) matching variables are the same in the two processes; however, the more liberal approach uses the existence of a 100% renewable goal in a community, and the more conservative approach is limited to a solar goal specifically.

The balanced statistics after matching suggest that SolSmart participation is plausibly random across the treated and matched control groups (*SI Appendix*, Tables S1 and S2). The distribution of propensity scores before and after matching is in *SI Appendix*, Figs. S1 and S2. The matched pairs of treated and control communities are reported in *SI Appendix*, Tables S3 and S4. In particular, the climate action plan (CAP), renewable goal, and solar goal measures are all statistically insignificant between treated and matched control groups after matching. These variables reflect a local government/community's environmental orientation regarding climate mitigation and adaptation broadly as well as support for renewables and solar energy specifically (43–48).

The control communities being considered for matching come from the most comprehensive dataset for solar installations in the United States, the Tracking the Sun (TTS) dataset. As TTS disproportionately represents larger solar markets in California, Arizona, Massachusetts, New Jersey, and New York, only 76 of 245 SolSmart-designated cities and towns have available data in TTS (more details are in *Methods*). Thus, this analysis includes 76 SolSmart communities and 76 matched non-SolSmart communities (152 communities total). We present the representativeness of regions, designation levels, and community characteristics among SolSmart communities that are included in our models, those that are not included in our models, and the full sample of SolSmart communities in *SI Appendix*, Tables S5–S7. We found that the environmental orientation and general intent to support renewables or solar were not related to data availability. Our sample is largely representative of all SolSmart communities in terms of demographics and environmental orientation. However, our analysis best represents wealthier communities in SolSmart, which may tend to have more solar installations in general.

Estimated Effect of SolSmart. Fig. 1 shows monthly estimated effects of SolSmart on installed capacity, the number of installations, and soft costs before and after designation between treated and matched control groups. As shown, there is an overall trend toward increased installation and lower soft costs, even after controlling for time fixed effects and a linear time trend. In addition, Fig. 1 suggests that there is a 1- to 2-mo time lag between completing the SolSmart actions and achieving a SolSmart designation. In order to pursue designation, communities first contact SolSmart for a consultation to learn more about the program. If needed, they may leverage technical assistance provided by SolSmart to complete the necessary steps and acquire appropriate documentation. After completing the required actions, communities prepare and submit an

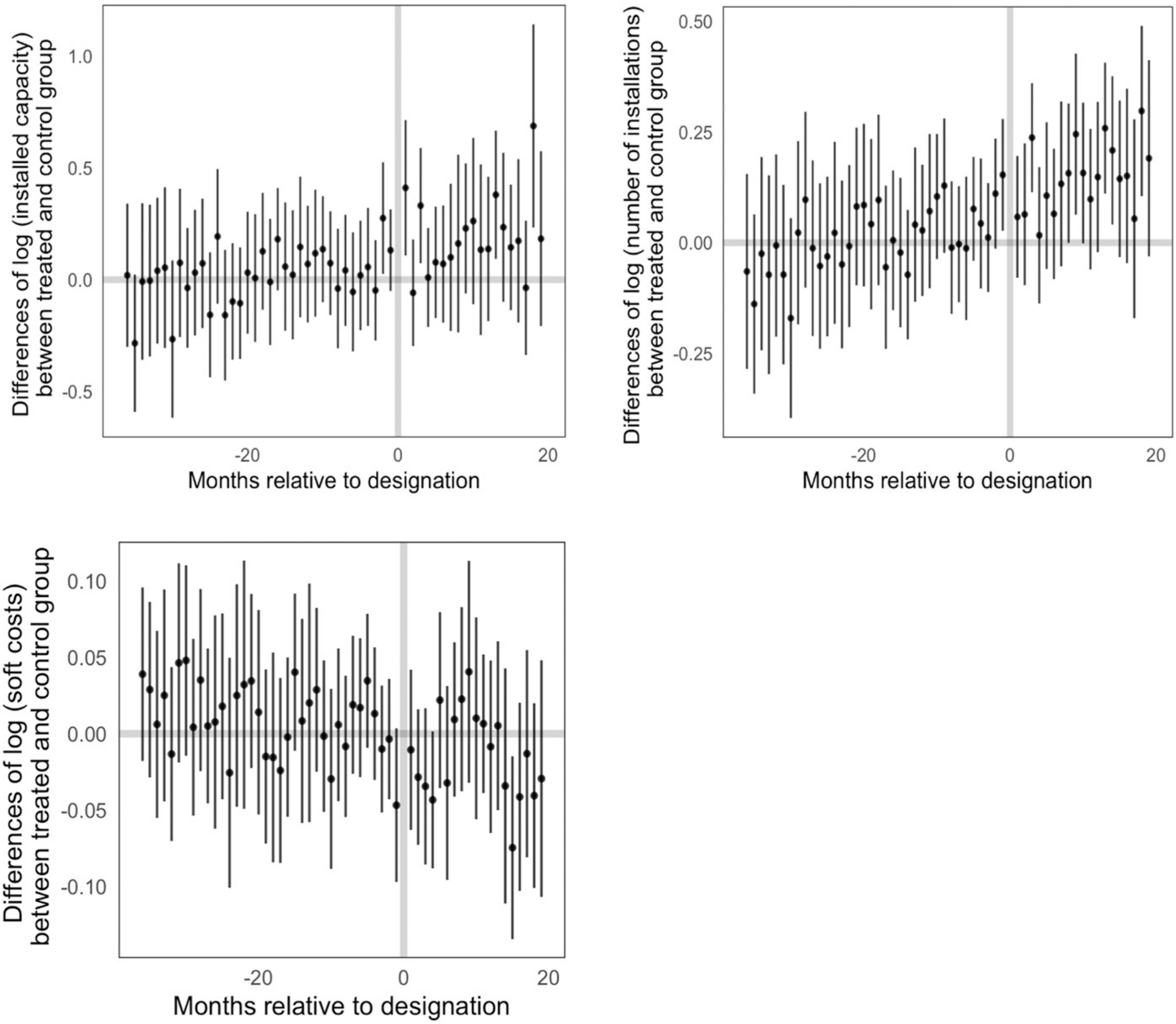

Fig. 1. The parallel trend for each outcome variable. The graph presents 90% CI bars. The *y* axis is the difference of installed capacity, the number of installations, and soft costs between SolSmart and non-SolSmart communities before and after designation. The *x* axis is the months relative to designation. The figures present the treatment–control difference for 36 mo before the designation, the designation month, and 18 mo after the designation.

application to SolSmart for review, leading to some time lag between when actions are enacted and when designation is achieved.

We use DID models to estimate the average treatment effect on the treated. In Table 1, models 1, 3, and 5 include renewable goal as a matching variable in PSM and control variable in DID models, and models 2, 4, and 6 include solar goal. The control variables at the community level include CAP, renewable goal or solar goal, the number of installers, the annual performance-based incentive, rebate, median home value, occupied housing units, median household income, the number of installations (for the soft costs models), and average efficiency of systems (for the soft costs models). More details on these variables are in *Methods*.

We find that the SolSmart program is associated with increased installed capacity and installations but not reduced soft costs. Models 1 and 2 in Table 1 present the DID results for installed capacity, which suggest that the SolSmart designation is associated with an 18 to 19% increase in installed capacity per month in a community. Models 3 and 4 report the effect of SolSmart designation on the number of installations, which suggests that the SolSmart designation is associated with a 9 to 17% increase in installations per month, although these results have less statistical significance. The model with solar goal is insignificant, but this model has less than ideal matching between SolSmart and non-SolSmart communities, as the coefficient of the treatment variable (i.e., the dummy variable indicating whether or not a community is SolSmart designated) is still significant after matching. Robustness checks reported in *SI Appendix* suggest that there may be an effect of SolSmart on the number of installations, but it is more sensitive to model parameters. Another key factor that impacts the development of the solar market is solar soft costs. However, models 5 and 6 find a statistically insignificant impact of SolSmart on soft cost reduction.

SI Appendix, Table S9 shows the results of the absolute (rather than percentage) change of the SolSmart program on installed capacity, the number of installations, and soft costs. In models using renewable goal (i.e., the liberal approach), the SolSmart designation is associated with an increased installed

Table 1. The effect of SolSmart designation on installed capacity, the number of installations, and soft costs

	log(*Installed capacity*)		log(*No. of installations*)		log(*Soft cost*)	
Dependent variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SolSmart impact	0.188*	0.182**	0.171**	0.089	−0.039	−0.037
	(0.095)	(0.089)	(0.080)	(0.089)	(0.026)	(0.027)
Prepost	−0.098	−0.133*	−0.139**	−0.088	0.043*	0.028
	(0.090)	(0.074)	(0.060)	(0.066)	(0.023)	(0.024)
Treatment	−0.112	−0.042	−0.005	0.237*	0.054	0.186
	(0.475)	(0.130)	(0.150)	(0.302)	(0.090)	(0.163)
Constant	1.572**	1.563**	−0.089	0.089	−0.213	−0.323**
	(0.685)	(0.302)	(0.251)	(0.089)	(0.173)	(0.150)
Renewable vs. solar goal	Renewable goal	Solar goal	Renewable goal	Solar goal	Renewable goal	Solar goal
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trends	Yes	Yes	Yes	Yes	Yes	Yes
Community FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,677	4,842	4,677	4,842	4,169	4,292
Communities	152	152	152	152	152	152
R^2	0.887	0.886	0.754	0.756	0.332	0.288

The regression results in models 1, 3, and 5 include renewable goal as both a matching and control variable. The regression results in models 2, 4, and 6 include solar goal as a matching and control variable. SolSmart impact is the interaction term between SolSmart communities and prepost designations, which captures the causal effect of SolSmart designation on soft costs, installed capacity, and number of installations. Treatment is a dummy variable indicating whether or not a community is designated by the SolSmart program. Prepost is a dummy variable representing the time period after designations. Robust SEs that are clustered at the community level are reported in parentheses. FE means fixed effects. The complete regression results with the coefficients of control variables can be found in *SI Appendix*, Table S8. *Significance level of 10%; **significance level of 5%.

capacity of 83 kW/mo, an increase of six installed systems per month (statistically insignificant), and a soft cost reduction of $0.16/W. In models using the existence of solar goal (i.e., the conservative approach), the coefficients for the absolute effects are less robust and not significant.

SI Appendix, Tables S10 and S11 report the regression results after removing outliers. Most of the price and system size data are self-reported by system owners or installers, and thus, it is possible that some outliers are errors. The percentage change estimates are very similar but slightly larger than the results in Table 1. However, the estimates of the absolute change are much smaller than the results in *SI Appendix*, Table S9 and insignificant. This suggests that the absolute effects are less reliable estimates than the relative effects reported in Table 1, likely due to outliers skewing the distribution. The estimates of the percentage change are relatively robust across model assumptions.

Additional models included in *SI Appendix* suggest that our results are generally robust to different model specifications. *SI Appendix*, Table S12 tested the robustness to pair-specific linear time trends. We include an interaction between the linear time trend and each matched pair to control for varying time trends for each matched pair. In most of the models, the treatment effects are smaller and less significant (although still significant at the 10% level). In *SI Appendix*, Table S12, we find that a local government's participation in SolSmart is associated with 14% more installed capacity per month, 16% more installations per month, and a 4.7% reduction in soft costs, which are largely consistent with (albeit smaller than) the results reported here when controlling for renewable goal. *SI Appendix*, Tables S13 and S14 tested the robustness when excluding specific outlier months after designation. *SI Appendix*, Tables S15 and S16 include both solar goal and renewable goal as matching variables in PSM and control variables in DID.

To further examine why the effect of SolSmart on the number of installations is less robust than installed capacity, we explored two potential mechanisms in *SI Appendix*: 1) net metering policies and 2) percentage of ground-mounted installations. *SI Appendix*, Tables S17–S28 show the effect of adding net metering policies and the percentage of ground-mounted systems with various model specifications. Our analysis suggests that both net metering and percentage of ground-mounted systems may be confounds, but the original conclusions are robust. However, these additional models suffer from poor matching quality and reduced observations (more details are in *SI Appendix*).

Survey Results of Perceived Impacts. Survey data from local governments and installers provide context to understand how SolSmart has impacted the local solar market. Fig. 2 shows that government respondents from SolSmart communities perceived positive impacts of SolSmart on the local solar market. They perceived that SolSmart primarily increased local government staff knowledge (98%) as well as residents' and business owners' knowledge (67%) about solar energy and installation processes. Many government officials believed that SolSmart reduced permitting time lines (70%) and inspection time lines (60%), increased installed capacity (58%), and reduced overall installation costs (42%). Designees may have focused on reduced time line outcomes since this was one of the primary goals of the SolSmart program.

If the SolSmart designation is to serve as a market signal to installers that a community is "open for business," installers need to recognize the impact of the designation. However, most installers had not previously heard of SolSmart. After an explanation of SolSmart, solar installers believed that SolSmart would increase installed capacity (62%), improve relationships between local government and installers (61%), and increase solar jobs (57%) (Fig. 2). Consistent with government officials, solar installers perceived that SolSmart likely increased knowledge, particularly among government staff but also, among the community (i.e., residents and business owners). Approximately half of solar installers believed SolSmart would help with permitting time lines, interconnection time lines, and installation costs. Although these survey results are the perceptions of a small sample, this suggests that the estimated benefits, at least for installed capacity, are somewhat perceptible.

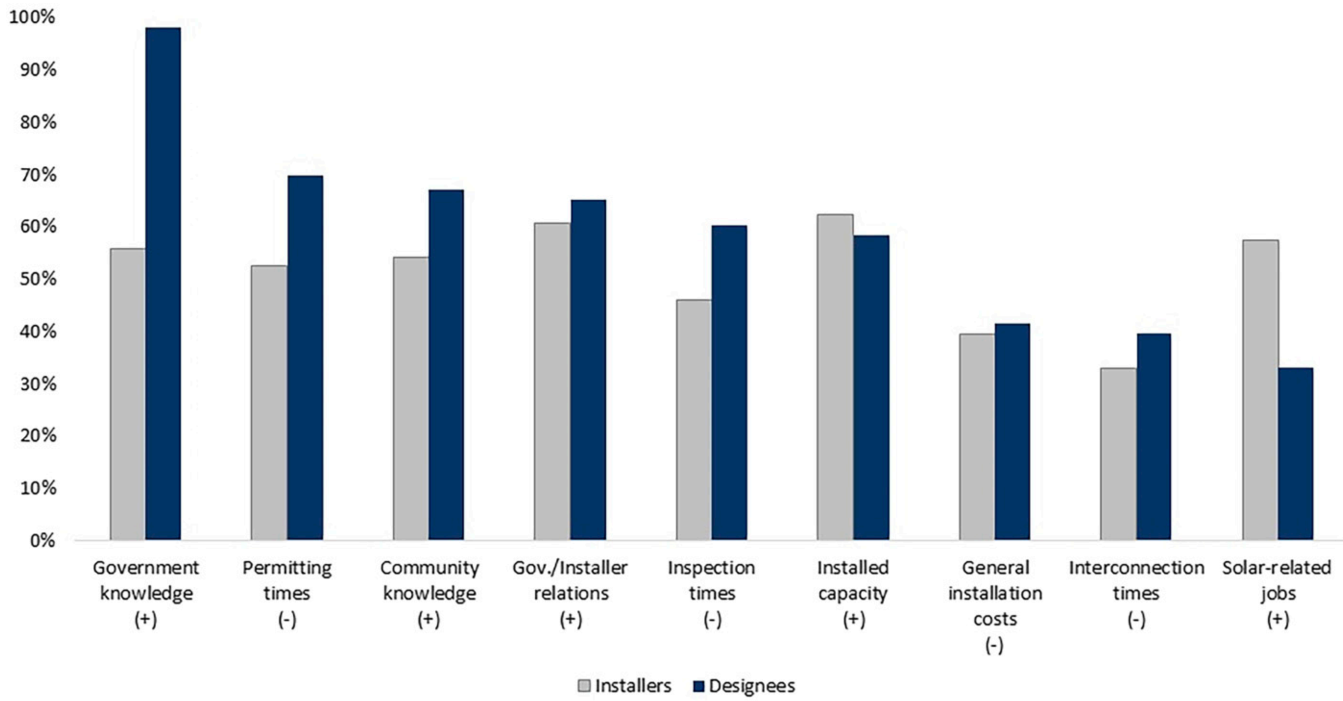

Fig. 2. Proportions of 1) solar installers (n = 117) and 2) SolSmart designees (local governments, n = 121) reporting at least moderate impact of SolSmart.

Discussion

This study combines unique program data from SolSmart with a detailed, system-level solar PV installation dataset (Berkeley Lab's TTS) and conducts PSM and DID models to estimate the impacts of the SolSmart program, a national voluntary program that encourages local governments to adopt solar-friendly practices. Our analysis shows that SolSmart is associated with an 18 to 19% increase in installed capacity (robust across multiple model variations) and a 9 to 17% increase in the number of installations (sensitive to model specifications). However, we do not find a reduction in soft costs. Designated communities and solar installers largely agreed on the perceived impacts of SolSmart, which included much more than was empirically evaluated here.

While SolSmart, as a VEP, includes a wider range of best practices than the solar programs and regulations examined in previous studies, its estimated impacts are smaller. For solar installation, one study found a 22% increase in the number of installations associated with improved permitting procedures in California (12). However, another study found no effect of streamlined solar permitting on installation rates, in part due to data limitations (8). For soft costs, we estimated small reductions of \$0.12 to \$0.16/W, which were not robust to model variation. Other studies of improving regulatory procedures found larger effects ranging from \$0.27 to \$0.77/W (11) in California and \$0.64 to \$0.93/W (7) in a national sample (albeit dominated by California). Previous studies have estimated larger effects as they compare communities with the most and least favorable processes while controlling for differences across time, location, and PV systems. The present study is unique in the construction of a matched control group to perform DID analysis.

In these results, the effect of SolSmart on installed capacity is more statistically significant than the effect on the number of installations. Additional analyses reported in *SI Appendix* suggest that the number of installations may be more sensitive to potential confounds, such as net metering policies and percentage of ground-mounted systems (49). Lower net metering rates are associated with fewer installations and, for the same level of installed capacity, communities with more ground-mounted systems tend to have fewer systems. We found a statistically significant effect of SolSmart on the number of installations in these alternative models, suggesting that the conclusions here are robust. Unfortunately, models that include these additional variables suffer from poor matching quality and reduced observations due to data availability issues, so they are not our primary models.

Ultimately, this study suggests that covering a comprehensive set of basic actions could be an effective strategy for VEPs. Our findings suggest that the effect of SolSmart on solar adoption cannot be directly attributed to reductions in soft costs from streamlined permitting processes. However, the comprehensive program structure may allow multiple pathways for the observed effects on increased solar installation. It is possible that other actions, such as community or utility engagement, may have more observable effects across locations. For example, community engagement requires local governments to provide access to information on costs and benefits, which may ultimately encourage local solar adoption through peer effects (50–52).

In addition, this study indicates that a flexible implementation may not be a barrier to the success of a voluntary program. The potential limitation of a flexible implementation is to allow local governments to get credit for actions they have already completed, which may bias estimates of the impact of voluntary programs. It is possible that the combination of required and optional actions across various categories with different degrees of difficulty makes the effect of SolSmart more robust. As reported in *SI Appendix*, Fig. S3, most communities do require technical assistance to achieve designation, suggesting that at least some of the actions are being pursued because of SolSmart. Different actions are likely to lead to different direct and indirect effects, but a combination of these actions may lead to a relatively stable program impact, as observed here for installed capacity. For example, in SolSmart, best practices to simplify and streamline permitting, inspection, and interconnection processes may facilitate customer acquisition and retention (42, 43). Actions in zoning, construction codes, and solar rights expand market potential by making more properties eligible for solar installations. The effectiveness of different actions may vary by community. Future research should investigate whether community characteristics influence the effectiveness of specific actions.

This study is subject to data availability bias, which limits the generalizability of the findings. The analysis is primarily limited by TTS data. Although TTS data represent 81% of all installed solar, there are notable gaps for Florida, Illinois, Maryland, and Texas. As a result, our conclusions may not generalize to those states or states with smaller solar markets. Smaller solar markets may also have a less measurable effect due to low overall installation. Due to the limited data availability in TTS, our analysis includes 31% (76/245) of all the city- and town-level SolSmart communities. This sample is largely representative of the population of SolSmart communities in terms of demographics, their environmental orientation, and general intent to support renewables or solar. However, the included communities tend to overrepresent Gold designees (*SI Appendix*, Table S6) and have higher median home value and education and fewer minority residents than the entire SolSmart population (*SI Appendix*, Table S7). Thus, our findings may not generalize to less wealthy communities that tend to stop at Bronze.

While our study suggests the overall effectiveness of a solar VEP, future research is needed to better understand how these impacts are realized across time and space. The SolSmart program was launched in 2016, and different communities achieved designations in and after that year. Thus, our dataset covers, at most, data for 2 y postdesignation and only 1 y or less for communities designated in or after 2017. In addition, there is a possibility that SolSmart has a spillover effect, where designation affects nearby communities either positively or negatively. For example, a positive spillover may occur when peer effects drive increased solar installations in nearby towns (i.e., a social spillover) (51). Alternatively, there may be a knowledge spillover, where knowledge sharing between installers reduces soft costs (53, 54). On the other hand, there may be a negative spillover if solar installers are specifically avoiding communities with more burdensome permitting processes (55). Based on our interviews and surveys, most installers are unaware of SolSmart designation. However, they may still perceive the impact of SolSmart designation and prefer communities that are employing best practices.

As SolSmart and similar VEPs continue to grow, we need to better understand the motivation and barriers for local governments to participate. The effectiveness of VEPs depends on both the improvements that result from participation and the number of participants in these programs (25, 26). More research is needed on SolSmart and other VEPs to better understand the mechanisms and impacts beyond the aggregate estimates presented here. From a program design perspective, there is significant interest in determining whether higher levels of designation are associated with improved outcomes. However, it is challenging to address concerns related to selection bias as the sample size decreases. Exploratory analysis suggests there is not evidence at present that higher designation levels are associated with higher impacts. Future analyses should also investigate the effect of SolSmart on permitting and interconnection time lines, cost-effectiveness of SolSmart compared with other financial incentives, and alternative analytical approaches, such as a Heckman selection model. The results to date suggest that VEPs like SolSmart are an effective strategy for encouraging local governments to take actions toward sustainability. As these programs proliferate and SolSmart evolves, it will be possible to conduct further studies comparing program designs.

Methods

Data. To conduct this analysis, we combined data from six sources. The first source is the SolSmart program data, which include the government type, designation date, designation levels awarded to each SolSmart community, specific actions taken by communities, and points earned in each SolSmart category. The SolSmart program was initiated in 2016 and includes 245 city- and town-level communities (plus an additional 40 smaller communities, such as villages, boroughs, and townships) that have achieved designations since then. To access SolSmart program data, researchers should contact SolSmart to set up a data-sharing agreement (https://solsmart.org/contact-us/).

The second source is the PV system-level TTS dataset, which includes the PV system size, system zip code, system installation date, system efficiency, rebate, performance-based incentive, and other financial incentives received by each system (10). While TTS is the most comprehensive dataset for solar installations and includes 81% of grid-connected distributed solar in the United States through 2018, it has notable gaps for several states, including Florida, Hawaii, Illinois, Iowa, Maryland, Minnesota, and Texas. Only 89 SolSmart-designated cities and towns have data in TTS for installed capacity and number of installations. After removing observations due to missing data on performance-based incentives, rebates, system sizes, and installation prices, we had 76 treated communities. The matched control communities were selected from 2,215 unique communities with available data in TTS.

The third source is monthly hardware price data from BloombergNEF. Based on the price data of the PV module, inverter, and balance of system (BOS) from BloombergNEF, we constructed the soft costs variable as the transaction price of a solar PV system minus the price of the PV module, inverter, and BOS. We used national module and inverter index data partially because the self-reported module and inverter price data from installers in TTS are very unreliable and incomplete, and this price index is the most available data used by previous literature (54, 56). More importantly, for such competitive and standardized products, as Gillingham et al. (56) stated, "both modules and inverters are globally traded commodities, and thus the trends in these costs will generally be similar across systems installed in the U.S." However, we acknowledge that module and inverter costs can vary significantly from one manufacturer or product to another. Therefore, it would be important for future studies to improve the soft costs measurement at a fine-grained level.

The fourth source is the presence of local-level voluntary commitments as a proxy for environmental orientation. We use three measures of the presence of local-level voluntary commitments as a proxy for environmental orientation and general intent to support renewable and solar development: 1) if a local government adopted a CAP before SolSmart, 2) if it had 100% renewable energy goals before SolSmart, and 3) if the local government had solar-specific goals in the CAP (44–48). CAP existence and year of adoption were obtained from the Zero Energy Project's directory of all known municipal CAPs in the United States and Canada. Sometimes referred to as "sustainability plans," CAPs detail and guide municipal efforts aimed at climate change mitigation based on local threats, preferences, and resources. Solar-specific goals in the CAPs were used to denote governments that specifically prioritized solar. All data were verified using available links to municipalities' CAPs. The directory was last updated 14 January 2020 (57). Place-level 100% renewable energy goal commitments were obtained from the Sierra Club's "Ready for 100" directory. The data indicate whether a city has made a formal commitment to being 100% powered by renewable energy sources by a specified date. All data were verified using available links citing the cities' 100% renewable energy goal commitments. The directory was last updated 10 June 2021 (58).

Finally, this analysis includes community characteristics from the US Census Bureau's 2015 American Community Survey 5-y estimates (59), as well as net metering data and residential electricity prices from DeepSolar (60). Community characteristics include total housing units occupied by owners, the percentage of minority residents, the percentage of people with an education level at or above a bachelor's degree, median home value, median household income, and median age.

Across these sources, the data are monthly and span 2013 to 2018. This covers 3 y before and 2 y after the launch of SolSmart in 2016. The panel is unbalanced, as not every community has data across all months from 2013 to 2018 and communities varied in what month they received SolSmart designation.

In addition to integrating multiple quantitative data sources, the study also included stakeholder interviews and surveys to understand the perceived impacts of the SolSmart program and provide context for our quantitative analyses. This study received exempt approval from the Missouri University of Science & Technology Institutional Review Board, and all participants provided informed consent. We conducted 36 interviews with local governments and solar installers. We successfully recruited 212 government officials after emailing 3,183 contacts collected by The Solar Foundation (response rate of

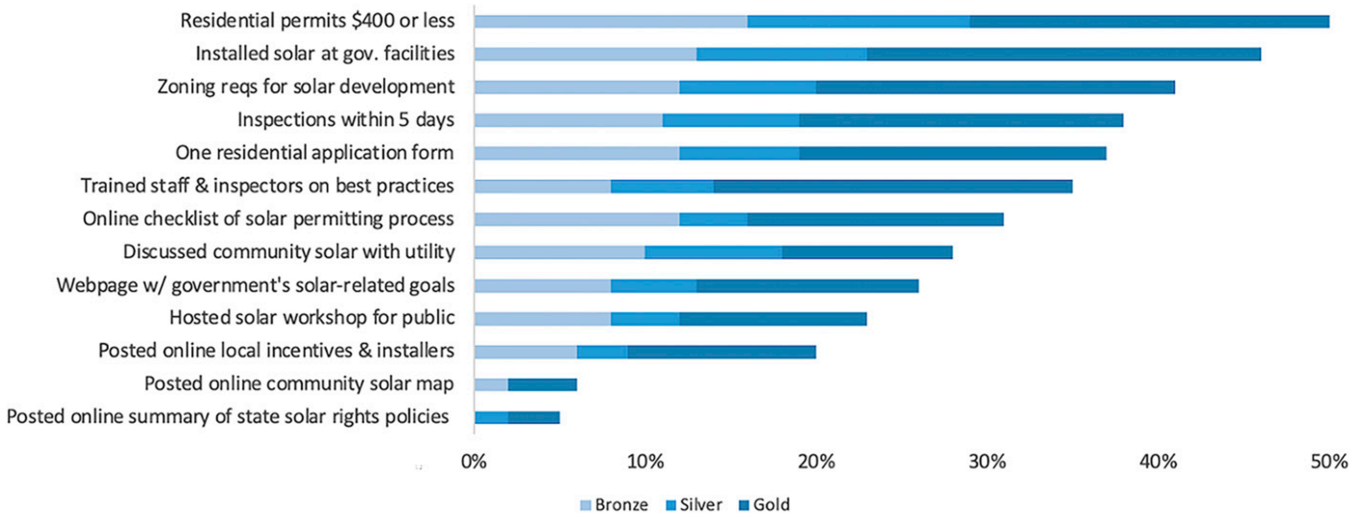

Fig. 3. The percentage of communities completing actions before SolSmart by designation level (n = 121).

7%). The participants included 50 Gold designees, 31 Silver designees, 40 Bronze designees, and 91 nondesignees. The designated survey sample represented 104 unique jurisdictions, which is 36% of all SolSmart designees. The survey sample roughly approximated the ratios between Gold (41% sample vs. 38% population), Silver (26 vs. 23%), and Bronze (33 vs. 38%) designees, although Gold and Silver designees were slightly more represented. Illinois, Minnesota, California, Florida, and Colorado have the most SolSmart designees (45% of all SolSmart designees). In the survey results, respondents from these states represent 39% of all respondents. There was lower representation from California communities in the survey responses (2% of survey responses vs. 9% of SolSmart designees) and higher representation from Florida (12 vs. 8%). We also recruited 117 solar installers after emailing 2,181 contacts collected via web scraping (response rate of 5%). The installers were located in 27 different states and 66 different jurisdictions. The reported response rate is a conservative estimate and assumes that all emails were active. For both government officials and installers, all recruitment was administered and branded by the Missouri University of Science & Technology to ensure that participants knew that the survey information was collected by a third party.

Econometric Model. The SolSmart program aims to lower local regulatory barriers, reduce soft costs in solar PV installation, and foster the development of local solar markets by requiring designees to perform specific actions across eight categories.* Communities qualify for a SolSmart designation of Bronze, Silver, or Gold by meeting progressively higher thresholds of action criteria. Each action under the eight categories is directly or indirectly related to reducing soft costs and boosting local solar adoption (a more detailed description of SolSmart requirements can be found in *SI Appendix*). This study used a combination of PSM and DID (61–63) approaches to identify the impact of the SolSmart program on multiple outcome variables. The SolSmart program can be viewed as an intervention in which the treatment is assigned to SolSmart-designated communities, where treatment refers to the adoption of solar-friendly actions. With SolSmart communities as treated units and non-SolSmart communities as control units, we compare outcome variables before and after designation. However, since SolSmart designations were not assigned randomly, endogeneity issues due to self-selection need to be addressed. For example, more solar-friendly communities are more likely to participate in the SolSmart program. Therefore, we constructed a matched control group of non-SolSmart communities using PSM. The control group aims to capture what outcomes would have been if the treatment had not been implemented for the treatment group (i.e., the counterfactual). Therefore, we assume that any difference in outcomes between the treatment and control groups before and after the treatment can be plausibly attributed to the treatment (i.e., SolSmart program).

The PSM approach identifies a control group of non-SolSmart communities that are most similar to SolSmart communities. The matching is based on seven demographic (total housing units occupied by owners, percentage of minorities, percentage of people who have a bachelor's degree or higher, median home value, median household income, total population, and median age), six solar PV market (residential electricity price, performance-based incentives, net metering, rebate, average system size, and number of installers), and two of three environmental (CAP and renewable or solar goal) attributes. Including environmental attributes helps to reduce potential selection bias from environmental orientation and interest in renewables or solar. In addition, there may be selection bias associated with performing actions before SolSmart. Survey results suggest that SolSmart communities have tended to engage in ∼30% of the most common SolSmart actions before obtaining SolSmart designation, which is twice the rate of nondesignees (Fig. 3). In other words, communities that have already completed SolSmart actions may be more motivated to pursue the designation. We assume that this is correlated with interest in renewables or solar, and it is addressed by including variables that capture a community's environmental and solar orientation in the PSM and DID models. The need for technical assistance suggests that not all actions are completed before SolSmart, even for motivated communities (*SI Appendix*, Fig. S3).

Based on these matching covariates, we used logistic regression to estimate the propensity score and check the overlap between the treated group and the potential control group. The logistic regressions impose a linear relationship between the propensity to be treated and characteristics (i.e., independent variables) we included in the model. We used logistic regression to calculate the propensity score and used one-to-one nearest neighbor matching to select the most similar matched control unit. The control group was sampled without replacement, meaning that the same control community was only used as a match for one treated community.

To test the quality of matching, we conducted t tests for these 15 matching covariates between the treatment and control groups after matching to test whether the preexisting differences between treatment and control groups would become statistically insignificant (*SI Appendix*, Tables S1 and S2). As the data are only available for 76 treated communities, we also conducted a t test among communities that are included in our analysis and all the SolSmart communities to examine the representativeness of the included communities and to discuss the potential bias of our results (*SI Appendix*, Table S7). We also present the distribution of propensity scores before and after matching (*SI Appendix*, Figs. S1 and S2) and the list of all the matching pairs in *SI Appendix* (*SI Appendix*, Tables S3 and S4).

Based on the treatment group and its matched control group, we use DID models to estimate the effect of SolSmart designation on multiple outcome variables. The DID model allows us to estimate this effect by comparing the changes in the outcome variables before and after designations between the SolSmart communities and the matched control group of non-SolSmart communities. Thus, we estimate the average treatment effect on the treated. There is at least a 1- to 2-mo lag between when actions are enacted and when the designation is achieved, leading to a fuzzy boundary for the DID model. Local communities begin implementing actions before the designation, which may lead to underestimation of the impact of SolSmart. The equations to estimate the effect of SolSmart designation are below:

*The eight categories include permitting; planning, zoning, and development regulations; inspection; construction codes; solar rights; utility engagement; community engagement; and market development and finance.

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SUSTAINABILITY SCIENCE

$$\ln\,(outcome_{it}) = \beta_0 + \beta_1 \times After_t + \beta_2 \times SolSmart_i + \beta_3 \times After_t \times SolSmart_i + X_{it} + \alpha_i + \gamma_t + \eta_y + \omega_m + \varepsilon_{it} \quad (1)$$

$$outcome_{it} = \beta_0 + \beta_1 \times After_t + \beta_2 \times SolSmart_i + \beta_3 \times After_t \times SolSmart_i + X_{it} + \alpha_i + \gamma_t + \eta_y + \omega_m + \varepsilon_{it}. \quad (2)$$

Each observation in this analysis is for a single community in a single month. We run separate DID models for three outcome variables in the model, namely installed capacity (kilowatts), the number of installations (count), and soft costs (dollars per watt) in each community in each month. If ln($outcome_{it}$) is used in the model (Eq. **1**), the effect of SolSmart designation measures the difference in the change of growth rate of outcome variables before and after designation between the treatment group and the control group. If $outcome_{it}$ is used in the model (Eq. **2**), the effect of SolSmart designation measures the change of the absolute value of outcome variables before and after designation between the treatment group and the control group. Eq. **1** takes into account the baseline value of outcome variables and is a more objective and commonly used measurement in DID models, but the results of Eq. **2** are more straightforward for interpretation as it measures the change in absolute value of outcome variables, such as kilowatt per month change of installed capacity and dollars per watt reduction of soft costs.

The effect of SolSmart designation is captured by β_3, which is the coefficient of the interaction term between the time variable ($After_t$) and treatment variable ($SolSmart_i$). $After_t$ is a dummy variable, the value of which is one if t is after the community has received the SolSmart designation and zero if t is before the designation. $SolSmart_i$ is also a dummy variable that captures the SolSmart status. The value of $SolSmart_i$ is one if the community i is a SolSmart-designated community (treatment group) and zero if i is not a SolSmart-designated community (control group). Therefore, the interaction term between $After_t$ and $SolSmart_i$ captures the differences of the changes in the outcome variables before and after designations between the SolSmart communities and the matched control group of non-SolSmart communities.

We include community, year, and month fixed effects to control for the time-invariant unobservable variables at the community level and the time trend. As there is an overall trend toward increased installation and lower soft costs, we also included a linear time trend in the model. Furthermore, we include several control variables (X_{it}) in the models, including the number of installers, climate plan, renewable or solar goal, average efficiency of systems, total number of installations, annual performance-based incentives payment, rebate payment, median household income, and occupied housing units (reported in full in *SI Appendix*, Tables S8 and S9).

Data Availability. Previously published data were used for this work. The following datasets are available online: Tracking the Sun, Cities with Climate Action Plans, Ready for 100, American Community Survey, DeepSolar Database (10, 57–60). SolSmart Program data are available on request.

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1. F. Creutzig *et al*., The underestimated potential of solar energy to mitigate climate change. *Nat. Energy* **2**, 17140 (2017).
2. S. Pacala, R. Socolow, Stabilization wedges: Solving the climate problem for the next 50 years with current technologies. *Science* **80**, 968–972 (2004).
3. L. Strupeit, Streamlining photovoltaic deployment: The role of local governments in reducing soft costs. *Energy Procedia* **88**, 450–454 (2016).
4. X. Gao, V. Rai, Local demand-pull policy and energy innovation: Evidence from the solar photovoltaic market in China. *Energy Policy* **128**, 364–376 (2019).
5. C. L. Crago, I. Chernyakhovskiy, Are policy incentives for solar power effective? Evidence from residential installations in the Northeast. *J. Environ. Econ. Manage.* **81**, 132–151 (2017).
6. S. Carley, L. L. Davies, D. B. Spence, N. Zirogiannis, Empirical evaluation of the stringency and design of renewable portfolio standards. *Nat. Energy* **3**, 754–763 (2018).
7. J. Burkhardt, R. Wiser, N. Darghouth, C. G. Dong, J. Huneycutt, Exploring the impact of permitting and local regulatory processes on residential solar prices in the United States. *Energy Policy* **78**, 102–112 (2015).
8. L. V. White, Increasing residential solar installations in California: Have local permitting processes historically driven differences between cities? *Energy Policy* **124**, 46–53 (2019).
9. X.-P. Lei *et al*., Technological collaboration patterns in solar cell industry based on patent inventors and assignees analysis. *Scientometrics* **96**, 427–441 (2013).
10. G. Barbose *et al*., *Tracking the Sun: Pricing and Design Trends for Distributed Photovoltaic Systems in the United States 2019 Edition* (Lawrence Berkeley National Laboratory, Berkeley, CA, 2019).
11. C. Dong, R. Wiser, The impact of city-level permitting processes on residential photovoltaic installation prices and development times: An empirical analysis of solar systems in California cities. *Energy Policy* **63**, 531–542 (2013).
12. J. H. Y. Hsu, Predictors for adoption of local solar approval processes and impact on residential solar installations in California cities. *Energy Policy* **117**, 463–472 (2018).
13. M. Taylor, "Understanding streamlined solar permitting practices: A primer" (Rep., Lawrence Berkeley National Laboratory, Berkeley, CA, 2019; https://doi.org/10.20357/B70K5Q).
14. H. Yi, "Policy choice for local sustainability: Predicting the ICLEI membership in the U.S. cities" in *Proceedings of the Midwest Political Science Association* (MPSA, Bloomington, IN, 2010).
15. M. Mullin, *Governing the Tap: Special District Governance and the New Local Politics of Water* (The MIT Press, 2009).
16. L. O. Næss, G. Bang, S. Eriksen, J. Vevatne, Institutional adaptation to climate change: Flood responses at the municipal level in Norway. *Glob. Environ. Change* **15**, 125–138 (2005).
17. R. Kube, K. von Graevenitz, A. Löschel, P. Massier, Do voluntary environmental programs reduce emissions? EMAS in the German manufacturing sector. *Energy Econ.* **84**, 104558 (2019).
18. D. Li, F. Tang, L. Zhang, Differential effects of voluntary environmental programs and mandatory regulations on corporate green innovation. *Nat. Hazards* **103**, 3437–3456 (2020).
19. S. Lim, A. Prakash, Voluntary regulations and innovation: The case of ISO 14001. *Public Adm. Rev.* **74**, 233–244 (2014).
20. T. H. Arimura, A. Hibiki, H. Katayama, Is a voluntary approach an effective environmental policy instrument? A case for environmental management systems. *J. Environ. Econ. Manage.* **55**, 281–295 (2008).
21. W. Antweiler, K. Harrison, Canada's Voluntary ARET Program: Limited success despite industry cosponsorship. *J. Policy Anal. Manage.* **26**, 755–773 (2007).
22. J. C. Borck, C. Coglianese, Voluntary environmental programs: Assessing their effectiveness. *Annu. Rev. Environ. Resour.* **34**, 305–324 (2009).
23. A. Prakash, M. Potoski, *The Voluntary Environmentalists: Green Clubs, ISO 14001, and Voluntary Environmental Regulations* (Cambridge University Press, 2006).
24. S. Hughes, Voluntary environmental programs in the public sector: Evaluating an urban water conservation program in California. *Policy Stud. J.* **40**, 650–673 (2012).
25. J. A. Carmin, N. Darnall, J. Mil-Homens, Stakeholder involvement in the design of U.S. voluntary environmental programs: Does sponsorship matter? *Policy Stud. J.* **31**, 527–543 (2003).
26. D. A. Koehler, The effectiveness of voluntary environmental programs—a policy at a crossroads? *Policy Stud. J.* **35**, 689–722 (2007).
27. T. P. Lyon, J. W. Maxwell, Environmental public voluntary programs reconsidered. *Policy Stud. J.* **35**, 723–750 (2007).
28. A. Prakash, M. Potoski, Low-performing schools attract and keep academically talented teachers? Evidence. *J. Policy Anal. Manage.* **31**, 123–138 (2012).
29. L. Elgert, The double edge of cutting edge: Explaining adoption and nonadoption of the STAR rating system and insights for sustainability indicators. *Ecol. Indic.* **67**, 556–564 (2016).
30. L. Elgert, Rating the sustainable city: 'Measurementality', transparency, and unexpected outcomes at the knowledge-policy interface. *Environ. Sci. Policy* **79**, 16–24 (2018).
31. M. E. Flowers, D. C. Matisoff, D. S. Noonan, For what it's worth: Evaluating revealed preferences for green certification. *J. Environ. Plann. Manage.* **62**, 843–861 (2019).
32. SolSmart, "SolSmart guide" (Rep., Washington, DC, 2019).
33. E. J. Altman, F. Nagle, M. Tushman, "Innovating without information constraints: Organizations, communities, and innovation when information costs approach zero" in *The Oxford Handbook of Creativity, Innovation, and Entrepreneurship*, C. Shalley, M. A. Hitt, J. Zhou, Eds. (Oxford University Press, 2015), pp. 353–379.
34. E. R. Frederiks, K. Stenner, E. V. Hobman, Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *Renew. Sustain. Energy Rev.* **41**, 1385–1394 (2015).
35. P. Sheeran, Intention-behavior relations: A conceptual and empirical review. *Eur. Rev. Soc. Psychol.* **12**, 1–36 (2002).
36. J. L. Freedman, S. C. Fraser, Compliance without pressure: The foot-in-the-door technique. *J. Pers. Soc. Psychol.* **4**, 195–202 (1966).
37. J. P. Dillard, J. E. Hunter, M. Burgoon, Sequential-request persuasive strategies: Meta-analysis of foot-in-the-door and door-in-the-face. *Hum. Commun. Res.* **10**, 461–488 (1984).
38. J. M. Weyant, Application of compliance techniques to direct-mail requests for charitable donations. *Psychol. Mark.* **13**, 157–170 (1996).

39. J. M. Burger, The foot-in-the-door compliance procedure: A multiple-process analysis and review. *Pers. Soc. Psychol. Rev.* **3**, 303–325 (1999).
40. D. J. Bem, Self-perception theory. *Adv. Exp. Soc. Psychol.* **6**, 1–62 (1972).
41. M. Taylor *et al.*, "Explaining jurisdictional compliance with California ' s top-down streamlined solar permitting law (AB 2188)" (Rep., Lawrence Berkeley National Laboratory, Berkeley, CA, 2019; https://doi.org/10.20357/B74880).
42. M. J. J. Handgraaf, M. A. Van Lidth de Jeude, K. C. Appelt, Public praise vs. private pay: Effects of rewards on energy conservation in the workplace. *Ecol. Econ.* **86**, 86–92 (2013).
43. G. C. Homsy, M. E. Warner, Cities and sustainability: Polycentric action and multilevel governance. *Urban Aff. Rev.* **51**, 46–73 (2015).
44. R. M. Krause, An assessment of the impact that participation in local climate networks has on cities' implementation of climate, energy, and transportation policies. *Rev. Policy Res.* **29**, 585–604 (2012).
45. H. Yi, R. M. Krause, R. C. Feiock, Back-pedaling or continuing quietly? Assessing the impact of ICLEI membership termination on cities' sustainability actions. *Env. Polit.* **26**, 138–160 (2017).
46. M. R. Boswell, A. I. Greve, T. L. Seale, An assessment of the link between greenhouse gas emissions inventories and climate action plans. *J. Am. Plann. Assoc.* **76**, 451–462 (2010).
47. E. Bassett, V. Shandas, Innovation and climate action planning: Perspectives from municipal plans. *J. Am. Plann. Assoc.* **76**, 435–450 (2010).
48. D. J. Hess, H. Gentry, 100% renewable energy policies in U.S. cities: Strategies, recommendations, and implementation challenges. *Sustain. Sci. Pract. Policy* **15**, 45–61 (2019).
49. M. A. Brown, J. Hubbs, V. X. Gu, M. K. Cha, Rooftop solar for all: Closing the gap between the technically possible and the achievable. *Energy Res. Soc. Sci.* **80**, 102203 (2021).
50. K. S. Wolske, P. C. Stern, T. Dietz, Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories. *Energy Res. Soc. Sci.* **25**, 134–151 (2017).
51. B. Bollinger, K. Gillingham, Peer effects in the diffusion of solar photovoltaic panels. *Mark. Sci.* **31**, 900–912 (2012).
52. D. Noll, C. Dawes, V. Rai, Solar community organizations and active peer effects in the adoption of residential PV. *Energy Policy* **67**, 330–343 (2014).
53. T. Matsuo, Fostering grid-connected solar energy in emerging markets: The role of learning spillovers. *Energy Res. Soc. Sci.* **57**, 101227 (2019).
54. G. F. Nemet, J. Lu, V. Rai, R. Rao, Knowledge spillovers between PV installers can reduce the cost of installing solar PV. *Energy Policy* **144**, 111600 (2020).
55. X. Gao, The comparative impact of solar policies on entrepreneurship in the U.S. solar photovoltaic installation industry. *Energy Policy* **156**, 112389 (2021).
56. K. Gillingham *et al.*, Deconstructing solar photovoltaic pricing. *Energy J. (Camb. Mass.)* **37**, 231–250 (2016).
57. Zero Energy Project, Cities with Climate Action Plans (2021). https://zeroenergyproject.org/climate-action-plans/. Accessed 14 September 2021.
58. Sierra Club, Ready for 100 (2021). https://www.sierraclub.org/ready-for-100. Accessed 14 September 2021.
59. US Census Bureau, American Community Survey (2015). https://www.census.gov/programs-surveys/acs. Accessed 30 December 2020.
60. Y. Jiafan, W. Zhecheng, A. Majumdar, R. Rajagopal, DeepSolar Database (2018). Accessed 30 December 2020.
61. P. J. Gertler, S. Martinez, P. Premand, L. B. Rawlings, C. M. J. Vermeersch, *Impact Evaluation in Practice, Second Edition* (The World Bank, 2016). https://openknowledge.worldbank.org/bitstream/handle/10986/25030/9781464807794.pdf?sequence=2&isAllowed=y. Accessed 13 February 2022.
62. E. A. Stuart *et al.*, Using propensity scores in difference-in-differences models to estimate the effects of a policy change. *Health Serv. Outcomes Res. Methodol.* **14**, 166–182 (2014).
63. G. W. Imbens, J. M. Wooldridge, Recent developments in the econometrics of program evaluation. *J. Econ. Lit.* **47**, 5–86 (2009).