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Effective information channels for reducing costs of environmentally-friendly technologies: evidence from residential PV markets

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Abstract
Realizing the environmental benefits of solar photovoltaics (PV) will require reducing costs associated with perception, informational gaps and technological uncertainties. To identify opportunities to decrease costs associated with residential PV adoption, in this letter we use multivariate regression models to analyze a unique, household-level dataset of PV adopters in Texas (USA) to systematically quantify the effect of different information channels on aspiring PV adopters' decision-making. We find that the length of the decision period depends on the business model, such as whether the system was bought or leased, and on special opportunities to learn, such as the influence of other PV owners in the neighborhood. This influence accrues passively through merely witnessing PV systems in the neighborhood, increasing confidence and motivation, as well as actively through peer-to-peer communications. Using these insights we propose a new framework to provide public information on PV that could drastically reduce barriers to PV adoption, thereby accelerating its market penetration and environmental benefits. This framework could also serve as a model for other distributed generation technologies.

Keywords: residential solar PV, diffusion of innovations, peer effects, consumer decision-making, distributed generation

S Online supplementary data available from stacks.iop.org/ERL/8/014044/mmedia

1. Introduction

The high costs of solar photovoltaic (PV) systems to consumers currently restrict the market and thus limit the potential emissions reductions benefits attributed to the technology—it is only at higher levels of penetration that PV begins to offset large amounts of coal-fired generation capacity, significantly reducing CO_2, criteria pollutant, and heavy metals emissions [1, 2]. While market analysis suggests that PV could be cost competitive if market externalities such as the environmental degradation and CO_2 emissions from conventional power generation are internalized [3], the current increase in residential sector PV adoption [4, 5] can be largely attributed to an attractive combination of financial incentives [4, 6, 7]. Despite recent trends, current adoption levels in the residential sector are below 2% of the market potential [8]. Several incentive programs are nearly a decade old, and best-practices for incentive programs are still unclear [9, 10]. Moreover, some of the largest incentives programs such as those in California are ending, while most others are scaling down, further underscoring the need for solar programs to become financially more efficient [11].

It has been suggested that PV diffusion is a function of system cost, and the cost of information to consumers [12–15]. Consumers must gather large amounts of information and make comparisons to alternative investment options before making a decision [16]. The information cost to consumers of PV is higher due to the capital intensive nature of the technology [17]. The *total cost* of PV to consumers takes into account the monetary cost of the technology, as well as *uncertainties and non-monetary costs* (UNMCs), such as information search costs and uncertainty about the future performance, operations and maintenance requirements, and perceptions of quality, sacrifice, and opportunity cost [18, 19].

People who are interested in a new technology may seek to reduce uncertainties by taking advantage of information from existing owners [7, 16]. As more people become adopters the observed performance of the technology spreads, further reducing uncertainties. Some recent studies have tried to systematically quantify the impact of previous adopter actions on non-adopter attitudes and behaviors in vehicle purchases [20–22] and in PV adoption in California [13].

While the financial barrier to PV diffusion has been well documented in the literature [4, 15, 23–25], the role of information networks and peer effects in overcoming non-financial barriers to PV adoption remains understudied [13, 14, 26]. As such, existing research has struggled to generate actionable policy and marketing insights. In this letter we use a new dataset built from a survey of PV owners in Texas to study the structure of information networks associated with the adoption of PV. We characterize the information networks that potential adopters employ to mitigate UNMCs of PV adoption. We identify those factors that are most effective from the consumer viewpoint in reducing UNMCs, and hence the length of the decision period, thereby leading to faster adoption of PV. We present a multivariate regression model describing PV adopters' reported *decision period*—the length of time (months) between the beginning of serious consideration of PV and the final decision (signing of contract) to install PV—as a function of information-related variables. Policy and marketing strategies that will reduce the impacts of UNMCs on potential adopters, thereby accelerating the rate of PV adoption, are inferred from this research.

2. Methods

Our analysis uses a new household-level dataset we have built through a survey of residents who have already adopted PV. The survey sought to measure the current PV owners' experience selecting and installing a solar PV system. A summary of the overall findings from the survey can be found elsewhere [26].

The survey was administered electronically (online) in Texas during August–November 2011. The total number of complete responses received was 365, or about 40% of the 922 PV owners contacted. In addition to complete responses, there were another 41 partial responses. The PV systems of these respondents were installed between 1999 and 2011, with a vast majority between 2008 and 2011. Most respondents were located in the Austin and Dallas–Fort Worth regions, with smaller numbers of respondents located in and around Houston, Temple, Waco, and Tyler/Longview. We estimate from solar program data that our sample of received complete responses (365) represents about 20% of the entire target population (residential PV adopters) as of July 2011 in the areas where we conducted the survey.

The length of time (in months) between the beginning of serious consideration of PV and the final decision (signing of contract) to install PV—the decision period (DP)—was modeled using ordinary least squares (OLS) multiple regression, and tested for robustness using best subsets procedures [27]. Additional models for peer effects and contact with other owners were developed in support of the main DP model. The survey data contains a mixture of continuous and categorical (ordinal) data. Categorical data is largely 5-grade Likert scale-based with multiple variables having potential cardinal uncertainty (variable magnitude between successive points). For this reason, either the categorical variables were coded as binary values during modeling, or individual Likert items measuring the same attitude were combined (i.e., 'summed by section') where appropriate to enhance the continuity of the variable, allowing for more robust parametric analysis [28].

Summed items in the Likert scale create a measure of attitudes, and must satisfy consistency and comparability criteria between items [29]. There are problems applying parametric statistics to single Likert items [30]. Significance between Likert-items was tested using Chi-square tests, or Kruskal–Wallis ANOVA. Where parametric statistics were used, the data satisfied the necessary assumptions of cardinality.

3. Descriptive statistics and hypotheses

In this section we present some descriptive statistics on PV adopters' information search process. Using insights from these descriptive statistics and prior literature we also form hypotheses that we test in section 4 using econometric modeling.

3.1. Uncertainty, non-monetary costs, and decision time

The distribution of survey responses to a Likert item regarding adopters' experiences finding dependable PV information is skewed toward the 'very easy' pole (mean 2.52, median 2, skewness 0.31, std. deviation 0.95). At the end of the DP most respondents seem to have developed confidence in the technical as well as financial attributes of PV. When asked if they understood what to expect regarding the performance of PV systems after completion of the decision period, the average response was between 'agree' and 'strongly agree' (Likert item mean 1.77, median 2, skewness 1.35, std. deviation 0.75). In other words, potential adoptors are able to access sources of information.

Descriptive statistics suggest that while information is abundant, potential adopters seem to have a difficult time in distilling that information into a coherent picture of how residential PV will affect them. The distribution of survey responses reflecting time spent researching PV was skewed toward the 'very large' pole (mean 3.38, median 3, skewness −0.11, std. deviation 0.96), which translates into a lengthy DP, 8.9 months on average (median 6, std. deviation 11.6, skewness 4.35). Analysis of an open-ended question regarding the information-search experience adds further confirmation. When asked how information could be more valuable during the process, by far the most often expressed theme (30%) was the desire for a 'centralized', independent information source hosted by government or electric utilities. Of these, over half (51%) specifically mentioned the need for this source to be available online.

In agreement with prior research in other areas of behavior change [31], these insights suggest that any given level of information certainty (about PV) desired by a potential adopter can be achieved faster when information from more trustworthy sources is accessible. If trustworthy information is not found, significant uncertainty may remain even after a lengthy DP (this may be termed as the 'residual uncertainty').

Adopters are diverse in their information needs. While access to information no doubt plays a large role in creating the wide range of DP (maximum reported DP was 119 months and minimum was 1 month), some categories of adopters are likely more tolerant of risk than others, lowering their need for information certainty about PV. Because respondents spent the greatest portions of the decision period researching financial (mean 3.82, median 4, skewness −0.56, std. deviation 0.95) and system performance aspects of PV (mean 3.57, median 4, skewness −0.40, std. deviation 1.05), which are closely related, we use financial variables to test the following hypothesis.

Hypothesis 1. PV owners who need greater information certainty have longer DP.

3.2. Peer effects in the adoption of residential PV

Peer influence is known to play an important role in the process of diffusion of innovations and in consumer decision-making [13, 16, 20, 32, 33]. Because potential adopters cannot try out a PV system before purchase, to inform their own decisions potential adopters must look to the experiences of others with the technology [16, 34]. As a result, we can expect that reduced UNMCs owing to increased peer effects should be manifested as a shorter DP. As the number of PV owners rises, increasing the potential for exchanges between existing PV owners and potential adopters, peer effects should become increasingly observable in the decision process of PV adopters. Accordingly, we hypothesize:

Hypothesis 2a. PV owners who experience greater passive peer effects have shorter DP.

Hypothesis 2b. PV owners with more systems in their neighborhood experience greater passive peer effects (and, thus, have shorter DP).

In this letter, we define peer effects as the influence of PV systems *in the neighborhood* on the final decision of a potential adopter to install PV. A house's neighborhood is defined as the area within a five to ten block radius. We further distinguish between two components of peer effects: *passive* peer effects and *active* peer effects. Passive peer effects refer solely to the attitudinal and behavioral stimulus that *seeing* PV systems in the neighborhood induces. It excludes the effect of contact with other PV owners, which, as discussed later, is captured separately as active peer effects. The total peer effects, then, is the sum of these two components. For simplicity we refer to the total peer effects as just peer effects. This choice of definition was driven by our intention to independently quantify the impact of these two factors.

We measure peer effects at two different locations in the survey instrument. First we ask respondents about the level of importance of PV systems in the neighborhood in their final decision to install PV. Second, we revisit the peer effects topic through a series of three 5-grade Likert scale-based statements: 'PV systems in the neighborhood motivated me to seriously consider installing one', 'Seeing other PV systems in my neighborhood gave me the confidence that it would be a good decision to install one', and 'Without the PV systems in my neighborhood, I would not have installed a PV system'.

The localized nature of these effects and the early stage of PV diffusion in Texas present a unique opportunity to study peer effects. While 72% of respondents reported being the first in their neighborhood to install PV, the remainder of respondents reported experiencing moderate to very strong levels of peer effects. For example, most of the PV adoption in Texas has been sparse from 2004 to 2008, so as expected, we find only weak evidence of the influence of peer effects during this period. But there are pockets where we do find moderate to very strong peer effects since 2009. As an illustration, figure 1(a) shows the influence of passive peer effects in the Austin area excluding data from certain pockets (zip codes) that have some of the densest level of PV installations; figure 1(b) shows the same measure when these pockets are included in the sample. Overall, there is substantial variation in our dataset in the level of peer effects experienced by (potential) PV adopters, a key explanatory variable in our model for the length of the decision period (see section 4). This variation improves the confidence of our hypotheses test results.

3.3. Contact

The next level of information gathering by adopters to reduce uncertainty during the decision-making period involves direct contact (discussion) with existing PV owners. Direct contact provides a tangible economic benefit—the opportunity to seek information that is directly relevant to the decision maker, thus reducing the risk associated with the investment [35].

Among the respondents 90.5% agreed or strongly agreed with the statement, 'Talking to owners of PV systems was

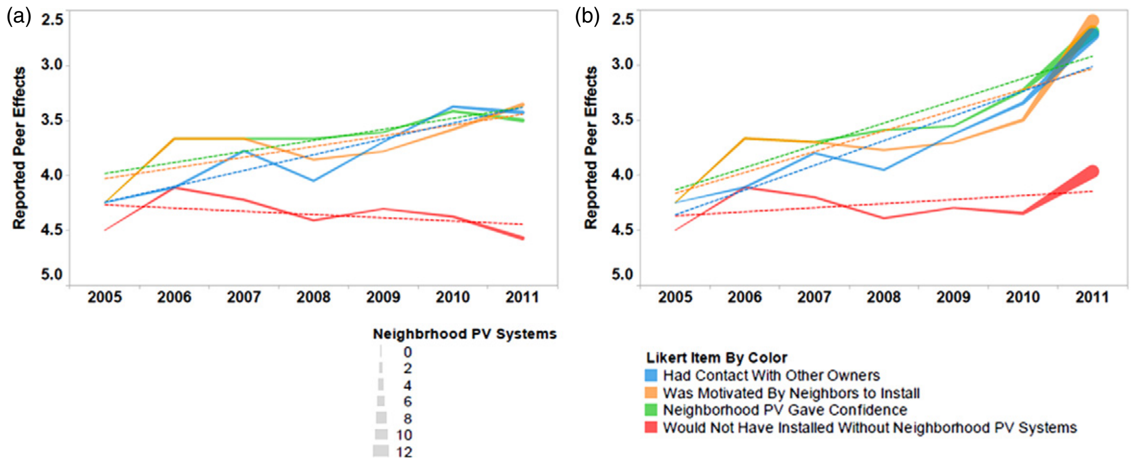

Figure 1. (a) The graph to the left shows the average responses and trends for four Likert items regarding peer effects from 2005 to 2011 Among respondents in the Austin area. Earlier years were discarded due to sample size. Width of the line represents number of systems in the neighborhood. The graph excludes members of PV dense communities. (b) The graph to the right shows all Austin responders, including those from PV dense communities, demonstrating the increase in peer effects that comes with greater numbers of PV systems in the neighborhood.

useful or would have been useful'. From a potential adopter's viewpoint existing PV owners represent a valuable source of trustworthy information, and their collective experiences form a stock of knowledge from which potential adopters can learn, thereby reducing UNMCs.

Of respondents who contacted other owners (31% of all respondents), 57% agreed or strongly agreed that, 'My discussions with PV owners *profoundly improved* the quality of information' (Likert item mean 2.42, median 2.00, skewness −0.24, std. deviation 0.93). Further, we find that potential adopters who had a difficult time finding dependable information are more likely to disagree with the statement, 'Talking to other PV owners is unnecessary' ($\chi^2 p < 0.001$). These same adopters were more likely to say that they would have liked to talk to other PV owners, but could not find any ($\chi^2 p < 0.02$). Potential adopters in need of information would like to access the stock of knowledge formed by existing owners.

We classify contacts based on whether those contacts were with PV owners in the neighborhood or outside the neighborhood. We divide the sample into four groups: those who had no contact with other PV owners before installation, but were aware of other PV systems in their neighborhood (NCN); those who had contact only outside the neighborhood (HCO); those that had at least one contact within the neighborhood (HCN); and, those who neither had any contact with any other PV owner nor were aware of any PV systems in the neighborhood (NN). Passive peer effects were significantly different among these groups (Kruskal–Wallis ANOVA $p < 0.001$). Passive peer effects seem to be the strongest for the HCN group. This suggests that there is a dual benefit for this group: not only are members of this group influenced by passive peer effects, but they also gain valuable information when they reach out to other PV owners in the neighborhood, a benefit we refer to as active peer effects. Accordingly, we hypothesize:

Hypothesis 3. PV owners who had direct contact with other PV owners in the neighborhood (the HCN group) will have the shortest DP compared to all other groups.

3.4. Buying versus leasing

While need exists among potential adopters for the quality of information provided by direct contact with other owners, this need, and thus the utility such contact provides, is not uniform across the spectrum. Given that operation and maintenance (O&M) of the equipment is covered under the lease agreements [36], leasers of PV systems should have reduced uncertainty regarding performance and guarantee of the PV system [37, 38]. In our survey, on average, compared to buyers of PV systems leasers report spending less time researching ($\chi^2 p < 0.01$), and report easier availability of dependable information ($\chi^2 p < 0.05$). Consistent with this, among leasers 87% agree or strongly agree that talking to other PV owners is unnecessary. Together this suggests that leasers do indeed face lower UNMCs than buyers, which should lead to a shorter decision period. Accordingly, we hypothesize:

Hypothesis 4. Leasers of PV systems have shorter DP than buyers.

4. Results: econometric modeling

4.1. Modeling the decision period

While descriptive statistics provide much insight, a full understanding of the factors influencing decision times (and hence, adoption rates) necessitates multivariate analysis to control for different factors that might affect DP. Based on Hypotheses 1–4, variables for need for information certainty (InvestVIEI), passive peer effects (PeerEfSum), neighborhood

Table 1. Partial results and sensitivity testing for the DP model in equation (1), with several controls discussed in the text. Full results available in the supporting information (available at stacks.iop.org/ERL/8/014044/mmedia). Coefficients and P values are reported where applicable. All variance inflation factors are <2 for all non-squared terms. (Note: table lists parameter estimates, standard errors in parentheses. $n = 332$.)

Results of regression analysis for DP						
	Model 1	Model 1a High income	Model 1b Full peer effects	Model 1c Contact type	Model 1d Contact type full peer effects	Model 1e PVDense
R^2	0.26	0.25	0.21	0.26	0.22	0.26
Adj R^2	0.24	0.23	0.2	0.24	0.2	0.23
P	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Variable						
Cons_Mo	DV	DV	DV	DV	DV	DV
InvestVIEI	2.70[a] (1.00)		3.01[a] (1.03)	2.64[a] (1.00)	2.29[a] (1.03)	2.73[a] (1.00)
PeerEfSum	1.46[a] (0.55)	1.57[a] (0.55)		1.38[b] (0.57)		1.42[a] (0.55)
HCN	−4.70[a] (1.60)	−4.72[a] (1.59)	−6.67[c] (1.46)	−5.68[a] (1.78)	−7.72[c] (1.66)	−4.56[a] (1.62)
Lease	−2.32[b] (1.18)	−2.43[b] (1.17)	−1.41 (1.20)	−2.56[b] (1.19)	−1.73 (1.21)	−2.3[d] (1.18)
Own_Cont	1.18[c] (0.31)	1.27[c] (0.31)	1.13[c] (0.32)	1.37[c] (0.36)	1.33[c] (0.38)	1.23[c] (0.33)
HighInc		−2.43[d] (1.49)				
NCN				−1.07 (1.43)	−2.08 (1.44)	
HCO				−1.42 (1.51)	−1.41 (1.56)	
PVDense						−0.95 (2.07)

[a] $p < 0.01$.
[b] $p < 0.05$.
[c] $p < 0.001$.
[d] $p < 0.10$.

contact (HCN), and leasing (Lease) were used to model DP, the length of a PV adopter's decision period in months. Detailed description of these variables and multiple control variables are described in the supporting information section (available online at stacks.iop.org/ERL/8/014044/mmedia). We modeled DP of a decision-maker i (denoted by the variable Cons_Mo$_i$) in equation (1) as:

$$\text{Cons\_Mo}_i = \beta_0 + \beta_1 \text{InvestVIEI}_i + \beta_2 \text{PeerEfSum}_i + \beta_3 \text{HCN}_i + \beta_4 \text{Lease}_i + \text{Controls} + \varepsilon_i. \quad (1)$$

To further understand the drivers of passive peer effects, we present the supporting equation (2) Passive peer effects (PeerEfSum), a key component of DP (hypotheses 2*a*), can be modeled as:

$$\text{PeerEfSum}_i = \beta_0 + \beta_1 \text{PV\_in\_Nei}_i + \text{Controls} + \varepsilon_i. \quad (2)$$

Unless otherwise noted, results and discussion apply to the model in equation (1).

4.2. Regression results

Table 1 displays the results of the regression as well as several sensitivities. Additional sensitivities are included in the supporting information (available at stacks.iop.org/ERL/8/014044/mmedia). The model explains about 24% (Adj. $R^2 = 0.24$) of the variation in DP for PV owners.

4.2.1. Information certainty. We find that installing PV for financial reasons requires more certainty, and trustworthy financial information may be the most difficult to find, particularly given the variation in value suggested by different financial metrics [39]. High uncertainty regarding financial aspects of PV installation can drive up decision times. On average, respondents who reported that their evaluation of solar as a financial investment was very important or extremely important to their decision to install PV (InvestVIEI) took 2.7 months longer to decide, holding all other factors constant (table 1). Therefore, we find support for (fail to reject) hypotheses 1: PV owners who need greater information certainty have higher DP. Further support of this hypothesis is gained from substitution of InvestVIEI with the variable HighInc, a binary variable for responders who reported household income of over \$250 000 (13% of respondents). The results are shown in model 1a of table 1. This was done under the hypothesis that the need for information certainty of adopters in higher income brackets is lower than average, as the capital investment represents a proportionally smaller financial risk, so one would expect the HighInc group to have systematically lower DP. This was supported by correlation between HighInc and residual uncertainty (Pearson's $r = 0.14$, $p < 0.01$), suggesting that on average, higher income respondents are willing to accept more risk. We find that while holding all other factors constant, HighInc reduces DP by 2.43 months, but is only marginally significant ($p = 0.10$). The implication of this finding is that providing accurate, trustworthy financial information can significantly lower DP, and thus, increase adoption rates.

4.2.2. Passive peer effects. Passive peer effects (PeerEfSum) significantly reduce decision times. An increase of one on this scale indicates movement toward the 'strongly disagree' (that passive peer effects were important) pole of the Likert scale. This variable uses the section sum average method [29], as the individual Likert items are symmetrical with roughly equidistant points (as measured from slope coefficients of individual binary variables and fulfillment of the proportional odds assumption). On average, a one unit decrease on the Likert scale toward 'agree' (i.e., stronger experience of passive peer effects) results in a decrease of 1.5 months in DP. Thus, we find support for (fail to reject) hypotheses 2*a*: PV owners who experience greater passive peer effects have shorter DP. We also tested a model that controlled for residence is some neighborhoods with very high density of PV installation. Our results are largely unchanged, as shown in table 1, model 1e, suggesting that the impact of passive peer effects is not limited to only areas with high density of PV, and that our results do not depend on strong passive peer effects in any special neighborhood(s). These findings suggest two things: first, that the shorter decision periods seen in these areas are the result of peer effects generated by the high density of systems in the neighborhood, and second, that peer effects are active in the many neighborhoods in our sample with lower PV densities.

While the reported number of systems in the neighborhood (PV_in_Nei) was not significant in the DP model and was removed, this is likely due to the fuller measure of the passive peer effects variable (PeerEfSum) combined with the importance active peer effects through neighborhood contact (HCN). Neighborhood systems in and of themselves do not decrease DP, but rather it is the peer effects they produce and the potential for contact they engender that is important. Therefore, it is likely that the impact of PV_in_Nei operates through PeerEfSum and HCN. Indeed, upon modeling PeerEfSum (equation (2)), we find that PV_in_Nei is the most significant explanatory variable generating peer effects. Controlling for Lease, InvestVIEI, Innovators, AE, and Income variables, each additional system in the neighborhood results in movement toward the 'strongly agree' (that passive peer effects were important) pole, and was highly significant ($p < 0.001$). When additional influential outliers were removed, the weight of the coefficient nearly doubled. Thus, we find partial support for hypotheses 2*b* (PV owners with more systems in their neighborhood have shorter DP), in that the number of systems in the neighborhood is linked to passive peer effects and contact, which reduce DP.

4.2.3. Active peer effects: neighborhood contact. On average, while holding all other factors constant, respondents who contacted a neighborhood PV owner prior to installation (HCN $= 1$) had shorter DP by 4.6 months. This measures the impact of direct contacts (in-person interactions). A potential adopter in the HCN group likely first experiences passive peer effects (motivation and confidence in PV induced by seeing other systems in the neighborhood) and then follows up with direct contact with other PV owners in the neighborhood. So the overall impact of PV systems in the neighborhood for the HCN group is the combined weight of the passive and active peer effects. Dropping the peer effects measure from the model yields a coefficient for this combined effect—the *full* peer effects—of -6.67 months. This is shown in table 1 as model 1b.

To further understand the impact of different types of social influences on adopters' decision period, we created variables for contact only *outside* the neighborhood (HCO) and for neighborhood systems but no direct contact (NCN) to the model, with the results shown in table 1, model 1c. Holding all other factors constant, on average both HCO and NCN decreased DP but were not significant. Recall that the NCN group has systems in the neighborhood, and so is likely to experience peer effects. It might be possible then that in model 1c which includes both NCN and PeerEfSum, the coefficient for NCN is being captured through PeerEfSum. Interestingly, adding the NCN and HCO variables while dropping the passive peer effects variable (model 1d) increased the coefficient and significance of NCN as well as that of HCN, adding further evidence of the importance of passive peer effects. Based on these results, we find support for (fail to reject) hypotheses 3: PV owners who had direct contact with other PV owners in the neighborhood will have the shortest DP compared to all other groups.

4.2.4. Buy versus lease. While holding all other factors constant, on average leasing PV decreases time spent by potential adopters researching PV. Thus, in addition to the already understood benefit of the leasing model, namely, no upfront capital cost of PV ownership, we also show that the leasing model significantly reduces UNMCs associated with PV adoption, leading to faster adoption rates as reflected in a shorter DP for leasers (table 1, model 1). That is, we find support for (fail to reject) hypotheses 4: leasers of PV systems have shorter DP than buyers. Our findings suggest that the dual benefits of the leasing model—no (or low) upfront capital costs *and* significantly reduced UNMCs—together explain the exponential burst in the growth of the leasing business model in the last few years.

4.2.5. Sensitivity analysis. The richness of the data used allowed multiple sensitivities to be conduced, including the substitution of financial variables, division of contact into sub-categories, inclusion/exclusion of various controls, and variable interactions. See the supporting information (available online at stacks.iop.org/ERL/8/014044/mmedia) for more information.

5. Conclusion

Realizing the potential emissions reductions attributed to PV technology would require facilitating the adoption process by making the decision to install simple. Uncertainties about technology performance and the lack of individually-relevant information increase the need for extensive research by consumers, thereby increasing the total cost of the technology to customers. To address such barriers to the diffusion of environmentally-friendly technologies, we have studied the effectiveness of different information channels in reducing uncertainties and non-monetary costs associated with the adoption of residential solar PV.

Information on PV systems is not difficult to access for most respondents, but access to information alone does not necessarily reduce research time and effort. This pattern is indicative of a lack of *trust* in available information. When trustworthiness of information is critical, as in the case of capital-intensive technologies like PV, individuals turn to trusted information networks made up of family, friends, and neighbors. Consistent with Nelson's view on the role of information networks for experience goods [40], and Diffusion of Innovations theory [13, 16], we find that potential PV adopters benefit from and tap into the knowledge stock of existing users. Our multivariate regression model suggests that leasing and peer effects (both passive and active) each significantly decreased decision times among survey respondents.

Our findings go further in that we are able to separate and quantify the key constituents in the 'black box' of peer effects. We find that peer effects operate via two main channels: first, the passive influence (increased confidence and motivation) that accrues through witnessing PV systems in the neighborhood; and second, the active influence that accrues through peer-to-peer communication through contact with neighbors. Among respondents, contact with neighbors before installation was the single most effective strategy for speeding decision times. Our results suggest that the combination of passive and active peer effects has the potential to create positive feedback loops as new adopters are added to the existing base, thereby dramatically increasing PV adoption rates.

The benefits of peer effects, especially neighborhood contact, are many, including motivation, confidence, convenience, relevance, and, perhaps most importantly, trustworthiness. However, this kind of communication is not adequately leveraged by existing policy or public information sources. An integrated information system for potential adopters would be composed of two main elements. First, existing information could be centralized and shared by linking regions, states, and utility service areas through a central hub administered by a credible source such as the US Department of Energy (DoE). The federal–state–local links could be managed via partnerships with universities, utility consortia, or non-profits. Information culled from national research laboratories, federal programs, state initiatives, and local utilities could provide users with a one-stop shop for their information needs.

Second, there could be significant value in designing incentive structures and communication platforms for PV that facilitate peer effects. Harnessing the demonstrated benefits of direct contact, this could take the form of (but is not necessarily limited to) an online social platform. Existing PV owners could share their PV ownership experience, and potential adopters would be able to connect with the owners in their neighborhood or community. As this research suggests, by increasing peer-to-peer interaction this initiative has the potential to decrease individual decision times by over six months, or by about two-thirds (HCN coefficient for *full* peer effects). Such an initiative would be relatively low-cost and would likely enable accelerated growth in the PV market, reducing the burden of support on the government as the residential PV industry expands.

While the insights from this work will be useful for the industry and policy makers, additional research in this area is needed to develop predictive models. There are still relationships affecting decision times yet unexplained in our model (Adj. $R^2 = 0.24$). Increased geographic and temporal granularity would allow more confidence in the application of these results across states and communities, and could potentially allow for forecasting of adoption rates based on efficiently achievable reductions in the non-monetary costs of technology adoption.

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