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Evolution of consumer information preferences with market maturity in solar PV adoption

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Abstract

Residential adoption of solar photovoltaics (PV) is spreading rapidly, supported by policy initiatives at the federal, state, and local levels. Potential adopters navigate increasingly complex decision-making landscapes in their path to adoption. Much is known about the individual-level drivers of solar PV diffusion that steer adopters through this process, but relatively little is known about the evolution of these drivers as solar PV markets mature. By understanding the evolution of emerging solar PV markets over time, stakeholders in the diffusion of solar PV can increase policy effectiveness and reduce costs. This analysis uses survey data to compare two adjacent markets across a range of relevant characteristics, then models changes in the importance of local vs cosmopolitan information sources by combining theory relating market maturity to adopter behavior with event-history techniques. In younger markets, earlier, innovative adoptions that are tied to a preference for cosmopolitan information sources are more prevalent than expected, suggesting a frustrated demand for solar PV that segues into adoptions fueled by local information preferences contemporary with similar adoptions in older markets. The analysis concludes with policy recommendations to leverage changing consumer information preferences as markets mature.

1. Introduction

The residential solar photovoltaic (PV) market has grown rapidly in recent years, driven in part by decreasing costs and novel financing structures and business models (GTM Research/SEIA 2014, Feldman *et al* 2013, Davidson *et al* 2015, Strupeit and Palm 2016). Potential adopters face increasingly complex decision-making landscapes and accrue information search costs to overcome barriers and uncertainties in the adoption value proposition (Rai and Robinson 2013, Rai *et al* 2016). Both barriers to adoption and the activities that overcome them have global salience; they share commonalities across economic development contexts (Kebede and Mitsufuji 2016). As solar PV enters more markets and market penetration within markets increases, the next wave of adopters, in general, are expected to be more risk averse (Rogers

2010). Thus it becomes increasingly important to know what drives the evolution of solar PV adoption both within a particular market and across diverse markets, in part to avoid 'cracks' and 'chasms' in the diffusion curve (Moore 1999). By understanding the way the emerging solar PV market evolves over time and across geographic locales at the level of the individual decision maker, policy makers, utility managers, and installers are likely to increase the effectiveness of solar PV policy designs such as rebate programs and to enable reductions in 'soft-costs' including customer acquisition (Ardani *et al* 2013). Previous work has identified drivers and behavioral levers relevant to energy transitions in general and to solar PV specifically (Langheim *et al* 2014, Rai *et al* 2016, Lopes *et al* 2007, Rai and Robinson 2013, Fouquet 2010, Sintov and Schultz 2015, Noppers *et al* 2014, Jager 2006), explored the role of local

information exchanges on adoption (Graziano and Gillingham 2014, Bollinger and Gillingham 2012, Palm 2016), and investigated local policy drivers of variation in pro-environmental behaviors (Palm 2016, Bedsworth and Hanak 2013). Though notable exceptions exist (Sigrin *et al* 2015), the evolution of drivers of adoption in solar PV markets over time is less well studied; we contribute to this nascent literature by examining how drivers of adoption change as markets mature with a focus on understanding the impact that information preferences have on adoption rates.

We use survey data of PV adopters in two adjoining markets, one mature and the other young, to study differences in the information search process of adopters across the two markets. We are especially interested in studying whether the information search processes within the younger market resemble a fresh market start or if they are significantly influenced by the presence of an adjacent more mature market, leading to a different starting point. Evidence for the latter—as we indeed find—suggests the importance of considering the pre-existing information context, not just within jurisdictional boundaries but also those in nearby jurisdictions, in the decisions of actors such as installers, utilities, and local governments. We begin by presenting a brief background, then describing the data and methodology before discussing the results. Results are presented in two groups by analytical approach: (a) a comparison of market differences in information search processes and (b) an event-history model of information preferences and adoption timing across and within markets. Finally, findings and implications are summarized in the conclusion.

2. Background

2.1. Market maturity and adopter information preferences

In this section we highlight aspects of two leading frameworks of technology diffusion—Rogers' diffusion of innovation theory and Bass' new product diffusion model—that provide context for the analyses presented in the following sections. Rogers identifies adopter categories by exhaustively partitioning adopters based on the timing of their adoption (Rogers 2010). He calls the first 2.5% 'Innovators,' the following 13.5% are 'Early adopters,' following them, the next 34% are the 'Early majority,' and so on. He then proposes that information channels important to adopters vary by adopter category; cosmopolitan information channels (often mass media) are more important to earlier adopters than later adopters (Rogers 2010, p. 213). It follows that adopters in a more mature market are expected to place higher value on local (often interpersonal) information channels—such as neighbors, friends, family members, and co-workers—than adopters in a less mature market.

The Bass model categorizes adopters differently, avoiding Rogers' partitions and allowing different categories of adopter to exist simultaneously (Bass 1969, Mahajan *et al* 1990). The Bass model's 'Innovators' decide to adopt independently of the decisions of others as opposed to the model's 'Imitators' whose adoption decision is influenced by the decisions of others. Formally, the Bass model describes adopter behavior with equation (1), where $F(t)$ is the cumulative fraction of adopters at time t, p is a coefficient of innovation, and q is a coefficient of imitation (Mahajan *et al* 1990). From this model, the proportion of adoptions associated with innovative and imitative adopters are given by equations (2) and (3), where $i_N(t)$ is the proportion of innovative adoptions and $i_M(t)$ is the proportion of imitative adoptions at time t. Formally, from equation (2) where p is the coefficient of innovation, $[1 - F(t)]$ is simply a term describing the stock of potential adopters. But from equation (3) where q is the coefficient of imitation, $F(t) * [1 - F(t)]$ is a *social interaction term* describing the spread of information among potential adopters.

$$f(t) = \frac{\mathrm{d}F(t)}{\mathrm{d}t} = [p + qF(t)][1 - F(t)]$$
$$= i_N(t) + i_M(t) \tag{1}$$

$$i_N(t) = p * [1 - F(t)] \tag{2}$$

$$i_M(t) = q * F(t) * [1 - F(t)]. \tag{3}$$

Both Rogers' diffusion of innovation theory and the Bass model's classification scheme share an underlying idea about the role of information channels among groups of adopters that has previously been mapped to solar PV adoption in the literature—that earlier, more innovative adopters are either not susceptible or less susceptible to interpersonal information channels and that later imitative adopters are more susceptible to interpersonal information channels (Dong *et al* 2016, Sigrin *et al* 2015, Bollinger and Gillingham 2012, Faiers and Neame 2006, Velayudhan 2003, Acker and Kammen 1996, Warren 1980).

Tanny and Derzko (1988) argue that Bass describes a model that categorizes adopters but that the Bass model itself actually describes homogenous population of adopters each capable of expressing both innovativeness and imitation. They find that a model which explicitly categorizes Innovators and Imitators is inferior to the original Bass model. Given that certain types of individuals with certain relatively stable, but latent, qualitative characteristics and preferences tend to adopt earlier while other individuals tend to adopt later, rather than try to identify and categorize adopters into one particular group or another, in this paper we attempt to identify characteristics and preferences that co-vary with market maturity. To approach this, we leverage

characteristics of information preferences that exist in the overlap of Rogers' and Bass' theories. Specifically, preferences for cosmopolitan, mass media information sources are tied to earlier innovative adoption while preferences for local information sources are tied to later, imitative adoption. This underlying framework is referred to hereafter as the *information preferences framework*. By using this framework to tie information preferences to adoption timing, we generate insights into the pattern of information search processes within and across markets of different maturities.

3. Survey methodology

We use a survey developed to describe adopters within a sample (Rai and Robinson 2013, Rai *et al* 2016) to compare across two samples from adjoining markets within a state in the western US (further described below). With results from two similar surveys fielded in geographically adjacent markets with different maturity levels, we disentangle the characteristics of adopters that are related to the maturity of the local market from those related to market maturity in a broad sense—and thus are shared among adopters in both markets—while accounting for localized market idiosyncrasies.

The data for this study come primarily from two similar surveys conducted during 2014 and 2015. The first survey, conducted in 2014, gathered data from the younger market. This survey was fielded to 2131 randomly selected solar-adopter residential customers (out of 6026 by the end of 2013). Respondents were contacted by mail and had the option to respond by hard copy or by completing an online survey. We received 380 responses to this survey for a response rate of 18% and matched the responses to administrative data (on system sizes, costs, interconnection dates, etc).

The second survey, conducted in 2015, gathered data from the older market. This survey contacted 6000 randomly selected residential solar PV adopters in an adjacent, larger utility with a longer history of solar PV adoption. This sampling frame included 49 468 residential customers[5] who had adopted solar PV by July 2014, had email addresses on file with the utility, and had matching administrative data (on system sizes, costs, interconnection dates, etc). Respondents were contacted by email and invited to complete an online survey. We received 690 responses to this survey for a response rate of 11.5%. Although this survey of the older market contacted a smaller percentage of the sampling frame than in the younger

market, we believe that the number of responses we received is sufficient to power the analyses we conduct.

Each survey instrument collected data on many variables divided into seven sections: system and decision details, decision-making process, financial aspects, sources of information, expectations/evaluation after installation, environmental attitude, and demographics. This analysis deals primarily with the sections related to decision-making, information channels, and demographics.

There are indications that the two survey samples represent different, separate markets. Differences between the two markets such as the date of the onset of diffusion, local utility provider, electricity rates, rebates, and qualitative characteristics of the adopters imply that the two markets surveyed constitute two different decision-making contexts. Consequently, this analysis proceeds under the assumption that the two adjacent markets considered here are separate markets, and are not merely sub-parts of the same larger market that happen to have different diffusion start times. By making this assumption, we are able to identify differences between the two markets and isolate them from both trends that appear in a larger market context as well as other historical factors.

4. Analyses and results

The analysis is presented in two portions. First, sections 4.1, 4.2, and 4.3 present a comparative analysis focused on identifying descriptive differences between the two samples from the older and younger markets. Section 4.1 highlights both similarities and differences between the two samples across a range of features including decision-making context, decision-making process, and adoption timing. Behavioral differences during the decision-making process, such as the tendency towards a particular spark event or a preference for a particular information channel, are thought to arise from the same latent characteristics and preferences that drive an individual to adopt earlier or later in the diffusion process. Sections 4.2 and 4.3 analyze which behaviors, apart from adoption timing, are linked to market maturity and thus may be likely to proceed in conjunction with market maturity as opposed to those which are geographically localized or fluctuate over time. Second, section 4.4 presents an event-history analysis to model the data within the context of the diffusion of innovations framework. While the comparative analyses in sections 4.1–4.3 isolate differences in information channel importance or susceptibility to a particular spark event among adopters, the event-history analysis considers adoption timing as an outcome arising from an adopter's preference for local or cosmopolitan information. Each section begins with a description of the analytical approach used.

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[5] Note that 546 adopters that had recently been selected and contacted by the utility for other purposes were removed from the sampling frame.

Table 1. Descriptive statistics of survey respondents and decision-making contexts, compared across older-market and younger-market samples.

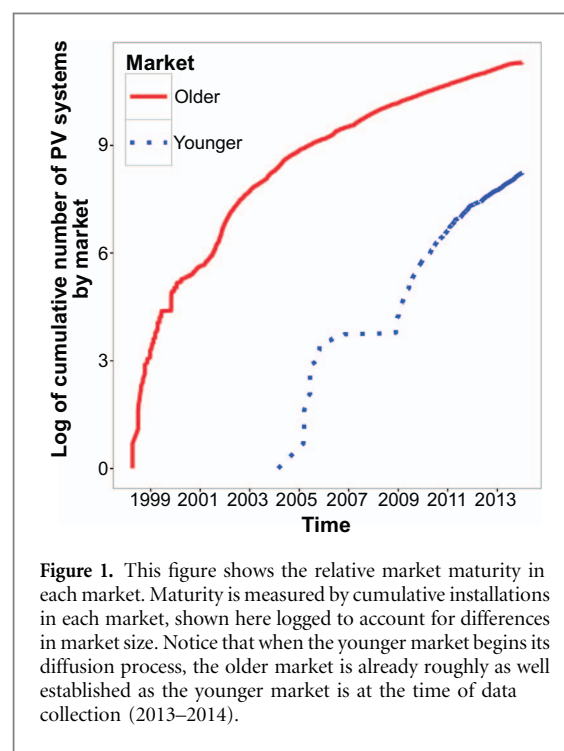|	Older-market sample	Younger-market sample
Demographics		
Median age	59	62
Percent female	20.9	24.0
Percent over 25 with at least a BA	86.7	74.0
Percent over 65	29.0	39.5
Median income	$100 000–$149 999	$100 000–$149 999
System descriptions		
Median nameplate capacity	4.6 kW	4.7 kW
Median installed price	$29 194	$27 817
Median installed price per Watt	$6.50	$5.66
Median net cost	$18 201	$16 521
Median net cost per Watt	$4.01	$3.34
Percent first installation in neighborhood[a]	33.5%	52.9%
Decision-making contexts		
Mean residential retail electricity rate (2000–2014)	**14.2 ¢/kWh**	**10.9 ¢/kWh**
Decision-making process differences		
Spark: Remodeling (proportion)	**0.149**	**0.055**
Spark: Retirement (proportion)	**0.183**	**0.282**
Spark: Adopter conversation (proportion)	**0.228**	**0.168**
Spark: Radio/TV (proportion)	**0.054**	**0.089**
Spark: Direct marketing (proportion)	**0.139**	**0.332**
Information Channel: Local utility	Not Very Important	Moderately Important

Note that **bolded differences** are significant at $\alpha = 0.05$.

[a] This describes the portion of respondents that replied that they were the first to install solar PV in their neighborhood, as opposed to those that had access to neighborhood peer effects by virtue of being aware of an existing installation in their neighborhood at the time of their installation.

4.1. Comparative analysis: demographics, systems, and decision contexts

In this section we present results of the comparative analysis of the two samples related to demographics, system details, and decision-making context. The two samples are very similar with respect to demographics. Table 1 presents a comparison of respondents in the two samples on key aspects. Demographically, both the older-market and younger-market samples are older, better educated, and wealthier than is common within the state and in the US at-large. This pattern is commonly observed of solar PV adopters (Rai *et al* 2016, Sigrin *et al* 2015, Rai and McAndrews 2012). The two samples are also very similar in the size of the systems that they choose to install; however, costs are generally higher in the older-market sample. This is expected, as adopters in the older-market sample have more early installations than in the younger market— installations undertaken at a time when solar PV was more expensive.

Yet, although the two markets are adjacent and located in the same state, they represent two distinctly different decision-making contexts for potential adopters, evidenced by the difference in the maturity levels of the two markets. Figure 1 shows the relative installations over time in each market; cumulative installations are logged to

Figure 1. This figure shows the relative market maturity in each market. Maturity is measured by cumulative installations in each market, shown here logged to account for differences in market size. Notice that when the younger market begins its diffusion process, the older market is already roughly as well established as the younger market is at the time of data collection (2013–2014).

account for the difference in market size. Notice that when the younger market begins its diffusion process the older market is already as well established as the younger market is at the time
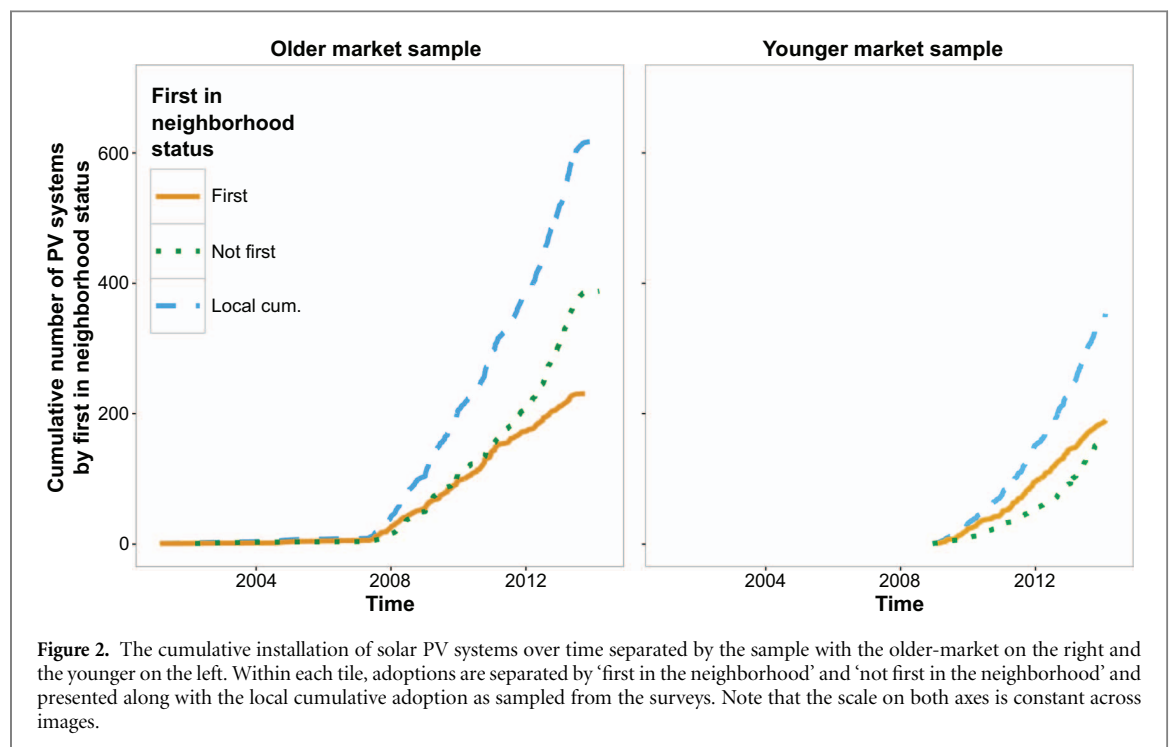
Figure 2. The cumulative installation of solar PV systems over time separated by the sample with the older-market on the right and the younger on the left. Within each tile, adoptions are separated by 'first in the neighborhood' and 'not first in the neighborhood' and presented along with the local cumulative adoption as sampled from the surveys. Note that the scale on both axes is constant across images.

of data collection (2013–2014). An interesting observation emergent from the survey is that by the time of the survey only 33.5% of older-market sample customers report having the first installation in their neighborhood, compared to 52.9% in the younger market. This is consistent with the assertion that the older market is more mature than the younger.

Figure 2 breaks down the cumulative adoptions in each sample by this 'first/not-first' metric. In the older-market sample, the number of 'not-first' installations outpace the 'first' installations beginning around 2011. At the same time in the younger-market sample, the 'first' installations are generally ahead of 'not-firsts.' The imbalance of 'not-first' installations between the two samples suggests that more customers in the older-market sample may be exposed to neighborhood peer effects, which are known to provide important information to potential solar PV adopters facing uncertainties (Rai and Robinson 2013, Bollinger and Gillingham 2012). In terms of the diffusion models as discussed in section 2, more 'not-first' installations suggests that there is a greater opportunity for imitation as opposed to innovation, as such more 'not-first' installations amounts to evidence of a diffusion process that is relatively more advanced.

4.2. Comparative analysis: spark events
'Spark events' are those events that ignite an adopter's initial interest in adopting solar PV; they have been shown to play an important role in shaping the decision-making process—and thus the information search—of solar PV adopters (Rai *et al* 2016). Here they are measured by asking respondents to select from the following list of situations or events that

prompted their initial interest in installing a solar system:

- Remodeling
- Electric rate increase
- Retirement
- Conversation with other adopter
- Home tour
- Retail
- Radio/TV ad
- Direct marketing
- Seeing a neighbor install
- Neighbor conversation

Table A1 in the appendix describes the proportion of respondents in each sample that selected each of the spark events listed in the question along with a significance test of the difference between samples.

In this section we examine the prevalence of spark events with a series of logistic regression models. The logistic models compare the two samples, one referred to as the 'older-market' and the other as a 'younger-market,' across demographics and system descriptives, as well as a range of spark events. We built separate models, one for each spark event as the dependent variable. Each of these models considers the dependent variable as a function of the same four independent variables: a dummy variable indicating the sample (i.e. the utility), cumulative installations in the local market prior to adoption (in 100 k's), cumulative installations in the statewide market prior

Table 2. Results from a series of logistic regression models disambiguating differences in spark events across the two samples by local and statewide cumulative installations, geographic locale, and year. In these regressions, the younger-market sample is the reference group and the coefficients in the older-market sample rows are interpreted as the difference in log odds between the two samples. When the older-market sample has greater (lower) log odds for a given dependent variable than the younger-market sample, the estimated coefficient of the difference is positive (negative). The second set of neighbor-related models, 'See neighbor install (2)' and 'Neighbor conversation (2),' include a variable indicating whether a respondent was the first in their neighborhood to instal and an interaction term between this variable and the older-market indicator.

	Log-likelihood of spark events						
	Remodeling	Electric rate increase	Retirement	Conversation other adopter	Home tour	Retail	Radio/TV
Older-market	1.031	-0.658	−0.846**	0.630	4.638	−0.773	−0.623
	(0.711)	(0.417)	(0.428)	(0.538)	(3.033)	(0.688)	(0.719)
Local Inst. (100 k)	−0.290	1.850*	0.699	−0.104	−9.652	1.253	0.773
	(1.890)	(1.109)	(1.141)	(1.319)	(6.517)	(1.657)	(1.806)
CA Inst. (100 k)	2.245	0.049	−1.436	−1.228	7.609**	2.039	2.730*
	(1.518)	(0.975)	(1.021)	(1.049)	(3.160)	(1.546)	(1.651)
Constant	−16.609	−13.909	−14.713	−15.190	15.891	−16.803	−16.957
	(1455.398)	(882.743)	(1455.398)	(882.744)	(17 730.370)	(3956.180)	(3956.180)
Year fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1037	1037	1037	1037	1037	1037	1037
Log Likelihood	−354.160	−582.862	−532.416	−505.871	−84.921	−253.511	−241.109
	Direct marketing	See neighbor install	Neighbor conversation	Neighbor related	See neighbor install (2)	Neighbor conversation (2)	
Older-market	−1.626***	1.233	0.970	1.053	1.242	14.872	
	(0.450)	(0.887)	(0.754)	(0.702)	(1.185)	(785.420)	
Local Inst. (100 k)	1.686	−1.632	−1.329	−1.581	−1.465	−0.165	
	(1.179)	(2.052)	(1.852)	(1.670)	(2.106)	(1.956)	
CA Inst. (100 k)	−0.660	1.616	2.990*	1.607	1.961	3.112*	
	(1.028)	(1.453)	(1.535)	(1.278)	(1.547)	(1.642)	
Not-first					2.587***	17.818	
					(0.750)	(785.419)	
Older-market * Not-first					−0.363	−14.764	
					(0.920)	(785.419)	
Constant	−13.937	−16.807	−16.551	−16.627	−16.817	−34.453	
	(1455.398)	(1455.398)	(1455.398)	(1455.398)	(1455.398)	(10 782.660)	
Year dummies?	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	1037	1037	1037	1037	958	958	
Log Likelihood	−494.389	−291.659	−296.240	−367.026	−250.789	−238.382	

Note: Standard errors in parentheses.
Significance stars: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

to adoption (in 100 k's), and fixed effects by year of adoption to control for unobserved heterogeneity. Market maturity is measured by total cumulative installations of residential solar PV in the relevant area prior to the interconnection date of the observed adoption; for local maturity the relevant area is the utility service area and for statewide maturity the relevant area is the entire state (Barbose and Darghouth 2015). This approach identifies differences between the two samples and estimates the degree to which those differences have a relationship with local market maturity, broader market maturity, or are idiosyncratic to a particular market.

The coefficient on cumulative local installations in the 'Electric rate increase' model in table 2 shows a positive and significant relationship between local installations and electric rate increases. As local installations increase, the probability of the electric rate increase spark event increases. This is not

surprising as electric rates are specific to the local context and generally increase over time, consistent with the assumption that the two markets can be treated as separate decision-making contexts.

From the coefficients on the statewide installations variable, we find that several spark events are significantly and positively associated with increasing statewide cumulative installations: home tours, conversation with a neighbor adopter, and radio or TV ads. This suggests that as the broader market matures and grows, solar firms and other solar promoters that operate across the state are increasing contact opportunities with potential adopters through advertising and organizing events like home tours. Notice that no significant difference is found between markets for any of the neighborhood-relevant dependent variables (from the coefficients in the 'Older-market' row in columns 'See neighbor install' through 'Neighbor conversation (2)'). The 'See neighbor install

(2)' and 'Neighbor conversation (2)' models include a variable indicating whether a respondent was the first in their neighborhood to instal—recall the 'first/not-first' analysis in section 4.1—and interact this 'Not-first' indicator with the older-market indicator. The 'Not-first' indicator has a significant and large positive association with the spark event 'See neighbor install', suggesting that witnessing systems being installed in the neighborhood acts to initiate the adoption decision-making process among non-adopters. However, from the coefficient on the interaction term in the 'See neighbor install (2)' model we find that there is no significant difference in the probability of being sparked to install by seeing a neighbor's installation among 'Not-first' adopters across the two markets. This suggests that neighborhood peer effects are operating similarly across the two markets.

Furthermore, comparing the coefficient on statewide installations between the models for 'Neighbor conversation' and 'Neighbor conversation (2)' we find that not only are neighbor conversations significantly and positively associated with statewide cumulative installations, but the coefficient is stable and still significant even when controlling for access to neighborhood peer effects through the 'Not-first' variable. Again, recall the 'first/not-first' imbalance noted in section 4.1; the older market had more adopters that reported not being the first in their neighborhood to install (i.e. already having at least one installed PV system in the neighborhood), while the younger market was still dominated by adopters that installed the first system in their neighborhood. The stability of the relationship between statewide installations and neighbor conversations, even when the analysis controls for 'Not-first' adopters, suggests that the social interaction term of equation (3) is similar in both markets, and may be linked to broader market maturity *through* the first-in-the-neighborhood innovative adopters. Early in a diffusion cycle, cosmopolitan information preferences fuel the spread of innovative adoptions—adoptions that are likely to be the first in their neighborhood. As the market matures, both in a local and broader sense, these innovative first-in-the-neighborhood adoptions provide the model that is imitated by later adoptions fueled by local information preferences.

4.3. Comparative analysis: information channels

The importance of each information channel during the decision-making process was measured through a five-point Likert item. Respondents were asked to rate the importance of information received from the following groups in their decision to install solar PV:

- Coworkers
- Online forums
- Online resources
- Roofing contractors
- Solar installers
- Neighbors
- Local non-profits
- Acquaintances
- Family
- Local utility

A full comparison of median responses is provided in table A2 in the appendix. Responses range across 'Not important at all,' 'Not very important,' 'Moderately important,' 'Very important,' and 'Extremely important.' These responses are then transformed into a dichotomous indicator of whether or not the respondent rated a particular information channel as 'Very important' or 'Extremely important' (represented by the shorthand 'VIEI'). For example, if a respondent were to rate the importance of a particular channel as 'Moderately important' the corresponding dichotomous VIEI indicator would be set to zero; alternatively, if a respondent were to rate the importance of that channel as 'Very important' the corresponding dichotomous VIEI indicator would be set to one.

The transformed responses are used as the dependent variable in a series of logistic regression models on the same set of independent variables used in section 4.2: (a) an indicator for the older market, (b) the local maturity of each market, (c) the maturity of the broader statewide market, and (d) time fixed effects to control for unobserved heterogeneity. Again, we build a separate model for each information channel. Regressing information channel importance on both local market maturity and broader market maturity allows us to identify and isolate changes in information channel importance tied to maturing local markets from changes in information channel importance that are tied to broader market maturity, all while accounting for both idiosyncratic differences between the two samples and historical factors.

Table 3 presents the results of the series of separate logistic regression models, each with a different information channel as the dependent variable. From the negative coefficient for the older-market indicator under the 'Roofing Contractors' model, we find that respondents in the older-market sample are significantly less likely to value information from roofing contractors than their younger-sample counterparts, but the positive coefficient on local installations in that same model shows that across *both* samples the tendency to value information from roofing contractors increases significantly and by a very large magnitude as local markets mature, all else equal. One explanation for this finding is that the content of local information exchanges—such as neighborhood

Table 3. Series of logistic regression models disambiguating the differences in information path importance across the two samples by cumulative installations, geographic locale, and year. Following the convention established in table 2, the younger-market sample is the reference group, and the estimated coefficients in the older-market sample rows are interpreted as the difference in log odds between the two samples. A positive (negative) estimated coefficient of this difference indicates that the older-market sample has greater (lower) log odds for a given dependent variable than the younger-market sample. Note that missing values for Likert responses are excluded from the dichotomized analysis, therefore models have different numbers of observations.

| | Rating a source as very important or extremely important | | | | |
	Coworkers	Online forums	Online resources	Roofing contractors	Solar installers
Older-market	1.159	0.047	0.087	−1.657**	−0.413
	(0.827)	(0.908)	(0.459)	(0.669)	(0.417)
Local Inst. (100 k)	−3.167	0.578	0.078	4.199**	−0.307
	(2.094)	(2.388)	(1.181)	(1.821)	(1.095)
CA Inst. (100 k)	1.912	2.359	1.366	−1.013	−0.830
	(1.621)	(2.146)	(1.027)	(1.845)	(0.960)
Constant	−18.734	−16.625	14.473	−13.904	−14.148
	(3956.180)	(2399.545)	(882.744)	(1455.398)	(882.743)
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observations	694	651	797	664	889
Log Likelihood	−251.133	−176.287	−536.659	−214.811	−597.876
	Neighbors	Local non-profits	Acquaintances	Family	Local utility
Older-market sample	0.689	0.676	0.831	−1.533**	−1.536***
	(0.835)	(0.986)	(0.727)	(0.606)	(0.477)
Local Inst. (100 k)	−1.764	−0.930	−1.558	1.956	1.026
	(2.011)	(2.577)	(1.889)	(1.547)	(1.275)
CA Inst. (100 k)	−0.267	−0.201	1.317	−1.004	2.181*
	(1.554)	(2.143)	(1.544)	(1.321)	(1.206)
Constant	−16.253	−17.241	−16.403	−14.028	−14.041
	(1455.398)	(2399.545)	(1455.398)	(1455.398)	(1455.398)
Year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observations	728	652	726	720	817
Log Likelihood	−262.512	−178.450	−300.179	−323.608	−401.124

Note: Standard errors in parentheses.
Significance stars: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

peer effects—may be related to particular installations and therefore to particular contractors. In a localized context, a subset of roofing contractors may be able to achieve local prominence that encourages local potential adopters to trust in them. However, this finding could also be driven by installers that invest systematically over time in marketing and brand positioning to signal their trustworthiness, for example, through the use of local testimonials.

Respondents in the older market are idiosyncratically different from those in the younger market; the coefficient on the 'Older-market' variable in the 'Local utility' model shows that the older-market sample are significantly less likely to rate the local utility as VIEI than the younger-market sample, all else held constant. Customer trust is positively related to corporate reputation (Groenland 2002); differences in trust and satisfaction are localized and utility specific. Alternatively, it is also possible that the utility in the younger market was proactive with information dissemination while the older utility waited for the market to provide information as demand for it increased.

However, despite this idiosyncratic difference, the positive coefficient on the statewide installations variable under the 'Local utility' model shows that as broader statewide cumulative installations increase respondents in both samples are significantly more likely to rate the local utility as a VIEI information channel. This finding suggests that the importance of local utility companies as an information channel increases as the adoption of solar PV spreads *without regard to locality*. According to Rogers (2010), as diffusion progresses beyond those adopters that are 'venturesome' and onto those that are 'deliberate,' adopters become more risk-averse and may seek out sources of information with greater perceived objectivity, name recognition, and with whom they have already established contractual relations. Consistent with Qiu *et al* (2014), we find that as potential adopters face an increasingly complex landscape of installers and methods of acquisition but tolerate less risk and uncertainty, local utilities have an opportunity to serve as a increasingly valuable resource by objectively communicating risk levels to potential adopters.

4.4. Event-history analysis of information preferences

This portion of the analysis employs event-history techniques that allow us to probe deeper into latent characteristics of adopters than in the comparative analyses reported in sections 4.2 and 4.3.

We first operationalize the information preferences framework (see section 2), then develop a model of solar PV adoption undergirded by the distinction between cosmopolitan and local information channels and their relationship to innovative versus imitative adoption behavior. To explore differences in information preferences across samples, we use a Cox proportional hazard model. The Cox model takes the individual's hazard as its dependent variable, where the event of interest is installing solar PV. The independent variables of interest from the information preferences framework are operationalized by creating indices of geographically local and cosmopolitan information channels. In light of a growing literature on the importance of neighborhood peer effects in solar PV adoption, we use geographic proximity to define local and non-local information sources in our operationalization of the information preferences framework (Palm 2016, Rai *et al* 2016, Graziano and Gillingham 2014, Bollinger and Gillingham 2012). The local index is an additive composite of three equivalently weighted dummy variables: the two spark events 'seeing neighbor install' and 'conversation with neighbor' and 'neighbor information: very important or extremely important.' The cosmopolitan index is similarly constructed, but with different variables: the two spark events 'radio/TV ad' and 'conversation with non-neighbor' and 'coworker information: very important or extremely important.' These two indices then describe the tendency for a given respondent to express a preference for locally-sourced information and for more geographically diffuse information sources. The two preferences are not mutually exclusive; we find that the two indexes are positively correlated with Pearson's $r = 0.43$. Therefore, this technique does not explicitly categorize adopters by their preferences[6] (Tanny and Derzko 1988).

Formally, the model is specified in equation (4) where $h(t)$ is the hazard function of adoption, $a(t)$ is an unknown function of time, S is a dummy variable indicating the sample (older or younger), I_c is the cosmopolitan information preference index, I_l is the local information preference index, and $\vec{X}$ is a vector of covariates.

$$
\begin{aligned}
h(t) = a(t) &+ \beta_1 S + \beta_2 I_c + \beta_3 I_l + \beta_4 I_c(t) + \beta_5 I_l(t) \\
&+ \beta_6 I_c S + \beta_7 I_l S + \beta_8 I_c(t) S + \beta_9 I_l(t) S \\
&+ \vec{\phi}\vec{X} + \vec{\delta}\vec{X}(t).
\end{aligned} \tag{4}
$$

The covariates control for respondent demographics, system details, and the local average annual residential retail electricity rate. The choice of origin time is assumed to be relatively unimportant as historical factors are expected to affect all individuals in roughly the same way except where modeled explicitly in equation (4), and the semi-parametric Cox model depends only on the order of events through the unknown function of time $a(t)$ (Allison 2014). As such 1 January 2000—a date before the earliest observation—was chosen as the origin time.

We develop three model variations to explore the relationship between local information channels and cosmopolitan information channels across the two samples. In model 1, β_4 through β_9 and δ are constrained to 0; it is truly a proportional hazard model. The Cox proportional hazard model assumes that each variable has a stable impact on the hazard over time (thus it is proportional); this assumption may be relaxed with the inclusion of time-varying values where appropriate. However, even when the proportional hazard assumption is violated, the Cox model can produce a useful approximation (Allison 2014, p. 43). Thus, model 1 serves as a baseline model; it includes only the 'main effects' of the indices. The baseline model is less than ideal for two reasons: the data indeed violate the proportional hazard assumption, and the model does not distinguish effects between the two samples. These shortcomings are addressed in models 2 and 3.

Model 2 allows for time-varying hazards by removing the constraint on coefficients β_4, β_5, and δ. Removing this constraint introduces an interaction between relevant variables and elapsed time (measured in weeks), thereby relaxing the proportional hazard assumption and separating effects into time-invariant and time-varying components. Finally, model 3 allows for hazards related to information preferences to vary by sample by removing the constraint on the interaction term coefficients, β_6 through β_9. Further relaxing of the constraints introduces a second interaction between the older-market dummy variable and both the time-invariant and the time-varying components of the index variables to distinguish differential effects between the two samples.

Table 4 presents the results of the three models. Model 3 is the preferred model because of its better model performance (as indicated by lower AIC and BIC) compared to models 1 and 2, and because it more fully explores the nuanced relationship between information preferences and adoption timing. Overall, we find evidence of a different relationship between cosmopolitan information preferences and adoption timing across samples, and a more similar relationship between local information preferences and adoption timing across samples.

As noted in section 2, theory suggests that cosmopolitan information preferences should be more

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[6] Table A3 in the appendix presents the distribution of local and cosmopolitan index values.

Table 4. Results from a series of Cox proportional hazard models derived from theories of diffusion, treating adoption as the hazard, with local and cosmopolitan information channels. Model 1 (the baseline) relates the individual hazard to local and cosmopolitan information channel indices. Model 2 relaxes the proportional hazard assumption by interacting relevant variables with time measured in weeks. Model 3 interacts both the time-invariant and time-variant indices with the sample ID.

	Individual log-Hazard of adoption measured in days		
	(1)	(2)	(3)
Older-market	7.795*** (0.307)	4.029*** (0.346)	4.819*** (0.383)
Local Index	−0.058 (0.054)	2.141*** (0.338)	3.138*** (0.727)
Local Index ∗ Weeks		−0.003*** (0.001)	−0.005*** (0.001)
Cosmo. Index	−0.129** (0.059)	4.197*** (0.374)	5.339*** (0.594)
Cosmo. Index ∗ Weeks		−0.007*** (0.001)	−0.008*** (0.001)
Older-market: Local Index			−1.596* (0.830)
Older-market: Local Index ∗ Weeks			0.002 (0.001)
Older-market: Cosmo. Index			−2.999*** (0.771)
Older-market: Cosmo. Index ∗ Weeks			0.005*** (0.001)
Residential Electric Rate	−2.056*** (0.084)	−1.026*** (0.092)	−1.129*** (0.093)
Nameplate Rating	−0.037*** (0.013)	−0.030** (0.013)	−0.027** (0.013)
Cost per kW	0.0002*** (0.00003)	0.004*** (0.0001)	0.004*** (0.0001)
Cost per kW ∗ Weeks		-0.00001*** (0.00000)	−0.00001*** (0.00000)
Num. Nei. Sys	0.002 (0.004)	0.108*** (0.026)	0.111*** (0.028)
Num. Nei. Sys. ∗ Weeks		−0.0002*** (0.00004)	−0.0002*** (0.00005)
Over 25 & > = BA	0.117 (0.091)	0.033 (0.092)	0.044 (0.092)
Age > = 65	0.149** (0.072)	0.171** (0.075)	0.180** (0.075)
Income: High	0.174** (0.088)	0.028 (0.091)	0.045 (0.091)
Income: Low	0.102 (0.089)	−0.099 (0.090)	−0.148 (0.091)
Observations	352 946	352946	352 946
Log Likelihood	−4803.436	−4266.146	−4243.661
AIC	9629	8562	8525
BIC	9682	8635	8617

Note: Standard errors in parentheses.
Significance stars: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

active in spurring earlier adoptions, before segueing into adoptions that are fueled by local information preferences, which continue throughout the diffusion process. Put another way, cosmopolitan information preferences are expected to increase the individual hazard more than local information preferences and trail off more rapidly than local information preferences. In model 1, across both samples only the cosmopolitan index is significantly related to the individual hazard and not in the expected direction. Compared to model 1, model 2 shows that including time-varying hazards greatly improves model fit as evidenced by the relatively large changes in log-likelihood, AIC, and BIC. In model 2, both the 'main' time-invariant portion and the time-varying portion of the effect of both indices are significantly associated with the individual hazard (the coefficients on 'Local/ Cosmo. Index' and 'Local/Cosmo. Index ∗ Weeks,' respectively). Across both samples, the time-invariant hazard associated with increased values on the cosmopolitan index is of greater magnitude than that associated with the local index, yet both are positive. This suggests that adopters with greater preferences for cosmopolitan information channels are adopting earlier than those with greater preferences for local information channels, all else equal, which is consistent with the undergirding theory.

Furthermore, from the model 2 coefficients on the information preference indices interacted with time ('Local/Cosmo. Index ∗ Weeks'), we find that across both samples the time-varying portion of the indices effect is significant and negative and the magnitude for the cosmopolitan index is once again greater than for the local index. This shows that those with high cosmopolitan information preferences have a higher hazard of adoption that falls relatively rapidly with the passage of time, segueing into adoptions by those with high local information preferences associated with a relatively lower hazard of adoption that tapers off more slowly.

Model 3, the preferred model, elaborates on the relationship between information preferences and adoptions by disaggregating both the time-invariant and time-varying components of the cosmopolitan and local indices across the two samples. From the 'Older-market:' pane in table 4, three of the four information preference index components interacted with the sample ID are significant: both time-invariant components ('Older-market: Local Index' and 'Older-market: Cosmo. Index') and the time-varying component of cosmopolitan information preferences ('Older-market: Cosmo. Index ∗ Weeks'). These coefficients indicate that in the older-market sample, relative to the younger sample the 'main effect' of

Table 5. Component results from model 3, table 4, presented as relative marginal difference in hazard rates by sample-information preference pairs for increasing values of information preference indices. For example, an increase of one unit on the cosmopolitan information preferences index in the older market is associated with a 10 × increase in hazard at time = t, and a 0.005 × reduction in hazard in time = t + 1.

Sample-information pair	Marginal time-invariant factor	Marginal time-varying factor
Older-market: Local	4.674	0.995
Younger-market: Local	23.06	0.995
Older-market: Cosmopolitan	10.38	0.997
Younger-market: Cosmopolitan	208.3	0.992

greater preferences for cosmopolitan information channels is significant and negative (yet the overall effect is positive: 5.339 − 2.999 = 2.34), while the time-varying effect is significant and positive; cosmopolitan information preferences are associated with a significantly different hazard of adoption in the two markets that changes at a significantly different rate over time.

To help parse the difference in the relationship between information preferences and adoption timing between the two markets, table 5 gathers and exponentiates the relevant coefficients from model 3 into relative marginal impact factors. For example, the relative marginal time-invariant factor associated with increasing local information preferences in the older market is *exp* (3.138 − 1.596) = 4.674. Note that the coefficient on the 'Older-market' dummy variable is omitted from this calculation; this allows the pattern of adoption in the two markets to be compared to one another while accounting for the difference in the date of onset of diffusion between the two markets. The relative marginal time-invariant impact factors for local information preferences show that all else held constant a single unit increase in local information channel preferences is associated with a greater increase in hazard within the younger market—23 times as opposed to roughly five times in the older market. Similarly, the relative marginal time-invariant impact factors for cosmopolitan information preferences show that increasing cosmopolitan information channel preferences within the older-market sample are associated with a 10 times increase in hazard, but within the younger-market sample the associated increase in hazard is nearly 210 times. The relative marginal time-varying factors associated with increasing local information preferences are identical across markets, meaning that the hazard associated with increased local information preferences decreases (because the factors are less than one) at the same rate over time in each sample. Conversely, the relative marginal time-varying factor associated with increasing cosmopolitan information preferences in the older

sample is larger than the corresponding factor in the younger market—0.997 in the older market compares to 0.992 in the younger market, meaning that the hazard associated with increased cosmopolitan information preferences decreases more rapidly over time in the younger market than in the older market. In summary, greater local information preferences are associated with higher hazard in the younger market than in the older market and that hazard decreases at the same rate over time in both markets, but greater preferences for cosmopolitan information sources is associated with an *even greater* increase in hazard in the younger market that decreases *even more rapidly* over time than in the older market.

The preferred model (model 3) shows that the pattern of information preferences in the older market is similar to what was expected—and indeed what was found—in model 2: cosmopolitan information preferences are associated with earlier adoptions that segue into adoptions motivated by local information preferences. However, model 3 offers the additional nuanced and novel insight that this pattern of information preferences is exaggerated in the younger sample. Innovative adoptions fueled by cosmopolitan information preferences still occur in the younger sample, but they are more likely to occur *much* earlier in the local diffusion context and they segue into imitative, local information preference adoptions more rapidly.

Theory suggests that cosmopolitan information preferences would generally not be tied to local installation contexts, setting the expectation that potential adopters with cosmopolitan information preferences should develop a demand for solar PV without respect to their local context. In the case of the older market that demand is met relatively early, as the market itself co-develops along with the demand for solar PV by adopters with cosmopolitan information preferences. Relatively higher electric rates combined with high rebate levels spurred demand and created a context that encouraged the development of the supply-side. However in the younger market the demand from potential adopters with cosmopolitan information preferences is unmet due to an underdeveloped local supply side context resulting in a 'frustrated demand' for solar installations.

When the adjacent younger market kicked off its own diffusion process (possibly initiated by significant rate changes or changes in local incentives that draw local installers into the market or an expansion into the new territory by suppliers in the adjacent older market) those with cosmopolitan information preferences rushed to play 'catch up' wherein they adopt in large numbers as soon as the option to adopt becomes available. This explanation is consistent with the very high increase in hazard for adopters with cosmopolitan information preferences in the younger market, coupled with their accelerated decline in hazard over time (see table 5).

Compared to the difference between the two markets with respect to the role of cosmopolitan information preferences, table 5 shows that the relative marginal time-invariant impact factors are much more similar for local information preferences than for cosmopolitan preferences across the two samples, yet increasing local information preferences are still associated with higher hazard in the younger market than in the older market. As the younger market rapidly satisfies the frustrated demand of adopters with cosmopolitan information preferences, potential adopters with local information preferences rapidly gain access to local sources of valuable information in the form of their neighbors that have recently become adopters. These findings are consistent with the information preferences frameworks described in section 2 in that increasing innovative adoptions provide the foundation that seeds increasing imitative adoption. Finally, as discussed in sections 4.3 and 4.2, the intervening link that connects the innovative and imitative adopters appears to be provided by local factors such as neighborhood peer effects and local marketing by solar installers.

5. Conclusions

We find that the two adjacent localized markets sampled here are composed of demographically similar adopters, yet the pattern of diffusion is different in each. Variation in the information preferences of the adopters in the two samples, operationalized through valuable information channels and spark events, sheds some light on which preferences have a local character (like valuing information from roofing contractors) and which are more non-local (like valuing information from the utility). Not surprisingly for roofing contractors, who are likely to be tied to a particular locality through localized supply lines, the value that adopters place in information from roofing contractors increases as local installations increase. Interestingly though for local utilities, whose service areas are clearly defined, the value adopters place on their information increases as broader, global, installations increase. As the broader market grows, adopters place increased trust in information from local utilities and are increasingly sparked to adopt by contact opportunities like broadcast advertising, home tours, and conversations with neighbors that increased penetration provides.

When adoption begins to take off in younger markets, adopters with cosmopolitan information preferences—who are likely to be aware of adoptions occurring outside of their local context—may be satisfying a frustrated demand for solar PV by adopting very rapidly. Younger market adoptions then move past that initial blitz and relatively quickly segue into local information preference driven adoptions. From the perspective of the broader market, the rapid satisfaction of this frustrated demand combined with a resumption of local information preference stability underscores the importance of the role of valued information channels and spark events. When a new market opens, local contractors have a small and feverish window of opportunity to gain local prominence.

Even with more than a decade of adoption in the youngest of the two residential solar PV markets considered here, we must acknowledge that both of these markets are still relatively young from the perspective of long-term potential for solar adoption in these markets. There is ample opportunity for information channels to arise and gain prominence that simply do not exist at this stage in the broader diffusion of residential solar PV. It is plausible, though, that such novel information channels would exhibit a geographically local (e.g. big box electronics or home improvement retailers) or geographically cosmopolitan (e.g. social networking sites, mobile apps, etc) orientation. Thus the analytical framework presented here should be applicable for capturing information channels that arise over time.

Given that both markets are relatively early in the diffusion process, it is likely that the extremely high relative hazard associated with cosmopolitan information preferences will attenuate as diffusion continues. However, the relative hazard associated with local information preferences—while different across samples—is much *less* different and changing at the *same* rate over time. As markets mature and segue into local information preference driven adoptions, they become more homogeneous. The emergent homogeneity is consistent with a shift to adopters that are more risk-averse (Rogers 2010). Neighbors exchange information in local information exchanges similarly in each market when they have access to neighborhood peer effects. This points to a potentially useful difference between the two sorts of information preferences; across both samples local information preferences have a more stable relationship with adoption. This suggests that in 'post-rebate' environments, where the initial wave of adoptions has passed, there still exists the possibility to leverage local information preferences to spur adoption especially in order to reach less motivated potential adopters (Hine *et al* 2016, Lund 2015, Yang 2010, Moore 1999).

Programs that attempt to harness local information preferences among potential adopters, such as referral bonuses and discounts, neighborhood open houses, or similar, seem poised to benefit from the relative stability of local information preferences as diffusion progresses. As discussed previously, local utility companies are well situated to encourage these sort of activities by virtue of the increased value potential adopters place in information from them as the solar PV adoption decision-making landscape becomes increasingly complex.

Appendix: Supporting tables

Table A1. This appendix table presents the spark event frequency compared across the two samples. Respondents were asked to identify the situation or event that initially ignited their interest in adopting solar PV. For each question, the proportion responding in the affirmative is shown, along with the number of responses to each particular question. The right-most column tests the significance of each difference (calculated as older − younger).

Statistic	Older-market sample		Younger-market sample		
	Proportion	N	Proportion	N	Diff. & Signif.
Remodeling	0.149	690	0.055	380	0.094***
Electric rate increase	0.259	690	0.271	380	−0.012
Retirement	0.183	690	0.282	380	−0.099***
Conv. other adopter	0.228	690	0.168	380	0.059**
Home tour	0.020	690	0.021	380	−0.001
Retail	0.059	690	0.089	380	−0.030*
Radio/TV	0.054	690	0.089	380	−0.036**
Direct marketing	0.139	690	0.332	380	−0.192***
See neighbor install	0.093	690	0.076	380	0.016
Neighbor conversation	0.093	690	0.068	380	0.024

Note: Significance stars: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A2. This appendix table presents a comparison of valuation of information pathways across the two samples. Respondents were asked to rate the importance of information received from each of the listed groups in their decision to install solar PV. Responses are made in a five-level Likert item rating the importance of the following sources ranging from 'Not important at all' to 'Extremely important.' Responses are coded in the table below as follows: 'Not important at all' = NI; 'Not very important' = NVI; 'Moderately important' = MI; 'Very important' = VI; 'Extremely important' = EI. Because responses are ordinal, the median response is shown for each sample, along with the number of responses to each particular question.

Statistic	Older-market sample		Younger-market sample	
	Median	N	Median	N
Coworkers	NI	495	NI	216
Online forums	NI	477	NI	189
Online resources	MI	564	MI	257
Roofing contractors	NI	470	NI	212
Solar installers	VI	597	VI	315
Neighbors	NVI	518	NVI	231
Local non-profits	NI	472	NI	199
Acquaintances	NVI	517	NVI	228
Family	NVI	511	NVI	232
Local utility	NVI	550	MI	289

Table A3. This table shows the distribution of local and cosmopolitan information preferences. The two indices are related with Pearson's $r = 0.43$.

	Local index values			
Cosmopolitan index values	0	1	2	3
0	453	140	27	1
1	51	253	69	4
2	13	36	10	0
3	8	17	4	2

Acknowledgments

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