On Information Channels and Peer Effects in the Adoption of Residential Solar PV

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Abstract

We quantify the effect of different information channels on aspiring PV adopters' decision period, the time between when a household begins to seriously consider PV and the date when they sign a contract to install a PV system. Using data from a household-level survey of solar PV owners in Texas, we find that the length of the decision period depends on the information context (e.g., leasing) and on special opportunities to learn (e.g., peer effects). We also find that peer effects operate via two main channels, each of which reduces the decision period. First, the largely psychological influence (increased confidence and motivation) that accrues simply through witnessing PV systems in the neighborhood. And second, the more economic influence in the form of highly relevant and trustworthy information—an economic good—that accrues through peer-to-peer communications. The psychological channel (of peer effects) operates independently of, and is usually a precursor for the economic channel. But the economic channel reduces the decision period by twice as much as the psychological channel. Based on these findings, we outline an integrated information system that could be effective in reducing uncertainties and non-monetary costs of adopting PV, and thus, might help accelerate the adoption of PV.

Keywords: Residential Solar PV; Diffusion of Innovations; Peer Effects

1. Introduction

Largely due to a combination of attractive federal, state, and local financial incentives, over the last few years the adoption of solar photovoltaic (PV) technologies has dramatically accelerated in the residential sector in several states in the U.S., particularly in California, New Jersey, Colorado, and Texas. Yet, current adoption levels in this (residential) sector are below 2% of the market potential (Paidipati *et al.*, 2008). Several incentive programs are nearly a decade old, and still several states and utilities are not clear what the most effective and efficient incentives schemes should look like. Many of these programs are in a state of continual flux.

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Clearly, PV technologies not only have a tremendous scope for broader adoption but also face substantial challenges in a world of uncertain policy environment, energy markets, and intense technology competition.

Information is paramount in the adoption of capital intensive consumer technologies like PV. A large body of research within the diffusion of innovations framework (DoI) has established that technologies that diffuse widely are sequentially adopted by different adopter categories (innovators; early adopters; early majority; late majority; and laggards) that vary in their socioeconomic status, risk aversion, and opinion leadership (Rogers, 2003). Digging deeper into the consumer decision-making process, DoI has shown that there are additional critical elements involved in the diffusion of technologies than just the financial aspects. According to DoI, five intrinsic characteristics of innovations guide an individual's decision to adopt or reject an innovation—relative advantage, compatibility, complexity, observability, and trialability. Evaluation of a technology along these dimensions is an *information (and time) intensive process*, as it involves information gathering and comparison with alternative investment options before a final decision is made. The higher risk associated with capital intensive technologies like PV makes accurate information in this context even more valuable to consumers. Such purchase decisions are made only so often, and any mistake in judging the value of such technologies comes with high cost. As pointed out by Nelson (Nelson, 1970), in part the capital intensive nature of these technologies acts as a selective guide in the development of the associated information channels that support the consumer decision-making process. In particular, these information networks typically have either a "brand" bias—only a few brands of a particular product/technology are supported because of brand reputational effects—or, they exhibit strong overlaps with interpersonal networks (family, friends, neighbors). In general, the more complex, novel, and expensive the technology, the more intense is the consumers' information requirement.

Although the market and institutional context, including price, tax incentives, local rebates and so on, greatly affect market development, social and communication networks that provide product-relevant information are also key determinants in the actions of individuals who make up the socio-technological system. Extensive DoI research strongly suggests that diffusion of new consumer technologies is fundamentally a social process, and that "the heart of the diffusion process consists of interpersonal network exchanges and social modeling by those individuals who have already adopted an innovation to those individuals who are influenced to follow their lead" (Rogers, 2003).

Perceived uncertainties and non-monetary costs (UNMCs) associated with the adoption of new technologies are key to understanding why social and communication networks are so important for the diffusion of technologies. In the context of PV, for example, the "value of PV" is a characteristic of the individual adopter and takes into account not only the monetary cost of the technology, which includes both equipment and installation costs, but also non-monetary costs, such as information search costs and uncertainty about the future performance, operations and maintenance requirements, and perceptions of quality, sacrifice, and opportunity cost (Zeimthaml, 1988; Faiers & Neame, 2006). To reduce their UNMCs people rely on the personal evaluation of the technology by those who have already adopted it (Rogers, 2003). Since direct experience pre-purchase through trialability is limited, especially for high capital cost technologies, much information gathering is done through "trial by others", utilizing interpersonal networks (Labay and Kinnear, 1981). Thus, information flows from existing adopters to potential adopters, making the diffusion of technology a social process (Rogers, 2003). As more people become adopters the observed performance of the technology spreads through the networks at a faster pace, further reducing the uncertainties associated with adopting the technology. Effectively, the actions of previous adopters have *peer effects* that influence non-adopter's attitude and behavior toward the new technology. These effects have been studied recently in vehicle purchases (Narayanan and Nair, 2011; Bradlow *et al.*, 2011; Axsen and Kurani, 2009), and a recent study suggests that peer effects could be playing a significant role in the adoption of PV by residential consumers in California (Bollinger and Gillingham, 2011). This social learning process and the concomitant knowledge spillovers reduce the costs and uncertainties associated with adopting a new technology. This key function of social networks—namely, the reduction of UNMCs associated with the adoption of new technologies—is believed to make the diffusion of innovations an inherently social process.

Just as markets and institutions can fail to support the diffusion of new technologies, network failures in the communication and interpersonal networks due to lack of connectivity among the actors within the network could have a chilling effect on technology diffusion

(Jacobsson, 2000). Consequently, even if favorable contextual factors (such as high electricity prices and local incentives for PV) are present, if the connectivity within the underlying information networks is poor, technology diffusion might not be sustained.

Important as it is, the role of information networks and peer effects in the diffusion of residential PV is relatively unexplored. While the financial barrier to PV diffusion has been well documented in the literature (Timilsina *et al.*, 2011; Guidolin and Mortarino, 2009; Margolis and Zuboy, 2006), the role of information networks and peer effects in overcoming non-financial barriers to PV adoption remains understudied (Margolis and Zuboy, 2006). The limited and coarse understanding of these often critical factors have largely failed to generate actionable policy and marketing insights.

In this paper we use a new dataset to study the structure of information networks associated with the adoption of PV. Specifically, we characterize the information networks that potential adopters employ to mitigate UNMCs of PV adoption: what uncertainties and barriers do potential adopters face? What information sources (other PV owners, websites, electricity utilities, government reports, etc.) do consumers use to inform their decision to install PV? How valuable are these different sources? How do social networks and interactions influence the adoption process? We also identify those factors that are most effective from the consumers' viewpoint in reducing UNMCs, and hence the length of the decision period. Our analysis is based on data from a survey on the adoption experience of PV owners in Texas. Descriptive statistics are used to gain insight into the decision process for PV installation and for hypothesis generation. Finally, 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. The keystone of these recommendations is the establishment of state-specific partnerships to better internalize the benefits of information sharing between current owners and potential adopters and serve as a central hub of information on solar PV technology.

2. Data and Methodology

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 study the experience in selecting and installing a solar PV system by those who have installed PV at their homes. Only households that have already adopted PV were part of this survey. The survey consisted of sixty questions, which were organized in the following seven sections: (i) system details (ii) decision-making process (iii) financial aspects (iv) sources of information (v) expectations/evaluation (vi) environmental attitude (vii) demographics. A summary of the overall findings from the survey is also under preparation (Rai and McAndrews, 2012).

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 2008-2011. The majority of 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. Although we do not have the exact figures, we estimate from Texas solar program data that our sample of received complete responses (365) represents about 20% of the entire target population (residential PV adopters) in July 2011 in the areas where we conducted the survey. A geographic summary of responder locations is shown in Figure 1 at the zip-code level.

[FIGURE 1 ABOUT HERE]

The length of time (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. Referenced survey questions are listed in Appendix A, Figures A.1-8. The survey data contains a mixture of continuous and categorical (ordinal) data. Categorical data is largely 5-grade Likert scale-based (e.g. Strongly Agree, Agree, Neutral, Disagree, Strongly Disagree), with some 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, potentially allowing for more robust parametric analysis (Norman, 2010).

Summed items in the Likert scale create a measure of attitudes, and must satisfy consistency and comparability criteria between items (Mainieri *et al.*, 1997). There are problems applying parametric statistics to single questions (Likert items)—for example, when estimating central tendency, strong disagreement, and strong agreement are averaged, providing the misleading impression of neutrality (Gob *et al*., 2007). However, use of the median for central tendency may have the related problem that different patterns of response may have the same median score. For this reason, where appropriate, multiple indicators are given. 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 Results and Hypotheses

3.1 Uncertainty, Non-monetary Costs, and Decision Time

According to survey responses, information on PV systems is widely available to potential adopters. The distribution of responses to a Likert item regarding adopters' experiences finding dependable PV information is right-skewed, indicating that information was relatively easy to find (mean 2.52, median 2, skewness 0.31, std. deviation 0.95). At the end of the decision period (DP)—the time period between when a household begins to seriously consider PV and the date when they sign a contract to install a PV system—most respondents seem to have developed a good understanding of the technical as well as financial attributes of PV. In other words, the necessary information is out there.

While there is no dearth of PV-related information for potential adopters, the relevance and trustworthiness of information continues to be an issue. The left-skewed distribution of survey responses reflecting time spent researching PV (mean 3.38, median 3, skewness -0.11 std. deviation 0.96) suggests that the respondents spent significant amount of time and effort sifting through all this information during their DP. Further, as shown in Figure 2, the average reported DP was 8.9 months (median of 6 months).

[FIGURE 2 ABOUT HERE]

Analysis of an open-ended question regarding the information-search experience further confirms that while information is easily available, potential adopters are not quick to trust it. We find that prospective adopters rarely complain about too little information; instead they face an information overload from a variety of sources, not all of which are trustworthy. This makes it difficult for adopters to distill information into a coherent picture showing how residential PV will affect them. As a way to improve the value of information that is available many respondents expressed a desire for a "centralized" information source hosted by government or electric utilities.

In agreement with prior research in other areas of behavior change (Dietz, 2010), these insights suggest that trustworthiness of the information source is a key factor in determining DP. That is, 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”). Accordingly, we hypothesize:

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

3.2 Peer Effects in the Adoption of Residential PV

Peer effects are known to play an important role in the process of diffusion of innovations (Gerowski, 2000; Rogers, 2003). Typically consumers go through an evaluation period wherein they estimate the value, including both monetary costs as well as UNMCs, of the technology in question. Due to the limited trialability of PV systems, potential adopters must overcome UNMCs through “trial by others.” Thus, as elaborated above in Section 1, information passes from previous adopters to potential adopters through observation and communication. In the process, 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.

The localized nature of these effects and the early stage of PV diffusion in Texas make it difficult to study them at the macro level—even as overall adoption increases in the population, individuals may still be among the early adopters to install in their neighborhood, making utility, state, city, and even zip-code level data somewhat problematic. One way out of this issue is to look for pockets of areas that have a relatively high density of PV adoption. Austin, Texas is one such area within the sample, and for the remainder of this subsection we focus on data from only Austin. Within the Austin sample we further scrutinize data from the Mueller community. This 700 acre redevelopment project, sited at the location of an airport closed in 1999, will eventually include more than 4900 homes and 4.5 million ft^2 of commercial and office space. PV installations started soaring in Mueller since 2009. In August 2011, when the survey administration began in Mueller, about 10% homes in the community (of about 650 homes) had already installed PV systems (as of this writing the penetration level is close to 30%, making Mueller one of the densest pockets with PV installations at the neighborhood level in the U.S).

In this paper, we define peer effects as the influence of PV systems in the neighborhood on the final decision of a potential adopter to install PV. Further, a house's neighborhood is defined as the area within a five to ten block radius from it. Note that this definition of peer effects focuses solely on the attitudinal and behavioral stimulus that *seeing* PV systems in the neighborhood induces; it *excludes* the impact of contact with other PV owners, which, as described later, is captured separately. 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, early on in the instrument, we ask respondents about the level of importance of PV systems in the neighborhood in their final decision to install PV. Second, midway through the instrument, we revisit the peer effects topic in more details through a series of four 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”.[1]

Most of the PV adoption in Austin has been sparse between 2004-2008, and so we find only weak evidence of the influence of peer effects during this period. But where PV systems are more densely located, such as in Mueller, we do find strong peer effects. Largely because of the inclusion of this group (Mueller) the percent of respondents who state that the influence of PV

[1] Responses to these statements track each other closely, suggesting that the netting term “peer effects” has value.

owners in the neighborhood was at least "moderately important" in their final decision to install has been increasing rapidly since 2009 in these areas (Figure 3). Slicing the data a little differently further supports these findings. Figure 4a shows the influence of peer effects in Austin excluding data from Mueller; Figure 4b shows the influence of peer effects in Austin including data from Mueller. The inclusion of Mueller data shows the tremendous impact that peer effects have had on PV adoption in this community. In sum, these insights suggest that *peer effects reduce UNMCs* by providing motivation and confidence to potential adopters. As a result, we can expect that reduced UNMCs owing to peer effects should be manifested as a shorter DP. Further, we might expect peer effects to increase with the number of systems in the neighborhood. Accordingly, we hypothesize:

Hypothesis 2a: PV owners who reported greater peer effects have shorter DP.

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

[FIGURE 3 ABOUT HERE]

[FIGURE 4a ABOUT HERE]

[FIGURE 4b ABOUT HERE]

3.3 Contact

The next level of information gathering to reduce UNMCs during the decision-making period involves direct contact (discussion) with existing PV owners. As discussed above, in this paper we separate this effect from peer effects, which we define as only the influence of PV systems in the neighborhood, excluding the influence that accrues through direct contact. Direct contact provides the opportunity to seek information that is directly relevant to the decision maker. As such, we expect direct contact to be one of the most effective information channels in reducing UNMCs.

Among the respondents 90.5% agreed or strongly agreed with the statement, “Talking to owners of PV systems was useful or would have been useful.” Thus, 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, reducing UNMCs. This shows, in accordance with DoI, that contact is a way of accessing trustworthy information if such information is not available otherwise (for example, through a trusted government website).

Of the respondents who contacted other PV owners prior to installation 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, standard deviation 0.93). Further, as shown in Figure 5, we find that potential adopters who had a difficult time finding dependable information are more likely to disagree with the statement, "Talking to other owners is unnecessary" (χ^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 (χ^2 $p < 0.02$). This suggests that direct contact is perceived as an effective channel for reducing uncertainty: potential adopters in need of information would like to access the stock of knowledge formed by the experience of existing owners.

[FIGURE 5 ABOUT HERE]

Further we classify direct contacts based on if those contacts were with PV owners in the neighborhood or outside the neighborhood. Essentially, 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*). As demonstrated in Figure 6, we see that the impact of peer effects on these groups is different. We also note that 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 peer effects, but they also gain valuable information when they reach out to other PV owners in the neighborhood. 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.

[FIGURE 6 ABOUT HERE]

3.4 Buying vs. Leasing

While there is need 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. For example, the solar leasing model makes information gathering for potential adopters redundant along several dimensions, especially regarding performance and guarantee of the PV system (Mont, 2004; Shih and Chou, 2011). That is, those who lease do not spend as much time researching any other attribute of solar but finances. This is consistent with the fact that typically performance, and operation and maintenance (O&M) of the equipment is covered under the lease agreements; so these aspects do not concern leasers much. In our survey, on average, compared to buyers of PV systems leasers report spending less time researching (χ^2 $p < 0.01$), and report easier availability of dependable information (χ^2 $p < 0.02$). Further, compared to buyers their average DP is lower by about 2 months (mean 7.34 months, median 6, std. deviation 0.99). Consistent with all this, among leasers 87% agree or strongly agree that talking to other PV owners is unnecessary. These insights suggest that the form of ownership is expected to impact DP because different ownership models impose different UNMCs on potential adopters. In particular, the UNMCs associated with the leasing model are inherently low. That should lead to a shorter decision period, or equivalently to faster adoption of PV. Accordingly, we hypothesize:

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

4. Modeling the Decision Period

While descriptive statistics provide much insight, a full understanding of the factors influencing decision times necessitates multivariate analysis. Based on *Hypotheses* 1-4, variables for intensity of information required (*InvestVIEI*), peer effects (*PeerEfSum*), neighborhood contact (*HCN*), and leasing (*Lease*) were created to model DP, the length of a PV adopter's decision period. Control variables were added for residual uncertainty (*MnPRsh*), number of contacts (*Own_Cont*), and adopters with hallmark of "innovators", who, for idiosyncratic reasons, appear to demand very little information (*Innovators*). We modeled DP (denoted by the variable *Cons_Mo*) in equation 1 as:

$$Cons\_Mo_i = \beta_0 + \beta_1 InvestVIEI_i + \beta_2 PeerEfSum_i + \beta_3 HCN_i + \beta_4 Lease_i + \beta_5 MnPRsh_i + \beta_6 MnPRsh_i^{\,2} + \beta_7 Innovators_i + \varepsilon_i \qquad (1)$$

Variables are listed in order, and are defined in Table 1.

[TABLE 1 ABOUT HERE]

4.1 A Note on the Control Variables

Post-research, or residual uncertainty, measured by *MnPRsh*, is an indirect measure of the effectiveness of the research period. Effective research will create certainty regarding value, and yield low UNMCs at the time of installation. *MnPRsh* is the sum of Likert items regarding understanding of installation, warrantee, maintenance, financial aspects, and impact on home value. These Likert items demonstrated a high degree of equidistance and symmetry and fulfilled the proportional odds assumption. This variable was transformed to create a second-order polynomial to better represent its curvilinear relationship with DP (this is further discussed in Section 5). *MnPRsh* and its square *MnPRshSq* are individually significant ($P < 0.0001$) and jointly significant ($P < 0.0001$). Both were centered by mean-subtraction (the mean and median of the variable were roughly identical: 3.03 and 3.00, respectively) to reduce variance inflation factors, as discussed in the diagnostics section. Holding all other factors constant, responders who reported very low or low residual uncertainty (i.e., small values of *MnPRsh*) have slightly higher decision times on average than those who reported middling uncertainty—likely reflecting the time investment required to reduce UNMCs to low levels. Holding all other factors constant, responders who reported very high residual uncertainty (i.e., large values of *MnPRsh*) have much higher consideration times on average than those who report middling uncertainty. This is indicative of significant difficulty accessing reliable information, leading to a relatively unsuccessful research period. By measuring residual uncertainty, the control in effect captures those aspects of the adopters' information search process that are not explicitly modeled through the explanatory variables.

Ceteris Paribus, every additional owner contact (in or outside the neighborhood) might be expected to increase DP. This can be explained by consideration of what each additional contact means for a potential adopter: if one contact is enough to reduce UNMCs to the threshold of adoption, the potential adopter will not seek additional contacts. Potential adopters with large number of contacts either did not get all the information they need, or feel the need for the increased trust gained by redundancy. This takes time, increasing DP. So we control for the number of owner contacts (*Own_Cont*).

An additional variable, *Innovators,* controlled for respondents who did not think talking to others was useful and experienced no peer effect; and those who bought their system, did not experience peer effects, and had decision times under three months. In effect, this variable controls for the "true innovators"—those who were already convinced about adopting PV. As discussed in Section 5, this control variable also reduces heteroskedasticity associated with some of the explanatory variables.

4.2 Regression Results

Figure 7 displays the results of the regression. The model explains about 24% (Adj. R^2 = 0.24) of the variation in DP for PV owners. Despite this, the root MSE (standard deviation) of the model is high (8.00), limiting its predictive potential. As such, the model is more useful as a descriptor of the components of the information channels associated with solar PV adoption that impact adopters' UNMCs and the decision process, rather than a predictor of DP for specific potential adopters.

[FIGURE 7 ABOUT HERE]

Installing PV for financial reasons requires more certainty, and trustworthy financial information may be the most difficult to find. So 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 (Figure 7). Therefore, we find support for (fail to reject) *Hypothesis 1:* PV owners who need greater information certainty have higher DP.[2]

The positive coefficient for peer effects (*PeerEfSum*) demonstrates that peer effects reduce decision times ($P < 0.008$). An increase of one on this scale indicates movement toward the "strongly disagree" (that peer effects were important) pole of the Likert scale measuring reported peer effects (Appendix A, Figure A.8). This variable uses the section sum average method (Mainieri *et al.*, 1997), 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 peer effects) results in a decrease of 1.5 months between initial consideration and installation of PV. Thus, we find support for (fail to reject) *Hypothesis 2a:* PV owners who reported greater peer effects have shorter DP.

While the reported number of systems in the neighborhood (*PV_in_Nei*) was not significant in the model and was removed ($P > 0.1$), this is likely due to the more direct measure of the peer effects variable (*PeerEfSum*) combined with the importance of 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* we find that *PV_in_Nei* is the most significant explanatory variable generating peer effects.[3] Thus, we find partial support for *Hypothesis 2b (*PV owners with more systems in their neighborhood have shorter DP), in that number of systems in the neighborhood is linked to peer effects and contact, which reduce DP.

On average, while holding all other factors constant, having contact with a neighborhood PV owner prior to installation (*HCN*) decreases decision time by 4.6 months ($P < 0.004$). Based

[2] We are performing additional tests for this hypothesis using *EnvVIEI* with the contention that those who report environmental concern as very or extremely important in their decision to adopt PV would have shorter DPs (because, presumably, they do not need as much information); and using *HighInc* with the contention that the information requirements of those in the higher income brackets is also lower than the average, so their DPs will be lower.

[3] Controlling for *Lease*, *InvestVIEI*, and *Innovators* variables, each additional system in the neighborhood results in movement toward the "strongly agree" (that peer effects were important) pole (see Appendix A, Figure 8), and was highly significant ($P<0.0001, \beta=0.05$). Environmental variables were not significant and were removed from the model.

on these results, we find support for (fail to reject) *Hypothesis 3:* PV owners who had direct contact with other PV owners in the neighborhood will have the shortest DP compared to all other groups. Recall that we separate the impact of peer effects and direct contact in the model. A potential adopter in the *HCN* group likely first experiences 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 peer effects and of direct neighborhood contact. Dropping the peer effects measure from the model yields a coefficient for this combined effect—the *full* peer effects—of -6.67 months ($P < 0.0001$).

To further understand the impact of different types of social influences on adopters' decision period, we added variables for contact only *outside* the neighborhood (*HCO*) and for neighborhood systems but no direct contact (*NCN*) to the model (see Figure 6). On average holding all other factors constant, *HCO* decreased DP (β=-1.41) but was not significant ($P > 0.35$). *NCN* also decreased DP ($\beta = -1.07$) but was not significant ($P > 0.45$) either. 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 the model that includes both *NCN* and *PeerEfSum* the coefficient for *NCN* is being captured through *PeerEfSum*. Interestingly, adding the *NCN* and *HCO* variables while dropping the peer effects variable (*PeerEfSum*) from the model increased the coefficient of *NCN* ($\beta = -2.08$) and significance ($P = 0.15$) as well as of *HCN* ($\beta = -7.71$, $P < 0.0001$), strengthening our claim that peer effects (as defined here) occur primarily through observation.

While holding all other factors constant, on average leasing PV decreases consideration time by 2.23 months ($P < 0.047$). Thus, in addition to the already understood benefit of the leasing model, namely, no upfront capital cost of PV ownership (Mont, 2004; Shih and Chou, 2011; Drury *et al.*, 2011), we also show that the leasing model significantly reduces UNMCs associated with PV adoption, leading to faster adoption rates as reflected in a lower DP for leasers. That is, we find support for (fail to reject) *Hypothesis 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.

Sensitivity testing also revealed that if the variables for residual uncertainty, *MnPRsh* and *MnPRshSq*, are dropped from the model, the *Lease* variable becomes more significant ($\beta = 2.74$ $P < 0.03$). This suggests that some of the variation in decision times attributed to leasing in the sensitivity model without a residual uncertainty term is attributed in the full model to *MnPRsh*, and *MnPRshSq* due to low levels of multicollinearity between leasing and residual uncertainty. Because leasers have inherently lower UNMCs, it is more likely that they will have lower residual uncertainty when compared to buyers. This also supports using residual uncertainty as a control variable in our model.

5. Model Diagnostics and Sensitivity (PRELIMINARY)

The length of the survey created the potential for larger number of potential variables to be added to the model, as well as the potential for large uncertainty in model specification. The variables selected in the final model were tested for robustness through a best subsets procedure from Beal (2005) utilizing the SAS® system for minimization of Akaike's Information Criteria (AIC). Multiple rounds were used due to the fact that the SAS® system best subsets procedure is limited to ten variables per round. This procedure was repeated over 124 rounds, with 1024 models simultaneously evaluated each round. Demographic variables, environmental beliefs, and system specifications (size, final cost, etc.) could not be shown to significantly influence DP. The main explanatory variables resulting from *Hypotheses* 1-4 (*InvestVIEI*, *PeerEfSum*, *HCN*, and *Lease*) were consistently selected through the (optimal) best subsets procedure. This procedure gives us a high degree of confidence in the model.

In early stages, with the inclusion of only *HCN*, *Lease*, *PeerEfSum*, *Own_Cont*, and *InvestVIEI* based upon *Hypotheses* 1-4, the model displayed heteroskedasticity among independent variables. Heteroskedasticity was tested using White's test (White, 1980). Initial Chi-square test statistics led to rejection of the null hypothesis (H_0: Variance of the residuals is homogenous). Examination of residual plots showed increasing variance in the *PeerEfSum* variable. The addition of two control variables, *MnPRsh*, and *Innovators*, decreased heteroskedasticity beyond significance ($\alpha = 0.05$, $P < 0.15$). The *Innovators* variable controlled for respondents who bought their system, had a decision period of less than three months, experienced no peer effects, had no contact with other owners, and also disagreed that talking to others was useful or would have been useful. In effect, this variable controls for the "true innovators"—those who were already convinced about adopting PV, perhaps for some other specific reason(s). As discussed in Section 4.1, *MnPRsh* controls for residual uncertainty. The addition of these control variables did not significantly alter variable coefficients or P values ($\Delta\beta < 0.1$, $\Delta P < 0.01$).

While these controls do much to reduce heterogeneity in residual variance, some variables, such as *Lease*, *HCN*, *PeerEfSum*, and *Own_Cont* continue to display greater residual variance where the variable effect is lowest (i.e. *Lease* = 0; *PeerEfSum* = 5) as is shown in Figure 8. This suggests that other influential variables, though perhaps with only marginal significance, may be absent.

[FIGURE 8 ABOUT HERE]

OLS regression models must satisfy the linearity requirement for the coefficients. The observed-to-predicted plot for the model suggests that full inclusion of the outliers (those with very large DP) could be problematic. For the results reported here (Figure 7), this has been mitigated by the removal of three large outliers (DP > 60). While values are fairly evenly distributed around the fit line for most observations, outliers still have a fair amount of leverage in the model. This can be seen in the Cook's D plot (Figure 8). The sample has been ordered according to DP, demonstrating the increasing leverage (Cook's D > 0.4) of the responders with the longest decision times. This effect is seen again in the histogram of the residuals (Figure 9), which has positive skew, suggesting that the coefficients may be slightly biased.

[FIGURE 9 ABOUT HERE]

Multicollinearity is not a major problem in this model, as is demonstrated by the low variance inflation factors (VIF) shown in Figure 7. Variance inflation between *MnPRsh* and *MnPrshSq* was reduced through mean centering as described in Section 4.

6. Conclusion

In this paper we have studied the effectiveness of different information channels in reducing uncertainties and non-monetary costs associated with the adoption of residential solar

PV. We built the data for this analysis through a survey of residential PV owners in Texas. Based on survey responses, we find that potential adopters of solar PV systems invest large amounts of time—nearly nine months on average—and effort into researching the technology. Information on PV systems was not difficult to access for most respondents, suggesting that the availability of information alone does not cause long research times. Uncertainty and non-monetary costs remain, even when information is available. This pattern may be indicative of a lack of *trust* in available information.

Consistent with Nelson's (Nelson, 1970) view on the role of information networks for experience goods, we find that potential PV adopters benefit from and tap into the knowledge stock of the existing user base. Our multivariate regression model suggests that leasing, peer effects, and contact with neighbors each significantly decreased decision times among survey respondents. Among respondents, contact with neighbors before installation was the single most effective strategy for speeding decision times. This is because in practice this contact provides a double dividend for potential adopters: through *peer effects,* it first instills interest and confidence in the technology and the motivation to find out more; additionally, it also provides access to trustworthy information by talking to the neighbors. These results are consistent with the Diffusion of Innovations framework, which suggests that peer-to-peer communication is critical for increased technology adoption (Rogers, 2003; Bollinger and Gillingam, 2011).

Our findings go a step further in that we are able to separate and quantify the key constituents in the black box of "peer effects". Specifically, we find that peer effects operate via two main channels: first, the largely psychological influence (increased confidence and motivation) that accrues simply through witnessing PV systems in the neighborhood; and second, the more economic influence in the form of highly relevant and trustworthy information—an economic good—that accrues through peer-to-peer communication. We find that the psychological channel (of peer effects) can operate independently of the economic channel and is usually a precursor for the economic channel. But the magnitude of the effect of the economic channel is twice as much as that of the psychological channel.

The benefits of peer effects and neighborhood contact are many, including motivation, confidence, convenience, relevance, and, perhaps most importantly, trustworthiness. However, this kind of communication is not *proactively* forwarded by the current system of information available on PV. Our findings hint at the potential structure of an integrated information system that could be effective in reducing uncertainties and non-monetary costs of adopting PV, and thus, might help accelerate the adoption of PV and broaden the potential market. Such an integrated information system would be composed of two main elements. First, a central information clearing house, perhaps administered by the US Department of Energy (DoE), that would be linked to regions, states, and utility service areas, through a standardized process of information sharing across these scales to allow for local information to be available in a transparent manner, which would increase the value and trustworthiness of this information. 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. Access to relevant, location-specific, concise information that has been vetted by a trusted third-party entity such as the DoE would most certainly decrease the research component of household's decision-making process.

Second, designing an incentive structure and communication platform for PV that maximizes peer effects could provide tremendous leverage. For example, considerable benefit could be derived through incentivizing the first few systems in a neighborhood to create a knowledge stock for potential adopters. This would initiate the psychological influence of peer effects and whet others' curiosity and interest in the technology. A communication platform, then, would facilitate peer-to-peer communication, harnessing the strongly effective 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 6 months, or by about two-thirds (*HCN* coefficient for *full* peer effects). Such an initiative would be relatively cheap and would likely enable accelerated growth in the PV market, reducing the burden of support on the government as the residential PV industry expands. Overall, our results suggest that combining these two drivers—the indirect (psychological) and direct (economic) influence of peer effects—have the potential to create positive feedback loops as new adopters are added to the existing base, thereby dramatically increasing PV adoption rates.

We end by noting where our work needs further research and elaboration. 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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Table 1. Description of variables included in the regression model. The output is shown in Figure 7.

FULL MODEL VARIABLES	
Variable	**Explanation**
Cons_Mo	Months responder spent between serious consideration of PV and installation of a PV system (DP).
Intercept	Months of decision period (DP) when all independent variables are equal to 0.
InvestVIEI	Binary variable, respondent indicated that financial aspects of PV were very important or extremely important to the decision to install.
PeerEfSum	Sum of section 4.6, level of agreement with statements regarding neighborhood influence: motivation, confidence and "would not have installed without." See Appendix A, Figure 8.
HCN	Binary variable, whether or not the responder had contact with at least one PV owner in the neighborhood before installation.
Lease	Binary variable, whether the responder leased the PV system, as opposed to bought.
Own_Cont	Number of other PV owners contacted by responder before installation of a PV system.
MnPRsh	Sum of section 2.10, level of agreement with statements regarding post-research uncertainty in performance, operation, maintenance, warranty, installation, and impact on home value. Used as a proxy for "residual uncertainty." Varible in conjunction with MnPRshSq. Has been centered on the mean (3.00).
MnPRshSq	The square of MnPRsh. Together used to estimate the curvilinear relationship of residual uncertainty and DP.
Innovators	Binary Variable: Control for individuals with DP < 3 months who did not lease, experience peer effects, have contact with other owners, and disagreed that talking to others was useful or would have been useful

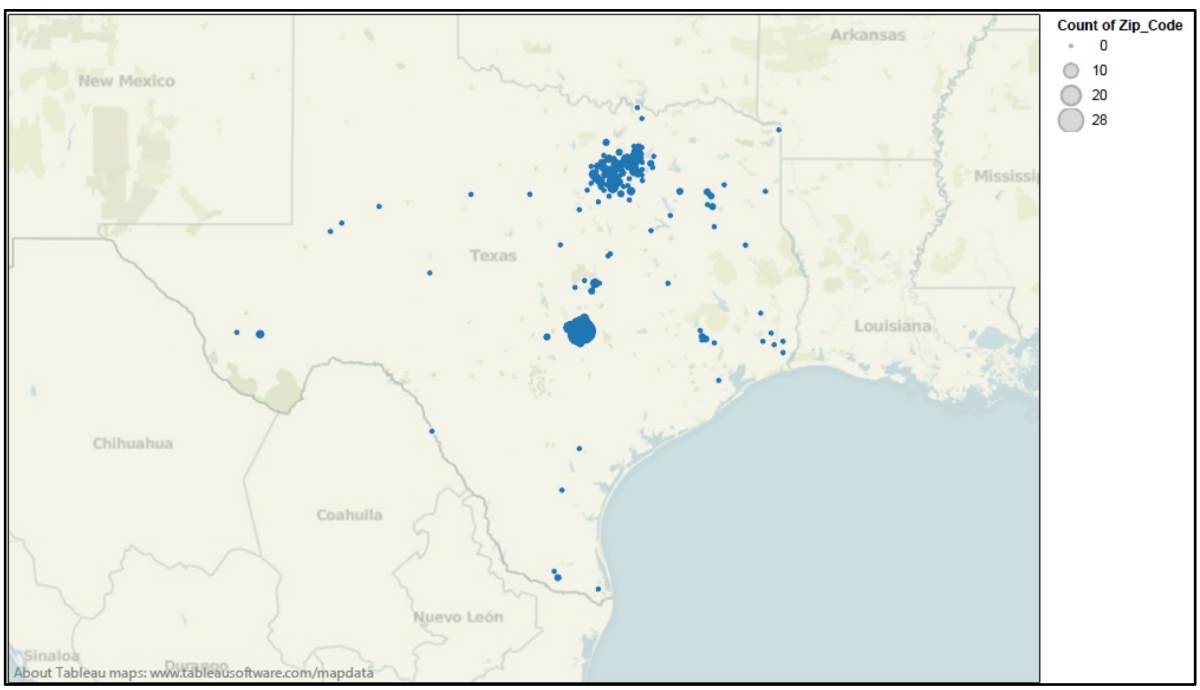
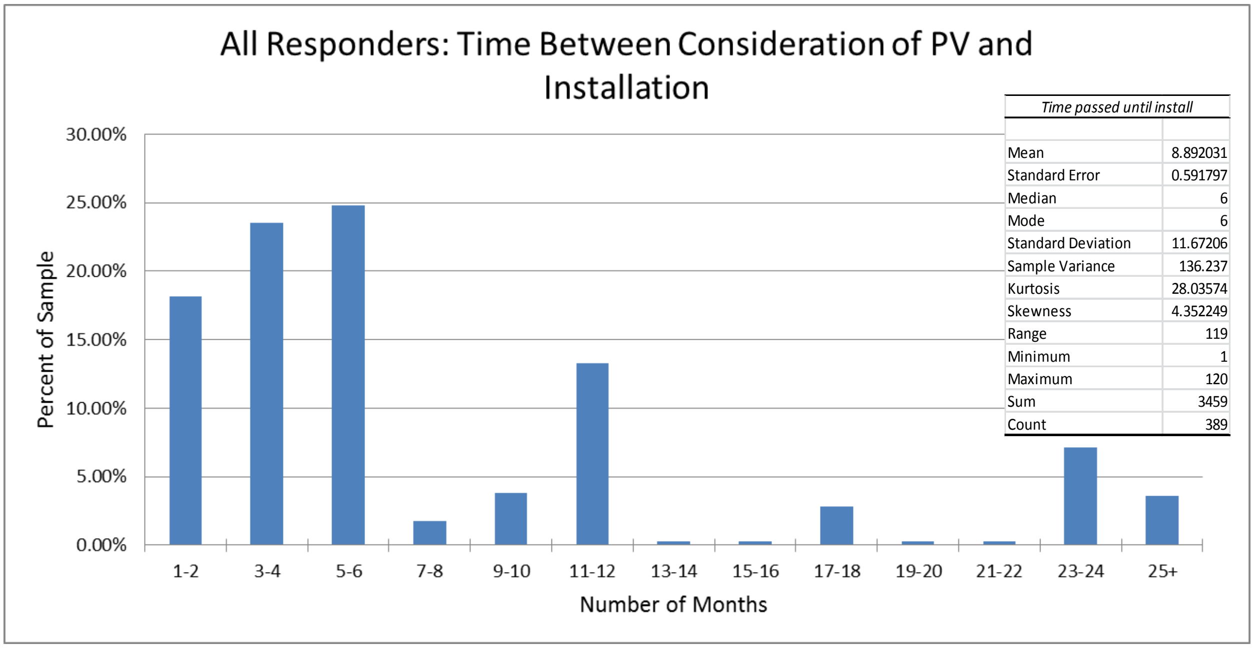


Figure 1: Geographic distribution of survey responders. Size of bubble corresponds to the sample size from each zip code.



Time passed until install	
Mean	8.892031
Standard Error	0.591797
Median	6
Mode	6
Standard Deviation	11.67206
Sample Variance	136.237
Kurtosis	28.03574
Skewness	4.352249
Range	119
Minimum	1
Maximum	120
Sum	3459
Count	389

Figure 2: Histogram displaying number of months spent between serious consideration of PV and installation. The mean value is 8.92, median 6, with skewness of 4.35 and standard deviation of 11.67.

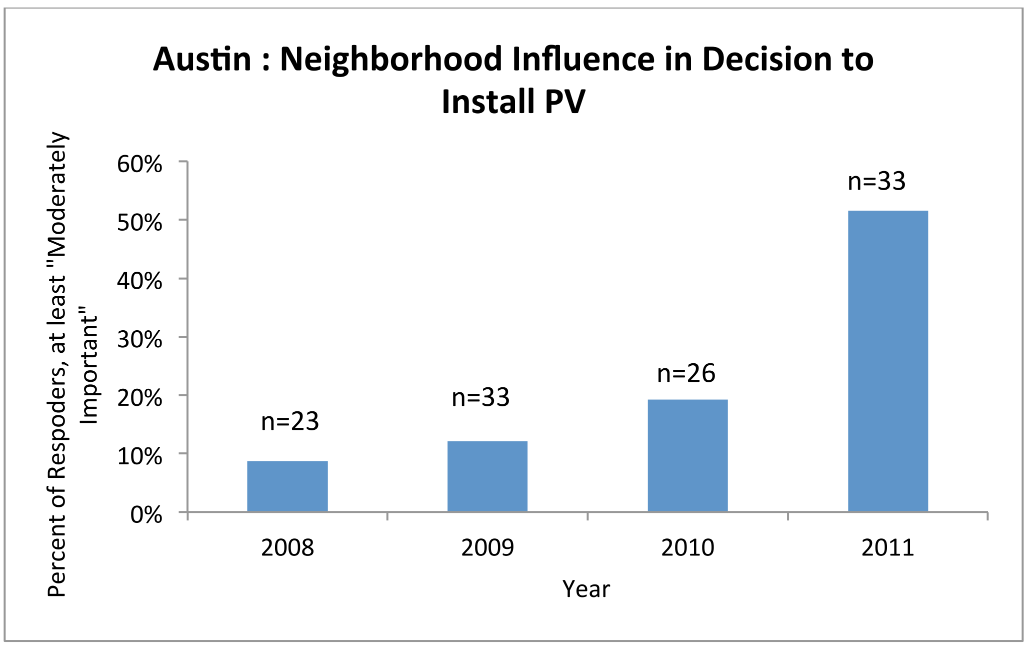


Figure 3: Histogram of responses to the question "How important was the following factor in your final decision to install a PV system: Influence of others in the neighborhood with PV systems" for PV adopters in Austin, Texas. Note that (i) years before 2008 had few observations (n < 12) and were removed from this figure, and (ii) data for 2011 is only through July 2011. The Austin sample is used to demonstrate recent growth in peer effects in a single geographic region. The recent rapid increase in the influence of neighbors is consistent with the hypothesis that peer effects become increasingly influential as the local installed base increases. Peer effects sensitivity to responders from the Mueller community are shown in Figure 4a and 4b.

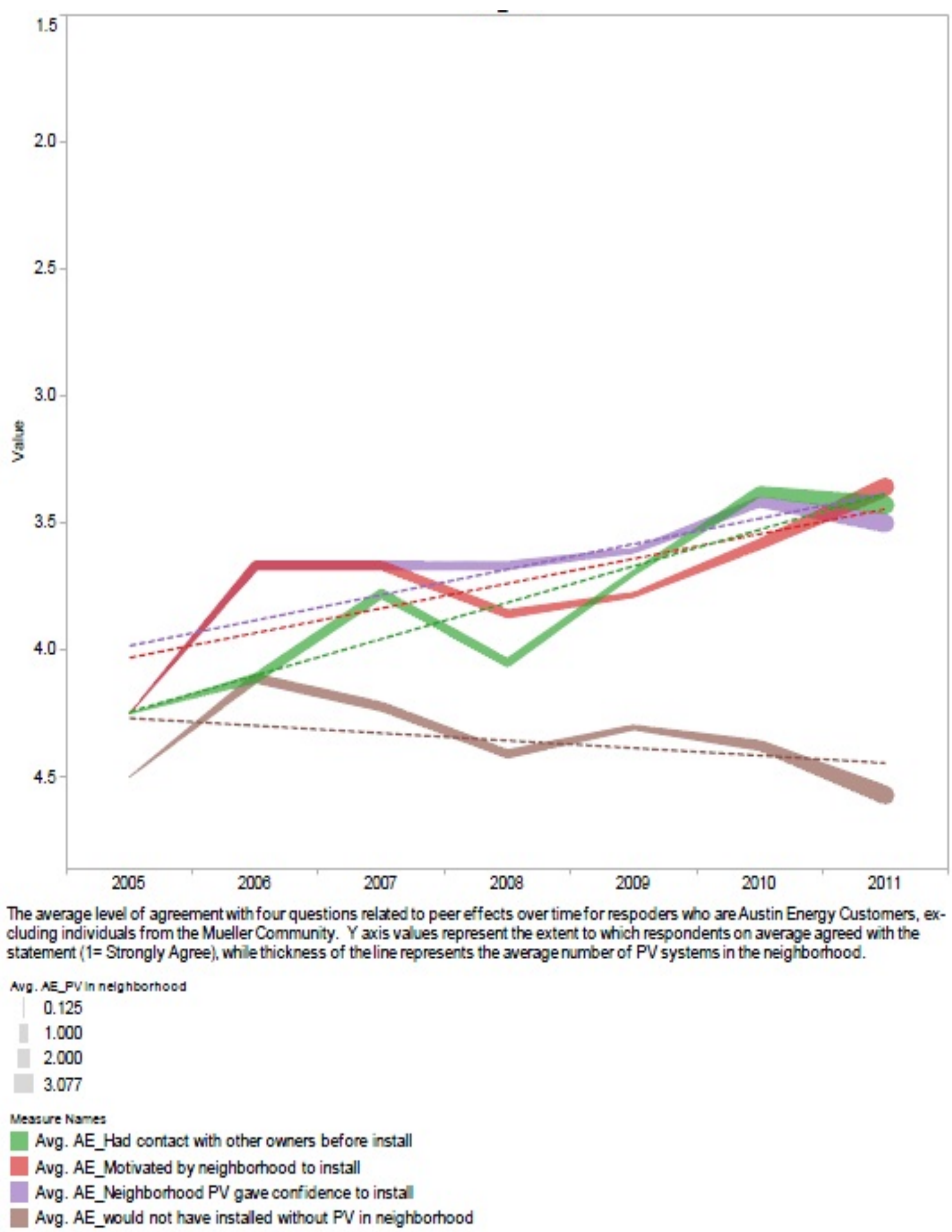


Figure 4a: The graph shows the average responses and trends for four Likert items regarding peer effects from 2005-2011. Earlier years were discarded due to sample size. Width of the line represents number of systems in the neighborhood. The graph excludes members of Austin's Mueller community, while Figure 4b includes all responders, demonstrating the effect of high density installations on peer effects.

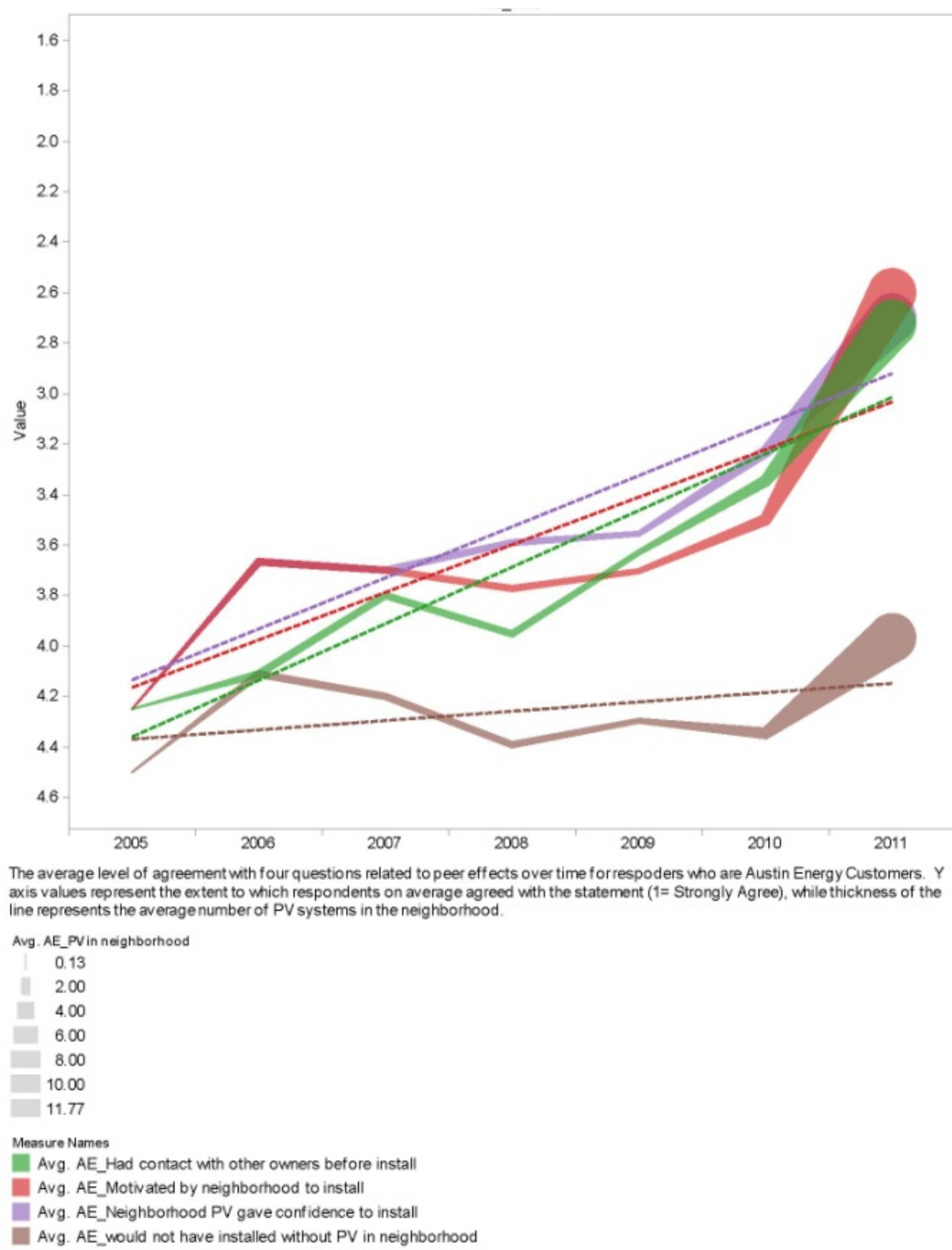


Figure 4b: The graph shows the average responses and trends for four Likert items regarding peer effects from 2005-2011. Earlier years were discarded due to sample size. Width of the line represents number of systems in the neighborhood. The graph includes data for all responders, while Figure 4a excludes members of Austin's Mueller community, demonstrating the effect of high density installations on peer effects.

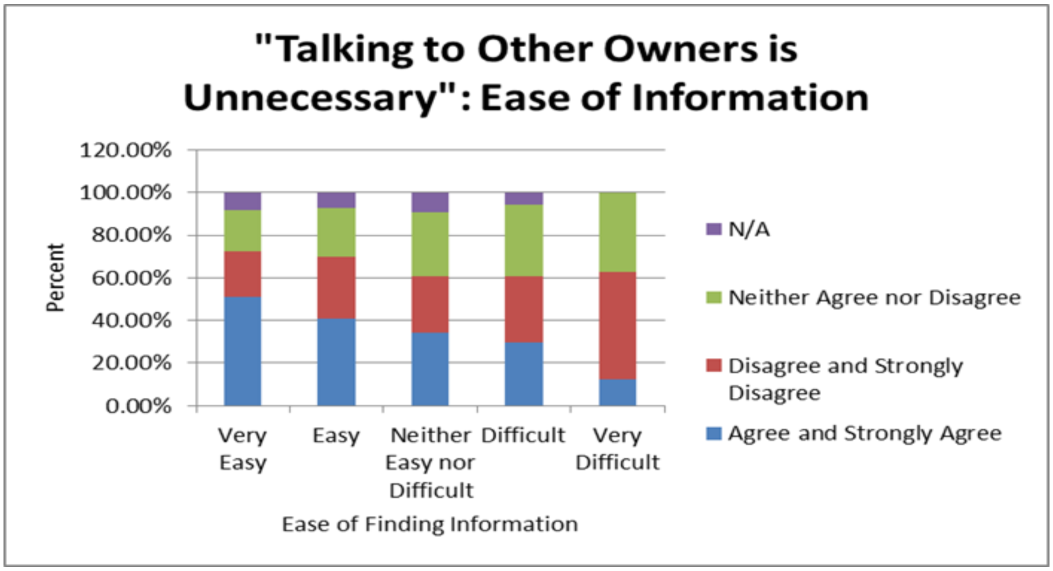


Figure 5: Breakdown of the percent of responders by color according to level of agreement with the statement "I did not find it necessary to talk to other PV owners" and by column for "Overall, how would you characterize the experience of finding dependable information during the time you were researching PV?" Responders without access to information seek to resolve this need through contact.

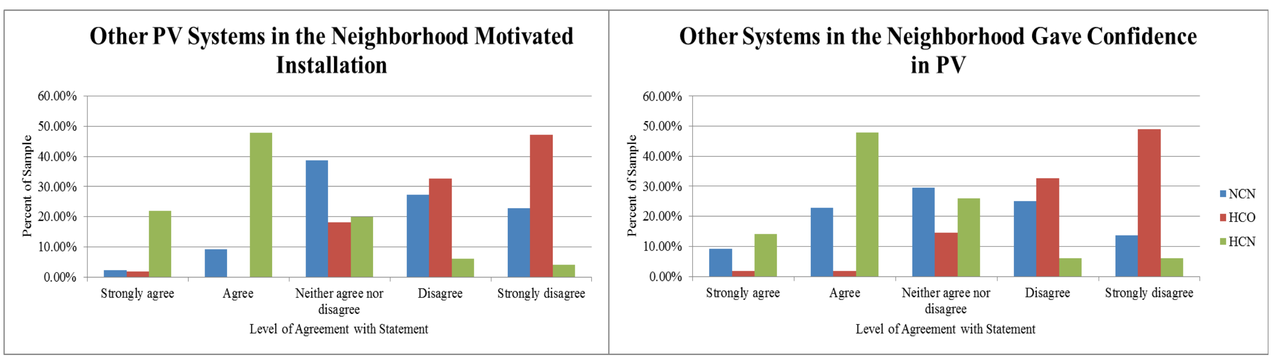


Figure 6: Peer effects affect groups differently based on type of contact. NCN = No contact, systems in the neighborhood; HCO = Had contact only outside neighborhood; HCN = Had contact within the neighborhood. Kruskal-Wallis ANOVA testing shows significantly different population distributions for "Motivated" ($p < 0.001$) and "Confidence" ($p < 0.001$). Average number of systems in the neighborhood varies by group: HCN: 9.80, HCO: 0.29, NCN: 2.43. Median HCN: 2, HCO: 0, NCN: 1.

Root MSE	8.06924	R-Square	0.2569
Dependent Mean	8.18373	Adj R-Sq	0.2385
Coeff Var	98.60092		

Parameter Estimates						
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.29899	2.64196	2.38	0.0177	0
InvestVIEI	1	2.69559	0.99882	2.70	0.0073	1.05198
PeerEfSum	1	1.46139	0.54572	2.68	0.0078	1.47569
HCN	1	-4.69517	1.59155	-2.95	0.0034	1.73269
Lease	1	-2.31624	1.17520	-1.97	0.0496	1.09582
Own_Cont	1	1.18047	0.30842	3.83	0.0002	1.33757
MnPRsh	1	10.28100	1.64652	6.24	<.0001	4.02455
MnPRshSq	1	4.26399	0.80196	5.32	<.0001	4.08387
Innovators	1	-8.47814	1.68863	-5.02	<.0001	1.04944

Figure 7: SAS® output for the model shown in equation 1. Variables chosen for hypothesis testing and checked for robustness via the best subsets selection procedures and model diagnostics described in Section 10. For variable descriptions, see Table 1. Select diagnostic plots are displayed in Figure 8.

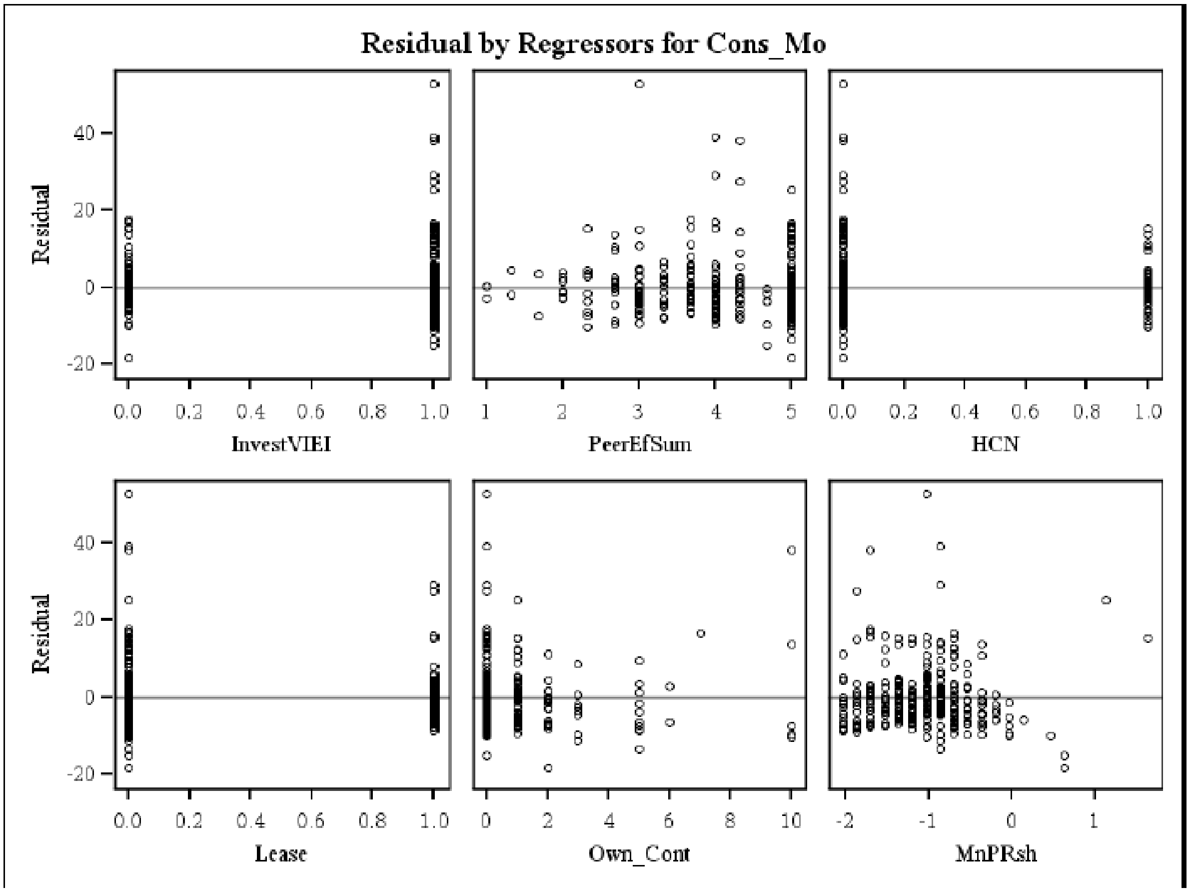


Figure 8: Residual plots for several variables. Heteroskedasticity has been moderated by the addition of controls, discussed in Section 5. While heteroskedasticity is not a problem for the model as a whole, individual variables demonstrate some non-uniform variance.

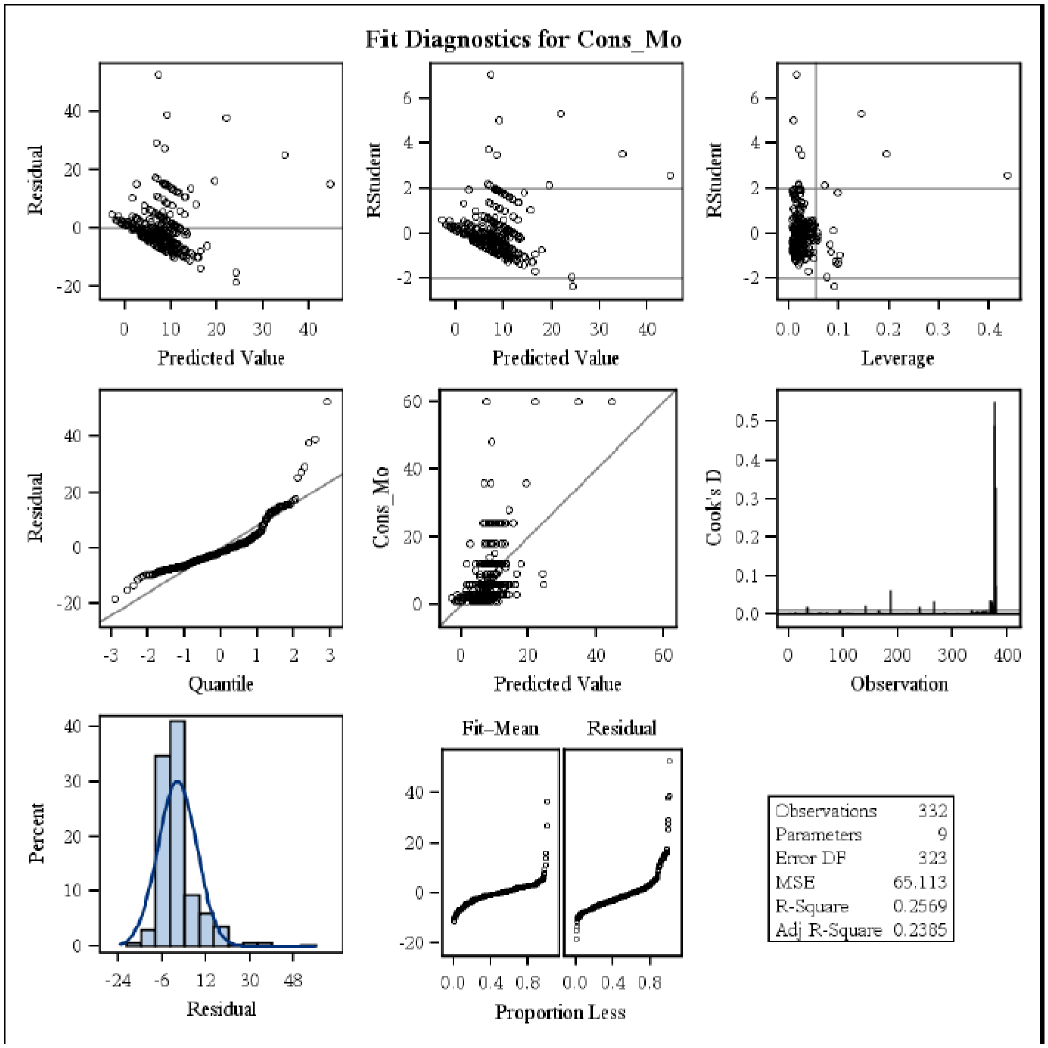
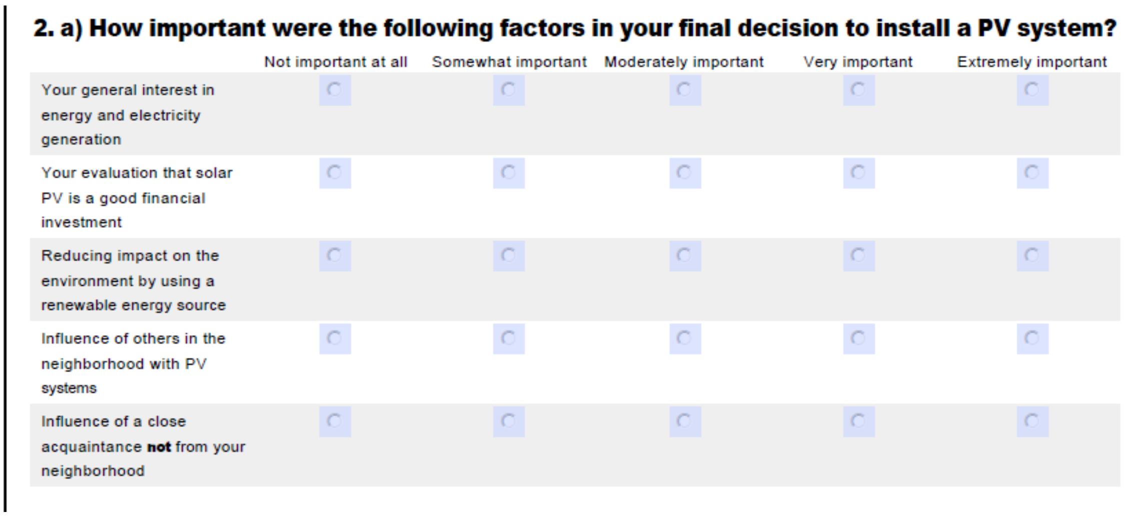


Figure 9: Selected diagnostic plots for the full model shown in equation 1. Banding in observed values and residuals is the result of responders converging around convenient temporal choices (3, 6, 12, 24). The influence of outliers is moderated by removal of three outliers (DP>60).

APPENDIX A

Sample Survey Questions

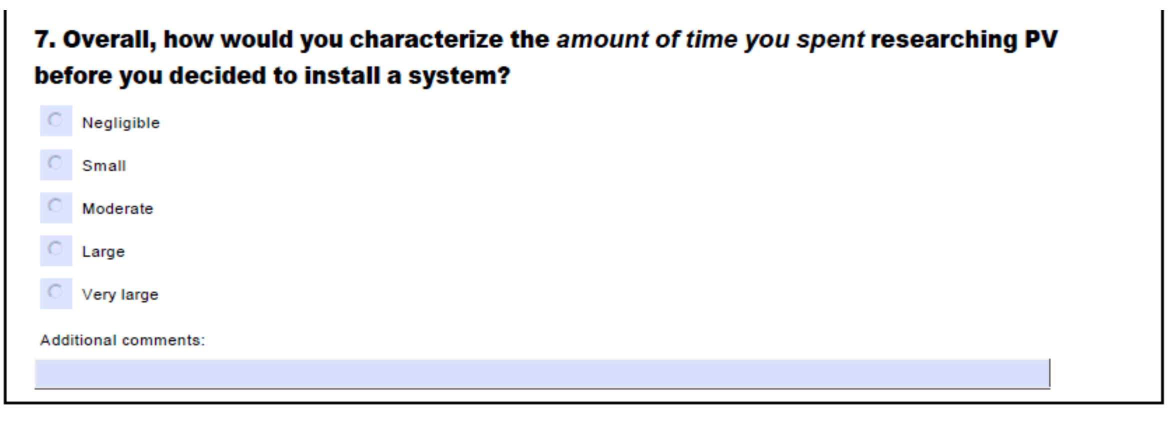
Note: The numbers before each question refer to section numbers in the original questionnaire, and have no particular significance here.



2. a) How important were the following factors in your final decision to install a PV system?

	Not important at all	Somewhat important	Moderately important	Very important	Extremely important
Your general interest in energy and electricity generation					
Your evaluation that solar PV is a good financial investment					
Reducing impact on the environment by using a renewable energy source					
Influence of others in the neighborhood with PV systems					
Influence of a close acquaintance **not** from your neighborhood					

Figure A.1: Likert item regarding factors behind installation decision.

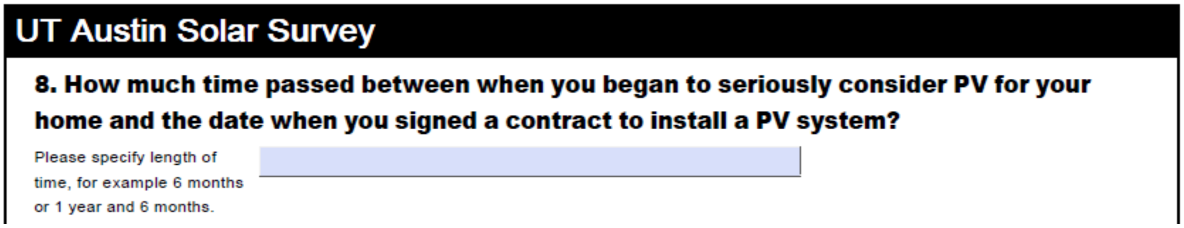


7. Overall, how would you characterize the *amount of time you spent* researching PV before you decided to install a system?

- Negligible
- Small
- Moderate
- Large
- Very large

Additional comments:

Figure A.2: Likert item regarding length of research time.

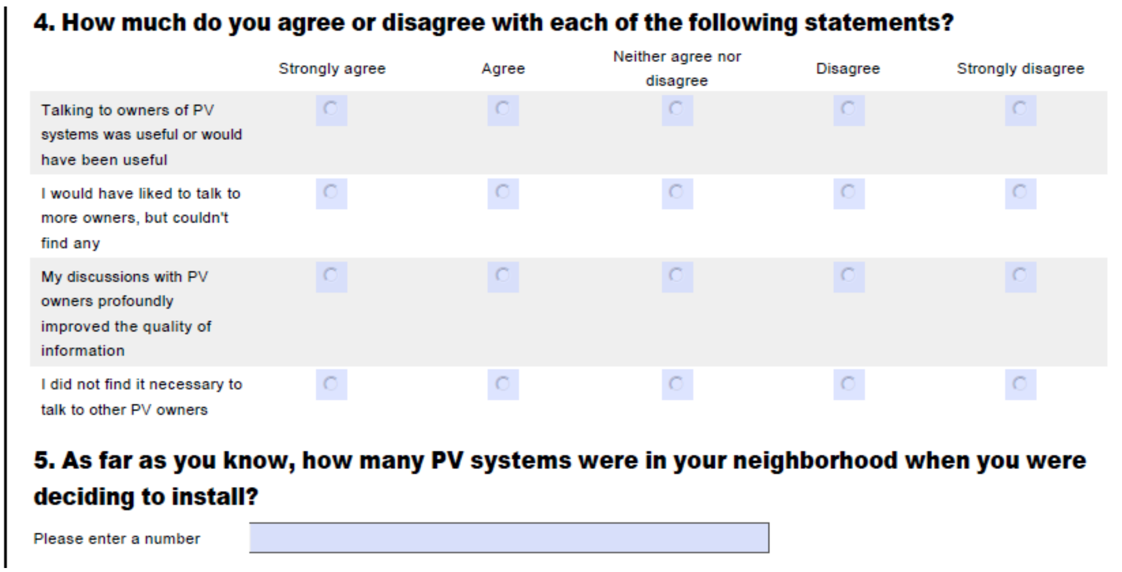


UT Austin Solar Survey

8. How much time passed between when you began to seriously consider PV for your home and the date when you signed a contract to install a PV system?

Please specify length of time, for example 6 months or 1 year and 6 months.

Figure A.3: Survey question regarding decision times. Given as numerical response.



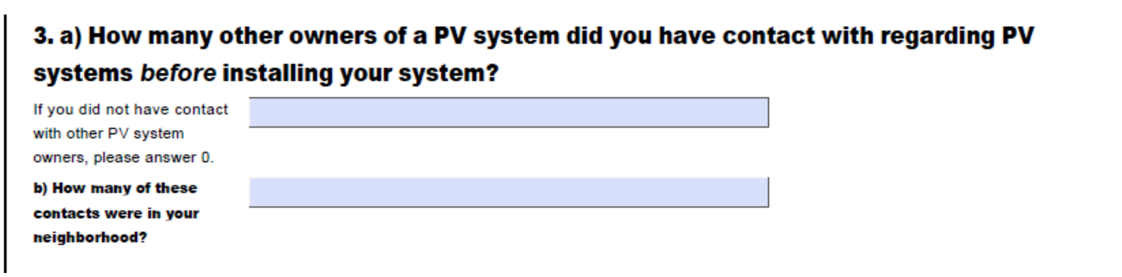
4. How much do you agree or disagree with each of the following statements?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
Talking to owners of PV systems was useful or would have been useful					
I would have liked to talk to more owners, but couldn't find any					
My discussions with PV owners profoundly improved the quality of information					
I did not find it necessary to talk to other PV owners					

5. As far as you know, how many PV systems were in your neighborhood when you were deciding to install?

Please enter a number

Figure A.4: Four Likert items regarding contact with other owners (#4). Question regarding number of PV systems in the neighborhood (#5).

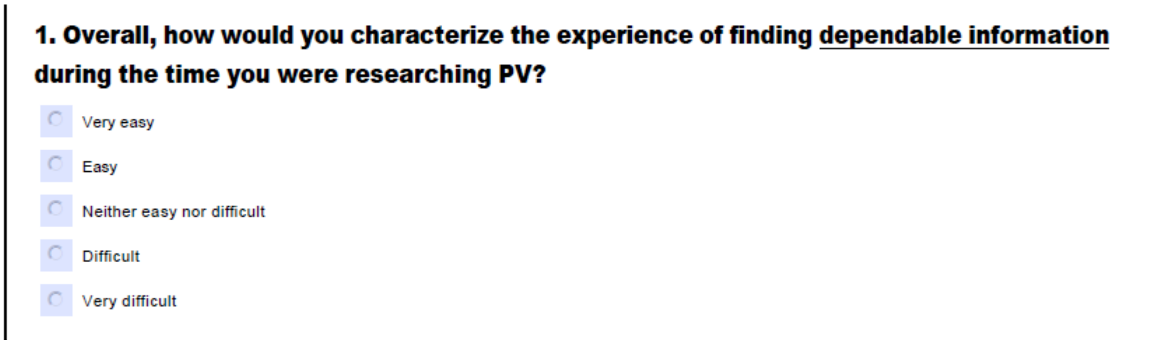


3. a) How many other owners of a PV system did you have contact with regarding PV systems *before* installing your system?

If you did not have contact with other PV system owners, please answer 0.

b) How many of these contacts were in your neighborhood?

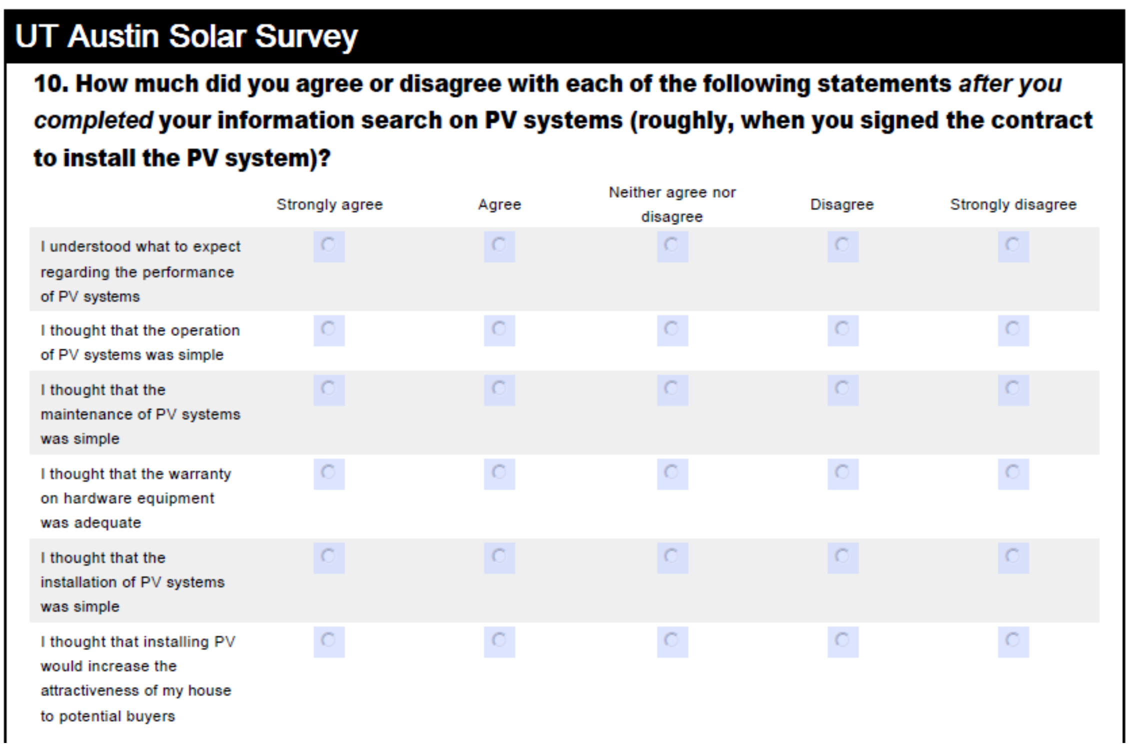
Figure A.5: Survey question regarding the number of other owners of PV systems who were contacted.



1. Overall, how would you characterize the experience of finding <u>dependable information</u> during the time you were researching PV?

- Very easy
- Easy
- Neither easy nor difficult
- Difficult
- Very difficult

Figure A.6: Likert item regarding access to dependable information.

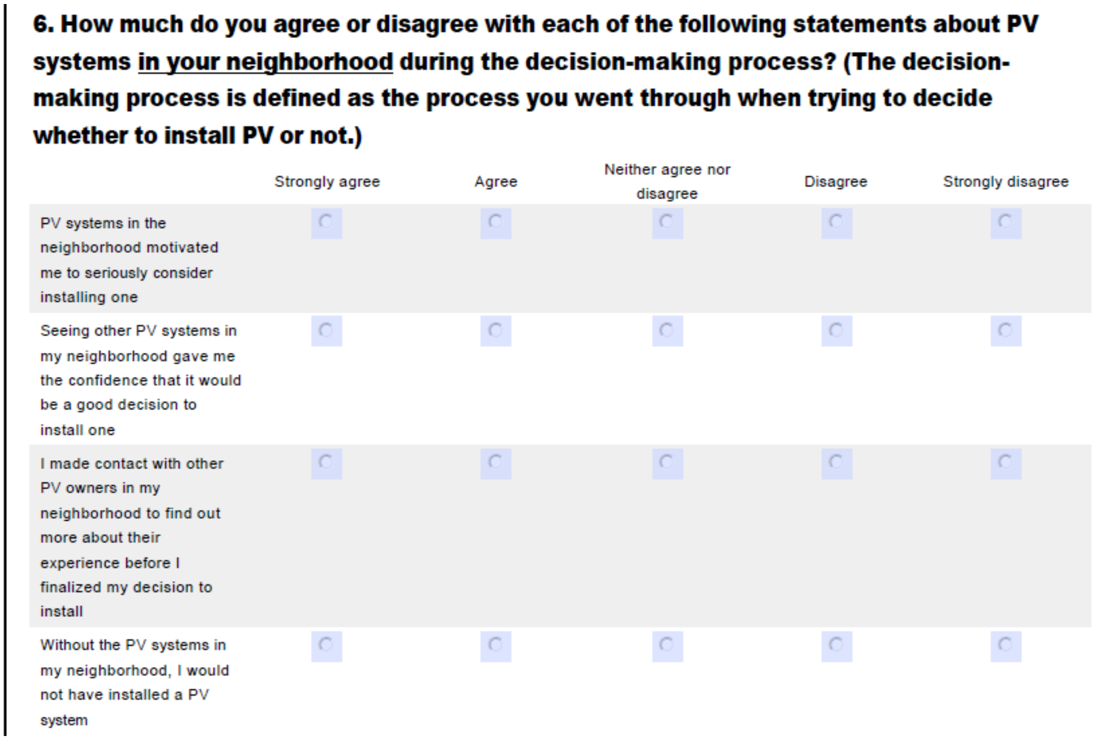


UT Austin Solar Survey

10. How much did you agree or disagree with each of the following statements *after you completed* your information search on PV systems (roughly, when you signed the contract to install the PV system)?

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
I understood what to expect regarding the performance of PV systems					
I thought that the operation of PV systems was simple					
I thought that the maintenance of PV systems was simple					
I thought that the warranty on hardware equipment was adequate					
I thought that the installation of PV systems was simple					
I thought that installing PV would increase the attractiveness of my house to potential buyers					

Figure A.7: Six Likert items regarding residual uncertainty.



6. How much do you agree or disagree with each of the following statements about PV systems <u>in your neighborhood</u> during the decision-making process? (The decision-making process is defined as the process you went through when trying to decide whether to install PV or not.)

	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree
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					
I made contact with other PV owners in my neighborhood to find out more about their experience before I finalized my decision to install					
Without the PV systems in my neighborhood, I would not have installed a PV system					

Figure A.8: Four Likert items regarding peer effects.