Information Searching in the Residential Solar PV Market

Jacquelyn Pless,[a] Harrison Fell,[b] and Ben Sigrin[c]

ABSTRACT

This paper examines the consumer information search behavior of households in San Diego County with solar photovoltaic (PV) systems. We focus on whether solar PV households financing the technology through third-party ownership (TPO) versus host-ownership (HO), which is equivalent to leasing or buying goods in other markets, have heterogeneous preferences as reflected by information search. Conditional on adoption, we find that TPO households tend to seek more information on home modifications required for solar installation whereas HO households seek more information on the financial returns of solar investments. These preferences may be correlated with the consumption of other goods and services, and thus, if used to inform marketing strategies, our results could help reduce solar PV customer acquisition costs and accelerate technology diffusion. They also have indirect implications for marketing goods and services in other contexts where consumers exhibit similar preferences.

Keywords: Renewable Energy, Technology Diffusion, Customer Acquisition, Information Search, Third-Party Ownership

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1. INTRODUCTION

The market for solar photovoltaic (PV) systems has experienced tremendous growth over the past decade, with installed capacity in the U.S. expanding from less than 500 MW in 2008 to more than 40 GW in 2016 (SEIA 2017).[1] This growth can be attributed to steep capital cost declines, government financial incentives, reduced technology uncertainty, and market maturation more generally. Some of it also can be attributed to the availability and use of third party ownership (TPO) financing options (Drury et al., 2012; Corfee et al., 2014).[2] The TPO model, which is similar to leasing in other markets (e.g., automobiles), offers customers the option of paying a third-party owner for using a solar system by either signing a lease or a power purchase agreement (PPA) with little or no money down. Increasing in use from just 10% to 20% of solar PV installations in 2009

1. Solar PV market growth in the residential market—where TPO is most common—has been a bit slower relative to non-residential solar PV. This makes TPO customers a particularly relevant market segment to study in the context of residential solar PV.

2. Trends in adoptions using HO versus TPO suggest that third-party PV products were rapidly gaining market share over the time period studied here (Drury et al., 2012).

a Corresponding author. MIT Sloan School of Management and University of Oxford, 100 Main Street, Cambridge, MA 02142. E-mail: jpless@mit.edu.

b Department of Agriculture and Resource Economics, North Carolina State University

c National Renewable Energy Laboratory

to roughly 65% in 2013 (GTM Research, 2014), TPO allows customers to overcome some of the key barriers to solar PV adoption by reducing or eliminating upfront costs, technology risk, and the installation process complexity (Margolis and Zuboy, 2006). It also enables the monetization of tax-based incentives, lowering costs to the customer, and provides a source of financing in an early market. On the other hand, host-ownership (HO)—or buying the system outright—requires homeowners to purchase solar panels directly, incur technology risk, and bear installation process complexity, though HO customers also often enjoy larger financial benefits over the system lifetime.

Innovative approaches to financing technology adoption such as TPO can open up markets to new customer bases and remove barriers to entry (Rai and Sigrin, 2013; Drury et al., 2012; Margolis and Zuboy, 2006). However, while TPO use has increased substantially in some residential solar PV markets, solar PV customer acquisition costs still remain high (in both TPO and HO markets), potentially dampening future technology diffusion. They could be reduced with a better understanding of solar PV adopter preferences. In particular, if consumer preferences for TPO versus HO among solar adopters are correlated with other observed consumption patterns, the amount of time between a customer's initial interest in solar and actual adoption can be improved with customer segmentation and targeted marketing strategies. This can reduce the resources that firms allocate to customer acquisition, potentially helping to accelerate technology diffusion and improving firm competitiveness.

In this paper, we explore heterogeneity in the preferences of households that adopt solar PV as measured by their information searching behavior. Our objective is not to estimate the causal relationship between information search and the solar PV financing decision, as we do not have an adequate identification strategy or the necessary data for addressing endogeneity concerns such as selection bias, nor can we fully model the decision-making process with our data. Rather, by exploring the correlation between information search and the financing decision of solar PV adopters, we recover information on consumer preferences conditional on adoption, controlling for many other factors that could influence the decision.

We examine households that installed solar systems in San Diego County between 2010 and the first quarter of 2013, focusing on differences in the research conducted prior to adoption for those that opted for TPO versus HO. We estimate probit and bivariate probit models to examine the relationship between information search and the financing decision of solar adopters. This requires merging multiple proprietary household-level datasets as well as additional public system-level data. We use information from two surveys of San Diego households that were fielded during 2014 that elicited new data exploring factors that determine a household's decision to adopt solar PV, such as their motivations, potential barriers, how they accessed information, and the type of information they sought. Second, we use data on actual TPO contract terms to determine the 'price' that TPO households paid for such systems over their contract lifetimes, as publicly reported TPO pricing data is known to be inconsistent across installers. We also match these datasets to two other public datasets for additional information such as the system size and market concentration.

Our main results suggest that solar PV households using HO versus TPO seek different types of information throughout their decision-making process. Solar PV households using TPO spend more time researching the required home modifications associated with installing solar while solar PV households using HO spend more time researching expected financial returns. These correlated preferences indicate that information search is heterogeneous for solar PV households that use different financing options for adoption. We also explore how other household and market characteristics are correlated with whether solar PV households use TPO or HO. Interestingly, we find no clear demographic differences between solar PV adopters that use TPO versus HO, although HO customers are more likely to live in slightly larger homes and face slightly higher utility bills.

This paper makes three main contributions. First, understanding differences in the types of information sought by solar PV households that use alternative financing models can help guide solar companies' marketing strategies, which in turn can reduce customer acquisition costs and accelerate technology diffusion. Our results can be interpreted as a reflection of heterogeneous conditional consumer preferences. On the one hand, TPO customers may place a higher value on reducing home modification hassle related to technology whereas HO customers may be more concerned with long-term investment returns. If these preferences are also correlated with other household consumption patterns, solar companies may be able to identify which households are more likely to respond to marketing materials targeted towards TPO versus HO solar financing options given the consumption of other goods and services. For example, households that value reducing hassle associated with home ownership also may be more likely to hire external assistance to handle other household responsibilities, such as certain home renovations, maintenance, or lawn care. They also may be more likely to lease a vehicle. Identifying these types of households in advance by observing consumption of these other goods and services may help reduce customer acquisition efforts if a firm is aiming to market the TPO option. Similarly, by observing the financing decision of solar adopters, non-solar firms can target marketing of other goods and services to these households more effectively.

Second, this paper contributes to a growing literature aiming to understand differences in TPO and HO markets in technology adoption. Sigrin et al. (2015) use the same data that we use to observe descriptive differences between TPO and HO customers in the motivations for initially adopting solar PV. Rai and Robinson (2013) compare the length of time of the solar adoption decision-making process between TPO and HO customers. Drury et al. (2012) conduct a correlation analysis and find that solar PV households using TPO in southern California tend to be younger, less affluent, and less educated populations relative to those using HO. On the other hand, Rai and Sigrin (2013) consider the solar PV financing decision in Texas and find that, although TPO seems to have opened up the market to those with a tight cash-flow situation, TPO and HO customers do not differ on socio-demographic variables. Overall, this literature has not yet examined differences in information searching behavior. Doing so can be useful for reducing customer acquisition costs, which remain quite high in the U.S.

Third, this paper complements the growing body of work exploring the demand for solar PV by focusing on the subsequent decision of how to finance the asset. While we are not able to estimate demand with our data, a better understanding of the financing decision can have implications for demand. Several papers directly examine solar PV demand in residential markets. Bollinger and Gillingham (2012) study peer effects and demonstrate the impact of previous nearby adoptions on PV uptake in California. Graziano and Gillingham (2015) examine the diffusion of residential solar PV systems using installation data from Connecticut to identify spatial patterns of diffusion and clustering of adoptions, finding a strong relationship between adoption and the number of nearby previously installed systems as well as policy variables and the built environment. Richter (2013) asks whether installation rates of solar PV are affected by social spillovers and finds a small but statistically significant neighbor effect in PV system adoption in the United Kingdom. Hughes and Podolefsky (2015) study the impact of subsidies on solar installations, finding that the CSI rebate program has had a large effect on adoptions. Lastly, Gillingham and Tsvetanov (2019) estimate price elasticity of demand for solar PV. None of these studies explore differences between solar PV households that use different technology adoption financing options, however.

The remainder of this paper is organized as follows. Section 2 describes the factors that influence a household's decision to use TPO or HO when adopting solar PV. Section 3 presents our empirical strategy and Section 4 describes our data and variable construction. Section 5 summarizes our main empirical results, Section 6 demonstrates that our findings are stable across several robustness checks and alternative specifications, and we conclude in Section 7.

2. FINANCING SOLAR PV WITH TPO VERSUS HO

Abstracting from the details of market structure and demand, the empirical approach we take in this paper estimates the reduced form relationship between stated household information search (as well as other household, solar system, and market characteristics) and the decision to finance a solar PV adoption through TPO or HO. Understanding these relationships sheds light on factors impacting the financing decision in technology adoption, as leasing (the TPO option) can be a substitute for debt financing (the HO option) in many solar PV residential markets.

Under a TPO contract, payment structures between the solar customer (homeowner) and the system owner (third-party financer or solar integrator) can take the form of either a lease or a power purchase agreement (PPA). In leases, customers pay a specified amount every month regardless of energy production. In PPAs, customers pay a specified amount per kilowatt-hour (kWh) of generation, so that the amount paid varies monthly as a function of generation. Both types of contracts generally range from 15 to 25 years and may or may not include an annual escalation rate. Customers also have the option of making an upfront payment to reduce the contract terms, and often there is the option to prepay the entire lease upfront. This translates into a total of four financing options. Three of the options fall within the TPO classification (lease, PPA, or prepay), and the fourth is host-ownership (HO) where the customer purchases the system outright. We simplify the consumer choice problem by considering just the decision to buy (HO) or lease (TPO) solar PV. Installers often provide homeowners with a menu of contract options, varying the parameters that define the terms of the contract and affect its total price (Davidson et al., 2015). In theory, homeowners therefore have the opportunity to compare prices of TPO to HO by aggregating payments over the duration of the contract and discounting the payments. This is the real contract cost that the customer faces, which we define as the net present cost (NPC) of the TPO contract.

Consumers' decisions to buy or lease goods are derived from budget constraints and their determinants (income and relative prices) as well as preferences and information. For example, the leasing option can reduce or eliminate upfront costs. Thus, when holding all other factors constant, a consumer with a binding liquidity constraint is more likely to lease, and a consumer with a higher preference for liquidity is more likely to prefer leasing because it avoids tying up assets. On the other hand, there may be concerns regarding the impact of financing solar through TPO in the case of home resale, since home buyers sometimes are required to take over the lease.[3]

Furthermore, although the relative economic attractiveness of HO versus TPO is a complex function of system characteristics, local conditions, and available incentives. The TPO model is sometimes more financially attractive because third parties can monetize the federal Investment Tax Credit (ITC) for solar and modified accelerated cost recovery system (MACRs) depreciation, which can be passed-through to customers in the form of lower PPA or lease contract prices (Pless and van Benthem, 2019). At the same time, lessees must either surrender the assets or purchase the assets at the end of the lease (if this is an option) while buyers acquire ownership. The buying option thus

3. As described in Section 4, there are mixed perceptions regarding the impact of solar on home resale for both the HO and TPO contexts.

builds equity, so consumers aiming to build wealth may prefer HO. Classically, we expect the HO option to provide larger lifetime benefits.

Buyers may also just have a strong ownership preference. Individuals make different choices even when facing the same budget conditions because each consumer exhibits unique preferences and the characteristics of leasing versus buying make each financing option preferable to different types of customers. For example, the TPO option reduces risks associated with ownership such as uncertain operations and maintenance (O&M) costs or technology performance risk because this risk is transferred to the third-party owner. As such, a consumer who prefers to reduce O&M costs or technology risk may prefer to lease.[4]

3. EMPIRICAL FRAMEWORK

To examine whether consumer preferences are correlated with the decision to use TPO or HO, conditional on solar PV adoption, we focus on a household's information search behavior through the solar adoption process and estimate the following probit model:

$$y_i = \beta_0 + \mathbf{X}_\mathbf{i}^{'}\beta_1 + \lambda_t + \varepsilon_i \tag{1}$$

where y_i is equal to one if solar adopter *i* uses TPO and zero otherwise. Matrix $\mathbf{X}_\mathrm{i}$ contains measures of how much time solar adopters spend researching different components of the technology adoption decision. These are our main variables of interest, which we interpret as proxies for consumer preferences.

We interpret the coefficient estimates associated with the information search variables as correlations between preferences and the solar PV financing decision conditional on solar adoption. We also include several household-, solar system-, and market-level variables to control for other potential influences on the solar financing decision, which we describe in Section 4.

We include year by quarter fixed effects, λ_t to control for common time-varying unobservables that affect the financing decision. One of the problems with our dataset is that TPO observations are heavily skewed to later years, when the market is more developed. There are a number of factors that contribute to this that are a function of time, such as the availability and awareness of TPO financing options and the general visibility of solar companies offering TPO. Furthermore, there are unobserved factors that could enable trends towards more information searching of later adopters, including the rise of online platforms and retail partnerships that place solar company representatives in visible public spaces. Some observed factors also vary over time, such as installer concentration and market saturation, which we control for directly (see Section 4 for details on how we construct these variables).

Finally, one may be concerned that some solar installers only offer one financing option rather than a menu of options. We considered using installer-level fixed effects to control for this. Their inclusion is not straight-forward given the mergers that occurred throughout our sample time period, however we estimate our model with fixed effects for installers with large market shares. If anything, the results become much stronger and larger in magnitude. We opt for omitting them throughout our analysis since their inclusion is not particularly clean given our data, and our main findings can be interpreted as conservative.

4. See Speer (2012) for a more detailed analysis of the financing options for residential solar PV and their benefits.

4. DATA

We merge four household-level datasets to conduct our analysis: 1) proprietary surveys of solar PV adopters and non-adopters in San Diego County, 2) interconnection data that allows us to calculate market concentration variables, 3) solar system data providing information on the transaction and system characteristics, and 4) proprietary TPO contract term data to calculate the prices that TPO consumers agree to pay over the lifetime of their contracts.

4.1 Household-Level Survey Data

We obtained data from two surveys conducted by the National Renewable Energy Laboratory (NREL) in conjunction with the Center for Sustainable Energy (CSE) of homeowners that had adopted and not adopted solar PV in San Diego County, California, from 2007 to 2013.[5] The surveys were designed to elicit data exploring the factors that drive households to adopt solar PV, including stated motivations (e.g., wanting to save money, wanting to stabilize electricity expenditures, etc.), personal attributes (e.g., political beliefs, demographics), and information searching conducted throughout the solar PV adoption process for solar adopters. The full set of responses from the surveys include 1,234 adopters and 790 non-adopters, although not every respondent answered every question. This reduces our sample size a bit. See Appendix A for more details on the survey instrument design and population representativeness.

Our primary variables of interest about information searching are obtained from the solar adopter survey. The survey asked respondents how much time they spent researching various components of solar adoption, categorizing time on a scale from 0 (no time at all) to 4 (more than one day). We have information search times for six categories related to the solar adoption decision: how much power would be generated by the solar system, required home modifications, equipment, required maintenance, financial returns, and whether a good deal was offered. We do not have this information for non-adopters, as they were not questioned about their information search given that they did not adopt the technology.

We use a number of other variables from this survey data as well, primarily as controls in our regression framework. First, we include a dummy for adopters who received price quotes for both financing options as opposed to only one. This proxies for high information access or high information search, controlling for the possibility that some firms target certain households in their customer acquisition strategies and provide more information that might reduce search time as well as the possibility that some households exhibit more searching on average. We also include nine variables about the types of events or situations that initially motivated interest in solar adoption (referred to as "prompts" hereafter)—such as planning a remodeling project, seeing a neighbor install solar, or speaking with a solar homeowner during a home tour—which may also be related to the information that may have been provided upfront and which may inherently bias the adopter towards one financing option or the other.

Table 1 provides descriptive statistics of the survey responses for our key variables of interest as well as the prompt controls. The primary observation to note is that solar adopters choosing TPO appear to spend slightly more time researching aspects of solar adoption related to hassle (home modifications, maintenance requirements, and equipment requirements), whereas adopters

5. Note that although our surveys covered years 2007 to 2013, our final sample period is limited to 2010 through Q1 2013 because of limitations on the other datasets used in the regression analysis, as described in this section.

choosing HO appear to spend slightly more time researching aspects of solar adoption related to the potential financial benefits (financial returns, power generation, and whether they are receiving a "deal"). Note that the descriptive statistics provided here summarize these variables for the final sample of solar PV adopters used in the regression analysis. The sample size is greatly reduced in comparison to the starting set of survey responses once we include the full set of control variables in the regressions, but these descriptive statistics are very similar to those of the full survey responses, which includes between 250 and 350 responses from TPO adopters and between 450 and 500 responses from HO adopters, depending on the question. We use the more limited sample throughout our analysis so that we can include the richest set of control variables possible.

Table 1: Descriptive Statistics of Primary Variables of Interest

	Means		Standard Deviations		Observations	
	TPO	HO	TPO	HO	TPO	HO
Information Search Related to Financial Benefits						
Financial returns	2.204	2.369	1.452	1.432	113	187
Power generation	1.956	2.134	1.472	0.491	113	187
Whether it's a "deal"	2.257	2.310	1.557	1.463	113	187
Information Search Related to Hassle						
Home modification requirements	1.947	1.711	1.469	1.279	113	187
Maintenance requirements	1.805	1.684	1.445	1.271	113	187
Equipment requirements	1.991	1.904	1.436	1.333	113	187
Interest in Solar Prompts (dummies)						
Remodeling project	0.044	0.080	0.207	0.272	113	187
Electricity rate increases	0.522	0.422	0.502	0.495	113	187
Retirement planning	0.186	0.385	0.391	0.488	113	187
Seeing a neighbor install solar	0.097	0.134	0.298	0.341	113	187
Conversation with a neighbor with solar	0.124	0.123	0.331	0.329	113	187
Conversation with friend/family with solar	0.239	0.262	0.428	0.441	113	187
Conversation with a solar owner on tour	0.009	0.080	0.094	0.272	113	187
Conversation with solar company at retail store	0.080	0.070	0.272	0.255	113	187
Radio or television advertisement	0.186	0.107	0.391	0.310	113	187
Direct marketing by solar company	0.195	0.187	0.398	0.391	113	187

Note: Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Descriptive statistics of information search and solar adoption prompts for final sample used in the main regression analysis. Information search variables capture the amount of time solar PV households spent researching various benefits associated with solar adoption and are measured on a scale from 0 (no time) to 4 (more than one day). The solar interest prompt variables are dummies equal to one if the solar adopter indicated this was a prompt for adoption and zero otherwise.

Table B1 in Appendix B provides summary statistics of all other variables from the surveys used in the baseline specification. This includes the aforementioned controls as well as a number of demographic variables: household income, education, age, whether the adopter is married, and whether the adopter is retired. In the surveys, income is measured as an ordinal variable that ranges from 1 to 10, covering income groups from less than $50,000 to $500,000 or more. Since the income groups do not have consistent ranges, we use the midpoint value for each income group. Education reflects the highest level of education completed, included as an ordinal variable ranging from less than high school to doctoral or professional degree. Furthermore, it is possible that one's beliefs about economic issues, politics, or social issues impact the solar financing decision. We include three variables that capture stated beliefs on economic, social, and political issues (ranging from 1=very liberal to 7=very conservative) to control for this possibility.

A few house characteristics are included to control for electricity consumption levels, which impact the economics (via electricity bill savings) of solar adoption differently between financing options. Solar adopters save on electricity bills as solar generation offsets electricity load, however the net present value of these incurred savings differ between TPO and HO customers depending upon how much is paid for the system upfront. We include house built year, summer utility bills (ordinal), home size (square footage), whether there is a pool (dummy), and whether there is air conditioning (dummy), all of which capture some aspect of electricity consumption.

We include four additional survey responses in our baseline specification related to individual perceptions about the market and solar adoption. First, electricity rate increase expectations capture how the individual thinks his or her electricity rates will change in the next five years. This is an ordinal variable ranging from believing that rates will be about the same in five years to believing that rates will be more than 50 percent higher. The last three control variables from the survey reflect factors that might be important in the business model decision if the adopter plans to move in the near future. Home buyers with solar must take over leases or PPAs in the case of a TPO and fulfill the terms through the end of the contract, and more generally, home buyers typically incur the solar system with the house purchase despite which financing option is used. Furthermore, there are mixed perceptions about the impact of solar on home resale value, which could further complicate the decision-making process. While some may worry that selling one's home when solar is installed could be a challenge because the new buyer would acquire the lease in the case of TPO or handle maintenance in the case of HO, some research has shown that California homes with PV systems have sold for a premium relative to comparable homes without PV systems and thus PV systems have value (Hoen et al., 2011; Hoen et al., 2013). As such, we include the number of years the homeowner expects to be in the home as well as the importance of being able to resell the home and the importance of home value (ranging from 1 being not important at all to 5 being very important) as controls.

4.2 Constructing Market Concentration and Saturation Variables

The second dataset used in this study is interconnection data from California Solar Statistics, which publishes all Investor-Owned Utility (IOU) solar PV net energy metering (NEM) interconnection data. This provides details on all interconnected systems in our sample region, which we use to calculate market competition and concentration variables to include as control variables. We measure market competition by the unique number of installers in the zip code in which an adopter resides active within the quarter-year that the adoption decision is made. This aims to control for the availability of the TPO model increasing over time, increasing market competition, and the potential of targeted marketing efforts at different points in time influencing adopters' business model decisions. We measure market concentration by the cumulative number of solar installations in the zip code in which an adopter resides within the quarter-year that the adoption decision is made. This captures the potential influence of social interaction (peer) effects and increased marketing over time, as this may be reflective of installers targeting marketing efforts, which in turn might be focused on offering one particular business model. These variables are summarized in Table B1 of Appendix B for the sample used in the main regression analysis.

4.3 Solar System Characteristics

We match the household survey and interconnection data to publicly available data on residential solar system installations from the California Solar Initiative (CSI). This dataset reports various dates associated with installation, location, and solar system characteristics. We use the date of the "first new reservation request" as the date of the customer's adoption decision for each installation. Since the actual installation date depends on permitting, construction, and installation timing, we consider the reservation request date to be the best approximation of the customer's actual business model decision date.

We use various variables from this data as controls in our regression analysis. We include the nameplate rating (kW), which controls for the potential electricity bill savings received from installation. Furthermore, we use information on system characteristics such as size, location, and design (tilt, azimuth, tracking type, etc.) to generate year 1 system production estimates through simulation in NREL's PVWatts tool. This helps us to further control for the potential savings incurred from installing solar and the expected financial benefits. We include this production estimate as a control as well as production multiplied by income. Recent work has shown that the electricity rate structures customers face are related to income group because of their tiered design (Borenstein, 2015), and since electricity bill savings incurred from installing solar depends on the rate structure customers face, potential savings is a function of production interacted with income. These variables are summarized in Table B1 of Appendix B.

4.4 Constructing Solar System "Prices"

Lastly, we match our data to transaction-level price data, which entails using both the reported prices in CSI for HO systems as well as proprietary TPO contract data to construct a comparable "price" for TPO contracts. We need to control for the price of solar systems as well as the price of substitutes in our analysis of the solar financing decision. The primary challenge in doing so is finding an equivalently measured \$/Watt price for each financing methodology. The CSI dataset includes a 'total cost' measure for each solar transaction. This cost measure includes parts, labor, fees, etc. and captures the total cost of the system reported to CSI without incentives. It is a reliable cost measure for HO systems. However, for TPO systems, costs are reported differently and inconsistently, making direct comparisons to HO systems difficult. Complicating this is the fact that HO customers are eligible for directly receiving financial incentives, while TPO customers do not receive these directly but rather they are presumably passed on indirectly to some degree in the form of more generous contract terms. Therefore, calculating the prices faced by TPO customers in a way that is comparable to HO prices requires information on the actual TPO contract terms.

One method for doing this is calculating a net present cost (NPC) measure based upon contract terms for TPO systems. This is similar to a traditional net present value calculation, except that we only include the amount paid by the consumer as costs and do not capture benefits associated with technology adoption. For leases, this requires data on monthly lease payments, contract term, escalation rate, and upfront payment. Similarly, for PPAs, this includes data on PPA rate, estimated production, contract term, escalation rate, and upfront payment. For TPOs paid in full upfront, this requires data on the upfront payment amount.

The California Public Utilities Commission provided NREL with access to residential TPO contracts from 2010 through Q1 2013 through a non-disclosure agreement, which NREL sampled and transcribed, with sampling stratified by quarter based on the 'completed date' as recorded in the CSI database.[6] This results in a sample of about 2,500 TPO contracts with usable contract price data and provides us with the TPO contract price parameters needed for calculating NPCs. To evaluate contract prices across TPOs with varying payment horizons, rates, and escalators, we rely on

6. Note that because our TPO contract data was limited to 2010 through Q1 2013, this is also the sample period for our regression analysis (even though our survey data covered more years).

a discounted cash flow methodology. For each contract in our dataset, we aggregate all payments faced by the customer over the contract term to assign a net present cost (assuming a 10% nominal discount rate in our baseline specification, but varying this assumption through robustness checks). We refer to this as the 'contract price' or the 'net present cost'. For leased systems, monthly payment amounts and escalation rates allow us to calculate annual payments over the contract life. In the case of PPAs, annual payments are based upon the PPA rate as well as estimated year 1 production simulated again in NREL's PVWatts tool according to system characteristics detailed in the CSI database and assuming a 0.5% annual output degradation rate over the contract term (Jordan and Kurtz, 2011). Because annual payments for PPAs are based upon estimated production, the NPC of PPAs should be interpreted as an "expected" NPC. For prepaid TPO systems, the net present cost is simply the amount paid upfront.[7]

An additional consideration is the impact of financial incentives on the NPC. Households installing solar PV are eligible for several financial incentives. First, the CSI subsidy program awards rebates for all residential solar PV owners. These rebate amounts vary over time, across utilities, and in their design depending upon the program through which the adopter chooses to participate. However, CSI reports the total incentive amount in all cases, providing a comparable incentive amount across adopters that can be normalized to system size. In addition, a federal investment tax credit (ITC) provides a 30% tax incentive to all solar PV system owners. For HO systems, the homeowner receives these incentives directly, but the incentives go to third parties under TPO models and the third party can pass-through the incentives (to some unknown degree) in the form of lower contract prices. Lastly, commercial owners are eligible for the Modified Accelerated Cost Recovery System (MACRS), which is an additional benefit for TPO customers.

Our NPC calculations for TPO systems embed these three incentives in the form of lower contract prices. Therefore, it is not necessary to net out the incentive amounts from the net present costs of TPO systems, as this would be double-counting the incentives in the price faced by adopters. However, we must consider the additional financial incentives for HO customers, since they affect prices faced but are not incorporated into the total cost reported in CSI. The CSI rebate for HO systems is simply the total incentive amount reported in the CSI database. To calculate the federal ITC, the CSI rebate is considered a price reduction for tax credit purposes and thus the 30% ITC applies to the after-rebate net price paid by the customer:

$$ITC_{HO} = 0.3*\left(TC_{HO} - rebate_{HO}\right) \tag{2}$$

where ITC_{HO} is the federal ITC provided for each HO customer, TC is the total system cost reported in CSI, and $rebate_{HO}$ is the CSI rebate received. The NPC for HO systems is the total cost reported in CSI minus both the CSI rebate incentive total and the federal ITC tax credit. This assumes the ITC is fully monetized. While this varies in practice, we do not observe the actual ITC amount received.

Finally, to control for the price of the system adopted and the prices of substitutes, we find the average NPC ($/watt) for each zip code in the quarter-year of adoption for each financing type. This results in the inclusion of four additional control variables: the average NPCs for leases, PPAs, prepaid TPOs, and HO systems. Table B2 in Appendix B provides summary statistics of our NPC calculations across business models, which demonstrate the expected patterns for this market. The TPO options (leases, PPAs, and prepaid leases) have lower NPCs relative to the HO alternative

7. This makes them similar to HO systems in regards to how the consumer pays. However, other attributes of the TPO option that are important for whether a household prefers one financing option over the other, such as operations and maintenance coverage, mean that they are more similar to TPOs on most margins and should be grouped with TPOs.

when assuming a nominal discount rate of 10 percent and higher.[8] We also control for one additional cost variable that is not included in the NPC calculation—inverter price. We use the average inverter price ($/watt) in the quarter-year of adoption (Feldman et al., 2015).

5. MAIN RESULTS

This section presents our primary results from the baseline specification of Equation 1, estimating a probit model for the decision to finance solar adoption through TPO or HO conditional on solar adoption. Table 2 presents the coefficient estimates and marginal effects for the information search variables of interest (as well as the solar adoption prompt variables). The full set of controls described in Section 4 and quarter-year fixed effects are included in the estimation, and standard errors are clustered at the zip code level to allow for the possibility of correlations in errors within zip codes.

Our main findings suggest that, conditional on solar adoption, TPO and HO households exhibit different preferences as measured by the time spent researching various aspects of solar adoption. Solar PV households financing their systems using TPO spend more time researching the required home modifications associated with solar installation whereas those using HO spend more time researching the financial returns expected from the solar system. These correlations are statistically significant at the 5% level conditional on a rich set of controls. Although the other information search variables are not statistically significant, a clear pattern emerges: solar PV households using TPO consistently spend more time researching things related to hassle associated with adoption (home modifications, maintenance requirements, and equipment requirements), whereas those using HO consistently spend more time researching things related to the financial benefits of solar adoption (financial returns, power generation from the solar system, and whether they are receiving a "deal"). We also estimate the model with fewer controls and larger samples, and the results are consistent with the main results (see Table B3 in Appendix B).

Using the coefficient estimates, we calculate marginal effects at the mean, which tells us the probability of choosing TPO with a one-unit change in the stated time researching that component of the solar adoption decision, conditional on solar adoption. The probability that the adopter uses TPO increases by 9.9% with a one unit change (on the ordinal ranking) in the stated time spent researching home modifications. A one-unit change in the time spent researching financial returns is associated with an 8.6% increase in the probability that the solar adopter uses HO.

We interpret these results as reflecting correlated consumer preferences that are heterogeneous for solar PV adopters choosing to finance their solar systems through either TPO or HO. That is, conditional on solar PV adoption, households using TPO exhibit a preference towards reducing the hassle associated with adoption whereas households using HO exhibit a preference towards maximizing financial returns. To the extent that these preferences are correlated with other household consumption patterns, the results can help guide marketing strategies to better target solar PV adopters that are more likely to prefer TPO or HO financing options.

Consider the following example. Perhaps households aiming to reduce the hassle associated with solar adoption also have a preference towards reducing other types of hassle related to home ownership, such as house renovations, interior decorating, or lawn care. These preferences may be reasonably correlated with hiring external assistance for such tasks. Identifying these types

8. Although there are many factors contributing to TPO market share growth, this provides circumstantial evidence of at least one reason why the TPO model is becoming popular in this market. However, the relative economic attractiveness of HO versus TPO depends on a range of factors, including state and local incentives, and thus this should not be interpreted as a reflection of TPO options having lower NPCs relative to HO alternatives in other markets.

Table 2: Main Results—Estimates from Probit Model Conditional on Solar Adoption

	Estimated Coefficient	Marginal Effect
Information Search Variables		
Information Search Related to Financial Benefits		
Financial returns	–0.249**	–0.086**
	(0.114)	(0.039)
Power generation	–0.141	–0.049
	(0.095)	(0.033)
Whether it's a "deal"	–0.027	–0.009
	(0.078)	(0.027)
Information Search Related to Hassle		
Home modification requirements	0.285**	0.099**
	(0.116)	(0.040)
Maintenance requirements	0.181	0.063
	(0.126)	(0.043)
Equipment requirements	0.005	0.002
	(0.143)	(0.05)
Solar Adoption Prompts		
Remodeling project	–0.328	–0.104
	(0.389)	(0.11)
Electricity rate increases	0.316*	0.110*
	(0.183)	(0.064)
Retirement planning	–0.700***	–0.222***
	(0.219)	(0.062)
Seeing a neighbor install solar	–0.514	–0.157*
	(0.343)	(0.089)
Conversation with a neighbor with solar	0.236	0.085
	(0.297)	(0.112)
Conversation with friend/family with solar	0.0158	0.005
	(0.212)	(0.074)
Conversation with a solar owner on tour	–1.009*	–0.248***
	(0.535)	(0.076)
Conversation with solar company at retail store	0.073	0.026
	(0.333)	(0.119)
Radio or television advertisement	0.284	0.103
	(0.265)	(0.101)
Direct marketing by solar company	–0.295	–0.097
	(0.226)	(0.069)
Observations	300	
Wald test (prob >chi2)	610.18	
Log pseudolikelihood	–128.20906	

Significance codes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Year by quarter fixed effects included. Marginal effects are calculated at the mean. Errors clustered by zip code. Demographic controls include (none of which are statistically significant): income ($1,000s), age, education, retired married. Electricity cost savings proxies are included as controls (nameplate rating, estimated year 1 production, estimated year 1 production * income, house built year, pool, AC) as well as the average inverter cost per watt at the time of adoption. We also include other survey variables: electricity rate increase expectations, years to remain in home, importance of home value, importance of being able to resell, quotes (dummy), and social, economic, and political beliefs (from 1=very liberal to 7=very conservative).

of households based upon their consumption of these other goods and services may help solar companies better target marketing materials for TPO, highlighting the non-financial benefits such as the provision of O&M services. Targeting marketing strategies is important for customer acquisition, and thus improved understanding of the heterogeneity in solar PV consumer preferences may help reduce customer acquisition costs.

Our results also exhibit other interesting correlations that are worth mentioning. Solar PV adopters using HO are more likely to have been prompted to adopt solar by retirement planning (22.2%) and conversations with other solar owners on home tours (24.8%), which implies that marketers may wish to target households that are near retirement age and/or increase marketing efforts during solar home tours if marketing HO. On the other hand, solar PV adopters using TPO are more likely to have been prompted by expected electricity rate increases (11%), and thus electricity rate projections may be beneficial for marketing when aiming to promote the TPO financing model.

A few other variables are statistically significant in the regression results as well but the effects are very small and near zero in some cases. For instance, solar adopters using HO tend to live in larger homes and face higher utility bills than those using TPO. Solar adopters using TPO are also more likely to be located in areas with a higher market saturation (cumulative solar PV installations in the zip code where the adopter is located within the quarter-year at the time of adoption). There are at least two potential explanations for this. This estimate may partially capture peer effects, suggesting that peer effects are stronger for TPO in comparison to HO. It also could reflect the presence of a firm that is specifically marketing the TPO financing option within a region. Nonetheless, this correlation is small in magnitude. Interestingly, we find that no demographic variables are statistically different for solar PV households using TPO versus HO financing options, contrary to some common beliefs they represent different populations.

6. ROBUSTNESS CHECKS AND LIMITATIONS

The primary objective of this paper is to explore preferences of solar PV adopters as measured by information search and whether they are heterogeneous for adopters that use TPO or HO for financing their solar systems. We do not seek to estimate the causal effect of information search on this decision but rather to estimate correlations between information search and the financing decision conditional on solar adoption while controlling for a rich set of variables that influence the decision. Nonetheless, there are still other external factors that could affect the financing decision that our model does not capture but which could bias our results.

One concern with interpreting our results is that the time spent researching various components of the solar adoption decision could be a function of information availability or the ways in which households conduct research. In other words, it is possible that information about some aspect of the decision is more readily available than others. We attempt to control for this in our main estimations with our inclusion of controls on market competition (number of unique installers within zip code in the quarter-year of adoption) and whether the adopter received quotes for both types of financing options (which could either suggest a higher aptitude to search more or a greater availability of information). However, these controls are not perfect and information may be more readily available from certain information sources—such as the internet—relative to others. This implies that the ways in which individuals search for information about new products—such as either on the Internet, the news, or through conversations with friends—might be related to the type of information that they researched for longer periods of time.

We estimate our baseline model with additional controls capturing the ways in which the customer typically learns about new technologies. The survey presented seven ways in which customers might learn about new products (advertisements, news, Internet, neighbors, friends or family, coworkers, and other) and asked respondents to check all that apply. We include dummy variables for each. Table 3 presents these results, which indicate that the inclusion of these variables does not change the results. None of the learning measures are statistically significant, and if anything, the correlations associated with information search become stronger.

Table 3: Probit Model Results for Information Searching and Interest in Solar Prompts

	Estimated Coefficient	Marginal Effect
Information Search Related to Financial Benefits		
Financial returns	–0.266**	–0.092**
	(0.113)	(0.039)
Power generation	–0.123	–0.042
	(0.092)	(0.032)
Whether it's a "deal"	–0.022	–0.007
	(0.082)	(0.028)
Information Search Related to Hassle		
Home modification requirements	0.310***	0.106***
	(0.114)	(0.039)
Maintenance requirements	0.153	0.053
	(0.124)	(0.043)
Equipment requirements	0.009	0.003
	(0.142)	(0.049)
Observations	300	
Wald test (prob >chi2)	3367 (0.000)	
Log pseudolikelihood	–125.58	

Significance codes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Year by quarter fixed effects included. Marginal effects are calculated at the mean. Errors clustered by zip code. The same controls are included as in the baseline model (results from Table 2) but with additional controls for the information sources solar adopters used to learn about their options.

Second, it is possible that our nominal discount rate assumption of 10% in the NPC calculations is poor or inaccurate particularly because each individual is likely to exhibit his or her own preferences and implied discount rates and discount rates change over time. To check whether our results are sensitive to the discount rate assumption, we estimate our baseline specification assuming discount rates from 5% to 15%. The results remain identical to our baseline results.[9]

Although our focus is on exploring preferences conditional on solar adoption, one may also be interested in estimating the causal impact of information search on the solar financing decision. Relatedly, one may be interested in examining heterogeneous preferences for all households as opposed to just solar adopters. Our probit model estimation ignores the multinomial nature of the financing decision, whereby there is an initial decision to adopt solar and then a second decision of how to finance the investment conditional on adoption.

Our estimates also suffer from selection bias, as solar adopters are unlikely to be similar to non-adopters across numerous dimensions. There are unobservables leading households to adopt, such that households adopting are systematically different than potential adopters. Furthermore, the adoption and financing decisions could be made simultaneously, as the decision to adopt solar PV in the first place may be influenced by the availability and knowledge of the TPO model. This would cause the error term associated with an equation that only specifies the financing decision to be correlated with the variables that explain the adoption decision.

We are not able to fully address these concerns with our data. For instance, one potential approach would be to find suitable instrumental variables, but we are unable to identify any. Another

9. We do not include a table of these results because there are no changes to report relative to our baseline specification estimates.

option would be to estimate a nested logit model that captures the multinomial nature of the decision-making process. This is problematic with our data because we do not observe a “date” associated with non-adopters because they did not install solar. This means that we are unable to include many of the critical control variables in a nested logit that aims to fully model the decision-making process, such as prices at the time of potential adoption and time fixed effects. We also do not have an exclusion restriction for a selection model. These data limitations mean that our results from the censored probit model must be interpreted as conditional correlations.

Nonetheless, the availability of information on non-adopters from the household surveys allows us to estimate simultaneous equations for the adoption and financing decisions to take advantage of the non-adopter survey data. Using this detailed household information on non-adopters in the San Diego region can help demonstrate further robustness of our conditional correlations. We estimate a bivariate probit model, which consists of two probit specifications and independent, identically distributed errors that are correlated. One probit equation estimates the selection equation (the adoption decision) and the other estimates the outcome equation (the financing model decision), and thus the outcome equation is only partially observed. We estimate the following model in one step by maximum likelihood:

$$y_i = \beta_0 + \mathbf{X}_\mathbf{i}^{'}\beta_1 + \lambda_t + \varepsilon_i \quad (3)$$

$$A_i = \beta_0 + \mathbf{X}_\mathbf{j}^{'}\beta_1 + \varepsilon_i \quad (4)$$

where Equation 3 represents the outcome equation for the decision to use the TPO or HO financing option (e.g., the same equation estimated by Equation 1 in Section 3) and Equation 4 is the selection equation for whether the household adopts solar. The matrix $\mathbf{X}_\mathbf{i}^{'}$ contains all other covariates, as it did in earlier estimations. In the selection equation, A_i is the adoption decision of household *i,* equal to one for adopters and zero for non-adopters. There are two benefits of this approach: it relaxes the independence of irrelevant alternatives (IIA) assumption and it allows for correlation of the coefficients across the two models. However, we do not have a convincing exclusion restriction, which limits its advantages in our context and does not remove any potential selection bias that may be present.

Table B4 of Appendix B provides summary statistics for adopters and non-adopters for the variables included in the selection equation. The main observation to note is that the demographics reflect the expected relationships. That is, solar PV adopters appear to have higher incomes and live in larger homes in comparison to non-adopters. In addition to the lack of an exclusion restriction, one additional caveat to estimating the bivariate probit model is that, although we have survey data on non-adopters, some questions are asked in slightly different ways in comparison to the adopter survey. Therefore, the variables that we can include in both equations do not align perfectly. For instance, we do not have comparable information searching or interest in solar prompt data for non-adopters, as these would be hypothetical questions for non-adopters rather than stated behavior. We also do not have information on solar system production for non-adopters since these individuals have not installed solar and thus no production data exist, and we cannot include the controls in the adoption decision equation that rely upon dates of solar adoption.

Table B5 in Appendix B presents the results from estimating the bivariate probit model. The outcome equation estimates are comparable to the baseline specification results in Table 2: the coefficient estimates for time researching home modifications and time researching financial returns do not change much in magnitude and remain statistically significant at the 5% level. The coefficient estimates are just slightly reduced in magnitude, suggesting that the bivariate probit estimation perhaps removes some bias associated with allowing for the errors to be correlated across the two decisions, but the overall conclusion remains the same.

7. CONCLUSIONS

This paper explores the preferences of homeowners with solar PV systems as measured by the amount of time they spent researching different aspects of solar adoption. We focus on whether the exhibited information search behavior is correlated with the decision to use TPO or HO financing options. To do this, we combine information from several unique and proprietary datasets, including household surveys and transaction-level leasing contract data, allowing us to control for a rich set of variables capturing household, solar system, and market characteristics.

Our main findings suggest that consumer preferences are indeed heterogeneous among solar PV households. Those using TPO spend more time researching factors related to hassle—such as the additional home modifications required for solar installation. Considering how the TPO option reduces risks associated with solar system installation associated with uncertain technology performance as well as operations and maintenance costs, this finding aligns with the theory in financial economics that consumers preferring to reduce such risks may prefer to lease goods. On the other hand, solar PV households using the HO option spend more time researching investment returns associated with solar adoption, such as the amount of power that will be generated by the system, which results in electricity bill savings as well as direct financial returns. Initially, there is a financial advantage associated with leasing relative to buying due to the low upfront costs, however this advantage diminishes over time due to wealth positions at the end of the lease or loan terms. This finding suggests that HO solar customers may have a stronger preference for acquiring wealth and thus ownership of the system.

Effectively designing marketing strategies is critical for customer acquisition and reducing some of the soft costs associated with technology diffusion. Our results therefore may be helpful in reducing solar PV customer acquisition costs and accelerating technology diffusion. For example, once potential solar PV adopters are identified, solar companies can better understand whether these households are more likely to prefer TPO or HO by examining their preferences as exhibited by other consumption patterns. If some of these households tend to favor reducing technology performance risk—by leasing a vehicle, for instance—they may be more likely to prefer the TPO option. Customer segmentation and targeted marketing strategies such as these could reduce the amount of time between a customer's initial interest in solar and actual adoption, which reduces customer acquisition costs. While the solar market has experienced significant cost improvements over the past decade, customer acquisition costs remain substantial. Nearly 60% of today's solar prices is a function of on-site labor, permitting, engineering, and other soft costs, and while hardware costs are falling, soft costs are actually rising in some cases (SEIA, 2015). Reducing such costs through strategic marketing and customer segmentation can accelerate technology diffusion while also improving firm competitiveness.

Our results also have indirect implications for the demand of other goods and services. If preferences for reducing hassle and technology risk versus wealth accumulation are indeed correlated with other household consumption patterns, observing whether solar PV households finance their systems through TPO or HO may be informative for marketing of goods and services in other contexts.

This paper certainly comes with its limitations. The most obvious and important limitation is that interpretation of our estimates must remain cautious. Our aim was not to estimate the causal effects of information search on the solar financing decision, but rather to better understand the preferences of solar adopters that use TPO versus HO, as reflected by information search that is conditional on solar adoption.

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APPENDIX A: SURVEY DESIGN DETAILS AND REPRESENTATIVENESS OF SURVEY RESPONSES

Two surveys of San Diego households were fielded during 2014 for: (1) homeowners that had adopted PV, and (2) homeowners that had not adopted PV. The survey instruments were designed to elicit new data exploring the factors that drive households to adopt PV, including household-level motivations (e.g., wanting to save money, wanting to lock in stable electricity costs, etc.), adoption barriers (e.g., upfront costs, impacts on home value, etc.), personal factors (e.g., political beliefs, demographics), social network characteristics (e.g., how many neighbors/friends have adopted), and access to information. Several survey questions were tested in a series of three focus groups with PV adopters who owned their systems, PV adopters who had leased their systems (or signed a power purchase agreement), and PV non-adopters. Responses from focus group participants were used to clarify and improve the survey instrument.

PV Adopter Survey

The PV adopter survey was administered in Oct/Nov 2014 as an online survey using SurveyGizmo and two rounds of reminders were sent to increase response rate. The survey was sent to 10,064 PV adopters in San Diego County who had applied for California Solar Initiative incentives from January 2007 through the first quarter of 2013. Of these, participation in individual sections ranged from about 880 – 1,230. Final response rate was approximately 15%, defined as the number of fully or partially completed surveys divided by the number of emails that did not bounce back.

To evaluate the representativeness of survey respondents to the general population of PV owners, we examined the distribution of sample responses in regards to: (1) if the respondents generally represented the breakdown between third-party owned PV customers and host owned PV customers, (2) that the respondents included adopters from early years (pre-2009) as well as more recent years (2012–2013), and (3) political affiliation. For both (1) and (2) the sample fails to reject the null hypothesis that the distribution of sample responses is different than that of the general PV population; for (3) respondents are found to be slightly more conservative than the general population.

While we confirm that the sample is representative of the PV adopter population, we do not expect necessarily PV adopters to represent the general San Diego population. On social issues, the majority of PV adopters described their views as liberal (43%), while on economic issues the strong majority of respondents described their views as conservative (54%). While it is difficult to directly compare political affiliation, if 'Liberal' political views from survey respondents can be associated with 'Democrat' party affiliation, and 'Conservative' political views can be associated with 'Republican' party affiliation, we find that PV adopters appear to be more conservative than the underlying San Diego population and significantly more than the Californian electorate. While this goes against the conventional narrative that renewable energy adopters are more liberal than their peers, there are several factors associated with PV adopters that are also associated with higher percentages of voters holding 'conservative' political views in California, such as older age demographics and higher household income brackets.

PV Non-Adopter Survey

In addition to the PV adopter survey, we also fielded a survey through Qualtrics for non-adopters based on sampling from the San Diego population of single-family homeowners that do not have rooftop solar systems. The non-adopter survey was administered from March/April 2014. The sampling method is somewhat different than the adopter survey in that responses are solicited until reaching a pre-determined goal. In total the survey collected 790 complete responses.

This instrument used many of the same questions from the PV adopters survey so that responses could be compared across the populations of PV adopters and non-adopters. These include demographics, home location (zip code), and people in their social networks that have adopted PV. The non-adopter survey also included additional questions exploring any contacts that they had with solar installers, adoption barriers that had led them to decide against installing PV, and questions exploring the minimum economic returns from a rooftop solar system that would make them interested in seriously considering adoption.

Like the sample of surveyed PV adopters, respondents to these online, opt-in surveys provide a sample that may not be exactly representative of the underlying San Diego population more broadly. One might suspect that those responding to the survey are already more interested in adopting solar, or have some knowledge of it. Furthermore, since the survey was administered online, the respondents must have had access to the Internet. Indeed, demographic summary statistics suggest that this sample may not be representative: respondents are slightly older and have higher incomes than the averages for the San Diego County general population.

Unfortunately, this is a data limitation that we are unable to overcome. Our bivariate probit regressions cannot fully address sample selection bias if the non-adopter sample is biased because we do not have an exclusion restriction. At the same time, the primary research question addressed in this paper examines differences in information searching between HO and TPO customers within the adopter sample (as opposed to between adopters and non-adopters), and thus we are most concerned with ensuring that our sample of adopters is representative of the solar PV adopters population (which we confirmed, as noted above).

APPENDIX B: ADDITIONAL TABLES

Table B1: Descriptive Statistics of Other Variables Used in Regression

	Means		Standard Deviations		Observations	
	TPO	HO	TPO	HO	TPO	HO
Availability of Information						
Quotes (1 if received price quote for both business models)	0.239	0.086	0.428	0.280	113	187
Electricity Cost Savings Proxies						
Nameplate rating (size in kW)	5.532	5.219	2.267	2.323	113	187
Estimated year 1 production (kWh)	8932	8416	3745	3845	113	187
*Year 1 production * income*	1030011	1294855	1388063	1845721	113	187
House size (square footage)	2484	2607	973	978	113	187
House built year	1980	1979	20.1	22.1	113	187
Summer utility bills (1 to 7 ordinal)	6.159	6.283	2.246	2.441	113	187
Pool (dummy)	0.407	0.390	0.493	0.489	113	187
Air conditioning (dummy)	0.814	0.781	0.391	0.415	113	187
Market Expectations						
Electricity rate increase expectations (ordinal 1 to 6)	2.743	2.717	1.406	1.320	113	187
Demographics						
Income ($1,000s)	107.01	134.41	104.50	123.45	113	187
Age (years)	57.2	58.0	11.9	12.6	113	187
Education (ordinal 1 to 8)	4.98	5.10	1.139	1.349	113	187
Retired (dummy)	0.398	0.390	0.492	0.489	113	187
Married (dummy)	0.832	0.893	0.376	0.310	113	187
Social issue beliefs (1=very liberal to 7=very conservative)	3.973	3.947	2.185	1.988	113	187
Economic issue beliefs (1=very liberal to 7=very conservative)	4.991	5.037	1.878	1.689	113	187
Political issue beliefs (1=very liberal to 7=very conservative)	4.549	4.465	2.138	1.968	113	187
Value of Home						
Expected years to remain in home	22.372	22.727	13.912	13.752	113	187
Importance of home value (1 to 5)	3.168	3.150	1.336	1.135	113	187
Importance of being able to resell (1 to 5)	2.522	2.476	1.376)	1.250	113	187
Market Characteristics						
Competition (unique installers per zipcode-Q-Y)	13.327	13.760	8.521	8.821	113	187
Concentration (cumulative installations per zipcode-Q-Y)	285.41	222.10	184.74	152.59	113	187
Other						
Inverter cost ($/watt) (average at time of adoption)	0.358	0.413	0.056	0.071	113	187

Note: Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Descriptive statistics of other variables used in the main regressions, including responses on the household-level surveys, market characteristic variables constructed from the interconnection data, and average inverter costs at the time of solar adoption.

Table B2: Average Net Present Costs ($/watt) by Financing Model

	5% Nominal Discount Rate			
	Mean	St. Dev.	Min	Max
Leases	$5.10	$0.52	$3.95	$5.87
PPAs	$5.14	$0.58	$3.89	$5.83
Prepaid	$4.19	$0.62	$3.36	$5.44
Purchased	$4.11	$0.39	$3.28	$4.54
	10% Nominal Discount Rate			
	Mean	St. Dev.	Min	Max
Leases	$3.56	$0.24	$3.07	$3.88
PPAs	$3.63	$0.38	$2.89	$4.10
Prepaid	$3.40	$0.32	$3.05	$4.04
Purchased	$4.11	$0.39	$3.28	$4.54
	15% Nominal Discount Rate			
	Mean	St. Dev.	Min	Max
Leases	$2.73	$0.12	$2.54	$2.91
PPAs	$2.81	$0.29	$2.30	$3.23
Prepaid	$2.97	$0.19	$2.63	$3.29
Purchased	$4.11	$0.39	$3.28	$4.54

Table B3: Results When Adding Progressively More Controls

	(1)	(2)	(3)	(4)	(5)
Information Search Related to Financial Benefits					
Power generation	–0.183**	–0.189**	–0.208**	–0.198**	–0.141
	(0.078)	(0.083)	(0.093)	(0.092)	(0.095)
Financial returns	–0.178*	–0.162*	–0.178*	–0.222**	–0.249**
	(0.093)	(0.090)	(0.093)	(0.097)	(0.114)
Whether receiving a deal	–0.035	–0.036	–0.029	–0.021	–0.027
	(0.065)	(0.064)	(0.065)	(0.068)	(0.078)
Information Search Related to Hassle					
Maintenance	0.195**	0.184*	0.171	0.179	0.181
	(0.097)	(0.099)	(0.112)	(0.115)	(0.126)
Home modifications	0.220**	0.228**	0.233**	0.253**	0.285**
	(0.095)	(0.093)	(0.102)	(0.107)	(0.116)
Equipment	0.032	0.042	0.075	0.071	0.005
	(0.091)	(0.094)	(0.113)	(0.123)	(0.143)
Quarter-by-year FEs	x	x	x	x	x
Market competition and system production	x	x	x	x	x
Solar adoption motivation prompts	x	x	x	x	x
Controls related to prices and system size		x	x	x	x
Controls related to future expectations			x	x	x
Controls related to home characteristics				x	x
Controls related to demographics and beliefs					x
Observations	446	430	372	364	300
Wald test (prob >chi2)	495 (0.000)	402 (0.000)	400 (0.000)	501 (0.000)	610 (0.000)
Log pseudo-likelihood	–206.11	–197.62	–162.78	–154.31	–128.21

Significance codes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. Results when adding progressively more controls in columns 1 through 5. Errors clustered by zip code.

Table B4: Descriptive Statistics for Adopters vs. Non-Adopters

	Means		Standard Deviations		Observations	
	Adopter	Non-Adopter	Adopter	Non-Adopter	Adopter	Non-Adopter
Electricity Cost Savings Proxies						
House size (square footage)	2555	2269	974	2826	303	544
House built year	1979	1979	21.2	19.0	303	544
Summer utility bills (1 to 7 ordinal)	6.224	3.809	2.359	2.031	303	544
Pool (dummy)	0.393	0.182	0.489	0.386	303	544
Air conditioning (dummy)	0.792	0.629	0.406	0.484	303	544
Demographics						
Income ($1,000s)	123.48	99.3	116.82	84.9	303	544
Age (years)	57.8	57.8	12.4	12.3	303	544
Education (ordinal 1 to 8)	5.05	5.08	1.36	1.40	303	544
Retired (dummy)	0.396	0.426	0.490	0.495	303	544
Married (dummy)	0.868	0.746	0.339	0.436	303	544
Social issue beliefs (1=very liberal to 7=very conservative)	3.954	3.868	2.058	1.773	303	544
Economic issue beliefs (1=very liberal to 7=very conservative)	5.017	4.601	1.754	1.690	303	544
Political issue beliefs (1=very liberal to 7=very conservative)	4.492	4.211	2.028	1.793	303	544
Value of Home						
Importance of home value (1 to 5)	3.172	4.013	1.217	0.905	303	544
Importance of being able to resell (1 to 5)	2.502	3.835	1.299	1.000	303	544

Note: Asterisks denote * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Descriptive statistics of adopters versus non-adopters capturing the sample used in the first stage of the bivariate probit and two-step Heckman selection model estimations.

Table B5: Bivariate Probit Estimation Results

	Outcome Equation (TPO = 1)		Selection Equation (Adoption = 1)
	Estimated Coefficient	Marginal Effect	Estimated Coefficient
Information Search Related to Financial Benefits			
Financial returns	–0.242**	–0.055**	
	(0.102)	(0.023)	
Power generation	–0.117	0.027	
	(0.094)	(0.021)	
Whether it's a "deal"	–0.022	–0.005	
	(0.073)	(0.017)	
Information Search Related to Hassle			
Home modification requirements	0.251**	0.058**	
	(0.104)	(0.024)	
Maintenance requirements	0.159	0.036	
	(0.118)	(0.027)	
Equipment requirements	0.024	0.005	
	(0.126)	(0.029)	
Variables Included in Both Equations			
Income ($1,000s)	–0.0003	–0.0001	–0.0003
	(0.002)	(0.0004)	(0.0006)
Age (years)	–0.003	–0.0006	0.002
	(0.011)	(0.003)	(0.006)
Education (ordinal)	–0.022	–0.005	–0.043
	(0.073)	(0.017)	(0.041)
Retired (=1 if retired)	0.082	0.019	–0.106
	(0.172)	(0.039)	(0.13)
Married (=1 if married)	–0.234	–0.054	0.086
	(0.236)	(0.054)	(0.117)
House built year	0.003	0.001	–0.003
	(0.005)	(0.001)	(0.003)
Importance of home value (ordinal)	0.216*	0.049*	0.087
	(0.115)	(0.026)	(0.072)
Importance of reselling home (ordinal)	–0.293**	–0.067**	–0.654***
	(0.14)	(0.031)	(0.069)
Summer utility bills (ordinal) (average)	–0.034	–0.008	0.241***
	(0.054)	(0.012)	(0.03)
Size of home (square footage)	–0.0002*	–0.00004*	0
	(0.0001)	(0.00002)	(0)
Pool (=1 if yes)	0.403**	0.092**	0.296**
	(0.18)	(0.041)	(0.127)
Air conditioning (=1 if yes)	0.218	0.05	0.233*
	(0.223)	(0.051)	(0.124)
Electricity rate increase expectations (ordinal)	0.02	0.005	0.183***
	(0.07)	(0.016)	(0.046)
Observations	758 (455 censored)		
Wald test (prob >chi2)	9007 (0.000)		
Log pseudolikelihood	–441.01		
Correlation between outcome and selection equations	0.622		
	(0.294)		

Significance codes: *** significant at 1% level, ** significant at 5% level, * significant at 10% level. All of the same control variables from the probit model estimation are included in the outcome equation. The selection equation includes the controls for which we have data for both adopters and non-adopters. Standard errors are clustered at the zip code level.