Examining the Influence of Solar Panel Installers on Design Innovation and Market Penetration

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ABSTRACT

This work uses an agent-based model to examine how installers of photovoltaic (PV) panels influence panel design and the success of residential solar energy. It provides a novel approach to modeling intermediary stakeholder influence on product design, focusing on installer decisions instead of the typical foci of the final customer (homeowners) and the designer/manufacturer. Installers restrict homeowner choice to a subset of all panel options available, and, consequentially, determine medium-term market dynamics in terms of quantity and design specifications of panel installations. This model investigates installer profit-maximization strategies of exploring new panel designs offered by manufacturers (a risk-seeking strategy) vs. exploiting market-tested technology (a risk-averse strategy). Manufacturer design decisions and homeowner purchase decisions are modeled. Realistic details provided from installer and homeowner interviews are included. For example, installers must estimate panel reliability instead of trusting manufacturer statistics, and homeowners make purchase decisions based in part on installer reputation.

We find that installers pursue new and more-efficient panels over sticking-with market-tested technology under a variety of panel-reliability scenarios and two different state scenarios (California and Massachusetts). Results indicate that it does not matter if installers are predisposed to an exploration or exploitation strategy—both types choose to explore new panels that have higher efficiency.
NOMENCLATURE

PV
$N_{market}$
$N_{panels}$
$N_{per}$
$N_{projects}$
$N_{watt}$
$T_{forecast}$
$V_{0,\theta}$

$Z_{0,\text{inst}}$
$b_{0,d}$
$b_d$

$c_{\text{administration}}$
$c_{\text{design}}$
$c_{\text{installation}}$
$c_{\text{maintenance}}$
$c_{\text{materials}}$
$c_{\text{marketing}}$
$c_{\text{permit}}$

$C_{t+\tau}(p(\text{maintenance}), \{q\}_{t_0}^{t+\tau})$
$e_{f_0}$
$e_{f_i}$

$f_c(\{q\}_{t_0}^{t+\tau}, p(\text{maintenance}))$

$\text{irr}_i$
$\text{irr}_{-i}$

$n_0$
$n_f$
$p_{\text{inst.switch}}$
$p(\text{maintenance})$

$p_{\text{h.switch}}$
$\text{price}$
$\text{price}_{\text{module,SEM}}$
$\text{price}_{\text{watt}}$
$\text{prod}_{t,i}$
$q_{t+\tau}(\text{price})$

Photovoltaic
Market size
Number of panels in PV system
Number of periods for estimating reputation
Number of active projects for installer
STC power rating for PV module
Forecasting horizon for expected profit
Bayesian prior for the variance of the distribution for demand function
Prior values for demand function estimation
Initial value for parameter for prior for demand function distribution
Parameter of a Bayesian prior of the demand function distribution
Administrative costs for installer
Cost of designing PV system
Costs of installing PV system
Maintenance costs for installer
Cost of material for PV system
Marketing costs for installer
Cost of obtaining permits for PV system
Design costs at time $t+\tau$
Initial level of efficiency
Efficiency of a PV module
Estimated labor costs of maintenance
Internal rate of return offered by design by firm $i$
Internal rate of return offered by design by other firms
Parameter for reputation stickiness
Number of failures
Probability of switching to new design for installer
Probability distribution for expected maintenance costs given current and expected portfolio of projects
Probability of accepting design for homeowner
Price of a PV system
Manufacturer’s price of a PV module
Price per watt for PV module
Production for project $i$ in time $t$
Demand for current design at time $t+\tau$ for price $p$
rep_i Reputation of a firm i
rep_{-i} Reputation of other firms
w_t Prevailing labor wage
z_{inst} Demand function parameters
α Parameter of a Bayesian prior for probability distribution for maintenance
α_0 Initial value for prior for probability distribution for maintenance
α_{0,d} Initial value for parameter for prior for demand function distribution
α_{0,f} Initial value for prior for failure distribution
α_d Parameter of a Bayesian prior for demand function distribution
α_f Parameter of a Bayesian prior for failure distribution
α_{t,rep} Parameter of installer reputation at time t
β Parameter of a Bayesian prior for probability distribution for maintenance
β_0 Initial value for prior for probability distribution for maintenance
β_{0,f} Initial value for prior for failure distribution
β_f Parameter of a Bayesian prior for failure distribution
β_{rep} Fixed in time parameter of installer reputation
ε_{0,1} Random variable with N(0, 1) distribution
θ_{administrative} Parameter for administrative costs
θ_{complexity install} Parameter for complexity of installation
θ_{design} Parameter for design costs
θ_{l,e} Parameter values for explorer/exploiter decision process
θ_{marketing} Parameter for marketing costs
θ_{permit general} Parameter for cost estimation of permitting, general part
θ_{permit specific} Parameter for cost estimation of permitting, design specific part
θ_d Parameters of an estimated demand function
θ_{h,i} Parameter i of homeowner’s decision function
λ_0 Initial value for reliability
λ_f Parameter for failure distribution
μ Parameter of a Bayesian prior for probability distribution for maintenance
μ_0 Initial value for prior for probability distribution for maintenance
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{0,maint}$</td>
<td>Initial value for parameters for complexity of maintenance distribution</td>
</tr>
<tr>
<td>$\mu_{0,\theta}$</td>
<td>Bayesian prior for the mean of the distribution for demand function</td>
</tr>
<tr>
<td>$\mu_{ef}$</td>
<td>Parameter for efficiency distribution</td>
</tr>
<tr>
<td>$\mu_{maint}$</td>
<td>Parameter of probability distribution for maintenance</td>
</tr>
<tr>
<td>$\mu_{\epsilon_{maint}}$</td>
<td>Parameters for complexity of maintenance distribution</td>
</tr>
<tr>
<td>$\mu_{\lambda}$</td>
<td>Parameter for reliability distribution</td>
</tr>
<tr>
<td>$\sigma^2_{0,maint}$</td>
<td>Initial value for parameter for complexity of maintenance distribution</td>
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<tr>
<td>$\sigma^2_{ef}$</td>
<td>Parameter for efficiency distribution</td>
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<td>$\sigma^2_{maint}$</td>
<td>Parameter of probability distribution for maintenance</td>
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<tr>
<td>$\sigma^2_{\lambda}$</td>
<td>Parameter for reliability distribution</td>
</tr>
<tr>
<td>$\nu$</td>
<td>Prior for parameter of probability distribution for maintenance</td>
</tr>
<tr>
<td>$\nu_0$</td>
<td>Initial value for prior for parameter of probability distribution for maintenance</td>
</tr>
<tr>
<td>$\Pi_t$</td>
<td>Total expected future profit at time $t$</td>
</tr>
<tr>
<td>$x_{c,i}$</td>
<td>Complexity of the failure</td>
</tr>
<tr>
<td>$x_{f,i}$</td>
<td>Time between failures for project $i$</td>
</tr>
<tr>
<td>$\Sigma_{\epsilon_{maint}}$</td>
<td>Parameters for complexity of maintenance distribution</td>
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</table>
1 INTRODUCTION

The United States (U.S.) residential solar energy market is more than 20 years old and is beginning to mature. In the past ten years, the solar PV penetration rates in the residential segment have increased from virtually zero to 0.8% of all U.S. households [1]. With maturity comes new challenges. The Department of Energy (DOE) has recognized the need for novel approaches to pushing penetration rates higher, for example, studying solar installation as a social phenomenon via the SunShot Initiative [2]. If the growth rate declines from the current optimistic industry projections, solar installation and equipment businesses built on an assumption of constant growth will fail, as perhaps foreshadowed by the recent restructuring and acquisition of SolarCity by Tesla [3].

As the mechanical design community increasingly views products as systems, the design concerns of stakeholders within the system, in addition to final consumers, will receive increasing attention in research. This paper provides such an investigation for the residential PV market using an agent-based model to understand the design concerns of different stakeholders. Here, we investigate a system that includes manufacturing design and positioning installers’ material-selection strategies with regard to the adoption of new technologies, and final consumer behavior.

The main questions asked in this study are:

1. How are market outcomes shaped by different decision processes used by stakeholders? Specifically, how do panel installers decide what technologies to offer for sale?
Here, instead of creating a detailed expression of end-customer needs, we simplify these needs and focus on a detailed expression of installer decisions and interactions with manufacturers and homeowners. We expect that this will identify new recommendations for improving panel adoption.

2. How does the strategy of installers change with time and environmental conditions?

The agent-based model explores the interactions between multiple stakeholders. In the model, installers can choose between two strategies: exploration or exploitation. The former is a risk-seeking behavior of choosing to sell a new technology, and the latter a risk-averse behavior of sticking with the current offering. Both strategies are distinct ways of managing situations with incomplete information.

In addition, two scenarios simulate different environmental and market conditions: one represents a high solar irradiation level with a high PV penetration level, and one represents a low solar irradiation level with a lower PV penetration level. We expect to reveal insights about stakeholder strategy changes under different environmental conditions, defined by the levels of solar irradiation, and in new or mature markets, defined by the solar PV penetration level.

This paper details the structure of the agent-based model and the rationale for the decisions made on what to include and exclude. It provides the explanation of model calibration to create reasonable behavior for the U.S. PV market. The work then makes a number of assumptions in order to examine some broad-level conclusions and recommendations for increasing PV adoption rates. Levers manipulated include: technical
properties (solar panel efficiency), environmental factors (level of solar irradiation), and economic factors (income levels of homeowners).

The paper proceeds as follows: Section 2 reviews existing studies on solar PV adoption, including modeling efforts for the PV market; Section 3 presents the simulation methods of decision processes modeling and engineering modeling; Section 4 presents the simulation results and discussion; and Sections 5 provides conclusions.

2 BACKGROUND

This literature review provides an overview of the different stakeholders in the solar PV market and focuses on the important role that installers play. In addition, it introduces the modeling tool used in this study.

2.1 Stakeholders in the residential PV market and the important role of installers

There are many stakeholders in the residential PV market, all of who play important roles in the diffusion of the technology. Other than homeowners, who make the final decisions to adopt the product, there are manufacturers, regulatory agencies, and installers. Manufacturers produce equipment for PV systems. Regulatory agencies are responsible for issuing regulations, such as building requirements and grid-connection requirements. Installers configure systems to satisfy customer needs and install systems on houses.

Research on residential solar PV adoption traditionally focuses on homeowners as final consumers of the product. For example, Karakaya and Sriwannawit [4] identified barriers to homeowners adopting solar panels, such as the high price of PV systems, the
complexity of the interaction between people and the PV system, and ineffective policy measures. Islam and Meade [5] studied user preference for solar PV and proposed that an educational campaign for homeowners might be effective at increasing adoption rates. From the manufacturers’ perspective, effort has been put into improving the technology and the PV panel production.

For an overview of PV systems technology research, see the National Renewable Energy Laboratory (NREL) publications [6], and for improvements in manufacturing over the last decade, see [7]. Both manufacturers and DOE allocate significant resources to increasing PV panel efficiency and expanding the range of environmental conditions in which they deliver optimal efficiency. For an overview of recent advances in that area, see [6]. Overall, manufacturers tailor distinct types of PV panels that exist on the market to work better in different deployment scenarios. This paper focuses on the residential PV market, where installers offer primarily mono and poly PV panels. Thin film technology is mainly the domain of utility-scale installations and thus falls outside the scope of our work.

The impact of installers on the PV market is extensive. Both Chen et al. [8] and our interviews of installers, conducted at the Intersolar North America 2016 conference, confirmed that installers make product design choices and offer homeowners only a subset of all panels available on the market [9]. Therefore, installers are also consumers, in a business-to-business relationship. Installers specialize in specific designs from a manufacturer’s catalogue and offer a limited range of these selections to homeowners.
We are exploring the role of installer choices in a working paper [9] using linked journey maps for installers and homeowners. Traditionally a journey map is a visual representation of a customer’s end-to-end experience with a business; typically this is a flowchart with branch points representing customer decision points. A linked journey map represents a combination of a number of journey maps and describes the collective experience of multiple agents; this linked map can highlight major issues in their integrated experience. We discovered that installers’ decisions regarding their portfolio of products guide and limit homeowners’ choices and effectively determine which technologies will be deployed on the market. In this sense, installers serve as gatekeepers for the new developments of PV system manufacturers.

Installers face complex decisions, not only while choosing from a limited range of offered technologies, but also when designing a PV system for homeowners. Their choices for products reflect a desire to maximize their own profits and may not be perfectly aligned with the homeowners' preferences, the manufacturers' drive to push technology forward, or the government’s goals for increasing adoption at a manageable rate. While the installers' role in solar market dynamics is apparent, there is very little research into their actual decision patterns. Research concentrates on either general trends, such as report [1] which provides an overview of recent trends in market prices and volumes, or on modeling energy production, such as in [10, 11], which detail models of energy production, including renewable energy sources, to assess impact on utility costs. Another example of this line of research is [12], where Janko et al. focus on estimating effects on net loads under changing environmental factors. They found that the coverage area, the
direction of the dust storm, and the time of day affected the net load differently. Frischknecht and Whitefoot created a static model that captures a single period of PV panel market sensitivities to changes in engineering parameters [13]. They found that an early-stage engineering design performance model could be incorporated into a decision framework.

2.2 Investigating solar market dynamics with an agent-based model

There are many modeling tools available to investigate the penetration of technologies, such as the system dynamic model or technology diffusion models. For example, Islam [14] predicts the probability of time to adoption of solar panels by households using discrete choice experiments and a Bass diffusion model. These models are good at capturing the overall trends of the market; however, they lack the capacity to model all individual agents’ behavior and information flows. Over the past ten years, agent-based models have emerged as a preferred method for a more targeted approach to modeling technology adoption [15], [16]. This research focuses on capturing the uncertainty of deploying complex engineering products through the multi-stage sale process. The residential PV market is one of the few markets where a complex engineering system is being utilized by a final consumer while needing constant maintenance and monitoring, thus providing detailed, lifelong information to the maintenance contractor. Thus, it is a perfect candidate for the more modern, agent-based modeling approach.

We chose the agent-based model as our main tool because we want to be able to predict the effects of individual installers’ choices on a market with complex offerings that
are tailored to specific homeowners and explicitly model the distribution of technological and socio-economic parameters that may influence installers’ choices. The agent-based approach allows for explicit modeling of penetration dynamics. As is customary for this approach, the choices for individual-level rules ultimately create diffusion dynamics from the bottom up. For example Nasrinpour et al. [17] use an agent-based model to explore the diffusion of information.

An agent-based model is simulation-based and explicitly models individual agents’ actions while also modeling the network of interactions and interdependencies between the agents. Simulation of the associated physical environment is customary. For a brief introduction to agent-based models, see [18]. Some of their advantages are an ability to capture multiple complex distributions and an ability to naturally model network interactions. The latter is an integral part of environmental considerations as argued in [19].

Agent-based models have been successfully used for evaluating demand-oriented policies, for example, by [20–24]. Zhao et al. [20] concentrated on multi-level modeling of solar energy generation and the way that consumers make purchase decisions taking into consideration the potential energy production, which is based on the geographic characteristics of where they live. Zhao et al. concluded that sensitivity of homeowners to changes in incentives is different for different geographical regions. Robinson and Rai expanded on spatial agent-based modeling for the analysis of PV systems adoption rates [21]. They concluded that agent-level behavior and social interactions are important for explaining patterns of adoption. For other examples of this line of work, see [15].
Robinson and Rai brought together multiple social, economic, and environmental factors into a complex agent-based model to analyze penetration rates arising from homeowners’ possible choices [21], suggesting that explicit modeling of agents’ characteristics is crucial for accurate policy analysis. However, none of this agent-based modeling work in solar adoption provided a high-resolution articulation of the installers’ role in the system, and we argue that this absence, in fact, underestimates the type and level of existing barriers to adoption.

The developed model has extensive socio-economic elements, which require the use of probabilistic methods and lead to unavoidable error bands on parameter specialization. Another property of the PV market is the high level of unpredictability regarding the development of new PV panels. It is simply not possible to be as precise about how a person might behave or how research will progress as it is to be about the amount of electricity produced by a solar panel. The model aims to keep the minimum level of complexity while preserving the ability to explore installer decisions. This approach of working with a probabilistic model and studying trends is valuable and useful for learning about socio-technical models. Note that this is not an optimization study that recommends one final design outcome. Instead, our discussion is structured around trends and changes of trends under model manipulations.
3 MODEL DESCRIPTION

3.1 General flow of the model

The dynamic agent-based model simulates market dynamics for a number of years. The simulation is run for a fixed number of steps, each step representing approximately one year of actual time.

This section provides an overview of important agent actions, with detailed descriptions given in the sections to follow. Figure 1 describes the overall flow of the model.

Figure 1. Major attributes of the model and agents’ decision processes
Each agent in the model has a different goal. Manufacturers, represented by an icon of a factory, play a passive role in this model. Installers, represented by a hard hat icon, evaluate new panels from manufacturers and propose systems to homeowners. Homeowners, represented by a house icon, evaluate the financial viability of investing in PV systems given their specific set of parameters. Government decisions, instead of being modeled directly, are embedded in the pricing structure of the panels. All projects are connected to the grid after completion, which removes the need for explicit modeling of utility decisions.

**Installers.** The model focuses on the decision behavior of installers. At the start of each year (model step), installers choose what equipment to use in their installation bids to homeowners. Installers can choose to keep using their current technology or explore new options and switch to another design from the same or different manufacturer. Some installers are more inclined to explore existing offerings on the market; and some may switch to a new technology if the expected gain is high enough. After an installer settles on a specific design, she customizes it to the homeowner’s needs, creating a specific PV system for the electricity demand level and house size.

Available technologies for PV modules differ in their efficiency levels and in their reliability. The efficiency of the panel is its ability to convert a given amount of solar energy into electricity per square meter and is immediately known to everyone. The reliability, or probability of experiencing a breakdown, is revealed after the projects are deployed. Reliability, in part, determines the production of energy for each project per
year: if the system goes down, it will require maintenance for a period of time, and it will not generate electricity during this time.

**Manufacturers** represent exogenous technological progress and price their current panel offerings on their expected efficiency. As time goes by, manufacturers invest in research and development to improve the efficiency of their panels in a gradual manner. As they do not focus on improving reliability, it may either decrease or increase per model step. The residential PV market has the classic form of a signaling market with hidden information. In this case, the hidden information is the realized performance of the PV panel. Fudenberg and Tirole in [25] provide equilibrium solutions for such markets. A 2014 IEA report [26] highlights very high levels of reliability. These reliability levels suggest that a solution will focus on efficiency.

**Homeowners** evaluate the financial viability of investing in PV systems and make the decision to adopt or not. A fixed portion of all homeowners respond to marketing information during each year and decide to accept or reject installation offers from installers, depending on the offered rate of return of investment and the reputation of the installers.

This paper focuses on the residential solar panel market. Within this market, there are two modes of owning solar panels: host ownership (56% of market) and third-party ownership (44% of market). Host ownership is either financed or paid for upfront with cash. There is no hard data on the latter option; but a DOE report [27] implies that cash upfront is the most common mode of acquiring host-owned systems, while financing has been replaced by third-party ownership schemes. Adding lease or external financing
options would greatly complicate the analysis, so the paper focuses only on the cash upfront mode of financing.

Generally, manufacturers have access to actual performance information for PV panels while installers have to rely on their field observation of the performance. We modeled one of the ways information might flow during the real-life deployment of an extended-life engineering project, and we did it at the level of individual projects. Installers gather the information about each deployed PV system and use it in an aggregate way to get updated estimates for expected maintenance costs. They also have estimates of homeowners’ demand. Homeowners can only observe the reputation of installers and do not have access to raw efficiency and reliability data. Figure 2 summarizes the availability of the information to each party.

![Image](image_url)

**Figure 2. Information available to manufactures, installers, and homeowners**
The model was tested under two different scenarios corresponding to two geographic regions within the U.S. General parameters represented two distinct environments. The CA scenario represents San Jose, California, with high levels of solar irradiation and a 5% PV market penetration; and the MA scenario represents Massachusetts, with lower levels of solar irradiation and a 0.5% PV market penetration. Levels of irradiation were set to 6.0 kWh/m$^2$/day for CA and 4.0 for MA, taken from [28]. Other scenarios with varying levels of solar irradiation and PV market penetration are possible, but are outside the scope of this work.

In the following sections, we provide details of the decision process for installers, manufacturers, and homeowners.

### 3.2 Installer’s decision process

The best approach for modeling installers within an agent-based model is to use intelligent learning agents [18], as they allow a way to represent the process of constantly weighing the benefits and risks of changing PV offerings. Intelligent learning agents are agents that are allowed to update their beliefs in response to the observed dynamics of the environment.

There are different approaches to modeling the decision process of intelligent learning agents. Wilson and Dowlatabadi [29] provided an overview of existing approaches in the field of environmental research. In the case of installers, a reasonable approach is to maximize profit. Sinitskaya and Tesfatsion argue in [30] that this is an appropriate decision procedure for learning agents in a highly volatile environment. Bayesian methods are used because of the amount of information that installers get from
serving already installed PV systems. As installers observe the actual output of the installed systems, they can update their estimates of reliability of the panel. Bayesian methods provide a way of combining their initial guesses regarding reliability of the PV system and the observed data.

Research into Bayesian learning shows that it effectively captures the learning dynamic [31, 32]. Gill in [33] provides details of the standard learning techniques. While operating in the market, installers constantly acquire new information that they incorporate into their decision process. We capture these features in our agent-based model by allowing installers to update their expectations after observing market outcomes of their decisions.

We allow installers to pursue different decision processes that can be either explorative or exploitive. The former assumes that agents are more open to exploring other panels on the market if it seems that it might be beneficial to them. The later strategy describes agents that are less inclined to explore new options and prefer to stay with their current choices for longer. The exploration vs. exploitation question has traditionally been a key part of learning. The classic approach uses multi-armed bandit problems, as explained in [34]. A multitude of methods for reinforcement learning are described in [35]. Experiments show that in conditions when the learning environment is not extremely noisy, it is plausible to assume that people use dynamic optimization with Bayesian learning to arrive at optimal strategies for exploration vs. exploitation [36], and this is the approach used here. We extend our analysis to the case of applied problem solving in a distributed-agents environment.
3.2.1 Installer’s decisions regarding PV modules and pricing

In our model, each installer offers only one type of panel at a time to homeowners. This assumption is the result of our interviews with homeowners, who confirmed that they were offered one, and rarely more than one, option for their PV system. Additionally, during our interviews with installers, they stated that they limit the types of solar modules because of availability issues. We interviewed a total of 12 homeowners (4 in California and 8 in Massachusetts) and 9 installers (all from California). Paper [9] provides detailed questions and procedures for those interviews.

The installers don’t want to wait on the manufacturer before beginning a job; if all their customers use the same modules, then they can maintain some inventory, knowing it will be used for the next customer. During each step in the simulation, each installer investigates replacing their current offering with a randomly selected PV module that is available from manufacturers. Whether or not they decide to adopt a different PV module depends on their propensity to explore (rather than exploit). If they decide to adopt, they estimate the expected profit of PV system designs for the panel under consideration. The expected profit equals the expected revenue minus the costs of services. The revenue depends on the installation price that the installer decides to offer during each step. Next, we describe this decision process in detail.

Installers maximize their profit given the specific PV panel that they are offering as a basis for their design.

\[
max_{price} \Pi_t
\]  

(1)

The expected profit at time \( t \) is calculated over the forecasting horizon \( T_{forecast} \):

Ekaterina Sinitskaya  MD-18-1303  20
\[ \Pi_t = \sum_{\tau=0}^{T_{\text{forecast}}} q_{t+\tau}(\text{price}) - C_{t+\tau}(p(\text{maintenance}), \{q\}_{t_0}) \]  

(2)

where demand \( q_{t+\tau}(\text{price}) = q \) is estimated based on the offered rate of return and reputation of the installer. We will first explain this term in detail and then the cost term, \( C \). Eq. (2) is a standard profit maximization formulation; for further details, see, for example, [37].

Simple specification in the form of linear regression provides the demand estimation:

\[ q = (z_{\text{inst}}\theta^d + \varepsilon)N_{\text{market}} \]  

(3)

where \( z_{\text{inst}} = [z_{\text{inst}, t}] \) is the collection of observations at time \( t \) that is used in sequential updating of Bayesian estimates of regression coefficients. Eq. (3) uses a Bayesian linear regression specification for agent learning; [38] elaborates on detailed estimation for this type of learning. \( z_{\text{inst}, t} \) includes the main demand parameters that influence homeowner choice: the internal rate of return for installer \( i \), its reputation \( r_{\text{rep}, i} \), the internal rate of return (\( irr \)) of other installers \( irr_{-i} \), and the reputation of other installers (excluding installer \( i \)) \( rep_{-i} \). \( irr \) is calculated in the standard way.

\[ z_{\text{inst}, t} = [1, irr_{i,t}, rep_{i,t}, irr_{-i,t}, rep_{-i,t}] \]  

(4)

\( \theta^d \) are randomly distributed regression coefficients for estimated demand. Bayesian prior on \( \theta^d \) has normal-inverse-gamma distribution.

\[ p(\theta^d) = p(\theta^d | \sigma^2)p(\sigma^2) \]  

(5)
\[ N(\mu, \Sigma) \times IG(a_d, b_d) = NIG(\mu, \Sigma, a_d, b_d) \]

Under these assumptions, the posterior predictive distribution is

\[ MVSt_{2\alpha}\left(\tilde{\mu}, \frac{b_d}{a_d} \left(1 + \tilde{Z}V\tilde{Z}^T\right)\right) \]

where MVS stands for Multi-variate student distribution.

The mean of this distribution is used as a predictive: \( \tilde{q} = Z\tilde{\mu} \). Appendix I describes the components of MVS; it also contains initial parameters representing expectation of equal market shares for installers at the prevailing rates of return.

There is no assumption of labor and equipment constraints. This assumption is reasonable because the time horizon for maximizing the expected profit is five years, and one step in the model is equivalent to one year. Over these time intervals, installers can use a flexible amount of labor and equipment.

Now we will explain \( C \) from Eq. (2). Eq. (6) introduces all incorporated costs:

\[
C_{t+r}(p, \{q\}'t') = c_{installation} + c_{design} + c_{permit} + c_{materials} + c_{administration} + c_{marketing} + c_{maintenance}
\]  

(6)

Installers have both fixed per period costs and variable costs. Variable costs depend on the size and specifications of each installation. Eqs. (7)–(13) give details of cost calculations:

\[
c_{installation} = \theta_{t, complexity install} \times w_t \times q \]  

(7)

\[
c_{design} = \theta_{design} \times w_t \times q \]  

(8)

\[
c_{permit} = \theta_{permit general} \times w_t + \theta_{permit specific} \times w_t \times q \]  

(9)

\[
c_{materials} = N_{panels} \times q \times \text{price}_{module, SEM} \]  

(10)
\[ c_{\text{administration}} = \theta_{\text{administration}} \times w_t \quad (11) \]
\[ c_{\text{marketing}} = \theta_{\text{marketing}} \times w_t \quad (12) \]
\[ c_{\text{maintenance}} = f_c(q_{l_0}^{t+\tau}, p(\text{maintenance})) \quad (13) \]

Maintenance costs in (13) depend on the expected probability of failure for the installed system \( p(\text{maintenance}) \) and required labor costs to repair the systems \( f_c(q_{l_0}^{t+\tau}, p(\text{maintenance})) \). Eq (13) includes standard cost estimation, as well as detailed maintenance estimation that uses agent-specific data to update the probability distribution function for maintenance costs. Agent-based models have an advantage of being able to use agent specific information in simulation, for example [39] utilizes it to make a forecast for penetration levels. \( price_{\text{module}_{\text{SEM}}} \) is the price of a PV module that is determined by the module’s manufacturer. \( w_t \) is the prevailing labor wage at time \( t \). \( N_{\text{panels}} \) is the number of panels that is required by the specific design.

Appendix I provides specific fixed cost levels which correspond to average costs of operating in the U.S. residential PV market for a large-scale installer. The model verification and validation section elaborates further on specific choices for cost levels. Each \( \theta_l \) parameterizes part of the overall costs as specified in Eqs. (7)–(13). For each time period \( t + \tau \), where \( t \) is the current time period and \( \tau \) is the forecasting offset, total costs include all mentioned parts in Eq. (6). One of the parameters that defines a variable portion of the costs is \( N_{\text{panels}} \). It is the number of solar modules that provides “enough” electricity to the homeowner. In profit calculations, “enough” means 100% of electricity consumption for an average homeowner, under the assumption that there is enough physical space on the roof for the installation and that all other conditions are favorable.
for installing PV panels. When the actual design is offered to the homeowner, roof size considerations will become part of the actual offer.

**Exploration vs. exploitation.** Each installer has the option to switch to offering a different PV panel. The decision to switch is based on the expected difference in profit and the propensity to switch. The propensity to switch is specific to each installer, who is classified as either an explorer or an exploiter. In this model simulation of three installers, one installer is an explorer and the other two are exploiters. The number of installers reflected the number of big installers present on the market today. Also, during our interviews installers expressed risk-averse attitudes; thus two out of three installers were assigned risk-averse behavior.

Eq. (14) uses a logistic function to calculate the probability for switching

$$P_{\text{inst,switch}} = \frac{1}{1 + \exp \left( -\frac{\Pi_{\text{new}} - \Pi_{\text{old}}}{\theta_{i,e}} \right)}$$

(14)

Appendix I has parameter values for $\theta_{i,e}$. Each set of parameters $\theta_{\{\text{explorer,exploiter}\}}$ (for explorer and exploiter) specifies the propensity to switch to a different design. $\Pi_{\text{old}}$ is calculated for expected maintenance, demand, and efficiency of the current panel; $\Pi_{\text{new}}$ is calculated based on the expected maintenance for the new panel and is subject to the same demand estimations as the current panel. Eq. (14) ensures that an installer switches panels only if expected profits are significantly higher, represented as a continuous function rather than a discrete cut-off. The baseline assumption was that the probability of switching is proportional to the distance between
the current and the expected profit. This functional form implicitly includes the assumption that other considerations, such as market uncertainty, enter into the installers’ decision-making procedure. Eq. (14) generally specifies randomized action selection for an agent who is utilizing reinforcement learning (Bayesian learning); the coefficients reflect two levels of risk-aversion and were selected to be representative of the observed levels of risk-aversion in real situations. The expected profit, given the portfolio of projects, is the agent’s reward, and the agent is assumed to use the ε-greedy algorithm for selecting his actions. For examples of such algorithms see [40].

3.2.2 Installation and maintenance of PV panels

Installation. The installer uses her currently-offered panel to create specifications for installation, given the homeowner’s parameters. Fixed parameters for all agents and all simulations include environmental parameters, such as level of solar irradiation, and difficulty in acquiring permits. Homeowner-specific parameters are roof size, electricity consumption, and household income. When a homeowner approaches an installer for a proposal, the installer designs a system to provide enough electricity to cover demand under ideal conditions, constrained by the roof size. To determine the price, the installer works within the constraints of the cost of installation and the price per watt; the price per watt is determined during the profit optimization procedure. The price per watt is multiplied by the total wattage produced by the system to calculate the price offered to the homeowner. If the homeowner accepts the proposal, then the project is installed.

Maintenance. During each model step, installed projects might experience failure according to the probability distribution specific to each PV panel design. The complexity
of the failure is also randomly distributed. Both determine the cost of maintenance that is specified in Eq. (13).

**Reliability from installer's perspective.** Unlike manufacturers, installers do not have perfect information on panel reliability in the model. This assumption stems from (a) conversations that we had with installers who suggested manufacturers' reliability statistics were sometimes inflated or based on ideal conditions, and (b) reported solar panel failings, which are higher than warranty information would suggest. Additionally, reliability can vary with environmental conditions, such as solar radiation levels and grid stability. The installers must determine the reliability of two panels: the one they currently use *(current)* and the new one that a manufacturer offers them *(new)* in each model cycle. For the current panel, the installer determined its reliability using the strategy described below.

Once the installer knows the number of failures \( n_f \), the period from one failure to another \( x_{f,i} \) for project \( i \), and the severity of failures \( x_{c,i} \), the installer/agent can update his internal estimate for the probability distribution for failures and their complexity.

Under the standard distribution assumption for failure rates of the system, reliability of the installation has an exponential distribution.

\[
\lambda_f e^{-\lambda_f x}
\]  

(15)

The installer does not know the exact parameter of the distribution of Eq. (15) but learns it by observing the performance of installed systems during the simulation. The prior distribution for parameter \( \lambda_f \) is the gamma distribution
Prior parameters $\alpha_{0,f}$ and $\beta_{0,f}$ correspond to the optimistic assessment of an actual system reliability, such as estimated for the example in [41], a study which investigated different sources and frequencies of PV module failures. To get some intuitive understanding for the parameter values in Appendix I, it is possible to think about the prior values as describing a situation when 1 failure in 25 years is expected.

For assessing the reliability of new panels, we investigate the results of installers using one of three estimation strategies. 1) Optimistic: Installers assume that the panels fail only once every 25 years, using parameter values from Appendix I; 2) Same as current: Installers estimate that the new panel will have the same reliability as their current panel, by their own assessment (Eq. 15); or 3) Average: Installers estimate that the new panel will have a reliability equivalent to the average installer-reported reliability of the panels on the market now. Section 4 presents the results of exploring each of these scenarios.

Regardless of the scenario, $\alpha_f$ and $\beta_f$ in Eq. (16) update with new information using standard formulas for a gamma distribution. The resulting posterior predictive distribution for the expected time before the next failure follows a Pareto Type II distribution. Complexity of maintenance has a normal distribution, with parameters $\mu_{\text{maint}}$ and $\sigma_{\text{maint}}^2$. The prior distribution for these parameters is the normal-inverse-gamma with the parameters $\mu_0$, $\nu$, $\alpha$, and $\beta$, which update using standard formulas. The resulting posterior predictive distribution is
\[ t_{2\alpha'}(x|\mu', \frac{\beta'(v' + 1)}{v'\alpha'}) \]  

(17)

which is a non-standard t-distribution with scale and location parameter:

\[ X = \mu' + \frac{\beta'(v' + 1)}{v'\alpha'} T \]  

(18)

where \( T \sim t_{\alpha'} \), which is a standard t-distribution with \( \alpha' \) degrees of freedom.

Appendix I provides initial values for prior parameters of the distribution: \( \mu_0, v_0, \alpha_0, \beta_0 \).

**Installer reputation.** An installer's reputation relies on the uptime (productive energy creation) of their existing projects, as equipment failures result in downtime. The update procedure for estimates of reputation uses total production from all of an installer's projects, \( prod \). Reputation follows the inverse-gamma distribution. This distribution corresponds to the assumed exponential distribution for failures in Eq. (15).

This distribution provides the best fit for the case when installer's reputation depends on \( prod \) only. The \( \beta_{rep} \) scale parameter of the distribution is fixed at the level 1.0. The prior value for parameter \( \alpha_{rep} \) of shape is 1.0. Eq. (19) is the result of applying method of moments to estimating the parameter \( \alpha_{t,rep} \). For every other period, except the initial, Eq. (19) describes the way to update the shape parameter:

\[ \alpha_{t,rep} = 1 + \frac{1}{\frac{1}{\alpha_{t-1,rep} N_{per}} + \frac{prod_t}{N_{per} + 1}} \]  

(19)

Where
\[
prod_t = \frac{1}{N_{\text{projects}}} \sum_{i=1}^{N_{\text{projects}}} \prod_{t,i}
\]  

(20)

is the average uptime production over all of an installer's projects. \(N_{\text{per}}\) is the adjusted number of periods for estimation, which is equal to \(n_0 + t\). \(t\) is the current period of the simulation, and \(n_0 = 10\) defines initial reputation "stickiness," meaning that realized failures affect estimated reputation with a weight of less than one.

### 3.3 Manufacturer’s decision process (passive)

The manufacturer researches, designs, and prices new panels, represented by the model as passive actions following rules for pricing and exogenous speed of technological progress.

#### 3.3.1 Researching and designing new PV panels

In every period, each manufacturer updates their PV panel design if their research efforts are fruitful. The design of the new panel begins with drawing a randomly-determined efficiency improvement, as well as expected reliability (time between failures) and maintenance complexity. This assumption is a significant simplification of an actual design for reliability. For examples and discussion of problems that face designers who design for reliability, see [42]. Even a simplified model can still provide insights into optimal design choices by manufacturers, as argued in [43].

Efficiency, \(ef\), improves over all manufacturers at an individual random rate, so that in the time period \(t\) for each manufacturer

\[
e_{f,t} = e_{f,t-1} e^{μ_{ef} + σ_{ef} ε_{0.1}}
\]  

(21)
and

\[ \epsilon_{0,1} \sim N(0,1) \quad (22) \]

Both manufacturer and installer know the efficiency of the new panel. Expected reliability is formed in the same way as expected efficiency, but is only known to the manufacturer (see Section 3.2.2 and Eq. (15) for installer's equations):

\[ \lambda_t = \lambda_{t-1} e^{\mu + \sigma \epsilon_{0,1}} \quad (23) \]

Generally, all panel design parameters can increase or decrease with each model step. The manufacturer decides to offer the panel to installers only if it offers a benefit over their existing offering, in terms of efficiency. Reliability does not affect this decision.

Expected maintenance costs, known only to the manufacturer, are \( N(\mu_{\text{maint}}, \sigma_{\text{maint}}^2) \), and update with each model step in the same fashion as efficiency and reliability, with an appropriate adjustment for multivariate generation. Let \( \theta_{\text{maint}} = (\mu_{\text{maint}}, \sigma_{\text{maint}}^2) \) be the combination of parameters for distribution of maintenance costs. Eq. (24) and Eq. (25) describe new values for \( \theta_{\text{maint}} \):

\[ \theta_{t,i,\text{maint}} = \theta_{t-1,i,\text{maint}} e^{\epsilon_{\text{maint}}} \quad (24) \]

\[ \epsilon_{\text{maint}} \sim N(\mu_{\text{maint}}, \Sigma_{\text{maint}}) \quad (25) \]

Appendix I has levels for other parameters of the distribution: \( \mu_{\text{ef}}, \sigma_{\text{ef}}^2, \mu_{\lambda}, \sigma_{\lambda}^2, \)

\( \mu_{\text{maint}}, \Sigma_{\text{maint}} \).
3.3.2 Manufacturer’s pricing scheme

Eq. (26) and Eq. (27) describe the initial calculations of prices. They use estimated price per efficiency unit.

\[
\text{price}_{\text{watt}} = 0.65
\]  
(26)

\[
\text{price}_{\text{module,SEM}} = \text{price}_{\text{watt}} N_{\text{watt}}
\]  
(27)

\(N_{\text{watt}}\) is peak production in watts under standard test conditions. After the initial period, \(\text{price}_{\text{watt}}\) decreases along a learning rate; data from [6] determined the choice of a specific learning rate of 8%.

3.4 Homeowner’s decision process

In every model step, installers present homeowners with a PV system proposal, which homeowners accept or not. The promised internal rate of return and the installer’s reputation guide this decision, which is also, in part, determined by the income level of the homeowner. Higher income levels require lower levels of expected return, with the assumption that at a certain level of income, people choose PV systems for reasons other than financial, such as environmental concerns or propensity to be an early adopter. This nuance is included based on the results of our interviews with current PV system owners. During those interviews, homeowners who belonged to the highest income bracket expressed their desire to contribute to the green movement and were less stimulated by the promised returns on their investment, while still requiring positive returns. Another assumption is the importance of the installer’s reputation, which includes how much hassle is involved for the homeowner in maintaining the equipment. The internal rate of
return incorporates the installer’s reputation, which allows us to include the homeowners’ concerns expressed during interviews.

The probability of a homeowner accepting any given proposal is a logistic function with the following specification:

\[
\begin{align*}
  p_{n,\text{switch}} &= \frac{1}{1 + \exp\left(-\frac{\text{IRR} \times \theta_{h,3} - \frac{1}{\theta_{h,1}} \left(1 + \theta_{h,0} \frac{1}{\theta_{h,1}1000}\right)^{-1}}{\theta_{h,2}}\right)} \\
  \text{(28)}
\end{align*}
\]

Figure 3 provides intuition regarding the response of Eq. (28) to changes in income level, from $10K to $100K, and internal rates of return. Note that the threshold value of the required rate of return depends on the homeowner’s income. Appendix I has other parameters for the logistic function. Figure 4 illustrates the response of the distribution to changes in other parameters. Homeowners will make a decision to adopt PV if the promised rate of return is high enough, with the caveat that homeowners with higher levels of income are happy with lower rates of return to consider adoption. Parameters in Eq. (28) control the general slope of the function and the location of the switch point. Eq. (28) is based on a number of heuristics that homeowners expressed during their interviews, as well as on studies, such as [44], that used return on investment. The specific form is one of the possible ways of aggregating both those heuristics and modeling uncertainty with respect to other parameters of agent’s decision-making. The choice that a homeowner makes is probabilistic, and there exists no specific threshold for his decisions.
A homeowner, who does not know the reliability of the panel, uses the reputation of an installer $rep_i$ to adjust the expected rate of return for the offered design $irr_r$. The resulting rate of return is $irr_r \cdot rep_i$. Based on assumptions of Section 3.2.2 and Eq. (19), Eq. (29) uses the mean of the estimated distribution to calculate reputation:

$$rep_i = \frac{1}{\alpha_{t,rep} - 1} \beta_{rep}$$  \hspace{1cm} (29)
The internal rate of return can be negative in the model. The figures show a simplified visual presentation of a range of [0, 1], but this does not represent the constraint on the internal rate of return. A negative internal rate could happen when savings on the electricity bill are not offset to a high enough degree by the purchase price of the PV system, or when net-metering prices will result in low realized savings.

We further explain our reasons for choosing specific parameters in the next section.

3.5 Model verification and validation

This paper is part of an ongoing project to investigate the residential PV market, and our primary focus at this stage is to test a small-scale model that demonstrates the possibilities of the agent-based approach. We have performed a variety of calibration and validation activities to this end.

3.5.1 Calibration

We used data from multiple sources for calibrating parameters of the model. Statements from SolarCity Corporation served as a starting point for calibrating installers’ profit function parameters. We used the cost structure from [45] for cross-checking initial estimates. We did not use the current PV system prices, reported in [45], to initialize the model; instead we allowed the installer to offer profit maximizing prices. We ensured that NREL-reported prices were close to those coming from the profit maximizing solution.

We used actual data regarding the total number of installations and each installer’s market share, given in [1], to define the market size for our simulation and to
assign equal portions of the market to each installer. We assumed moderate risk aversion to calibrate the level of incentives for exploring or exploiting.

We used the IEA report [26] as a foundation for setting parameters governing the reliability of the panels. We used information from [6] as a source of forecasts for future prices for new PV panels. We also used this source to discover manufacturers’ research processes for developing new panels. It should be noted that the research process for developing new panels is highly unpredictable for a time horizon of 5 years. While results of the simulation provide insights into market dynamics, the precision of the results significantly decreases over time.

Homeowner preferences reflect current market returns on investment with adjustment for perceived risk of investing in PV panels. Homeowners’ physical and socio-economic parameters replicate distributions inferred from RECS [46]. For all model scenarios, residential electricity prices are fixed at $0.15 per kilowatt hour. Each solar purchase receives the actual current federal investment tax credit of 30% of the purchase price. The inflation rate was 2%.

The number of agents in our model (7 manufacturers, 3 installers, and 1000 homeowners) reflects the actual number of major manufacturers and installers currently in the market. We chose this set-up based on an analysis of the NEM database [47] and a DOE report [48], which highlights eight major producers of PV panels, with four of them having much smaller shares, and three of them being major installers (Vivint, SolarCity Corporation, Sunrun) that operate in the U.S. residential solar market. We model the leaders in the market and assume that smaller installers will follow their decision patterns
and pricing. We picked the conservative assumption with respect to their decision patterns and leave the exploration of alternatives to future work.

3.5.2 Verification

Verifying the software code involved multiple steps. The first step was documenting the codebase; the second step was conducting multiple code reviews by other team members. Debugging was a major part of our verification efforts, as well as a step-by-step verification of each method. Another part was functional testing of the main simulation blocks, such as manufacturers’ decisions, installers’ decisions, and homeowners’ decisions. Independent implementation of the engineering model in Python served as a verification for the C++ counterpart.

3.5.3 Qualitative and empirical validation

We based our qualitative validation on a range of assumptions about the reliability and efficiency of PV panels. Our model performed in a reasonable way for the tested range. Islam [14] tested the range of hypothesis on the adoption time probabilities for households. While our model represents a different methodological approach and is focused on installers, some of the results could be validated against those presented by Islam. Islam’s results support the hypothesis that households that are less sensitive to the financial benefits of installing PV systems will have a higher probability of adopting. The same result holds in our model, where households with higher incomes adopt PV systems more. Another hypothesis that [14] confirmed is the higher adoption rates for households that have higher preferences for energy cost savings. In our model, higher energy cost
savings are also associated with the higher probability of adopting a PV system. Sections 4 and 5 below present our results based on the range of assumptions that match the historical data.

Industry specialists confirmed that industry participants gave less weight to the reliability of PV panels than to the expected financial benefits from deploying specific types of PV panels.

4 RESULTS AND DISCUSSION

This section describes the results of running two scenarios (CA, MA) under a number of different conditions. For each scenario, there were 7 manufacturers, 3 installers, and 1000 homeowners. The model verification and validation section above provides the reasons for our choice of specific numbers. Each 15-year run took 5 minutes to complete in compiled C++. The results presented here represent the average of 100 runs using different seeds.²

There are three main indicators that give a sense of market conditions over the years:

1. **Hit percent.** The percent of homeowners who adopt a PV system each year. Note that Hit percent is constrained to a maximum of 10%, which is the maximum number of homeowners approached by installers each year. Hit percent indicates *PV penetration* for a given year.

² The model is available at the public github repository https://github.com/wilfeli/ABMIRISLab.
2. **Accumulated percentage of installations, total number of installations.** The percentage (or number) of all the homeowners that have ever installed PV systems on their roof, which indicates the *accumulated PV penetration level*.

3. **Price per watt.** The average purchase price per watt *for systems installed in a given year*.

   There are two additional indicators that are useful to follow, while noting that they are partially determined by model parameters, as indicated in Section 3.1:

4. **Efficiency.** Efficiency is the percentage of energy from the sun that a panel converts into electricity. The efficiency of modern panels in the U.S. currently hovers around 20%.

5. **Reliability.** In the results, reliability is reported as the number of years with one failure, from the manufacturer's point of view (as opposed to the installers' and homeowners' estimates). For example, a reliability of "20" means that the panel is predicted to fail once in 20 years.
Figure 5. Overall market behaviors in both CA and MA scenarios

An overview of the market behavior is shown in Figure 5. The hit percent, taken together for both CA and MA, fluctuates year over year and does not show a definitive trend, although it seems, in general, to decrease for CA; however for MA, it seems to peak and then decline. The total number of installations trends slightly higher in the CA scenario compared to the MA scenario. For both scenarios, the penetration level increases to around 14% (140 of the 1000 homeowners) by the end of the simulation, as shown by the total number of installations at time 15. Overall, roof sizes present a physical limitation to the number of possible effective installations, but this should be at least partially offset by increases in panel efficiency, which decreases the effective size of installations.
Figure 6 shows that efficiency increases over time. It presents the three different scenarios that installers can use to gauge panel reliability: market average, same-as-current panel offering, and optimistic. While these three strategies do affect the actual reliability of the panels offered by manufacturers, the strategies have no effect on the
push for efficiency. Manufacturers have a strong tendency to switch to designs with a higher level of efficiency, evident from the upward trend in efficiency presented in Figure 6. Installers who are explorers (er) and exploiters (el) all pursue panels with higher levels of efficiency, as effects of lower reliability are very limited. Installer reputation has little effect on homeowner decisions. The growing market provides a good incentive for adopting new technology and decreases its risks.

Thus, when the benefits of improving efficiency are well-known to all market participants, and the knowledge (or reality) of system-failure is low, it pays for manufacturers to invest in efficiency improvements. For installers, it is better to pursue an exploration strategy when benefits are high and general risk levels are low—even for installers assigned to prefer an exploitation strategy. This is promising model behavior, as it matches both intuition and actual industry performance.
Figure 7. CA scenario: the changes of hit percent and price per watt (top panel), and accumulated percentage of installations (lower panel) over time

Figure 7 presents results for price-per-watt dynamics and penetration level by income category and by level of electricity consumption in the CA scenario. The hit percent decreases gradually, while price per watt remains steady. Homeowners with more income and electricity consumption make up the majority of those that opt to install.

Figure 8 shows the simulated results for the MA scenario. Over time, partially controlled by parameterization, price per watt remains stable in the CA scenario but decreases in the MA scenario. Prices stabilize at higher levels in the CA scenario compared
to the MA case. High CA energy prices allow homeowners to accept higher prices and still receive a reasonable return on their investment. In the MA scenario, price per watt stabilizes at lower levels than in CA, because less solar energy means homeowners require a higher rate of return.

![Diagram showing general dynamics and penetration level over time.](image)

**Figure 8.** MA scenario: the changes of hit percent and price per watt (top panel), and accumulated percentage of installations (lower panel) over time

The model prices are higher than those reported in the DOE analysis [6], $3.0-4.0W_{dc}$ in our model vs. $1.8W_{dc}$ for year 2020 in 2020 prices. The DOE report projects that those prices might be achieved if the strong push from the government for the development of photovoltaics continues. Our model does not include new measures and...
initiatives that the government might implement to achieve that goal; and thus our model gives a conservative price estimate.

A number of assumptions would shift the modeled forecasted price, such as assumptions about exogenous price dynamics. But the qualitative conclusions would remain the same.

Agent-based modeling allows us to look at the dynamics of the penetration level by income group and electricity bill. As results in Figure 7 and Figure 8 are averaged across simulation runs with different seeds, it is instructional to investigate the general dynamics of increasing penetrations shares for higher income and electricity bill groups. Each bar in the bottom panel of Figure 8, for example, has lower income (and lower electricity bill) groups at the bottom and high income (and high electricity bill) at the top. It is no surprise that the relative penetration level is much higher for high income groups and those families that have high electricity bills for both CA and MA scenarios.
5 CONCLUSION

Figure 9. Factors that determine market outcomes in the presence of different decision processes by installers and homeowners

The matrix in Figure 9 summarizes, in qualitative form, the sensitivity analysis results of the model. In the matrix, all factors that influence the current penetration level ("immediate characteristics") or expected future sales belong to a few categories: physical characteristics (including design characteristics), market characteristics, and preferences characteristics. All factors were evaluated in terms of changes of total penetration levels with respect to the baseline scenario for California. Sensitivity in the table below provided the data for the summary Figure 9.

Table 1. Sensitivity values for the model characteristics. Sensitivity is defined as change of penetration rate with respect to the baseline scenario when the model characteristic is varied around the baseline scenario value and other parameters are fixed at their baseline values.
<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Sensitivity</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maintenance cost</td>
<td>0.002</td>
<td>Low</td>
</tr>
<tr>
<td>Market size</td>
<td>0.027</td>
<td>Low</td>
</tr>
<tr>
<td>Reliability</td>
<td>0.062</td>
<td>Moderate</td>
</tr>
<tr>
<td>Propensity of firms to switch</td>
<td>0.065</td>
<td>Moderate</td>
</tr>
<tr>
<td>Roof size</td>
<td>0.079</td>
<td>Moderate</td>
</tr>
<tr>
<td>Efficiency</td>
<td>0.213</td>
<td>High</td>
</tr>
<tr>
<td>Hard costs</td>
<td>0.233</td>
<td>High</td>
</tr>
<tr>
<td>Solar irradiation</td>
<td>0.598</td>
<td>High</td>
</tr>
<tr>
<td>Propensity of homeowners to choose</td>
<td>0.978</td>
<td>High</td>
</tr>
<tr>
<td>Soft costs</td>
<td>1.419</td>
<td>High</td>
</tr>
</tbody>
</table>

We explicitly model the design parameters of the solar PV systems as their efficiency and reliability. We find that between efficiency and reliability, efficiency dynamics shape the market outcomes the most, while reliability parameters only guide some of the decision-making and have a less-profound effect. Maintenance costs, tied to the reliability of the system, do not represent a major decision factor for homeowners or installers, due to the relative rarity of maintenance events and their low cost. Installers track all of their PV system installations through their lifetime to directly estimate the maintenance costs and other performance measures. The Installers use maintenance information on existing projects to update their predictions of expected cost of maintenance, as shown in Figure 1. We model this to demonstrate how a complicated
technology product that has an extended lifespan can be integrated into a system model and provide additional information for decision-making in design.

We also find that roof size introduces restrictions on the possible system size and, as such, the potential market size. Interviews with installers support this finding. Installers stated that the physical properties of roofs contribute directly to the estimated installation price. Future improvements in panel efficiency will partially mitigate the roof-size effect. Also, exogenous changes in the level of solar irradiation, as exhibited in the CA vs. MA scenarios, alter the realized market price per watt. In both scenarios, the tendency to follow exploration strategy dominates.

As for market characteristics, the potential market size determines the financial viability of any strategy and thus is important to the decision-making agents. However, costs (hard and soft) are more important factors since they directly decide the expenses and determine the profitability of the systems and at what price point. Costs, representing the economics of currently available panels, are particularly important in the analyzed scenarios. This conclusion is supported, for example, by the NREL report by Fu et al. [45], who analyzed installation dynamics and PV systems. The efficiency levels of PV panels directly influence the attainable hard costs levels. This finding explains why installers track efficiency levels so closely.

Other factors might influence the choices that installers make on the PV market. For example, shocks to government policy might shift demand curves and result in temporary out-of-stock events. Testing those scenarios is possible with the current model but is outside the scope of the work.
A possible limitation of the qualitative conclusions is that we fixed the electricity price instead of it fluctuating over time. If the price of electricity increased, the adoption rate may have increased. However, allowing too many parameters to vary makes it more difficult to understand the reasons for the output; thus, this potential variable was held fixed.

Also important are the model's assumptions about the preferences of installers (exploration vs. exploitation) and homeowners (rates of return on investment). Future work will explore more sophisticated models, including expanding homeowners’ decision choices to include design parameters of the PV system. We will use survey data, specifically choice-based-conjoint models built from surveys, to articulate homeowner preferences. We also plan to include in future models representations of government and utility decisions. Additionally, this paper does not explore different purchase models, such as leasing. Researchers could adapt the current model to address this. We do not discuss home renters in this study, as a typical home rental lease agreement forbids the modification of or addition to the house structure, nor do renters carry the proper insurance to permit installation. Renters could be modeled as an influencer on a homeowner's decision.

As the model cycles to maturity, the dynamics of the balance between exploration and exploitation change, and the reliability is weighted more heavily by homeowners. Another factor that continues to shape these dynamics is low-price, low-quality competition from manufacturers that specialize in such systems. The reason why efficiency is the dominant factor in decision-making is because of our model assumptions
and because of the existing cost and information structure of the market. The research into residential solar PV owners by Rai et al. [49] supports some of these conclusions. Rai et al. found that financial considerations are important for solar adopters. But other results, such as how specific installers make their decisions and what their overall role is, are open questions for further investigation by researchers.

Our assumptions and generalizations do impose limitations on the implications of the work. These limitations include not explicitly modeling manufacturers' research priorities. Explicit modeling of these might change the unanimous dominance of efficiency as the major deciding factor for installers. The restrictions on choice also limit our conclusions. For example, installers can only consider one manufacturer each cycle, and homeowners can only consider one installer, who offers only one panel type, each cycle. These choice restrictions provide clarity on the agent-based model conclusions, without too many "moving parts," but it is difficult to perform basic validation of the results and explore high-level trends, as presented here.

Another potential issue lies with imposing specific functional forms on the reliability and complexity distributions. While our assumptions are conservative, it could be argued that we should investigate other possible approaches. We have not been able to find comparable research papers to provide the comparative analysis. There are also limitations on the installer when choosing potential PV panels for new proposals or considering only profit as the goal. But it is unclear if more explicit modeling of this procedure would alter the results, while the level of model complexity would significantly increase. Our model does not include government and utility permitting processes, but
they will be added in future work. Properly addressing some problems, such as changes in the PV industry standards at the state and county level, requires changing the focus of the model and is therefore outside of the scope of the work.

To summarize, the analysis investigated the dynamics of PV system penetration in the U.S. residential solar energy market using an agent-based model. In particular, we focused on an intermediary agent, installers; this was articulated in the model as guiding design developments of PV panels. The more traditional approach is to directly model homeowners as guiding these developments through their preferences/choices. The model articulated the installers' decision process as one of exploration vs. exploitation, while maximizing profits. Whether the exploration or the exploitation technology adoption strategy dominates depends on the specifics of the market, such as effect of reputation, which was possibly under-represented in the model.

As represented, the installers explore new panel offers more than they exploit existing panels, and this drives technological development (panel efficiency). This result has potential implications for policy-makers at the state and national level; if policies can alleviate risks from new panel technologies, perhaps by financially compensating homeowners for system downtime, efficiency should be highly-sought over reliability, which would be a boon to the progress of the solar industry.

ACKNOWLEDGMENTS

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expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.
REFERENCES


### APPENDIX I

#### Parameter values for the model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial parameter values for the installer's demand estimation procedure.</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>μ</strong>₀,θ</td>
<td>(-0.002375 5.9375, 0.002375 -2.375, -0.002375)</td>
<td>Bayesian prior for the mean of the distribution for demand function</td>
</tr>
<tr>
<td><strong>V</strong>₀,θ</td>
<td>0.5I₁</td>
<td>Bayesian prior for the variance of the distribution for demand function</td>
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<tr>
<td>α₀,d</td>
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<td>Initial value for parameter for prior for demand function distribution</td>
</tr>
<tr>
<td>b₀,d</td>
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<td>Initial value for parameter for prior for demand function distribution</td>
</tr>
<tr>
<td>Z₀,inst</td>
<td>(1.0, 0.1, 1.0, 0.1, 1.0)</td>
<td>Prior values for demand function estimation</td>
</tr>
<tr>
<td>N-market</td>
<td>50000</td>
<td>Market size</td>
</tr>
</tbody>
</table>

Parameter values for the installer's decision procedure: cost function.

| θcomplexity install | 100 | Parameter for complexity of installation |
| θdesign | 350 | Parameter for design costs |
| θpermit general | 200 | Parameter for cost estimation of permitting, general part |
| θpermit specific | 50 | Parameter for cost estimation of permitting, design specific part |
| θadministration | 2000000 | Parameter for administrative costs |
| θmarketing | 2500000 | Parameter for marketing costs |

Parameter values for the installer's decision procedure: propensities to switch.

<p>| θ₀,explorer | 1 | Parameter values for explorer/exploiter decision process |
| θ₁,explorer | 0.25 | Parameter values for explorer/exploiter decision process |
| θ₀,exploiter | 1.5 | Parameter values for explorer/exploiter decision process |</p>
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$\theta_{1,\text{explorer}}$</td>
<td>0.5</td>
<td>Parameter values for explorer/exploiter decision process</td>
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<tr>
<td>Parameter values for the installer’s decision procedure: priors for reliability distribution.</td>
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</tr>
<tr>
<td>$\alpha_{0,f}$</td>
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<td>Initial value for prior for failure distribution</td>
</tr>
<tr>
<td>$\beta_{0,f}$</td>
<td>25</td>
<td>Initial value for prior for failure distribution</td>
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<td>Parameter values for the installer’s decision procedure: priors for complexity distribution.</td>
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</tr>
<tr>
<td>$\mu_0$</td>
<td>50</td>
<td>Initial value for prior for probability distribution for maintenance</td>
</tr>
<tr>
<td>$\nu_0$</td>
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<td>Initial value for prior for probability distribution for maintenance</td>
</tr>
<tr>
<td>$\alpha_0$</td>
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<td>Initial value for prior for probability distribution for maintenance</td>
</tr>
<tr>
<td>$\beta_0$</td>
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<td>Initial value for prior for probability distribution for maintenance</td>
</tr>
<tr>
<td>Parameter values for the design of PV panels for manufacturers.</td>
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<td>$\mu_{\text{eff}}$</td>
<td>0.0025</td>
<td>Parameter for efficiency distribution</td>
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<td>$\sigma_{\text{eff}}^2$</td>
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<td>Parameter for efficiency distribution</td>
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<td>$e_{\text{f}_0}$</td>
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<tr>
<td>$\mu_{\lambda}$</td>
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<td>$\sigma_{\lambda}^2$</td>
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<td>Parameter for reliability distribution</td>
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<tr>
<td>$\lambda_0$</td>
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<td>Initial value for reliability</td>
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<td>$\mu_{\text{maint}}$</td>
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<td>Parameters for complexity of maintenance distribution</td>
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<td>$\Sigma_{\text{maint}}$</td>
<td>$\begin{bmatrix} 0.01 &amp; 0.01 \ 0.01 &amp; 0.02 \end{bmatrix}$</td>
<td>Parameters for complexity of maintenance distribution</td>
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<td>Initial value for parameters for complexity of maintenance distribution</td>
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<tr>
<td>$\sigma_{0,\text{maint}}^2$</td>
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<td>Initial value for parameters for complexity of maintenance distribution</td>
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<td>Parameter values for the homeowner’s decision procedure.</td>
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<tr>
<td>$\theta_{h,0}$</td>
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<td>Parameter 0 of homeowner’s decision function</td>
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<td>$\theta_{h,1}$</td>
<td>2</td>
<td>Parameter 1 of homeowner’s decision function</td>
</tr>
<tr>
<td>$\theta_{h,2}$</td>
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<td>Parameter 2 of homeowner’s decision function</td>
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<tr>
<td>---------------</td>
<td>------</td>
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<tr>
<td>$\theta_{h,3}$</td>
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<td>Parameter 3 of homeowner’s decision function</td>
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</table>
Table captions:

Table 1. Sensitivity values for the model characteristics. Sensitivity is defined as change of penetration rate with respect to the baseline scenario when the model characteristic is varied around the baseline scenario value and other parameters are fixed at their baseline values.
Figure captions:

Figure 1. Major attributes of the model and agents’ decision processes

Figure 2. Information available to manufactures, installers, and homeowners

Figure 3. Probability of homeowner accepting PV proposal, given rate of return (irr) and level of income

Figure 4. Probability of homeowner accepting PV proposal, given rate of return (irr) and different levels of parameters

Figure 5. Overall market behaviors in both CA and MA scenarios

Figure 6. CA scenario: three approaches to estimating panel reliability and the efficiency choices by installers

Figure 7. CA scenario: the changes of hit percent and price per watt (top panel), and accumulated percentage of installations (lower panel) over time

Figure 8. MA scenario: the changes of hit percent and price per watt (top panel), and accumulated percentage of installations (lower panel) over time

Figure 9. Factors that determine market outcomes in the presence of different decision processes by installers and homeowners