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Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach

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HIGHLIGHTS

- We present an agent-based model of residential solar photovoltaic (PV) adoption.
- Model integrates social, behavioral, and economic elements of agent decision-making.
- Real-world, large-scale integrated dataset used for model validation and testing.
- We study the importance of using disaggregated empirical data on model performance.
- Social and attitudinal components are critical for spatial and demographic accuracy.

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ABSTRACT

Energy technology adoption is a complex process, involving social, behavioral, and economic factors that impact individual decision-making. This paper uses an empirical, geographic information system (GIS)-integrated agent-based model of residential solar photovoltaic (PV) adoption to explore the importance of using empirical household-level data and of incorporating economic as well as social and behavioral factors on model outcomes. Our goal is to identify features of the model that are most critical to successful prediction of the temporal, spatial, and demographic patterns that characterize the technology adoption process for solar PV. Agent variables, topology, and environment are derived from detailed and comprehensive real-world data between 2004 and 2013 in Austin (Texas, USA). Four variations of the model are developed, each with a different level of complexity and empirical characterization. We find that while an explicit focus only on the financial aspects of the solar PV adoption decision performs well in predicting the rate and scale of adoption, accounting for agent-level attitude and social interactions are critical for predicting spatial and demographic patterns of adoption with high accuracy.

1. Introduction

Demand-side behavior has important implications for local and global emissions reductions [1–4] and for the future of the electric grid [5–9]. In particular, a robust understanding of the rate and pattern of consumer adoption of durable energy technologies is critical for forecasting energy demand and emissions, as well as for infrastructure planning and development [6,10–12]. Modeling of energy technology adoption is particularly challenging, since the nominal economics (price) of the technology is but just one determinant of consumers' likelihood to adopt [13–15]. Other behavioral and social phenomenon such as decision heuristics, anchoring, path-dependence (past experiences), risk aversion, trust-based information networks, and social norms are also quite important in understanding decision-makers with bounded rationality in general [16–18], and energy-related consumer decision-making in particular [2,14,15,19–22]. As such, the development of analytical techniques that are able to appropriately represent and model the bounded rationality of economic agents, including the relevant social and spatial factors, is important for better understanding of the technology adoption process and the resultant emergent phenomena [23,24].

Agent-based modeling (ABM) has emerged as a methodology that provides a suitable framework for explicitly modeling decision-makers with bounded rationality, their social interactions, and the (physical and economic) environments surrounding them

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[23,25–28]. Energy and environment related consumer technology adoption has been a particular area of growth in the development and applications of ABM [29–44]. Because the underlying components of the system and how they interact with each other are modeled explicitly in ABM, the processes that lead to observable emergent phenomena (such as the rate and pattern of adoption) can be altered through simulation experiments, creating virtual laboratories [24,45,46]. The depth, generalizability, and flexibility of ABM make it applicable to a wide range of problems such as the modeling of traffic patterns, growth of civilizations, land use change, group dynamics, molecular self-assembly, electricity markets, and stock markets (see [24] for a more comprehensive review). However, there are important challenges for ABM in consumer energy technology adoption – and human-technical systems in general – especially regarding the integration of theoretical elements and empirical patterns in the model structure, initialization, and validation efforts. While the potential of ABM in enabling detailed bottom-up modeling of technology adoption is quite promising, ABM has been criticized on two important fronts [47–50]: (i) agent decision rules in ABM are often over simplified or even *ad hoc*, rendering connections to the broader theoretical context difficult, and (ii) models often have inadequate empirical emphasis on initialization and validation against real-world data [51]. These factors have drawn increasing attention in the literature toward the importance of methodological rigor and the use of adequately-resolved empirical data within ABM [49,52–54]. It is now recognized in the literature that the extent to which the strengths of ABM techniques offer an advantage over conventional modeling techniques in policy analysis and system design is not a given, rather it depends critically upon careful theoretical and empirical underpinning of agent-based models [47,54].

This paper uses a theoretically and empirically grounded agent-based model of residential solar photovoltaic (PV) adoption (henceforth, the "solar ABM") to analyze the importance of using localized (disaggregated) empirical data and of including social and attitudinal components in the adoption model in addition to purely economic factors. Specifically, we develop four different variations of the solar ABM – "Base-case", "Simple Environment," "Random Fitted," and "Economic Only" – to study residential solar PV adoption through a thorough integration of economic valuation, attitudinal evolution, and social interactions. Each of the four models has a different level of model complexity and empirical characterization. Using a rich and comprehensive dataset between 2004 and 2013, the models simulate the adoption of residential solar PV in the city of Austin (Texas, USA), which has a population of approximately 900,000. Using the four variations of the solar ABM we systematically examine the effect of progressively increasing the empirical basis and the complexity of agent-based models on model outcomes through external validation. We emphasize that these are four different *models*, not just different scenarios – as we discuss later, they vary in the basic model formulation in important ways. We focus on aspects of model fitting and validation, with the goal of identifying features of the solar ABM that are most critical for accurately describing the solar PV adoption process. We analyze the cost (in terms of predictive power) of decreasing the empirical foundation and complexity of the model.

We chose solar PV as the empirical test-bed in our study for two reasons: (i) the growing importance and impact of solar PV in the electric industry globally [55,56], and (ii) the relatively complex decision-making process associated with solar PV adoption, which offers a unique opportunity to study and quantify how economic, attitudinal, and social factors impact individual behavior and lead to emergent phenomena [57,58]. The two main contributions of this paper are: (i) identification of variables and processes key to the successful modeling of residential solar PV adoption using an ABM approach, and (ii) detailed comparisons of different model variations in order to quantify the value of increasing model complexity and of using empirical distributions in terms of increased accuracy of the model for predicting the rate *and* pattern of solar PV adoption.

2. Material and methods

In this section we provide a conceptual overview of the model components and how they fit together. All model components were integrated in the R programming language and additional supporting methods were written in Python. We also briefly describe the integrated dataset and the validation procedures that are used for the analysis in this study. A more comprehensive discussion of the underlying data and methodology is covered elsewhere [59]. All simulations were run on the 10PF Stampede Supercomputer at the Texas Advanced Computing Center (TACC), utilizing 16 tasks per server node (each with two 350GF Intel Xeon E5-2680 processors and one 1070GF Intel Xeon Phi SE10P Coprocessor) on 100 nodes per batch (1 batch = 100 simulations). Depending on the exact specification, each batch took between 20 and 35 min to execute.

2.1. Data

We use a granular household-level dataset including: (i) *for solar adopters* ($N = 2738$): time-series utility solar program data (rebate; price; system technical details; timing of adoption) and survey data (attitude; motivators; perception; information seeking; financial aspects)[1] and (ii) *for all households* ($N = 173,466$): geo-location, home value, and environmental variables (roof size; lot size; tree cover; elevation; slope; shading; insolation). The utility solar program data for Austin ranges from 2004 to mid-2013. Additional datasets including solar-adopter surveys, appraisal district data, and light detection and ranging (LiDAR) data were overlaid upon the solar program data to build the comprehensive and granular integrated dataset. The solar program data for *each* installation were matched to geocoded addresses, allowing for the analysis of solar adopter distribution over space and time. Each geocoded address was matched to a single family residential parcel from the Travis County Appraisal District, and a home footprint from the City of Austin. These polygons were overlaid with household-level home value and environmental layers in a geographic information system (GIS) to define the agent attributes. Finally, solar adopter survey data were joined to the solar program data. These data streams were combined to create agent and environment classes that were rigorously grounded in real-world data and closely reflected the actual population they were intended to represent, allowing for an empirical ABM methodology [59].

2.2. Model design

The solar ABM used in this paper is a *household-level agent-based model* able to generate the empirically observed temporal and spatial patterns of the adoption of residential solar [59]. There is only one agent type – a household. The number of agents in the solar ABM is 173,466: all the actual single-family residential households in Austin, Texas as of mid-2013. The study period is from 2004 to June 2013, during which the solar adoption level in Austin grew from only $N = 20$ to 2738. Data from 2004 through 2007 is used for initialization, while 2008–mid-2013 is the simulation period.

[1] For the solar adopter survey data, $N = 616$ (22.5% response rate).