Spatial household preferences of decentralized solar photovoltaic and thermal systems

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Abstract

Small-scale, residential solar systems have been increasingly recognized as a key sector for future carbon emission reduction in cities. This study investigated customer preferences of solar thermal and photovoltaic systems through a crowdsourced discrete choice experiment and latent class choice modeling targeting Boston, Massachusetts and Atlanta, Georgia. Key motivating factors for adoption in both testbeds are installation cost, environmental benefits, and annual savings. Despite the latent classes' similarity in their preferences of different system features, all classes present different socioeconomic characteristics across the two testbeds, indicating preference heterogeneity across cities. We also found that both cities have significant early adopters residing in lower-property-value regions, revealing a potential to achieve both carbon emission reduction and community renaissance objectives when combining infrastructure renovation projects with decentralized energy systems installation. This study presents a framework for assessing and understanding the social demand of decentralized energy systems to facilitate their future promotions.

Keywords

Decentralized household energy supply; Solar photovoltaic system; Solar thermal; Discrete choice experiment; Latent class choice modeling; User preference heterogeneity

1. Introduction

Solar energy is one of the fastest-growing renewable energy sources around the world (IEA, 2020; Weiss and Spörk-Dür, 2020). It is currently harnessed through two dominant technologies: solar photovoltaic (PV) and solar thermal systems. By the end of 2019, the global installed solar PV and thermal capacities were 627 GWel and 479 GWth, respectively, with China, Europe, and the United States leading the chart (Weiss and Spörk-Dür, 2020). Despite the industry's unprecedented growth, solar systems currently meet only around 2.8% of the global electricity demand and 0.7% of the global heat demand (Adib et al., 2020; IEA, 2020), while the majority of the global solar potential is still untapped (Davidson, 2005). Small-scale, residential solar systems are perceived as a dominant force to further the growth of the global solar industry (Lee et al., 2018). A recent study reported that small buildings (<465 m^2) represent about 65% of the total rooftop solar potential in US cities (Gagnon, 2019). An enhanced understanding of households' preferences of solar PV and thermal systems is hence imperative to support effective policy and incentive designs for their broader penetration in the residential sector.

Traditional economic and behavioral studies typically examine the influence of prescribed individual factors, such as economic cost or incentives (Haas et al., 1999; Jager, 2006; Matisoff and Johnson, 2017; Schelly, 2014; Sun et al., 2020), environmental attitudes (Haas et al., 1999; Jager, 2006; Schelly, 2014; Sun et al., 2020), peer effects (Bollinger and Gillingham, 2012; Jager, 2006; Palm, 2016; Rai et al., 2016; Reeves et al., 2017), information channels (Haas et al., 1999; Palm, 2016; Rai et al., 2016; Reeves et al., 2017; Wolske et al., 2017), technology innovation (Haas et al., 1999; Sun et al., 2020; Wolske et al., 2017), system reliability and independency (Haas et al., 1999; Jager, 2006), business model (Rai et al., 2016), and beliefs (Wolske et al., 2017) on consumer adoption of decentralized solar PV systems. While the knowledge about whether and to what degree these individual factors influence consumer behaviors is important in guiding policy design and evaluating policy effectiveness, it does not enable a holistic understanding about the demand of decentralized, residential energy systems to facilitate the prediction of their adoption trajectories at a regional scale. Furthermore, solar thermal systems are hugely underrepresented in the consumer behavior literature.

Only a few studies have attempted to predict consumer adoption of decentralized energy systems based on the combined effect of multiple factors in an integrated modeling framework. Best et al. (2019) developed a logit model to examine the combined effect of demographics, housing characteristics, environmental attitudes, and geographical location on both solar PV installation and intention to install using Australian survey data. They found household economic status, electricity expenses, environmental attitudes, property tenure, and space constraints were predictors of either the installation or the intention to install solar PV systems. Rai and Robinson (2013) developed a multivariate regression model to predict solar PV adoption rates (i.e., decision time) based on information certainty, peer effects, neighborhood contact, business model, and income using a household-level PV adopter dataset from Texas, US. Korcaj et al. (2015) applied path analysis to predict the intention to purchase solar PV systems based on perceived collective environmental and economic benefits as well as perceived individual social status, autarky, financial benefits and overall cost, using a sample of 200 households in Germany. They found the subjective norm (i.e. peer behavior and expectations) and the attitude towards PV were strong predictors of purchase intention. Several other studies have developed such predictive models for solar thermal systems. Schelly (2010) conducted logistic regression modeling to predict US counties with five or more households using solar thermal systems based on demographics, environmental attitudes, and local climate characteristics. Woersdorfer and Kaus (2011) developed probit models to predict solar thermal system adoptions in northwestern Germany, and found environmental attitude, knowledge, household income are important determinants of prospective adoption of nonowners. None of these studies, however, included both solar PV and thermal systems to investigate the future growth of decentralized energy systems as a whole. Given the different study location, factors, and methods applied, the critical factors identified through these modeling efforts often diverge, which indicates a potential preference heterogeneity across different cities, regions, or countries. For instance, an individual in Region A and an individual in Region B sharing similar preferences of decentralized energy systems may have different socioeconomic characters. However, the existence of such preference heterogeneity has not be tested through a scientific framework. To the authors' knowledge, no study has further applied these integrated prediction models to investigate the spatial distribution of consumer preferences of decentralized energy systems to inform spatial-explicit policy designs.

Accordingly, this study developed an integrated modeling framework to predict decentralized energy system adoption based on a discrete choice experiment and investigated the spatial distributions of consumer preferences of the decentralized, residential solar PV and thermal systems, using Boston, Massachusetts, and Atlanta, Georgia as two testbeds. These two areas were selected given their comparable population size and a strong trend in solar growth (SEIA, 2020). Boston currently has significantly more residential solar installations as compared to Atlanta (849 and 64 homes out of 100,000 for Boston and Atlanta, respectively) (CAPE, 2019) which could be attributed to its higher quantity and quality of residential solar incentives (DSIRE, 2021a, DSIRE, 2021b). User preference, socioeconomic, and housing condition data were first collected through a discrete choice experiment survey administered in the two testbeds. The collected and treated data were then analyzed using latent class choice modeling to identify the hidden classification of households with distinct preferences of solar PV and thermal systems. Last but not least, the identified latent classes were spatially configured to highlight their distributions across the two testbeds. By applying the same modeling framework to two different testbeds, this study allows the testing of the preference heterogeneity across different cities.

2. Methods & materials

The following sections introduce the survey design and administration (Section 2.1), the discrete choice experiment (Section 2.2), the latent-class choice model (Section 2.3), and the spatial visualization (Section 2.4).

2.1 Survey design and administration

We designed, tested, and administered a choice experiment survey to investigate user preferences/choices of residential solar PV and solar thermal systems. The survey was developed in Qualtrics®. Solar PV system hereby refers to one or more rooftop solar panels installed to produce electricity for household uses. The solar thermal system refers to systems that utilize sunlight for water heating. A solar thermal system is supplemented by a gas or electric booster when there is insufficient solar heat gain. The survey includes questions related to a discrete choice experiment, the respondents' socioeconomic and personal characteristics (Table S1 of the supporting information (SI)), and their location and housing information. The initial survey draft was developed based on our literature review, and was tested with around 70 undergraduate and graduate students in an introductory sustainability class at the University of New Hampshire. While the survey was considered generally easy to understand, an outstanding recommendation was to reduce the number of options and choice sets to ease cognitive stress. Accordingly, the survey was revised to include only two options in each choice set. The semi-finalized survey was further tested through Amazon Mechanical Turk, a widely used crowdsourcing platform (Crump et al., 2013), to elicit feedback. Data collected from this step were used to check the statistical significance of different system design features' impact on consumer choices, and six features that were found to be the most influential were included in the final survey. The finalized survey was launched in April 2017 targeting the Greater Boston and the Metro Atlanta areas as two testbeds. Respondents were limited to the residents of these two areas through self-identification. The locations of the respondents were further verified based on their IP addresses upon completing the survey. The finalized survey used in this project can be found in the SI. Data were collected over a four-month period and the project paid $1 USD for each survey submission.

A data treatment process was conducted to exclude any incomplete responses. The numbers of complete responses used for data analyses were 602 and 697 for Boston and Atlanta, respectively. The sample sizes meet the minimum thresholds with an acceptable range of random error, which was calculated to be 536 (α=β=0.05 and Δ=10%) based on the reference limit method (Bellera and Hanley, 2007). Finalized responses were further weighted based on census data to remove random error of the sample. The processed data were analyzed through latent class choice modeling to assess the preference heterogeneity in the two testbeds.

2.2 Discrete choice experiment

The discrete choice experiment is a survey-based method to discover an individual's preference using hypothetical yet realistic system attributes for pairwise selections (Watson et al., 2017). It has wide applications in economics and engineering (Mangham et al., 2009). The finalized survey contains 12 pairwise choice sets. Each choice set describes two potential home upgrade choice options with solar PV or thermal systems. Each choice option is further illustrated by six upgrading features including system type, ownership, installation cost, environmental benefits, neighbor's choices, and annual saving (Table 1). These upgrading features come with different levels, and each choice option represents a unique combination of the upgrading feature levels. Particularly, the selected numerical cost and saving values were derived from data collected from different decentralized energy system vendors (SolarWorld Grid-Tie, 2021). We used the most generic levels in operationalizing environmental benefits and neighbors' choice to avoid confusion as well as to reduce potential cognitive stress associated with more detailed level definitions. We also used the D-optimal algorithm embedded in JMP software (SAS, 2012) to design the 12 choice sets to ensure the lowest possible covariance between the upgrading features of each choice option. Accordingly, each choice option can be considered as independent. Respondents can select either one of the two choice options or neither of them.

Table 1 – Decentralized energy system design features and the levels associated with each feature.

Upgrading Features	Levels	Variable coding for latent-class choice modeling
System Type	Solar PV	Categorical variable
	Solar Thermal	
Ownership	The system will be sized for and owned by your own household	Categorical variable
	The system will be owned communally; you will own a share of it, pay for that share and accumulate the benefits shown	
Upfront installation cost	$3,000.00	Numerical variable, scaled to 0.25 ($3000/$12,000)
	$6,000.00	Numerical variable, scaled to 0.50 ($6,000/$12,000)
	$9,000.00	Numerical variable, scaled to 0.75 ($9,000/$12,000)
	$12,000.00	Numerical variable, scaled to 1.00 ($12,000/$12,000)
Environmental benefits (e.g., improve air quality; reduce carbon emission; reduce water consumption to produce energy)	No benefit	Categorical variable
	Insignificant	
	Moderate	
	Significant	
Neighbors' choice	No installation yet Some of your neighbors already installed one Most of your neighbors already installed one	Categorical variable
Saving per year (e.g., electricity and gas billing saving)	Avg. $480	Numerical variable, scaled to 0.33 ($480/$1440)
	Avg. $960	Numerical variable, scaled to 0.67 ($960/$1440)
	Avg. $1440	Numerical variable, scaled to 1.00 ($1440/$1440)

2.3 Latent-class choice modeling

The latent-class model is based on mixture modeling, which is widely used to identify hidden preference heterogeneity in a studied population (Nylund et al., 2007). The model includes socioeconomic/personal variables of the respondents as well as the different upgrading features of the system design as independent variables to predict an individual's choice of decentralized energy systems (Eq. (1)). The operationalization of the socioeconomic/personal variables and the six system design features in the latent-class model was provided in Table S1 of the SI and Table 1, respectively. The Latent GOLD 5.0 software was used to develop the latent-class choice model using the expectation-maximization (EM) theory. EM algorithm provides an iterative approach to predict the maximum likelihood estimators in presence of latent variables (Bishop, 2006). This algorithm runs through two modes: estimation (E-Step) and maximization (M-Step). During the E-Step, the algorithm attempts to estimate the latent variables and during the M-Step, it optimizes the model coefficients to explain the data more efficiently (Bishop, 2006). In order to determine an optimal latent class number, we tested the model for a range of class numbers, each with 150 runs to minimize the possibility of converging at a local optimum. Bayesian Information Criterion (BIC) was chosen as the model performance indicator as previous studies have indicated its better performance than other information criteria for class number selection (Lu et al., 2019; Nylund et al., 2007). Models with the lowest BIC were selected for the subsequent analyses.

$$P(y_{it} = m|Z_i) = \sum_{c=1}^{C} P(X = c|Z_i)P(y_{it} = m|X = c) \quad (1)$$

where $P(y_{it} = m|Z_i)$ is the conditional probability of observing response *m* to choice set *t* from individual *i*, given the individual having socioeconomic/personal characteristics of Z_i. $P(X = c|Z_i)$ is the conditional probability that an individual belongs to latent class *c* while holding the socioeconomic/personal characteristics of Z_i. *C* is the number of latent classes. $P(y_{it} = m|X = c)$ is the conditional probability of observing a certain response *m* in latent class *c*. It is calculated based on the ratio between the utility associated with response *m* and the overall utility of all possible responses in choice set *t* using Eq. (2).

$$P(y_{it} = m|X = c) = \frac{\exp(U^t_{m|c})}{\sum_{m'=1}^{M} \exp(U^t_{m'|c})} \quad (2)$$

where $U^t_{m|c}$ indicates the system's upgrading features of response *m* in choice set *t*. It is calculated using Eq. (3).

$$\exp(U^t_{m|c}) = \beta_{no\ adopt|c} d_{no\ adopt,m} + \sum_{j=1}^{D} \beta_{j|c} d_{j,m} \quad (3)$$

where $d_{j,m}$ denotes the value of the j^{th} design feature in response *m* (Table 1 Column 3) and $\beta_{j|c}$ is the class-dependent coefficient associated with the j^{th} design feature. In the model, each design feature has a coefficient associated with it. The sum of the coefficients for all levels of categorical variables equals zero (James et al., 2013). The class-dependent coefficients were calculated using the Expectation Maximization algorithm (Bishop, 2006; Vermunt, 2002). $d_{no\ adopt,m}$ is a dummy variable associated with the choice of neither of the options in our survey and will be equal to 1 when neither of the options is chosen. $\beta_{no\ adopt|c}$ is the coefficient associated with the dummy variable, showing the impact of choosing neither of the options under the conditional probability of observing each survey response.

Similarly, $P(X = c|Z_i)$ was calculated based on the utility of individual *i* belonging to latent class *c* over the summed utility of all *C* types of latent classes. A set of class-dependent coefficients were then estimated for all considered socioeconomic and personal characteristics. Details of the probability functions and the expectation-maximization method can be found in the Latent GOLD Choice manual (Vermunt and Magidson, 2005).

2.4 Spatial visualization

We applied the population synthesizer method developed by Arizona State University to predict and visualize the spatial distributions of the latent classes in the two testbeds (Choupani and Mamdoohi, 2016). We first created representative synthetic samples of individual households in each census block of the two testbeds using Public Use Microdata Sample (PMUS) and the census summary statistics of socioeconomic variables (Choupani and Mamdoohi, 2016). The mean values of the PMUS variables for each census block, including age, education, gender, housing type, household size, household income, ownership, and race, were matched with the summary statistics of the census data. For additional personal variables that were not available from the PMUS (e.g., satisfaction level of the current electricity supply, knowledge of decentralized energy systems, installation by neighbors), we assigned the mean values obtained from our surveys to the synthetic households. These values were assumed constant within each city based on city averages. These synthetic households were then used to generate the presence probabilities of different latent classes within each census block. We further visualized these probabilities across Boston and Atlanta using QGIS V3.14 and analyzed the spatial distributions of the latent classes in these two cities.

3. Results and discussion:

3.1 Summary of respondents from Mechanical Turk

Table 2 presents the socioeconomic characteristics of the survey respondents as well as the average socioeconomic characteristics for both cities based on the U.S. census data. Most of the socioeconomic variables in our results had a similar distribution as the census data except age, education, and household head. Population that are older than 60 years old and population that are high school graduate or less are underrepresented, while population that are household heads are overrepresented. These sampling biases were corrected by post-stratification weighting of the survey data and corrected the weights of individual responses before conducting latent-class modeling (Kolenikov, 2016; Lu et al., 2019). This is to improve our model representativeness of the general population in each of the two testbeds.

Table 2. Summary and comparison of sample and census results in Metro Atlanta and Great Boson.

Socioeconomic Variables	Levels	Atlanta, Survey	Atlanta, Census	Boston, Survey	Boston, Census
Do you own or rent a property for you and your family?	Own	50.82%	63.00%	45.60%	59.60%
	Rent	47.25%	37.00%	52.83%	40.40%
What is the type of your dwelling?	Single-family detached house	59.89%	66.90%	44.34%	45.30%
	Multifamily units	38.87%	29.90%	53.46%	53.90%
What is your current age?	20 to 24	19.97%	9.18%	22.64%	9.55%
	25 to 29	24.68%	9.60%	25.95%	10.34%
	30 to 34	18.83%	9.87%	23.47%	9.42%
	35 to 39	13.27%	9.87%	9.75%	8.12%
	40 to 44	8.42%	10.43%	7.27%	8.64%
	45 to 49	6.13%	10.29%	3.97%	9.29%
	50 to 54	3.71%	9.87%	3.97%	9.69%
	55 to 60	3.14%	8.62%	1.82%	8.77%
	> 60	1.85%	22.25%	1.16%	26.18%
Which statement best describes your current employment status?	Working	83.03%	75.03%	87.60%	64.50%
	Not Working	16.97%	24.97%	12.41%	35.50%
What is your gender?	Male	41.65%	48.44%	50.91%	48.44%
	Female	57.92%	51.56%	48.76%	51.56%
Are you now married, widowed, divorced, separated, or never married?	Married	44.37%	47.40%	40.17%	46.10%
	Single (including widowed, divorced, separated, and never married)	55.63%	52.50%	59.83%	53.90%
Are you the head of the household (who is running the household)?	Yes	71.61%	38.07%	76.20%	39.34%
	No	28.39%	61.93%	23.80%	60.66%
How many people live in your household?	1	14.55%	26.05%	19.17%	28.80%
	2	30.67%	31.54%	30.74%	31.80%
	3	24.25%	17.35%	23.31%	16.50%
	4+	30.52%	25.07%	26.78%	22.80%
What level of education you have completed?	Less than high school or some high school	0.14%	10.40%	0.00%	8.80%
	High school graduate	8.84%	24.60%	6.12%	22.30%
	Some college or vocational training	31.24%	27.10%	24.79%	21.10%
	Bachelor's degree	41.65%	23.60%	43.80%	25.70%
	Graduate or professional degree	17.55%	14.30%	25.29%	22.20%
Choose one or more races that you consider yourself to be	White	64.51%	55.15%	77.07%	75.58%
	Black or African American	24.56%	33.46%	9.36%	8.72%
	Others	10.93%	11.39%	13.57%	15.70%
Do you have kids under 18?	Yes	41.08%	35%	34.38%	30.40%
	No	58.92%	65%	65.62%	69.60%
What is your approximate average household income?	$0 to $24,999	11.55%	19.60%	10.74%	17.80%
	$25,000 to $49,000	26.68%	22.80%	20.83%	16.20%
	$50,000 to $74,999	25.39%	18.40%	23.97%	14.80%
	$75,000 to $99,999	15.69%	12.60%	17.19%	12.20%
	$100,000 to $149,999	13.70%	14.20%	18.35%	17.80%
	$150,000 to $199,999	3.99%	6.00%	6.11%	9.60%
	$200,000 and up	3.00%	6.40%	2.81%	11.60%

3.2 Selection of an optimal class number and summary of the model statistics

The optimal latent class models for both Atlanta and Boston resulted in eight latent classes, with the lowest BICs of 10,883 and 9,290, respectively (Fig. 1). All studied independent variables have a p-value of lower than 0.07 (Tables S3 and S4 of the SI) (Lanza et al., 2007). These models explain 49.97% and 51.08% of the responses for Boston and Atlanta participants, respectively. The detailed latent class modeling results as well as the significance and relative importance of the upgrading features can be found in Tables S3 and S4 of the SI.

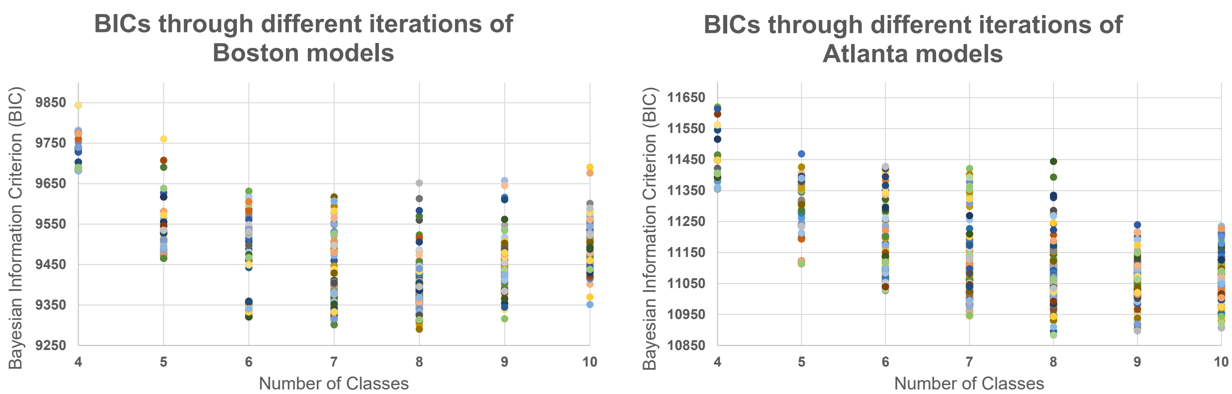

Fig. 1. Selecting the optimal class number in Atlanta and Boston using Bayesian Information Criteria (BIC)

3.3 Latent classes in Metro Atlanta and Greater Boston

The preferences of the eight latent classes in the Metro Atlanta and the Greater Boston areas for all system features (including acceptability) are shown in Figs. 2 and 3, respectively. We labeled the classes based on their preferences inferred from their responses to the system features. The eight latent classes are rational adopters, rational late adopters, undiscerning late adopters, cost-effective later adopters, laggards, early adopters, undiscerning decision-makers, and pioneers. The detailed latent class models and class information can be found in Tables S2-4 of the SI.

Rational adopters represent the largest population in Metro Atlanta (33.23%). This class is sensitive to economic savings and costs, and prefers a high environmental benefit. Members in this class may wait until the decentralized systems' economic benefits are proven before they adopt. Overall, the class shows a high acceptance of decentralized energy systems. Rational late adopters (13.82% of the population) show similar preferences but are highly insensitive to system type and neighbor's choice. They also have a slightly lower acceptance of decentralized energy systems as compared to rational adopters. Undiscerning late adopters (13.30% of the population) are a lot more sensitive to the initial installation cost than the annual savings, as compared the two previous classes. They demand a high environmental benefit and can be easily influenced by neighbor's choices. Cost-effective later adopters (10.04% of the population) place the highest importance on environmental benefits out of all classes. They care more about annual savings than the installation cost. System ownership also has a relatively high influence on the class' decision in decentralized energy system adoption. Laggards (9.21% of the population) are highly unlikely to adopt decentralized energy systems no matter what. Although they care about annual savings and initial costs, system ownership, and neighbor's choices and have a strong preference on solar thermal systems over solar PV systems, changes in these attributes may not effectively increase their intention to adopt decentralized energy systems. Early adopters (9.01% of the population) care the most about environmental benefits, followed by installation cost, ownership, and annual savings. They have a high acceptance of decentralized energy systems, but they mostly prefer to share than to own a decentralized energy system. Undiscerning decision-makers (7.26% of the population) place a high importance on environmental benefits, neighbor's choices, and system type. Pioneers are the smallest class in Metro Atlanta (4.13%). They show the highest acceptance of the decentralized systems. They are sensitive to environmental benefits, installation cost, and ownership. Overall, installation cost and annual savings, and environmental benefits are important determinants of households' adoption of decentralized energy systems in Metro Atlanta. This aligns with previous findings in Best et al. (2019) and Korcaj et al. (2015) about the significance of these factors in influencing consumer behaviors. The general Metro Atlanta population have a high acceptance of decentralized energy systems with a slight preference on owning a solar PV system.

Fig. 2a). The conditional probability of a latent class choosing a certain level of a system feature while holding other features constant in Metro Atlanta. Percentages in parentheses indicate the percentages of Metro Atlanta population that belong to each latent class. b). The relative importance of the six system design features to each latent class (IC: installation cost; AS: annual saving; EB: environmental benefits; NC: neighbor's choice; ST: system type; OS: ownership).

Rational adopters are also the biggest class in Greater Boston, representing 28.65% of the total population. Both rational adopters and rational late adopters (11.55% of the population) in

Boston share similar preferences as in those in Atlanta, placing a high importance on installation cost and annual savings and relatively sensitive to environmental benefits. Rational adopters have a higher acceptance of decentralized energy systems than rational late adopters. Unlike those in Atlanta, undiscerning late adopters (17.19% of the population) in Boston place a relatively equal importance on annual savings, system type, environmental benefits, and installation cost. They are also relatively sensitive to neighbor's choices. Similar as those in Atlanta, cost-effective later adopters (7.02% of the population) have the strongest preference on environmental benefits out of all classes in Boston, and laggards (8.55% of the population) are highly unlikely to adopt decentralized energy systems. Although they care about annual savings and initial costs, system ownership, and neighbor's choices and have a strong preference on solar thermal systems over solar PV systems, changes in these attributes may not effectively increase their intention to adopt decentralized energy systems. Laggards in Boston, however, prefer to share rather than to own a system. Early adopters (12.03% of the population) care the most about environmental benefits, followed by installation cost and neighbor's choices. Undiscerning decision-makers (6.38% of the population) are the smallest class in Greater Boston. They place a high importance on environmental benefits, neighbor's choices, and annual savings. Pioneers (8.63% of the population) place the highest importance on environmental benefits, followed by installation cost, and annual savings. They mostly prefer to share rather than to own a system. Early adopters, undiscerning decision-makers, and pioneers all have a very high acceptance of decentralized energy systems. Overall, acceptance of decentralized energy systems in Greater Boston is also generally high. Installation cost, environmental benefits, and annual savings are the top three factors that influence people's adoption of decentralized systems in the region. There is no class in Greater Boson that has an outstanding preference on solar thermal systems, indicating a potential barrier to promoting solar thermal systems in the region. The Greater Boston population also has a slightly higher preference on sharing a system than Metro Atlanta.

Fig. 3a). The conditional probability of a latent class choosing a certain level of a system feature while holding other features constant in Greater Boston. Percentages in parentheses indicate the percentages of the Greater Boston population that belong to each latent class. b). The relative importance of the six system design features to each latent class (IC: installation cost; AS: annual saving; EB: environmental benefits; NC: neighbor's choice; ST: system type; OS: ownership).

3.4 The impact of socioeconomic status on preferences

Tables S5 and S6 in the SI illustrate the impact of personal and socioeconomic variables in class membership. The "Time to complete the survey" variable has been included in our model to show how fast the respondents can make their decision (Table S1). This variable reflects the level of certainty of the respondents in making their decisions, which resulted in an improvement in our model performance (Uggeldahl et al., 2016).

In Atlanta, the early adopters class responded faster than the other classes on average. The average age of this class is younger than all other classes. Around 63% of the people in this class are married but most of them do not have kids. This class also has the lowest average income compared to other classes while they have the highest proportion of college-educated people (more than 80% of bachelor's degree or above). Early adopters can be pictured as young married college graduates who are more likely to embrace technology innovations. On the other hand, the undiscerning decision-makers class in Atlanta has the longest average response time. This class are mostly married people with kids at home. Most people in this class live in rental houses, yet the class, on average, has the highest satisfaction level with the centralized energy supply and the lowest desire to upgrade their properties, which might hinder the class's willingness to adopt decentralized systems. This class also has the most knowledge about the decentralized systems, despite having the lowest education level among all classes. The highest number of their neighbors have at least one type of decentralized systems already installed. Rational late adopters in Atlanta have the highest average income among other classes, mostly living in single-family households with relatively large housing size and family size. The class of laggards is primarily comprised of older population. The least number of their neighbors have already adopted decentralized energy systems and most people in this class do not have a desire to upgrade their properties. Cost-effective later adopters, on average, live in the smallest houses and have the smallest family sizes. Most of them live in rented properties. They have the strongest desire to upgrade their properties. Similarly, undiscerning late adopters are mostly unmarried people that live in multi-family houses (70.34%) with relatively low education level. The average income of this class is the second lowest. This class also does not have much willingness to upgrade their properties. Rational adopters do not have any overwhelming socioeconomic features, except that they have the least knowledge about the decentralized systems. Similarly, pioneers do not show any overwhelming socioeconomic characteristics.

In Boston, laggards were the fastest respondents of the survey. This class has a relatively older average age, a higher education-level, and a relatively higher percentage of households with kids. Very few of their neighbors have decentralized systems already installed (0.52%). On contrary, rational late adopters in Boston have the longest response time. They have the highest income, and the population age is relatively old. This class has a relatively high education level but not many of them know or have installed the decentralized systems, neither do their neighbors. Pioneers have the highest property ownership across all classes in Boston. They are mostly highly educated, high income, young and single population, who share multi-family housing with others. They are extremely dissatisfied with the current energy supply yet have the least prior knowledge of the decentralized systems and the least number of installations in their neighborhoods. Given their high acceptability of decentralized energy systems, pioneers might elect to install decentralized systems once they become acquainted with these systems. Rational adopters are mostly well-educated married people. Other than that, they do not have outstanding socioeconomic features. Early adopters in Boston are mostly young, unmarried population with the lowest income on average across all classes. Their housing and family sizes are the smallest, and they mostly live in rented properties. Undiscerning late adopters appear to have the most knowledge about the decentralized systems with more than 20% already have at least one decentralized system installed. The neighborhoods they live in have the highest decentralized installations across all classes. They also have the strongest desire to upgrade their properties across all classes. Cost-effective later adopters in Boston are relatively older population. Compared with other classes, their satisfaction level of the centralized system is relatively high. Undiscerning decision-makers in Boston do not have any outstanding socioeconomic features as compared to other classes.

3.5 Diffusion of decentralized energy systems in Atlanta and Boston

We developed an innovation diffusion curve that estimates how fast decentralized energy systems will be adopted in both testbeds (Fig. 4). We constructed the diffusion curve based on the relative adoption timing of the eight latent classes in each city by considering their stated preferences. Pioneers and early adopters have been recognized as our first classes to adopt the systems, because of their high acceptability of the decentralized systems and the short response time. Pioneers will adopt earlier than early adopters as their response time suggested a more determined decision-making process. Following these classes, undiscerning decision-makers will adopt regardless of the initial installation costs and rational adopters will follow them as the fourth class since they are less dependent on their neighbors' choices. These two classes can add around 35-40% of increments to the adopted population. Rational late adopters follow this adoption trend as they need to realize annual savings of the systems to support their decision-making. Similarly, undiscerning late adopters need to realize the environmental benefits of the systems to support their decisions. Cost-effective later adopters have been recognized as an inactive group since they will consider decentralized energy systems after seeing a drop in system installation costs. Finally, the class of laggards will adopt the latest given their low acceptability of the decentralized systems, high demand of environmental and cost benefits, and their desire to sharing the system rather than owning the systems.

The innovation diffusion curves show that the two cities have distinct characteristics in terms of decentralized energy system adoption, which has implications in policy design. Given the larger pioneer and early adopter populations in Boston, adoption initiation might be easier as well as faster in Boston with appropriate policy incentives. Atlanta has larger undiscerning decision-maker, rational adopter, and rational late adopter populations, which indicates further technology diffusion might be easier in Atlanta once a certain threshold adoption rate has been reached. Atlanta also has a larger cost-effective later adopter and laggard populations, indicating its highest achievable adoption rate might be lower than Boston. As each class has a probability of choosing or not choosing the decentralized solar technologies, the diffusion pattern should be further examined with market-based simulation models.

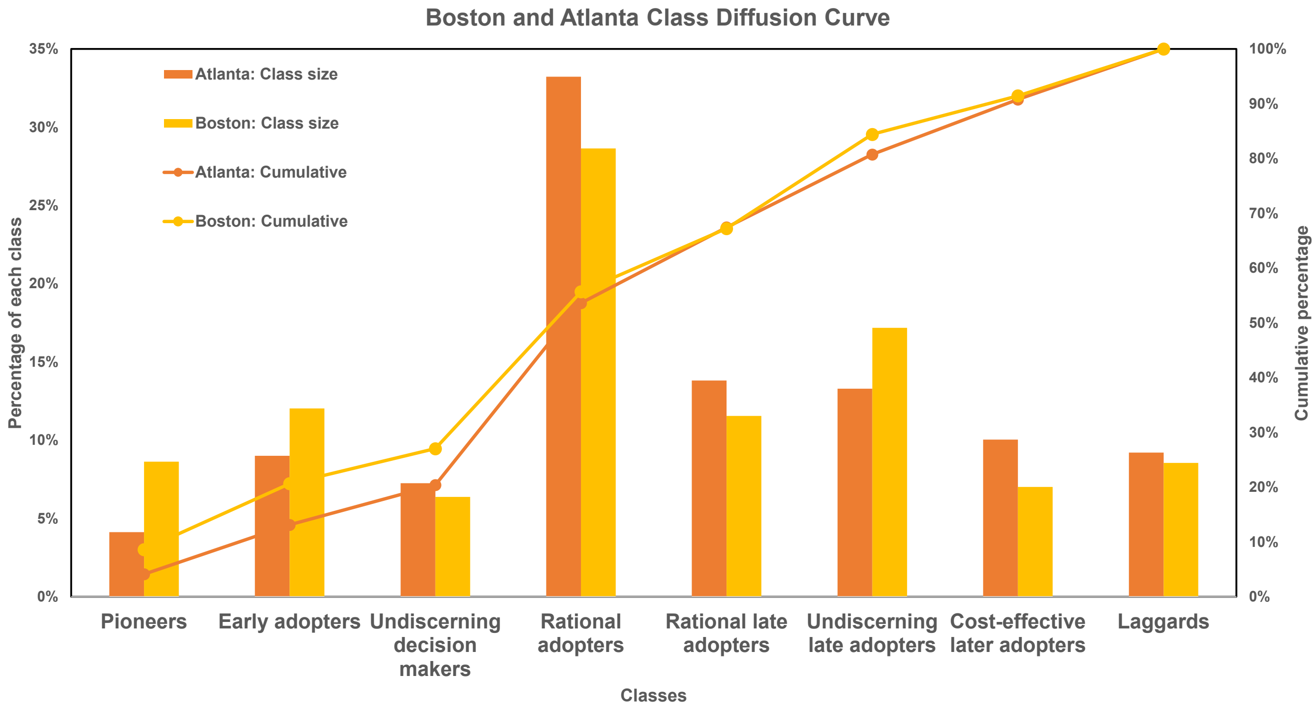

Fig. 4. Diffusion curve of decentralized energy facilities in Metro Atlanta and Greater Boston

3.6 Spatial distribution of classes in the Cities of Atlanta and Boston

Figs. 5 and 6 present the predicted distributions of different latent classes in Atlanta and Boston, respectively. In City of Atlanta, undiscerning late adopters, laggards, early adopters, and undiscerning decision makers dominate the population residing in southern Atlanta, indicating mixed interests in this region. Adoption of decentralized energy systems are most likely to initiate in this region, but there is also a significant barrier to broader penetration. Given that early adopters often reside in lower-property-value communities with poor infrastructure services and have a high demand for property upgrade or purchases, proper policy incentives targeting these communities could create an opportunity for community renaissance through the improvement of community energy service and management quality. This finding aligns with what has been found about the spatial distribution of decentralized water systems in the same city by Lu et al. (2019), indicating a potential co-benefit when the decentralized water and energy systems are planed together. Population in northern and northeastern Atlanta are primarily comprised of rational adopters, rational late adopters, cost-effective later adopters, and undiscerning decision makers. A significant portion of this population has a relatively high income and show a rational consideration of decentralized energy systems. This population may not adopt decentralized energy systems until their economic and environmental benefits become clear. As such, policies that help increase the return of investment of the decentralized energy systems and the awareness of their environmental benefits might help motivate adoption in this region. Pioneers' presence is extremely small in Atlanta, and hence may not significantly influence policy outcomes.

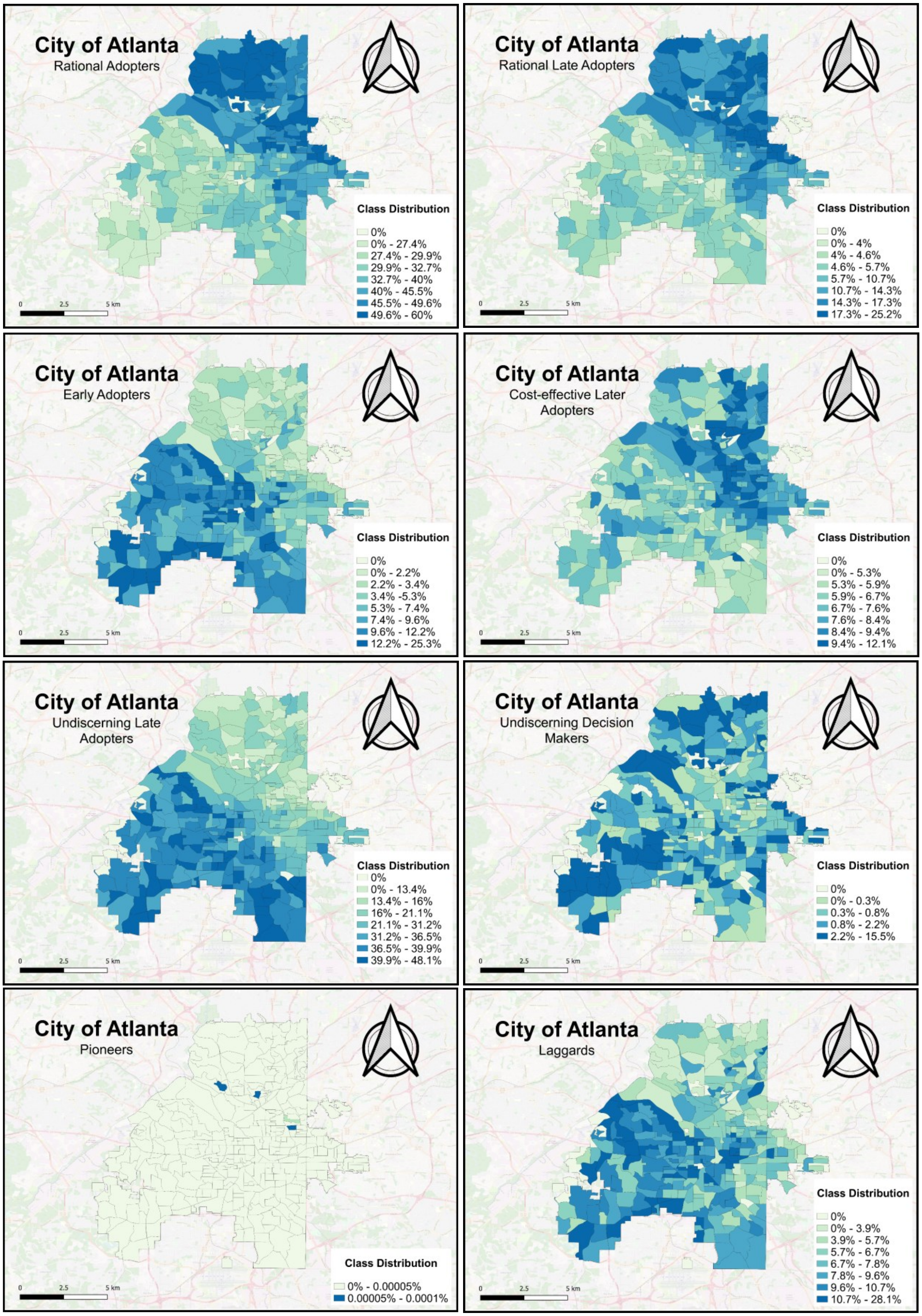
City of Atlanta
Rational Adopters
Class Distribution
0%
0% - 27.4%
27.4% - 29.9%
29.9% - 32.7%
32.7% - 40%
40% - 45.5%
45.5% - 49.6%
49.6% - 60%
0 2.5 5 km
City of Atlanta
Rational Late Adopters
Class Distribution
0%
0% - 4%
4% - 4.6%
4.6% - 5.7%
5.7% - 10.7%
10.7% - 14.3%
14.3% - 17.3%
17.3% - 25.2%
0 2.5 5 km
City of Atlanta
Early Adopters
Class Distribution
0%
0% - 2.2%
2.2% - 3.4%
3.4% -5.3%
5.3% - 7.4%
7.4% - 9.6%
9.6% - 12.2%
12.2% - 25.3%
0 2.5 5 km
City of Atlanta
Cost-effective Later Adopters
Class Distribution
0%
0% - 5.3%
5.3% - 5.9%
5.9% - 6.7%
6.7% - 7.6%
7.6% - 8.4%
8.4% - 9.4%
9.4% - 12.1%
0 2.5 5 km
City of Atlanta
Undiscerning Late Adopters
Class Distribution
0%
0% - 13.4%
13.4% - 16%
16% - 21.1%
21.1% - 31.2%
31.2% - 36.5%
36.5% - 39.9%
39.9% - 48.1%
0 2.5 5 km
City of Atlanta
Undiscerning Decision Makers
Class Distribution
0%
0% - 0.3%
0.3% - 0.8%
0.8% - 2.2%
2.2% - 15.5%
0 2.5 5 km
City of Atlanta
Pioneers
Class Distribution
0% - 0.00005%
0.00005% - 0.0001%
0 2.5 5 km
City of Atlanta
Laggards
Class Distribution
0%
0% - 3.9%
3.9% - 5.7%
5.7% - 6.7%
6.7% - 7.8%
7.8% - 9.6%
9.6% - 10.7%
10.7% - 28.1%
0 2.5 5 km

Fig. 5. Spatial distribution of latent classes in Atlanta. Percent values represent the proportion of a census block's population belonging to a certain class.

In City of Boston, undiscerning late adopters, early adopters, and undiscerning decision-makers dominate the relatively low-income communities in central Boston, including Roxbury, Dorchester, and Mattapan neighborhoods. The presence of these classes in this region indicates a mixed interest, potentially an earlier initiation of adoption but a significant barrier to higher penetration. Similar as in southern Atlanta, infrastructure improvement projects that include the installation of decentralized energy systems can help promote community renaissance in areas with a high early adopter presence. Rational adopters and rational late adopters dominate the population residing in the northern part of the city, close to downtown, in wealthier communities with a relatively high population density. Similar as in Atlanta, policies that target increasing the return of investment and the awareness of the environmental benefits of decentralized energy systems might help motivate adoption in this region. Southern Boston is primarily dominated by laggards and cost-effective later adopters, indicating a potential difficulty in promoting decentralized energy systems in this area. Pioneers do not have a strong presence in Boston and may not significantly influence policy outcomes.

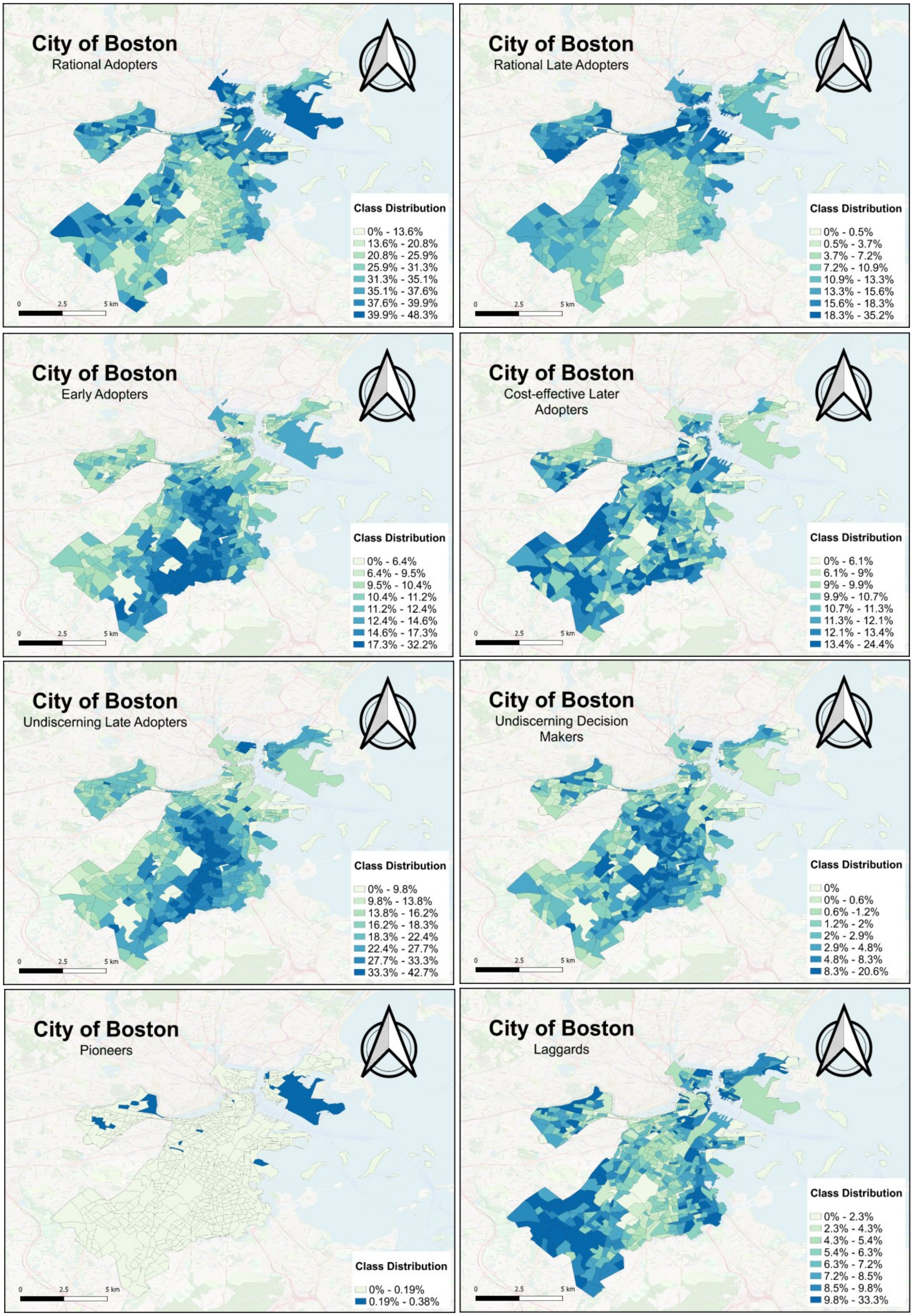
City of Boston
Rational Adopters
Class Distribution
0% - 13.6%
13.6% - 20.8%
20.8% - 25.9%
25.9% - 31.3%
31.3% - 35.1%
35.1% - 37.6%
37.6% - 39.9%
39.9% - 48.3%
City of Boston
Rational Late Adopters
Class Distribution
0% - 0.5%
0.5% - 3.7%
3.7% - 7.2%
7.2% - 10.9%
10.9% - 13.3%
13.3% - 15.6%
15.6% - 18.3%
18.3% - 35.2%
City of Boston
Early Adopters
Class Distribution
0% - 6.4%
6.4% - 9.5%
9.5% - 10.4%
10.4% - 11.2%
11.2% - 12.4%
12.4% - 14.6%
14.6% - 17.3%
17.3% - 32.2%
City of Boston
Cost-effective Later Adopters
Class Distribution
0% - 6.1%
6.1% - 9%
9% - 9.9%
9.9% - 10.7%
10.7% - 11.3%
11.3% - 12.1%
12.1% - 13.4%
13.4% - 24.4%
City of Boston
Undiscerning Late Adopters
Class Distribution
0% - 9.8%
9.8% - 13.8%
13.8% - 16.2%
16.2% - 18.3%
18.3% - 22.4%
22.4% - 27.7%
27.7% - 33.3%
33.3% - 42.7%
City of Boston
Undiscerning Decision Makers
Class Distribution
0%
0% - 0.6%
0.6% -1.2%
1.2% - 2%
2% - 2.9%
2.9% - 4.8%
4.8% - 8.3%
8.3% - 20.6%
City of Boston
Pioneers
Class Distribution
0% - 0.19%
0.19% - 0.38%
City of Boston
Laggards
Class Distribution
0% - 2.3%
2.3% - 4.3%
4.3% - 5.4%
5.4% - 6.3%
6.3% - 7.2%
7.2% - 8.5%
8.5% - 9.8%
9.8% - 33.3%
0
2.5
5 km

Fig. 6. Spatial distribution of latent classes in Boston. Percent values represent the proportion of a census block's population belonging to a certain class.

4. Conclusion and policy implications

The promotion of decentralized energy systems looks compulsory due to the lack of resources in today's world as well as the need for low-carbon or carbon-neutral urban infrastructure. In this study, we used a research framework that combines discrete choice experiment, latent class modeling, and spatial analysis to understand the preference heterogeneity of residential solar PV and solar thermal systems in two testbeds: Boston and Atlanta. In general, respondents from both testbeds show a relatively high acceptance of decentralized energy systems, indicating promotion of distributed low-carbon energy systems might be a promising carbon mitigation strategy with proper incentive and policy designs. Key motivating factors for adoption in both testbeds are installation cost, environmental benefits, and annual savings. Eight latent classes with unique preferences and socioeconomic characteristics were identified within each of the testbeds. While there is an overall general preference of solar PV systems over solar thermal systems in both testbeds, there is an outstanding interest in solar thermal systems amongst the pioneers class in Atlanta. This presents a general barrier to the broader penetration of solar thermal systems; however, policies that target certain groups that have a special interest in solar thermal systems, such as the pioneer class in Atlanta, might be effective. The Boston population has a higher preference on sharing a system than the Atlanta population, showing the importance of developing strategies and technologies to enable and promote community-based decentralized energy systems in the Boston area. Despite the classes' similarity in their preferences of different system features, all classes present different socioeconomic characteristics across the two testbeds. This indicates the importance of understanding preferences case-by-case and there might not be a one-size-fit-all type of approach when it comes to incentivizing decentralized energy system adoptions. Based on our technology diffusion curves, adoption initiation might be easier as well as faster in Boston given its larger pioneer and early adopter populations. Once a certain threshold adoption rate has been reached, further technology diffusion might be easier in Atlanta given its larger undiscerning decision-maker, rational adopter, and rational late adopter populations. Given the unique class distribution of each city, the forms and the focuses of policies should be designed based upon the characteristics of local consumer preferences. In terms of class spatial distribution within the cities, we found a prominent spatial “grouping” effect in both cities, with certain classes tend to reside in one region and others in another. Nevertheless, both cities have a substantial number of early adopters residing in lower-property-value regions, revealing a potential to achieve both carbon emission reduction and community renaissance objectives when combining infrastructure renovation projects in these areas with the installation of decentralized energy systems.

While this study presents an initial effort in quantifying the spatial households’ preference of decentralized solar PV and solar thermal systems, our analysis is limited by the sample size, the geographical areas that were considered, as well as the uncertainties associated our approach (e.g., post-stratification weighting for sample bias correction). While our research framework and some general findings are transferable to other areas, the specific latent class models developed in this study cannot be directly applied in cities. Rather, our study suggests that such models need to developed case-by-case for individual cities. Future studies targeting confined geographical boundaries might benefit from better participatory approaches that enable the engagement of more representative populations. Further research in this area can include the application of latent class models to predict the dynamic adoption trajectory of the household solar PV and thermal systems. This will enable future investigation of urban energy sustainability considering the interactions of the decentralized systems and the electricity grid as well as the interactions across energy and water systems, as a potential solution to challenges related to the energy-water nexus.

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