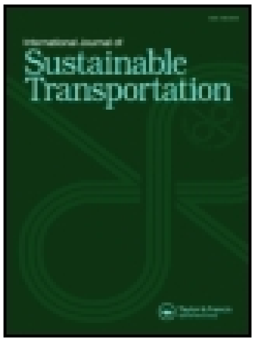

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Patterns and predictors of early electric vehicle adoption in Massachusetts

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ABSTRACT
In Massachusetts and beyond, ambitious long-term initiatives seek to curtail increases in carbon pollution that contribute to climate change and carry detrimental impacts to population health and safety. Widespread electrification of the passenger vehicle fleet is celebrated as a fundamental strategy for achieving substantial long-term transportation-related greenhouse gas reductions. Unfortunately, in spite of this understood need, the number of EVs on our roadways remains relatively insignificant and the evidence base remains limited in its ability to inform decisionmakers as to what set of factors related to an individual, their surrounding context, or the new technology itself will contribute most to increasing passenger EV adoption. This study utilizes a unique data set enumerating passenger vehicle purchases and utilization in Massachusetts from 2008 to 2016 to (i) describe geographic and temporal patterns of EV adoption and (ii) identify the environmental factors that have predicted the purchase and utilization of EVs by these early adopters. Our study finds that early EV adoption in Massachusetts has largely been an urban phenomenon displaying a gradual and incremental increase in the consumer market share. At a neighborhood scale, early EV adoption in Massachusetts has been limited primarily to higher-income households residing in single-family homes. However, if policy actions follow, the significant association of public charging stations with EV adoption and other informative study findings can carry the potential to direct investments and incentives to ensure the Commonwealth's lofty legislatively-mandated targets are met in coming years.

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Electric vehicles; propensity score matching; vehicle ownership

1. Introduction

Electrification of the vehicle fleet is a fundamental strategy for reducing the global dependency on crude oil production and curtailing transportation-related dioxide emissions that contribute to climate change and carry detrimental impacts to population health and safety (Shareef et al., 2016). Still, in spite of the many purported short- and long-term benefits of electrifying the vehicle fleet (Holland et al., 2016), the number of light duty electric vehicles (EVs) on our roadways remains insignificant (Rezvani et al., 2015). Across the United States, policies, regulations, and incentives aimed at promoting EV adoption rates and concurrently decreasing the prevalence of internal combustion engine (ICE) vehicles from the passenger fleet have been pursued at the state level in recent years (Carley et al., 2013; Jenn et al., 2018).

In Massachusetts, the Department of Energy Resources started its support of the Massachusetts Offers Rebates for Electric Vehicles (MOR-EV) program in 2014 to promote EV production and utilization by incentivizing their adoption. In 2018, Senate Bill 2505 was adopted to increase general public access to EV charging stations and allow Massachusetts municipalities and businesses to restrict parking spaces to only EVs. An advancement of these and other EV incentive programs and regulations is necessary for the Commonwealth to achieve the ambitious goals of its 2008 Global Warming Solution Act, which requires a reduction of greenhouse gas emissions by 25 percent below 1990 levels by 2020 and 80 percent by 2050, and Executive Order 569, which was signed in 2016 and requires Massachusetts to the registration of 300,000 EVs by 2025.

A significant challenge to accomplishing this mass commercialization of EVs is that a limited knowledge base exists at present to inform decisionmakers as to what set of predictors—specific to an individual, their surrounding context, or the new technology itself—will contribute most to increasing passenger EV adoption. By using a unique data set enumerating vehicle registrations and utilization in Massachusetts from 2008 to 2016, the objectives of this study are to (i) examine the spatiotemporal patterns of early adopters of EVs in Massachusetts and (ii) identify the neighborhood-level socioeconomic features that impact the decision to purchase a new passenger EV rather than an ICE vehicle. This study is intended to inform statewide scenario planning efforts by identifying barriers and facilitators to EV adoption, while also providing uncommon population-level insight into the patterns and predictors of early EV adoption.

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2. Literature review

Although EV adoption studies date back several decades, the evidence base has only grown substantially in recent years as researchers across the world seek to better understand the behavioral patterns and complexities underlying EV purchases (Hardman et al., 2016). Given the topic's increased attention and global extent, the study areas examined have varied by physical setting, time period, and data analyzed (Javid & Nejat, 2017). Yet, the diffusion of EVs into the consumer market remains in its early stages, with variations between national and local contexts (Westin et al., 2018) limiting the number of multiyear, observational studies at a population level. Adapting a prior taxonomy (Sierzchula et al., 2014), a review of the individual and psychosocial, environmental, and technological and economic predictors of EV adoption found within a selection of studies is provided below. Relevant studies of the past five years were selected from an initial search of Web of Science articles on the topics of "electric vehicle" and "ownership" from 2014 to 2018 that returned 98 articles; next supplemented by studies that investigated the neighborhood predictors of EV adoption which were conducted before 2014 and summarized by Hardman et al. (2016) and Javid and Nejat (2017).

2.1. Individual and psychosocial predictors of EV adoption

Regarding the individual and psychosocial predictor of age, Musti and Kockelman (2011) modeled stated preference (SP) data in Texas, finding that younger respondents were less likely to own a hybrid or plug-in hybrid EV. Analyzing survey results of registered vehicle owners in Sweden, Westin et al. (2018) found that older adults were more likely to purchase an EV than a conventional fuel vehicle. In an investigation into the process of behavioral change in EV adoption for Stockholm residents, Langbroek et al. (2017) found that an increase in age negatively predicted a consideration to start using an EV (contemplation stage), but that this relationship was only marginally significant where individuals actually purchasing an EV in the past six months. Similarly, with a sample of American adults residing in urban areas, Carley et al. (2013) modeled that with each additional year of age, an individual was less interested in purchasing a plug-in EV.

Several studies have found that male adults are more likely to have purchased or express an intention to purchase an EV (Carley et al., 2013; Westin et al., 2018). In a 2010 SP survey of Maryland residents, Liu and Cirillo (2017) more specifically noted that male respondents were more likely to purchase an EV, while similarly educated female participants were more likely to have chosen a hybrid vehicle. Musti and Kockelman (2011) also found that female survey respondents were more likely to purchase a mid-size hybrid rather than a compact ICE car. In a study of German travel survey data, an estimated suitability model describing the probability of EV ownership found that males between 40 and 50 years of age, who have a higher income, had the highest interest in EV ownership (Weiss et al., 2017).

With the 2012 introduction of the Tesla Model S, the international EV consumer market is believed to have shifted toward higher-income households (Hardman et al., 2016). In fact, most recent studies have concluded that EV owners tend to earn more than non-EV owners as well as the general public (Langbroek et al., 2017; Tal & Nicholas, 2013). By modeling California household survey data with validation data from the Delaware Valley region, Javid and Nejat (2017) found an increase in annual household income significantly predicted the likelihood to adopt an EV rather than a convention ICE vehicle. Higher-income households have also exhibited a preference for purchasing plug-in hybrid EVs, but authors of this study point out that higher-income households also tend to purchase other vehicle types since they can presumably afford the higher ownership and maintenance costs (Musti & Kockelman, 2011).

Fernandez-Antolin et al. (2018) concluded that French residents with at least a bachelor's degree were more likely to purchase new EVs or hybrids when compared to their counterparts. Westin et al. (2018) similarly noted that people in Sweden with higher educational attainment—a factor largely correlated with income—were more likely to buy an EV than a conventional fuel vehicle. In the American context, Javid and Nejat (2017) found that as maximum level of education in a household increased, an individual was more likely to have purchased an EV; while, Carley et al. (2013) also found lower education attainment levels were significantly associated with a decreased interest in purchasing an EV.

2.2. Environmental, technological, and economic predictors of EV adoption

Research into the environmental predictors of alternative fuel vehicle adoption is less common. In a study of vehicle adoption in Texas, Bansal et al. (2015) investigated tract-level attributes of socioeconomic composition and the built environment as predictors of hybrid car ownership. Using 2010 Census and vehicle registrations data, the authors found that Census tracts in Dallas County with a higher median age for adults was associated with an increase in registered hybrid vehicles. In separate models for Harris and Travis Counties—encompassing Houston and Austin, respectively, a higher percent of male residents was associated with an increase in county-level hybrid ownership rates. Regarding land development patterns, an increase in employment and population density, which were only included in the Travis County model, was predictive of lower hybrid ownership rates; while, land use balance was found to have opposite relationship. Looking at the physical local context, Fernandez-Antolin et al. (2018) found an increased likelihood for French residents living in cities and suburbs to buy a hybrid than those living in towns or rural areas but, surprisingly, that individuals living in towns or rural areas were more likely to purchase EVs. However, Musti and Kockelman (2011) revealed that individuals living in urban areas (traffic analysis zones with at least 8 residents or jobs per acre) appeared to prefer plug-in hybrid EVs.

Similarly, an analysis of EV consumers in China (Li et al., 2017) discovered the effect of perceived risk of EV adoption intention to be strongest in rural households, where charging infrastructure is limited and inconvenient to consumers.

As for technological and economic predictors of adoption, Javid and Nejat (2017) found that the number of public charging stations per capita within a California county was significantly associated with increased EV ownership, while others have found that EV adoption may be encouraged by an awareness of charging stations in the community (Carley et al., 2013). Additionally, Liu and Cirillo (2017) revealed that vehicle capacity was positively linked to the adoption of EVs as well as other vehicle types; highlighting a household-level preference for larger cars. A finding substantiated by Miwa et al. (2017), who noted the number of available car seats as a positive predictor of EV purchase intention. The fixed nature of economic incentive policies within jurisdictional boundaries has limited the analysis of monetary subsidies on the decision or intention to purchase an EV (Javid & Nejat, 2017); however, several studies have examined the impact of vehicle price. In a sample of Maryland residents, Liu and Cirillo (2017) noted households were more sensitive to purchasing prices of EVs than market prices for hybrid or ICE vehicles. Fernandez-Antolin et al. (2018) similarly found individuals to be more sensitive to higher prices for EVs than to the prices of other vehicle types. An outcome echoed by Miwa et al. (2017), who found the intention to buy an EV rather than another vehicle type was negatively associated with vehicle price.

2.3. Synopsis and study motivation

In general, past studies have found the purchase or intention to own an EV is positively associated with individuals who are younger, male, or have higher levels of educational attainment and household income. However, few studies have examined the environmental determinants of electric or hybrid vehicle adoption. Those studies have commonly found that lower density suburban areas with some land use mixing and areas with a higher median age or share of male residents were positively associated with hybrid car ownership. As for technological and economic predictors, the physical presence and personal awareness of charging infrastructure is positively associated with an individual's purchase of an EV; an outcome that is more sensitive to higher vehicle prices than the purchase of hybrid or ICE vehicles.

In contributing to the reviewed literature, this study seeks to address two identified research gaps. First, few studies to date have examined the environmental predictors of EV demand, with those that have generally looking only at a handful of built environment attributes and neglecting the neighborhood-level socioeconomic context. By assessing the neighborhood effect and spatial distribution of EV demand, this study can offer new insights into how EV adoption may be related to demographic homophily, or whether residents of neighborhoods with shared socioeconomic characteristics may exhibit similar EV consumption behaviors, and social contagion, or whether early EV adopters who perhaps observed these vehicles on the roads of their neighborhood or municipality were more likely to purchase an EV rather than another vehicle type (Keith et al., 2012). Second, past studies of early EV adoption have overwhelmingly relied on survey data—often without a comparison group and commonly only looking at consumer intentions—or household travel survey data that observe ownership trends over a short period. This study, in contrast, utilizes a multi-year population-level data set to examine the spatiotemporal patterns and contextual predictors of early EV adoption in Massachusetts.

3. Methods

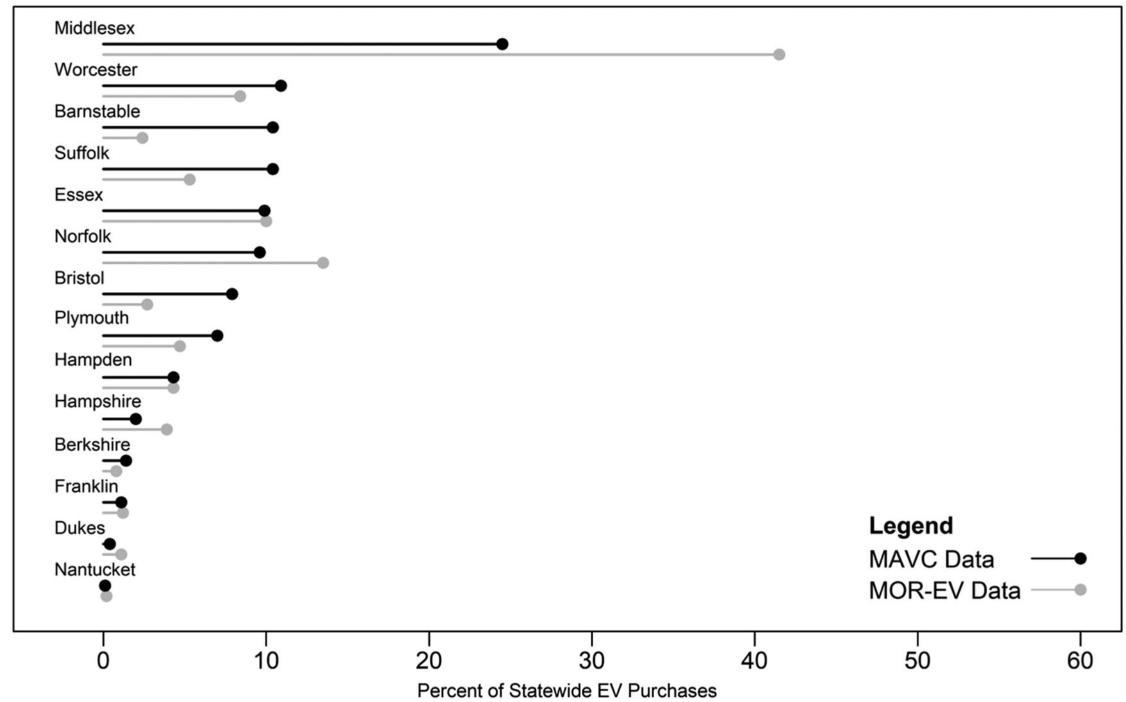
3.1. Massachusetts vehicle census

This study uses data from the Massachusetts Vehicle Census (MAVC); a catalog of information about vehicles registered in the Commonwealth from 2008 to 2016. The MAVC combines both registration and annual safety inspection data provided by Massachusetts Registry of Motor Vehicles (RMV) with fuel economy standards from a vehicle identification number decoder purchased and maintained by Kenneth Gillingham at Yale University and standardized assessor's parcel data developed by MassGIS to detail the ownership and mileage history of all vehicles garaged within the Commonwealth at a parcel geography. Vehicle-level records in the MAVC data set cover a defined period of time when the specified vehicle had a unique combination of owner, garaging address, and estimated daily mileage. These data describe characteristics of the vehicle recorded at the time of its registration (e.g., make/model, fuel type) and at each required annual inspection (e.g., odometer miles).

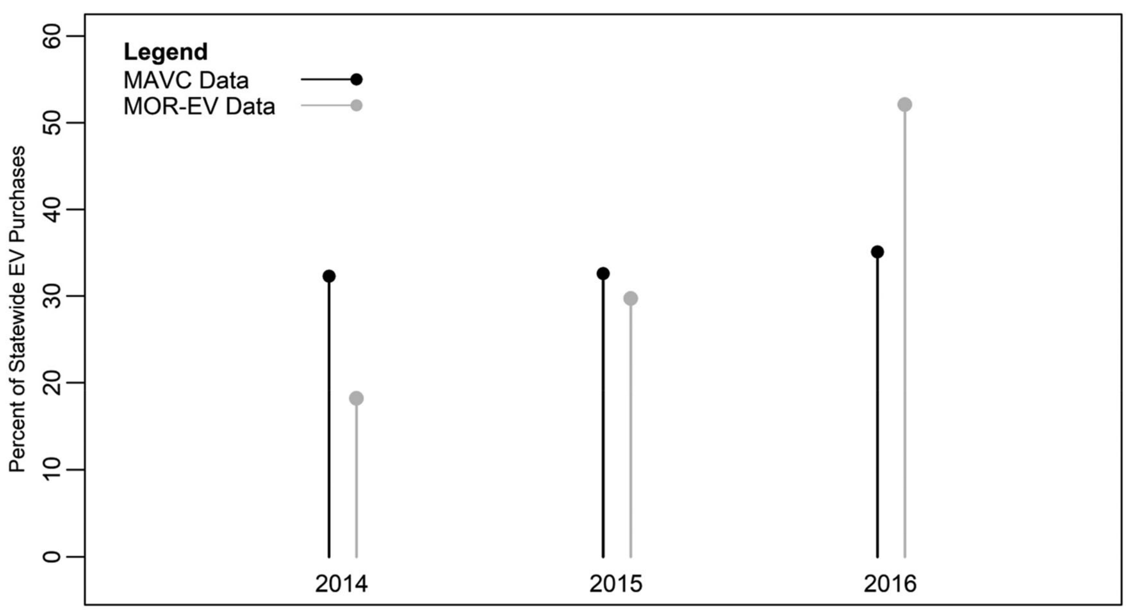
Using the MAVC, this study defines a new vehicle as one registered by an individual, which entered the fleet with an odometer reading of less than 1,000 miles. For this study, only new passenger cars in the vehicle fleet were analyzed since other all-electric powertrain vehicles types (SUVs, trucks, vans, and wagons) were not recorded in the registrations and inspections data. Thus, a subset of the MAVC data set—classified as new passenger cars with gasoline, hybrid, or all-electric powertrain technologies—was developed for this study. A decision further informed by findings in the literature regarding household preferences for vehicles with increased capacity.

An important caveat of this microdata set is that some vehicle registrations—both newly purchased and recently introduced to Massachusetts—appear to be omitted from the latter two years of the nine-year timeframe. While the MAVC, as its name implies, aims to provide a comprehensive enumeration of each registered vehicle, its accuracy depends on the quality and completeness of data received from the Massachusetts RMV. Fortunately, the MAVC can still be confidently considered to reflect a vast majority of the Commonwealth's fleet; representative of the garaging location, vehicle characteristics, and mileage traveled for new and older vehicles.

Figure 1 offers insight into the spatiotemporal representation of the MAVC data set in terms of EV adoption in



(a) Spatial Distribution Comparison of Electric Vehicle Data Sources by County of Registration



(b) Temporal Distribution Comparison of Electric Vehicle Data Sources by Year of Registration

Figure 1. Spatiotemporal comparison of EV adoption in MAVC and MOR-EV data sources, 2014-2016.

comparison to the publicly-available data set of the MOR-EV program (Center for Sustainable Energy, 2020), where some important differences can be found over the time periods in which the sources overlap. Regarding the spatial distribution of EV adoption, a larger share of new EV registrations between 2014 and 2016 were recorded in the MOR-EV data set for Middlesex County than in the MAVC; a 17.0% difference. In turn, the MAVC contains a relative larger share of new EV registrations in its data set for the Counties of Barnstable (8.0% difference), Bristol (5.2% difference), and Suffolk (5.1% difference). These differences in spatial distribution may be related to new EV owners having multiple residences, unclaimed MOR-EV program rebates, an uptick in EV adoption by Massachusetts residents in the later periods with a delay in reported or conducted safety inspections for the following year, or other possible considerations. Regarding the temporal distribution of EV adoption, more than one-half of observations in the three-year MOR-EV data set reflected EV rebate claims in 2016; whereas, the year-to-year distribution in the MAVC

Table 1. Neighborhood context variable definitions and data sources.

Variable Name and Definition	Data Source
Individual and Psychosocial Characteristics	
Sex distribution: Share of male or female residents in US Census tract	2012-16 ACS
Age distribution: Share of residents under 18 years, 18 to 34 years, 35 to 44 years, 45 to 64 years, or 65 years and older in US Census tract	2012-16 ACS
Median age distribution: Median age in years for residents in US Census tract	2012-16 ACS
Educational attainment distribution: Share of residents at least 18 years old who have less than bachelor's degree, bachelor's degree, or graduate degree	2012-16 ACS
Annual household income distribution: Share of household wages and salaries over the past 12 months categorized as under $35,000, $35,000 to $74,999, $75,000 to $149,999, and $150,000 and above in US Census tract	2012-16 ACS
Median income distribution: Median household income in dollars over past 12 months in US Census tract	2012-16 ACS
Race and ethnicity distribution: Share of White (non-Hispanic), Hispanic or Latino, Black or African-American, Asian, or other designations in US Census tract	2012-16 ACS
Housing tenure: Share of owner or renter occupied units in US Census tract	2012-16 ACS
Household vehicle ownership: Share of passenger cars, vans, or trucks available per household (zero, one, two, three or more) in a US Census tract	2012-16 ACS
Environmental, Technological, and Economic Characteristics	
Activity density: Number of jobs and residents per acre in US Census tract	2012-16 ACS, 2016 LEHD
Jobs-persons balance: Ratio of jobs-to-residents in US Census tract	2012-16 ACS, 2016 LEHD
Connected node ratio: Number of street intersections divided by sum of intersections and cul-de-sacs in a US Census tract	2016 TIGER
Electric vehicle charging sites: Number of public charging sites in a US Census tract	2018 Open Charge Map

data set displayed a much more balanced distribution. This finding appears to confirm the missingness in MAVC observations in the latter two years. However, despite these spatiotemporal differences in the two EV data sources, the MAVC is the only data set capable of showing the patterns and predictors of earliest EV adoption in Massachusetts at a neighborhood-level scale, with any omissions in vehicle registrations having no adverse impacts on the sample-based study design described later in this section.

3.2. Neighborhood context

Table 1 provides an overview of the neighborhood-level variables created for this study. The first set of variables reflect the operationalization of individual and psychosocial characteristics that were found in the reviewed literature to be predictive of electric or hybrid vehicle adoption as neighborhood context metrics. These socioeconomic measures were created using the 2012–16 five-year American Community Survey (ACS) and later explored as neighborhood-level determinants of EV adoption. The remaining four variables represent three built environment concepts common to studies of land use and vehicle ownership (Cervero & Kockelman, 1997) and the technological variable of public EV charging station availability. The former variables were created using ACS data as well as 2016 Longitudinal Employer-Household Dynamics (LEHD) and 2016 Topologically Integrated Geographic Encoding and Referencing (TIGER) network files; whereas, the latter variable was constructed using Open Charge Map data and noting the date-time stamps in which charging stations were added to the online database. The three environmental measures related to land use development patterns and the street network were employed within the propensity score matching technique described below.

Table 2 offers descriptive statistics of the above neighborhood-level variables. To summarize the predominate socioeconomic attributes in the study area, the average Census tract had a higher share of female residents as well as individuals who were between 45 and 64 years of age, self-identified as White, non-Hispanic, did not have a four-year college degree, and were more likely to own their residence. The household income distribution of residents in the study area was even across the three cohorts earning under $150,000 annually, while most households reported owning two vehicles. In terms of housing stock, the average neighborhood was slightly more likely to have homes built after 1945 and slightly less likely to have mostly single-family units. Finally, most Census tracts did not have a public EV charging station.

3.3. Propensity score matching

Beyond an identification of spatiotemporal patterns in EV adoption throughout the Commonwealth, this study aims to discover what context-specific attributes are most likely to impact an individual purchasing an EV rather than an ICE vehicle. Given the timeframe spanning the MAVC data set, a disproportionately low number of EVs (early technology adopters) in comparison to new ICE vehicle registrations is likely to exist in the data set. To account for an unbalanced sample and the influence of the built environment on the decision to purchase a new passenger car, a propensity score matching (PSM) technique was applied to generate a matched sample of new ICE and electric passenger car purchases from the MAVC data set. The process of matching observations in two groups based on approximately equivalent residential built environments resembles the steps taken for an experiment with random assignment of the treatment (Cao et al., 2010).

Conceptually, PSM, a method adopted in previous observational studies of car ownership (Cao et al., 2010; Mishra et al., 2015), offers a statistical mechanism in which subjects (new vehicle purchasers) can be assigned to either a control

Table 2. Descriptive statistics of predictors tested in electric vehicle adoption model.

Individual and Psychosocial Variables	Mean	Std. Dev.	Median	Min	Max
Sex distribution					
Male	0.48	0.03	0.48	0.31	0.69
Female	0.52	0.03	0.52	0.31	0.69
Age distribution					
Under 18 years	0.20	0.06	0.21	0.02	0.44
18 to 34 years	0.24	0.12	0.21	0.05	0.93
35 to 44 years	0.12	0.03	0.12	0.02	0.23
45 to 64 years	0.28	0.06	0.28	0.02	0.42
65 years and older	0.16	0.06	0.15	0.01	0.48
Median age distribution	40.11	7.04	40.80	20.30	64.40
Educational attainment distribution					
Less than bachelor's degree	0.40	0.15	0.44	0.03	0.69
Bachelor's degree	0.16	0.07	0.16	0.00	0.51
Graduate degree	0.13	0.10	0.10	0.00	0.51
Annual household income distribution					
Under $35,000	0.27	0.14	0.24	0.01	0.87
$35,0000 to $74,999	0.26	0.08	0.26	0.05	0.50
$75,0000 to $149,999	0.29	0.09	0.30	0.02	0.52
$150,000 and above	0.18	0.14	0.14	0.00	0.66
Median income distribution	77,459	35,155	72,604	12,628	215,250
Race and ethnicity distribution					
White, non-Hispanic	0.74	0.23	0.82	0.00	1.00
Hispanic or Latino	0.06	0.08	0.03	0.00	0.74
Black or African American	0.07	0.12	0.03	0.00	0.86
Asian	0.06	0.08	0.03	0.00	0.58
Other distinctions	0.08	0.09	0.04	0.00	0.62
Housing tenure					
Owner-occupied	0.61	0.24	0.67	0.00	0.98
Renter-occupied	0.39	0.24	0.33	0.02	1.00
Household vehicle ownership					
Zero	0.07	0.10	0.03	0.00	0.62
One	0.25	0.14	0.23	0.02	0.68
Two	0.42	0.13	0.44	0.02	0.76
Three or more	0.26	0.13	0.26	0.00	0.64
Additional Variables	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**
Electric vehicle technology					
EV charging sites (US Census tract)	0.07	0.32	0.00	0.00	6.00
Building type					
Single-family	0.48	0.50	0.00	0.00	1.00
Building development era					
Post-WWII	0.57	0.50	1.00	0.00	1.00

(new ICE vehicle adopters) or treatment (new EV adopters) group based on a set of observed attributes, when sample randomization is not feasible (Rosenbaum & Rubin, 1983). Three covariates—the number of jobs and residents per acre, ratio of jobs-to-residents, and number of street intersections divided by sum of intersections and cul-de-sacs—measured at the US Census tract geography and which exemplify the density, diversity, and design of the built environment (Cervero & Kockelman, 1997) were selected as criteria for generating the balanced set. This covariate selection process was informed by inspecting the unadjusted correlations between the percent of new cars in a Census tract that were electric in the MAVC data set and the three environmental metrics to ensure the produced coefficients were below 0.6. Each chosen covariate was also hypothesized to not be associated with the treatment since the built environment is associated with vehicle ownership, but not necessarily purchase of any vehicle type (e.g., EV, ICE vehicle). Automobile ownership has been found to be negatively responsive to residing in neighborhoods with increased population and employment density (Bhat & Guo, 2007), increased jobs-population ratio (Potoglou & Kanaroglu, 2008), and increased network connectivity (Ding et al., 2017).

After confirming the built environment covariates were not correlated with one another or the outcome of EV purchase, the individual-level sample of new car owners was then created. To do so, a logit model with an optimal matching method without replacement, where a one-to-one ratio of control units were matched to a treatment observation based on the smallest average absolute distance across matches, was estimated (Gu & Rosenbaum, 1993). A caliper length of 0.2 of the standard deviation was defined as the maximum permissible difference in propensity scores; where, observations from the groups were dropped from consideration if this threshold was exceeded (Austin, 2011). Observations in the control data set were randomly sorted prior to creating the matched sample in which treatment assignment was determined by estimating a logit model based on the three neighborhood context covariates that affect the individual outcome to purchase a new EV rather than ICE vehicle.

3.4. Logistic regression modeling

Estimation of which neighborhood socioeconomic composition, housing structure, and electric vehicle technology measures predict early EV adoption was next undertaken. An

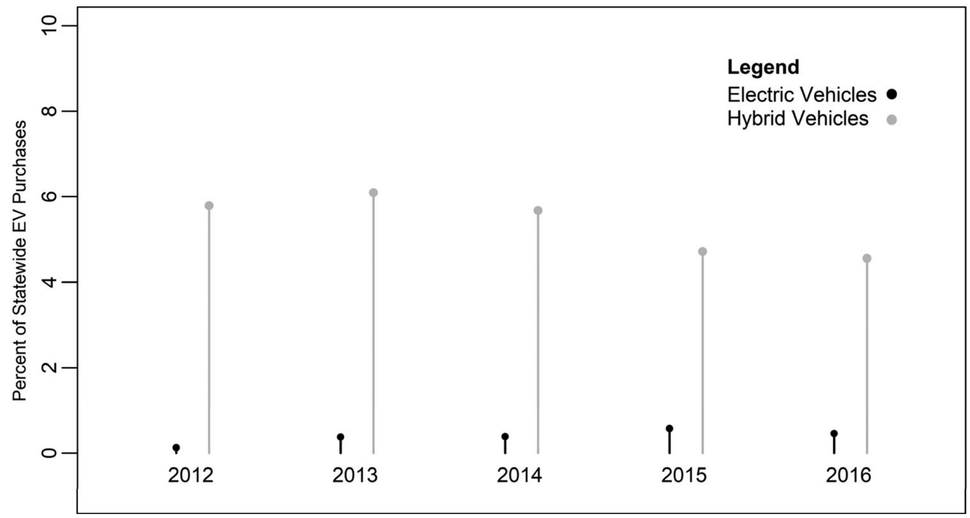


Figure 2. Relative percent change in new passenger vehicle purchases across Massachusetts, 2012-2016.

important analytic endeavor in understanding the varying mechanisms behind an individual's decision to purchase a new EV rather than an ICE vehicle. First, an unadjusted odds ratio—from a single-variable logistic regression model—was estimated for a set of socioeconomic neighborhood-level determinants of EV adoption. These tract-level indicators measured the distribution of residents by sex, age, educational attainment, annual household income, and race/ethnicity and their households by tenure and vehicle ownership using 2012–16 ACS data. Second, a binary logit model to account for multicollinearity in these various neighborhood socioeconomic predictors and then examine the impact of housing structure and tract-level EV charging site prevalence during year of purchase was estimated. The traditional logistic regression model is represented as:

$$p(\mathbf{X}) = \frac{\exp(b_0 + b_1X_1 + \ldots + bX_k)}{1 + \exp(b_0 + b_1X_1 + \ldots + bX_k)} = \frac{1}{1 + \exp(-\mathbf{X}b)}$$

Where, $p(\mathbf{X})$ is the probability of an individual purchasing an EV as a function of $\mathbf{X}$ variables with b as their estimated coefficients. This simple modeling strategy was utilized because the expected outcome is dichotomous and odds ratios for the significant predictors can be more easily computed and expressed. Model specification was conducted by applying a dredging strategy in which all independent variable combinations were tested, which was then followed by an assessment of whether the interaction terms of those significant predictors improved the model's goodness of fit. Specifically, the model specification producing the lowest Akaike information criterion in which all predictors were statistically significant ($p < 0.05$) was selected. Using the chosen model specification, the interaction of independent variables was assessed and maintained if the model's goodness of fit improved.

4. Results

4.1. Spatiotemporal patterns of electric vehicle adoption

In the MAVC, roughly 1.14 million new ICE vehicles entered the fleet from 2008 to 2016, with only 1,738 having an all-electric powertrain. Of the approximate 1.14 million new ICE vehicles, about 675,000 (59%) were passenger cars, with the remaining vehicle types including SUVs, trucks, vans, and wagons. Even after filtering by vehicle type, the small share of new EVs in the individual-owned passenger car fleet was unsurprising given the limited availability of EVs in the United States auto market prior to the introduction of the first high-performance, all-electric powertrain vehicle to the general public in 2008—Tesla's Roadster, which ended production three years later having sold less than 2,500 vehicles globally (US SEC, 2016).

An examination of new car purchases in 2012—by which time both Ford Motor Company and General Motors had released passenger EV models, found that 101 new EVs were purchased in Massachusetts that year, a stark increase of more than 20-fold from the prior year. Tracking new car holdings from that watershed year through the study period (Figure 2), revealed a small but strong and relatively sustained growth in EV adoption rates across the Commonwealth, with the caveat that EV purchases for 2015 and 2016 are likely underestimated as a result of the MAVC data limitations noted above.

Comparatively, the percent of new vehicle purchases ascribed to ICE cars (the remaining share of new car registrations in Figure 2) has remained fairly consistent (93.5-95%) since 2012, while the share of hybrid vehicles in the passenger fleet has actually decreased. In 2012, 579 out of 10,000 new vehicle purchases in Massachusetts were hybrids, but by 2016 this statistic dropped to 456 out of 10,000 new passenger cars. This decrease in the share of new hybrid cars compared to the increase in new EV shares suggests that former ICE car owners may be skipping the intermediate step of hybrid vehicle ownership or that more recent hybrid car owners are replacing their existing vehicles for new EVs at a faster rate than ICE vehicle owners.

Figure 3 illustrates the spatial distribution of EV adoption (or new passenger car purchases) across the Commonwealth. Unfortunately, due to missing spatial information that did not permit the geocoding of all garaging locations, municipal-level reporting was available for only 76% (1,322 out of 1,738) of

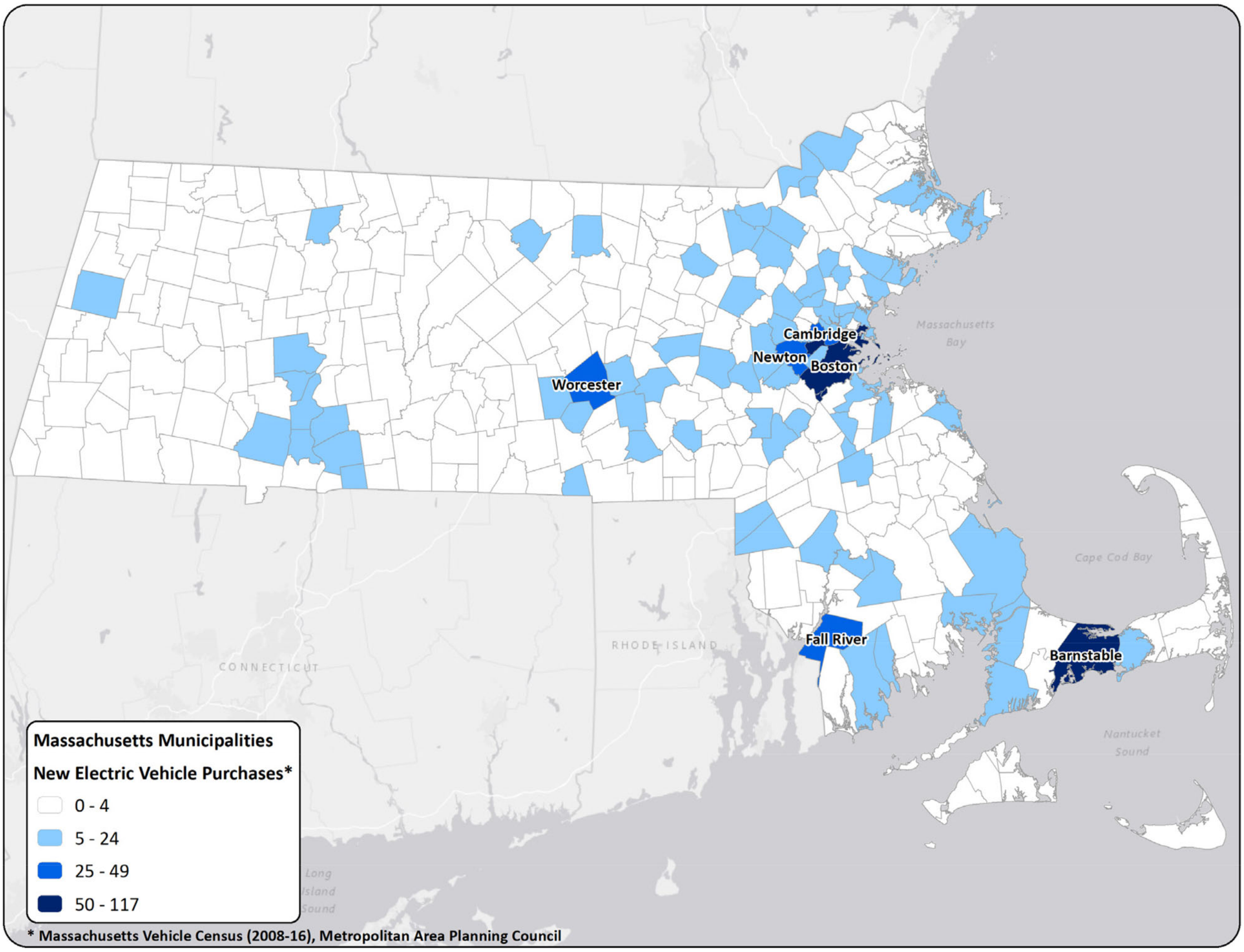


Figure 3. New passenger electric vehicle purchases by municipality in Massachusetts, 2008 to 2016.

Table 3. Massachusetts municipalities with the most registrations of new electric passenger cars, 2008 to 2016.

	Year of Vehicle Purchase						
Municipality	2008-11	2012	2013	2014	2015*	2016*	Total Vehicles
Boston	0	3	29	35	30	20	117
Barnstable	0	1	7	12	41	17	78
Cambridge	1	3	11	3	5	13	36
Worcester	0	2	7	12	2	9	32
Newton	0	1	4	4	11	9	29

Notes. * All new vehicle purchases are likely underreported because of omitted registrations data.

new EVs purchased from 2008 to 2016. While municipal totals would increase if all spatial information were available, as one would expect, relatively large numbers of new EVs were purchased by early adopters in the heavily populated cities of Boston, Worcester, and Cambridge (Table 3). Yet, surprisingly, Barnstable, which is not among Massachusetts's 25 most populous municipalities, had the second highest count of new EV purchases from 2008 and 2016. In 2015, Barnstable saw 41 new EVs purchases, the highest annual total of any municipality over the study period. As a point of comparison, the MOR-EV data set reports 75 rebate claims for new EVs in Barnstable County from 2014 to 2016. The high EV adoption total may be related to the presence of second homes in Cape Cod's most populous municipality or social contagion effects, as the Town had half of the Cape's 30 publicly-accessible Level 2 charging stations in 2017 (Waegelein, 2017).

4.2. Propensity score matching based on the built environment

In order to assess the factors that best explain new EV purchases, it is important to account for the other factors that influence vehicle purchases more generally. Stated otherwise, the likelihood of someone to purchase a new passenger car, whether it be an ICE vehicle or EV, is a function of various socioeconomic and built environment characteristics that should be controlled for prior to investigating the predictors impacting the likelihood of that individual buying an EV *instead of* a conventional ICE car. Our study's use of PSM enabled the creation of a matched sample of early EV adopters with spatial information and new ICE car owners who reside in a similarly situated Census tracts in terms of the number of jobs and residents per acre (activity density), jobs-to-residents balance (land use diversity), and connected

Table 4. Means and standard differences of observed covariates for unmatched data and matched sample.

	Unmatched sample		Matched sample		
Built Environment Indicators	EV (mean)	ICE (mean)	EV (mean)	ICE (mean)	Mean Diff. ICE (mean)
Activity (persons + jobs) per acre	23.79	22.06	23.79	24.54	2.48
Jobs-persons balance	0.81	0.80	0.81	0.86	0.06
Connected node ratio	0.76	0.75	0.76	0.75	0.00

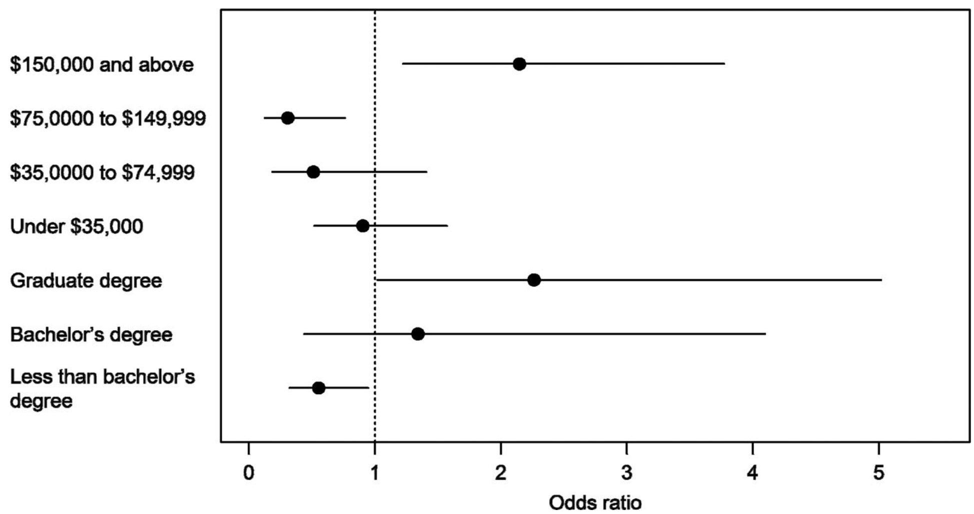


Figure 4. Unadjusted odds ratios with 90% confidence intervals for socioeconomic predictors of new EV adoption.

node ratio (street design). Importantly, each built environment indicator was not significantly predictive of the share of new EV registrations in the 1,478 Census tracts in Massachusetts, nor were the indicators highly correlated with one another. After removing observations with insufficient data, Table 4 summarizes the three built environment indicators for the unmatched MAVC data set and matched sample (n = 1,692).

4.3. Neighborhood predictors of electric vehicle adoption

With a balanced data set, the next analytic steps were to identify the neighborhood-level socioeconomic characteristics associated with early EV adoption and then model their significance as predictors of new EV car ownership when also accounting for technological and housing structure metrics. Figure 4 details the results of the single-variable logistic regression models by displaying the unadjusted odds ratio for those socioeconomic neighborhood features with a significant association with the choice to purchase a new EV car rather than an ICE vehicle. The position on the x-axis indicates the odds ratio for each socioeconomic indicator of EV adoption, with accompanying segments reflecting a 90-percent confidence interval. This preliminary analysis found that car buyers were more likely to purchase an EV than an ICE car if they lived in a Census tract with a higher share of households having an annual income above $150,000, or a higher share of adults over 25 years old possessing a graduate degree. Conversely, individuals residing in a Census tract characterized by a higher share of adult residents without a four-year college degree were more likely to have purchased a new ICE car rather than an EV. The percent of households earning between $75,000 and $150,000 per year was also significantly associated with a lower likelihood of EV purchase. Of note, the percent earning $35,000 to $75,000, or less than $35,000 had odds ratios closer to 1.0, but not statistically significant. This outcome may be explained by a lower number of new vehicle purchases being made in lower-income Census tracts. The association between EV adoption and neighborhood-level socioeconomic measures pertaining to sex, age, race and ethnicity, housing tenure, and household vehicle ownership was also examined, but not found to be statistically significant.

In addition to these socioeconomic measures, three other variables were tested in the binary logistic regression model: whether the purchaser lived in a single-family unit and the era of development for a resident's home as well as the count of public EV charging sites in a tract at the end of the year in which a car was purchased. Table 5 shows the estimation results of the final model specification. In this full model specification, residing in a Census tract with a higher share of households earning over $150,000 remained predictive of new EV adoption. However, with the addition of an interaction term between this housing structure indicator and neighborhood-level income, the direction and interpretation of this indicator changes. Someone residing in a single-family house in a neighborhood with zero households earning an income of at least $150,000 is less likely to purchase a new EV than an ICE car. Similarly, a negative coefficient for the household income indicator now refers to how an increase in the percent of higher-income households within a Census tract decreases the likelihood of an individual not residing in a single-family house to purchase an EV rather than ICE car. Interestingly, the addition of an interaction term between neighborhood-level income and

Table 5. Estimation results of binary logistic regression model of new EV adoption with a matched sample.

Indicators	beta	std. error	odds ratio	significance
Intercept	0.05	0.11	1.05	–
EV charging sites (US Census tract)	0.57	0.19	1.77	***
Building type: Single-family	−0.30	0.17	0.74	*
Household income: $150,000 and above	−1.12	0.62	0.33	*
Interaction: Single-family * $150,000 and above	2.74	0.79	1.62	***

Notes. p-value > 0.10 (-), p-value < 0.10 (*), p-value < 0.05 (**), p-value < 0.01 (***). AIC = 2,121.20, n = 1,552.

household-level housing type revealed that an individual residing in a single-family detached home was 62% more likely to have purchased an EV than an ICE vehicle if the neighborhood-level share of households earning an income of $150,000 or above was equal in the matched pair. This result appears to highlight the benefit of dedicated off-street parking on a driveway or in a garage to household EV adoption, as affluent EV owners in single-family housing are more likely to have both the benefit of at-home vehicle charging and the additional space needed to store the vehicle while doing so.

However, the results also highlight one way in which public policy may be able to influence EV adoption rates. For each EV charging station site introduced in an individual's neighborhood during the year a new vehicle was purchased, the individual was 77% more likely to have purchased an EV rather than an ICE vehicle. Given our prior finding that single-family residency, where at-home charging is a viable option, is such a powerful predictor of EV adoption, this non-intuitive finding merits further inspection. Perhaps, this finding points to how the improved provision of more local EV charging options reduces so-called "range anxiety" concerns by giving EV owners an ability to charge their vehicle's battery when at-home convenience may not be an option (Bonges & Lusk, 2016). In turn, an increase in the presence of EV charging stations may be another outcome of local efforts to promote their adoption, which may include promotional efforts, social marketing, preferential parking locations, and other incentives not modeled.

5. Conclusions

This study utilized a unique multiyear dataset of statewide vehicle registrations to inspect the patterns and predictors of early EV adoption within the passenger vehicle fleet. In examining the spatiotemporal patterns across Massachusetts, our study determined that EV adoption—within this preliminary stage—has largely been an urban phenomenon displaying a relatively slow but incremental increase in its share of the car consumer market since 2012. Findings corroborated by a state-by-state analysis, which noted Massachusetts had a cumulative EV market share below 0.1 percent from 2010 to 2014 (Vergis & Chen, 2015), and reports of a national lag in initial EV sales due to market and technological constraints as well as policy biases toward cultivating niche, urban markets (Green et al., 2014).

At the neighborhood scale, our study employed a statistical matching technique to the registration data set, which mimicked a randomized experiment and allowed the identification of the socioeconomic and technological features that predicted an individual's purchase of an EV rather than ICE car when residing in a similar built environment. Based on this approach, our study confirmed what others have suspected (Fletcher et al., 2011): EV adoption in Massachusetts, far from being widespread, is limited primarily to higher-income households who live in single-family homes. Outside of the home, our study findings also underlined the importance of public charging stations toward increasing electric car ownership; whether the introduction of this requisite infrastructure is a marketing tool for increased adoption or a response to new EV owners desiring greater recharging convenience.

Our study's findings also have implications for planning policy. First, although socioeconomic factors of a neighborhood do not lend themselves to transportation planning actions, the ability of planners to inform public EV charging station siting decisions should be leveraged (Javid & Nejat, 2017). A significant association between EV adoption and infrastructure availability highlights the potential for increased EV fleet penetration in neighborhoods with a denser stock of multi-family housing units and limited out-of-home charging capabilities through strategic siting decisions. Second, the decision to match new EV and ICE car owners for model development based on land development patterns and network connectivity of their home location was driven by an insensitivity of these built environment factors to this tradeoff. As such, pro-EV policies and interventions should continue to be sought after by communities outside of the Boston metropolitan region where households in the current market niche (e.g., educated) currently reside (i.e., college towns), while safeguarding against a reinforcement of status roles based on income that may be symbolized with EV adoption. Third, our illustration of the persistent (albeit slow) growth of EV shares in the Massachusetts passenger car fleet—when contrasted with the Commonwealth's lofty legislatively-mandated, market penetration goals—has highlighted a pressing need for greater financial and nonfinancial incentives to sway present ICE car owners and future vehicle holders to purchase EVs and bypass the intermediate stage of buying a hybrid or more efficient conventual fuel vehicle.

While instructive for potential EV policies, any extension of this study should seek to address its limitations. Foremost, our preliminary inspection of the MAVC revealed missing vehicle registration records, which will require the development of new methods for imputing or weighting the information to generate population-based statistics. Second, the MAVC does not offer any individual-level psychosocial attributes that are recognized in the literature to be significant predictors of EV adoption. To address the former limitation, future extensions of this research should assess the prospect of imputing EV registrations in later years with the more spatially-aggregate MOR-EV data set. While this imputation process might improve future work investigating the spatiotemporal patterns of population-level EV adoption, estimation results of this study's sample-based analysis would likely be unimpacted. Regarding the latter limitation, a survey of individuals in the matched sample, akin to prior studies of vehicle registration data (Westin et al., 2018), might be one strategy for merging individual psychosocial predictors into this analysis. The inclusion of individual- and household-level attributes in future analyses would provide further understanding into the roles of demographic homophily and social contagion in EV adoption and better quantify the true neighborhood effects of social environment predictors on EV rather than ICE vehicle adoption. Similarly, assumptions regarding vehicle purchasing price could also be asserted to augment the Massachusetts data set and test if this economic indicator predicts the purchase of EVs, which are priced significantly higher than ICE vehicles (Hagman et al., 2016), after controlling for residential location, household income, and housing type. Finally, given the longitudinal structure of the MAVC, an exciting advancement of this work would be to model the vehicle usage of early adopters of EVs, which produce greater emissions at the manufacturing stage than ICE vehicles (Nealer et al., 2015), and determine their true environmental benefit over the life cycle of the vehicle.

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