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Electrifying the road: Navigating the transition to electric vehicles in Connecticut through hybrid insights and fleet evolution

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ABSTRACT

The adoption of light duty electric vehicles (EVs) in the past 5 years has accelerated dramatically. As EVs continue penetrating the U.S. market, it is critical to understand what a sustainable transition within the transportation sector will look like in relation to mitigating impacts of climate change. This work aims to fill two existing gaps in the current literature: 1) investigate the positive and negative potential influences of the emerging EV transition within the U.S. market and 2) investigate the types of vehicles EVs are replacing. We fulfill these objectives by utilizing a unique attribute dataset of all vehicles in Connecticut (USA) on the road between 2013 and 2020. Our findings suggest that the penetration rate of traditional hybrid vehicles (e.g., Toyota Prius) is an important predictor of EV adoption. Furthermore, our results show that in Connecticut most of that transition is occurring among hatchbacks (e.g., Chevrolet Bolt), a body style where internal combustion engine (ICE) versions have relatively high fuel efficiencies compared with other major vehicle types (e.g., pickup trucks or SUVs). Our results offer important implications for policymakers in terms of maximizing the deployment of EVs and EV infrastructure and the path in which the automotive sector is progressing towards decarbonization.

1. Introduction

The finite supply of fossil fuels, national energy security, and the challenge of climate change have all led to a growing interest in electric vehicles (EVs) (Banister, 2008; Muratori et al., 2021). Overall, EVs contain the potential to provide multiple benefits to society such as increased energy efficiency of passenger vehicles, diversification of energy resources (i.e., electricity vs fossil fuels), improved local and regional air quality, and potential to reduce global greenhouse gas (GHG) emissions (Wu et al., 2015; Teixeira and Sodré, 2018; Choma et al., 2020). From 1990 to 2021, transportation was the second largest contributor to global CO_2 emissions and in 2021 contributed around 23% of total emissions (IEA, 2023a). Furthermore, the sector is expected to experience increasing demand and subsequent emissions (Creutzig et al., 2015; Davis et al., 2018). With public transport use in the United States declining (Erhardt et al., 2022), and Covid-19 further pushing users to personal transportation (Liu et al., 2020; Loa et al., 2022), identifying and deploying a range of technologies and policies aimed at decarbonizing personal transportation will be vital for addressing the climate crisis.

To address these concerns, nations around the world have outlined policies designed to transition the transportation sector from fossil fuel energy sources to cleaner technologies (Rockström et al., 2017). The United States for example has recently outlined a goal of shifting 50% of new vehicle sales towards zero-emission vehicles—battery electric, plug-in hybrid, or hydrogen fuel cell—by 2030, and to further decarbonize the entire transportation sector by 2050 (White House, 2021; DOE et al., 2022). Furthermore, passage of the US Inflation Reduction Act (IRA) of 2022 will further bolster EV adoption, infrastructure development, and production supply chains in the coming decade (White House, 2023). As of March 2023, cars and vans within the European Union are required to reduce emissions by 55% and 50% respectively by 2030 compared to 2021 levels and 100% across the board by 2035 (IEA, 2023b). In yet another example, China has launched a target to electrify 80% of all public sector vehicles while simultaneously build out charging stations by 2025 (IEA, 2023a).

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Although ambitious, the dynamics between innovative EV technologies, and consumer adoption behavior remain complex and vary geographically (Tamayao et al., 2015; Yuksel et al., 2016; Ryghaug and Skjølsvold, 2022).

To date, EVs have emerged as the most likely alternative to fossil fuels within the personal passenger transportation sector. Throughout this paper we use the term EV to represent a combination of battery electric vehicles (BEVs) and plug-in hybrid vehicles (PHEVs) (see Supplemental Table S2 for detailed description). Although there are distinct differences in terms of technology, climate mitigation potential, and incentive structures, both vehicles use battery technology and place added demand on the electricity grid. For this reason, we have combined them into one category. The widespread replacement of internal combustion engine (ICE) vehicles with EVs offers a promising route to decarbonize the transportation sector (Casals et al., 2016; Teixeira and Sodré, 2018). Between 2010 and 2022 the global share of EV sales grew from 0.011% to 14%; despite this rapid growth, the overall share of EVs remains minimal at only 2.1% as of 2022 (IEA, 2023c). Although the last decade brought about favorable conditions (i.e., diversity of vehicle options, government adoption incentives, and a maturing technology), successfully decarbonizing personal transportation faces multiple barriers (Berkeley et al., 2017). There currently exists a rich body of literature on factors influencing EV adoption (Kumar and Alok, 2020). Like other renewable energy technologies (e.g., rooftop solar) (Graziano and Gillingham, 2015), EV adoption is associated with a mix of general and regional factors (see e.g., Lebrouhi et al., 2021 and the regional works cited within). The potential negative impact of a rapid EV transition on US carbon emissions could further complicate overall decarbonization efforts and the ongoing energy transition. A recent assessment suggests that an EV transition in the United States could increase electricity consumption by 35% thereby placing additional stress on efforts to decarbonizing the electricity grid to fully realize the benefits of EVs (Galvin, 2022). In addition, the types of vehicles that are replaced by EVs will influence the perceived benefits of EVs as they relate to climate change goals.

To fill these gaps, and to further understand the regional patterns of adoption of EVs in North America we aim to fulfill two main objectives in this paper. Firstly, we estimate what factors (i.e., socioeconomic, demographic, and technological) might influence EV adoption, how those factors vary intraregionally, and what influence, if any, do spatial spillovers have on local adoption rates (Dharshing, 2017). Secondly, we evaluate vehicle fleet replacement dynamics and CO_2 emission implications by body style for personal passenger vehicles. To answer our main research questions, we rely on two datasets, a spatial panel dataset of vehicle counts by fuel type, sociodemographic, and charging infrastructure data and another dataset of vehicle makes, models, fuel type, body style, and year. Both datasets span the years 2013–2020. We leverage panel and spatial-panel econometric approaches to identify factors associated with EV adoption and lifecycle analysis approaches to evaluate fleet wide replacement dynamics by body style.

In brief, our findings suggests that work modality, charging infrastructure, and the share of traditional hybrid vehicles (e.g., Toyota Prius) are associated with EV adoption. Contrary to previous research, our results show that areas with increased shares of multi-car single family homes are not positively associated with EV adoption (Gärling and Thøgersen, 2001; Campbell et al., 2012; Morton et al., 2018), raising questions about the idea that EV adoption is part of a “two car” model (i.e., EVs are adopted for short distances only when an ICE vehicles is on tap for longer trips). With respect to fleet replacement dynamics, we found between 2013 and 2020 vehicles on the road in Connecticut increased by 7.85% with the passenger van (aka minivan or multi-purpose vehicle) segment representing the largest increase. Focusing specifically on EVs, we found that the hatchback body style (e.g., Volkswagen Golf) is undergoing the largest shift towards electrification. Considering current EV availability, efforts towards electrifying the passenger van fleet would likely result in the greatest emission reductions. Unfortunately, options for passenger van EVs are limited thereby posing a barrier to realizing emission reduction in this ripe segment.

The remainder of this paper is as follows: section 2 provides an overview of relevant EV adoption literature ranging from purely temporal studies to those investigating the influence of geography, section 3 is a description of the study area and dataset used in the analysis, section 4 provides an overview of the methodological approach, followed by section 5 which presents the results, and lastly section 6 contains our conclusions and highlights the studies limitations and suggestions for future research.

2. Theoretical framework & literature

The diffusion of innovative technologies rarely takes a direct path. Rather, multiple paths work together or against one another leading to the success or failure of integration within society. Geels (2002) described how the success or failure of innovative technologies, under certain conditions (e.g., exogenous shocks to the socio-technical regime) shape and transform societal interactions from existing technologies to emergent ones (e.g., transition from fossil fuel vehicles to EVs). Given the relatively recent introduction of modern EVs, much remains to be learned about what factors will influence EV adoption. Currently, much of the research related to this question is often viewed through a temporal lens, employing models to predict adoption rates and uptake trajectories (Shepherd et al., 2012; Tran et al., 2013; Gnann and Plötz, 2015; Kumar and Alok, 2020). Less attention has been given to spatial elements of EV adoption, specifically how EVs propagate over time across different geographies (however see e.g., Delmas et al., 2017; Morton et al., 2018; Lyu, 2023; Rode, 2024). Understanding EV adoption variation at local scales and considering the potential for spatial spillovers (LeSage and Pace, 2021) can provide public officials more effective policymaking tools, such as incentive programs, electricity grid planning, and other supportive infrastructure that can facilitate a successful transition to a fully electrified vehicle fleet (Broadbent et al., 2017). Coffman et al. (2017) review 50 studies on factors that influence EV adoption. They distinguish internal factors, like vehicle ownership costs, driving range, and charging time, from external factors like fuel prices, consumer characteristics, availability of public charging stations, public visibility, and social norms. They conclude that high purchase prices are a major barrier to adoption, and that certain consumer characteristics, such as income, education, and age, significantly influence interest in EV ownership. In a separate review, of 40 articles published after 2011, Li et al. (2017) largely corroborates those results, but also note that income is not a key factor when focusing specifically on battery electric vehicles. More recent studies also confirm that more education, being male, and being closer to charging stations increase EV adoption (Sierzchula et al., 2014; She et al., 2017; Melliger et al., 2018; Sovacool et al., 2018; Gillingham et al., 2023). Consumer profile studies suggest that younger people are less likely to adopt an EV, possibly owing to the mix of capital and marginal costs for ICE vehicles and EVs (Sierzchula et al., 2014; Mukherjee and Ryan, 2020; Fevang et al., 2021).

Exploring both the spatial and temporal aspects that charging infrastructure, situational contexts, and the influence neighboring geographic units have on the spatial diffusion of EVs can enhance our overall understanding of an emerging EV transition (Morton et al., 2018). For example, Campbell et al. (2012) used a spatial cluster model to identify locational hot spots of consumers most likely to adopt an EV within Birmingham, UK. Using UK census data, the authors found that sociodemographic data associated with that of an “ideal” EV adopter was clustered to surrounding Birmingham suburbs (primarily to the north of the city center), while the city center region of Birmingham was part of the cluster least likely to adopt EVs. Overall, Brimingham was an unlikely location for EV adoption, the authors found variability in EV adoption when disaggregating to smaller spatial units of analysis.

Morton et al. (2018) expands the study EV adoption in the UK by analyzing neighborhood effects. By examining the whole of the UK, compared to a single city, the authors found higher concentrations of EV ownership in urban settings which contained higher incomes, education, and shares of traditional hybrid vehicles. In the United States, Liu et al. (2017) also found units with higher education had higher shares of traditional hybrid vehicles, possibly linking the two technologies (i.e., traditional hybrid vehicles and EVs) among potential adopters. In yet another study, Plötz et al. (2014) found German EV adopters tended to live in non-urban locations (presumably due to increased likelihood of owning a garage), own multiple vehicles (i.e., two car model), and who economically benefited from EV ownership compared to urban owners whose timeline for return on investment via vehicle miles traveled was far greater. Similar geographic patters were observed in Norway and Sweden, finding higher rural EV ownership rates (Kester et al., 2020). Schulz and Rode (2022) found that the presence of public charging infrastructure in Norway increased the rate of EV adoption by 200% over five years. Similarly, Namdeo et al. (2014) found higher urban EV adoption provided there was adequate public charging infrastructure a feature of an EV transition that could act as a barrier if not properly planned (Biresselioglu et al., 2018).

Among the literature reviewed, some clear trends emerge. Socio-demographic variables such as income, age, education level, employment, gender, and commuting patterns are consistently evaluated as possible factors associated with EV adoption. Less studied, although equally important, is the association that public charging and multi-car ownership has on EV adoption. A summary of literature covering the adoption of EVs can be found in Table 1.

3. Study area and data

We focus our research on Connecticut for several reasons. First, Connecticut is a relatively early mover in the EV adoption race, ranking 15th in share of EVs in the US (Fig. 1). Second, the state faces a strained electrical grid, and the existing research on EV adoption in the US, has not paid much attention to regions prone to unreliable grid conditions (Graziano et al., 2020; Gallaher et al., 2021). Third, when assessing sustainable transitions, regionalism and spatial considerations provide a valuable perspective in that each location is distinct and might require a different path to decarbonization (Truffer and Coenen, 2012). Thus, a focus on Connecticut provides the opportunity to explore sustainable transitions within the New England transportation sector while simultaneously engaging with possibly implications to electricity grid reliability. Beyond the abovementioned motivations for studying EV adoption using Connecticut as a case study, the state has faced a unique barrier in how popular EVs (e.g., Tesla) are purchased.

Connecticut, along with 13 other states are subject to a direct-to-consumer sale ban[2] on EVs sold outside of traditional dealership organizations. As the only state in New England to enact such a restriction on purchasing an EV, it highlights the unique nature of this study within the regional context. Currently, purchasing an EV, specifically a BEV (e.g., Nissan Leaf or Tesla Model 3) requires individuals to travel beyond Connecticut's borders to states like New York or Rhode Island so that they may take delivery of their vehicle, ordered directly from the auto manufacture. In fear of losing business, dealerships have leaned on policymakers to craft restrictions against taking delivery of vehicles ordered online directly from the manufacture (i.e., Tesla and Rivian). Realizing the barrier placed on Connecticut residents, policy makers have introduced state bill 214 *An Act Concerning the Sale of Electric Vehicles in The State* to spur adoption of EVs.

However, the bill was ultimately stifled, potentially further delaying

[2] New Hampshire, Massachusetts, and Rhode Island who had similar laws have all since updated those in some capacity to allow for direct-to-consumer sales.

Table 1
Summary of research on the consumer adoption of electric vehicles (EVs).

Source	Region	Country/ State	Method	Covariates
Mukherjee and Ryan (2020)	Europe	Ireland	Non-linear regression; general nesting spatial models	Distance to charging point; dealerships; Large homes; Long commutes; Renters; Higher ed.; age; population
Fevang et al. (2021)	Europe	Norway	Regression	Income; region (urban); nationality; education; selected education degrees; age; distance to work; travel characteristics; employment sector
Campbell et al. (2012)	Europe	United Kingdom	Cluster analysis	Age; home ownership; home structure; commute mode; multi-car ownership; occupation; education
Plötz et al. (2014)	Europe	Germany	Logistic regression	Gender; age; location of residence; household size; number of children; employment; commute distance; income; education
Kester et al. (2020)	Europe	Norway & Sweden	Survey; expert interview; focus group	Gender; household size; country; income; education; employment; political affiliation; environmental values
Liu et al. (2017)	North America	United States (Ohio)	Spatial autoregressive; spatial error; geographically weighted regression	Population; number of homes; commute mode; vehicle ownership; income
Morton et al. (2018)	Europe	United Kingdom	Ordinary least squares; spatial Durbin model	age; education; employment; median income; population density; hybrid vehicles per 1000 cars; EV charging points; housing structure; commute mode; single vehicle house
Schulz and Rode (2022)	Europe	Norway	Difference in Difference	Population density; income; median age; education; environmental political affiliation

(continued on next page)

Table 1 (*continued*)

Source	Region	Country/ State	Method	Covariates
Namdeo et al. (2014)	Europe	United Kingdom	Spatial hotspot analysis	Gender; age; occupation; household income; multi-car household; housing structure; commuting mode
Sovacool et al. (2018)	Europe	Denmark; Finland; Iceland; Norway; Sweden	Survey; frequency analysis; single level statistical analysis	vehicle background; mobility patterns; willingness to pay; preference for vehicle attributes; gender; age; occupation; political affiliation; education; household income
Melliger et al. (2018)	Europe	Switzerland; Finland	Focus groups	Gender; age; education; multi-car household
Axsen et al. (2016)	North America	British Columbia	Stated choice survey	Gender; age; household income; education; housing structure; vehicle ownership; charging access
Nayum et al. (2016)	Europe	Norway	Survey	Gender; age; household size; material status; education; occupation; household income; multi-car household
She et al. (2017)	Asia	China	Survey	Gender; age; household size; driving experience; vehicle ownership; education; income
Sierzchula et al. (2014)	Global	30 countries	Regression	Incentives; EV charging points; environmental regulation; fuel prices; EV manufacturing; income; education; vehicles per capita; electricity prices; EV market price; urban density
Gillingham et al. (2023)	North America	United States	Regression	Income, household size, education, population density

meeting clean air and climate targets set out by the state. Although, each year auto manufacturers are offering an increasing number of EVs in their lineup such as the Ford Mustang Mach-E, Lightning F-150, Kia EV6, etc. which are sold through traditional dealership networks. Despite an increasing number of EV models available through traditional auto manufacturers (e.g., General Motors or Ford), there remains a large gap in achieving EV policy goals.

In 2020, the Connecticut Department of Energy and Environmental Protection (CT DEEP) developed a policy framework designed to accelerate EV adoption in tandem with climate and clean air goals. Connecticut, in coordination with 10 other states,[3] have agreed to a goal of deploying 125,000 to 150,000 EVs by 2025 (CT, 2020). However, as of 2020 there are 12,380 EVs in the state of Connecticut, representing between 8.25% and 9.90% of 2025 goals. Moreover, the Governor's Council on Climate Change (GC3) determined that in order to meet goals outlined in the 2008 Global Warming Solutions Act 20% of the light duty vehicle (LDV) fleet, or 500,000 vehicles, would need to be replaced by EVs by 2030 (CT, 2020). Given the unique connection between electricity, buying, and the large gap in EV policy goals, elucidating the various drivers and barriers of EV adoption in Connecticut could help bring to light challenges similar regions might face when attempting to electrify personal transportation.

To evaluate factors associated with EV adoption and the spatial patterns in Connecticut, we rely on a dataset constructed from combining data on vehicular, infrastructural, and sociodemographic information. The summary statistics of the variables used in this analysis are listed in Table 2 (see Supplemental Table S3 for list of sources). The geographic unit of analysis is the US Census Zip Code Tabulation Areas (ZCTAs). ZCTAs are a generalized representation of US Postal Service zip code service areas, which are not geographic units, but rather service routes used for mail delivery. The use of ZCTAs provides a stable geographical unit over time in locations that, in Connecticut, experienced low population change: 0.9% growth between 2010 and 2020 (Proto, 2022). Variables used to evaluate factors associated with EV adoption are based on commonly used indicators from the literature. The dataset covers, annual vehicle registrations by energy/fuel type and vehicle body style, American Community Survey (ACS) 5-year averages of sociodemographic data, and information about the EV charging infrastructure recorded by the Department of Energy's Alternative Fuels Data Center station locator (AFDC, 2023) for years 2013–2020. We dropped 19 ZCTAs that contained missing data for total population, total households, or were identified as PO boxes or special designation areas (e.g., Universities or major companies). This resulted in a 6.7% reduction in the original data going from 282 to 263 ZCTAs across all time periods.

Data on vehicle registrations at ZCTA level is provided by IHS Markit (now S&P Global). Contained within our vehicle registrations dataset is information related to vehicle make, model, sub-model, engine size, body style (e.g., pickup truck, wagon, sedan, etc.), fuel type (e.g., gasoline, electric vehicle, etc.), and vehicle year. Vehicle year is obtained from the Vehicle Identification Number (VIN). Data was aggregated to the ZCTA level for our initial EV adoption analysis by fuel type and data year (other details from the IHS Markit dataset are used in the later analysis of fleet replacement dynamics). To obtain sociodemographic data, we used the end year of each ACS 5-year average from 2009 to 2020. For example, we use the 2009–2013 ACS 5-year average to represent sociodemographic information for the year 2013. Lastly, we summarize the cumulative number of charging stations (e.g., level 1, 2, or DC fast charger) per ZCTA in each year, with all chargers installed prior to 2013 included in the 2013 data year.

4. Methodology

This study takes a two-stage approach, whereby we begin with a regression analysis of EV adoption in Connecticut from 2013 to 2020.

[3] California, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont. See: State Zero-Emission Vehicle Programs https://www.nescaum.org/documents/zev-mou-10-governors-signed-20191120.pdf.

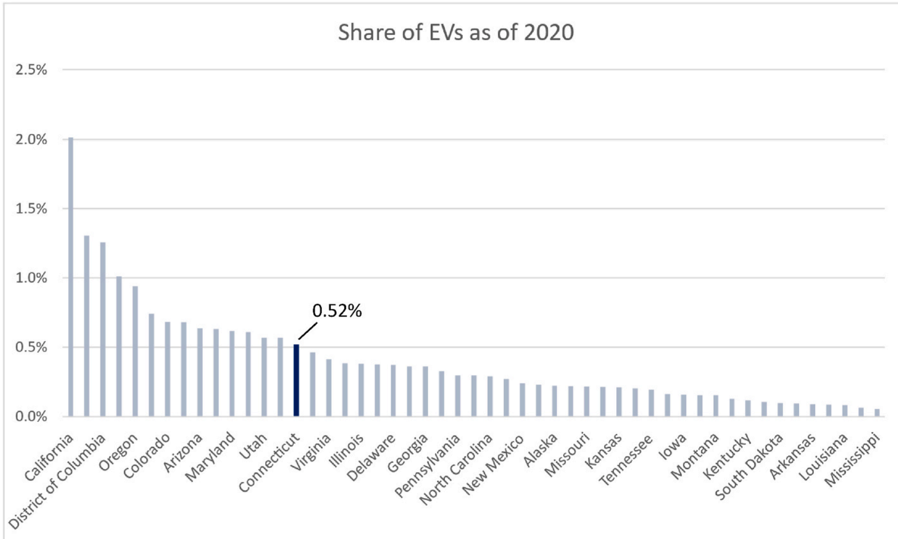

Fig. 1. Market share of EVs as of 2020.25th percentile is equal to 0.16% and 75th percentile is equal to 0.57% with a median value of 0.30% (AFDC, 2022).

Table 2
Summary statistics of data used in EV adoption analysis. See Table S3 in appendix for list of data sources.

Variable	Obs.	Periods	Mean	Std. Dev.	Min	Max	Rationale
Electric vehicles per 1000 LDV (%)	2104	7	210	269	0	3254	Dependent variable
Hybrid vehicles (%)	2104	7	1.78	0.77	0.12	8.16	Morton et al. (2018)
Median Household Income ($ 10,000)	2104	7	8.64	3.38	1.13	25.00	Morton et al. (2018)
Housing density (%)	2104	7	633.44	1016.54	3.29	8779.38	Campbell et al. (2012); Plötz et al. (2014); Kester et al. (2020)
Active age 25–44 (%)	2104	7	22.76	6.11	3.39	58.26	Liu et al. (2017); Coffman et al. (2017)
Long commute (>60min) (%)	2104	7	7.14	4.93	0	58.33	Plötz et al. (2014); Kester et al. (2020)
Female Pop (%)	2104	7	50.92	2.83	28.21	64.41	
Service Sector (%)	2104	7	77.78	7.06	0	100	
Multi-Car (%)	2104	7	63.99	15.89	0.84	100	Plötz et al. (2014); Kester et al. (2020)
Charging Stations (#)	2104	7	2.09	4.85	0	60	Namdeo et al. (2014); Schulz and Rode (2022)
Work from home (%)	2104	7	5.76	4.05	0	29.67	

This is followed by an estimation of greenhouse gas implications of an emerging EV transition in Connecticut. For the regression analysis, our methodological approach follows that of Gallaher et al. (2021), in that we begin by evaluating EV adoption from a temporal perspective. However, geographic data tends to exhibit spatial dependence (i.e., the presence of spatial autocorrelation or a clustering of similar values) and thus is best handled using spatial statistical methodologies. Unique to this approach is the ability to understand the influence neighboring geographic units have on one another (i.e., spatial spillovers). Before we describe the methods used in our analysis, we briefly describe a directed acyclic graphic (DAG) model to elucidate the underlying assumptions of panel data models and the use of fixed effects (Fig. 2). Our variable of interest (share of EVs per 1000 light-duty vehicles (LDV) henceforth referred to as share of EVs) has repeated measurements at the same unit (Y_{it}), and we have included a set of independent variables (D_{it}). Within panel data, there is also a single-unit specific unobserved variable (U_i) and some unit-specific time-invariant variable (X_i). We know from the DAG and the works of Imai and Kim (2019) that D_{i1} influences both Y_{i1} and D_{i2} and we note that the unobserved cofounder, U_i influences all Y and D variables. Therefore, we can conclude that D is endogenous because U_i is unobserved and absorbed into the structural error term of the regression model. Lastly, we know that past outcomes do not directly affect current outcomes or current treatments and past treatments do not directly affect current outcomes. It is under these assumptions that we can use the fixed effects panel method to understand the relationship between D and Y.

4.1. *Temporal specification*

Our panel model can be parsimoniously stated as:

$$EVs_{i,t} = \alpha + \beta_{1-11}\gamma_{i,t} + \beta_{12}\delta_{i,t} + \beta_{13}\varphi_{i,t} + \eta_i + \varepsilon_{i,t}$$

Whereby: $EVs_{i,t}$ is the share of EVs per light duty vehicles (LDV) occurring in ZCTA (i) in each year (t); α is our intercept; $\beta_{1-11}\gamma_{i,t}$ represents each of our sociodemographic variables (see Table 2); $\beta_{12}\delta_{i,t}$ contain the total number of public charging stations ports within each ZCTA-year; $\beta_{13}\varphi_{i,t}$ contains the share of traditional hybrid vehicles per LDV (replacement effect); η_i is a ZCTA level fixed effect; and $\varepsilon_{i,t}$ is our error term.

4.2. *Spatial-panel models and specification*

Although the temporal model can evaluate the association between independent variables and EV adoption, geographic data often exhibits spatial dependence (i.e., spatial autocorrelation), which, if not accounted for, result in biased parameter estimates (Chun and Griffith, 2013). Like traditional correlation, spatial autocorrelation can be positive (i.e., similar values are clustered in space) or negative (i.e., dissimilar values are clustered in space). Spatial autocorrelation within geographic datasets results from one of the foundational laws within the field of Geography, *everything is related but near things are more related than distant things* (Tobler, 1970). In essence, geographic data violates the basic assumptions associated with ordinary least squared (OLS) models (e.g., independence and identically distribution of data). Therefore, leveraging methods designed to account for spatial autocorrelation in

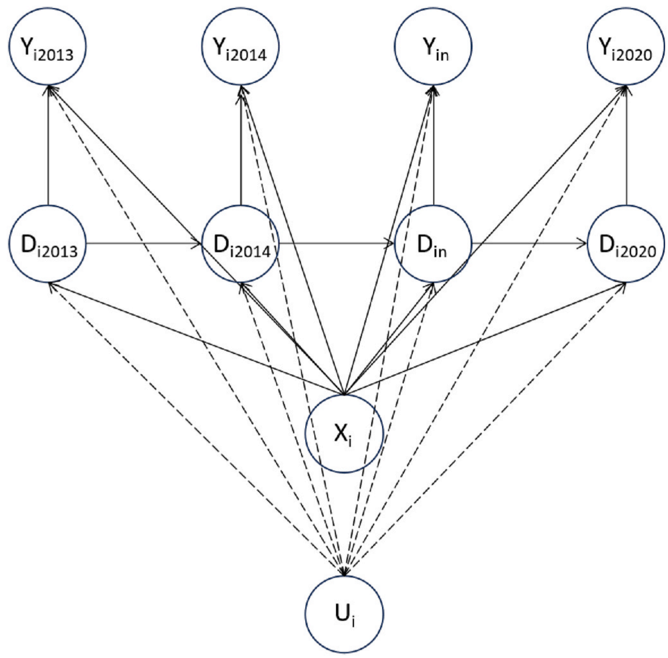

Fig. 2. Directed acyclic graphic model of EV adoption in Connecticut. Y_i represents share of EVs per ZCTA per year from 2013 to 2020, D_i represents a matrix of independent variables (Table 2) which vary over time. U_i is a single unit-specific unobserved variable that varies across units but not across time and a unit-specific time-invariant variable X_i that is observed unlike U_i. For additional information on panel-data DAGs see Cunningham (2021) chapter 8 and Imai and Kim (2019).

geographic data results in less biased estimates of regression coefficients.

There are several methods used in testing for spatial autocorrelation; however, the most widely used is Moran's I. One of the key benefits of Moran's I is that it can index data across all four measurement scales: normal, ordinal, interval, and ratio (Griffith, 2010). Moran's I is a normalized index whereby values fall between −1 (perfect negative spatial autocorrelation) and 1 (perfect positive spatial autocorrelation). We can define Moran's I by the following equation.

$$I = \frac{N}{W}\frac{\sum_i \sum_j w_{i,j}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{2}$$

Where N is the number of spatial units indexed by i and j, x is our variable of interest, in this case the share of EVs, x bar is the mean and w is our weighting matrix. Global measures of spatial autocorrelation provide a nice overview of how clustered the data are; however, we are assuming that any spatial autocorrelation is uniform across space. In this case, a more detailed measure of local spatial autocorrelation can provide valuable insights. One such method is the Local Indicators of Spatial Association (LISA) first introduced by Luc Anselin (1995). Based on this approach, we can know the location of where spatial autocorrelation is occurring in addition to establishing a proportional relationship between the sum of each local statistic and a corresponding global statistic (e.g., Moran's I) (Anselin, 1995). Building on the global spatial autocorrelation equation, we can define LISA by the following equation:

$$I_i = \frac{N}{W}\frac{\sum_j w_{i,j}(x_i - \overline{x})(x_j - \overline{x})}{\sum_i (x_i - \overline{x})^2} \tag{3}$$

To investigate EV adoption in Connecticut, and to correct for spatial autoregressive correlation we deploy a Spatial Autoregressive model (SAR; Cliff and Ord, 1970). The SAR model is motivated based on time-dependency; in other words, we model the space-time lagged values of the dependent variable via the spatial autoregressive process (see LeSage (2008) for more details). Most importantly, the SAR model has been used in many studies (see e.g., Balta-Ozkan et al., 2015; Dharshing, 2017; Graziano et al., 2019; Gallaher et al., 2021 for additional examples) and can accommodate the analysis of spatial relationships within panel datasets (see e.g., Elhorst, 2014). The unique characteristics of spatial models is the construction of a weighting matrix, we use a row standardized queen's weighting matrix, because such a configuration allows for the greatest number of spatial interactions (see e.g., Cabral et al., 2017; Dharshing, 2017; Lan et al., 2020).

Our spatial panel model can be parsimoniously stated as the following:

$$EVs_{i,t} = \alpha + \rho W_{i,t}\, EVs_{i,t} + \beta_{1-11}\gamma_{i,t} + \beta_{12}\delta_{i,t} + \beta_{13}\varphi_{i,t} + \eta_i + \varepsilon_{i,t} \tag{4}$$

Equation (4) mirrors equation 1, with the addition of the row standardized queen's spatial weighting matrix appended to the dependent variable. Moreover, SAR models account for spatial dependency among neighboring geographic units (e.g., ZCTAs) through the spatial weighting matrix. Parameter estimates in SAR models cannot be interpreted directly from output coefficients as with an OLS model. Therefore, approaches have been developed to interpret output coefficients from SAR models either directly (i.e., within our unit of analysis), or indirectly (i.e., units of analysis neighboring any one unit), or total (i.e., the sum of direct and indirect impacts). Additional details can be found in LeSage (2008) and LeSage and Pace (2009).

4.3. Estimation of fleet-wide greenhouse gas emissions

EVs have long been promoted as an ideal solution for mitigating GHGs within the transportation sector, specifically among LDVs. However, research conducted on the replacement dynamics of EVs is limited. We estimate vehicle fleet emissions from the ten most common vehicles by body style on the road in Connecticut between 2013 and 2020. To assess fleet-wide replacement (i.e., the composition of vehicle fleet by body style) we implemented a change analysis whereby we evaluated the vehicle stock in 2013 and compared to the stock in 2020. Our objective is to understand the GHG implications of an electrified vehicle fleet in Connecticut and determine which body style has been driving vehicle electrification.

Our estimated values for emissions (grams of CO_2 per mile) originate from the US Department of Energy fuel economy database (DOE, 2023). For ICEVs we documented the tailpipe and upstream emissions. Tailpipe emissions include those that are emitted from the vehicle during normal operations and are represented in grams per mile of CO_2. Upstream emissions include CO_2, methane, and nitrous oxide emitted from all steps in the use of fuels from production and refining to the distribution and final use of fuel. Method and nitrous oxide are converted to a CO_2 equivalent value (see EPA, 2022 for additional details). To calculate emissions for EVs we used a similar approach, the main difference is we do not consider emissions during vehicle operation (e.g., tire or break emissions). To calculate upstream emissions from EV operations (i.e., charging) we used the US EPA's emissions calculator which uses regional electricity emissions based on pounds per megawatt hour of electricity. Because we focus on Connecticut, the calculator pulled data from the Independent System Operator New England (ISO-NE). This data is based on values from 2021. We used an average of 15,000 miles driven each year by those ages 20 to 54 as reported by the US Department of Transportation for our unit of analysis (US DOT, 2022).

5. Results

We first provide the temporal and spatial-temporal results followed by results on the fleet wide replacement dynamics from 2013 to 2020 and the estimated implications it has on greenhouse gas emissions. Overall, our results show of the factors considered eight are positively associated with and five are negatively associated with EV adoption under our preferred specification. We observe different results from our preferred specification, under a two-way fixed effects model with four factors positively associated with and seven factors negatively associated with EV adoption. Across all four specifications we found charging infrastructure, working from home, median household income, long commutes, and housing density to be positively associated with EV adoption (Table 3).

5.1. Panel results

When assessing the relationship between the share of traditional hybrid vehicles and EVs, we found consistent results for models 1 and 3 (2 and 4 were not significant). Model 1 has a β of 0.127 which is statistically significant at the 99% confidence level and model 3 has a β of 0.049 and is statistically significant at the 90% confidence level. This result suggests that on average if the share of traditional hybrid vehicles increases by 1% then the share of EVs is predicted to increase by 0.127% or roughly by 1572 new EVs on the road. This implies that when the share of one technology, in this case traditional hybrid vehicles increases, the share of EVs will also increase; either through shear presence on the road or by owners trading in "older" technologies for newer ones (i.e., trading in a Toyota Prius for a Plug-in Hybrid Toyota Prius or Chevy Bolt). Furthermore, we found the number of charging stations to also be associated with the adoption of EVs, although this result is unsurprising as they serve as a necessary component of an EV transition. While charging stations exhibit a limited influence on adoption of EVs β of 0.010, they still serve as a statistically significant indicator. Diverging from previous literature our results show β of −0.007 for multi-car households. Interestingly, longer commutes β of 0.007 and working from home β of 0.019 are positive indicators of EV adoption. Additionally, we found that median household income β of 0.107 positively influences EV adoption. ZCTAs where the share of incomes is below the median, large precent of the population work in the service sector, and are of an active age (i.e., 22 to 44), and are female are less likely to influence EV adoption.

Table 3
Results of panel regression of the share of EVs per 1000 LDVs in Connecticut from 2013 to 2020. Model 1 represents a one-way fixed effects using unit fixed effects while model 2 represents two-way fixed effects. Standard errors are reported in parenthesis, model 3 standard errors are clustered by town id. See equation 1 in section 4.1 for detailed description of OLS model and Table 2 in section 3 for motivation of variables used in the model.

Variables	(1) Unit Fixed Effects	(2) Two-way Fixed Effects	(3) Clustered Errors	(4) First Diff.
Hybrids (%)	0.127[c]	−0.0214	0.0498[a]	−0.00452
	(0.0146)	(0.0148)	(0.0302)	(0.0121)
Active Age 22–44 (%)	−0.685[c]	−0.270[a]	−0.436[b]	0.188
	(0.181)	(0.158)	(0.173)	(0.133)
Housing Density (%)	0.000451[c]	0.000215[b]	8.50e-06	−1.03e-05
	(9.86e-05)	(8.59e-05)	(1.02e-05)	(6.86e-05)
Female Pop. (%)	−0.00440[a]	−0.00180	0.000368	0.000660
	(0.00225)	(0.00195)	(0.00178)	(0.00184)
Service Sector Employment (%)	−0.00107	−0.000585	0.000414	−0.000196
	(0.00112)	(0.000972)	(0.00138)	(0.000912)
Multi-Car Home (%)	−0.00766[c]	−0.00423[c]	−0.00419[c]	0.000375
	(0.00116)	(0.00101)	(0.000961)	(0.000716)
Charging Stations (#)	0.0105[c]	0.00299[b]	0.00270	0.00253[b]
	(0.00151)	(0.00134)	(0.00195)	(0.00124)
Long Commute (>60 min) (%)	0.00768[c]	0.00187	0.00135	0.00216[a]
	(0.00144)	(0.00127)	(0.00127)	(0.00118)
Work-from-home (%)	0.0192[c]	0.00883[c]	0.00781[c]	0.00433[c]
	(0.00168)	(0.00155)	(0.00245)	(0.00128)
Median Household Income ($10,000)	0.107[c]	0.0557[c]	0.0385[c]	0.00553
	(0.00481)	(0.00468)	(0.00705)	(0.00446)
Constant	−0.464[c]	−0.114	−0.0913	0.0633[c]
	(0.161)	(0.140)	(0.156)	(0.00162)
Observations	2104	2104	2104	1841
R-squared	0.451	0.592	0.5814	0.023
Number of ZCTA	263	263	263	263
Unit FE	YES	YES	NO	YES
Year FE	NO	YES	YES	NO
Clustered Errors	NO	NO	YES	YES

Standard errors in parentheses.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

5.2. Spatial-panel results

Geography represents an interesting opportunity to explore relationships between variables of interest while simultaneously incorporating inherent spatial interactions. The motivation to use spatial methodologies results from identification of spatial autocorrelation. Having tested for spatial autocorrelation via Moran's I (Fig. 3) and LISA (Fig. 4) we found that the share of EVs in Connecticut exhibited positive spatial autocorrelation with a statistically significant Moran's I value for years 2015 through 2020 (Fig. 3). Zooming in, we found clustering of high-high and low-low share of EVs relative to the mean distributed across the state (Fig. 4). Much of the spatial clustering of EV adoption occurred in the Fairfield County region of Connecticut, a region characterized by high median household income (22.14% above the state average) and high median values of owner-occupied homes (54.29% above the state average).

Based on the panel results, our main variables of interest are the share of traditional hybrid vehicles and the number of charging stations (Table 4). Our results carry over from the panel analysis to the spatial-panel analysis in that we found positive correlation between EV adoption and independent variables of interest (i.e., share of traditional hybrid vehicles and charging stations). Our results are consistent across all three spatial-panel models although have diminishing significance. We found that the share of traditional hybrid vehicles is positively associated with the share of EVs by 0.071% (β 0.071) within a ZCTA and by 0.118% (β 0.118) on neighboring ZCTAs (i.e., spatial spillover). Simply put, if the share of traditional hybrid vehicles increases by 1% within a ZCTA we would expect the share of EVs to almost double in the surrounding ZCTAs. Furthermore, when considering the association charging stations have on EV adoption, we found within a ZCTA an increase of 0.004% (β of 0.004) and within neighboring ZCTAs (or spillover) an increase of 0.008% (β of 0.008). From this we can conclude that presence of charging stations within a ZCTA has less of an association with EV adoption compared to neighboring ZCTAs; suggesting charging stations might only need to be near potential adopters and not directly within their geographic unit. Practically, our results show that on average if the share of traditional hybrid vehicles increases by 1% the total number of EVs within a ZCTA will increase by 1864 and indirectly by 3098. Although small, we found that hybrid vehicles as a "green" technology are positively associated with the adoption of EVs within any given ZCTA in addition to indirectly represented by spatial spillovers.

5.3. Change in vehicle fleet from 2013 to 2020

As a way of visualizing changes in the statewide CT vehicle fleet over time, we mapped out the distribution of fuel type and body style in 2013 and 2020 (Fig. 5; Table S1). From Fig. 5, two things are apparent, the first is that the share of fossil fuel vehicles declines from 2013 to 2020 across all body styles. Secondly, the share of alternative fuel vehicles increases quite a lot for passenger vans. In the context of Connecticut, such a result is interesting, as there are a limited number of ethanol (e.g., E−85) fueling stations in the state. Currently, there are 13 ethanol fueling stations that support alternative fuel vehicles (i.e., Flex-Fuel) (AFDC, 2023). Although the share of alternative fuel vehicles

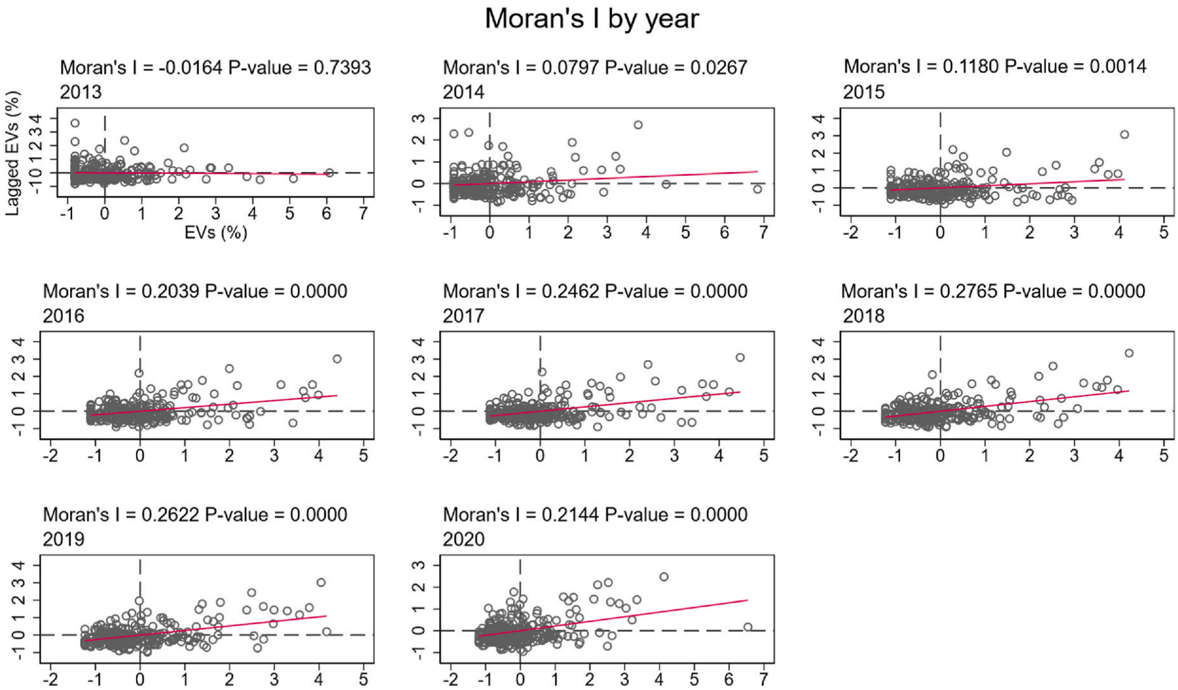

Fig. 3. Annual results of Moran's I test for spatial autocorrelation, positive values indicate the share of EVs are spatial correlated. Results for 2015 to 2020 are statistically significant.

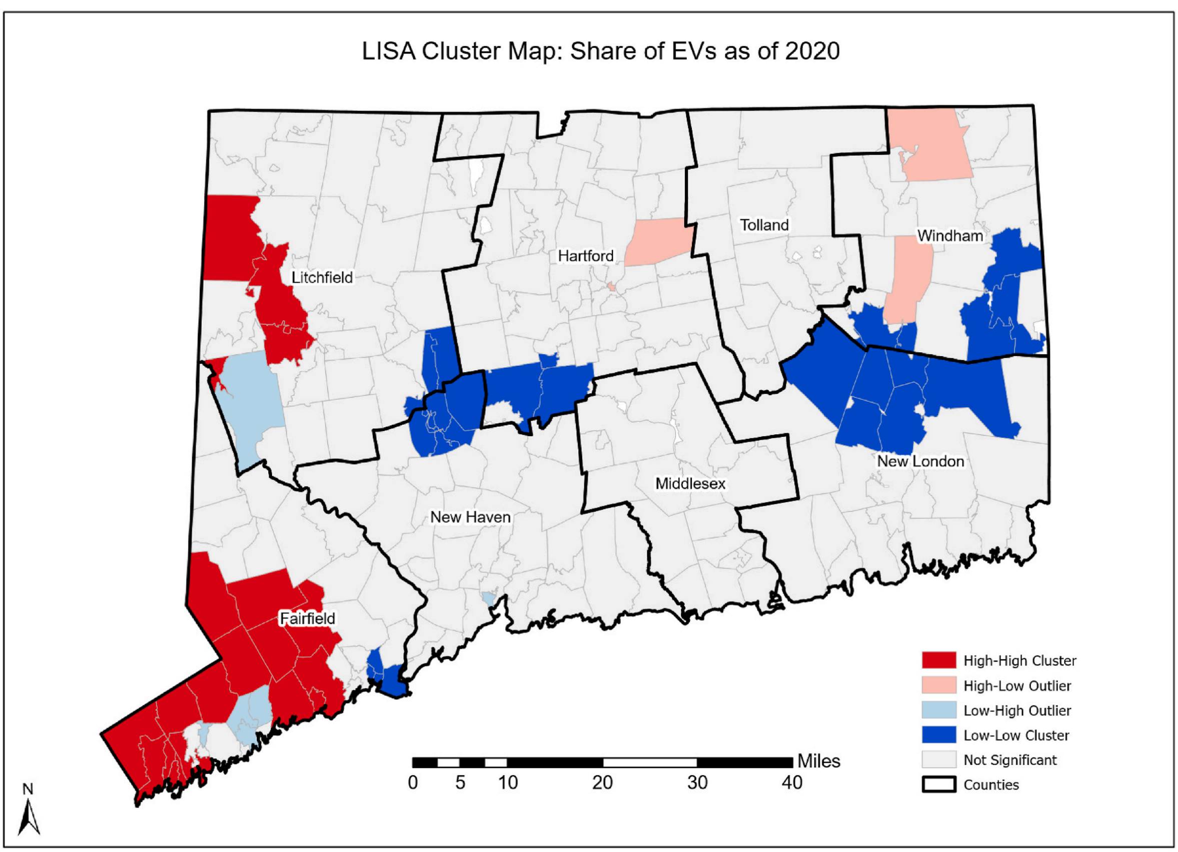

Fig. 4. LISA cluster map showing the share of EVs in 2020. High-High clusters indicate a high share of EVs relative to the mean, conversely Low-Low indicates a low share of EVs relative to the mean. Low-High and High-Low outliers indicating high or low values relative to neighbors. All values are relative to the mean and not absolute values. Note that ZCTAs are not drawn from county boundaries and therefore do not perfectly align. The inclusion of counties is used to contextualize the comparison of median household income and share of EVs.

Table 4
Results from spatial-panel regression of share of EVs per 1000 LDVs in Connecticut from 2013 to 2020. Our main variables of interest are the share of traditional hybrid vehicles and number of charging stations. For list of variables see equation (4) in section 4.2 and Table 1 in section 3 for motivation of each variable.

		(1)	(2)	(3)
Direct Effects	Model Type Dependent Variable	SAR Electric Vehicles (%)	SEM Electric Vehicles (%)	SDM Electric Vehicles (%)
	Hybrid Vehicles (%)	0.0712[c]	0.0294[b]	0.0235
		(0.0143)	(0.0126)	(0.0145)
	Charging Stations	0.0048[b]	0.0057[c]	0.0056[c]
		(0.0014)	(0.0014)	(0.0014)
Indirect Effects				
	Hybrid Vehicles (%)	0.1183[c]	0.1160[b]	0.1602[b]
		(0.0235)	(0.0268)	(0.0694)
	Charging Stations	0.0080[b]	0.0227[c]	0.0216[c]
		(0.0024)	(0.0056)	(0.0056)
Total Effects				
	Hybrid Vehicles (%)	0.1895[c]	0.1454[b]	0.01837[b]
		(0.0372)	(0.0599)	(0.0736)
	Charging Stations	0.0128[b]	0.0284[c]	0.0273[c]
		(0.0038)	(0.0069)	(0.0069)
N		2104	2104	2104

Standard errors are in parentheses.
$p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

increased from 77,414 to 155,108 between 2013 and 2020 (100% increase), most of these vehicles are not maximizing their fuel benefits, with the exception of compressed natural gas and propane vehicles which cannot run on gasoline. From 2013 to 2020 the total vehicles in Connecticut increased from roughly 2.4 million to 2.8 million with the largest value change occurring within the fossil fuel segment. However, when considering the percent change, EVs increased by over 2000% from 588 vehicles in 2013 to 12,399 vehicles in 2020. Although, in 2020 EVs in Connecticut only represent a fraction of the vehicles on the road, at less than 0.5%.

Given the large increase in EVs overall (Gillingham et al., 2023), we find it important to evaluate that increase within vehicle body segments. Doing so could allow for a better understanding of emission implications of an EV transition. When comparing body styles by fuel type we found between 2013 and 2020 fossil fuel vehicles experienced a decline of 28.2%. Put another way, for each body style and fuel type class fossil fuel vehicles are declining albeit slowly. Interestingly, when examining which fuel type is replacing fossil fuels for each body style, we found that EV hatchbacks contribute to the largest fuel shift. Across the board however, alternative fuel vehicles (i.e., E−85, CNG, and propane) are the fuel types most commonly replacing fossil fuels, limiting the potential emission savings of fleet wide transitions (Fig. 5; Table S1).

EVs have a goal of serving as an alternative transportation technology aimed at reducing greenhouse gas emissions over the long run. However, from the perspective of a sustainable energy transition such claims must be tested. Several studies from a well-to-wheel analysis show that EVs reduce greenhouse gas emissions anywhere from 10% to 41% on average compared to similar ICE vehicles (Muratori et al., 2021). One of the more important factors when considering the levels of greenhouse gas emission reductions from EVs compared to ICE vehicles is the electricity mix of the region, this is particularly true in the US where electricity mixes vary by region (Reichmuth, 2020). Furthermore, these values can change based on differing climate and weather patterns (Yuksel et al., 2016).

We identified the 10 most common vehicles on the road in Connecticut by body style for 2013 and 2020 and compared them with the 10 most common EVs on the road in 2020. Table 5 provides the list of 10 most common body styles for 2013 and 2020, their average emissions reported in grams per mile, annual emissions, and the emissions associated with the 10 most common EV models. Values for emissions (grams/mile) are a result of comparing side by side tailpipe and upstream emissions as reported by US Department of Energy fuel economy database. Our findings for EV emissions reflect a relatively "clean" electricity grid mix in ISO-NE with natural gas and nuclear providing most of the electricity in the region. We found that on average if any one of the 160 most common vehicles (10 per body style per year) on the road in Connecticut were replaced with an EV, from an annual basis, emissions would reduce by around 82.22% with the largest reductions resulting from replacing passenger vans with alternative electrified vans (e.g., Tesla model Y or Ford Mustang Mach-E) (see Table 4). Between 2013 and 2020, passenger vans had very little change in overall emissions suggesting a possible gap in increased efficiency of that vehicle body style. It is important to note that this does not supplement a full life cycle analysis and a more detailed statewide analysis should be conducted to fully capture changes in emissions because of widespread fleet transition from ICE vehicles to EVs. Furthermore, because of data limitation on registration, this analysis looks at the whole fleet replacement pattern, rather than individual choices. Therefore, we are unable to capture movement assoicated with de-registered vehicles entering or leaving Connecticut. However, this analysis serves as a starting point in grasping a holistic understanding of the impacts a clean energy transition will have on regional greenhouse gas emissions from within the transportation sector.

6. Discussion and conclusion

In 2012, there were only 11 EV models available for sale in the US and at the start of 2013 availability of EV models remained low, only adding six models (AFDC, 2022). However, by 2019 the landscape began to change with 45 EV models available for sale in the US (AFDC, 2022). As an increasing number of auto manufactures began to realize the demand and benefit of EVs, model availability will only continue to grow (Muratori et al., 2021). With a limited variety of vehicles available to consumers between 2013 and 2020, we found that Connecticut is still in the early stages of EV adoption and that the levels to which EVs are being adopted do not align with what policy makers are aiming for. Our results indicate that of the factors considered in this analysis, the share of hybrid vehicles had the strongest positive association with EV adoption in Connecticut over the study period and across space (i.e., spatial spillovers). Similar results were presented in Liu et al. (2017) whereby they assessed neighbor effects of hybrid vehicles on subsequent hybrid vehicle adoption in Ohio. This finding points towards the potential that when the share of one technology, in this case traditional hybrid vehicles, increases, the shares of EVs will also increase: either through shear presence on the road or by owners trading in "older" technologies for newer ones (i.e., trading in a Toyota Prius for a Plug-in Hybrid Toyota Prius or Chevy Bolt). Such spillover effects have been observed across other renewable energy technologies as well, for example rooftop solar (Graziano and Gillingham, 2015). However, we found that the spatial spillovers of EV adoption in Connecticut are not uniform, as visualized in Fig. 6. Connecticut is just behind New York as one of the most unequal states, in terms of income, with a Gini index[4] of 0.5 as of 2020 (US Census Bureau, 2021). For example, some neighboring ZCTAs with very different median household income values could contribute to the lack

[4] The Gini Index is a measure from 0 to 1 summarizing income inequality across the entire income distribution for a given region or spatial unit. See US Census Bureau (2020) for more information.

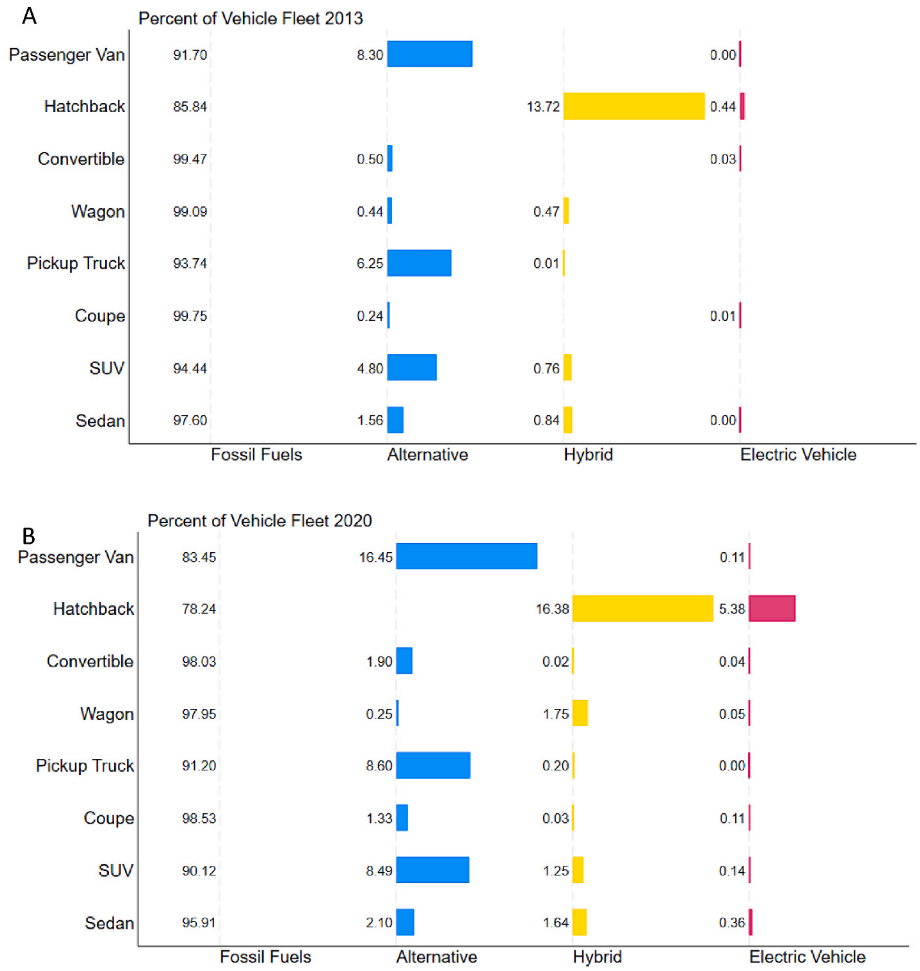

Fig. 5. Bookend vehicle composition in Connecticut (2013)(A) and 2020(B) by body style and fuel type, percent of vehicle body style fleet. Also see Table S1 in appendix.

Table 5
Assessment of the 10 most common vehicles on the road in Connecticut by body style for data years 2013 and 2020. EV emissions are the average emissions from the 10 most common EVs for 2023.

Body Style	Year	Average emissions (g/mi)	Average annual emissions (g/mi/yr.)	Relative change in average emissions (g/mi) (%Δ 2013–2020)	EV emissions (g/mi)	EV transition emissions (g/mi) (%)
Convertible	2013	509.5	7,642,500			
Convertible	2020	510.8	7,662,000	0.26%	76.25	−85.07%
Coupe	2013	377.5	5,662,500			
Coupe	2020	373.4	5,601,000	−1.09%	76.25	−79.58%
Hatchback	2013	289.7	4,345,500			
Hatchback	2020	242.1	3,631,500	−16.43%	76.25	−68.50%
Passenger Van	2013	574.4	8,616,000			
Passenger Van	2020	565.2	8,478,000	−1.60%	76.25	−86.51%
Pickup Truck	2013	698.9	10,500,000			
Pickup Truck	2020	605	9,075,000	−13.44%	145	−76.03%
SUV	2013	627.8	9,417,000			
SUV	2020	474.4	7,116,000	−24.43%	76.25	−83.93%
Sedan	2013	459.4	6,891,000			
Sedan	2020	388.1	5,821,500	−15.52%	76.25	−80.35%
Wagon	2013	503.3	7,549,500			
Wagon	2020	437.6	6,564,000	−13.05%	76.25	−82.58%
Average		477.3	7,160,813		84.84	−82.22%

of EV adoption across the state, writ large (Fig. 6).

Furthermore, we found housing density, number of charging stations, long duration commuters, median household income ($10,000), and work modality (e.g., working from home) to all be positively associated with EV adoption. Working from home substantially increased as a result of covid-19 lockdowns and, for some industries, has continued

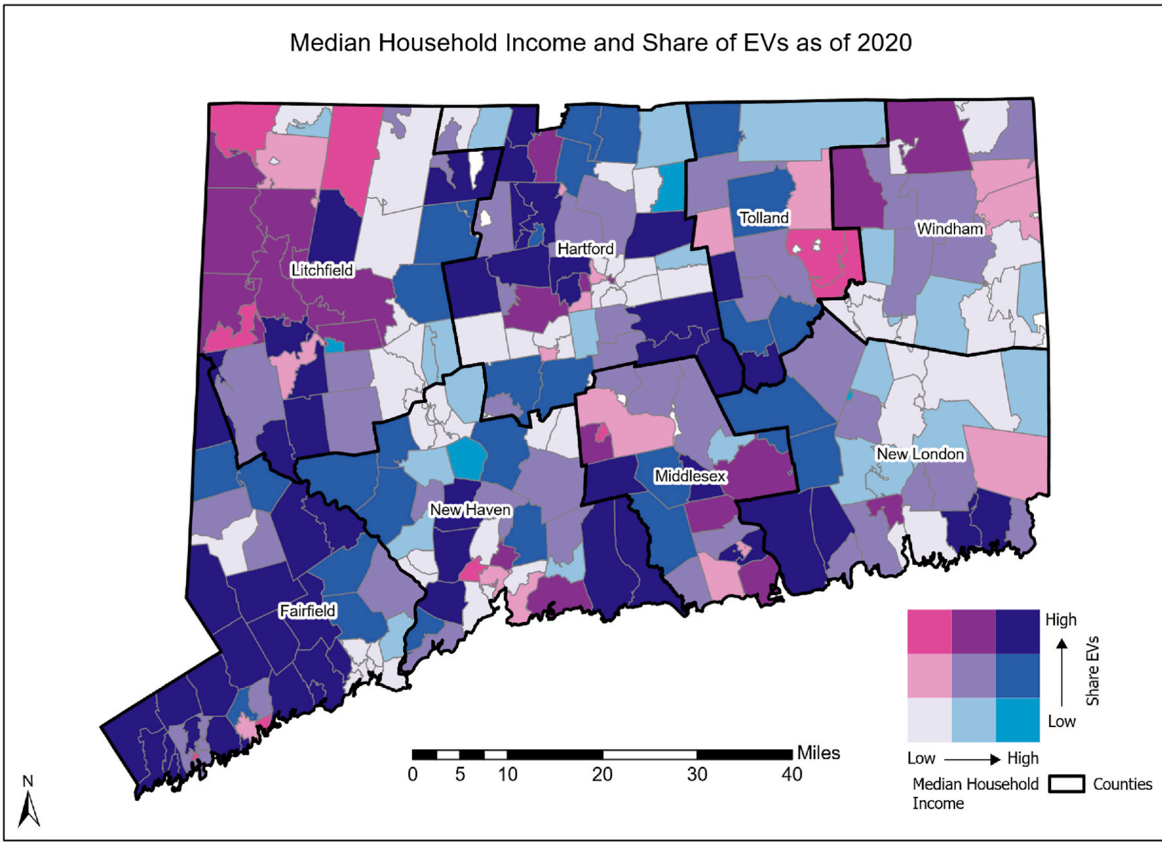

Fig. 6. Bivariate map showing the share of EVs and median household income in Connecticut as of 2020. Median household income data is from the American Community Survey 5-year average 2020 table. Note that ZCTAs are not drawn from county boundaries and therefore do not perfectly align. The inclusion of counties is used to contextualize the comparison of median household income and share of EVs.

post-covid. Given this new relationship with employment and commuting, there could be a larger proportion of consumers who consider switching to an EV without much consideration for any perceived impacts to their commuting times, potentially limiting the influence of "range anxiety"[5] on EV ownership. Despite only a subset of the economy having an ability to work from home, our results offer potential pathways for identifying locations of future EV adoption based off work modalities. Conversely, we found active age groups, females, service sector workers, and households with more than one vehicle to be negatively associated with EV adoption in Connecticut over the study period. Previous research identifying the potential for a gender gap in EV ownership similarly found that women are less likely to own an EV compared to men, although this is not indicative of their attitudes towards environmental issues (Sovacool et al., 2019). Although identifying factors associated with EV adoption provides insights for stakeholders, holistically evaluating the sustainability of an EV transition by assessing impacts on greenhouse gas emissions provides yet another layer of understanding in a rapidly changing mobility landscape.

A sector-wide transition to EVs has the potential to result in various impacts to the climate, the local environment, and transportation energy burden (i.e., percent of income spent on vehicle fuels see Vega-Perkins et al., 2023), any impacts resulting from a transition in the short run will be dependent on the dynamics between vehicle charging and electricity production along with incentive programs (Gan et al., 2021; Vega-Perkins et al., 2023). Recent studies have begun investigating fleet replacement dynamics within the EV transition (i.e., identifying which vehicles, by body style and or fuel type, are replaced with EVs) (Xing et al., 2021). By understanding the replacement dynamics of a vehicle fleet researchers can provide a baseline for evaluating the sustainability of transitioning the vehicle fleet from fossil fuels to electricity and the subsequent impact on global emissions. Our results suggest under a rapidly electrifying vehicle fleet, EVs have the potential to substantially curb emissions from the transportation sector. However, this depends on the energy profile of the electricity grid (Li et al., 2016). New England, like most of the US, has high shares of natural gas thereby limiting the resultant release of greenhouse gas emissions compared to regions that are highly reliant on more polluting energy sources like coal. Evaluating vehicle emissions by body style reveals some interesting avenues for future decarbonization. However, Connecticut, much like other regions (Stokes and Breetz, 2018), continues to advance and work towards increasing shares of renewable energy thereby minimizing the environmental impact of EVs from a "refueling" perspective. Passenger vans (e.g., Chrysler Pacifica or Honda Odyssey) with 1.6%, coupes (e.g., two-door cars) with 1%, and convertibles with 0.26% experienced the smallest change in emissions from 2013 to 2020. Vehicles within these body style segments pose the greatest potential for electrification owing to there minimal advancements in emission reductions over time. Currently, the Chrysler Pacifica ($52,495) is the only EVs available on the market for the passenger van segment and with the current average price of passenger vans at $47,958, the Chrysler Pacifica has a nearly 10% mark up compared to the average (Cox Auto, 2024). While there are more available EVs for coupe body style vehicles, those available tend to be high end vehicles except for Hyundai which offers two models of reasonable value. Therefore, the average consumer, particular families, have little choice when deciding if their next vehicle will be an EV.

Importantly, we outline some limitations of this work. Decisions and

[5] Range anxiety is the fear of not knowing if there is enough "fuel" in the battery to get someone from point A to point B given a lack of suitable charging infrastructure.

factors that influence the purchasing of a vehicle are extremely complex and sometimes may go against conventional thinking (e.g., the high penetration of American made vehicle ownership in Michigan despite poor reliability (Barber and Darrough, 1996). Thus, while we provide context for the spatial diffusion of EVs over time, we cannot be certain of the characteristics of the individual consumers. Additionally, when assessing the replacement dynamics of the vehicle fleet in Connecticut from 2013 to 2020, we are unable to determine if a vehicle was sold or moved between ZCTAs. The ability to obtain transactional data over the study period would greatly aid in assessing environmental implications of an EV transition. Furthermore, although we leverage lifecycle analysis approaches our evaluation did not follow conventional lifecycle methodologies and would benefit from further, separate analysis. Given these limitations, we leave the door open for future investigations of EVs from a regional perspective.

A possible future area of research could include the construction of a social network, thereby providing insights into understanding how EV adoption occurs over time and space, at the individual level. Previous work has studied the effects of such social networks and found they do affect individual perceptions of EV adoption (Axsen and Kurani, 2012). The increasing use of social media either directly or via interest groups (e.g., the EV Club of Connecticut) has opened the door for large scale evaluations of the public's perceptions of EVs. Along a similar vein, future research could involve a survey of individuals on their perceptions of EVs, willingness to purchase, and experience with EV ownership either via social networks or geographic proximity to neighbor ownership. As of now we were able to extend the previous literature on the spatial diffusion of EVs from a regional perspective in addition to providing ground for holistically analyzing the sustainability of an EV transition and what it means for climate and energy goals.

Our results have relevance to policy makers and transportation planners. The ability to identify regions experiencing hybrid vehicle adoption will likely follow with EV adoption and thus possibly require additional charging infrastructure. We can extend these insights to the power sector for capacity and distribution planning so as not to fall behind on what will become increasingly critical infrastructure in an age of transportation electrification, this is particularly important given the variability of charging patterns of EVs (Kapustin and Grushevenko, 2020). Moreover, policy makers can draw from these results to better tailor incentive programs designed to leverage spatial spillovers on subsequent vehicle technology adoption. Regions suffering from poor air quality have the potential to greatly reduce emissions from the transportation sector provided a large-scale transition to EVs. Of course, this is largely dependent on the fuel profile of the electricity sector. An increasing number of countries, regions, and states have outlined renewable energy goals and targets aimed at reducing shares of fossil fuels within energy profiles. As the US continues to experience a wave of incentives designed to decarbonize personal transportation and the electricity grid, EVs and the impact they could have on emissions and the environment continues to be of interest for global sustainability efforts.

CRediT authorship contribution statement

Adam Gallaher: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Conceptualization. **Marcello Graziano:** Writing – review & editing, Writing – original draft, Resources, Investigation, Conceptualization. **Carol Atkinson-Palombo:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition. **Lyle Scruggs:** Writing – review & editing, Writing – original draft, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2024.142574.

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