

**Exploring factors that are driving  
Electric Vehicle Demand in Massachusetts  
from built environment and socio-economics  
perspective**

Thesis submitted by

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## **Abstract**

Electric Vehicles (EV) are not a new concept, they have been in the minds of people since the days of Thomas Edison and Henry Ford. Recent developments in EV technology have put them in the center stage once again. Developing the infrastructure to aid the adoption of EVs is widely viewed as crucial for transportation policy and planning. Within this framework, I ask: where is the demand for EVs and where the infrastructure can be improved to create demand? One goal of my research is to identify clusters of areas where EV ownership is higher and correlate that to a set of variables. This thesis involves a spatial analysis to determine if the demand for EVs are clustering and whether this clustering can be predicted by a set of variables from built environment and socio-economics. My hypothesis is that there should be a higher demand for EVs in denser urban areas. I found variables such as walkability, commute times, population density to be statistically significant contributors to EV demand, however their effect on increasing sales is somewhat questionable.

## **Acknowledgements:**

I would like to start out by thanking my dear wife who supported me throughout the graduate school and push me to work harder. I would also like to thank my advisor Justin Hollander for his support and contributions and my reader Sumeeta Srinivasan for her feedback guidance. I would also like to thank Tufts Statistics and Research Technology staff and Tisch Library Data Lab staff for their help. Finally, I would like to thank all friends and family as well as the UEP administrative staff who have supported me throughout this process.

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# 1. Introduction

Climate change caused by global warming is one of the biggest threats to our society in our time. Disruptive wild weather patterns, food scarcity, global conflicts, climate refugees are all part of events resulting from climate change. Carbon dioxide emissions are a significant factor contributing to the global warming. We all can do our best as individuals to reduce our carbon footprint, however, bigger changes at the policy level are needed to make mitigation of CO<sub>2</sub> emissions possible.

Policies made to encourage an increase in Electric Vehicle (EV) ownership could be one way to affect CO<sub>2</sub> emissions. Increased EV use could also push for developing charging infrastructure and subsequently make adaptation easier in the future as electric grid gets cleaner (Holland et al. 2015). Currently a federal tax credit and various other state initiatives are available for electric vehicles or plug in hybrids. California is leading the way in promoting Electric Vehicles, in addition to the federal tax credit and other state rebates, the state issues a clean air vehicle sticker that allows the single occupancy vehicles to use California's high occupancy vehicle (HOV) lanes. According to California Center for Sustainability Plug-in Electric Vehicle Owner Survey, 59% of the respondents cited access to HOV lanes as an important factor in making their decisions towards purchasing an EV (CSE 2013). Innovative ideas like this are likely to increase EV ownership throughout the country.

In January 2017, Governor Baker signed a legislation to promote the purchase and use of Zero Emission Vehicles. To better promote the use of EVs we must understand the factors generating the demand for them. What makes people choose EVs over conventional

vehicles? Is the built environment conducive to EVs or does it create a barrier for people who are eager to purchase them? In this study I am going to explore factors driving EV demand. Are physical environments like a network of EV chargers, dense neighborhoods or neighborhoods that are easy to walk, and bike are enough to create the demand for EVs or public policy of price incentives are needed? International Council of Clean Transportation (ICCT) notes price, range anxiety, charging infrastructure, and charging time as main barriers in the EV market. However, if we consider the fact that according to National Household Travel Survey 45% of all vehicle trips are 3 miles or less thus making EVs ideal especially in urban environments.<sup>1</sup> In this project the research question I will be answering is: what are the factors that impact on EV demand? Specifically, I will investigate the role of 1) neighborhood density, 2) charging network, and 3) walkability. Upon examining the results, I will try to assess the role that the built environment or peoples' behavioral characteristics play in shaping people's demand for EVs over conventional vehicles. EVs, at least on surface, appear to be ideal for short urban commutes, with that assertion the main hypothesis of this thesis is that urban areas with short commutes have higher demand for EVs. First, by using GIS I will identify the clusters where EVs are being purchased. Second, I will examine if commute times effect peoples' decision making in purchasing EVs. By looking at spatial clusters and using spatial analysis tool I will try to identify if built environments and socio-economic are factors in determining EV demand. Finally, I will look into incentive policies and their overall effectiveness in overcoming EV market barriers.

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<sup>1</sup> <https://nhts.ornl.gov/vehicle-trips>

Electric vehicles are seen as the future of clean transportation. Anywhere from conventional hybrids to hydrogen cell EVs, these new vehicles are considered lot cleaner than conventional gasoline or diesel fueled vehicles. In addition to the possible benefits of greenhouse gas reductions, EVs also lower our demand on oil thus reducing possible military expenditures to prevent oil supply interruption (Holland et al. 2015). Since all electricity is produced in the United States EVs can reduce our reliance of foreign oil imports. Electric cars however, are not a new invention. First electric car was in use in 1834 in the United States. It wasn't until Henry Ford selected an internal combustion engine for his affordable Model T that the gasoline powered engines, or Internal Combustion Engine Vehicles (ICEVs) became the norm (Helmert and Marx 2012). The electric car itself may not be new but the lithium-ion battery that supplies the power is a relatively recent technology. Early electric cars in mid to late 90's used heavier and Lead-acid batteries, these batteries lacked power and had higher environmental impacts. Along with batteries other technological developments are allowing electric cars to be more common on our roads. Currently 26% of energy is used for transportation which includes aircrafts, ships, trains, and all types of street vehicles. 74% of transportation falls under street traffic which is caused by cars, trucks, motorcycles, etc., and creates a positive influx of CO<sub>2</sub> into the atmosphere (Helmert and Marx 2012). According to 2017 National Household Travel Survey 82% of the vehicles on the road are cars, SUVs and vans and 58% of all the vehicles are 10 years or older. Current EV models are mainly small to mid-size cars and light SUVs. There is a lot of room for the older vehicles on the road to be replaced by new ones and it is in our best interest to encourage those new vehicles to be non-gasoline models.

To understand Electric Vehicles, we need to understand different types of vehicles available for use. EVs separate into three main categories, Battery powered vehicles (BEVs), Hydrogen Fuel Cell (FCVs or FCEVs) vehicles that convert hydrogen gas into electricity to power the motor, and Plug-in Hybrids (PHEVs), which have both an electric motor as well as a conventional engine. Plug-in Hybrid vehicles switch between electric and gasoline engines depending on the trip distance. Standard hybrids, even though they have supplemental electric engines are not considered electric vehicles. PHEVs larger battery capacity than traditional hybrids, but less than typical EVs. PHEVs therefore less costly than EVs (Markel 2010). All alternative fuel vehicles are categorized under the moniker of Zero Emission Vehicles (ZEVs). Electric Vehicles tend to be more expensive than their gasoline powered counterparts, but they are closing the gap as the technology improves and demand increases. Below graph from U.S. Energy Information Administration shows the cost of gasoline vehicles vs. various alternative fuel vehicles.

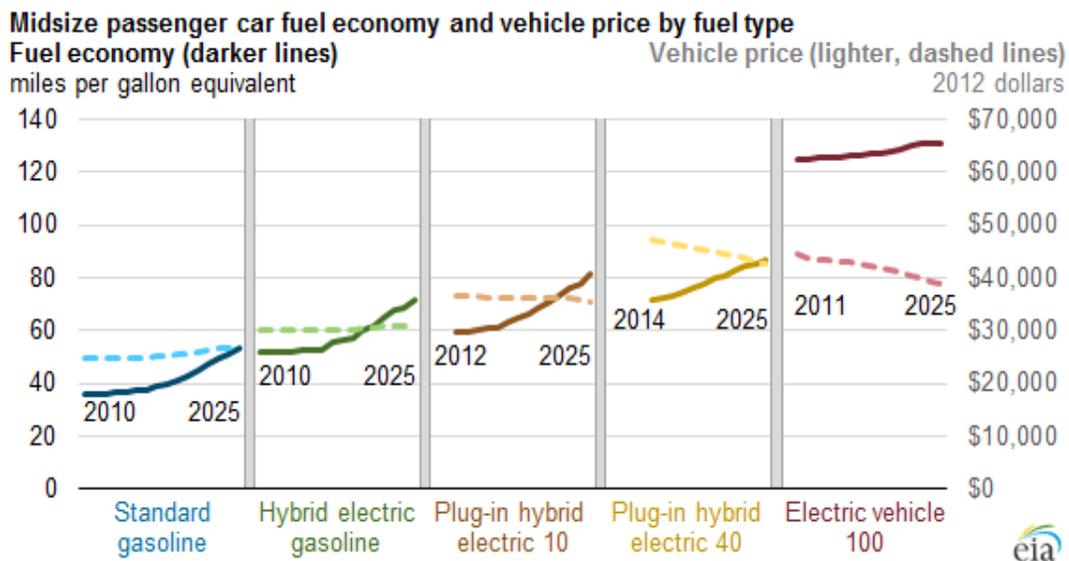


Figure 1: Midsize passenger car fuel economy

## **2. Background on Electric Vehicles**

The electrification of our vehicle fleet is a potential strategy to reduce carbon emissions (Heidrich et al. 2017). Policies than aim to encourage EV ownership could be one way to affect CO<sub>2</sub> emissions. Increased EV sales and use could also promote developing charging infrastructure and subsequently make adaptation easier (Holland et al. 2015). In the future as, electric grid gets cleaner the benefit of EVs will increase. Currently a federal tax credit and various other state initiatives are available for electric vehicles or plug in hybrids.

California is leading the way in promoting Electric Vehicles, in addition to the federal tax credit and other state rebates, the state issues a clean air vehicle sticker that allows the single occupant to use California's high occupancy vehicle (HOV) lanes (CSE 2013). According to California Center for Sustainability Plug-in Electric Vehicle Owner Survey, 59% of the respondents cited access to HOV lanes as an important factor in making their decisions towards purchasing an EV (CSE 2013). Innovative rewards like this are likely to increase EV ownership throughout the country. Evaluating the HOV access to single occupancy EVs as a program's outcome is important. If program is found to be successful it may result in other states to adopt similar programs.

Standard approach is a fiscal incentive generally manifested as a tax credit. Incentives are a tool we reach to influence people's choices in a desired direction and to generate the intended policy outcome (Grant 2011). Grant, writing about ethics of incentives, creates a distinction between incentive and motivation. She defines incentive as an economic means of altering cost and benefit of a person's choice to alter a particular

course of action (Grant 2011). Incentives are needed when the desired action is not achieved naturally. She raises the question of the fairness of incentives and ethics behind the process. For context we look at incentives as an instrument to direct people's behavior. Incentives may be an attractive public policy tool, but they can also be deceptive and sometimes counterproductive.

The HOV lane sticker program's intervention relies on the hypothesis that people value having access to an HOV lane. It may be easy to assume that a person commuting to work and back wants to take the shortest time possible during the process. The original incentive for the HOV lanes is to mitigate congestion traffic by pooling number of people in to a single vehicle, thus reducing the number of cars on the road. However, there are many reports on the underutilization of these HOV lanes. This underutilization maybe attributed to the inconvenience of carpooling for many commuters as well as to the accessibility of HOV facilities, such as the type of ramp and added time to connect to HOVs (Lipnicky and Burris 2010). Transportation practitioners that tend to focus on the time savings as an important factor for the design of HOV lanes may also need to consider Lipnicky and Burris's findings. Their research based on data collection, surveys and spatial analysis in Harris county, Texas, concludes that among the factors they examined convenience of carpool arrangements and the convenience of HOV lane access points, have the most significant effect on the utilization of HOV lanes.(Lipnicky and Burris 2010)

Ruth Grant describes that in contemporary economics incentives are considered trades and trades are voluntary and mutually beneficial (Grant 2011). However, if the offers become irresistible, then the incentives might be seen as coercive and might not be within the ethical boundaries. Government programs are often criticized by their opponents as

choosing winners and losers and that market will take care of its imperfections. Grant goes on to argue that volunteerism is not the sole criteria for judging whether the incentives are ethical or not. Incentives like the HOV access to single occupancy ZEVs have been an important tool for promoting the adoption of clean air vehicles (CARB 2012). The value gained by having access to an HOV lane could be a fair and ethical incentive for promoting the use of non-gasoline vehicles.

Tax credits are a valuable incentive tool, but it only applies to higher income earners with a healthy tax appetite and excludes lower income individuals as well as non-profits that might want to convert their fleets to electric. Tax incentives are popular method for encouraging economic growth (Lawrence, Briskin, and Qu 2012). Evaluating tax incentives can be difficult, one of the ways to evaluate a program is to compare different states, Lawrence et al explains that when it comes to examining state incentive programs it is useful to assess the benefits created in comparison to results achieved (Lawrence, Briskin, and Qu 2012). Incentives are offered to create a voluntary participation in efforts to lower carbon emissions and states are looking to tax rebates and car pool lane access as a way to make EVs more appealing (Davidson 2011).

Comparing states' performances in their EV incentive program success may not be enough to properly evaluate these programs. Evaluators of energy efficiency incentive programs are often asked to measure counterfactual question of what would happen in the absence of the program (Blumstein 2010). One of the key questions is that whether EV sales would be similar to its numbers under the current program, if these incentive programs did not exist. Carl Blumstein warns that tying all incentives to program outcomes would be misguided and the programs need to be reviewed and revised regularly (Blumstein 2010).

Blumstein also suggest including some qualitative measures such as corporate commitment in addition to the quantitative measures into the evaluation of performance. Corporate commitment can be described as organizational changes that the corporations adopt when there are new objectives. Energy efficiency programs to reduce our energy consumption as well as convert to greener alternatives would need support of private sector as well as government intervention. In his article Blumstein highlights how the program evaluation focus for California energy-efficiency programs, from what is needed to design energy efficiency programs to, providing basis for incentives for energy-efficiency program administrators (Blumstein 2010). In addition, he argues that, it is important to recognize the difficulties in judging the performance of the incentives because of external factors. While the Blumstein article focuses on the incentive programs imposed upon utility companies, his recognition of the difficulties parallels Heidrich et al article that identifying EV numbers in a city (Heidrich et al. 2017). There are number of external factors contributing to the increase in EV sales.

### **Are EVs truly Clean?**

The benefit of EVs in reducing Green House Emissions greatly depends on the grid that they are being charged from. If the grid is powered by a coal burning electrical plant EVs will have higher emission rates compared to a grid powered by Hydro or renewables. In some cases, carbon emission from EVs can be worse than conventional fuel based hybrids in different parts of the world (Wilson 2013). As we switch to cleaner power plants to produce our electricity the benefits of EV are only going to increase. There are conflicting reports that are coming from big oil companies like Exxon and BP in cleanness of EVs. One BP report published on The Guardian suggests that highly fuel efficient ICEVs

will generate less greenhouse gasses than an EVs (Vaughan 2017). BP claims the global energy demand will grow and the fossil fuels will still account for the 75% of energy use in the year 2035 for all emissions (Vaughan 2017). Same BP report also suggest 100-fold growth in EVs from 1.2 million vehicles to 100 million by 2035 globally (Vaughan 2017).

The greenness of EVs comes into a question also in the overall life-cycle of the vehicle. From production to its demise in the local junkyard the life-cycle of EVs is a concern. This concern however, might not be warranted or slightly exaggerated. An extensive review done by the Union of Concerned Scientist in 2012 finds the EVs generate half of the emissions of a comparable ICEV (Nealer, Reichmuth, and Anair 2015). Similar 2010 study finds that overall life-cycle externality cost of EVs and ICEVs and PHEVs to

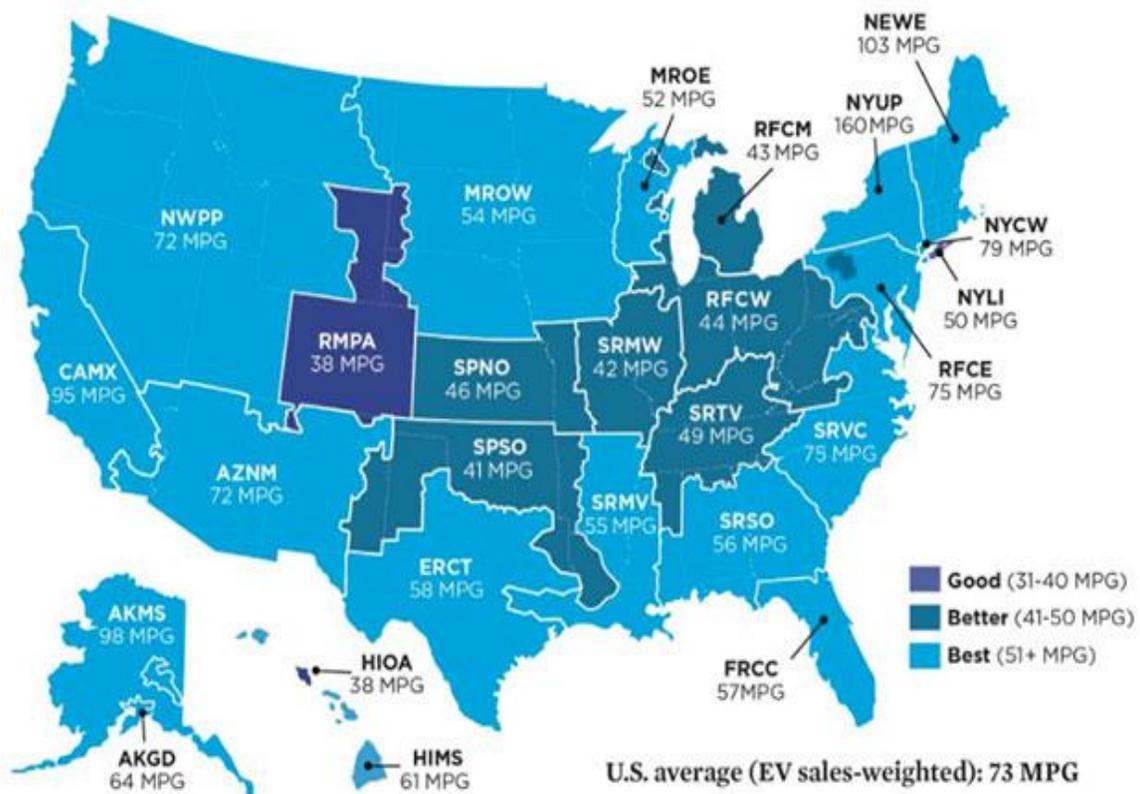


Figure 2: Electric Vehicle Global Warming Pollution Ratings and Gasoline Vehicle Emissions Equivalents by region  
Source: Union of Concerned Scientists

be very close assuming the power plant is not fueled by coal (Michalek et al. 2011).

Another aspect to consider when analyzing electric vehicles is the externality costs that comes from production. While the initial production of EVs have higher costs both monetarily and environmentally, once the vehicles hit the road these differences start to change. These changes are different on location based on how clean the power source is. Below figure show different regions for EVs and their miles per gallon equivalence. In Northeast, Northwest and California driving an electric car is equivalent to getting high 80 miles per gallon (Nealer, Reichmuth, and Anair 2015). A 2015 analysis on electric car subsidies done by Stephen Holland et al. also outlines similar findings that west coast sees significant positive benefits while benefits in northeast are less so (Holland et al. 2015). These are important findings in allocating subsidies to promote electric vehicles.

It is important to note majority of the increase in the cost of production of an EV comes from the batteries. As the battery gets larger this cost increases, however many studies assume a direct linear relation between the battery size and the overall cost of the vehicle. This approach undermines the unchanging incidentals like the factory lights and the economies of scale, overinflating the overall cost of one vehicle (Coalition 2011). In addition, the concentration of EVs might be higher in certain areas than others creating extra stress on a local grid. Study by Agathe Grenier and Shannon Page published on Energy Policy journal identifies that EV owners are likely to be clustered in certain parts of the city (Grenier and Page 2012). Grenier and Page study focuses on one town in New Zealand similarities are likely to be found elsewhere. While the clustering of EV owners was not the focus of their study, it is an important find and, spatial analyses are necessary to identify these cluster in order to further develop EV usage as well as EV infrastructure.

### 3. The Grid

The additional stress on the electrical grid has been studied and research came up with conflicting results. An MIT study found that conventional slow charging at 110v outlets and public fast charging stations do not affect the grid but the trouble comes when EV owners install fast charging 240v stations in their homes (Bullis 2013). Increased demand for electric could force power companies to use there “peaker plants” which more often are dirtier and more expensive (McDonald 2014). One relieving factor is that most EVs are charged overnight during off peak hours. Edison in Southern California is giving discounts on electric rates for charging overnight (Bullis 2013). Similarly, Duke energy of North Carolina is working with customers and offering pilot programs to install charging stations in EV owners’ homes and use the information they gathered to better prepare their grid.<sup>2</sup>

To mitigate the increased demand for electricity that puts additional stress on the grid, cities in conjunction with the electric companies are looking into an idea called Vehicle-to-grid power implementation. This idea uses EVs and PHEVs as a source to provide power in specific markets (Kempton and Tomić 2005). California Public Utilities Commission’s report describes the Vehicle-Grid integration as a great resource to stabilize the grid and allow them in achieving their Vision for Zero Emissions initiative by not tapping into dirtier peaker plants as they expect a substantial increase in watts consumed. Many of the new EVs, as well as the charging stations have networking capabilities, allowing power companies the schedule charging remotely (Langton and Crisostomo 2013).

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<sup>2</sup> Duke Energy sustainability report 2011

“Vehicle-Grid Integration (VGI) can harness the usage characteristics and technologies within PEVs to allow them to serve as a grid asset, reducing operating costs for facility and vehicle owners, the utilities’ distribution maintenance requirements, and energy prices in the wholesale market” . These can be implemented as a part of demand response program.

### Charging Infrastructure

The EV infrastructure is key to improving EV usage. According to the U.S Department of Energy website there are over 40,000 charging stations in the United States.<sup>3</sup>

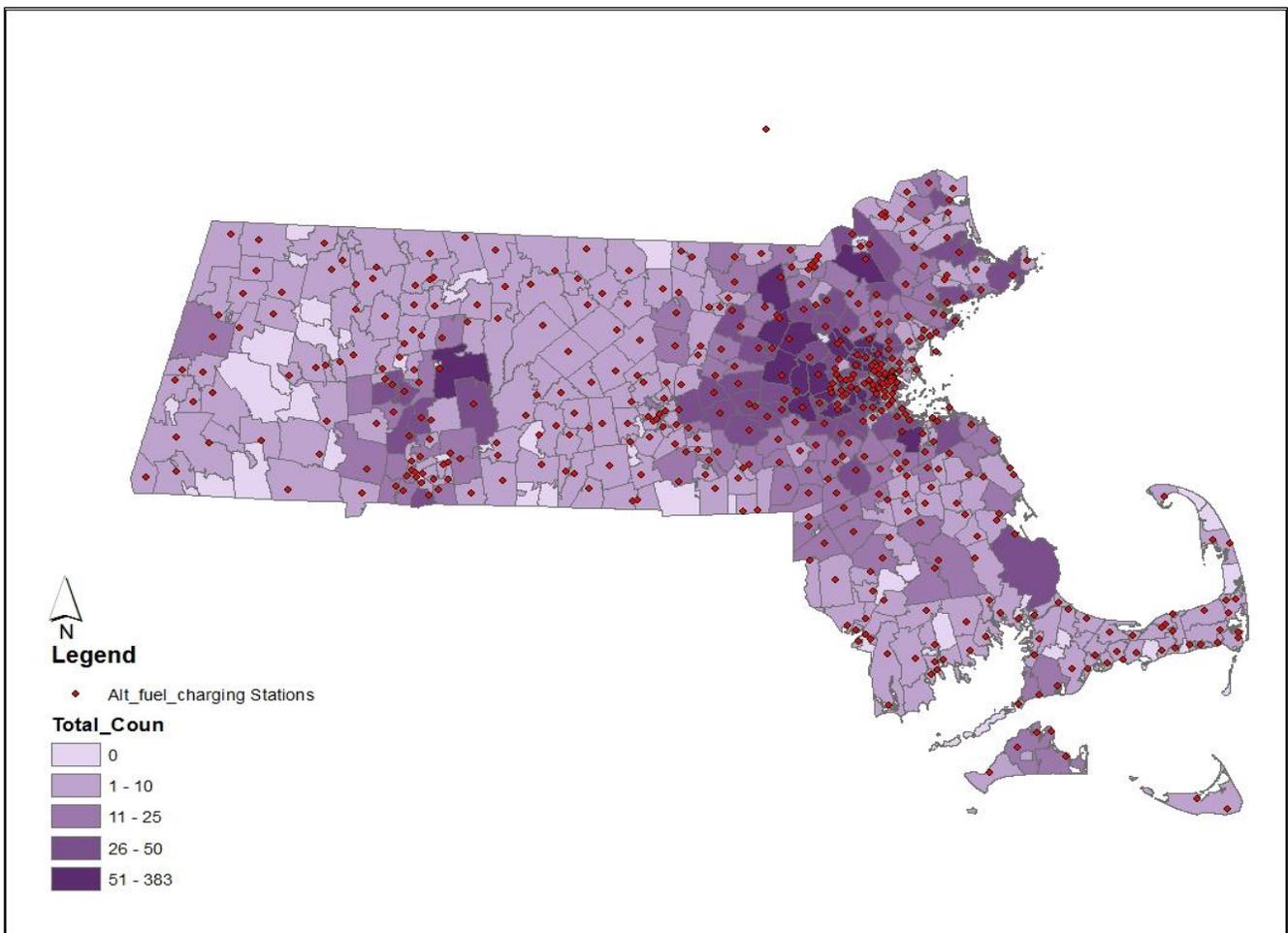


Figure 3: EVSE Concentration 2012 source: Alternative Fuel Data Center US Department of Energy.

<sup>3</sup> [http://www.afdc.energy.gov/fuels/electricity\\_benefits.html](http://www.afdc.energy.gov/fuels/electricity_benefits.html)

In the cities like Boston many of them are located in malls or hotel garages and they are not as ubiquitous as gas stations. A better prepared electric grid and conveniently placed charging stations could foster a higher level of EV ownership. Currently it is being limited to suburban areas and buildings with garages. Boston is a good example even though there is a large network of daytime charging stations throughout the city most people charge their cars overnight. When the only available parking is street parking charging your EV becomes problematic. Based on California Center for Sustainable Energy's EV owner survey, 71% of the respondents expressed some level of dissatisfaction with public charging infrastructure (CSE 2013). Given that electric cars have shorter ranges and the miles per gallon on conventional vehicles are higher for in-city use, EVs are ideal for short distance in city trip and urban dwellers. In addition, 78% of commuters commute 20 miles or less according to 2016 Commuter Driving Statistics.<sup>4</sup> This creates a very large consumer base for battery powered electric vehicles and raises questions on providing daytime charging in urban areas.

Electric Vehicle Supply Equipment (EVSE) or charging station locations prompt studies to be conducted by city or states to further develop EV infrastructure. There are three levels of charging stations. Level 1 that uses the standard outlet and charges at 120V, these can be installed at around \$400 a piece. Level 2 that charges at European Standard 240V and Level 3 direct current that charges at 200-500 VDC are costlier installations. A standard level 2 charger for home use can be purchased for \$400 to \$600, "smart" and

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<sup>4</sup> <http://www.statisticbrain.com/commute-statistics/>

networking features add to the cost. Commercial dual port charging stations can range from \$6000 to \$1,600 depending on their networking ability (America 2016).<sup>5</sup>

Charging times are important in determining how long the driver spends at each location. Above map from Alternative Fuel Data Center taken from a study done from New York State Energy Research and development Department, shows the EVSE locations in the Northeast region of the United States (WXY Architecture + Urban Design et al. 2012). A more detailed interactive list of charger locations can be found at [www.plugshare.com](http://www.plugshare.com). It is important for cities to identify operational clusters for building EVSEs, clusters like workplace cluster, retail cluster, commuter rail station cluster are all ideal EVSE development locations. Retail locations with their large parking lots are likely to be ideal spots for EVSE installations giving drivers incentive to shop longer while their cars are charging. Most retail parking spaces also able to incorporate solar panels to power up their charging stations and create additional green marketing opportunities.

In workplace clusters companies can offer free charging for their employees as a part of employee benefits package. In fact, several companies including Tufts Health Plan and UMass Lowell are using this type of incentives for their employees.<sup>6</sup> Tufts Health Plan parking is close to public and offers free charging up to four hours a day, while UMass Lowell charges students an access fee for their level 2 charging stations.<sup>7</sup> These are all formidable solutions to the lack of charging in urban areas outside the downtown area, however, it may not be enough to foster EV ownership growth in cities.

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<sup>5</sup> Plug in America, Massachusetts Drive Clean Workplace Charging Guide, 2016

<sup>6</sup> Id.

<sup>7</sup> Id.

Charging infrastructure creates unique challenges to urban planners and policy makers. It is more complex issue than an extension cord and an outlet. One of the challenges to charging infrastructure is to create a reliable, multi-party use, cost effective system outside one's home (Markel 2010). This challenge will also create many opportunities future research, planning and policy.

## **4. Urban density and vehicle use**

From ancient cities of Rome to modern metropolis, transportation has played a principal role in how cities formed. With the assembly line factory process of Henry Ford's Model-T automobile's popularity gained momentum. Cities and towns changed to suit the automobile. Along with Ford, Chrysler, and General Motors help create the middle class ushering in the manufacturing boom. Post 1920s came the automobile era and the decline of the walking cities (Melosi 2004). Compared to cities that developed pre industrial era like New York, Boston, and Philadelphia, cities that developed post 1920 automobile era like Los Angeles, Denver, Houston saw an urban development that was more sporadic, low density and fragmented (Melosi 2004). This type of sprawl characterized by lower density has two impacts on travel, one longer trip distances and two more reliance on the automobile (Handy, Cao, and Mokhtarian 2005).

There has been evidence that land use is correlated to travel demand and automobile ownership. Pushkarev and Zupan in their 1977 book titled *Public Transportation and Land Use Policy* provide the basis of association between land use and travel patterns. (Pushkarev and Zupan 1977). While the correlation between land use and travel maybe apparent, how one affects the other is not that clear. Studies have shown that in neighborhoods with high density, mixed land use, and transit accessibility combined with pedestrian friendliness, the residents drive less compared to neighborhoods with less of these characteristics (Handy, Cao, and Mokhtarian 2005). Residential density has a statistically significant impact on vehicle use, however upon analysis of cross-sectional data, the differences in travel behavior between dense urban neighborhoods versus

suburban neighborhoods is mostly explained by residents' attitudes (Brownstone and Golob 2009, Handy, Cao, and Mokhtarian 2005). It is common to see people who live in urban areas to be more public transit oriented and suburbanites to be more automobile centric (Kitamura, Mokhtarian, and Laidet 1997). This selection bias is noted in many studies and whether neighborhood design influences travel behavior or travel preferences influence neighborhood choice has been hard to establish (Handy, Cao, and Mokhtarian 2005). Because all these effects such as transit accessibility, pedestrian friendliness, cost of driving and parking a car in dense areas all occur simultaneously the effect of residential density on vehicle use is likely to be non-linear (Schimek 1996).

Residential density may have a statistically significant influence on vehicle use but the magnitude of this influence appears to be very minimal. Brownstone and Golob, in their 2009 study conclude that an increase of 40% in residential density yields to a 4.8% decrease in vehicle miles per year (Brownstone and Golob 2009). Figure 4 shows the changes in

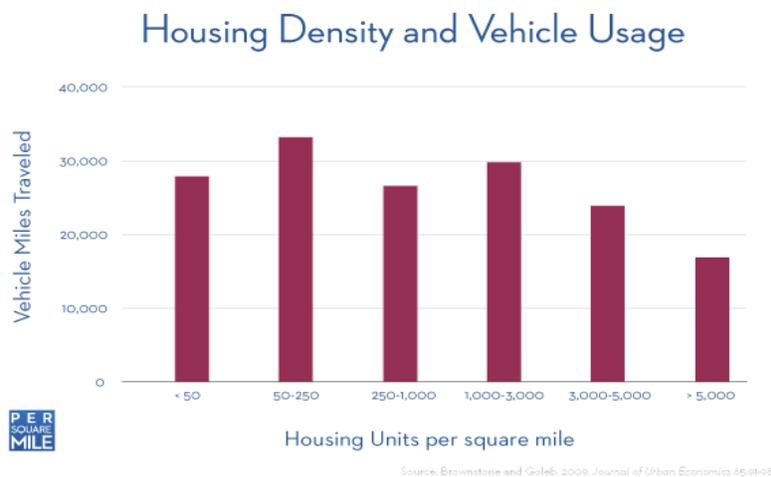


Figure 4: Change in Vehicle usage by housing density. Source: grist.org

Housing per square mile and vehicle miles traveled (VMT). Vehicle miles traveled is also directly correlated with household income that an increase in household income has a statistically significant effect on increase in distance traveled (Schimek 1996).

Household income is also part of the suburbanization, studies and data has shown that and increase in income has led people to move out of cities into suburbs (Mieszkowski and Mills 1993). Other factors like the development of highways in the 1960's exacerbated this effect. This sprawling and suburban land development is part of the blame for the levels of automobile travel and the subsequent air pollution issues (Handy, Cao, and Mokhtarian 2005). While income is known to be an influencing factor on driving behavior many studies control for socio-economic factors in order to reduce spurious conclusions when it comes to measuring correlation between built environment and driving behavior. Besides socio-economic factors self-selection bias also plays an important role in the relationship between built environment and travel behavior (Handy, Cao, and Mokhtarian 2005).

In this study I will be looking at different factors effecting EV demand with the understanding that income will be a big influencing factor, but we will see if it has any predictive value. By understanding different factors effecting EV demand cities can better support these vehicles and thus reduce tailpipe emissions.

## **5. Methodology**

In this chapter I will discuss the methods used to achieve the objective for this thesis. The main objective is to identify if the built environment influences EV demand. Do physical environments like a network of EV chargers, dense neighborhoods or neighborhoods that are easy to walk, and bike are enough to create the demand for EVs? This question is the main frameworks of the analysis in the next chapter. For this first, the distribution of Electric Vehicle rebate applications will be examined. My assumption is that the people who applied for EV rebates have purchased EVs therefore it is a good representation of EV demand in the region. In this study I will be looking into the correlation between the built environment, population densities and socio-economic factors and EV demand and analyze how each variable effects EV demand. Quantitative and spatial analysis will be performed to demonstrate the relationship between these independent variables and EV demand. We can analyze the correlation however we cannot infer any causation, to infer causation certain scientific criteria needs to be met. One of them is that there must be time order where the cause precedes effect in time (Handy, Cao, and Mokhtarian 2005). The analyses will try to establish a statistical association between variables listed in Table 1 and EV demand but will not establish if the cause precedes the effect. In this chapter will explain how correlation and influence of each factor will be analyzed.

### **Data Sources and Preparation**

The data for EV demand is collected from Massachusetts Offers Rebates for Electric Vehicles (MOR-EV) program initiated by the Massachusetts Department of

Energy Resources (DOER) and implemented by Center for Sustainable Energy (CSE). Center for Sustainable Energy runs EV rebate programs for California, New York, New Jersey, and Massachusetts. This dataset contains 6620 total rebates issued between 2014 and February of 2018. The rebates are divided between Battery powered electric vehicles (BEVs), which run exclusively on battery power and mostly represented by brands like Tesla and Chevy Volt. Plug-in Hybrids (PHEVs), which use a combination of battery and gasoline powered motors. Final category consists of various other zero emission vehicles which in Massachusetts are all electric motorcycles, Zero Motorcycles is the most prominent brand in this category. Of the vehicles purchased 52.4% of them are BEVs, 47.3% are PHEVs and 0.2% of them are ZEVs. Among all the vehicles 40% of them are leased and 60% of them are purchased. Table 1 and 2 shows the distribution frequencies.

**Table 1: Datasets and Sources**

| <b>Data</b>                                      | <b>Source</b>  |
|--|--|
| MOR-EV Rebate statistics                         | Center for Sustainable Energy (2018) Massachusetts Department of Energy Resources. |
| Mass Population data                             | MassGIS on Tufts GIS Data Server.  |
| Median Income data                               | MassGIS census tracts  |
| 2016 Presidential Election Results               | wbur.org   |
| Walk Score and Bike Score data from              | Walkscore.com  |
| Home ownership percentage, Commute Time and Type | ZipAtlas.com   |
| Charging stations                                | US department of Energy Alternative Fuels Data Center                              |

**Table 2: Vehicle Category**

|              | Frequency   | Valid Percent (%) | Cumulative Percent |
|--------------|-------------|-------------------|--------------------|
| BEV          | 3470        | 52.4              | 52.4               |
| PHEV         | 1675        | 25.3              | 77.7               |
| PHEV+*       | 1459        | 22.0              | 99.8               |
| ZEM          | 16          | .2                | 100.0              |
| <b>Total</b> | <b>6620</b> | <b>100.0</b>      |                    |

\*PHEV+ Plug in Hybrid Vehicle with battery capacity greater than 10kWh  
 Data Source: Massachusetts Department of Energy Resources

**Table 3: Purchase or Lease?**

|              | Frequency   | Valid Percent (%) | Cumulative Percent |
|--------------|-------------|-------------------|--------------------|
| Lease        | 2646        | 40.0              | 40.0               |
| Purchase     | 3974        | 60.0              | 100.0              |
| <b>Total</b> | <b>6620</b> | <b>100.0</b>      |                    |

Data Source: Massachusetts Department of Energy Resources

U.S. Census data is used for population density and income. This data was joined with zip code shape files in ArcGIS to create the heatmaps for Population and Income. It is projected into NAD\_1983\_StatePlane\_Massachusetts\_Mainland\_FIPS\_2001. EV rebate data was joined with a zip code shape file in ArcGIS to create the heatmap for EV demand. It is projected into NAD 1983 State Plane for Massachusetts mainland. Homeownership, commuting type and behavior data by zip codes were obtained from the website called ZipAtlas.com, which uses Census data to create structured reports with zip codes. This data was processed using Microsoft Excel and joined with zip code shape file in ArcGIS. Of the 682 unique zip codes in Massachusetts 497 of them were matched by a join. Using ArcGIS Ordinary Least Squares analysis was performed on each variable predicting EV rebate. In addition to ArcGIS, SPSS is used to examine the distribution frequencies of the EV rebates. SPSS is also used to perform a backward selection regression on explanatory variables to

better understand the model. One drawback to measuring correlation in zip code level is that it is too large of an area to be homogenous but the EV rebate data is only available at the zip code level from Massachusetts Department of Energy Resources (MA-DOER).

The voting data is from WBUR Boston Public Radio website for the 2016 elections. First I created a voting index for political affiliation by subtracting votes for the Democratic Party from the Republican Party. This helped me to create the map on Appendix I, page 71. I assigned red color for all the negative values and blue for all the positive ones. This assignment reflects on the results and explains the negative coefficient. According to the results obtained from Ordinary Least Squares analysis on GIS, for every change in vote from Democrat to Republican, we would expect a negative unit change in EV demand.

Electric Vehicle Supply Equipment (EVSE) or commonly referred to as electric vehicle charging station data is downloaded from the Department of Energy's (DOE) Alternative Vehicle Data Center website. This dataset contains the XY coordinates of each station (Figure 3).

**Table 4: Variable Details**

| <b>Variable (by zip code)</b>                          | <b>Mean</b> | <b>Standard Deviation</b> |
|--|-------------|---------------------------|
| Population (people)                                    | 12698.10    | 11955.286                 |
| Population density <sup>b</sup> (people/sqm)           | 2759.75     | 5309.70                   |
| Average household Income (US\$)                        | 55949.12    | 20213.85                  |
| Commute Time (minutes)                                 | 26.77       | 5.59                      |
| Percent Driving to Work (people)                       | 0.76        | 0.15                      |
| Walkscore index  | 6.97        | 18.12                     |
| Bikescore index  | 5.39        | 14.93                     |
| Political affiliation based on voting on 2016 election | n/a         | n/a                       |
| Home ownership (people)                                | 62.52       | 21.37                     |

Walk score and Bike score data is obtained from [walkscore.com](http://walkscore.com). Walk Score<sup>®</sup> is a private company that provides apartment search tools with relation to the walkability of the area. It assigns walk, bike and transit scores to points on the map and generate commuting reports. Data acquired from Walk Score<sup>®</sup> website is less comprehensive than other data that I have gathered, also Walk Score<sup>®</sup> has received criticism from Urban Planning professionals for the relevancy of its methodology, but despite its limitations, I believe it will give some basic insights into walkability of an area and its residents' tendency to purchase EVs.

In addition to the quantitative analysis of built environment and socio-economic factors affecting EV demand, I will also present a case study about a policy involving incentives to dealers for selling EVs. A mixed method research that combines both

qualitative and quantitative components will expand and strengthen the conclusions of the study (Schoonenboom and Johnson 2017).

### **Analysis:**

As the first step in understanding the patterns in EV rebate distribution ArcGIS is used to visualize the clustering rebates. For this study I am interested in high-high clusters, and whether these clusters are in wealthy, or in neighborhoods with high population density. Figures 6 through 8 show areas where EV rebate applications were filed with relation to zip codes in Massachusetts. Each map shows a type of EV, BEVs, PHEVs and PHEV+ which are plug in hybrids with a battery capacity greater than 10kWh. Global Moran's I is used to test for spatial clustering and the resulting high Z score indicates that the clustering of EV rebate applications is not a result of random chance (see appendix iii). A correlation report conducted in SPSS indicates that some of the variables in this study such as median income and homeownership, commute times and percentage of people driving to work are all correlated to each other. This report uses multiple univariate spatial regressions for each independent variable. In each of these regressions, the population, population density, income, commute times, and percentage of people driving to work, walk and bike score, political affiliation and homeownership were the independent variables, and the EV rebate applications, which I equate to EV demand, was the dependent variable. I also multivariate backward selection regression model to better understand the relationship between these variables.

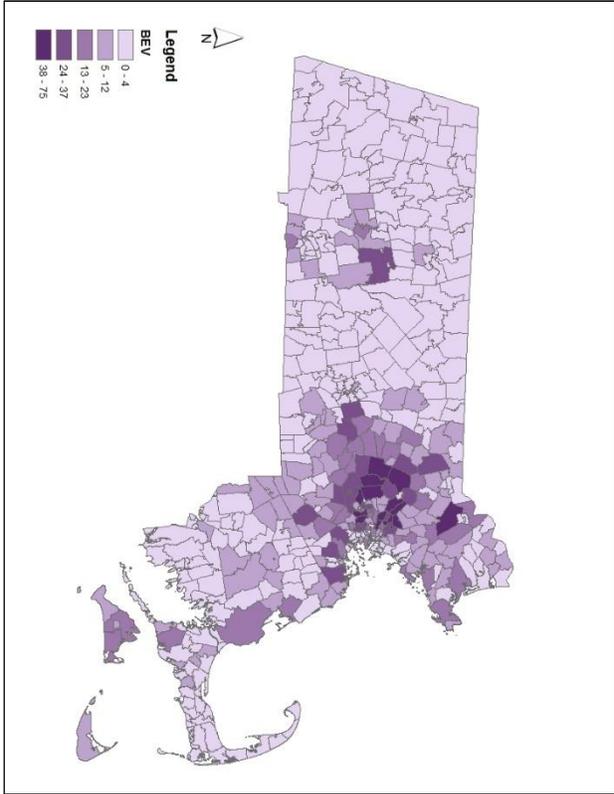


Figure 6: Battery powered EVs

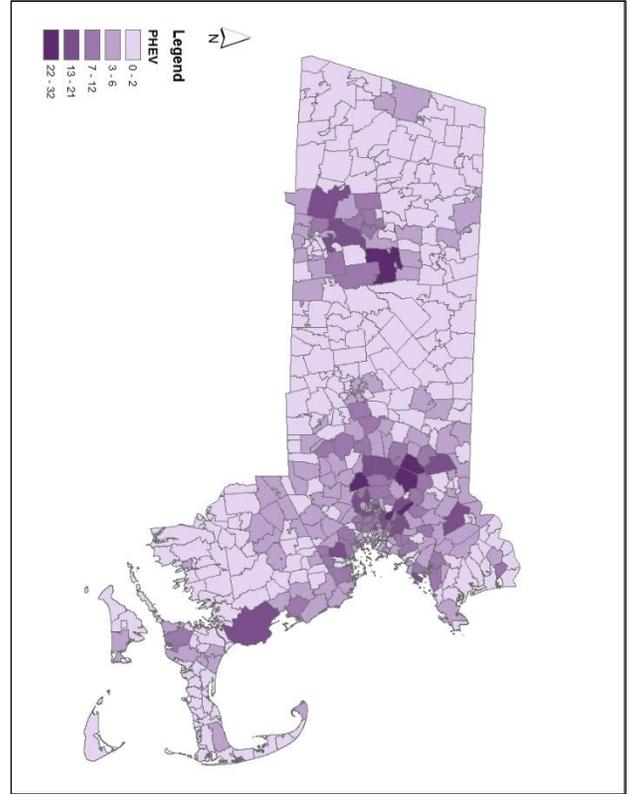


Figure 7: Plug in Hybrids

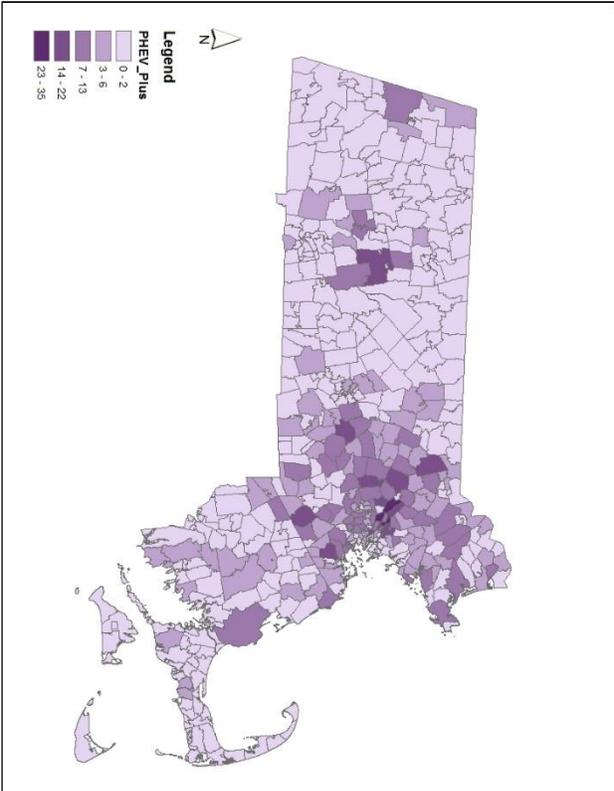


Figure 5: Plug in Hybrid Plus

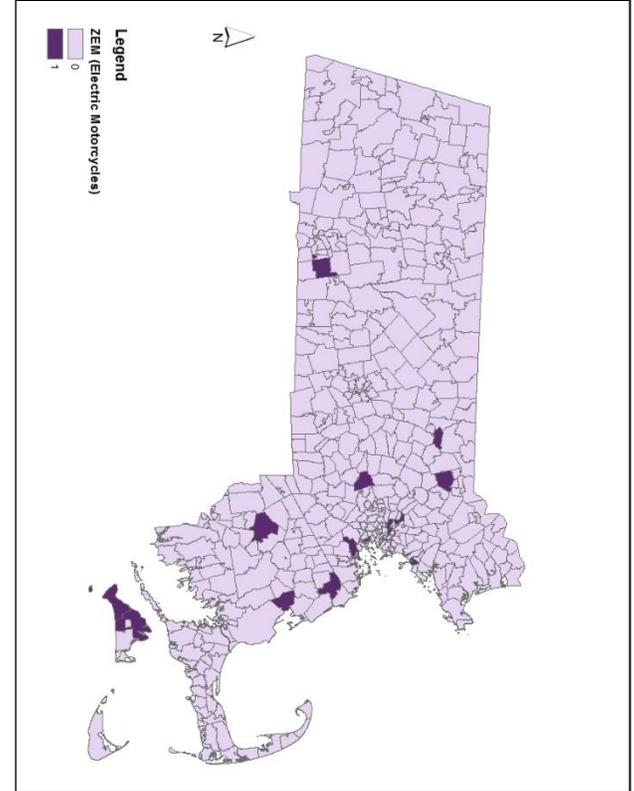


Figure 8: Zero Emission Vehicles

## 6. Results

This chapter will review the results from the analysis described in the previous chapter. The results from univariate regression are reviewed and explained. Table 5 lists regression results in order of their explanatory values. Many of the variables in the univariate analysis show statistically significant p-values. Two variables that are not statistically significant at a p value of 5% were population density and percentage of people driving to work.

**Table 5: Univariate Ordinary Least Square results (one to one correlation)**

| <b>Independent Variable (by zip code)</b>              | <b>Coefficient</b> | <b>P-Value</b> | <b>R square</b> | <b>Standard Error</b> |
|--|--------------------|----------------|-----------------|-----------------------|
| Population   | 0.0006             | 0.0000         | 0.1639          | 0.00006               |
| Political affiliation based on voting on 2016 election | -0.0040            | 0.0000         | 0.1599          | 0.0004                |
| Average household Income                               | 0.0003             | 0.0000         | 0.1357          | 0.00003               |
| Bikescore  | 0.4441             | 0.0000         | 0.1276          | 0.0004                |
| Walkscore  | 0.3202             | 0.0000         | 0.0958          | 0.0437                |
| Home Ownership   | 14.034             | 0.0001         | 0.0285          | 3.5576                |
| Commute Time   | 0.3719             | 0.0027         | 0.0160          | 0.1233                |
| Population Density                                     | 0.0002             | 0.0587         | 0.0051          | 0.0004                |
| Percent Driving to Work                                | -2.5575            | 0.5556         | 0.0013          | 4.3367                |

Dependent Variable = Electric Vehicle Rebates

Figures 9 through 17 are heat maps of each variable based on zip codes. A larger version of each map from chapter 6 can be found in Appendix i.

**Table 6: Backward Selection Regression Results ( $R^2 = 0.458$ )**

| <b>Independent Variables<br/>(by zip code)</b> | <b>Coefficient</b> | <b>P-Value</b> | <b>Standard Error</b> |
|--|--------------------|----------------|-----------------------|
| Population                                     | 0.001              | 0.000          | 0.000                 |
| Average household Income                       | 0.001              | 0.000          | 0.000                 |
| Bikescore                                      | 0.168              | 0.134          | 0.112                 |
| Walkscore                                      | -0.059             | 0.539          | 0.096                 |
| Home Ownership                                 | -0.126             | 0.040          | 0.061                 |
| Commute Time                                   | -0.262             | 0.083          | 0.151                 |
| Population Density                             | 0.000              | 0.096          | 0.000                 |
| Percent Driving to Work                        | -22.105            | 0.006          | 7.956                 |

Dependent variable = Electric Vehicle Rebates

**Table 7 : Backward Selection Regression Results Model 2 (Walkscore removed,  $R^2 = 0.458$ )**

| <b>Independent Variables<br/>(by zip code)</b> | <b>Coefficient</b> | <b>P-Value</b> | <b>Standard Error</b> |
|--|--------------------|----------------|-----------------------|
| Population                                     | 0.001              | 0.000          | 0.000                 |
| Average household Income                       | 0.001              | 0.000          | 0.000                 |
| Bikescore                                      | 0.168              | 0.051          | 0.055                 |
| Home Ownership                                 | -0.123             | 0.043          | 0.061                 |
| Commute Time                                   | -0.266             | 0.078          | 0.150                 |
| Population Density                             | 0.000              | 0.101          | 0.000                 |
| Percent Driving to Work                        | -22.152            | 0.006          | 7.950                 |

Dependent variable = Electric Vehicle Rebates

**Table 8: Backward Selection Regression Results Model 3 (Walkscore and Population density removed,  $R^2 = 0.454$ )**

| <b>Independent Variables<br/>(by zip code)</b> | <b>Coefficient</b> | <b>P-Value</b> | <b>Standard Error</b> |
|--|--------------------|----------------|-----------------------|
| Population                                     | 0.001              | 0.000          | 0.000                 |
| Average household Income                       | 0.001              | 0.000          | 0.000                 |
| Bikescore                                      | 0.168              | 0.049          | 0.055                 |
| Home Ownership                                 | -0.110             | 0.069          | 0.060                 |
| Commute Time                                   | -0.314             | 0.034          | 0.148                 |
| Percent Driving to Work                        | -14.322            | 0.025          | 6.382                 |

Dependent variable = Electric Vehicle Rebates

Table 6 shows the results from backward selection regression. Tables 7 and 8 shows with variables Walkscore and Population Density removed respectively. Backward selection regression run on SPSS shows that density and walkability score do not contribute to the multivariate model even though they are statistically significant variables in the univariate analysis. Backwards selection regression model details are shown in Appendix iv.

In the following section I will discuss each variable and its affect on EV demand individually and how they fit into the regression model.

## Population and Population density

Based on univariate model 16% of the variation in purchasing EVs can be explained by the size of the population ( $R^2 = 0.1639$ ). This could be explained by the fact that in the areas with more people more are vehicles purchased. Figure 9 and 10 shows Massachusetts population and population density, larger versions of these maps and other maps in this chapter can be found on Appendix i.

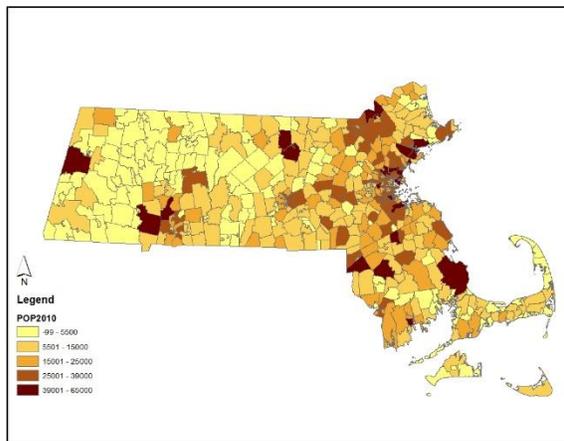


Figure 9: Massachusetts Population by zip code

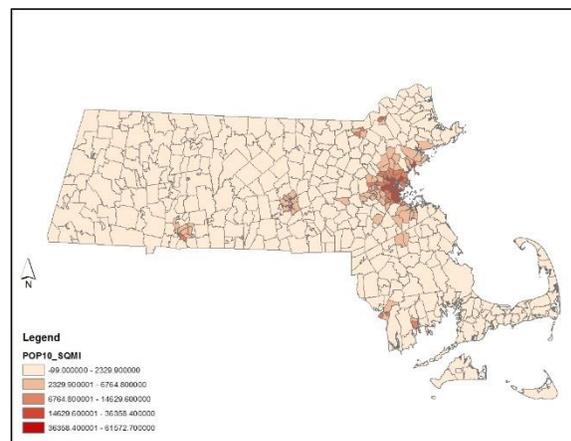


Figure 10: Massachusetts Population per sq. mile

The coefficient suggest that an increase of 1000 people in a given zipcode will result in an increase of 6 EVs, and this finding is statistically significant. High residuals shown in Ordinary Least Squares analysis suggests that Population is not a good predictor in locations close to the city of Boston for EV purchase rate. OLS maps along with larger maps for each variable can be found in Appendix i. Population as a variable in the regression model has almost identical coefficient and statistically significant.

The results are different when we look at the population density in Massachusetts. The population density is, as a variable is not statistically significant at a 95% level and

has low explanatory value ( $R^2 = 0.0051$ ). Backwards regression removes population density as one of the variable from the model, because of its high correlation rate with the other variables in the model. Also the OLS analysis shows that population density is not a good predictor in areas where there are high levels of EV purchase. This result could be explained by the fact that in dense neighborhoods people may be using alternative transportation methods like public transit, commuting by bike or walking. As discussed by Brownstone and Golob residential density has a small but statistically significant effect on vehicle use, this is likely to transfer into desire to own an EV, however, in dense neighborhoods parking is an issue and density is known to be a predictor for car sharing, transit use and alternative transportation modes which might hinder EV purchases (Brownstone and Golob 2009). Bikeability and walkability of a particular area and its effect on EV demand will be discussed in the later segment. Another factor that population density has a low correlation rate with EV demand maybe that people don't have personal spaces to store their vehicles like the people in suburbs. Lack of individual garages, or the fact that many people have to park on the street, might deter them from investing in an vehicle that requires to be plugged into an outlet. The multivariate OLS results suggest that population density is not a good predictor for EV demand in the areas where there is a high EV purchase rate.

## Political affiliation

About 16 percent of the variation in purchasing EVs can be explained by how people voted in the 2016 presidential election. ( $R^2 = 0.1599$ ) For every change in vote from Democrat to Republican we would expect a negative 0.0004 unit change in EV purchases.

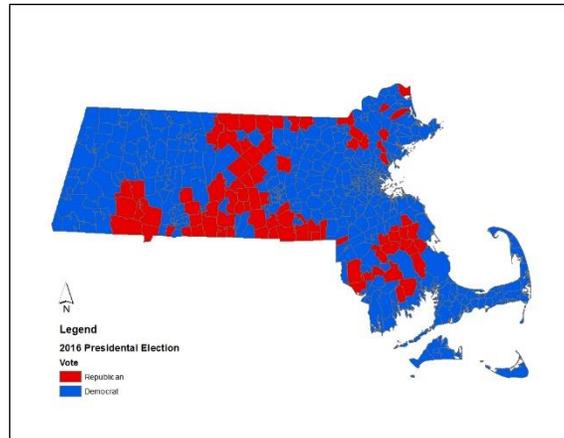


Figure 11: 2016 Presidential elections by zip code

Political affiliations or at least the way people voted in the 2016 presidential election has a high explanatory value in comparison to the other variables examined in this study, however OLS analysis this explanatory value is more complicated and not a reliable predictor. However, it is clear by the visual representation from the maps as well as the analysis, there is a statistically significant correlation between purchasing EVs and voting blue. Overall political affiliation alone may not be a good predictor of one's likelihood of purchasing and EV. Political affiliation is also tended to be correlated with education, and income. Political affiliation may have different effect in different states. Georgia a predominantly red state for example is second in EV sales after California.<sup>8</sup>

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<sup>8</sup> <https://cleantechnica.com/2017/05/04/us-electric-car-sales-state-whos-1-ohio-california/>

## Average household Income

Nearly 14 percent of the variation in purchasing EV's in the univariate model can be explained by household income ( $R^2 = 0.1357$ ).

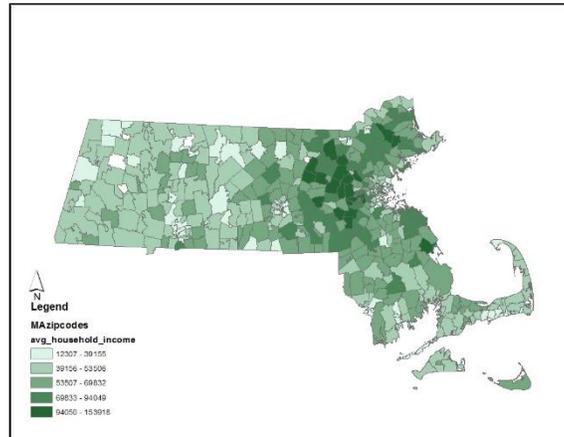


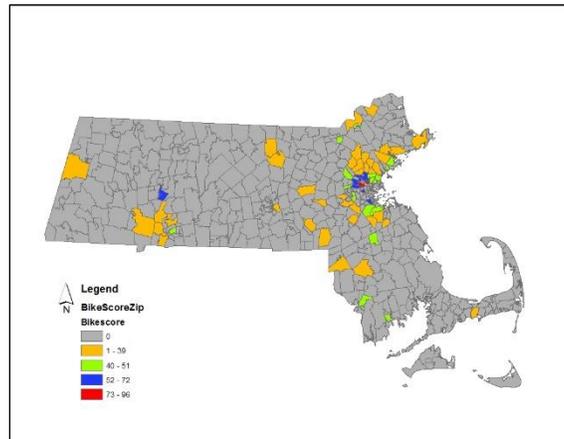
Figure 12: Average household Income zip code

Median household income is a statistically significant explanatory factor in EV purchases. The coefficient it shows that a \$10,000 increase in annual income results in an increase of EV purchase by 3 cars, which means an increase in income does leads to an increase in EV ownership. It is also clear from the map that zip codes with higher household income purchase more EVs. In the multivariate regression analysis income remains a statistically significant explanatory factor for EV purchases. EVs are still considered a high-priced item and out of reach of many families. A Forbes article citing a market analysis conducted by Experian Automotive shows that EV buyers tend to be younger and more affluent than hybrid or other internal combustion engine vehicle buyers (Gorzelany 2014). Federal and state rebates do alleviate some of the cost of these vehicles. If the demand for these vehicles increase and more models enter the market the prices should become more reasonable. In the meantime, rebates and other incentives should continue. If the history of the automobile is any indication, with time EVs will no longer be only

affordable by the wealthy and with most things sometimes the government support is needed to incubate and develop new technologies until they become self-sustainable.

### **Bike Score correlation**

Almost 13 percent of the variation in univariate regressions predicting the purchase of EVs can be explained by how bikeable a certain area is ( $R^2 = 0.1276$ )



*Figure 13: Massachusetts bike score by zip code*

Bike score measures if the location is suitable for biking. With the understanding that there are limitations to this data it still shows there is a statistically significant correlation between how bikeable an area is and how its residents have purchased EVs. This correlation remains statistically significant at the 95% level when this variable is plugged into the multivariate regression model. OLS analysis shows that bike score is not a good explainer in the zip codes with higher EV purchase rates. This might reflect on the lifestyle choices that the residents of these zip codes with high bike score and high EV purchase rate. Bicycle is often the symbol of green way of life and associated with environmentalism (Horton 2006). It might not come as a surprise when people live in zip

codes with high bike scores they are more environmentally conscious and may prefer EVs over conventional vehicles.

## Walk Score

Based on the univariate model roughly 10 percent of the variation in purchasing EV's can be explained by how walkable an area is ( $R^2 = 0.0958$ )

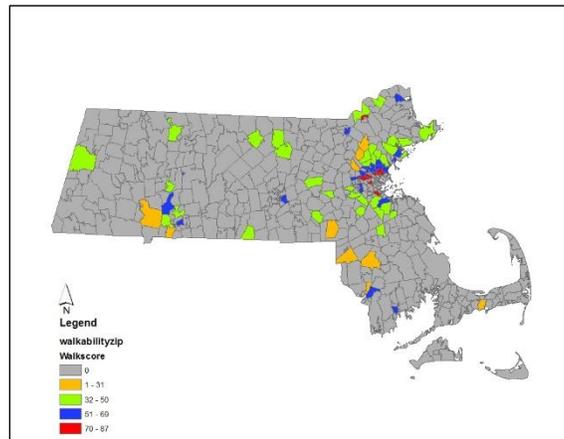


Figure 14: Massachusetts walk score by zip code

While as an individual variable walk score is a statistically significant as an individual variable affecting EV purchase, when it is included in the regression model it is not statistically significant. It is also one of the variables that was removed in backward selection regression.

Walk score is a number between 1 and 100 that measures the walkability of a certain address or zip code. Each point is awarded by analyzing walking routes to the nearby amenities. A higher point is given if the amenities are within a close distance, shortest distance being 5 minutes (highest point) and longest distance 30 minutes (0 points). Understandably if a certain area or a zip code has high walkability rate than the use for vehicles is likely to drop. Built environment that allows people to easily walk, bike or take

public transit is likely to reduce personal vehicle use and individuals who choose not to drive are likely to live in these neighborhoods (Handy, Cao, and Mokhtarian 2005).

## Home Ownership

Based on the univariate model approximately 3 percent of the variation in purchasing EV's can be explained by home ownership ( $R^2 = 0.0285$ )

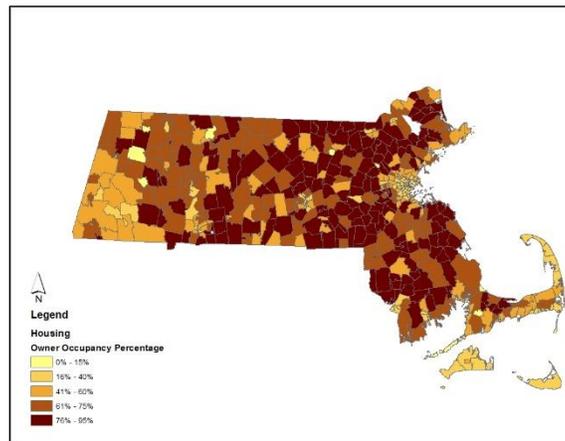


Figure 15: Owner occupied homes by zip code

Home ownership is significant predictor in explaining EV ownership. This finding is statistically significant with a p-value at 0.0001. This could be tied to the income as owning a home may indicate a certain level of income that is conducive to purchasing a higher priced vehicle. Once again OLS analysis shows that home ownership is not a good predictor for EV sales in the zip codes where there are higher number of EV purchases. When we look at the home ownership variable in the multivariate regression model it remains statistically significant, however the coefficient is negative. This can be perhaps explained by the multicollinearity of the variables examined. Home owner concentration appears to be in the suburban areas as well as less dense areas of Massachusetts. Home owners in these areas may find it harder to access a charging station. Renters on the other

hand live in denser walkable neighborhoods which appear to have a higher rate of EV purchase. For households that do not have off-street parking and those who park on the street accessibility public charging stations will be important to increasing demand for EVs (Namdeo, Tiwary, and Dziurla 2014).

### Commute Times

Close to 2 percent of the variation in the univariate model predicting the purchase of EVs can be explained by the amount of time it takes for people to commute to work ( $R^2 = 0.0160$ ).

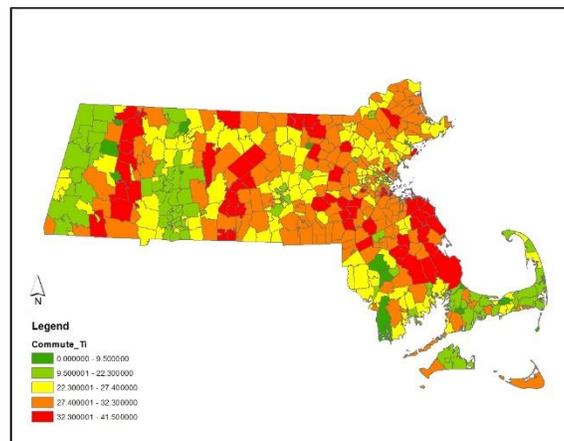


Figure 16: Commute times by Zip Code

Commute times is significant predictor for peoples' propensity to purchase EVs in Massachusetts. The coefficient is positive – this suggests that the higher the commute time the more likelihood of purchasing EVs. As an individual variable a unit increase in commute time (1 minute) leads to a 0.37 increase in EV sales. This suggests that places with higher commute time are more likely to buy EV possibly related to fuel savings. Visualization from the map suggest that optimum spot for EVs is 22 to 27 minutes of commute time which seems in line with the general range of EVs. When we put the Commute time variable into the multivariate regression model the coefficient becomes

negative suggesting that it may be affected by multicollinearity with other variables. However, it makes sense that the coefficient is negative since higher commute times are like to result in less use of vehicles that need to be charged. Higher commute times are also more prevalent in the suburbs which have a lower rate of EV purchase.

### Percentage of People driving to work

Less than 1 percent of the variation in univariate model predicting the purchase of EVs can be explained by the amount of percent of people who drive to work ( $R^2 = 0.0013$ )

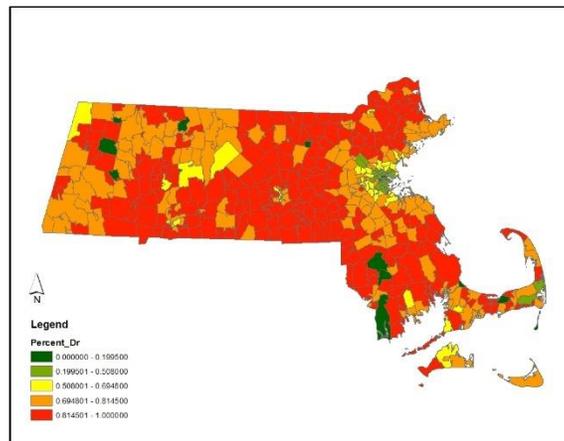


Figure 17: Percent driving to work

The percentage of people driving to work is not a significant predictor for predicting EV demand in Massachusetts. The pattern in the map suggest the percentage of people drive to work increases as it gets farther from Metro Boston area into the less dense parts of the state. This pattern maybe explained by the accessibility to public transit in Metro Boston, which may also turn people away from driving. The OLS analysis also shows that in the areas with high EV purchase rate the percentage of people driving to work is not a good explanatory factor as standard residuals are high in those zip codes. As an individual variable there is a negative correlation between percent of people driving to work and EV

purchases and this negative correlation stayed negative when we put the percent driving variable into a multivariate regression model.

## **7. Case Study: Connecticut Hydrogen and Electric Automobile Purchase Rebate, Dealer Incentive Evaluation**

One of the things that is not discussed in the above quantitative analysis is the peoples' perception of Electric Vehicles. A more qualitative research is needed to understand peoples' feeling towards EVs. On a consumer level the fear that vehicles, especially EVs, lack the necessary range to reach a desired destination and thus getting stuck, is known as "Range anxiety". Range anxiety has been cited as one of the main factors in hampering EV market growth (Markel 2010). Education of consumers partly lies on the automobile dealer. This section will examine a program evaluation to see the effect of incentives that geared towards the dealers rather than consumers.

The Connecticut Hydrogen and Electric Automobile Purchase Rebate (CHEAPR) program is a consumer rebate program with a dealer incentive component. CHEAPR provides a rebate up to \$5000 to the consumer for the purchase of a Hydrogen or EV and gives the dealer a \$300 incentive with each rebate claimed. CHEAPR program is an effort by the Connecticut state government to promote clean energy initiatives and support the states clean air goals by encouraging the use of alternative fuel vehicles. The state program is in addition to the Federal rebate program and unique with its dealer incentive component that garnered some attention with the EV market stake holders.(Johnson 2017) The program is funded by Eversource Energy (formerly Northeast Utilities) as a part of an arrangement settled by the Northeast Utilities and NSTAR merger. The program works as each dealer processes the rebate and receives a \$300 incentive for their efforts. The evaluation of this program was conducted by the Center for Sustainable Energy in 2016 and the report was published in June of 2017. Connecticut Department of Energy and

Environmental Protection (DEEP), Eversource, and the Connecticut Automotive Retailers Association (CARA) have all collaborated in this incentive program however the study and the resulting evaluation report are solely conducted by the Center for Sustainable Energy (CSE). Connecticut and the CHEAPER program is chosen because it is the only EV incentive program that directly gives incentives to dealers in addition to consumers.

The CHEAPR program is part of the state of Connecticut's efforts to provide cleaner, cheaper, and more reliable transportation energy and support its clean air goals. By embracing EVs as a cleaner alternative to fossil fuel burning vehicles Connecticut is initiating programs to increase the number of EVs. Other than investing in EV charging infrastructure the state of Connecticut is issuing a rebate up to \$5000 for the consumer who purchase EVs. The program is not time based but has \$2,000,000 allocated to promote the sale of EVs. As of May 2016, CSE reports that little over \$1.4 million has been claimed in rebates.<sup>9</sup> As the cost of EVs are higher than their conventional counterparts' monetary rebates are a way to mitigate the higher cost. For the rebates to work effectively, the consumer must be made aware of them. This is where the importance of the dealers come into play. CHEAPR's dealer incentive program is unique in the way that it incentivizes the dealer to help consumers to take advantage of the state's EV rebate program. Dealer incentive program theory centers on the idea that dealers are crucial in implementing the CHEAPR program effectively.

CSE's report highlights in both its introduction and executive summary that dealer participation in the CHEAPR program is key. One unique part of the CHEAPR program is

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<sup>9</sup> <http://energycenter.org/program/connecticut-hydrogen-and-electric-automobile-purchase-rebate-program>

that the state rebate can be issued at the point sale at the dealership level with an option called “dealer assignment”.<sup>10</sup> The rebate amount is deducted as a line item from the cost of the vehicle and the consumer receives the dollars instantly as opposed to waiting for a check to arrive weeks later. The dealer then receives a reimbursement from the state.

Center for Sustainable Energy (CSE) is a non-profit organization that provides clean energy program design, management, and technical services nationwide. Headquartered in San Diego, CA, CSE has offices in Oakland, Los Angeles California, and Boston Massachusetts. CSE was chosen by the Massachusetts Department of Energy Resources to run the electrical vehicle programs in 2014 and by the Connecticut Department of Energy and Environmental Protection in 2015.<sup>11</sup> CSE funded and conducted a study to evaluate the dealer incentive portion of the CHEAPR program surveying 269 individuals from 88 dealerships in the state of Connecticut. Neither the funder of the CHEAPR program, Eversource, nor DEEP or CARA participated in the study, but they are all important stakeholders in the EV market. This is important as CSE is an independent agency and it is not beholden to the politics between state and other private parties. CSE however, is the administrator of the CHEAPR program and therefore they are an internal evaluator evaluating the program they are administering. The evaluation report does not mention that CSE is the administrator of the program that they are evaluating.

The objective of the CSE report is to assess the impact of the dealer incentive of the program. The stakeholders wanted to know the effectiveness of incentive program and

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<sup>10</sup> <http://energycenter.org/program/connecticut-hydrogen-and-electric-automobile-purchase-rebate-program>

<sup>11</sup> <http://www.businesswire.com/news/home/20150812005996/en/Center-Sustainable-Energy-Establishes-New-Northeast-Regional>

whether it had an impact on the EV market. The initial objective, however, it was later revised as follows:

*“To develop an understanding of how the CHEAPR dealer incentive is distributed and used by different dealerships, and whether it is an effective method for promoting the development of the EV market.”(Johnson 2017, p10)*

It is not clear as to when the objective was changed but it is likely that it might happen during the survey process as the evaluators found out different uses of the dealer incentive dollars. The \$300 incentive were sometimes given to individual sales people and in some cases the sales people were not even aware of the dealer incentive. While the CSE was originally focused on the outcome they found that the process also played an important factor. The evaluation questions were set to answer several issues ranging from the effectiveness of the dealer incentives, to how do the behavior of the dealership employee change in response to the dealer incentives. The dealer incentive portion of the CHEAPR rebate program is unique among nationwide state programs with regards to EVs and it is important to understand how, if any, does it play a role in the overall program itself. CSE created this formative evaluation to answer that question to meet the EV market stakeholders' requests. While the CSE was mainly interested in the outcome of the program throughout the study they realized that process also played a big role in terms of how the dealer incentives were used.

CSE designed a study where they interviewed dealerships and set up a survey. The survey was sent to 269 individuals at various roles in 88 different dealerships. Their survey and interviews involved anybody from sales people, to general managers, to account

assistants. They used quantitative and qualitative analysis to study this data. CSE is in advantageous position because they administer various other EV programs in other states like California Air Resources Board Clean Vehicle Project and Massachusetts MOR-EV program. They were able to compare these different statistics to Connecticut EV sales and help better shape their evaluation report. CSE used quantitative data, which is likely to be more reliable to map out rebate distribution among the state as well as whether the consumer received the rebate directly or it went through the dealership. Quantitative data allow them to understand the reach of the dealer incentive, they found out 95% of the participants were familiar with the CHEAPR program, however over 30% of the sales people and 27% of all respondents were not aware of the dealer incentive component (Johnson 2017). CHEAPR program conducts a consumer survey on the participants of their program, since CSE administers this program they cross check their dealer survey with the programs consumer survey. They do this to ensure that the survey reached a reasonable degree of representatives.

CSE also conducted informal interviews which were critical to developing the evaluation. While the surveys were emailed to all the dealers only a handful of dealers of whom the CHEAPR staff had already developed a relationship were interviewed. These interviews and the qualitative approach appear to shape the nature of the evaluation and the questions that were being answered, resulting in a revised objective for the evaluation. The qualitative results of the informal interviews concluded that not all the dealer incentives were distributed evenly across the board. The empirical information collected from dealers coupled with the program data allowed CSE to better analyze and develop the survey to evaluate the dealer incentive component of the CHEAPR program.

The evaluators at the CSE reached out to people at different levels of employment at the dealerships. This ensured wide range of answers from different points of view. Since the program is not designed to deal with individuals' competency, nor the evaluation is about their performance certain cultural context is not apparent. It is interesting that some of the employees, especially at the sales level, did not know about the dealer incentive portion of the CHEAPR program. The dealer survey showed that there is a significant difference in sales employee's attitudes towards selling EVs if they received some or all the incentive money directly. It is up to the dealer how to use the \$300 incentive and there are differences among dealerships as to how that money is utilized. The CHEAPR program and the dealer incentive portion is not a secret but seemingly some sales employees learned the dealer incentives during the program evaluation survey. I don't believe it is the evaluators responsibility to inform the dealers but how people get compensated could be sensitive topic and must be handled carefully. The evaluators do give a suggested dollar amount that will motivate sales people and the dealership. From the survey the mean dollar amounts the CSE recommends for the sales people is \$233 and \$623 for the dealership itself.

The CSE's finding is that sales people would be more motivated to learn more about EVs and try to sell more EVs if they were compensated directly. The evaluation shows that dealer incentive is a motivational tool that gets sales people to spend more time with the customer and teach them about EVs and for the dealership to spend time on CHEAPR rebate applications. Another finding was that salespeople who owned EVs were more likely to be better motivated for selling EVs. CSE incorporates this finding into their recommendations. Their recommendations for the CHEAPR program include:

- Increasing dealer outreach to improve awareness
- Track the use of dealer incentive
- Consider formally defining the purpose of the dealer incentive
- Collect data from non-participant dealers for future evaluations

CSE also makes recommendations for the development of EV incentive programs, those include:

- Formalizing and documenting program design
- Using a split dealer incentive to motivate both dealers and salespeople
- Building data collection into program design
- Providing experience with EVs for the salespeople to increase positive attitudes towards EVs

All the recommendations were based on the findings from the evaluation study, however CSE acknowledges that these recommendations may not guarantee an increase in enthusiasm for EVs. CSE as an administrator of EV incentive programs has experience in implementing these programs, their experience is reflected on their evaluation of the program. Even though CSE is the administrator for the CHEAPR program, the evaluation is written as they are an external entity.

Many EV incentives by states and the Federal government focus on financial relief to lower the cost of purchasing an EV. While this is an important factor and may encourage more people to choose EVs, it can also be seen as another give away to the wealthy. Incentivizing dealers financially or otherwise may also positively affect public perception

of EV incentives as giveaways to the wealthy as well as increase consumer education on available rebates and alleviate the so-called range anxiety at the point of purchase level.

## 8. Conclusion and Recommendations

Automobile is the dominant mode of transportation, it also generates one sixth of the greenhouse gas emissions throughout the world (Potoglou and Kanaroglou 2007). It will be unreasonable to expect people to abandon driving. Public transit has its limitations, and urban development might take decades. Modern life demands mobility, and few things are better at providing that than the automobile. While the automobile may remain essential, contrary to the opinion expressed in Heidrich et. al., we should not make the automobile the center of urban deployment and policy, in order to promote EV acceptance (Heidrich et al. 2017).

According to 2017 National Household Travel Survey, almost half (50.9) of all trips are for the purpose of going home and work.<sup>12</sup> In most parts of Massachusetts over 69% of the people drive to work yet many of those areas have less than half an hour of commute time per figure 22. This combination might create an ideal setting for the use of EVs and might have the biggest benefit in reducing CO<sub>2</sub> emissions in Massachusetts. That being said, many of these areas do not have robust EV sales. This might be explained by the perceived range anxiety by the consumer. Longer drive times, especially the ones over 30 minutes, are likely to steer people away from purchasing EVs. On the other hand of the spectrum shorter commute times, especially the ones under 20 minutes may result in people looking to public transit or alternative transportation such as biking and refrain from driving altogether. People who live in dense neighborhoods by result of self-selection are

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<sup>12</sup> <https://nhts.ornl.gov/vehicle-trips>

less likely to drive however they may also be more sensitive to environmental issues and more likely to choose EV when it comes to automobile purchase.

One of the limitations of this research is that it is done at the zip code level which may be too large to be consistent and the urban density is measured as population density not accounting for nonresidential uses in the urban areas. Future research that might focus on quantitative and longitudinal studies would give us a better understanding of consumer choices when it comes to EVs. Studies that focus on renters and their perception of EVs and whether if they are inclined to choose an EV and if not why. A more qualitative research involving interview with renters in urban areas would give us a better understanding of their mindset and what kind of policies that can be implemented to persuade them to purchase EVs. This research also only looks at the state of Massachusetts which may have different traits than other states. As Massachusetts is one of the more liberal states it is likely to have an environmentally conscious population, however Massachusetts is 11<sup>th</sup> nationally in EV sales. California and Georgia taking the number one and two spots respectively.<sup>13</sup>

From the analysis we can infer that home ownership and average household income are big factors effecting EV demand. While Income and Population have better explanatory factors, they have very small coefficient numbers that any change in these variables may have minimal effect on increasing EV demand. Population, income, and political affiliation may be predictive as individual variables their effect on EV sales, while significant, is seemingly small.

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<sup>13</sup> <https://cleantechnica.com/2017/05/04/us-electric-car-sales-state-whos-1-ohio-california/>

In this research I set out to examine what are the factors effecting EV demand and whether built environment and socio-economic factors are affecting electric vehicle sales. After analyzing all the variables like walkability, population density, commute times I found all these to be statistically significant contributors however their effect on increasing EV sales is still questionable. As a result of this research and reading supporting literature it is difficult to reach a definitive conclusion that built environment has a big influence on the demand for EVs. Socio-economic factors like income, political affiliation and home ownership is also a statistically significant contributing factor and maybe more so than factors in built environment. Income and political affiliation have higher explanatory values than other variables in this research. Given that it was a republican president who created National Park Service and another republican president who created EPA, it is a topic another type of study as to why current republicans are anti-environmentalist. A brief look indicates the retreat started with republican takeover of the congress in 1992 (Jacques, Dunlap, and Freeman 2008) Since than a long and steady shift from supporting environmentalism to embracing anti-environmentalism in search of votes will be outside the scope of this report. Human element remains critical in understanding the demand for EVs. EV rebates which represent EV sales appear to cluster in the areas with high average household income and the analysis shows that income is a statistically significant factor which leads me to believe that price of EVs is a major obstacle in increasing EV demand.

#### Policy recommendations

- Policies centered toward increasing homeownership
- Policies improving charging infrastructure to alleviate “range anxiety” perception
- More accessible and visible charging stations

- Continue financial incentives both for consumers and dealers to make EVs more appealing.

In the future, as more car companies are getting into zero emission market the price of EVs should come down, in the meantime State governments as well as the Federal government needs to continue to support electric vehicles. While build environments effect on EVs or driving in general might not be crystal clear it will be wise to implement policies that make it easier for people to be able to buy zero emission vehicles.

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<https://www.gale.com/doc/1e31248022080?i=1&it=r&id=GALE%7CA248022080&asid=8fac46de87521cc94068465fccd8d7b2>.

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[http://www.transportationandclimate.org/sites/default/files/EVSE\\_Cluster\\_Analysis.pdf](http://www.transportationandclimate.org/sites/default/files/EVSE_Cluster_Analysis.pdf)

## Appendix i: Enlarged Maps from Chapter 6

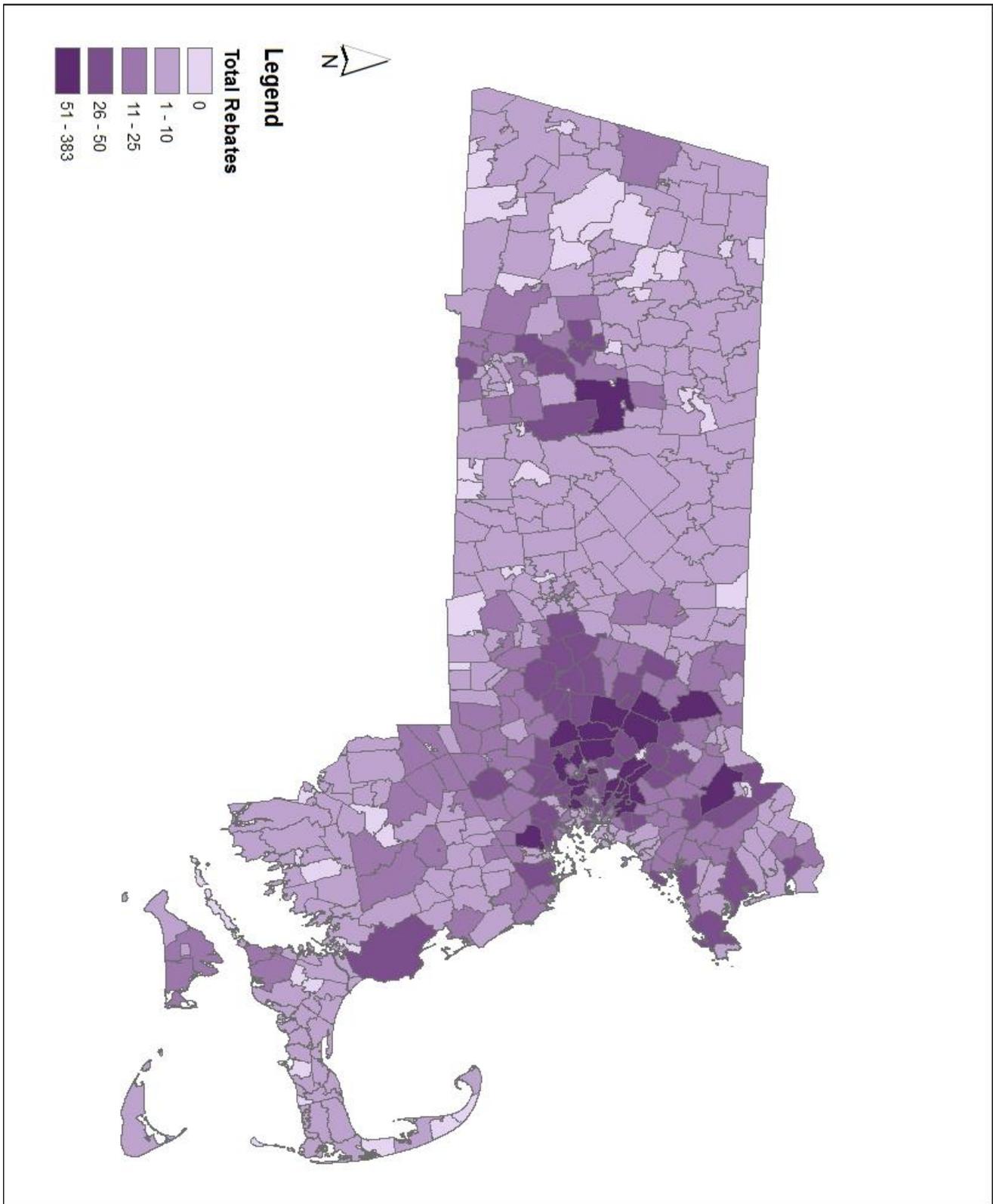


Figure 18: EV rebate concentrations by zip code

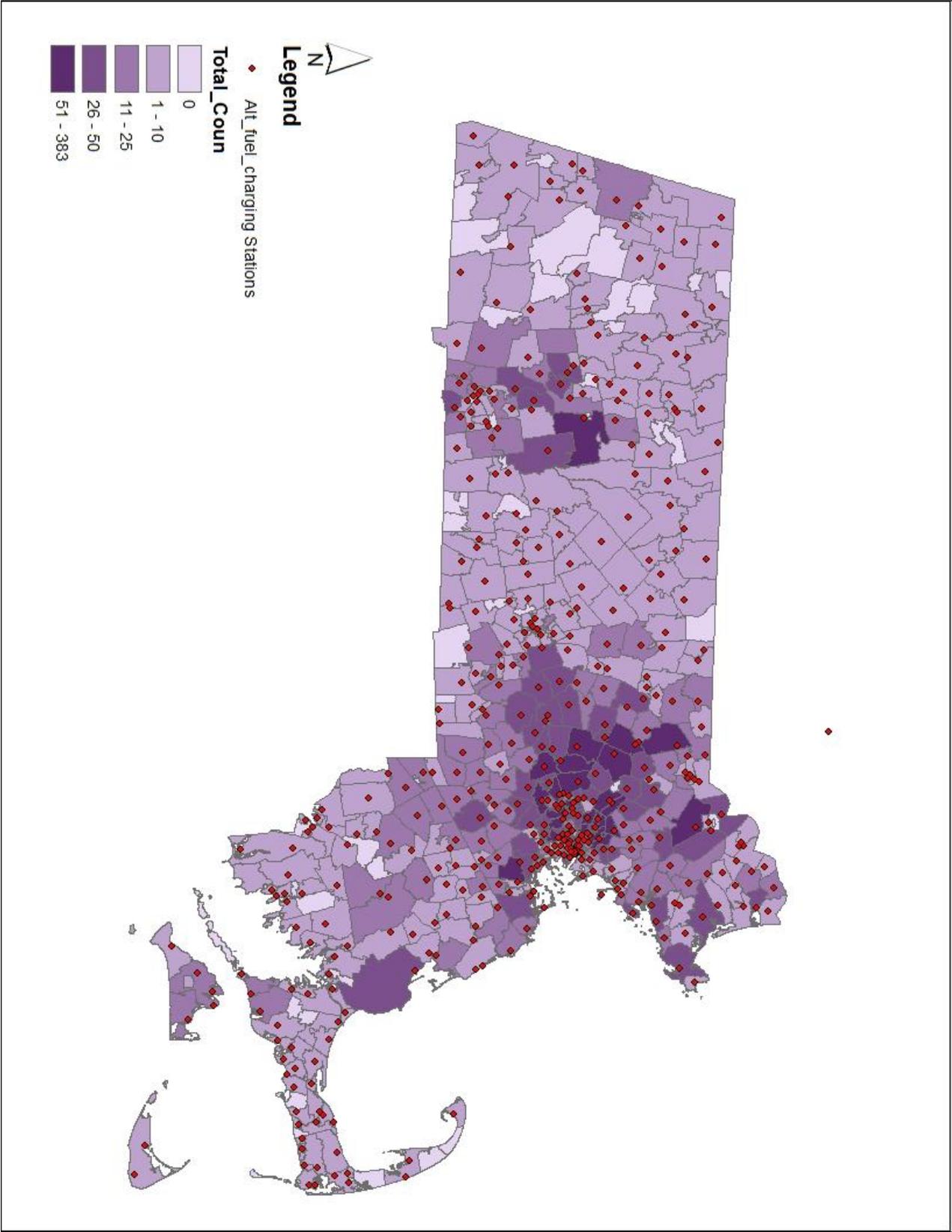


Figure 19: EV rebatet concentration and Charging locations

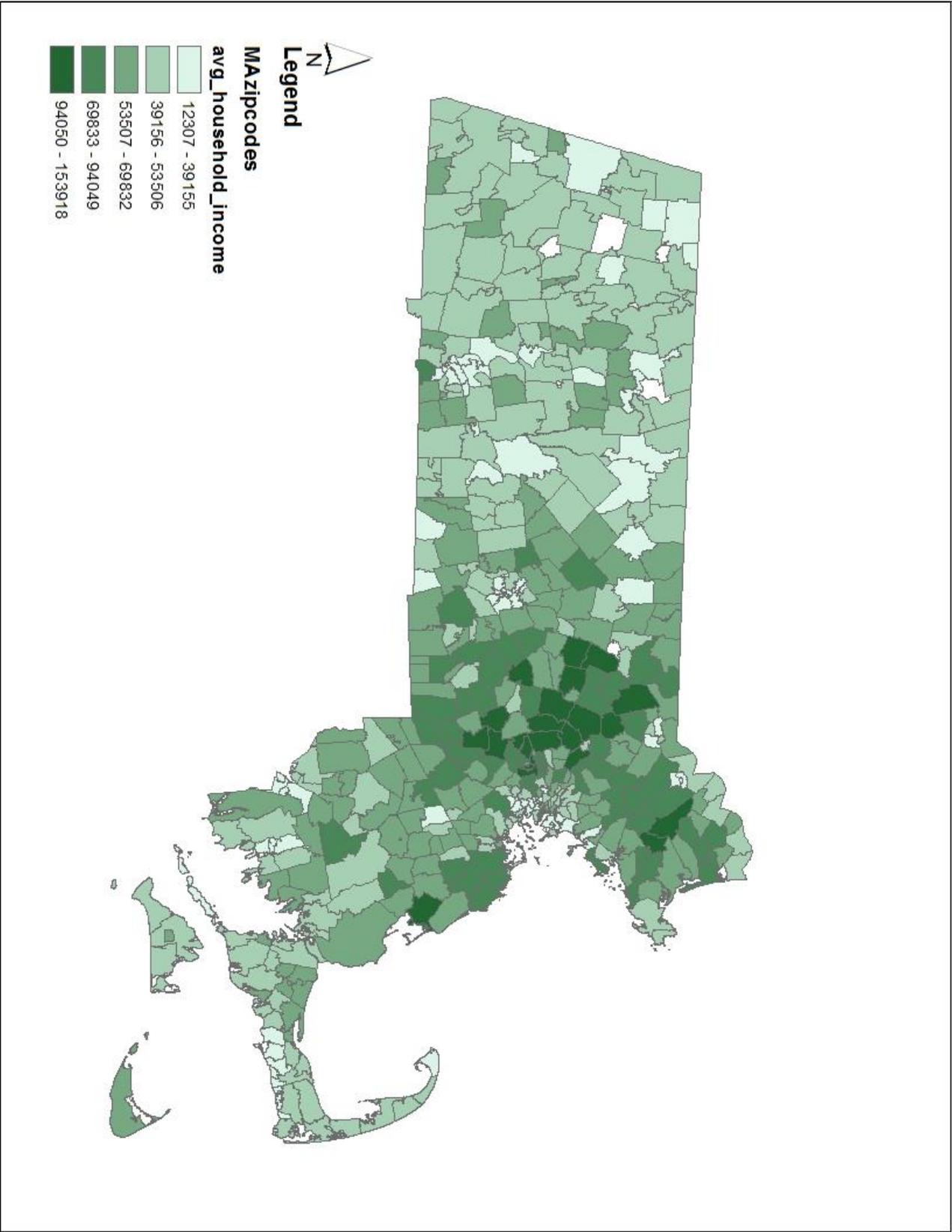


Figure 20: Median Household Income by Zip Code

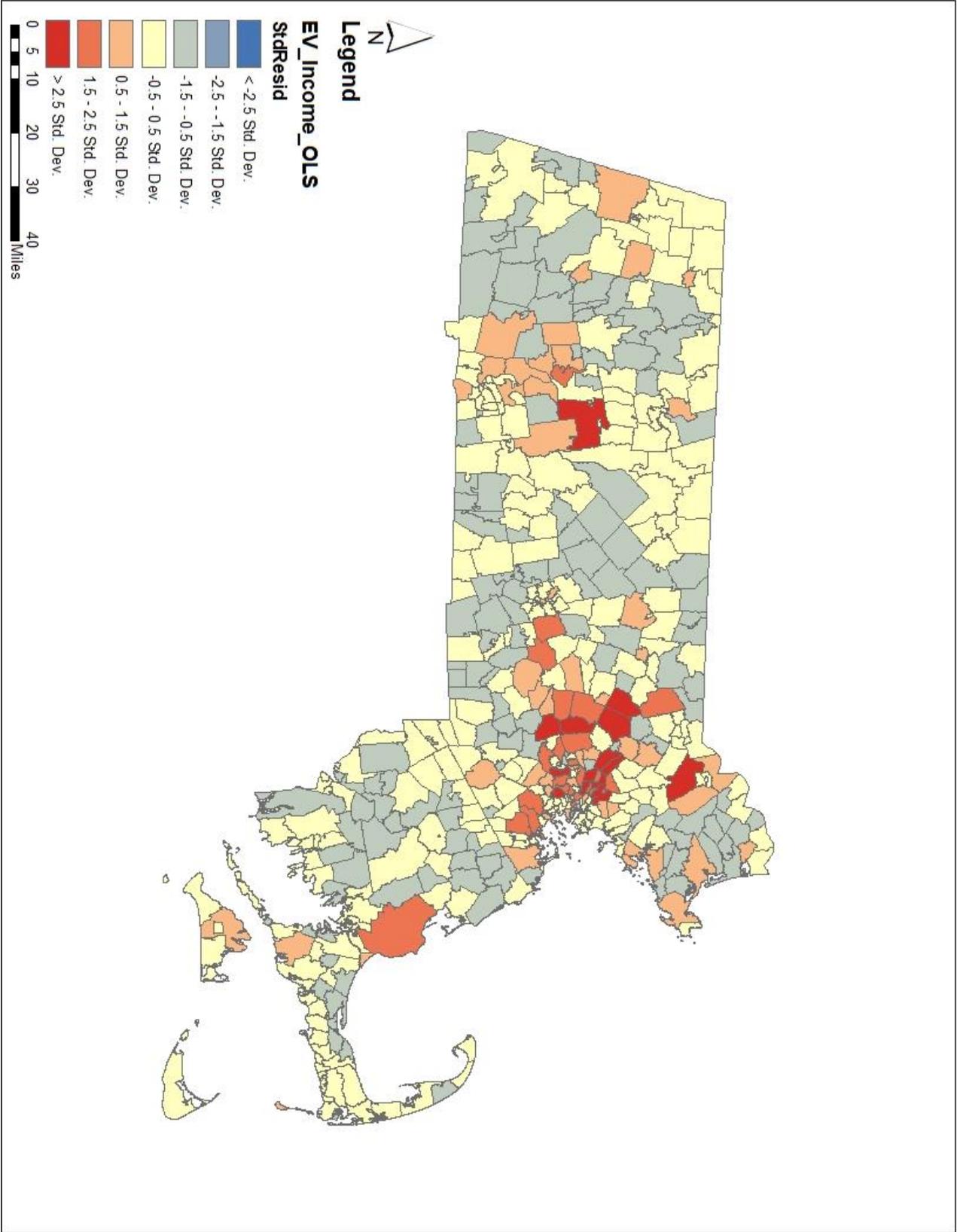


Figure 21: OLS Results of EV rebates and Income

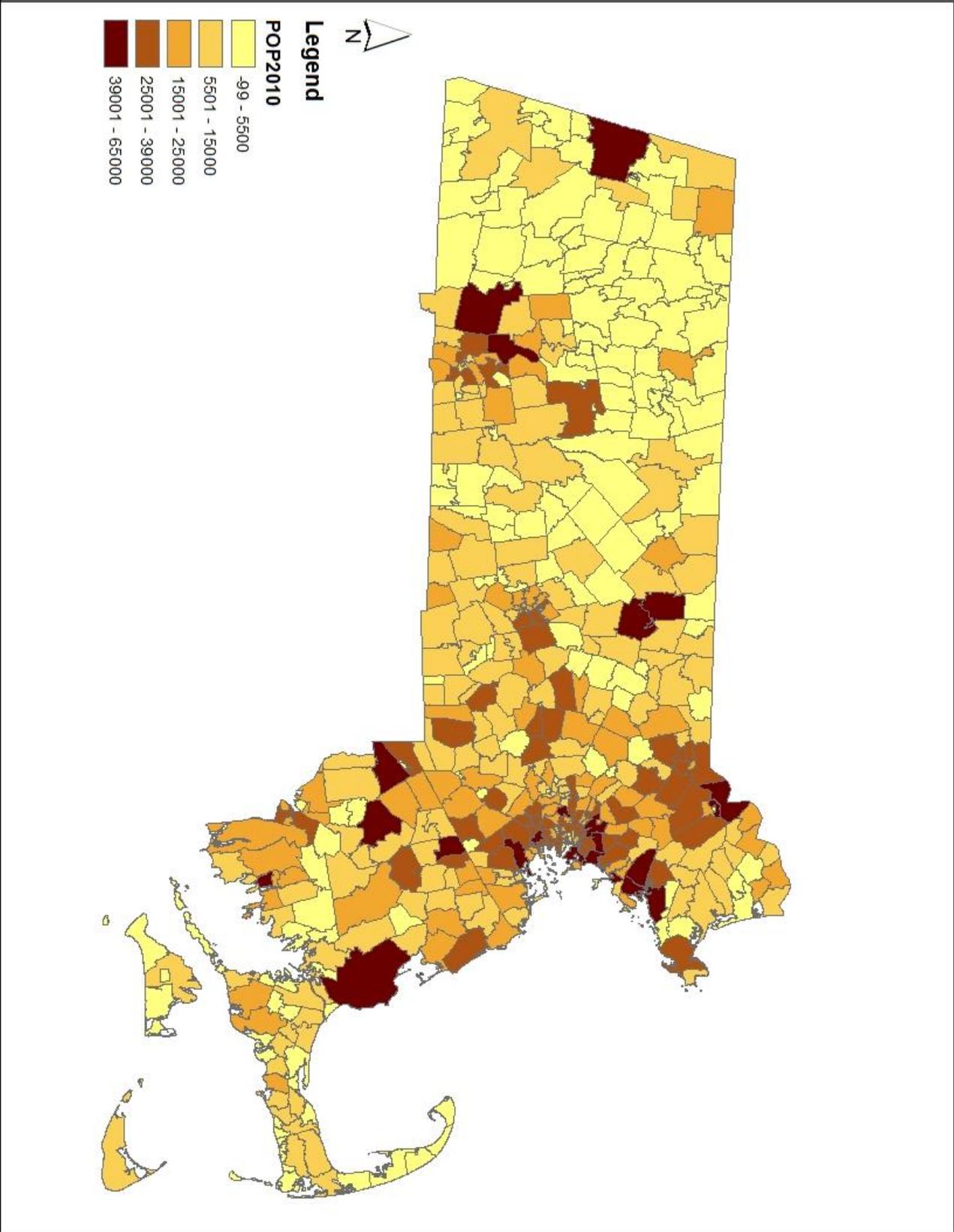


Figure 22: Population by Zip Code

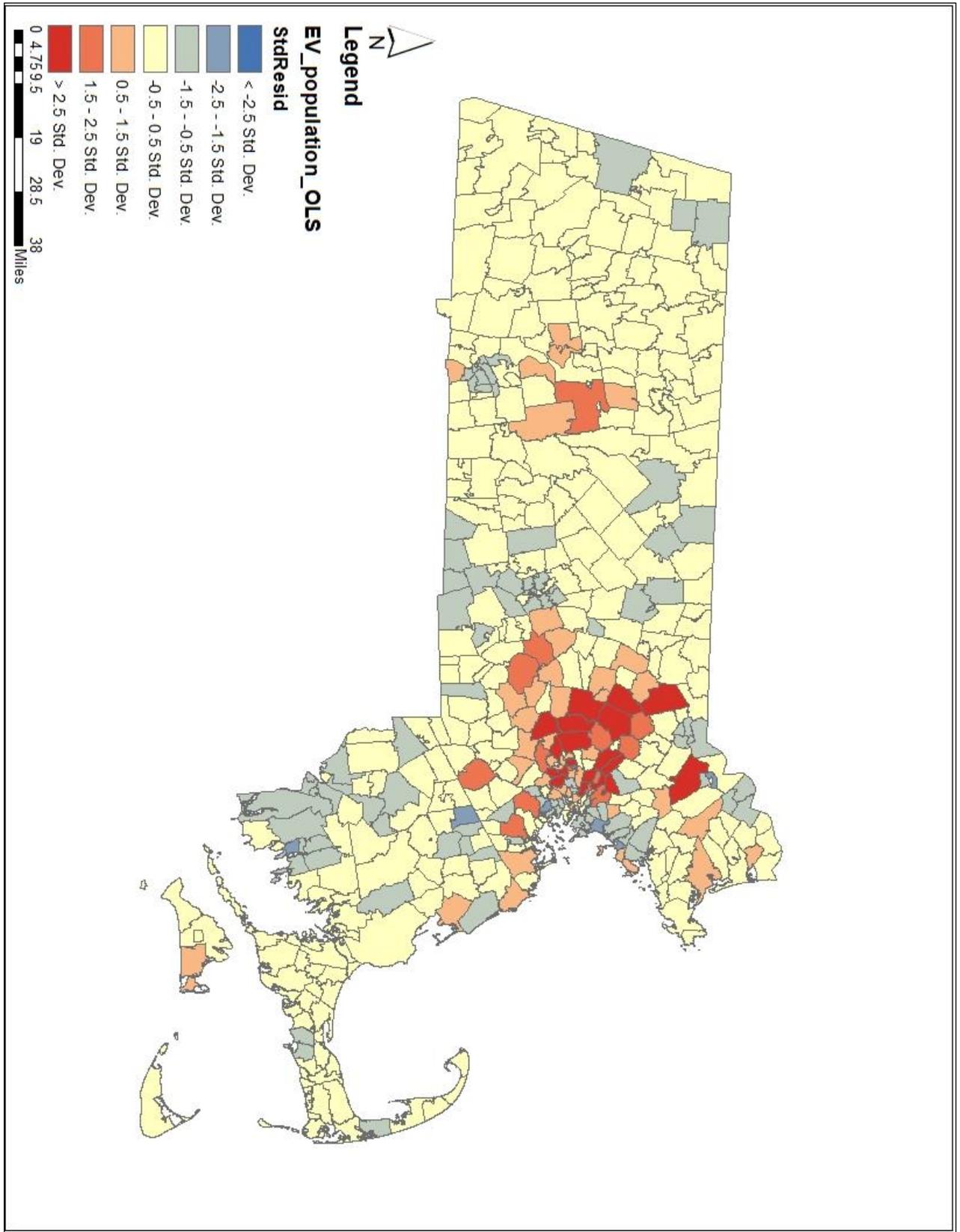


Figure 23: OLS results on EV rebates and Population

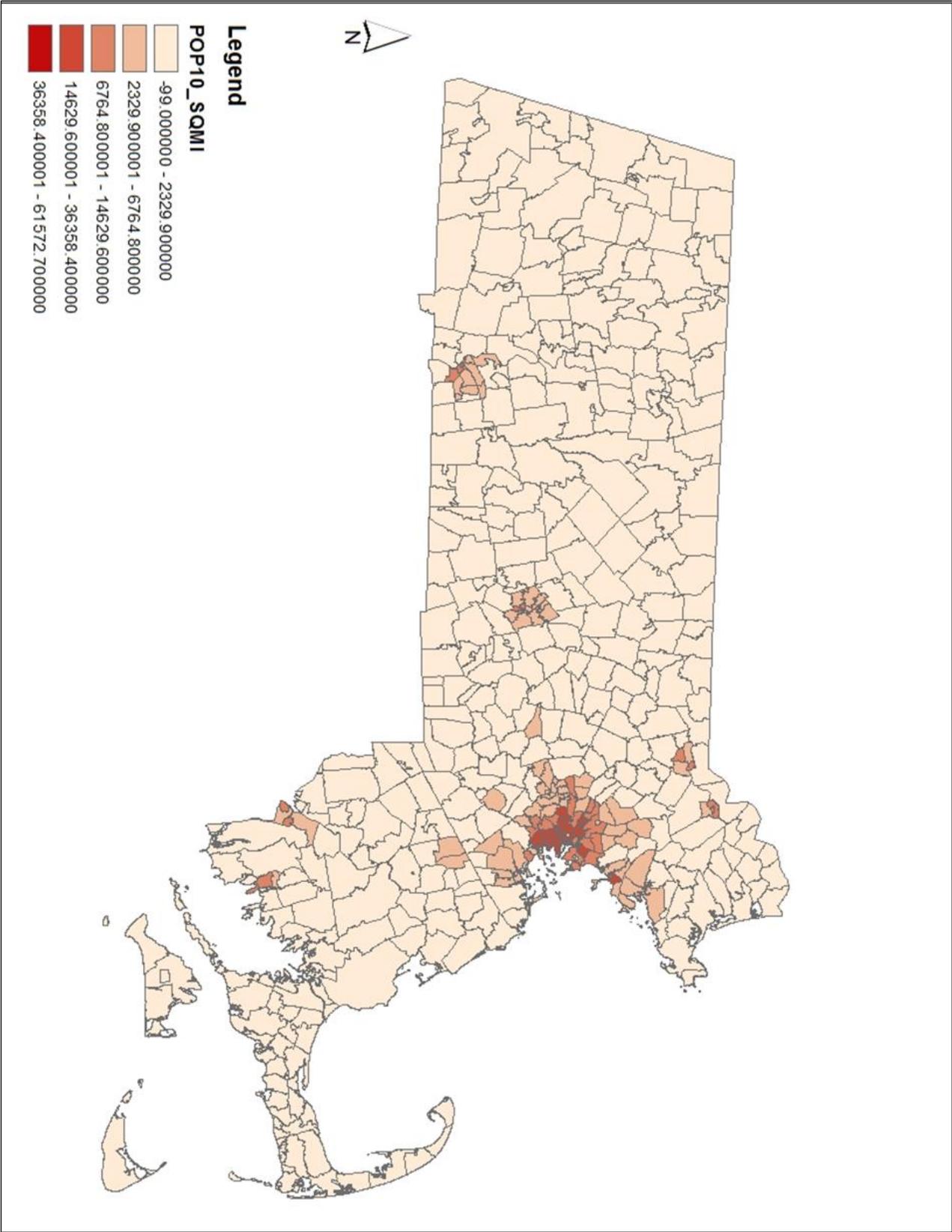


Figure 24: Massachusetts Population Density

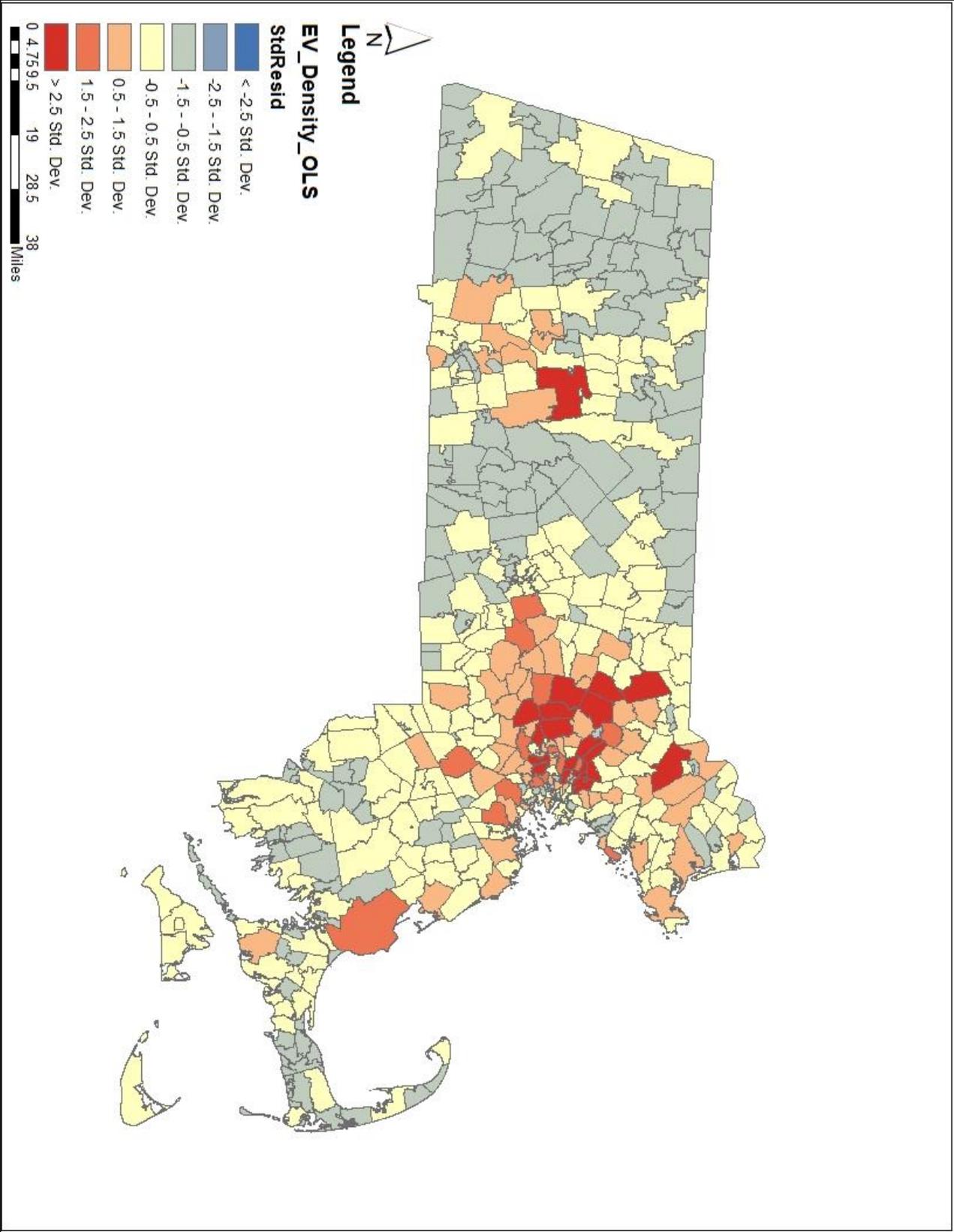


Figure 25: OLS results on EV rebates and Density

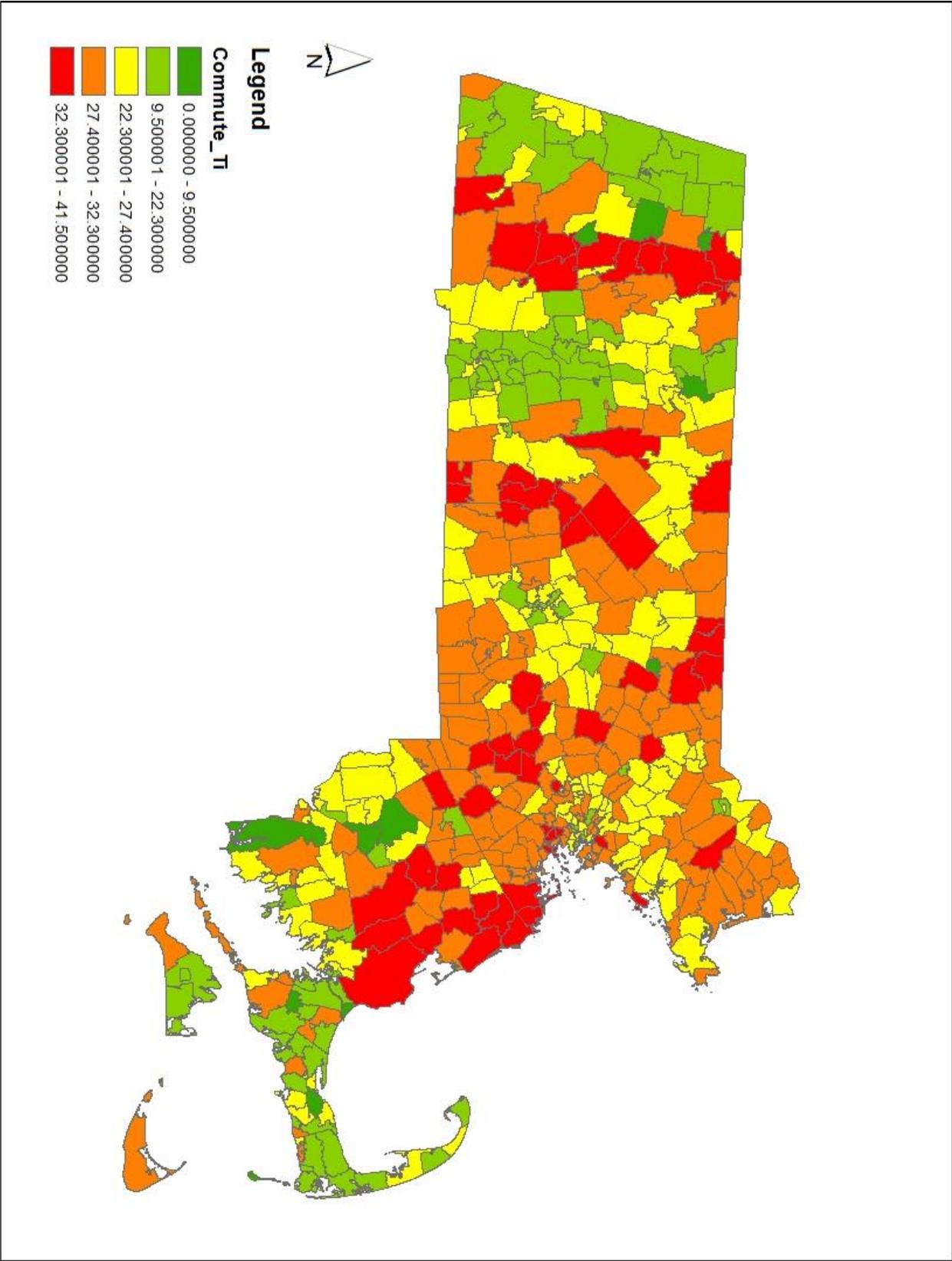


Figure 26: Average Commute times By Zip Code

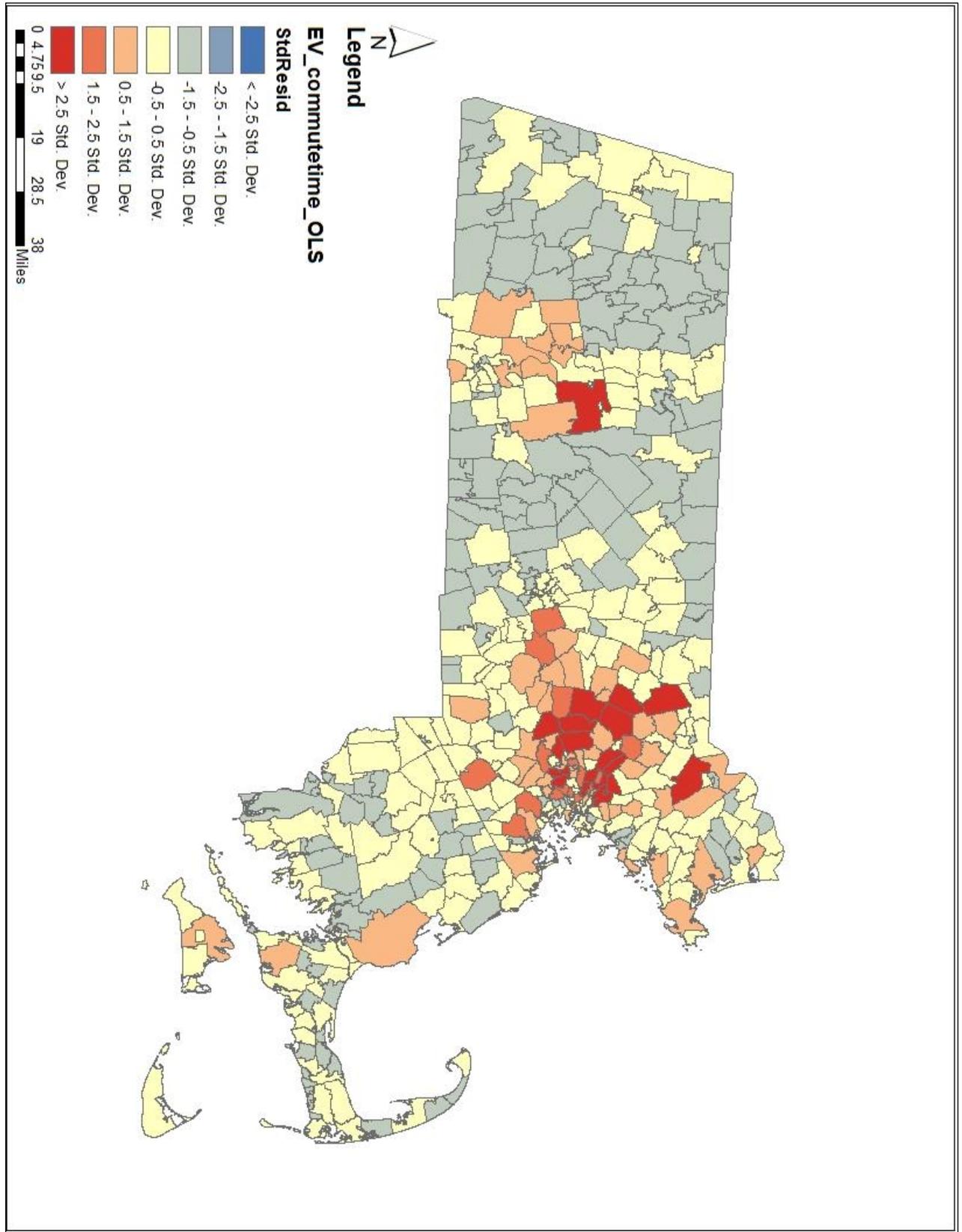


Figure 27: OLS result for EV rebates and Commute time

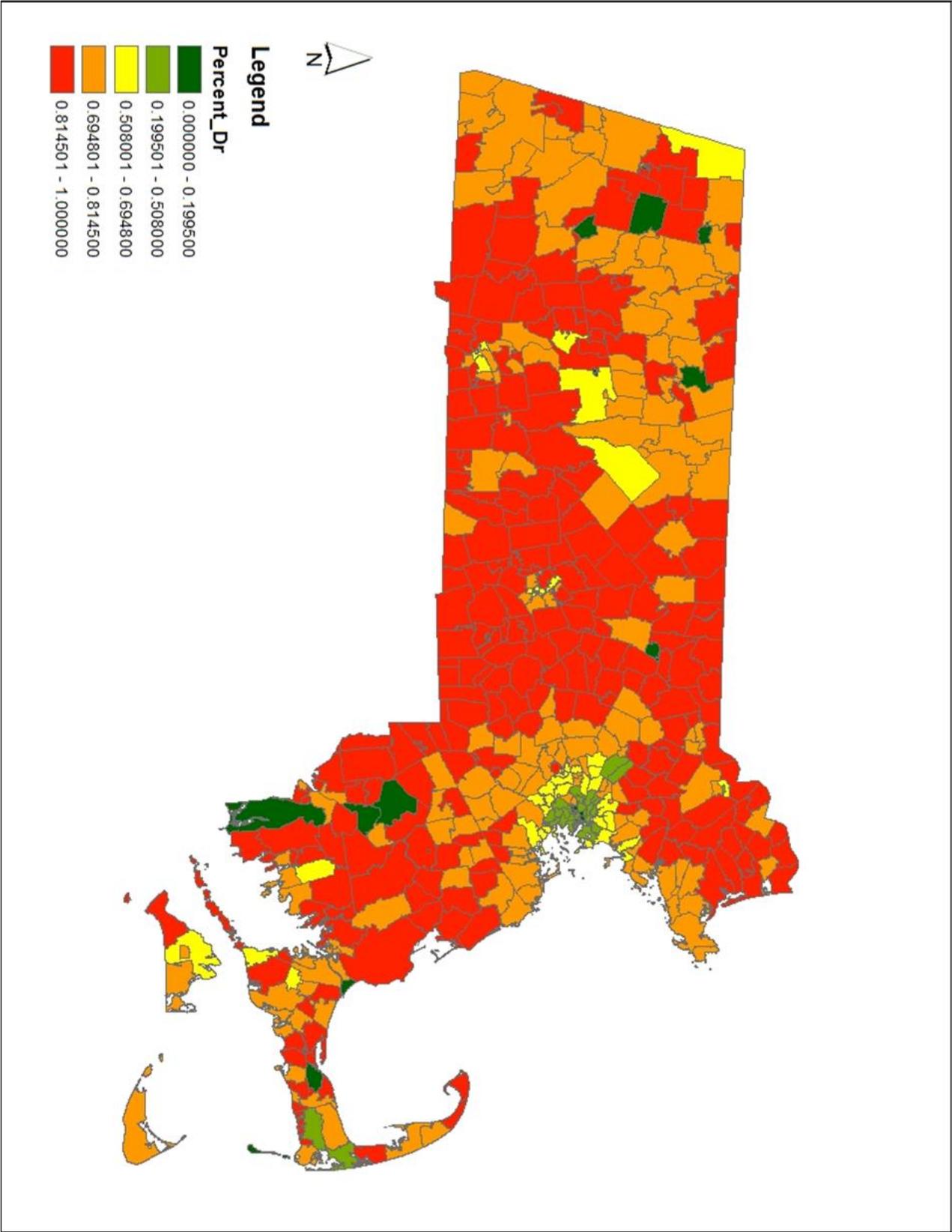


Figure 28: Percentage of People driving to work by Zip Code

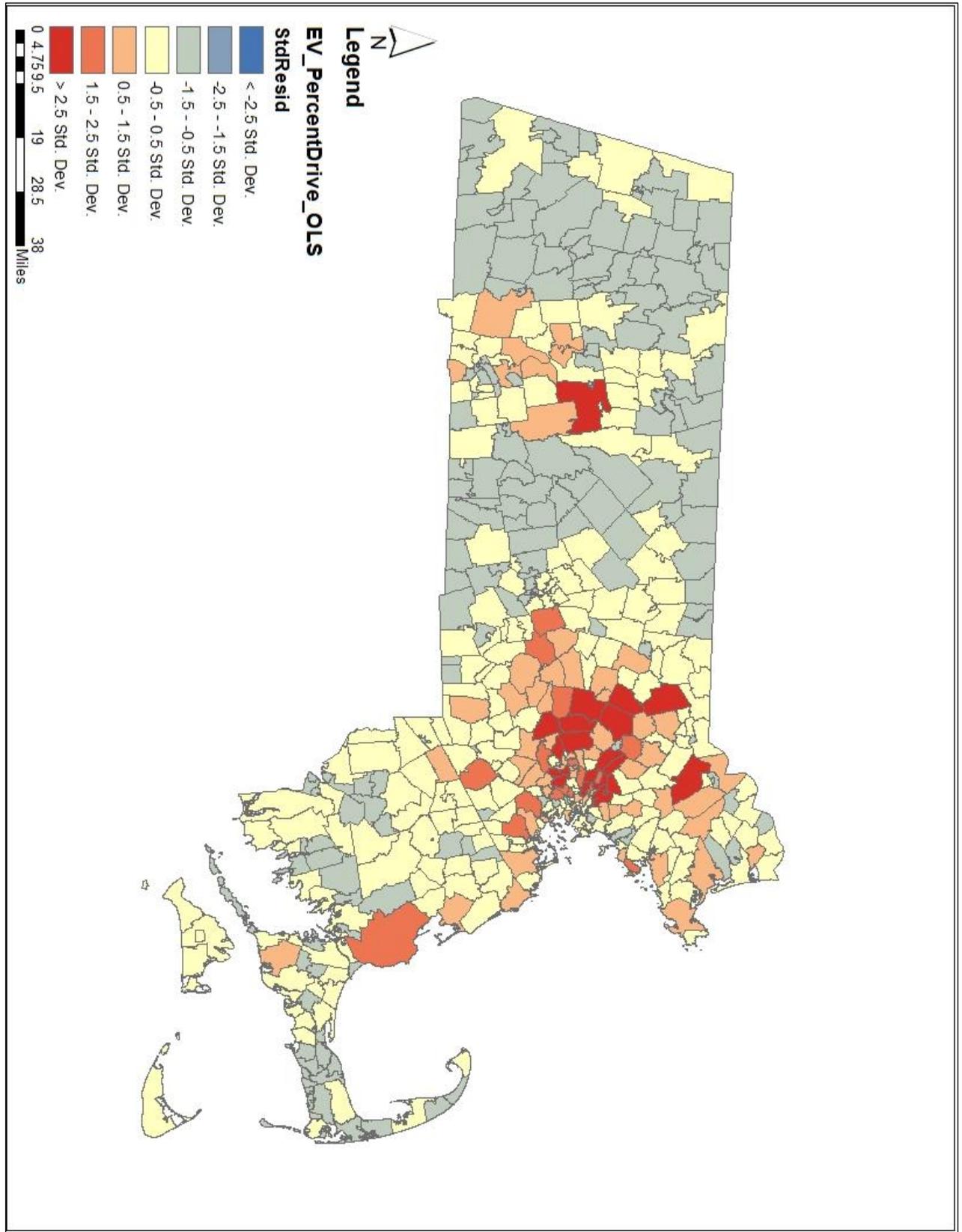


Figure 29: OLS result for EV rebates and Percent driving

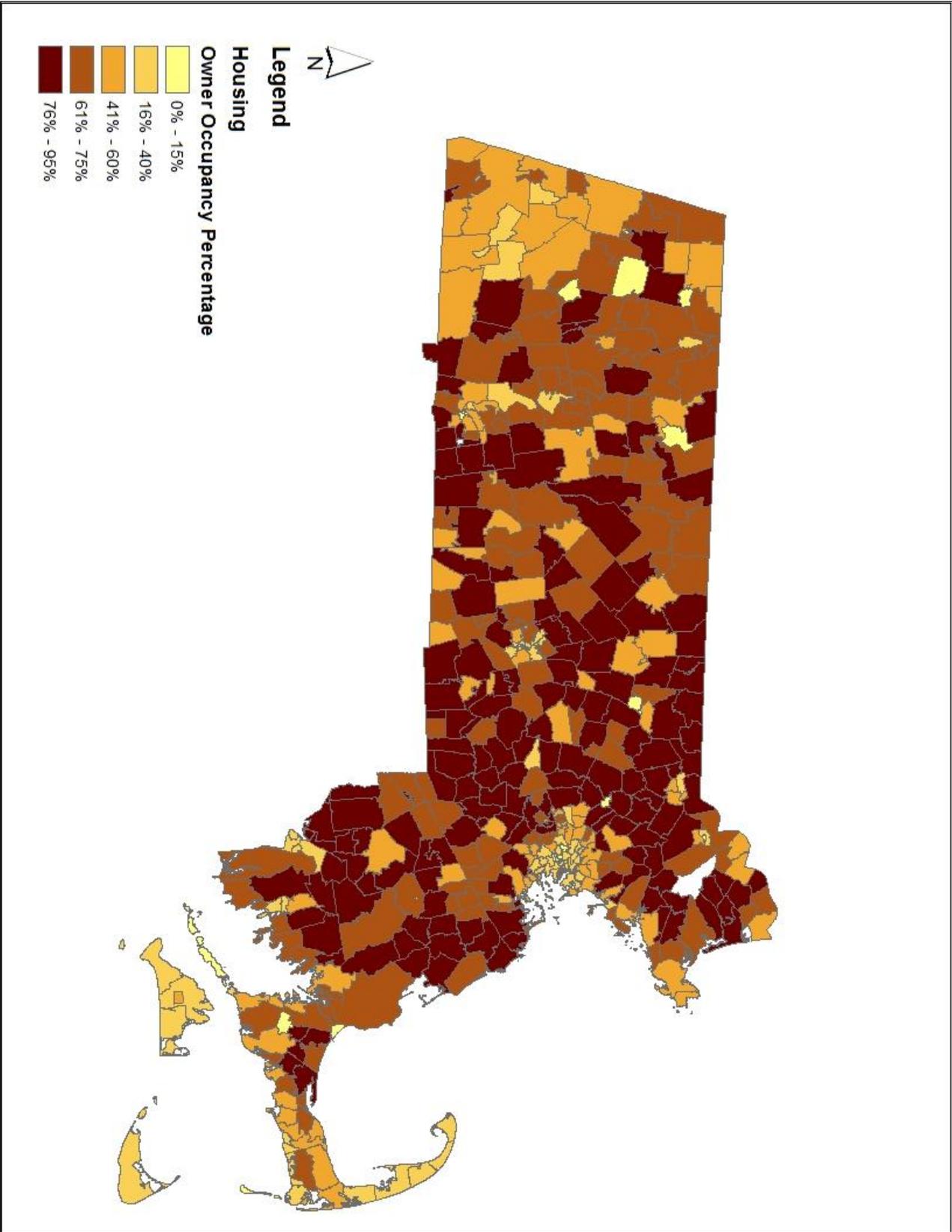


Figure 30: Owner Occupancy percentage by zip code

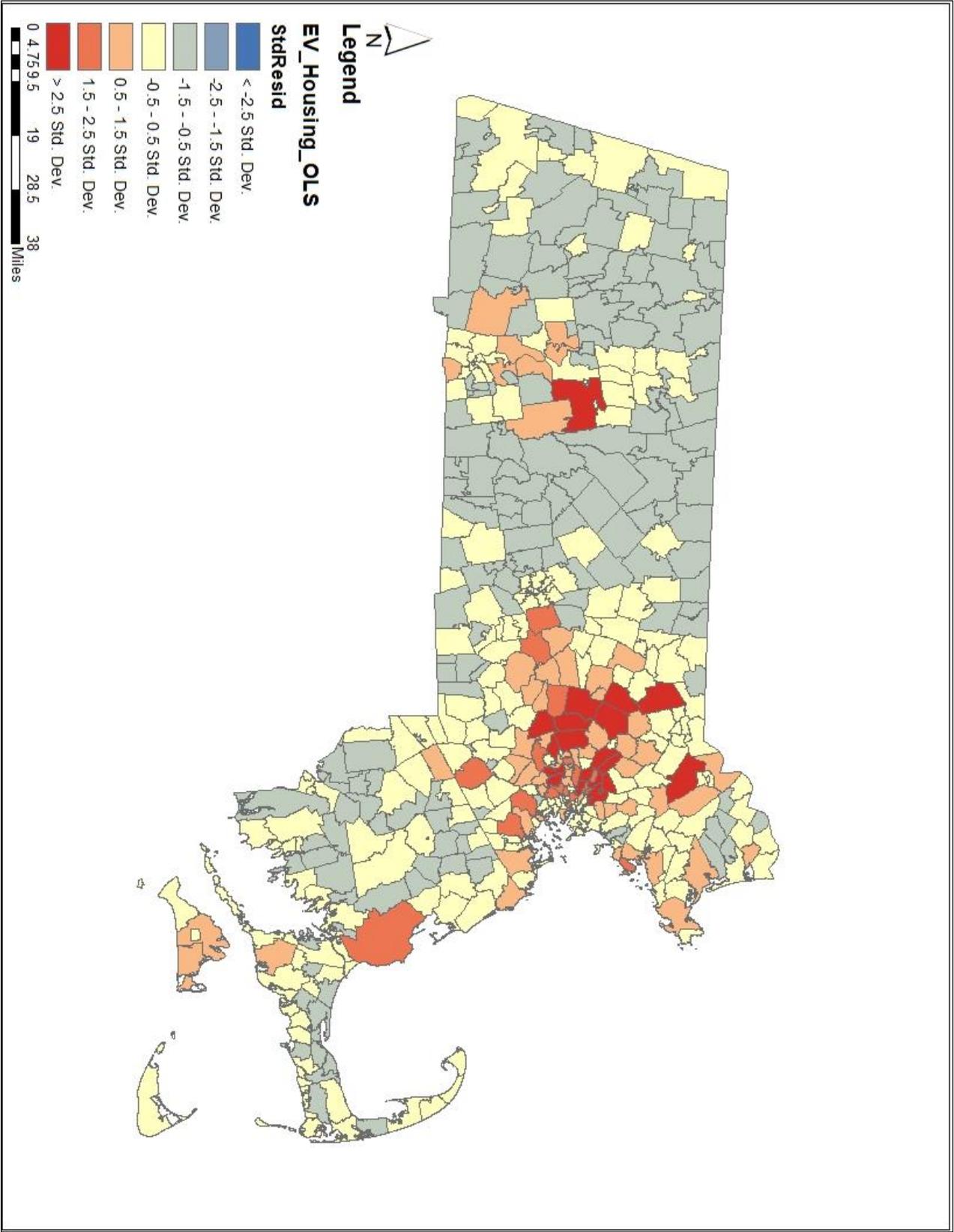


Figure 31: OLS analysis of EV rebates and Home ownership

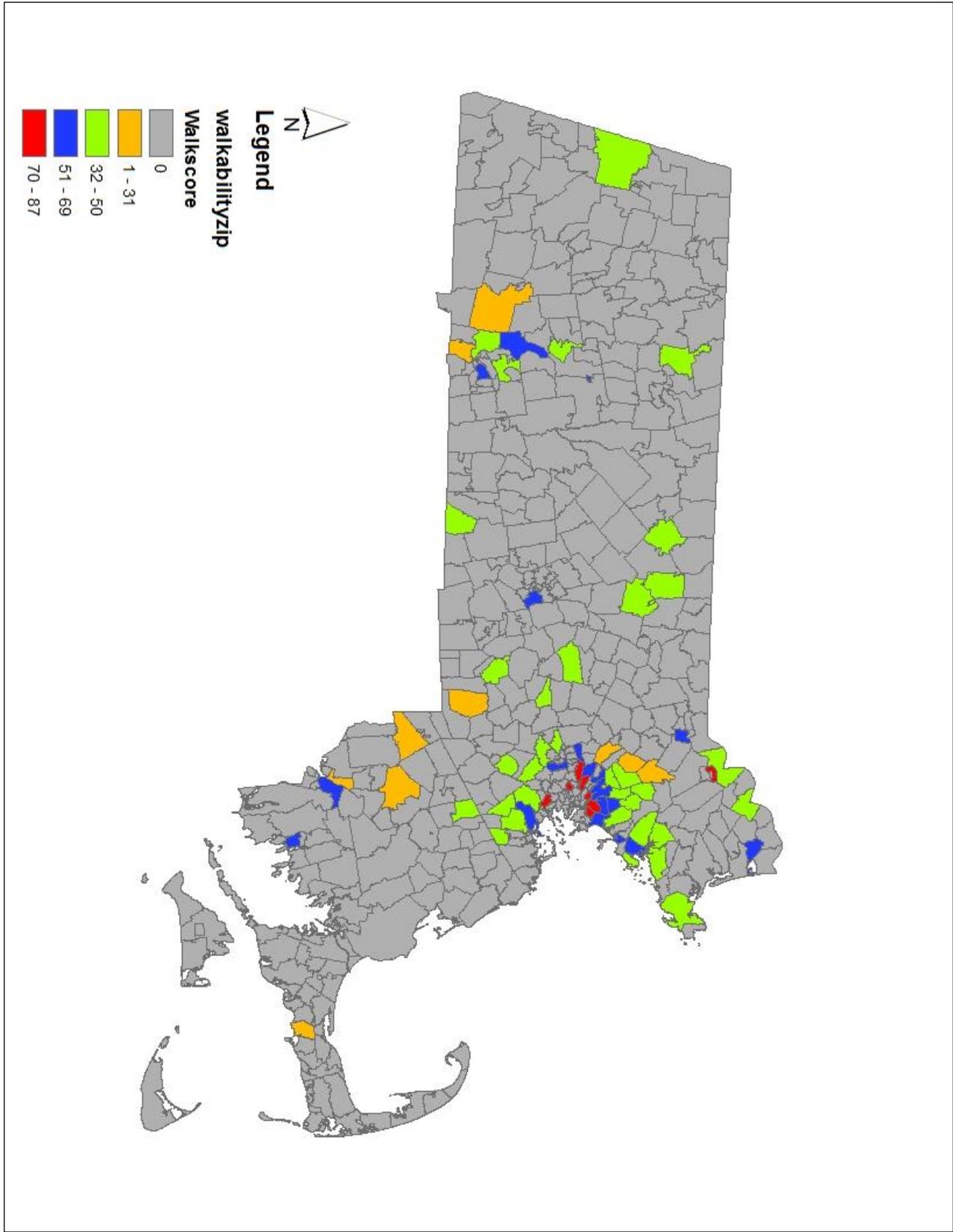


Figure 32: Walk Score by Zip Code

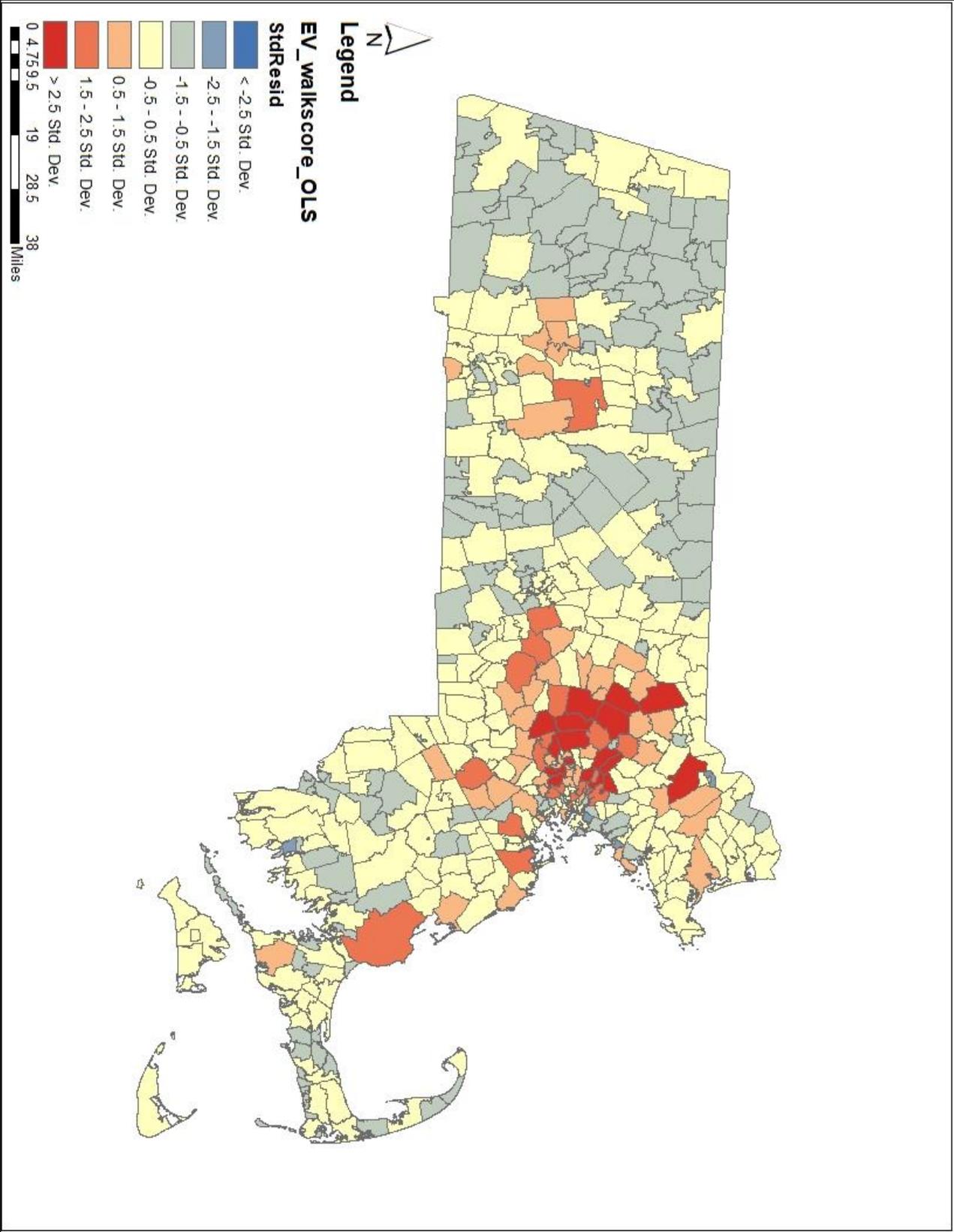


Figure 33: OLS analysis of EV rebates and Walk Score

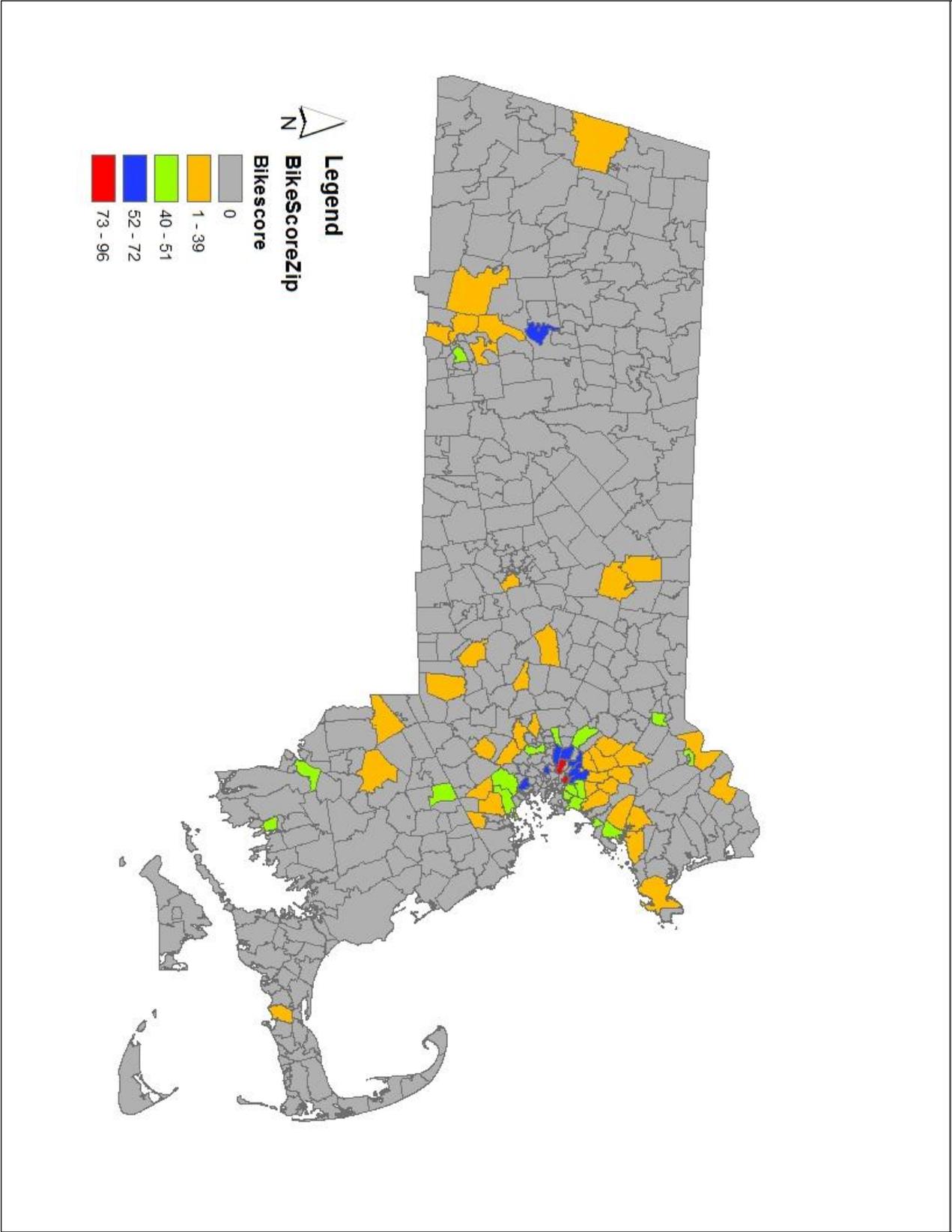


Figure 34: Bike score by Zip Code

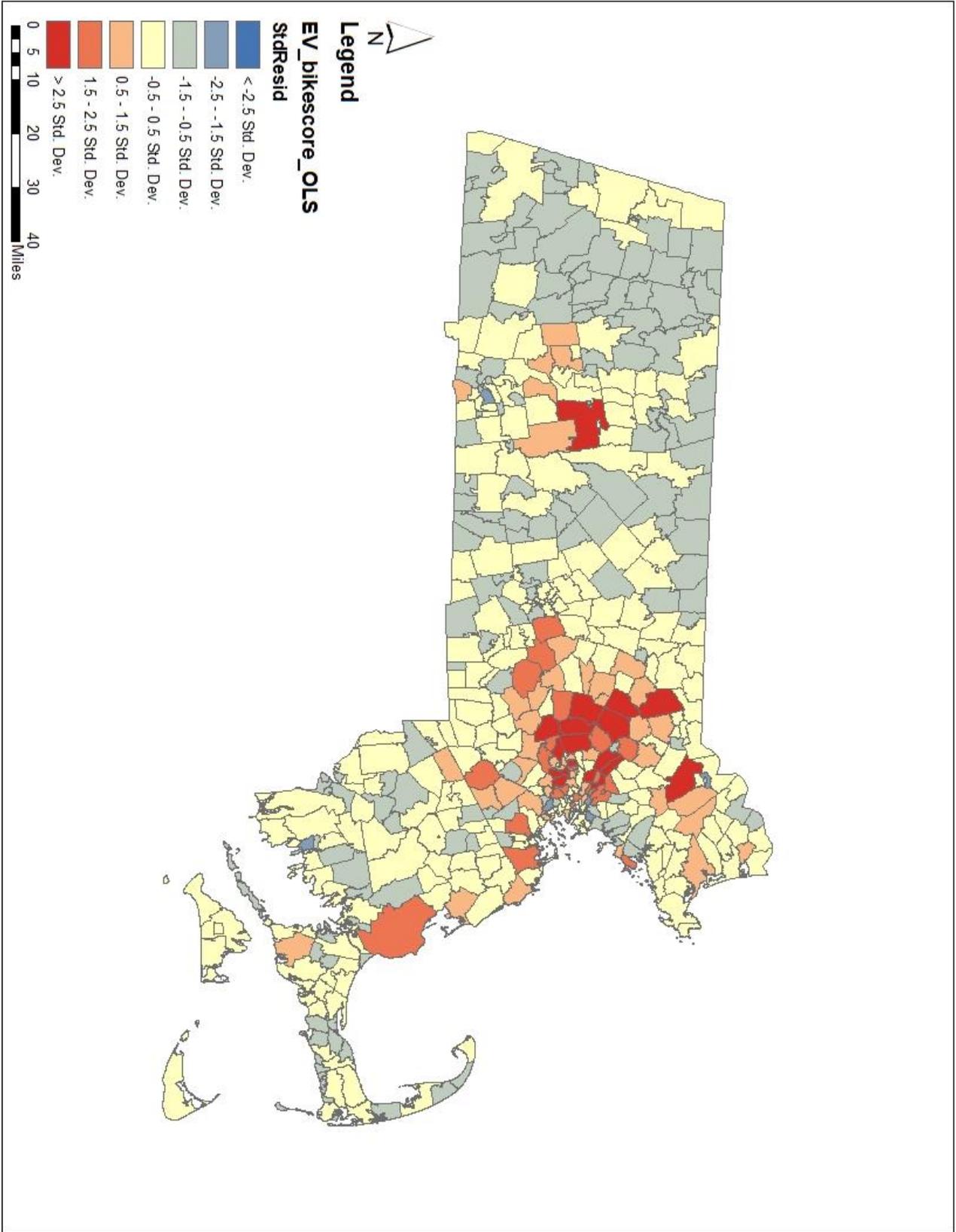


Figure 35: OLS analysis of EV rebates and Bike score

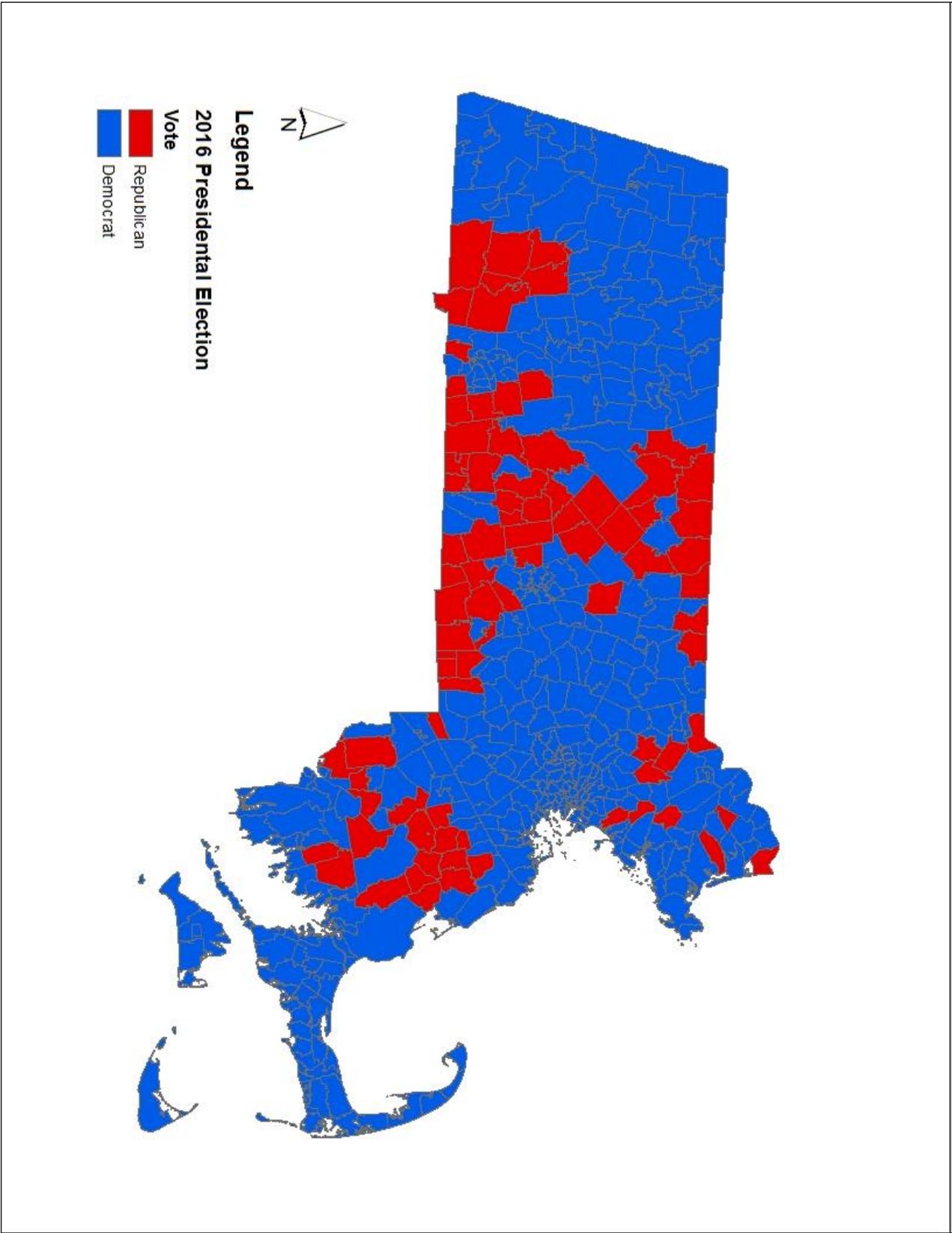


Figure 36: 2016 presidential election results by town

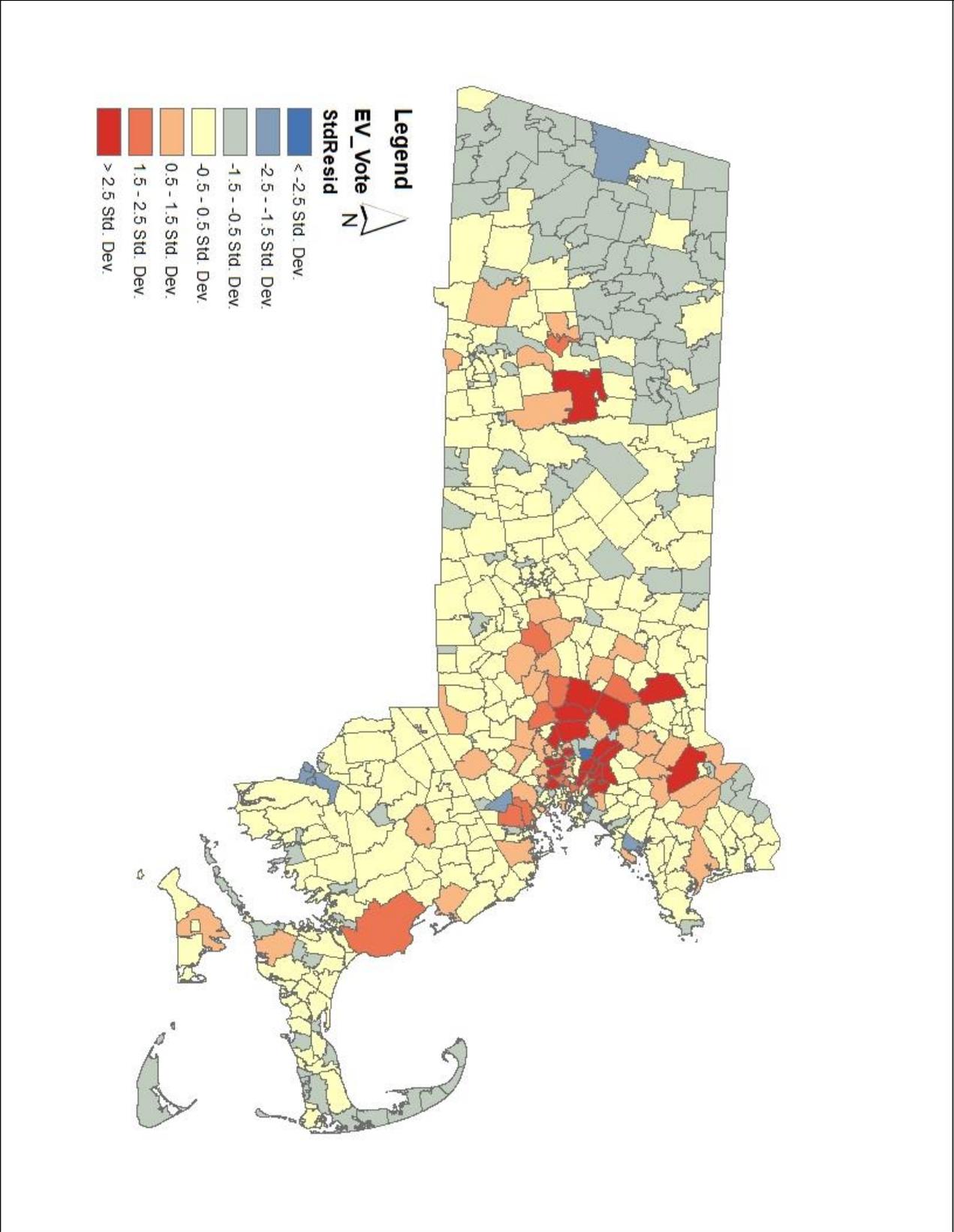


Figure 37: OLS analysis of EV rebates and vote

## Appendix ii: Correlation Matrix

### Correlations

|                        | Population | Percent Drive to Work | Commute Time | Median income | Density | Home Ownership | Walk score | Bike score |
|------------------------|------------|-----------------------|--------------|---------------|---------|----------------|------------|------------|
| Population             | 1          | -.185**               | .022         | -.116**       | .347**  | -.172**        | .654**     | .622**     |
| Percent Drive to Work  | -.185**    | 1                     | .314**       | .262**        | -.707** | .667**         | -.144**    | -.140**    |
| Commute Time           | .022       | .314**                | 1            | .379**        | -.066   | .449**         | -.047      | -.052      |
| Avg household income   | -.116**    | .262**                | .379**       | 1             | -.208** | .622**         | -.094*     | -.050      |
| Ppl per SqMile         | .347**     | -.707**               | -.066        | -.208**       | 1       | -.530**        | .226**     | .217**     |
| Owner Occupied percent | -.172**    | .667**                | .449**       | .622**        | -.530** | 1              | -.168**    | -.139**    |
| Walkscore              | .654**     | -.144**               | -.047        | -.094*        | .226**  | -.168**        | 1          | .920**     |
| Bikescore              | .622**     | -.140**               | -.052        | -.050         | .217**  | -.139**        | .920**     | 1          |

\*\* . Correlation is significant at the 0.01 level (2-tailed).

\* . Correlation is significant at the 0.05 level (2-tailed).

### Appendix iii: Moran's I

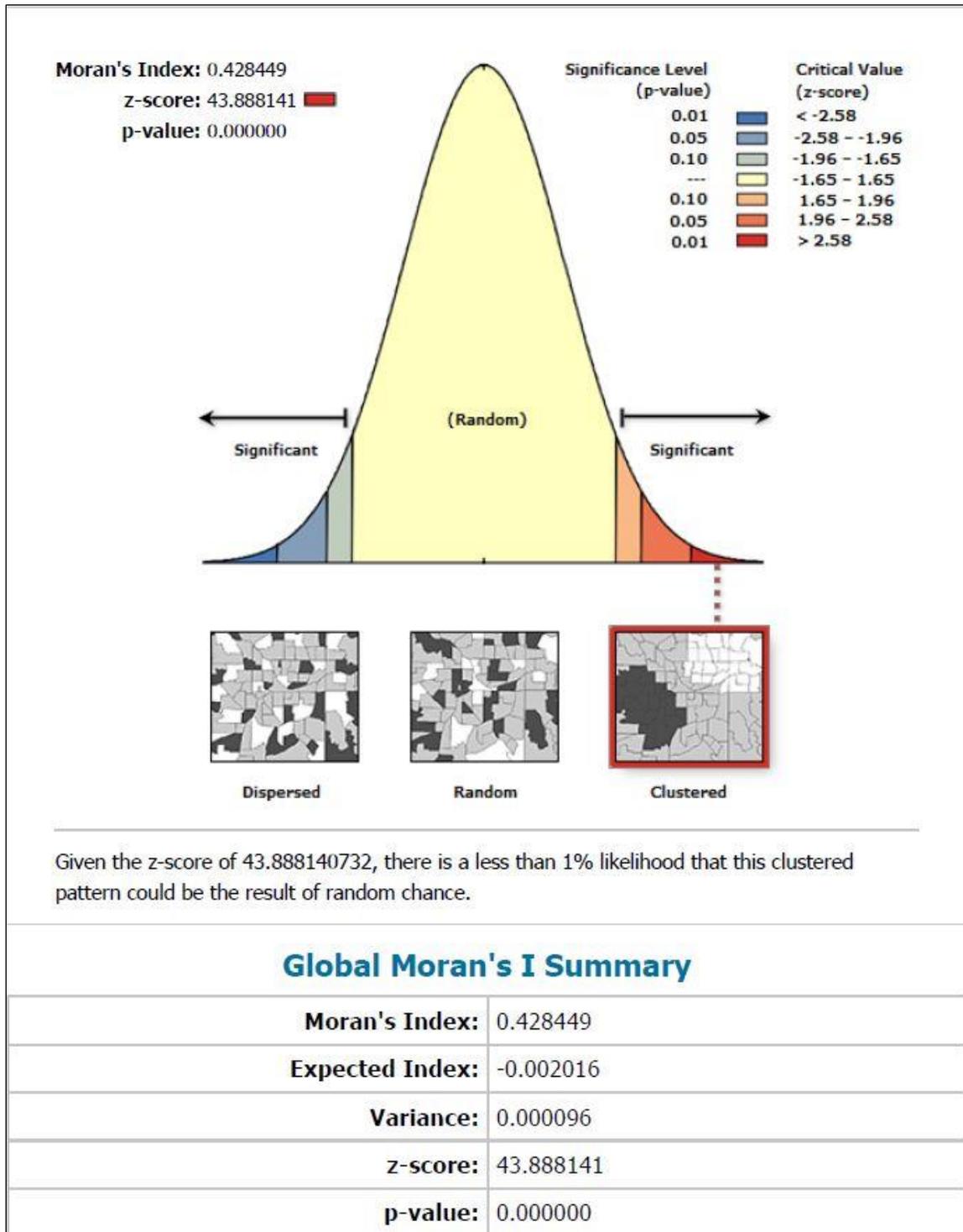


Figure 38 Moran's I for EV rebate clusters

## Appendix iv: Backward Selection Regression Model

| Variables Entered/Removed <sup>a</sup> |  |                   |   |
|--|--|-------------------|---|
| Model                                  | Variables Entered  | Variables Removed | Method  |
| 1                                      | Bikescore,<br>avg_household_income,<br>Percent_Drive_to_Work,<br>Commute_Time, Population,<br>Ppl_per_SqMile,<br>Owner_Occupied_percent,<br>Walkscore <sup>b</sup> | .                 | Enter   |
| 2                                      |  | Walkscore         | Backward (criterion: Probability of F-to-remove >= .100). |
| 3                                      |  | Ppl_per_SqMile    | Backward (criterion: Probability of F-to-remove >= .100). |

a. Dependent Variable: Total\_Evrebates

b. All requested variables entered.

### Model Summary

| Model | R                 | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | Change Statistics |     |     | Sig. F Change |
|-------|-------------------|----------|-------------------|----------------------------|-----------------|-------------------|-----|-----|---------------|
|       |                   |          |                   |                            |                 | F Change          | df1 | df2 |               |
| 1     | .677 <sup>a</sup> | .458     | .448              | 14.167                     | .458            | 46.274            | 8   | 438 | .000          |
| 2     | .676 <sup>b</sup> | .458     | .449              | 14.157                     | .000            | .379              | 1   | 438 | .539          |
| 3     | .674 <sup>c</sup> | .454     | .447              | 14.184                     | -.003           | 2.708             | 1   | 439 | .101          |

a. Predictors: (Constant), Bikescore, avg\_household\_income, Percent\_Drive\_to\_Work, Commute\_Time, Population, Ppl\_per\_SqMile, Owner\_Occupied\_percent, Walkscore

b. Predictors: (Constant), Bikescore, avg\_household\_income, Percent\_Drive\_to\_Work, Commute\_Time, Population, Ppl\_per\_SqMile, Owner\_Occupied\_percent

c. Predictors: (Constant), Bikescore, avg\_household\_income, Percent\_Drive\_to\_Work, Commute\_Time, Population, Owner\_Occupied\_percent

### Coefficients<sup>a</sup>

| Model |                        | Unstandardized Coefficients |            | Standardized         | t      | Sig. |
|-------|------------------------|-----------------------------|------------|----------------------|--------|------|
|       |                        | B                           | Std. Error | Coefficients<br>Beta |        |      |
| 1     | (Constant)             | 3.382                       | 6.332      |                      | .534   | .593 |
|       | Population             | .001                        | .000       | .360                 | 7.421  | .000 |
|       | Percent_Drive_to_Work  | -22.105                     | 7.956      | -.174                | -2.778 | .006 |
|       | Commute_Time           | -.262                       | .151       | -.070                | -1.738 | .083 |
|       | avg_household_income   | .001                        | .000       | .670                 | 13.757 | .000 |
|       | Ppl_per_SqMile         | .000                        | .000       | -.096                | -1.670 | .096 |
|       | Owner_Occupied_percent | -.126                       | .061       | -.134                | -2.062 | .040 |
|       | Walkscore              | -.059                       | .096       | -.058                | -.615  | .539 |
|       | Bikescore              | .168                        | .112       | .137                 | 1.502  | .134 |
| 2     | (Constant)             | 3.359                       | 6.327      |                      | .531   | .596 |
|       | Population             | .001                        | .000       | .353                 | 7.499  | .000 |
|       | Percent_Drive_to_Work  | -22.152                     | 7.950      | -.174                | -2.786 | .006 |
|       | Commute_Time           | -.266                       | .150       | -.071                | -1.767 | .078 |
|       | avg_household_income   | .001                        | .000       | .671                 | 13.803 | .000 |
|       | Ppl_per_SqMile         | .000                        | .000       | -.094                | -1.646 | .101 |
|       | Owner_Occupied_percent | -.123                       | .061       | -.132                | -2.029 | .043 |
|       | Bikescore              | .108                        | .055       | .088                 | 1.958  | .051 |
| 3     | (Constant)             | -2.851                      | 5.088      |                      | -.560  | .576 |
|       | Population             | .001                        | .000       | .338                 | 7.305  | .000 |
|       | Percent_Drive_to_Work  | -14.322                     | 6.382      | -.113                | -2.244 | .025 |
|       | Commute_Time           | -.314                       | .148       | -.084                | -2.125 | .034 |
|       | avg_household_income   | .001                        | .000       | .672                 | 13.788 | .000 |
|       | Owner_Occupied_percent | -.110                       | .060       | -.117                | -1.821 | .069 |
|       | Bikescore              | .109                        | .055       | .089                 | 1.974  | .049 |

a. Dependent Variable: Total\_Evrebates